Do For-Profit Colleges Expand Access to Higher Education? Evidence from Campus Closures

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Abstract:

For-profit colleges educate especially poor and non-traditional students, yet they cost more and yield lower wage gains than public colleges. To evaluate how the for-profit sector shapes economic opportunity, then, it is critical to understand whether these schools expand access to higher education or simply divert students away from public schools. I estimate the rate of substitution across sectors by tracking changes in first-time college enrollment before and after for-profit college closures. Since college exit decisions are endogenous, I focus on the abrupt, nationwide closures of 462 for-profit campuses owned by 11 large chains, leveraging spatial variation in market shares to identify substitution rates to other sectors. Though prior studies conclude that for-profit and public colleges are highly substitutable, I find contrary results using newer data: rates of substitution to public colleges are around 20%, and for-profit closures precipitate large declines in local college enrollment. In evaluating mechanisms, I show that substitution rates are much higher in the minority of counties where public colleges specialize in fields of study similar to those offered by the for-profit sector. Auxiliary evidence from a large community-college grant program further substantiates the hypothesis of differentiation on program offerings. On the whole, my findings show that the for-profit sector does not simply divert students from better colleges, but indeed draws new students into higher education, partly due to its distinctive vocation-oriented programs.

JEL Codes: I23, I24, I28, J24.
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1 Introduction

U.S. college earnings premia are large and tend to grow over the life cycle. Yet the benefits of higher education are unevenly distributed, as students from low-income households attend and complete college at lower rates. Moreover, some college credentials are more valuable than others, with large variation in returns across institutions and programs of study. Here again, low-SES students often miss out on the full benefits of higher education – those who do attend college disproportionately choose low-return options. As the literature on undermatching has documented, this relationship holds even among students academically qualified to attend those higher-quality schools (Hoxby and Avery (2013)).

Nowhere is this pattern more pronounced than in the for-profit college sector. For-profit college students come from significantly disadvantaged backgrounds, even compared to their peers at non-selective public colleges. Yet they pay three times more than community-college students on average and enjoy lower earnings premia (Lovenheim and Smith (2023)). Supply-side factors do not readily explain these sorting patterns, as most community colleges ("CCs") are open-admission, and most for-profit colleges are located near an inexpensive community college.

Consistent with these basic facts are two opposing views of how the for-profit sector shapes access to higher education and economic mobility. If most for-profit students, absent their first-choice college, would have enrolled in a public school, then the for-profit sector may reduce economic mobility by diverting particularly low-SES students from higher-return options (the "diversion" hypothesis). On the other hand, if the students who enroll in for-profit colleges would not otherwise have attended college, then the for-profit sector increases participation in higher education among historically under-represented groups and may narrow income inequality (the "democratization" hypothesis). It is an empirical question which view better characterizes the for-profit sector – in particular, the answer depends on for-profit students' second choices.

The substitution patterns of for-profit students also inform the effects of for-profit regulation. For-profit colleges receive substantial amounts of federal financial aid, but their eligiblity for these funds can be revoked by the Department of Education ("DoE") under so-called gainful-employment ("GE") requirements. DoE has varied the stringency of for-profit regulation substantially over recent years. Greater enforcement during the Obama administration helped precipitate many for-profit college closures over the last decade, and the Biden administration has recently bolstered GE regulations once again. In contrast to policies aiming to improve students' information or lower barriers to entry at public colleges, regulations which restrict students' choice sets may not promote human capital investment among low-SES students if, instead of pushing them toward higher-return colleges, they lead fewer students to enroll in college at all.

Understanding substitution rates across sectors is of fundamental importance both for evaluating the effects of sector-biased policies on the educational prospects of low-SES students, and more generally for interpreting the for-profit sector's role in shaping access to higher education and economic mobility. In this paper, I bring new evidence to bear on this important question, using the abrupt, nationwide closures of hundreds of for-profit chain campuses in response to heightened regulatory scrutiny. I leverage the across-cohort choice-set variation induced by these closures to infer the extent of substitution from closing schools to other sectors. In particular, I compare other sectors' enrollment growth following a chain closure across markets with varying exposure to the closing chain (i.e., with different pre-exit chain market shares).

I begin by modeling first-time college students' enrollment choices as the outcome of a standard random-utility discrete-choice demand model. The model predicts that, following a college closure, other sectors gain market share in proportion to the closing college's pre-exit market share, with coefficients of proportionality equal to the *diversion ratio* to that sector. I derive a simple reduced-form estimating equation which identifies the average diversion ratio to each sector under a variant of the parallel-trends assumption. I also consider a Wald-type estimator which is robust to heterogeneity in diversion ratios across markets.

I find evidence of minimal substitution from for-profit to public colleges: only about 20% of students who would have attended closing for-profit colleges instead enroll in public colleges. Diversion to non-profit colleges and other for-profits is also small. As a result, total local college enrollment declines by about 50-70% of the size of the for-profit closure. This core finding is robust to a variety of alternative specifications. IV estimates of public-sector diversion from the for-profit sector as a whole, rather than from closing for-profits alone, also show about 20% across-sector diversion.

In heterogeneity analysis, I find that substitution rates are much higher in counties where the target sector specialized in programs of study similar to those offered by the closing chain. As these estimates are imprecise, I next turn to an alternative source of variation for evaluating the importance of program-offering differentiation. I estimate the for-profit spillover effects of a $2 billion grant program which expanded CC programs of study in many fields offered by neighboring for-profit colleges. For-profits offering the same field as that of a newly introduced CC program suffer large and persistent enrollment losses, while those offering programs in different fields face negligible enrollment effects. Altogether, these results provide strong evidence that program offerings are a key source of the limited substitution between for-profit and public colleges.

To my knowledge, I am the first to evaluate the enrollment effects of the large national for-profit shutdowns which impacted hundreds of thousands of students across the U.S. over the last decade. My work complements two recent white papers describing how these closures impacted displaced students (Burns, Brown, Heckert, Weeden, Kim, Randolph, Pevitz, Karamarkovich and Causey (2022); Burns, Bryer, Brown, Heckert and Weeden (2023)). Beyond offering new evidence that many for-profit students do not readily substitute to public alternatives, I provide some of the first causal evidence that for-profits' distinctive program offerings are a key source of differentiation. My results help characterize the unique preferences of a set of students whose behavior has at times puzzled researchers. My findings are at odds with most prior literature, which generally concludes that public and for-profit colleges are close substitutes – using different instruments and data from earlier periods.

Cellini (2009) shows that the passage of CC bond referenda in California both diverted students from for-profit colleges and induced for-profit exit. Similarly, Chung (2012) finds that CC tuition variation matters for for-profit enrollment, and Goodman and Volz (2020) provide evidence that declines in state appropriations for public colleges over 2000-2010 increased for-profit enrollment without impacting total college enrollment. In the paper perhaps most similar to mine, Cellini, Darolia and Turner (2020) show that DoE sanctions against for-profits induced 60-70% diversion to public colleges, though their sample of Pell students from the 1990s likely differs in important ways from my setting of college closures between 2014-2018. Departing from these studies, Soliz (2018) does find low rates of substitution, using the *entry* of many for-profit colleges from the early 2000s through 2012, when many of the modern for-profit chains were started. She finds that CC enrollments remained steady following for-profit openings, though entry may be endogenous due to for-profits' strategic timing and location choices in response to local college demand shocks. More recently, Armona and Cao (2024) estimate a college demand model that also delivers low diversion ratios between two-year for-profits and community colleges.

Some of the disagreement in this literature may owe to the widely varying settings at play. In general, how students substitute among colleges in their choice sets depends on the features of all colleges and the distributions of student preferences and characteristics, all of which vary over time and space. For instance, Cellini et al. (2020) employ a strong research design for evaluating for-profit diversion from sanctioned colleges in the 1990s, but since then the for-profit sector has undergone dramatic structural changes, with a huge wave of net entry leading up to the Great Recession followed by more than 1,500 campus closures since 2010. In addition, state support for public colleges has gradually eroded over the last two decades. These shifts may help explain differences between Cellini et al. (2020) and Soliz (2018), for example.

Another source of disagreement in prior research appears to stem from the use of different instruments to identify LATEs for different complier groups. For instance, Cellini (2009), Chung (2012), and Goodman and Volz (2020) test for substitution using changes in public-college characteristics, which will deliver LATEs among marginal for-profit students who have especially strong preferences for those characteristics. On the other hand, Soliz (2018) and Cellini et al. (2020) mostly employ choice-set variation. Similarly to Cellini et al. (2020), my approach promises to overcome these issues of interpretation by tightly linking reduced-form results to a model of college choice, which gives clearer meaning to the size of estimated substitution effects and connects results more directly to policy-relevant questions. Rather than test for substitution or no substitution, I will estimate the extent of substitution and benchmark results to the predictions of a generic demand model.

Building on the work of Conlon and Mortimer (2021), I further show that the college-closure variation I leverage delivers a well-defined ATT parameter, rather than a LATE with an unknown complier group. My diversion estimates will represent the average substitution rates among all the for-profit chain students, both marginal and inframarginal. This is the relevant population for understanding the overall substitutability of the chain for-profits with other sectors, and my estimates are therefore particularly informative about the effects of large structural shifts in the sectoral composition of college supply. Additional such changes may be on the horizon given DoE's recent revival of GE policies intended to further restrict the for-profit sector. Still, the closing chain colleges I study may differ meaningfully from the rest of the for-profit sector, so I will compare these groups on their observable characteristics and the features of the markets they serve.

I begin by reviewing the data and institutional setting in Section 2, including the policy environment governing for-profit colleges and the pattern of for-profit chain closures. To develop hypotheses about potential sources of sector differentiation, I next provide descriptive statistics comparing student and college characteristics across sectors (Section 3). Section 4 then lays out a general college-choice model, derives reduced-form estimating equations, and describes how they are identified and estimated from for-profit chain closures. Section 5 presents estimated diversion ratios, followed by evidence in Section 6 on the importance of program-of-study differentiation as a mechanism for limited substitution. I then present robustness checks and consider the external validity of my results in section 7, before concluding with a discussion in Section 8.

2 Data and Institutional Setting

2.1 Data Sources

I combine institution-level data from two sources, both maintained by the National Center for Education Statistics ("NCES"). The first is a complete enrollment panel of Title-IV-eligible colleges spanning 2005 to 2019, sourced from the DoE's Integrated Postsecondary Education Data System ("IPEDS"). The second is a complete panel of Title-IV-eligible college campus closures between 2010 and 2019, maintained by the Postsecondary Education Participants System ("PEPS").

I match campus closure data to the enrollment panel at the UNITID level, identifying more than 1,500 closures between 2010 and 2019. Although closures are reported at the OPEID level, which can be more granular than UNITID identifiers, all of the chain campuses which I identify link each campus to a single UNITID identifier, so that I can observe campus-specific enrollment. To identify the campuses of closing chains, I use media reporting from various online news publications, combined with IPEDS data about college ownership and the listed institution names of different campuses, as well as the campus-level first-year enrollment series.

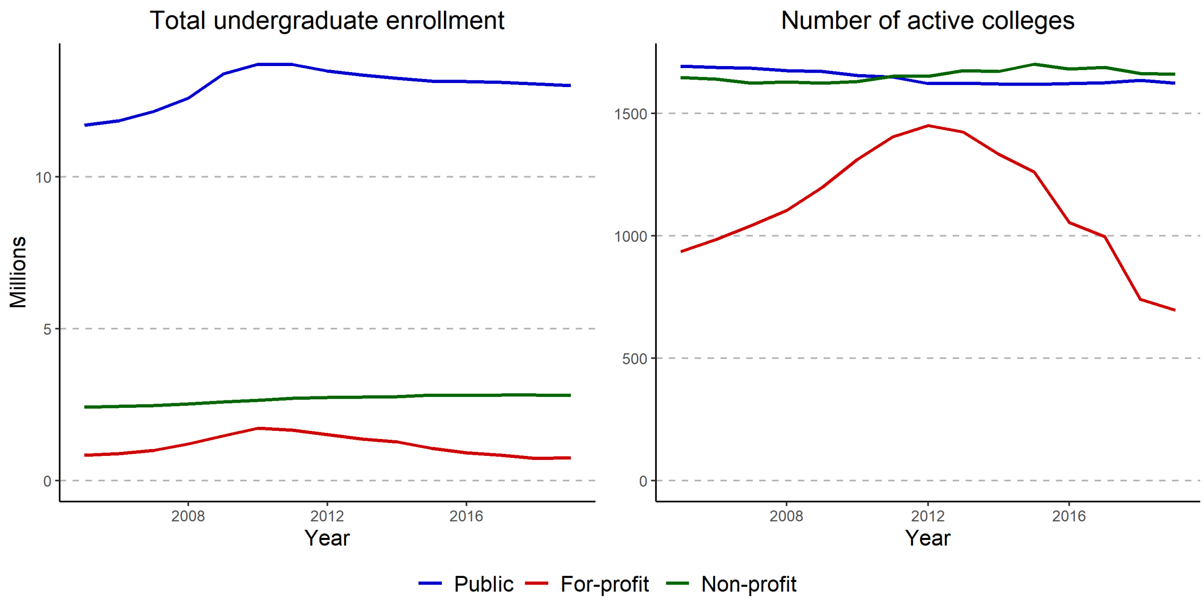
Beyond enrollment, I take several other key variables from IPEDS, including each campus' county, sector, and admissions rate (for defining the non-selective sample). For my analysis, I need annual data on *new* enrollment, as my research design compares college choices of successive cohorts of incoming college students facing different choice sets. For this purpose, I use the count of first-time, full-time, first-year, degree-seeking undergraduates.

In order to characterize demographic patterns across sectors in Section 3, I pull descriptive statistics from the 2016 and 2018 editions of the National Postsecondary Student Aid Study ("NPSAS"), which is an individual-level nationally representative administrative dataset of U.S. college students. The 2016 edition also contains a survey component for a small fraction of the sample.

2.2 Institutional Features

The private for-profit sector represents a small slice of U.S. higher education in terms of overall undergraduate enrollment, enrolling just 5% of U.S. college students in 2021. This is down from 9% in 2010, largely due to the intensity of for-profit college closures over the course of the decade. Figure 1 depicts these trends in college supply and enrollment. About 77% of undergraduates attended a public school in 2021, and 18% attended a private non-profit school. Despite their small share, for-profit colleges still serve nearly 800,000 students each year (National Center for Education Statistics (2023)).

Figure 1: Enrollment and Net Entry by Sector, 2005-2019

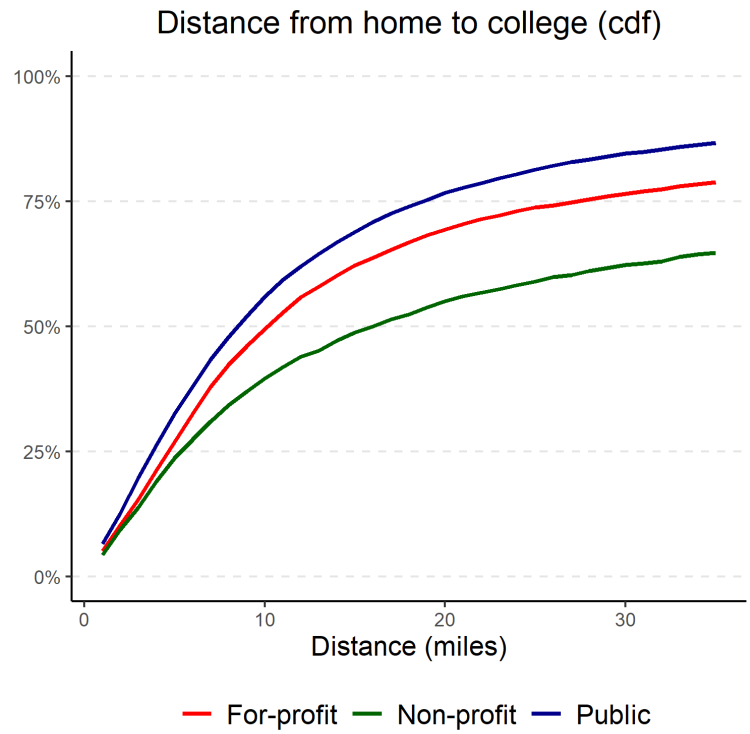


For-profit colleges are almost entirely non-selective, with 97% admitting at least 80% of students (the admissions-rate threshold I choose for defining non-selectivity). This compares to 82% for all public colleges and 55% for private non-profit schools.[1] Another important fact about the market for non-selective colleges is that search is highly localized, which motivates my use of counties for geographic markets. Over half of for-profit and public college students live within ten miles of their chosen school, and nearly 80% live within 25 miles.

In fact, students in my sample live even closer to their chosen colleges than shown in Figure 2, since I will restrict attention to counties which have both a non-selective public and for-profit college present. Note that non-profit students attend school farther from home, which is in part because non-selective non-profit schools are not as widespread. Overall these facts suggest limited consideration sets and/or strong location preferences, perhaps due to the extra costs of attending school beyond a reasonable commuting distance from home. Therefore, students displaced from their first-choice college will be most likely to consider alternatives in the vicinity of their first-choice college. This is important for my research design, as I primarily use spatial variation in college closures to identify the attendance spillovers of for-profit closures.

[1] Author's calculation based on 2019 IPEDS admissions data. Sample is all Title-IV eligible colleges, including both two-year and four-year schools. 95% of for-profit colleges are fully open-enrollment.

Figure 2



2.2.1 Policy Environment and the History of For-Profit Chains

The vast majority of for-profit students pay their tuition using federally funded student loans under Title IV of the Higher Education Act of 1965. These loans are generally provided at below-market rates, and repayment rates especially at for-profits are relatively low, so that the for-profit sector is in practice heavily subsidized by the federal government. Colleges are only eligible for financial aid under Title IV provided they are accredited and meet certain standards set out by the Department of Education. In particular, programs must lead to a degree at a non-profit or public institution or prepare students for "gainful employment in a recognized occupation." By expressly carving out for-profit colleges, the federal statutes empower DoE to moderate for-profit colleges' access to federal revenue sources through its interpretation of what constitutes "gainful employment." DoE only began seeking to enforce this provision in 2009, and after a court struck down the initial rule made in 2011, a final rule went into effect in 2014. This iteration of GE regulation established maximum debt-to-earnings thresholds for continued participation in federal student aid programs, but it was again tied up in courts and ultimately did not directly lead to any disqualifications (Weiss (2023)).

The promulgation of GE rules was part of a broader DoE effort under the Obama administration to scrutinize for-profit colleges' compliance with laws and DoE regulations. This heightened federal scrutiny ultimately led to the abrupt closure of many for-profit college campuses. In some cases, when either the DoE flagged a school for poor financial health or, in the case of ITT Tech, its accreditor announced a financial audit, DoE demanded that the school file a large surety and limited its access to federal aid disbursements. As for-profit colleges take up to 90% of their revenues from federal aid, losing access to this revenue stream can quickly lead to financial insolvency. For instance, in April of 2015, Corinthian Colleges simultaneously closed 28 campuses across the US without warning; at the time, it was the largest university closure in US history, impacting 16,000 actively enrolled students (Johnson (2015)). Shortly thereafter in September of 2016, ITT Tech shuttered all its 132 campuses at once across the US, setting another record with 35,000 displaced students (Douglas-Gabriel (2016)). In 2018, the Education Corporation of America closed its doors, shutting down 70 campuses at once (Kreighbaum (2018)).

Apart from these biggest failed brands in the profit-sector, multiple other lesser-known chains of for-profit campuses have abruptly closed nationwide since 2013. Drawing on the college-closure data described in Section 2, I identify 11 for-profit chain closures satisfying several criteria:

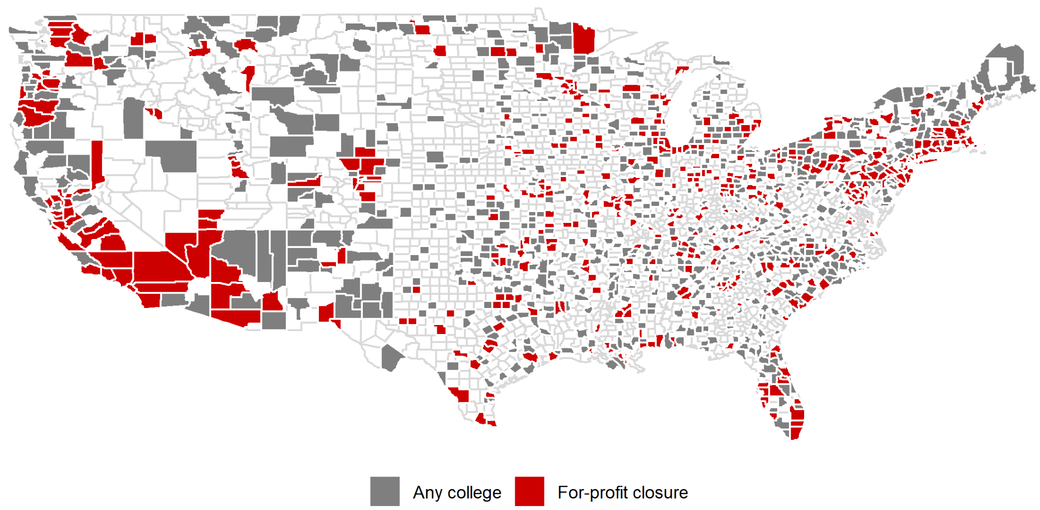
- Each chain operated at least ten campuses across the U.S. prior to closing.
- Each chain operated in more than one state.
- All chain campuses closed in the same year and without advanced warning. In most cases, closures occurred in the midst of financial troubles related to threatened or actual suspension of federal financial aid eligibility.[2]
- All campuses shut down and/or stopped admitting new students permanently.[3]

I restrict attention to large chains because closures of single-campus colleges could be caused by unobserved fluctuations in local college demand, which independently influence enrollment at other local colleges. It is much less likely that chains operating more than ten geographically dispersed campuses would decide to shut down due to local demand conditions, and there is ample qualitative evidence that many of these chain closures were in fact precipitated by federal regulatory pressure. Six of the largest chains, including ITT Tech, Corinthian, ECA, Argosy, Marinello, and Vatterott, were all directly sanctioned by

[2] In some cases, the chain had a handful of campus closures several years before. In the case of Corinthian Colleges, the closures came in two large waves, with one in 2014, and another in 2015. My results are not sensitive to the exclusion of this chain.

[3] In some cases, the chain simultaneously stopped all new enrollment without shutting down for existing students.

Figure 3: For-Profit Closures, 2010-2019



DoE with financial aid restrictions just before their closure. And two others, Anthem and Westwood, faced financial and legal troubles after investigations by DoE. The remaining three chains – Regency, Le Cordon Bleu, and Weston – did not face direct restrictions on their federal student aid participation prior to closure, instead citing worsening regulatory conditions and/or financial pressure due to declining enrollment.

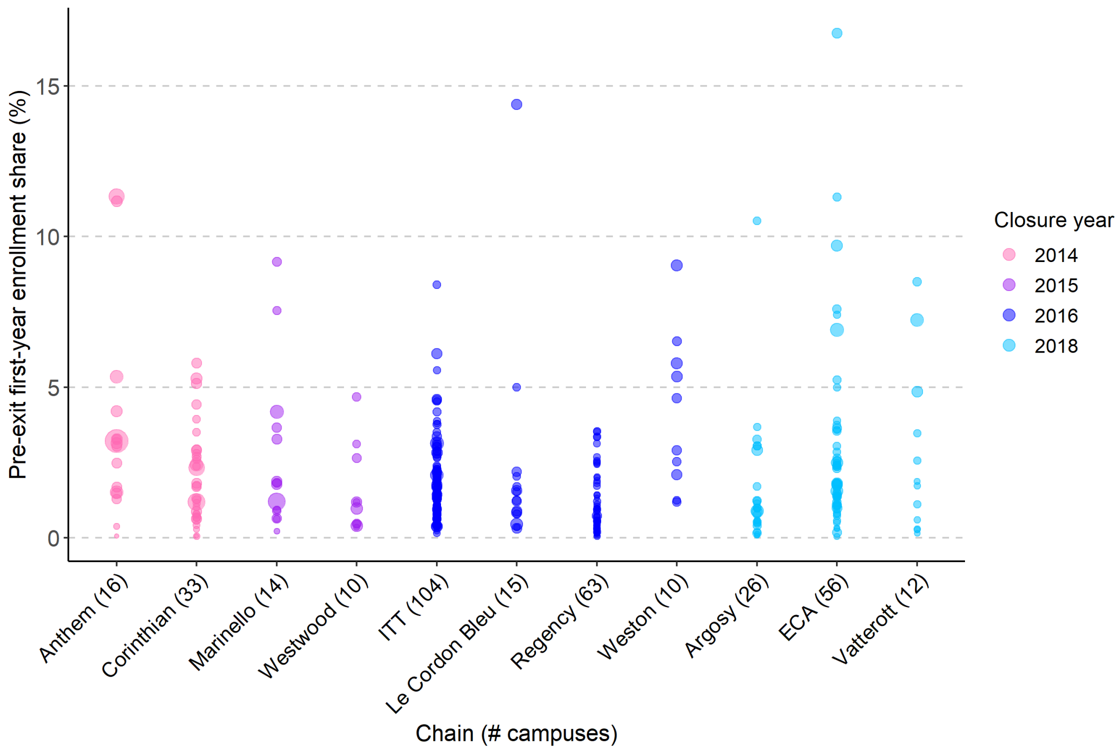
2.2.2 College Closures

These chain closures represent only a fraction of the total exit in the for-profit sector over this period. From 2010 to 2019, more than 1,500 for-profit college campuses have permanently shut down, disrupting hundreds of thousands of active students and reducing the set of available colleges for prospective students.[4] Some private non-profit colleges have also exited, though much less frequently than for-profit schools, which account for about 90% of closures. For-profit college exit is fairly geographically dispersed and occurred in approximately 40% of counties with any local college from 2010 to 2019, as described in Figure 3. In addition, many counties experience multiple for-profit closures over this period.

30% of these campus closures belonged to one of the 11 chains I identified. And as of 2009, prior to closures, these chains enrolled 54,200 *new* students, accounting for a whole

[4] A fair amount of college entry has also occurred over this time period, though far from enough to compensate the exit and often not in the same regions as closing schools.

Figure 4: Pre-Exit Campus-Level Market Shares of the 11 Large Chains



44% of first-time enrollment at closing colleges, as well as one-sixth of the entire sector's new enrollments in that year. Chain campus closures often overlap geographically: the 11 large chains collectively shuttered 462 campuses, all of which operated within 198 counties. Still, each of these chains had operations across multiple states, and in some cases across coasts.

There is also substantial variation within chains in their local market penetration. Figure 4 describes this intensive-margin variation in the share of closing chain campuses, for each of the 11 large chains. The plotted market shares are the chain campuses' share of the county's total first-year enrollment at non-selective colleges, in the year before the closure. This variation is critical for my research design, as I will compare local enrollment trends across counties with different pre-closure chain market shares, which serve as a measure of exposure to chain closures.

Having described the geographic distribution of for-profit closures, it is also important to understand how often for-profit colleges are in local competition with colleges of other sectors. 87% of counties where for-profit colleges operate and shut down also have a non-selective public college present. Only 30% of such counties have a non-profit college available, while 80% have some other non-closing for-profit college present. On the one hand, we might be interested in unconditional substitution rates which include counties where substitution is mechanically zero due to a lack of locally available colleges. Still, given that most counties have both public and other for-profit colleges, I restrict the sample to counties where both of these sectors are available, estimating substitution rates conditional on there being a locally available non-selective college of that sector. These estimates provide an upper bound on the unconditional rates of substitution. Since non-selective non-profit colleges are so rare, I do not restrict the sample to counties with an available non-profit to avoid loss of sample. Thus, estimates of diversion to the non-profit sector are unconditional and may be driven by the fact that these colleges are not locally available.

3 Descriptive Statistics

For-profit students' substitution patterns will depend on the characteristics of the competing alternatives to their chosen school, as well as the strength of their preferences over (and/or information about) such characteristics. Although I do not yet estimate a model of student preferences/information, here I provide some suggestive evidence about the potential sources of differentiation between for-profit and public colleges by comparing their observable features, and the characteristics of the students who choose them.

3.1 Potential Sources of Differentiation

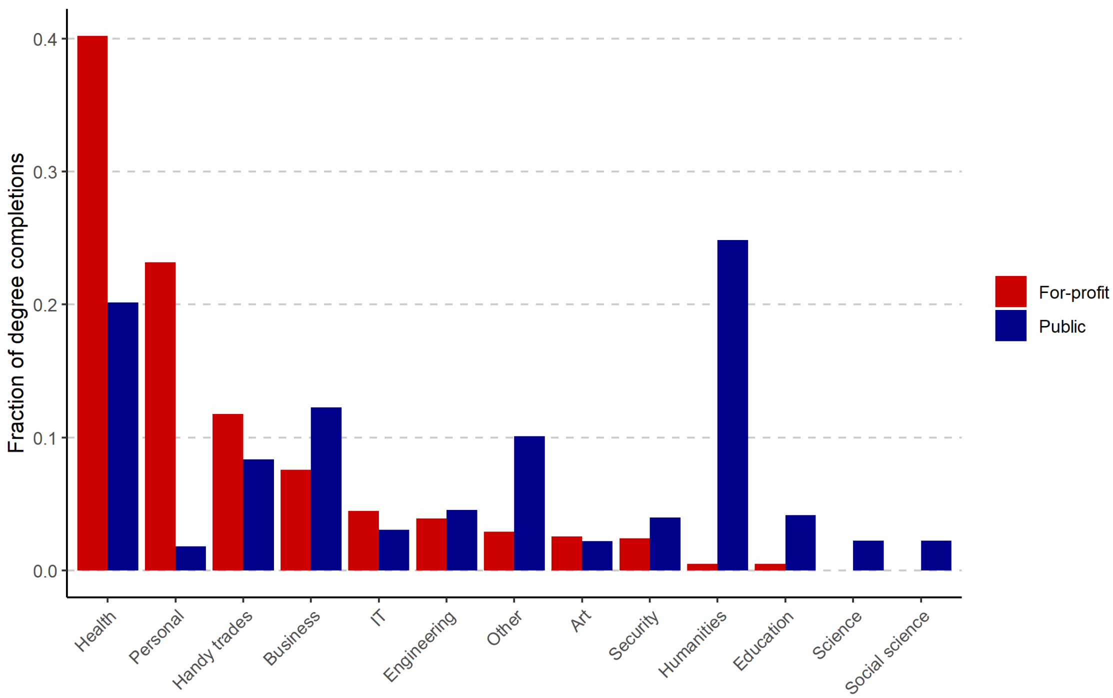
Given that at least one non-selective public college option is available within close proximity to most for-profit colleges, it is unlikely that for-profit attendance choices are driven by college availability. In addition, for-profit colleges are substantially more expensive than non-selective publics, and available evidence suggests that they yield lower earnings value-added, as shown in Figure 5. These value-added estimates come from Armona and Cao (2024), who estimate college-specific value-added for two-year for-profit and public colleges across the U.S. using earnings data from the College Scorecard. They estimate the returns to attending different colleges relative to no college, using a selection-on-observables approach (where observables include prior earnings). Note that these ATT effects do not imply that for-profit students would have earned more if they had attended public colleges, or vice versa. Note too that the cluster of for-profit colleges offering near-zero value-added is almost exclusively made up of cosmetology schools. Altogether, however, the evidence suggests that high relative prices at for-profit colleges are not offset by higher quality.

Figure 5

Notes: Non-selective, sub-baccalaureate colleges only. Densities weighted by enrollment. Value-added estimates from Armona & Cao (2024).

What other features of for-profit colleges might support such high prices? One of the most notable distinctions is that for-profits tend to specialize in just a handful of unique pre-professional programs, concentrated in healthcare, business, "personal services" like cosmetology and culinary arts, and IT. On the other hand, public community colleges usually offer a wide array of academic programs, with a greater concentration of humanities and general-studies offerings, as shown in Figure 6. Whereas on average public colleges offer 16 different fields of study (2-digit CIP codes), the average for-profit college offers just 2.4 fields of study and specializes in vocational programs (Table 1). To the extent that students' college choices are driven by strong field/occupational preferences, these differences could be a key source of sectoral differentiation. There is less differentiation on degree levels, with for-profits and publics both offering a wide array of sub-baccalaureate credentials. That said, public colleges offer Associate's degrees at higher rates.

Figure 6: Programs of Study: For-Profit vs. Public



Despite their lackluster returns, for-profit colleges graduate their students at much higher rates than non-selective public colleges – graduation rates are 20 percentage points higher overall, and the gap is larger within two-year colleges. To the extent that higher for-profit graduation rates reflect lower academic standards and/or fewer remedial and core requirements, this may be another important source of differentiation for students who doubt whether they could meet the graduation requirements of public schools. And even if the expected return to a public option exceeds that of a for-profit for a given student, a sufficiently risk-averse or low-ability student might reasonably opt for a for-profit with a higher completion probability.

Additional differences between for-profit and public colleges include different rates of advertising (with for-profits spending an order of magnitude more than public colleges per student), stricter remedial/general education requirements at public colleges, private-college grade inflation, and different degrees of program flexibility (Cellini and Chaudhary (2020); Deming, Goldin and Katz (2013)). For instance, for-profits are much more likely to operate on continuous academic calendars, potentially reflecting greater course-taking flexibility. On the other hand, for-profits do not appear uniformly more "flexible" than public colleges, according to Table 1 – they offer weekend/evening classes at a similar rate, and they offer online courses, part-time options, and daycare services much less often than public colleges.

In terms of financial characteristics, for-profit and public colleges spend similar shares of their total revenues, but a larger share of public-college spending goes to instructional activities (45% compared to 36% at for-profits). In exchange, for-profits spend more on "student services" outside of instruction *per se*. The accounting data leave unspecified what exactly constitutes non-instructional services spending, but for-profits' advertising spending may fall in this category. Finally, another important differentiator is the fact that some of the largest for-profit colleges like University of Phoenix offer fully online degree programs. These schools are not the focus of my analysis, as almost none of the chain colleges in my sample offered fully online programs. I will also be unable to identify substitution to fully online colleges, since I cannot define geographic exposure for such schools using aggregate market share data.

An alternative factor unrelated to student preferences which could explain for-profit college demand is misinformation or limited awareness about certain college characteristics like the institutional grant aid available at some public colleges, or relative value-added. Information asymmetries could induce misperceptions of actual net prices and lead marginal students to choose more expensive for-profit options. Though these conjectures are difficult to verify with data, since for-profit students are more likely to be the first in their family to attend college, we might expect misinformation to be particularly salient for this group.

Altogether, non-selective colleges of different sectors differ substantially in a number of characteristics which may be particularly salient to the kinds of non-traditional students who often enroll in for-profits. Differences in college characteristics are necessary, though not sufficient, to generate non-trivial substitution patterns – to infer the extent of differentiation due to any of these characteristics would require estimating a model of student preferences, which I leave for future work. For now, I abstract from the sources of differentiation and the drivers of for-profit demand, instead asking to what extent for-profit and public colleges are substitutable for students enrolling in for-profits. This question has substantial policy relevance in its own right, given the economic mobility implications of students' decisions about whether and where to attend college, as well as the scope for federal higher-education policy to shape sector-specific outcomes.

3.2 Who Chooses For-Profit Education?

Despite being far more expensive than public colleges, for-profits attract some of the poorest students who pursue higher education. After grants, for-profit colleges are typically 10 times as expensive as non-selective public options, as shown in Table 2. Yet the typical for-profit student's parents earn $20,000 less than those of the typical non-selective public college student. Though this pattern is puzzling as we might expect poorer students to be more

Table 1: Mean Institution Characteristics by Control

Panel A: *Core characteristics*	Public	Non-profit	For-profit
Full-time enrollment	2,834	728	295
Tuition & fees ($)	4,237	16,371	15,327
Graduated $\leq 150\%$ of expected time (%)	34.7	48.9	55.3
Earnings value-added ($)	8,985	3,867	2,192
Offers < 1-year certificate (%)	76.3	25.6	57.7
Offers 1-year certificate (%)	88.0	38.2	78.8
Offers Associate's (%)	74.2	48.9	33.7
Offers Bachelor's (%)	18.4	67.9	15.6
# degree programs	60.0	23.0	6.7
# 2-digit CIP offerings	15.8	7.5	2.4
Panel B: *Flexbility and other amenities*	**Public**	**Non-profit**	**For-profit**
Offers online classes (%)	83.0	39.6	16.3
% students fully online	7.6	3.4	1.0
% students partly online	15.3	6.7	2.8
Offers weekend/evening (%)	49.6	43.6	46.9
Offers part-time (%)	93.4	68.2	53.1
Continuous calendar (%)	6.1	11.9	51.3
Offers remedial services (%)	94.7	60.9	31.8
Offers academic counseling (%)	98.2	94.9	81.2
Offers on-campus jobs (%)	85.7	69.1	51.0
Offers placement services (%)	82.1	65.6	91.8
Offers daycare (%)	42.7	6.1	0.6
Panel C: *Financial characteristics*	**Public**	**Non-profit**	**For-profit**
Total revenue per student ($)	35,147	61,234	28,091
Total spending per student ($)	33,757	54,188	24,862
Instructional spending per student ($)	15,063	17,411	8,917
Services spending per student ($)	5,481	12,796	10,502
Number of colleges	1,517	683	2,366

Note: Sample includes all non-selective Title-IV-eligible colleges, not primarily online. Characteristics drawn from 2010-2013 IPEDS files (prior to the chain for-profit closures).

price-elastic, the widespread availability of subsidized student loans diminishes the relevance of price as a differentiating characteristic, as shown in Armona and Cao (2024). In addition, low-income students may also be more advertising-elastic due to relatively low information, and low-income or low-ability students might especially value higher graduation rates at for-profit colleges. Indeed, all of the other ways in which for-profits differentiate themselves from public colleges are likely to be valued differentially across the income distribution, which can help to explain the unadjusted negative correlation between price and family income.

Table 2: Financial Characteristics by Control

	Public	Non-profit	For-profit
Median after-grant tuition	\$479	\$3,215	\$7,680
Median parental income	\$49.8k	\$38k	\$30.2k
Median student income	\$16.1k	\$19k	\$13.3k
Independent (%)	57.2	69.9	78.6

Notes: Data from NPSAS (2016); non-selective colleges only. Parental income is conditional on being dependent, while student income is conditional on being independent.

Not only are for-profit students economically disadvantaged, but they also tend to be "non-traditional" college-goers – they are more likely to have served in the military or to have delayed post-secondary entry, to be a single parent, to maintain a full-time job during school, and to lack a high school diploma (Table 3). Although on many observable characteristics like online and weekend/night classes, for-profits do not appear more flexible than public colleges, some have speculated that for-profits may offer these kinds of non-traditional students more flexibility in their path to the degree, in ways which are difficult to observe and quantify (Deming et al. (2013)). Older students who are more attached to the labor market and who care for children may place relatively higher value on flexible learning options, since they face a unique set of demands and opportunities outside of education. Continuous academic calendars, for instance, might permit students with more frequent life disruptions – e.g., responsibility for children, part-time jobs, and life shocks that may be more salient for particularly disadvantaged students – to exit and re-enter schooling. Alternatively, grade inflation and relaxed academic requirements might permit for-profit students to more easily substitute time devoted to schooling activities for other needs. Altogether, the unique traits of for-profit colleges and their students suggest that students may attend these schools because of strong preferences for particular amenities which make education more accessible – in which case their next-best option may be no further schooling.

Table 3: For-Profit Students are Non-Traditional

	Public	Non-profit	For-profit
High school diploma (%)	84.6	83.9	79.8
Age at entry ≥ 20 (%)	36.3	41.6	51.4
Full-time job (%)	38.6	45.4	46.4
Veteran (%)	5.4	5.7	9.5
Single parent (%)	15.1	21.5	32.8

Notes: Data from NPSAS (2016); non-selective colleges only.

4 Empirical Model

Consider a standard random-utility model of discrete-choice demand, where each student $i \in I$ facing choice set $\mathcal{C}_i$ chooses college $j \in \mathcal{C}_i$ if $u_{ij} \geq u_{ik} \forall k \in \mathcal{C}_i$. Let d_{ij} be an indicator variable equal to one if i chooses j. The college utilities are a function of student i's preferences (β_i, ϵ_{ij}) and the college's and student's characteristics, (X_j, Y_i): $u_{ij} = f(X_j, Y_i; \beta_i) + \epsilon_{ij}$, where $\epsilon_{ij} \overset{\text{iid}}{\sim} F$ is a continuously distributed taste shock for college j. The model nests all commonly used discrete-choice demand models, from the simplest plain logit model (where $f(X_j, Y_i; \beta_i) = \delta_j$), to the richest models of preference heterogeneity like random-coefficients nested logit (RCNL) formulations. Note too that the model accommodates some forms of imperfect information via distortions of preference parameters.

Integrating out the $\boldsymbol{\epsilon}_i$ taste shocks yields individual choice probabilities

$$s_{ij}(\boldsymbol{X}) = \int \mathbb{1}\{u_{ij} \geq u_{ik} \forall k \in \mathcal{C}_i\} dF(\boldsymbol{\epsilon}_i)$$

so that $\sum_{j \in \mathcal{C}_i} s_{ij}(\boldsymbol{X}) = 1$. Aggregating individual choice probabilities yields market shares $s_j(\boldsymbol{X}) = \int s_{ij}(\boldsymbol{X}) dG(\beta_i, Y_i)$, where G is the joint distribution of student characteristics and preferences. Note that $\boldsymbol{X}$ includes all colleges' characteristics. For the remainder of the paper, I also subsume in $\boldsymbol{X}$ the distributions of students characteristics and preferences.

Given the demand system, individual diversion ratios are defined as

$$D_{jk,i}(p_j, \boldsymbol{X}) = \left| \frac{\partial s_{ik}(p_j, \boldsymbol{X})}{\partial p_j} \Big/ \frac{\partial s_{ij}(p_j, \boldsymbol{X})}{\partial p_j} \right| \in [0, 1]$$

where I split college j's price p_j out of $\boldsymbol{X}$. The diversion ratio measures the extent to which colleges j and k are substitutable for student i. That is, when a marginal price increase at college j induces i to leave, $D_{jk,i}$ is the chance they divert to college k. Product-level diversion

$D_{jk}(p_j, \boldsymbol{X}) \in [0, 1]$ is defined analogously and represents the fraction of students switching to college k, out of those induced to leave j due to a small price change. Importantly, the diversion ratio represents the effect of an exogenous price change, holding the rest of the market characteristics $\boldsymbol{X}$ fixed.

For larger price changes, the total diversion ratio due to a price change $p_j \to p'_j$ is

$$D_{jk}(p'_j, p_j, \boldsymbol{X}) = \left| \frac{s_k(p'_j, \boldsymbol{X}) - s_k(p_j, \boldsymbol{X})}{s_j(p'_j, \boldsymbol{X}) - s_j(p_j, \boldsymbol{X})} \right| \in [0, 1]$$

Letting $\bar{p}_j$ be the choke price for college j, i.e. the price such that $s_j(\bar{p}_j, \boldsymbol{X}) = 0$, we can represent a college closure as a large price increase, with the total diversion from product exit being

$$\bar{D}_{jk}(p_j, \boldsymbol{X}) = \left| \frac{s_k(\bar{p}_j, \boldsymbol{X}) - s_k(p_j, \boldsymbol{X})}{s_j(\bar{p}_j, \boldsymbol{X}) - s_j(p_j, \boldsymbol{X})} \right| = \frac{s_k(\bar{p}_j, \boldsymbol{X}) - s_k(p_j, \boldsymbol{X})}{s_j(p_j, \boldsymbol{X})}$$

These total diversion ratios are weighted averages of the incremental diversion ratios $D_{jk}(p'_j, \boldsymbol{X})$ over $p'_j \in [p_j, \bar{p}_j]$. As the price increases beyond p_j, inframarginal buyers of j are also induced to leave. Conlon and Mortimer (2021) show that under weak regularity conditions this total diversion ratio can also be represented as a weighted average of individual diversion ratios:

$$\bar{D}_{jk}(p_j, \boldsymbol{X}) = \mathbb{E}[D_{jk,i}(p_j, \boldsymbol{X}) \mid d_{ij}(p_j, \boldsymbol{X}) = 1]$$

That is, the total diversion from a college closure is the average diversion ratio among those who would have enrolled in j under $(p_j, \boldsymbol{X})$ (the "compliers").

In this way, the $\bar{D}_{jk}$ provide second-choice data on the subsample of students enrolling in college j. Raising p_j to the choke price is equivalent to an exogenous college closure; choices made under $(\bar{p}_j, \boldsymbol{X})$ reveal the second choices of students originally attending j, who must now reallocate to some alternative $k \in \mathcal{C}_i \setminus \{j\}$. This connection illuminates how college closures can identify the average diversion ratios of the choice model in reduced form.

Though I infer substitution patterns without parameterizing and estimating the demand model above, it will be useful to benchmark estimated diversion rates against the predictions of a simple demand model. In general, the diversion ratios depend on all features of the market – the characteristics of all products, as well as the distributions of student characteristics and preferences. Yet in the plain logit model, diversion rates are simply proportional to market shares. In particular, when $u_{ij} = \delta_j + \epsilon_{ij}$ and $\epsilon_{ij} \overset{\text{iid}}{\sim}$ Logit,

$$\bar{D}_{jk}(p_j, \boldsymbol{X}) = \frac{s_k(p_j, \boldsymbol{X})}{1 - s_j(p_j, \boldsymbol{X})}$$

Diversion ratios in this case are identified directly from pre-closure market shares, and preference heterogeneity is trivial, only arising from iid taste shocks. As a result, I can test for the relevance of richer preference heterogeneity by comparing the plain logit predictions to my estimated diversion ratios, which are consistent with virtually any underlying preferences.

4.1 Identification

Suppose we observe market shares over a distribution of markets m in which for-profit college $j(m)$ closes between $t = 0$ and $t = 1$. Let $(p_{j(m)}, \bar{p}_{j(m)})$ be the pre-closure and choke prices of college $j(m)$. In practice, I am interested in diversion across sectors, rather than between particular colleges. To that end, let $K(m)$ be the set of colleges in market m belonging to sector $K \in \{\text{public, non-profit, for-profit}\}$, and let $s_K(p_{j(m)}, \boldsymbol{X}_{mt}) = \sum_{k \in K(m)} s_k(p_{j(m)}, \boldsymbol{X}_{mt})$. Denote the total diversion from for-profit $j(m)$ to sector K under $(p_{j(m)}, \boldsymbol{X}_{m0})$ as

$$\bar{D}_m^K = \sum_{k \in K(m)} \bar{D}_{j(m),k}(p_{j(m)}, \boldsymbol{X}_{m0})$$

4.1.1 Distribution of Diversion Ratios

Consider identification of the whole distribution of total diversion ratios from closing college $j(m)$ to another sector $K(m)$. In each market m, we observe market shares of local colleges $J(m)$ before and after the closure, $\{s_{j0}, s_{j1}\}_{j \in J(m)}$. From these we can construct a simple Wald estimator for the total diversion from $j(m)$ to sector $K(m)$:

$$\begin{aligned}
\hat{D}_m^K = \sum_{k \in K(m)} \frac{s_{k1} - s_{k0}}{s_{j(m),0}} &= \sum_{k \in K(m)} \frac{s_k(\bar{p}_{j(m)}, \boldsymbol{X}_{m1}) - s_k(p_{j(m)}, \boldsymbol{X}_{m0})}{s_{j(m)}(p_{j(m)}, \boldsymbol{X}_{m0})} \\
&= \bar{D}_m^K + \frac{s_K(\bar{p}_{j(m)}, \boldsymbol{X}_{m1}) - s_K(\bar{p}_{j(m)}, \boldsymbol{X}_{m0})}{s_{j(m)}(p_{j(m)}, \boldsymbol{X}_{m0})}
\end{aligned}$$

The identification challenge is that we do not observe $s_k(\bar{p}_{j(m)}, \boldsymbol{X}_{m0})$, the counterfactual school-k share had school $j(m)$ not been available one year earlier. $\hat{D}_m^K$ identifies the total diversion ratio $\bar{D}_m^K$ provided that $\boldsymbol{X}_{m0} = \boldsymbol{X}_{m1}$, i.e. college characteristics and distributions of student preferences and characteristics remain fixed. Alternatively, we can directly assume that, but for the for-profit closure, sector-K market shares would have remained the same:

$s_K(\bar{p}_{j(m)}, \boldsymbol{X}_{m0}) = s_K(\bar{p}_{j(m)}, \boldsymbol{X}_{m1})$. This assumption implicitly restricts how $\boldsymbol{X}_{mt}$ changes following the closure. These are the assumptions maintained, e.g., in Raval, Rosenbaum and Wilson (2022), who estimate diversion ratios from disaster-induced hospital closures. Note that to the extent other market characteristics change immediately after the closure, the Wald estimator's bias will be most severe in counties with the smallest closing schools. This will motivate restricting attention to markets with sufficiently large closures when estimating diversion in this way.

4.1.2 Average Diversion from Closing For-Profits

These assumptions are restrictive, as many other features of the choice set may change from year to year, as can the characteristics and preferences of adjacent cohorts of entering students. Given my primary interest in the overall rates of for-profit-to-public diversion, I now show that average total diversion rates are identified under weaker (and in my setting, more plausible) assumptions. A simple reduced-form estimating equation identifies average diversion from closing for-profits to other sectors, under a variant of the parallel-trends assumption.

By manipulating the definition of the total diversion ratios, we arrive at a linear estimating equation – the first-differences (FD) estimator:

$$s_K(\bar{p}_{j(m)}, \boldsymbol{X}_{m1}) - s_K(p_{j(m)}, \boldsymbol{X}_{m0}) = \alpha + \beta \times s_{j(m)}(p_{j(m)}, \boldsymbol{X}_{m0}) + \epsilon_m$$

where

$$\alpha = \mathbb{E}[s_K(\bar{p}_{j(m)}, \boldsymbol{X}_{m1}) - s_K(\bar{p}_{j(m)}, \boldsymbol{X}_{m0})]$$

$$\beta = \mathbb{E}[\bar{D}^K_m]$$

$$\begin{aligned}\epsilon_m = &\overbrace{\big(s_K(\bar{p}_{j(m)}, \boldsymbol{X}_{m1}) - s_K(\bar{p}_{j(m)}, \boldsymbol{X}_{m0})\big) - \alpha}^{\text{excess trend due to } \boldsymbol{X}_{m0} \to \boldsymbol{X}_{m1}} + \\ &\underbrace{\big(\bar{D}^K_m - \mathbb{E}[\bar{D}^K_m]\big) s_{j(m)}(p_{j(m)}, \boldsymbol{X}_{m0})}_{\text{excess diversion}}\end{aligned}$$

The error terms consists of (1) deviations of the target sector's enrollment trend from the overall trend, and (2) a factor due to heterogeneous market-specific diversion ratios.

Regression will identify $\beta = \mathbb{E}[\bar{D}^K_m]$ under two mean-independence conditions. First, the trend in sector K's enrollment needs to be unrelated to the size of the closing for-profit, but for the effect of the closure – a variant of the parallel-trends assumption (PTA):

$$\mathbb{E}\big[s_K(\bar{p}_{j(m)}, \boldsymbol{X}_{m1}) - s_K(\bar{p}_{j(m)}, \boldsymbol{X}_{m0}) \mid s_{j(m)}(p_{j(m)}, \boldsymbol{X}_{m0})\big] = \alpha$$

This weakens the assumption of the simple Wald estimator. Notice too that average diversion is identified only from intensive-margin variation across closures of different sizes, making comparisons to never-treated markets unnecessary. If diversion ratios differ across markets, the first-differences estimator also requires that the strength of diversion is unrelated to the size of the closing for-profit:

$$\mathbb{E}\big[\bar{D}_m^K \mid s_{j(m)}(p_{j(m)}, \boldsymbol{X}_{m0})\big] = \beta$$

In other words, for least-squares regression to identify the unconditional average diversion ratio, heterogeneity in diversion ratios (effectively, random coefficients on the closing-school share) cannot be correlated with the independent variable.

A simple average of the Wald estimators, $\frac{1}{|M|}\sum_{m\in M}\hat{D}_m^K$, identifies the average diversion $\mathbb{E}[\bar{D}_m^K]$ without this restriction on the heterogeneity in $\bar{D}_m^K$, provided that

$$\mathbb{E}\left[\frac{s_K(\bar{p}_{j(m)}, \boldsymbol{X}_{m1}) - s_K(\bar{p}_{j(m)}, \boldsymbol{X}_{m0})}{s_{j(m)}(p_{j(m)}, \boldsymbol{X}_{m0})}\right] = 0$$

In other words, we assume that but for the closure, changes in sector-K enrollment are mean-zero – whereas the more efficient regression estimator allows for trends in sector-K enrollment, but restricts the heterogeneity in $\bar{D}_m^K$.

4.1.3 Across-Sector Diversion

When students choosing closing for-profits substitute to other for-profits, we observe their second-choice college, but not their second-choice sector. Second-choice sector data may be more pertinent for evaluating sector-level policy interventions, so I will also use for-profit closures to instrument for sector-wide for-profit enrollment. In particular, the change in closing-school share instruments for the overall for-profit enrollment trend, which then enters the second-stage model of public or non-profit enrollment trends. The equation from Section 4.1.2 for diversion from *closing* for-profits to other sectors is then the reduced-form of this model. The complier group will still only consist of students at closing for-profit chains, but it will restrict attention to those induced to leave the sector – those for whom it's as if the entire for-profit sector became unavailable.

Beyond the exogeneity condition also assumed in identifying the reduced-form diversion ratios in Section 4.1.2, we now require three additional assumptions for identification of these LATEs. First, for-profit closures only impact other-sector enrollment by reducing for-profit sector enrollment (exclusion). This requirement is an implication of the college-choice model.[5] Instrument relevance requires that diversion from closing for-profits to other for-profits is less than complete. And for a LATE interpretation, we further require monotonicity: the probability of for-profit enrollment is non-increasing in the extent of for-profit closures. This is once again implied by the choice model.[6]

4.1.4 Evaluating the Identifying Assumptions

Rather than use all for-profit closures over this period, I restrict attention to the nation-wide closures of the 11 for-profit chains described in Section 2.2. As such, I only identify diversion off variation in market shares within closing schools – that is, I do not compare counties with closing for-profits to those without a closure. These chain closures plausibly satisfy my identifying assumptions due to their abruptness, unexpectedness, their situation across dozens of geographic markets, and the fact that all chain campuses closed at once – generally due to heightened regulatory scrutiny. Here I elaborate how these facts support the identifying assumptions, taking guidance from the underlying choice model.

First, these closures were generally induced by federal regulatory changes rather than changes in local demand conditions. In general, college exit decisions depend on profitability, which is a function of (unobserved) local college demand shocks – and these demand shocks independently influence enrollment in other sectors. For instance, persistent local labor demand shocks may drive overall college enrollment by shifting the outside-good utility, while also influencing college profitability and exit behavior. Chains operating across dozens of markets dispersed across different states are not nearly as exposed to local college demand fluctuations. Adding to this the fact that these chains closed in response to federal regulatory changes and/or an overall decline in the for-profit sector's reputation, it seems reasonable to conclude that these closures were unrelated to local college demand shocks.

A second important feature of these closures is that the chains permanently shut down all their remaining campuses, rather than selectively closing the worst-performing locations. We might be concerned if chains selectively closed those campuses experiencing negative local demand shocks, or those which faced tougher competition from local public colleges –

[5] When the set of available colleges changes from J_0 to J_1, $J_1 \subset J_0$, students with $j^*_{i0} \equiv argmax_{j \in J_0} u_{ij} \in J_1$ continue to have $j^*_{i1} \equiv argmax_{j \in J_1} u_{ij} = j^*_{i0}$ after the closures. That is, for-profit closures cannot affect other colleges' enrollment, except through changes in for-profit enrollment (ruling out network effects in demand).

[6] The logic is essentially the same as before – closures do not change choices for students originally choosing other colleges, and within-sector diversion is capped at one.

say, due to public capacity investments or free-tuition programs. The fact that chains closed all their campuses allays these concerns.

Finally, these chains closed abruptly, in some cases even surprising the students in attendance at the time of the closure according to contemporaneous media reports. Therefore, these closures are unlikely to have been anticipated in advance by competitor colleges, leaving them unable to change their characteristics $\boldsymbol{X}_{-j(m)}$ in response, at least for the immediately following academic year. As a result, closures are unlikely to come with other changes in students' choice sets which could influence demand. Still, since competitor colleges may optimally adjust tuition, program offerings, and other characteristics in response to the closure, I restrict attention to the year immediately after closure and assume that any college responses occur with a lag.

As a robustness check, I will test whether observable college characteristics change right after the closure, and if so whether these changes are correlated with exposure (the pre-exit chain share). The relevant robustness tests take different forms for the Wald and first-differences regression estimators. Since the average of Wald estimators requires mean-zero trends in enrollment, there I test for average changes in components of $\boldsymbol{X}$. For the regression estimator, I test instead whether changes in components of $\boldsymbol{X}$ are correlated with exposure, $s_{j(m)}(p_{j(m)}, \boldsymbol{X}_{m0})$. These tests are informative about the parallel-trends assumption provided that the shares $s_K(\bar{p}_{j(m)}, \boldsymbol{X})$ are approximately linear on the support of the year-to-year variation in $\boldsymbol{X}$ (i.e., for small enough variation in $\boldsymbol{X}$).

Supposing the evidence is in favor of the parallel-trends assumption, the first-differences estimator still requires that heterogeneity in diversion ratios be unrelated to the closing chain's market share prior to closure. This condition would be violated, for instance, if larger chain campuses are large because of a weak public sector, which could induce low diversion (leading to downward bias). On the other hand, the kinds of students who choose a very small for-profit over a relatively strong public option (evidenced by market shares) may have lower public diversion rates (leading to upward bias). Nothing suggests that these potential biases should cancel out, so I relax this assumption in several ways. First, the Wald estimator is robust to violations of this condition. In addition, if diversion ratios are in fact correlated with closure sizes, this will generate a non-linearity in the relationship between sector-K share growth and closure size. To evaluate the linearity assumption, I also use a kernel smoother to estimate the conditional mean of sector-K share growth given the closing-school share.

The additional assumptions required for IV estimates of across-sector diversion are relatively innocuous. The closure instrument turns out to be quite strong, and the exclusion and monotonicity assumptions are implied by the simple mechanics of the discrete-choice model.

However, one data issue calls into question the exclusion restriction. Apart from the for-profit colleges I observe in IPEDS, some small for-profit schools without access to Title-IV federal financial aid operate outside the IPEDS data universe. Since this slice of for-profit enrollment is unobserved, exclusion may be violated if for-profit closures induce substitution to these non-Title-IV for-profits, and if students at these colleges would then substitute to public colleges under a for-profit ban. Though data limitations make it difficult to evaluate the extent of this issue, substitution to these small, unobserved for-profits may be limited by the fact that they cannot offer federally subsidized student loans, as can the Title-IV-eligible closing for-profits. In addition, substitution to the Title-IV-eligible for-profits I do observe is near zero, suggesting that diversion to for-profits without the same loan-granting abilities may be similarly low. Moreover, this issue does not threaten the validity of estimated diversion from the closing for-profits to other sectors.

Finally, even if these closures satisfy the identifying assumptions, the diversion ratios I estimate represent diversion from the subsample of closing chain for-profits, which is not a random subsample of the for-profit sector. Although closing chains did not selectively close particular campuses, the chains which closed as a result of worsening regulatory conditions may have been particularly unprofitable and under-performing relative to the portion of the sector which remained open. Though this does not bias my ATT estimates, I take up the question of external validity by describing the observable differences between closing chains and other for-profits in Section 7.

4.2 Estimation

In practice, the chain closures span four years between 2014 and 2018. To accommodate evolving target-sector enrollment trends, I fit calendar-year intercepts in the first-differences regressions. I also trim the one outlier closure with more than 15% market share. Upon further investigation, this county (Baltimore City) happened to open a new tuition-free program the year after ECA's closure in that county, which resulted in a large jump in its public enrollment. Due to its particularly high leverage, I remove this observation in the main analysis. Where multiple chain campuses close in the same market and year, I sum their market shares in defining the closing-college market share. In cases where a county experiences closures in more than one year, I include all closure events and define the market index m based on all county/closure-year combinations.

Letting $t \in T = \{2014, 2015, 2016, 2018\}$ index the calendar year, the first-differences estimating equation is

$$\Delta s_{K(m),t} = \sum_{s \in T} \delta_s \mathbb{1}\{t = s\} + \beta_K \times s_{j(m),t-1} + \epsilon_{mt}$$

The outcomes $\Delta s_{K(m),t}$ include the change in public, non-profit, and other for-profit market shares. The sum of the β_K coefficients is the total rate of substitution from the closing for-profits to local colleges, equal to 1 under full substitution to local colleges.

Since I do not observe the market size – that is, the number of "potential students" choosing not to attend college in each year – the public-college share is the fraction of total local college enrollment accounted for by local public colleges (i.e., it is the share of the "inside goods"). This means that the share's denominator is not exogenous as is often reasonable to assume when shares are defined as fractions of a market population determined by age and/or geography; instead, it depends on the utility of the inside goods relative to the outside good (no college), which is directly affected by for-profit closures. Therefore, I peg the share denominator at the pre-closure level of total county enrollment, so that changes in sector shares do not reflect changes in the inside-good share.[7] This does not change the interpretation of the coefficient as a diversion ratio, provided that changes in market size are uncorrelated with the closing for-profit share.

When estimating the average of Wald estimators, I trim closures of campuses which accounted for less than 1% of market share, since the Wald estimators for such small closures are particularly high-variance. As discussed in Section 3, I also restrict to markets with an available non-selective public college so that results for this sector are not mechanically driven to zero in cases where no local public colleges are available. Unconditional public diversion will be lower, but not by much, since about 90% of markets with a chain closure also have a local public option. Finally, I consider results both unweighted and weighted by the county's young adult population (annual Census estimates of the county's population of 18-24 year-olds). Throughout, I report heteroskedasticity-robust asymptotic standard errors.

[7] A simple example makes this point clear. Suppose in a market of 100 potential students that 50 choose a public college, 10 chose the closing for-profit, and suppose the true diversion to the public sector is zero, with all market characteristics fixed but the closure. If we allow the denominator of the inside-good share to update, the public-college share will increase by $50/50 - 50/60 \approx 16\%$, despite there being no substitution. Holding the denominator fixed gives the correct answer: $50/60 - 50/60 = 0\%$. Although in reality market size may change, we simply require that these changes not be systematically related to the closing-school share, as with other market characteristics.

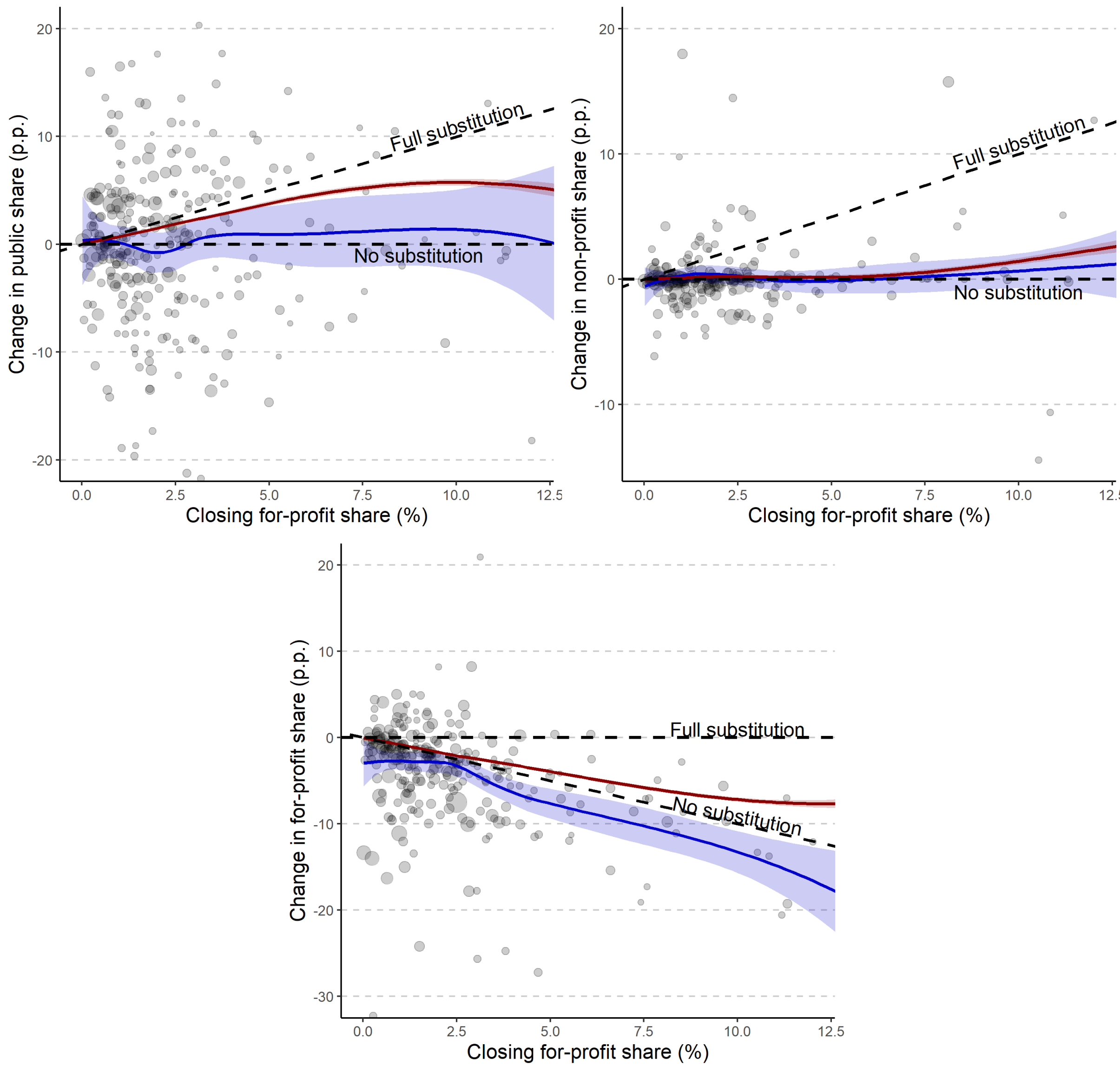
5 Diversion Ratio Estimates

5.1 Reduced Form: Diversion from Closing Colleges

First, Figure 7 shows raw data on changes in the public, non-profit, and for-profit market shares $\Delta s_{K(m),t}$, relative to the size of the closing chain $s_{j(m),t-1}$. For public and non-profit diversion, the $y = x$ line represents complete substitution to the target sector, while the $y = 0$ line represents no substitution. The change in *total* for-profit share should track the $y = 0$ line if diversion to other for-profits is complete, and the $y = -x$ line if there is no within-sector substitution. The red fitted curve represents the predicted diversion under a plain logit model with no substitution to the outside good – under this simple model, substitution rates are proportional to market shares. The blue fitted curve represents the diversion from the closures, estimated with a local polynomial regression of changes in sector-K shares on the closing-school share (where the shaded region marks a 95% pointwise confidence band). These relationships appear approximately linear, lending some support to the assumption that diversion-ratio heterogeneity is unrelated to exposure.

The unadjusted data show that diversion to the public sector falls well below the predictions of the plain logit model. This implies that preference/information heterogeneity is non-trivial, and that there is substitution to the outside good. Diversion to the non-profit sector appears near zero; this is consistent with the fact that non-profit college shares are small, and in some markets diversion is mechanically zero due to the absence of a local non-profit option. Diversion to the for-profit sector appears near zero as well, with roughly one-for-one declines in for-profit enrollment with the size of the chain for-profit closure. Although overall trends in public and non-profit enrollment are approximately zero, for-profit enrollment is trending downward across the distribution of closing-school shares due to an overall shift away from the sector over this period. This will bias downward the simple Wald estimator for estimates of diversion to other for-profits, so I will rely on the first-differences estimator in this case.

Figure 7: Unadjusted Data: Non-Parametric Diversion Estimates



Notes: Red curves represent predicted diversion under the plain logit; blue curves represent estimated diversion. Shaded regions are 95% pointwise confidence bands for the predicted mean of a loess regression. Dot size proportional to youth population.

Next, Table 4 shows estimated diversion from closing for-profits to other sectors, using both the average Wald estimator and the first-differences ("FD") regression. The first two columns provide the average predicted diversion from the plain logit demand model with no substitution to the outside good. The high predicted public-sector diversion reflects the fact that the non-selective public colleges have dominant market share in most markets. Predicted diversion to the non-profit sector is 9%, and about 20% to the rest of the for-profit sector.

Columns 3-6 show unweighted and population-weighted estimated diversion from the two estimators. Public-sector diversion is estimated to be small across specifications. Regression estimates indicate diversion of 27%, and 17% when weighting by population. The corresponding 95% confidence intervals for public-sector diversion are $[0, 0.68]$ and $[0, 0.64]$, respectively.[8] Diversion to non-profits is estimated to be between $6 - 21\%$ depending on specification. Unweighted and weighted regression 95% CIs are $[0, 0.30]$ and $[0, 0.44]$, respectively. Regression estimates of diversion to other for-profits are similarly small, with regression CIs of $[0, 0.17]$ and $[0, 0.41]$ when population-weighted.

Altogether, total local college enrollment declines by 71% of the closure size, or 53% when weighting by population. Unweighted, we can reject full substitution to local colleges ($p = 0.016$; $p = 0.16$ when weighting).[9] That said, we cannot rule out diversion to colleges outside the observed choice set – these include fully online colleges and non-Title-IV-eligible schools (almost all of which are for-profit), as well as selective colleges and colleges located outside the county. However, since the programs in which the chains specialized cannot generally be conducted online, if program preferences are indeed important elements of for-profit chain students' college demand, diversion to fully online colleges seems unlikely. As a robustness check, in Section 7 I will expand the market definition to the Commuting Zone ("CZ") level and allow for substitution to selective colleges as well, finding very similar rates of substitution.

[8] Diversion is bounded from below by zero.

[9] Note that since the change in the closing-college share is exactly equal to the (negative) pre-exit closing-school share (as its share drops to zero), the total college enrollment effect is the sum of diversion ratios to public, non-profit, and other for-profit colleges, minus one (the contribution of the closing school). That is, $\beta_{pub} + \beta_{np} + \beta_{fp} - 1 = \beta_{total}$.

Table 4: Diversion Ratios from Closing For-Profits to Other Sectors

	Prediction: IIA Logit		*Estimate:* Wald		*Estimate:* FD	
	(1)	(2)	(3)	(4)	(5)	(6)
Public	0.731***	0.695***	−0.023	0.068	0.274	0.169
	(0.012)	(0.012)	(0.303)	(0.282)	(0.248)	(0.285)
Non-profit	0.091***	0.086***	0.212	0.148	0.066	0.184
	(0.009)	(0.009)	(0.147)	(0.167)	(0.140)	(0.156)
Other for-profit	0.178***	0.219***	−0.749***	−1.176***	−0.051	0.116
	(0.009)	(0.011)	(0.178)	(0.253)	(0.136)	(0.178)
Total enrollment	0.000	0.000	−1.561***	−1.960***	−0.711**	−0.530
	(0.000)	(0.000)	(0.394)	(0.444)	(0.294)	(0.377)
Population-weighted	N	Y	N	Y	N	Y
$\geq$ 1% closure share	N	N	Y	Y	N	N
Calendar-year FE	N	N	N	N	Y	Y
Observations	278	278	207	207	278	278

Note: *p<0.1; **p<0.05; ***p<0.01

It may seem odd that diversion of for-profit students to other nearby schools in the same sector is near zero. However, during this time the for-profit sector overall faced a number of scandals and federal investigations related to misleading students and misreporting their outcome statistics – several of which implicated the very chains I study. These scandals were accompanied by extensive negative media coverage of the sector as a whole. Against this backdrop of the for-profit sector's deteriorating reputation, low diversion rates are not so hard to rationalize; Cellini et al. (2020) similarly finds low or even negative effects on other for-profit enrollment during a similarly fraught period for the for-profit sector.

5.2 IV Estimates: Across-Sector Diversion

So far, these results describe substitution rates from a particular set of for-profit colleges to other sectors, including other for-profits. An alternative notion of *across-sector* diversion asks where students would substitute if the entire for-profit sector became unavailable, rather than only the student's first-choice for-profit. When students barred from their first-choice for-profit instead substitute to another for-profit college, we do not observe their second-choice sector, so these students do not inform estimates of across-sector diversion. Results of the prior section show that within-sector diversion is very low, approximately zero, so that this distinction turns out not to matter much in practice. Still, I now present the results of an IV specification which yields exactly the *across-sector* diversion for those students induced to switch out of the sector by the chain closures.

In particular, I regress the change in public-sector market share on the change in total for-profit market share, instrumenting for the latter with the change in the closing-chain campus share (i.e., its pre-exit market share). Algebraically, these IV estimates simply scale up the estimated diversion to the public sector by the out-of-sector diversion rate, i.e., one minus the diversion to other for-profits. The public and non-profit diversion estimates in Table 4 are the reduced-form of this IV system. To keep the same interpretation of the coefficients, I use the decline in for-profit market share as the endogenous variable (multiplying the change in for-profit share by negative one).

The first stage is strong, consistent with the earlier result of low-to-zero diversion to other for-profits. The F-statistic is 61.7 in the unweighted version, and 32.4 when weighting by young-adult population. In Table 5, I present IV results along with the OLS version to show that naively correlating changes in sector shares may lead to biased estimates of substitution rates, likely due to unobserved local college demand shocks. Positively correlated shocks to the inside-good utilities cause sector shares to move together, so that the naive OLS estimates suggest no substitution at all (precise zeroes). Though IV estimates cannot be distinguished from zero, point estimates show larger substitution of about $19 - 26\%$ to the public sector, consistent with this source of bias. Unweighted estimates show that 67.7% of students leaving the for-profit sector do not substitute to any local colleges ($p = 0.005$), rejecting full substitution. Again, these results are very similar to those reported in the prior section, since chain closures result in approximately one-for-one declines in total for-profit enrollment. Yet the interpretation of these estimates is now that of the across-sector diversion ratio, rather than the diversion from the closing college alone.

Table 5: Across-Sector Diversion

	OLS		IV	
	(1)	(2)	(3)	(4)
Public	-0.038	-0.036	0.261	0.192
	(0.089)	(0.069)	(0.241)	(0.331)
Non-profit	-0.013	0.021	0.063	0.209
	(0.034)	(0.032)	(0.134)	(0.180)
Total enrollment	-1.050^{***}	-1.015^{***}	-0.677^{***}	-0.600
	(0.090)	(0.077)	(0.244)	(0.368)
First-stage regression	–	–	1.051^{***}	0.884^{***}
			(0.136)	(0.178)
Population-weighted	N	Y	N	Y
Calendar-year FE	Y	Y	Y	Y
Observations	278	278	278	278

Note: *p<0.1; **p<0.05; ***p<0.01

6 Mechanisms

Several commentaries on the puzzle of for-profit demand have suggested that distinctive programs of study may be an important source of differentiation (see, e.g., Deming, Goldin and Katz (2012) and Gurantz, Sakoda and Sarkar (2021)), yet little direct evidence exists for this hypothesis. Here, I employ two empirical strategies for evaluating the role of differentiated field-of-study offerings in driving low for-profit-to-public substitution.

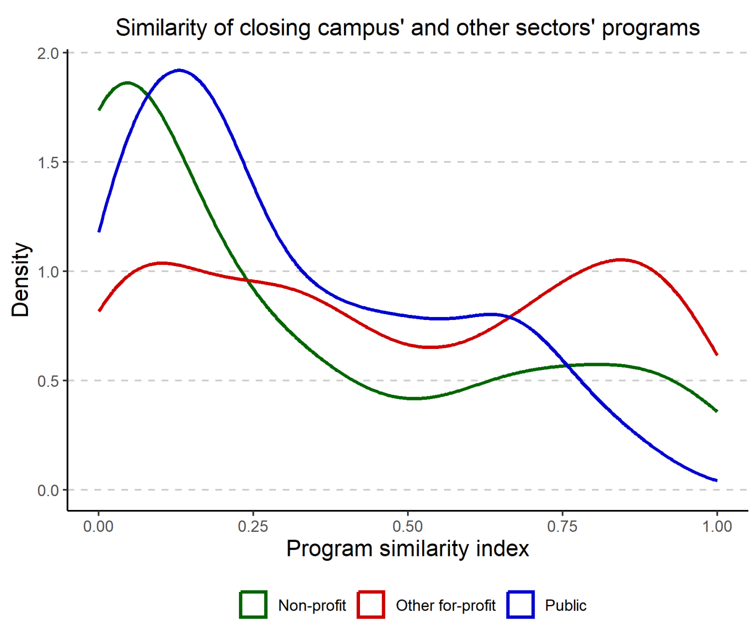
6.1 Heterogeneity by Program Similarity

Although it is difficult to evaluate the reasons for low substitution without estimating a college demand model, I offer suggestive evidence regarding one plausible explanation of low diversion: unique for-profit program offerings. To summarize the similarity of the closing for-profit campus' program offerings with those of other sectors, I take the vectors of historical degree completions by 2-digit CIP code for the closing chain campus, $\boldsymbol{C}_{j(m)}$, and for the local colleges in sector K, $\boldsymbol{C}_{K(m)}$. In each market, I then compute the cosine similarity between these degree-completion vectors as an index of program similarity (PS):

$$PS_m^K = \frac{\boldsymbol{C}_{K(m)} \cdot \boldsymbol{C}_{j(m)}}{\|\boldsymbol{C}_{K(m)}\| \|\boldsymbol{C}_{j(m)}\|} \in [0, 1]$$

As expected, closing chains are least similar to public colleges in terms of program offerings, with just one-quarter of local public colleges having more than 50% program similarity. The share of markets with non-profit similarity exceeding 50% is low too, at just 28%, and the share with other for-profit similarity exceeding 50% is nearly half. Figure 8 shows the distribution of closing chain program similarities across markets.

Figure 8



To evaluate diversion heterogeneity by program similarity, I interact exposure with an indicator for high program similarity, $HighPS_m^K = \mathbb{1}\{PS_m^K > 0.5\}$, in the first-differences regression, estimating the following equations:

$$\Delta s_{K(m),t} = \sum_{s \in T} \delta_s \mathbb{1}\{t = s\} + \alpha_K HighPS_m^K + \beta_{0K} s_{j(m),t-1} + \beta_{1K} s_{j(m),t-1} \times HighPS_m^K + \epsilon_{mt}$$

Diversion to low-similarity colleges is β_{0K}, while diversion to high-similarity colleges is $\beta_{0K} + \beta_{1K}$. Estimated diversion to low-similarity colleges is near zero across sectors, and relatively precisely estimated (Table 6). Estimated diversion to all three sectors is indeed higher when receiving-sector programs are highly similar to those of the closing chain, although standard errors on the interaction are large enough that these differences are only statistically significant at a 10% size for weighted public diversion and unweighted for-profit diversion. Still, point estimates show very large differences in diversion rates, with $69 - 98\%$ diversion to the public sector when program similarity is high. Diversion to high-similarity non-profits is $33 - 43\%$, and $38 - 43\%$ to high-similarity for-profits.

Table 6: Heterogeneity by Program Similarity

	Dependent variable: $\Delta s_{K(m),t}$					
	Public		Non-profit		Other for-profit	
	(1)	(2)	(3)	(4)	(5)	(6)
$HighPS_m^K$	-1.526	-2.144	-0.388	-0.335	-2.365	-1.138
	(1.987)	(1.629)	(1.109)	(0.915)	(1.451)	(1.619)
$s_{j(m),t-1}$	0.067	-0.206	-0.046	0.014	-0.209	-0.034
	(0.304)	(0.249)	(0.349)	(0.182)	(0.151)	(0.219)
$HighPS_m^K \times s_{j(m),t-1}$	0.622	1.188*	0.375	0.443	0.589*	0.464
	(0.532)	(0.662)	(0.406)	(0.377)	(0.308)	(0.380)
Population-weighted	N	Y	N	Y	N	Y
Calendar-year FE	Y	Y	Y	Y	Y	Y
Observations	277	277	194	194	274	274
Note:				*p<0.1; **p<0.05; ***p<0.01		

6.2 Supporting Evidence from the TAACCCT Grant Program

Given the imprecision of these estimates and concerns about false discovery when testing multiple forms of heterogeneity, I now test for this same mechanism using an alternative source of variation which directly shifted community colleges' program offerings.

6.2.1 Institutional Background

The Trade Adjustment Assistance Community College and Career Training ("TAACCCT") grant program was authorized in 2009 as part of the American Recovery and Reinvestment Act in the wake of the Great Recession. Across four waves from 2011-2014, the Department of Labor ("DoL") approved grants in excess of $1.9 billion designed to improve the quality of vocational education at community colleges across the country. Grantees used these funds to create new or redesigned degree programs targeted toward the needs of displaced workers and other adult learners seeking employment in growing local industries, primarily healthcare, manufacturing, and IT.

As part of their implementation of new and redesigned "career pathways," grantees were encouraged to partner with local employers, allow for online and technology-enabled learning, and develop structured program sequences awarding professional certifications and certificates at different stages. Other grant-funded activities could include recruitment of adult learners, academic support in the form of remediation services and career coaching, and work-based learning opportunities like sponsored internships. Nevertheless, the TAACCCT's primary aim and metric of success was capacity-building at community colleges through the development of career and technical education ("CTE") programs, deemed necessary to address the country's workforce needs following the Great Recession and a period of stagnating CC funding (Durham, Eyster, Mikelson and Cohen (2017)).

Grantees were chosen through a competitive application process administered by DoL. Colleges offering degrees of two years or less were eligible to submit individual applications, or to apply as a consortium with other eligible colleges. Individual applicants typically received $2.5 million, while consortia could receive up to $25 million. In all, a total of 256 grants funded 729 individual colleges across all 50 U.S. states, including more than 60% of all community colleges in the U.S. All grantees submitted quarterly progress updates to the DoL, and dozens of commissioned reports have documented colleges' compliance with their initial program-building targets. As of 2018, 96% of all planned programs of study had been implemented, totalling some 2,691 new or redesigned programs. And to that point, TAACCCT programs had awarded some 350,000 credentials among a total of 500,000 enrolled students (U.S. Department of Labor (2018)). Soliz and Ecton (2023) also document the TAACCCT's effects on CC grant recipients by comparison to CCs which never receive grants, finding that the program boosted enrollment and substantially increased completions in targeted CTE fields.

6.2.2 For-Profit Spillovers: Asymmetric Effects by Program Similarity

Given that CTE programs constitute the bulk of for-profit offerings, this grant program also provides an excellent environment for testing whether differentiation on program offerings contributes to limited rates of substitution between for-profit and public colleges. To do so, I leverage differences in the similarity of new TAA-funded CC programs with those offered by neighboring for-profit colleges. Given that my diversion estimates are substantially higher when for-profit and public colleges specialize in similar programs of study, grants which expand CCs' CTE offerings may divert students from for-profit colleges, despite low average substitution rates – and especially so for those grantees expanding offerings in fields of study closely related to those of neighboring for-profits.

Without grant-induced changes in CC program offerings, it would be challenging to identify whether for-profits divert students from CCs due to distinctive program offerings. For-profit entry and program-offering choices could be informative, but differences in local labor markets could confound this analysis – for instance, a region with a large hospital system may feature more health programs at both public and for-profit colleges, even if program offerings are in fact strategic substitutes. The rapid development of new CC programs in fields typically offered by for-profits allows an analysis of the demand effects of new programs, uncontaminated by for-profit supply responses and time-invariant location effects.

I split for-profits into three groups: those located in counties without any TAACCCT grantees (the never-treated), those located near TAACCCT grantees introducing programs in (2-digit CIP) fields *not* offered by the for-profit, and those located near a TAACCCT grantee introducing a program in a field offered by the for-profit. The latter two groups are both exposed to new CC programs, but only the third is exposed to a particularly similar new program. I begin by estimating TWFE models comparing the evolution of log for-profit enrollment in each treatment group to that of the never-treated for-profits. I normalize the 2010 coefficients to zero, the year before the first TAACCCT wave, and I allow trends to vary non-parametrically with for-profits' field offerings.[10]

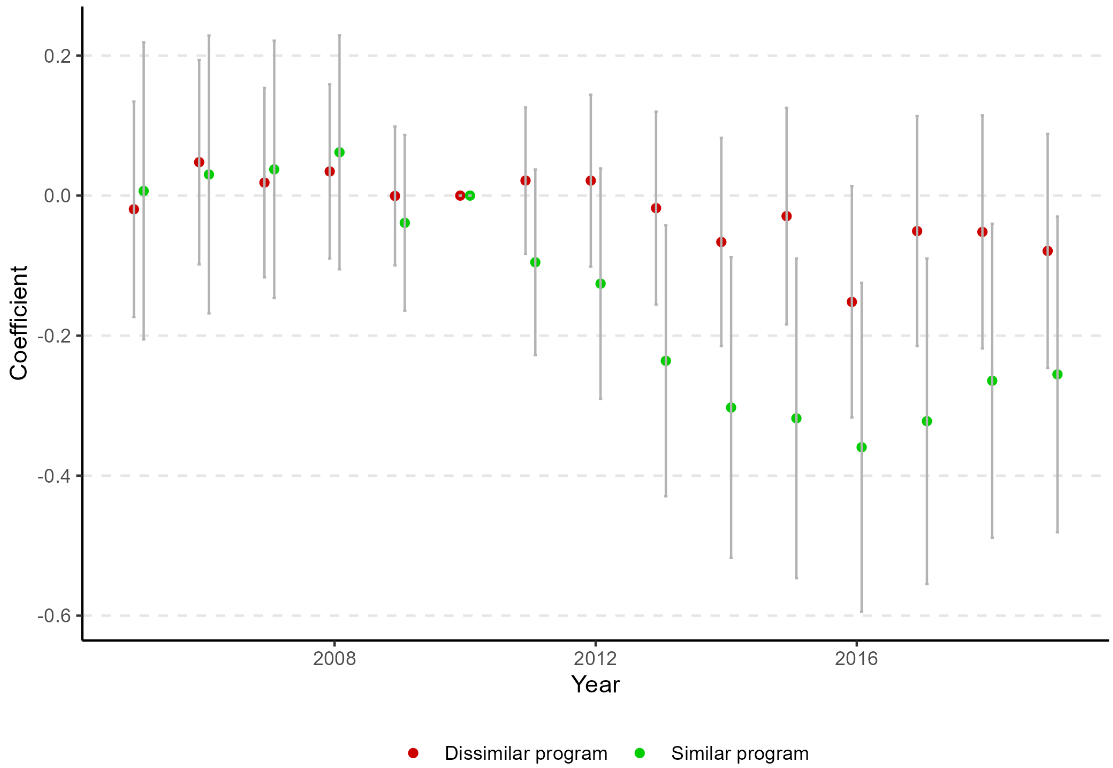
Figure 9 shows that as new TAACCCT programs were rolled out from 2011-2014, for-profits near CCs introducing dissimilar programs fared about as well as the never-treated, perhaps with slight enrollment declines. Yet for-profits offering programs similar to those introduced by TAA-funded CCs experienced substantial enrollment declines exceeding 30%.

Of course, grants are not randomly assigned, and the CCs which win grants may be making other kinds of investments to attract students from the private sector. The evidence in Soliz and Ecton (2023) of limited effects on other college inputs assuages this concern to

[10] Specifically, I fit FE for year × top 2-digit CIP field and year × number of 2-digit CIP offerings.

some degree. But we cannot rule out grantee selection for other reasons related to trends in local college demand which could themselves impact for-profit enrollment.

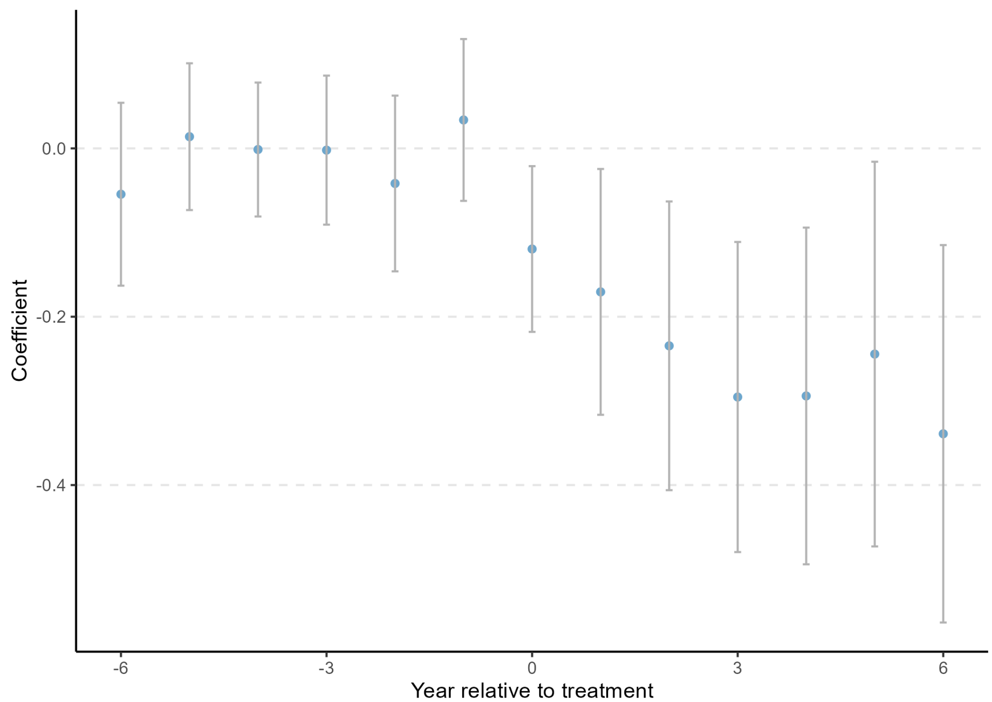
Figure 9: For-Profit Log Enrollment Responses to New TAA Programs



Next, I will omit never-treated for-profits and directly compare for-profits exposed to similar versus dissimilar TAA-funded programs. This limits concerns related to grantee selection and allows a more direct test of the hypothesis of differentiation on field offerings. I refine the specification by aligning event timing and estimating effects by year relative to first treatment. Given my staggered-treatment setting, I use the estimator proposed in Callaway and Sant'Anna (2021) to ensure robustness to heterogeneous treatment effects. Figure 10 shows excess enrollment losses at for-profits exposed to new programs in similar fields, relative to those exposed to new but dissimilar programs. These for-profits experience long-term relative enrollment declines of about 30%. See the Appendix for plain TWFE estimates, Gardner (2022)'s estimator, and de Chaisemartin and D'Haultfœuille (2024)'s estimator, which all show similar results.

Endogeneity concerns may remain even without comparison to never-treated colleges. For example, to the extent that CCs choose to introduce programs in fields with growing local labor market prospects, for-profits offering similar (dissimilar) programs would have gained (lost) enrollment even absent the TAACCCT grants. Yet if local field-specific labor market shocks do drive CCs' program choices, these will tend to understate any enrollment losses at for-profits offering similar programs. Reassuringly, the estimated pre-treatment enrollment trends are parallel and quite precisely estimated, and the enrollment response dynamics appear natural given that TAA program implementation was finalized no later than four years after grant receipt.

Figure 10: Excess Log Enrollment Effects of TAA-Funded Programs in Similar Fields



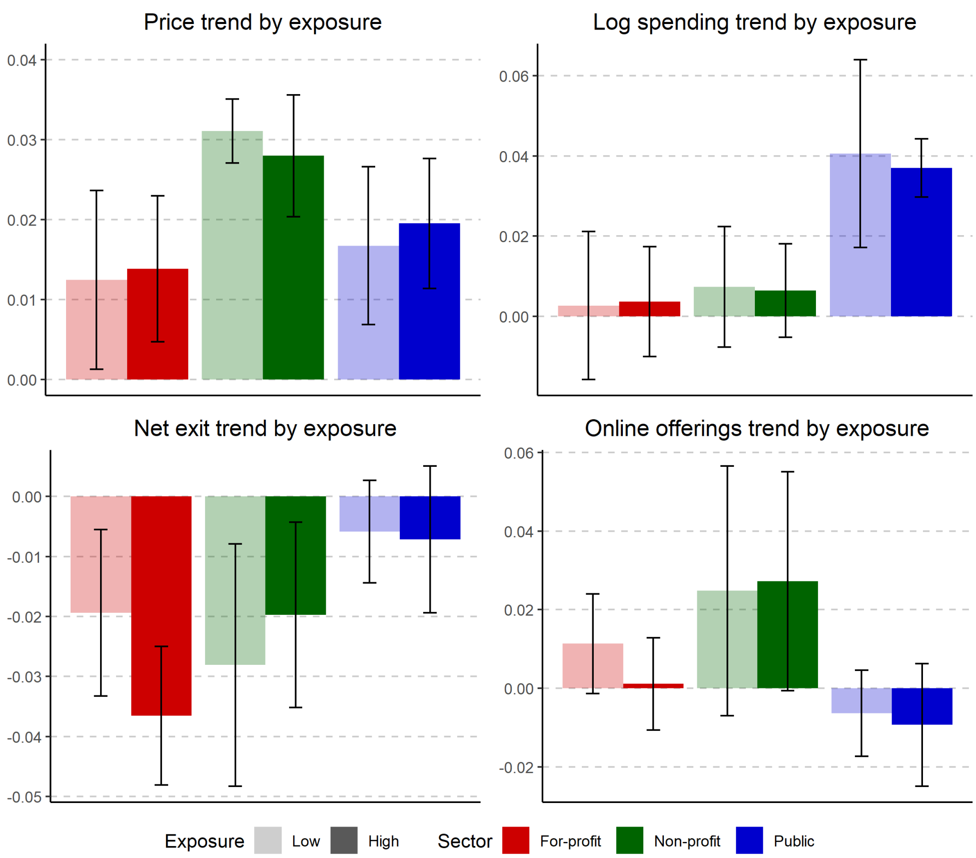
7 Robustness Checks

7.1 Concurrent Changes in Other Market Characteristics

Many drivers of college enrollment are observable, which allows for several natural robustness checks. For the first-differences regression estimator, exposure should be uncorrelated with changes in the college characteristics of other sectors relevant for demand. In addition, it should be uncorrelated with changes in variables like the unemployment rate, which may impact overall college enrollment. And for the Wald estimator, we would like to see mean-zero changes in demand-relevant characteristics.

Figure 11 plots mean changes before and after the closures in four demand-relevant college characteristics, by sector and exposure level. High-exposure means that the chain closure in that market was above the median closing-school market share. We see that tuition rises in all sectors by $1-3\%$, but not differentially so across exposure levels for any sector. Spending at public colleges rises by 4%, but again uniformly across exposure levels. The for-profit and non-profit sectors experience some net exit, but again relatively evenly by chain-closure exposure. The one exception may be for-profit exit, though the slightly higher levels of for-profit exit in high-exposure markets would if anything bias diversion to public and non-profit schools upward. Overall, other demand-relevant market characteristics appear relatively balanced, supporting the assumptions of the first-differences estimator.

Figure 11



In addition, I regress contemporaneous changes in the county unemployment rate with chain-closure exposure. Unemployment rates decline by just 0.059 percentage points more in high-exposure counties (s.e. 0.044). This is economically small, especially compared to the overall 0.58 percentage-point average decline in the unemployment rate, suggesting that local labor market conditions are also not changing differentially across exposure levels. Altogether, these checks provide evidence that the size of chain closures may be as-good-as-random with respect to changes in some of the important market characteristics likely to influence enrollment behavior.

7.2 Alternative Market Definitions

In the main analysis, markets were defined as all the non-selective colleges in a county, with inside-good market shares defined accordingly. The outside good therefore included not only the choice of no college, but also the choice of any selective college, or any college outside the county. Substitution on these margins is unlikely given the descriptive evidence about the strength of these students' location preferences and their below-average academic ability, but here I relax these restrictions to be sure that the main estimates do not miss legitimate substitution toward such options.

Table 7 presents results from the first-differences diversion estimator when re-defining markets to also include selective colleges, and when expanding the geographic market definition to the Commuting Zone to allow for substitution outside of counties within CZs. Results are quite similar overall. We again find limited substitution toward the public sector, of between $0 - 18\%$, and non-profit substitution remains modest. When allowing for substitution within the CZ, we find somewhat higher for-profit diversion, between $22 - 29\%$, though standard errors are large enough that we still cannot reject zero substitution. Total enrollment declines remain substantial, though harder to distinguish from zero in the CZ specification.

Table 7: FD Diversion Estimates: Alternative Market Definitions

	Dependent variable: $\Delta s_{K(m),t}$							
	Public		Non-profit		Other for-profit		Total enrollment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Including selective	0.007	0.177	0.136	0.063	-0.104	0.050	-0.961^{***}	-0.711^{**}
($N = 292$)	(0.235)	(0.258)	(0.109)	(0.120)	(0.152)	(0.192)	(0.305)	(0.349)
CZ markets	-0.055	0.170	0.089	0.114	0.219	0.290	-0.747^{*}	-0.426
($N = 230$)	(0.355)	(0.432)	(0.108)	(0.107)	(0.197)	(0.235)	(0.429)	(0.524)
Population-weighted	N	Y	N	Y	N	Y	N	Y
Calendar-year FE	Y	Y	Y	Y	Y	Y	Y	Y

Note: *p<0.1; **p<0.05; ***p<0.01

7.3 External Validity

Given that my empirical results exclusively use for-profit chain closures, in order to assess their external validity for the broader sector it may be helpful to compare the characteristics of chain for-profits with those of other for-profits which remained open. Prior to the wave of closures, chains accounted for about one-third of the entire sector's enrollment as of 2009

(Deming et al. (2012)). In addition, by taking a relatively large sample of chains distributed across the U.S., my sample is quite diverse in its characteristics, with primary program offerings spanning culinary school, cosmetology, IT, business, healthcare, and arts. While some chains offer partially remote education, the campuses I study have a limited online presence unlike the largest for-profits today specializing in fully online degrees, so my results may be less informative for this part of the sector as a result.

Table 8 provides further concrete evidence on similarities and differences between closing chains and the rest of the sector which remained open through 2019, using school and student characteristics from IPEDS. I exclude fully online for-profits. Especially when weighted by enrollment, other for-profit colleges resemble the closing chain sample in important ways. They charge very similar average tuition and both tend to be quite small. In terms of quality measures, chains have higher average value-added than other for-profits[11] and lower graduation rates (though graduation rates are nearly identical when weighted by enrollment). Chains tend to offer somewhat longer degrees, though both categories of for-profits specialize in sub-baccalaureate education. Unweighted, chains offer somewhat more online, weekend/evening, and part-time options than other for-profits, though they are less likely to use continuous academic calendars. Average revenue and spending measures are remarkably similar across these two groups of for-profits.

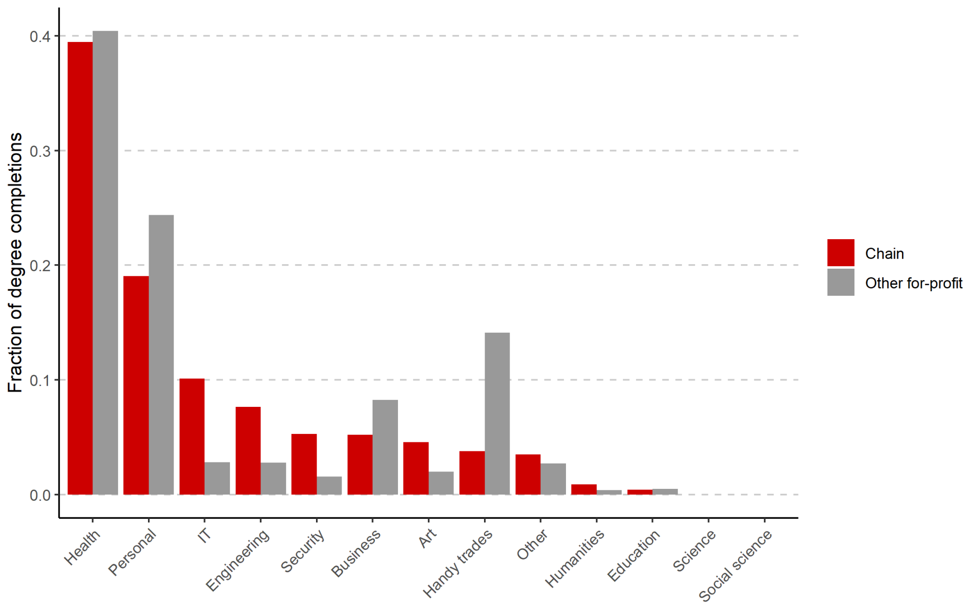
Given the importance of field-of-study offerings in explaining substitution patterns, I will further explore whether the closing chains are similar to for-profits which remained open in this dimension. First, Figure 12 shows the distribution of program completions by field for closing chains and other for-profits separately. Both chains and other for-profits specialize heavily in health degrees and “personal services” degrees (including cosmetology and culinary school). The chains are relatively more represented in the fields of IT, engineering, security, and art, and relatively less so in business and various “handy trades” like construction. Unlike public colleges, virtually none offer degrees in the humanities, natural science, and social science.

[11] These value-added measures come from Armona and Cao (2024) and are only available for two-year colleges.

Table 8: Balance of Mean Characteristics: Chains vs. Other For-Profits

	Unweighted		Enrollment-weighted	
	Chain	Other for-profit	Chain	Other for-profit
Full-time enrollment	413.3	267.4	714.4	1,179.4
Tuition & fees ($)	16,634.9	15,018.5	17,099.6	18,175.8
Graduation rate (150%)	42.1	58.3	46.4	45.9
Earnings value-added ($)	4,204.0	1,651.0	3,668.4	2,553.6
Offers < 1-year certificate (%)	21.8	66.0	30.7	44.0
Offers 1-year certificate (%)	61.2	82.9	74.0	64.5
Offers Associate's (%)	69.9	25.2	89.0	63.9
Offers Bachelor's (%)	39.4	10.1	43.7	46.6
# degree programs	11.0	5.7	14.2	20.5
# 2-digit CIP offerings	4.0	2.0	4.5	5.0
Offers online classes (%)	43.5	9.7	48.8	47.3
Offers weekend/evening (%)	56.3	44.7	62.7	77.2
Offers part-time (%)	68.4	49.5	58.9	36.4
Continuous calendar (%)	35.0	55.1	19.9	28.2
Total revenue per student ($)	31,261	27,446	23,520	21,941
Total spending per student ($)	27,012	24,424	18,832	19,168
Instructional spending per student ($)	8,210	9,061	5,558	6,162
Services spending per student ($)	14,384	9,711	9,806	9,261
Number of colleges	449	1,917	449	1,917

Figure 12: Programs of Study: Chain vs. Other For-Profit



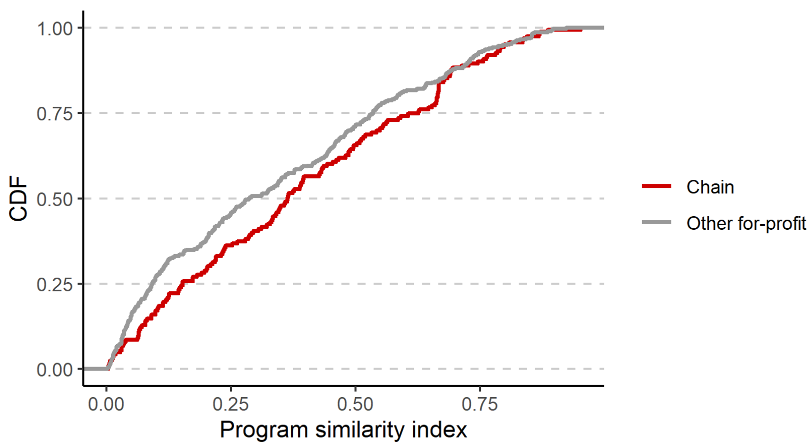
Next, I evaluate how for-profit colleges' program similarity with one another compares to their similarity with other sectors. I take the CIP program completion vectors from before and compute the cosine similarity of different sectors' program offerings, in the aggregate. Table 9 shows that chain for-profits are indeed highly similar to other for-profits in terms of their overall field-of-study specializations. Both groups of for-profit schools are much less similar to public and non-profit options by this metric.

Table 9: Aggregate Program Similarity across Sectors

	Chain	Other for-profit	Public	Non-profit
Chain	1	0.956	0.737	0.648
Other for-profit	0.956	1	0.735	0.628
Public	0.737	0.735	1	0.797
Non-profit	0.648	0.628	0.797	1

For substitution patterns, what matters is not aggregate program similarity, but the similarity of a given for-profit college with other colleges in its local market. To evaluate the similarity of chains' and other for-profits' program offerings with those of their local competitors, I compute the market-level program similarity indices for each chain campus and other for-profit college with the public colleges in their vicinity. Figure 13 displays the distribution of local for-profit–public program similarity, by whether the for-profit is a closing chain or another for-profit which remained open. Again, most for-profit colleges are quite dissimilar from local public options in this dimension, and if anything the non-chain for-profits are even more differentiated from public colleges.

Figure 13: Similarity of For-Profit and Public Programs



8 Discussion

Using aggregate market share data alone, I estimate the second choices of for-profit college students using quasi-experimental variation coming from the recent spate of for-profit chain closures. I relate my estimates to a rich and flexible model of college choice, showing that under a parallel-trends-like assumption my estimators identify diversion ratios between sectors of U.S. higher education. For example, these diversion ratios describe what fraction of for-profit students would consider a local public college to be the best alternative to their chosen school. Thus, they can inform policymakers about the college enrollment effects of policies which sanction for-profit colleges, either making them less attractive to students or leading to their closure.

I began by elaborating a highly general model of college choice, which rests on two core assumptions motivated by stylized facts: students can freely choose among non-selective colleges, and students strongly prioritize local colleges. I show that most students at non-selective colleges do indeed live quite close to their chosen school. Beyond these assumptions, the model does not require that choices purely reflect student preferences; in particular, it can accommodate misinformation about characteristics of the choice set via distortions of the preference parameters. Rather than parameterize and estimate the entire model, I show that the average rates at which students substitute across schools in their choice sets (the diversion ratios) are identified from data on exogenous college closures with simple reduced-form estimating equations.

In estimating these equations, I restrict myself to intensive-margin variation within for-profit chains in the pre-closure market shares of their different campuses. I argue that this variation is unlikely to be correlated with counterfactual trends in local college enrollment since they were generally induced by changes in the policy environment, leading to abrupt, unexpected, and complete shutdowns almost overnight. In support of my identifying assumptions, I show that the size of these closures is not systematically related to key drivers of college demand like tuition at other schools and the local unemployment rate.

My results show that most local public colleges are not particularly close substitutes for students who would have otherwise enrolled in a chain for-profit – enrollment at these colleges remains relatively steady following for-profit closures. Total local college enrollment declines by 50-70% of the size of the chain closure, showing that for-profit students tend not to reallocate to other local colleges in general. Data limitations mean that we cannot definitively say where they *do* reallocate. Though the vast majority of non-selective college-goers live very close to school, in principle students may move out-of-county for school, enroll in a fully online (typically for-profit) program, or enroll in a non-Title-IV-eligible program (also commonly for-profit). Still, I provide some evidence that these channels of substitution are unlikely, and many of these students' second choice may indeed be to exit higher education.

I go on to characterize heterogeneity in diversion ratios by the match of the closing schools' program specializations with those of other nearby colleges. Public-college diversion in particular is much higher in the minority of markets where local public colleges offer programs of study similar to those offered by the closing for-profit. I supplement this suggestive evidence with an evaluation of the TAACCCT, which expanded CCs' program offerings in exactly the kinds of vocational programs supplied by for-profits. For-profits exposed to new TAA-funded programs in similar fields suffer particularly large enrollment losses, substantiating the view that program-of-study differentiation is an important mechanism for limited substitution.

In terms of observable characteristics, the closing chain for-profits appear relatively representative of the sector at large, especially in terms of their offered programs of study, so my findings may also help characterize the broader role of the for-profit sector in the landscape of U.S. higher education. Rather than simply pull students away from cheaper and higher-return colleges, for-profits appear to expand access to college for what is a particularly low-SES and non-traditional student population. Of course, how these closures affected student welfare depends also on whether these colleges offered meaningful returns on investment. Though this is doubtful for much of the for-profit sector, given high tuition and relatively low estimated wage gains, Armona and Cao (2024) estimate fairly large earnings value-added for the chain for-profit colleges I study.

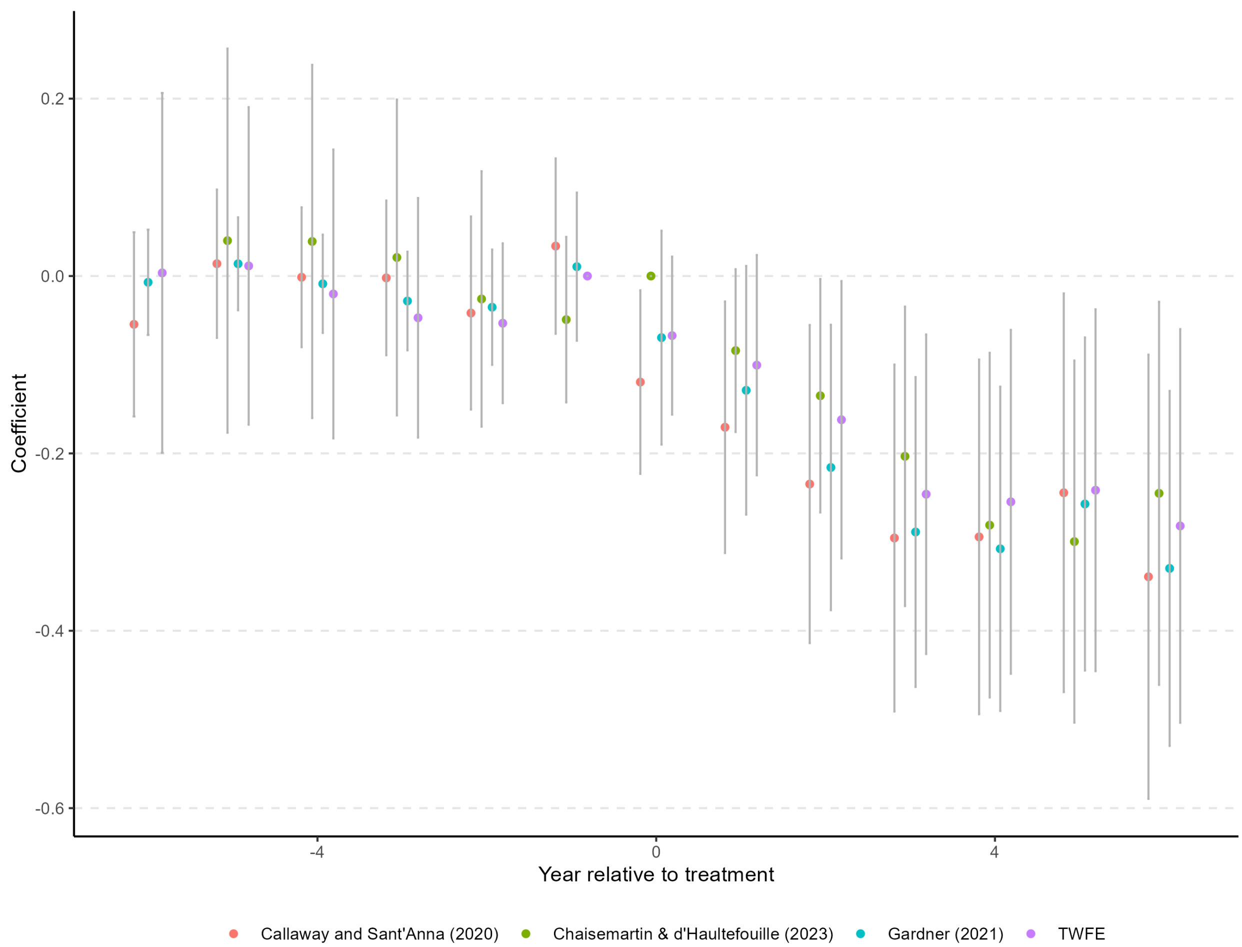
These findings also shed light on the possible consequences of sector-biased higher education policy, including the new round of GE regulations which took effect on July 1, 2024, bolstering the standards which for-profit colleges must meet in order to continue qualifying for federal student loans (Weiss (2023)). Of the 1,669 for-profit certificate programs required to pass the new graduate earnings threshold, DoE projected in 2022 that 65% would fail given the data at the time, suggesting that these new regulations could have even more bite than older iterations and induce further closures (Knott (2023)). Thus, the trajectory of the current policy landscape gives particular salience to my findings.

Appendix

Section 6.2.2

Here I plot alternatives to Figure 10 using four different event-study estimators. These measure the log for-profit enrollment effects of new TAA-funded CC programs in fields similar to nearby for-profits, relative to new but dissimilar programs.

Figure 14: Effect of Similar TAA-Funded CC Program on Log For-Profit Enrollment



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