Do For-Profit Colleges Expand Opportunities in Higher Education? Evidence from Campus Closures

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Abstract:

For-profit colleges typically offer lower returns than public colleges, but they may expand access to higher education for students who would otherwise forgo college. I evaluate the sources of for-profit demand – whether students are pulled into higher education or away from public options – by tracking enrollment responses to several abrupt for-profit chain closures spanning hundreds of U.S. counties. I find that only 20% of for-profit students would substitute to public colleges, were for-profit colleges unavailable. I next estimate the spillover effects of the largest-ever community-college grant program, showing that limited substitution results from for-profits' unique vocational programs.

JEL Codes: I23, I24, I28, J24.

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1 Introduction

For-profit colleges offer lower average returns and charge significantly higher prices than open-access public colleges (Lovenheim and Smith 2023). In an environment with extensive for-profit advertising and limited information about college quality, reducing public support for for-profit colleges is a simple and oft-discussed policy tool for encouraging better college choices (Cellini and Koedel 2017). Yet, it is an empirical question whether such policies will steer students toward higher-return public colleges or lead them to forgo higher education altogether. To weigh these effects, we must understand the sources of for-profit college demand – that is, where would for-profit students enroll, if anywhere, were their preferred for-profit unavailable?

For-profit students' second choices also help characterize how the sector shapes inequality, given that for-profits educate students from particularly disadvantaged backgrounds. Even compared to their peers at community colleges (CCs), for-profit students come from relatively low-income families and are more likely to enter college at an older age, without a high-school diploma, or as a single parent. How for-profit regulation impacts college demand will therefore matter for income mobility and the post-secondary attainment of students on the margins of higher education.

To quasi-experimentally evaluate the sources of for-profit demand, I study the abrupt, nationwide closures of 11 large for-profit chains between 2014-2018, which collectively operated 462 campuses across the U.S. I leverage the across-cohort choice-set variation induced by these closures to infer the extent of substitution from closing schools to other sectors. I propose a shift-share estimator, where abrupt college exit shifts residual demand for other colleges, but to different degrees in different local markets based on campuses' pre-exit market shares.

To guide interpretation, I derive the shift-share estimating equations as the reduced form of a generic discrete-choice college demand model. Building on work by Conlon and Mortimer (2021), I show that the average rates of substitution from for-profit colleges to other sectors

are identified from market share data before and after a set of college closures, provided they satisfy a suitable exogeneity assumption. Appealing to institutional evidence and a variety of empirical tests, I argue that the chain closures I identify satisfy this assumption.

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. 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. These core findings are robust to a variety of alternative specifications.

These estimates show that many for-profit students do not treat public colleges as a close substitute. But why? In the final part of the paper, I provide new causal evidence that for-profits' unique program offerings differentiate them from public colleges and constitute an important reason for limited substitution. Whereas public colleges offer a wide range of majors, for-profit colleges specialize in a small set of vocational fields of study. First, I show that the estimated substitution rates to the public sector are higher in the minority of counties where public colleges specialize in programs similar to those offered by the closing chain.

Second, I show that new public-college programs significantly reduce for-profit demand, but only when neighboring for-profits offer programs in closely related fields. To do so, I use variation in public program offerings induced by the Trade Adjustment Assistance Community College and Career Training (TAACCCT) grant program. This $2 billion effort expanded community college programs of study in many fields offered by neighboring for-profit colleges. I show that for-profits offering the same field as that of a newly introduced CC program suffer persistent enrollment losses of more than 30%, 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.

My results contribute to two main strands of the literature. First, I add to our understanding of how the for-profit sector shapes educational opportunities. Most studies conclude that public colleges are closely substitutable with for-profits, such that for-profits mainly divert students from higher-return options (Cellini 2021). By contrast, I find that for-profits primarily draw new students into higher education. Early studies used tuition and spending variation to show that some students are on the margin of for-profit and public college (Cellini 2009; Chung 2012; Goodman and Volz 2020). While these LATEs are relevant for understanding the marginal effects of policies like reducing CC tuition, they do not quantify the share of for-profit students diverted from other colleges. They are therefore less informative about the effects of sweeping changes in for-profit regulation.

Cellini, Darolia, and Turner (2020) overcome this limitation, showing that Department of Education (DoE) sanctions against for-profits induced 60-70% diversion to public colleges. However, their sample of Pell recipients from the 1990s may not generalize to today's market, especially given the multiple waves of entry and exit the sector has experienced over the last three decades. Although my results characterize only a subset of the for-profit sector, I am able to estimate the substitution patterns of more recent cohorts (from 2014-2018) attending modern for-profit chains. I show that this sample is broadly representative of the rest of the sector in Section 6, except for the fact that closing chains did not provide much online education.

Two studies find low rates of substitution, similar to my results. Soliz (2018) shows that CC enrollment did not dip following the entry of many for-profit colleges from the early 2000s through 2012, when many of the modern for-profit chains were started. My paper builds on this research by focusing on the plausibly exogenous exit of dispersed for-profit chains, alleviating concerns that college entry and exit choices respond to local college demand shocks. More recently, Armona and Cao (2024) estimate a national college demand model that also delivers low diversion ratios between two-year for-profits and community colleges.

Secondly, my results improve our understanding of what drives for-profit demand and differentiates for-profits from public alternatives. Much existing work provides suggestive evidence for different channels by documenting differences in for-profit and public college characteristics. These include for-profits' unique program offerings, reduced course requirements, extensive advertising, and enhanced flexibility (e.g., continuous academic calendars; Deming, Goldin, and Katz 2012; Deming, Goldin, and Katz 2013; Cellini and Chaudhary 2020). However, causal evidence on the impact of these distinguishing features is scarce. Differentiation is a matter of both product characteristics and student preferences, and measuring preferences can be challenging.

To this end, I offer some of the first causal evidence on the drivers of for-profit college demand. Not only do for-profits specialize in unique vocational programs, but I show that these differences have large effects on enrollment behavior. Armona and Cao (2024) also offer causal evidence on this question, showing that for-profit enrollment is highly sensitive to advertising. Their estimated demand model also supports the importance of for-profits' distinctive program offerings.

In addition, I offer the first quasi-experimental evidence on the 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 studies describing how these closures impacted displaced students (Burns, Brown, et al. 2022; Burns, Bryer, et al. 2023). Finally, I build on recent work in empirical IO showing how the diversion ratios of structural demand models can be recovered from different kinds of experimental interventions (Conlon and Mortimer 2021).

The remainder of the paper proceeds as follows. I begin by reviewing the data and institutional setting in Section 2, including the policy environment governing for-profit colleges, the pattern of for-profit closures, and the characteristics that distinguish for-profit and public colleges. Section 3 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 4 presents estimated diversion ratios, followed by evidence in Section 5 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 6, before concluding with a discussion in Section 7.

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 list of Title-IV-eligible college campus closures between 2010 and 2019, from 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.

For evaluating the for-profit enrollment effects of the TAACCCT grant program, I also use data on CC grantees' new programs of study from CareerOneStop, a website offering career resources sponsored by the Department of Labor (DoL). This data contains the fields of study in which CCs expanded their program offerings, using the Classification of Instructional Programs (CIP) taxonomy, along with other grant information. I then relate this to IPEDS data on nearby for-profits' existing 2-digit CIP offerings.

2.2 Institutional Features

The private for-profit sector accounts for a small slice of U.S. undergraduate enrollment, enrolling just 5% of U.S. college students in 2021. This is down from 9% in 2010, partly due to the intensity of for-profit college closures over the course of the decade.[1] Despite their small share, for-profit colleges still serve nearly 800,000 students each year (National Center for Education Statistics 2023).

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.[2] 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, as seen in Figure 1. Note that non-profit students attend school farther from home, which is in part because non-selective non-profit schools are not as widespread.

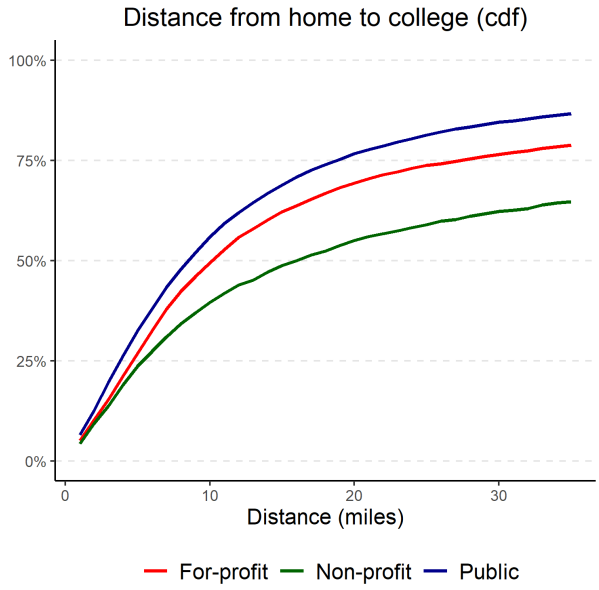
Overall these facts suggest limited consideration sets and/or strong location preferences, perhaps due to the extra costs of attending school beyond a reasonable commuting distance from home. Therefore, students displaced from their first-choice college will be most likely to consider alternatives in its vicinity. This is important for my research design, as I rely

[1] Appendix Figure A3 depicts these trends in college supply and enrollment.

[2] 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.

on spatial variation in college closures to identify the attendance spillovers of for-profit exit. Later, I also show that allowing for substitution outside counties within larger Commuting Zones does not significantly alter my results.

Figure 1



2.2.1 Policy Environment and the History of For-Profit Chains

Most for-profit students pay their tuition using federally funded student loans under Title IV of the Higher Education Act of 1965. As these loans are offered at below-market rates and default is relatively common among for-profit students, the federal government effectively subsidizes the for-profit sector. To remain eligible for these subsidies, for-profits must maintain accreditation and prepare students for "gainful employment in a recognized occupation." DoE can therefore moderate for-profits' access to federal revenue sources through its interpretation of the "gainful employment" (GE) standard.

The Obama administration promulgated rules to enforce this provision, which ultimately went into effect in 2014.[3] GE rules were part of a broader DoE effort under the Obama

[3]These rules would deny federal funding to for-profits whose graduates exceeded a maximum debt-to-earnings threshold. The provision was tied up in the courts and did not itself lead to any disqualifications (Weiss 2023), though schools have lost eligibility for other reasons.

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. When the DoE flagged a school for poor financial health or, as in the case of ITT Tech, its accreditor announced a financial audit, DoE would require the school to post a large surety and limit 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. Such financial pressures led ITT Tech to abruptly shutter all its 132 campuses in 2016 (Douglas-Gabriel 2016). In this and other cases, federal and state governments also sued and imposed fines for fraud and misleading job-placement claims. Corinthian Colleges was a leading example, closing all 28 campuses in 2015 after multiple lawsuits (Johnson 2015).

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 database, I identify 11 for-profit chain closures satisfying several criteria: each chain (1) operated at least ten campuses across the U.S. prior to closing, (2) operated in more than one state, (3) closed all campuses in the same year and without advanced warning,[4] and (4) permanently stopped admitting new students.[5] In most cases, closures occurred as a direct result of financial troubles caused by threatened or actual suspension of federal financial aid eligibility. Appendix A includes further details on the timing and causes of each chain closure. These features of the chain closures will be important for the credibility of the identifying assumptions described in Section 3.1.

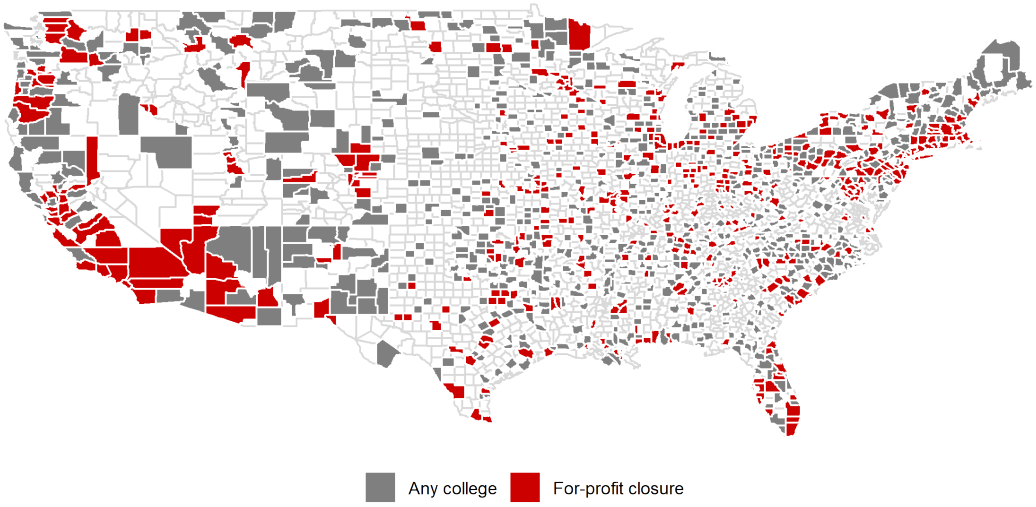
[4]In some cases, the chain had a handful of campus closures several years before. In the case of Corinthian Colleges, the closures came in two large waves, with one in 2014 and another in 2015, and 56 other campuses were sold to Zenith Education Group. My results are not sensitive to the exclusion of this chain.

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

2.2.2 Geography of College Exit

The for-profit chain closures represent only a fraction of total for-profit exit 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. 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 2.

Figure 2: For-Profit Closures, 2010-2019



30% of these campus closures belonged to one of the 11 chains I identified. And as of 2009, these chains enrolled 54,200 *new* students, accounting for a whole 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, described in Appendix Figure A1.

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.

Most of these local markets feature multiple college options: 87% of counties where for-profits have shut down also have a non-selective public college present, and 80% feature a surviving for-profit. In my analysis, I will restrict attention to those counties with both public and other for-profit options available. Otherwise, estimated spillovers would be attenuated by markets where substitution is mechanically zero due to a lack of local alternatives. Since only 30% of counties feature a non-profit college, I do not restrict the sample to such markets, so estimated substitution to non-profits will reflect these mechanical zeroes.[6]

2.2.3 Potential Sources of Differentiation

Although I will not estimate a complete model of student preferences and beliefs, here I review evidence that for-profits look systematically different from public alternatives in key dimensions.[7] These differences provide suggestive evidence about sources of differentiation and help rationalize imperfect substitution across sectors.

For-profit colleges are substantially more expensive than non-selective publics, and available evidence shows that they yield lower earnings premia (Appendix Figure A4).[8] For-profit students may be relatively price-inelastic due to the availability of subsidized federal student loans. In addition, students may lack information about prices or returns, resulting in undue optimism about their ability to repay large debt burdens. This is especially worrisome given the intensity of for-profit advertising – which has large enrollment effects – and several instances of misleading claims and fraud by for-profit recruiters (Cellini and Darolia 2016;

[6] Whether conditional or unconditional substitution rates are more relevant depends on the policy question of interest. Another motive for excluding counties without local alternatives is to make the assumption of localized substitution more plausible.

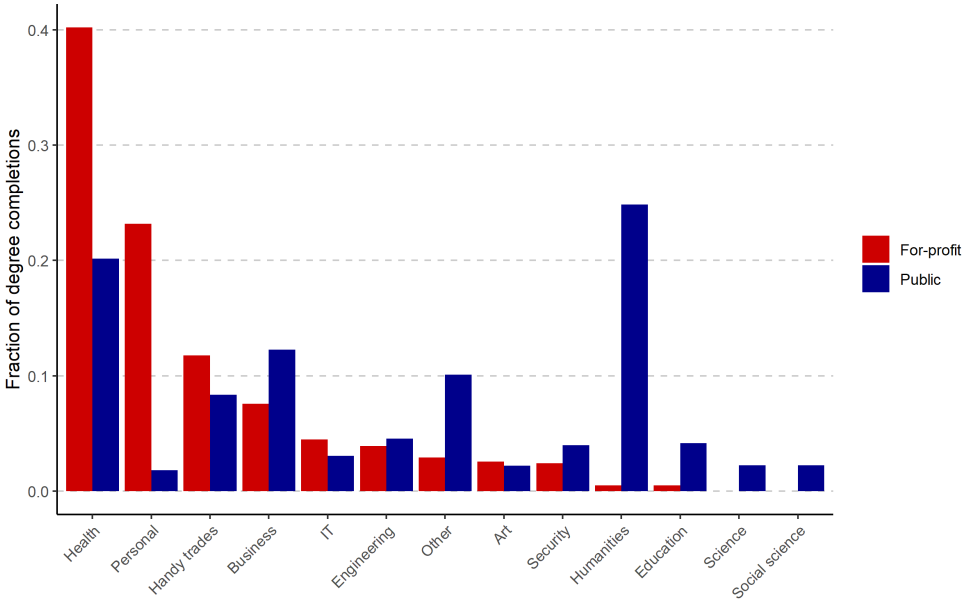
[7] I keep this review brief, as prior work already documents many of these distinctions. See, e.g., Deming, Goldin, and Katz (2012), Deming, Goldin, and Katz (2013), Cellini and Darolia (2016), Armona, Chakrabarti, and Lovenheim (2022), and Armona and Cao (2024).

[8] Note that existing estimates of college returns by sector do not isolate sector effects on returns, except under the implausible assumptions of constant treatment effects or negligible sorting on gains.

Armona and Cao 2024).

What other features of for-profit colleges might support such high prices? Most for-profit colleges reside within a few miles of an open-access public college, so college availability does not readily explain for-profit enrollment.[9] For-profits do differ substantially from public colleges in their program offerings, specializing in a handful of pre-professional fields including healthcare, business, "personal services" like cosmetology and culinary arts, and information technology (Figure 3).

Figure 3: 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, this may be another important source of differentiation for students who doubt whether they could meet the graduation requirements of public schools. Others may simply want a more direct path to their degree, as for-profits typically don't require the remedial and core coursework needed at many CCs. Along with

[9]That said, community colleges may face implicit capacity constraints due to funding limitations and course enrollment caps, which may in practice limit public-college accessibility (Robles, Gross, and Fairlie 2021).

limited course requirements, for-profits are known for other forms of flexibility like continuous academic calendars and accelerated programs. And several large for-profits specialize in online education, though the chains I study offered primarily in-person schooling. Other differences are documented in Appendix Table A2.

For-profit students also differ from their peers at non-selective publics. They come from much poorer families and take less traditional paths to college – they are more likely to have military experience, to delay post-secondary entry, to lack a high-school diploma, and to have caregiving responsibilities. Such students may have particularly strong preferences for for-profits' unique flexibility and degree paths, amenities without which they might not enroll in college. Appendix Tables A3 and A4 elaborate on these differences.

3 Empirical Model

Rather than specify and estimate a complete demand model, I now derive reduced-form estimating equations from a generic college-choice model. This exercise helps to clarify the appropriate functional form, to understand my estimator's complier group, to precisely characterize the counterfactual I identify, and to develop testable predictions from a plain logit model. None of the few modeling assumptions made here are necessary if we wish to take the reduced-form equations in Section 3.2 as given and interpret them as shift-share estimators justified under an "exogenous shares" assumption. An analogy can also be made to methods for estimating the mix of compliers coming from different alternatives in settings with multiple unordered treatments, as in Kline and Walters (2016) for instance.

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. 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. 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 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 prefer-

ence 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.

3.1 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

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

3.1.1 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.

3.1.2 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

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

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

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

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 $\beta = \mathbb{E}[\bar{D}_m^K]$ 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 $\bar{D}_m^K$.

3.1.3 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 3.1.2 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 3.1.2, 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.[10] 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.[11]

[10] 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).

[11] 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.

3.1.4 Evaluating the Identifying Assumptions

Rather than use all for-profit closures over this period, I restrict attention to the nationwide closures of the 11 for-profit chains described in Section 2.2. 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 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, we can reasonably conclude that these closures were not related to local demand conditions.

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 declining demand or tougher competition from local public colleges – 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). 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 this concern, I will compare the linear estimator to a kernel smoother and plot the raw data. In any case, the Wald estimator is robust to violations of this condition.

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 6.

3.2 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 one 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.[12] This does not change the interpretation of the coefficient as a diversion ratio, provided that changes in market size are

[12] 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.

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. 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.

4 Diversion Ratio Estimates

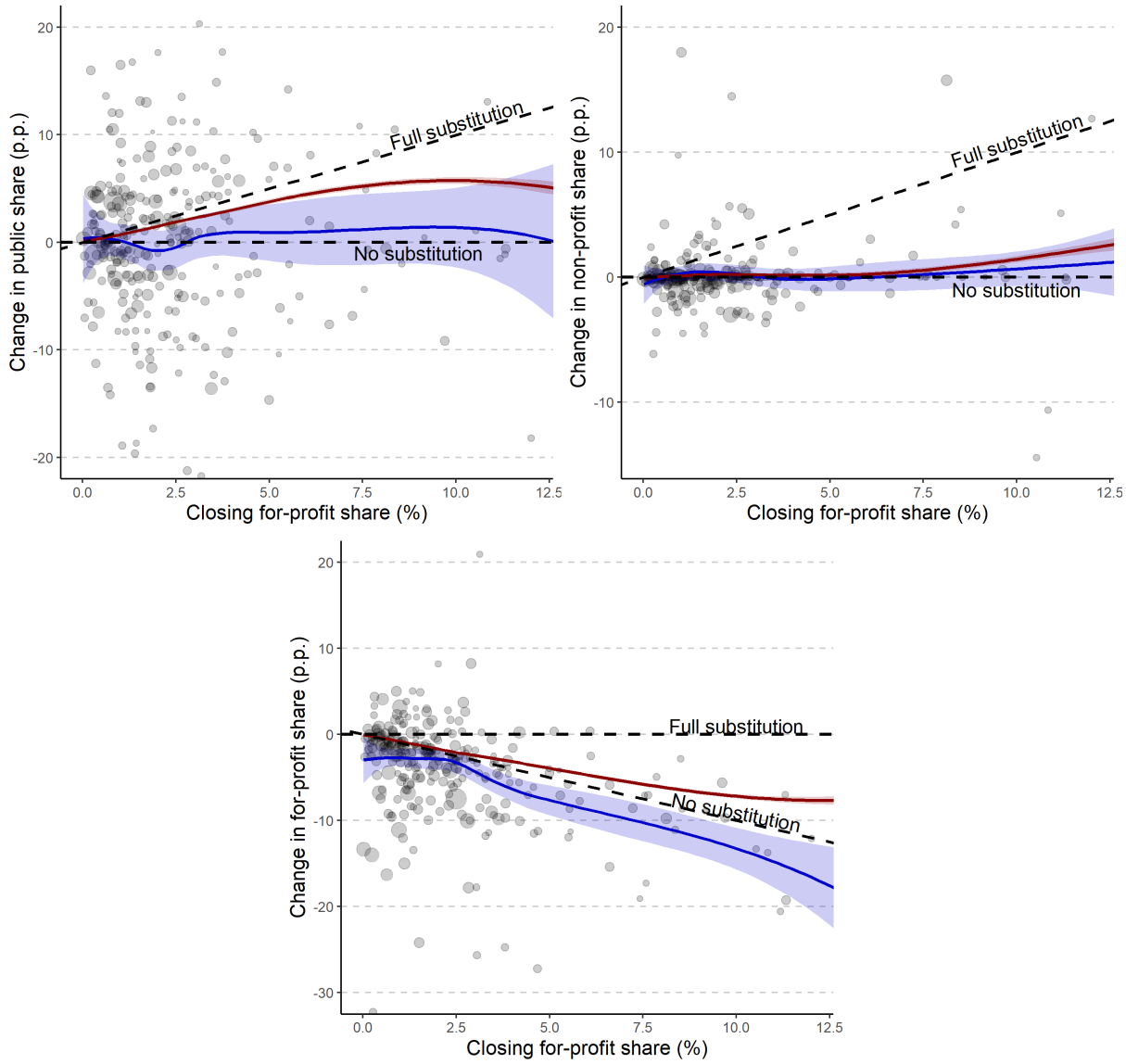
4.1 Reduced Form: Diversion from Closing Colleges

First, Figure 4 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 quadratic 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 4: 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 1 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.

Table 1: 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		✓		✓		✓
≥ 1% closure share			✓	✓		
Calendar-year FE					✓	✓
Observations	278	278	207	207	278	278

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

Columns 3-6 show unweighted and population-weighted estimated diversion. 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.[13] Diversion to non-profits is estimated to be between 6-21% depending on specification. Unweighted and

[13] Diversion is bounded from below by zero.

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 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).[14] 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 6 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.

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, Darolia, and Turner (2020) similarly find low or even negative effects on other for-profit enrollment during a similarly fraught period for the for-profit sector.

[14] 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, $\beta_{pub} + \beta_{np} + \beta_{fp} - 1 = \beta_{total}$.

4.2 IV Estimates: Across-Sector Diversion

So far, these results describe substitution rates from a particular set of for-profit colleges to other groups of colleges, 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).[15] 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 2, 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. These

[15] 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 1 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).

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 2: 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		✓		✓
Calendar-year FE	✓	✓	✓	✓
Observations	278	278	278	278
Note:				*p<0.1; **p<0.05; ***p<0.01

5 Mechanisms

Several commentaries on what generates 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. Although it is difficult to evaluate the reasons for low substitution without estimating a college demand model, here I offer two empirical strategies for evaluating the role of differentiated field-of-study offerings in driving low for-profit-to-public substitution.

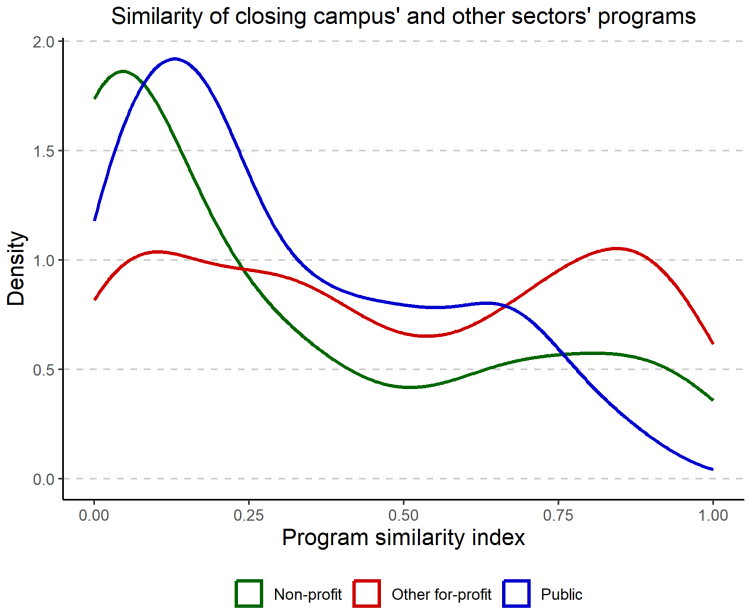
5.1 Heterogeneity by Program Similarity

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 5 shows the distribution of closing chain program similarities across markets.

Figure 5



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 3). 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 3: 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		✓		✓		✓
Calendar-year FE	✓	✓	✓	✓	✓	✓
Observations	277	277	194	194	274	274

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

5.2 Supporting Evidence from the TAACCCT Grant Program

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

5.2.1 Institutional Background

The Trade Adjustment Assistance Community College and Career Training 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 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 et al. 2017).

Grantees were chosen through a competitive application process administered by the 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.

5.2.2 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.[16]

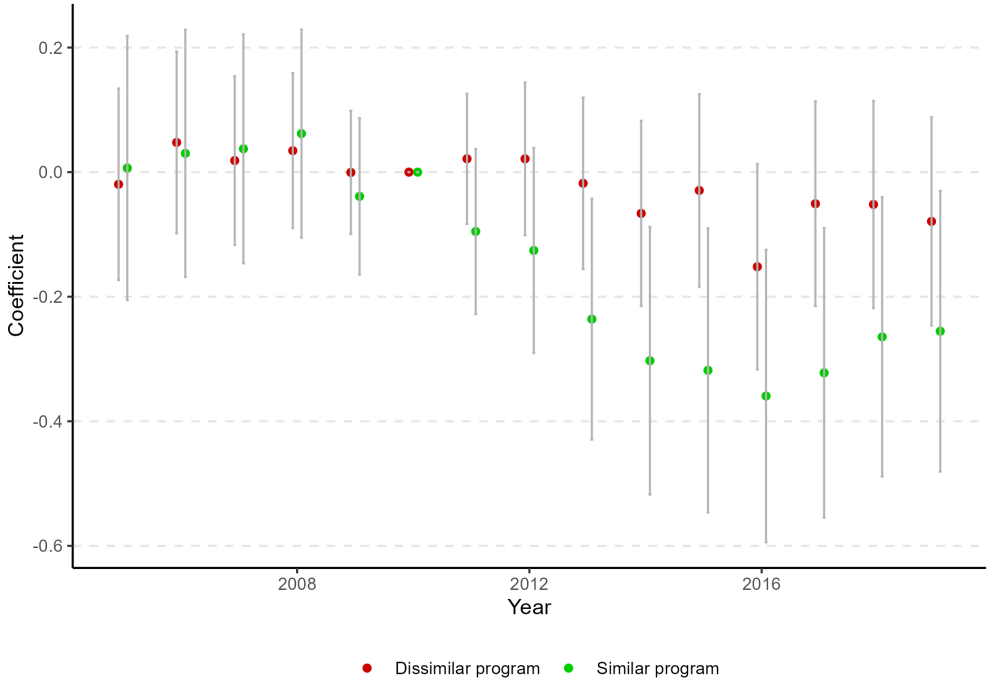
Figure 6 shows that as new TAACCCT programs were rolled out from 2011-2014, for-profits near CCs introducing dissimilar programs fared about as well as the never-treated, perhaps with slight enrollment declines. Yet for-profits offering programs similar to those introduced by TAA-funded CCs experienced 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 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.

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

[16]Specifically, I fit FE for year $\times$ top 2-digit CIP field and year $\times$ number of 2-digit CIP offerings.

Figure 6: For-Profit Log Enrollment Responses to New TAA Programs

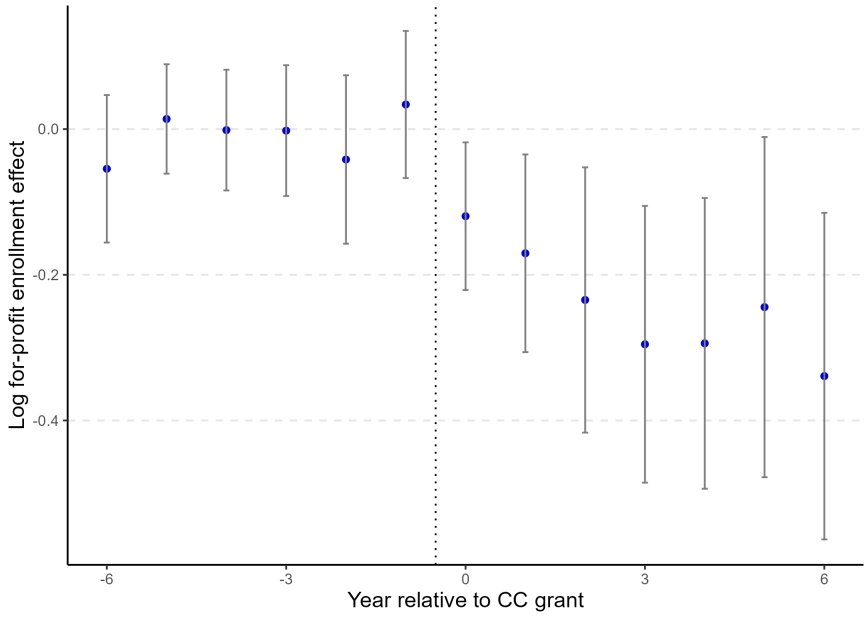


Callaway and Sant'Anna (2021) to ensure robustness to heterogeneous treatment effects. Figure 7 shows excess log enrollment losses at for-profits exposed to new programs in similar fields, relative to those exposed to new but dissimilar programs. These for-profits experience long-term relative enrollment declines of about 30%.[17]

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.

[17]See Appendix Figure A5 for plain TWFE estimates, Gardner (2022)'s estimator, and Chaisemartin and D'Haultfœuille (2024)'s estimator, which all show similar results.

Figure 7: Excess TAA Effect on Similar Programs



6 Robustness Checks

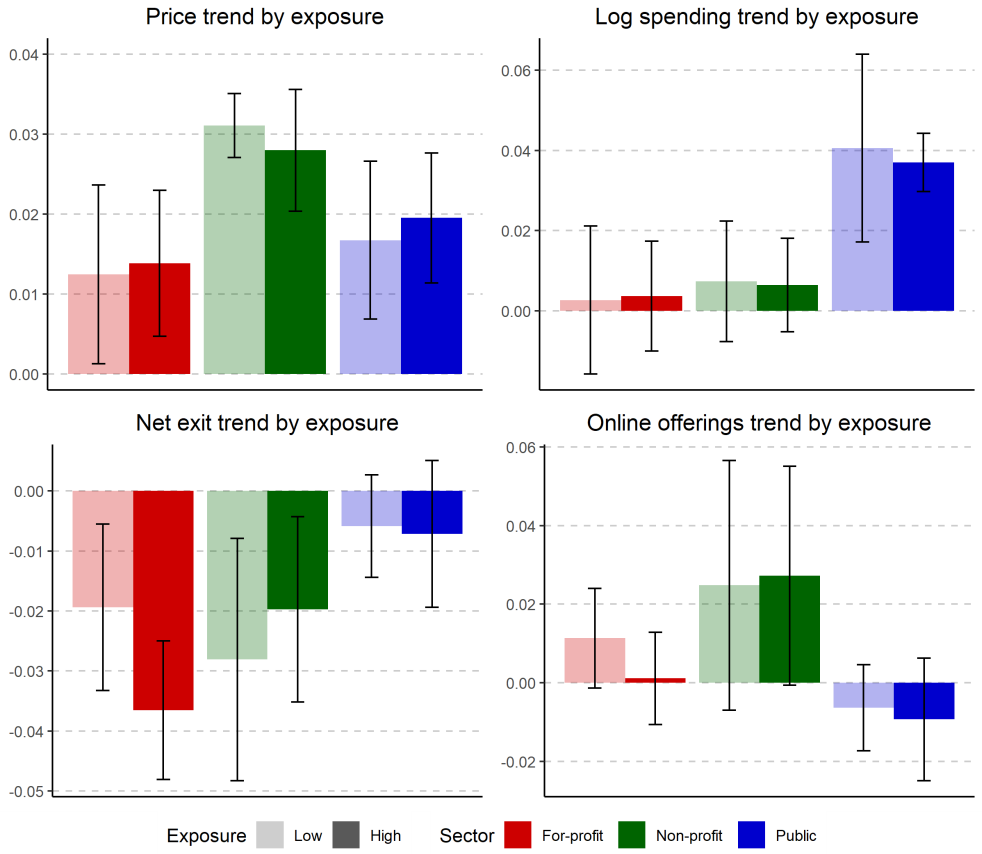
6.1 Concurrent Changes in Other Market Characteristics

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 variables.

Figure 8 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 8



In addition, I regress contemporaneous changes in the county unemployment rate on 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.

6.2 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 4 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 4: 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		✓		✓		✓		✓
Calendar-year FE	✓	✓	✓	✓	✓	✓	✓	✓

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

6.3 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, Goldin, and Katz 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 are less informative for this part of the sector as a result.

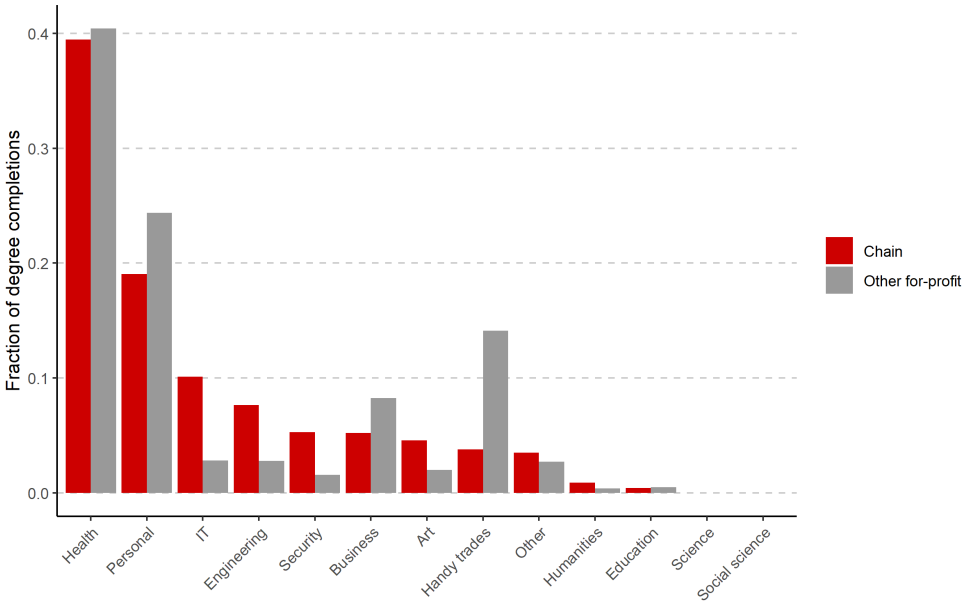
Table 5: Balance of Mean Characteristics: Chains vs. Other For-Profits

	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

Table 5 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[18] 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.

Figure 9: Programs of Study: Chain vs. Other For-Profit



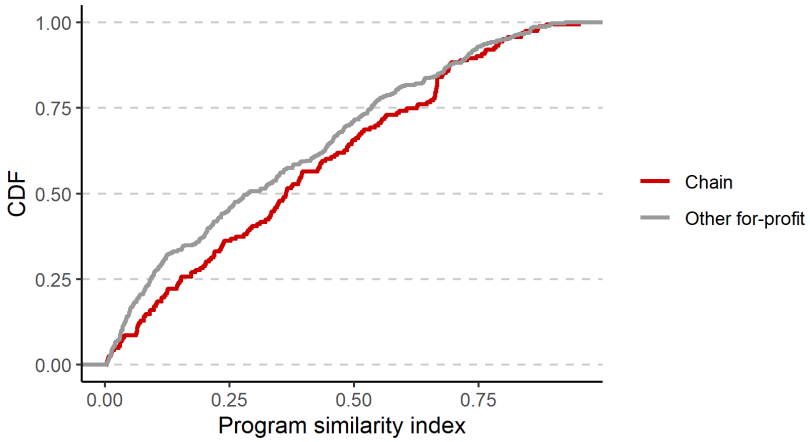
Given the importance of field-of-study offerings in explaining substitution patterns, I plot in Figure 9 the distributions of program completions by field. Both chains and other for-profits specialize heavily in health degrees and "personal services" degrees (including cos-

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

metology 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.[19]

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. Figure 10 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. 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 10: Similarity of For-Profit and Public Programs



7 Discussion

This paper makes two principal findings. First, I show that for-profit colleges expand educational opportunities for students on the margins of higher education – only about one-third of students are diverted from other sectors. Second, for-profits' appeal can be attributed in part to their narrow focus on a distinctive set of career-oriented program offerings.

[19]To quantify how similar these distributions are, I calculate the cosine similarity of different sectors' aggregate CIP program completion vectors. Chain and other for-profit colleges have a similarity of 0.956, compared to just 0.737 (0.735) between chain (other for-profit) and public colleges.

These results matter for education policy. Evidence that vocational program-offering differentiation contributes to for-profit demand suggests that public colleges can become more competitive and better serve non-traditional students by investing further in CTE programs. Meanwhile, efforts to constrain for-profit college supply through GE regulation, for instance, will impact students on multiple different decision margins – and the college/no-college margin cannot be ignored.

These policy implications come with at least two caveats. Since all the for-profits in my sample have closed, we must carefully consider their external validity for the rest of the sector. On this front, I show that surviving for-profits resemble my sample in important ways, and they share the same key differences relative to the public sector. Secondly, my estimates must be understood as partial-equilibrium results. To estimate for-profit students' second choices, it was important to hold other market features fixed. But understanding the full equilibrium impacts of for-profit closures would require estimating supply responses too.

To the extent that my findings do generalize, they come at an important time. The Biden administration finalized new GE rules in 2023 which could induce another wave of closures if they go into effect (Knott 2023). Even absent such regulatory changes, Kelchen, Ritter, and Webber (2024) forecast faster rates of for-profit closures in the coming years due to declining enrollment and a "demographic cliff." These developments lend extra salience to my findings.

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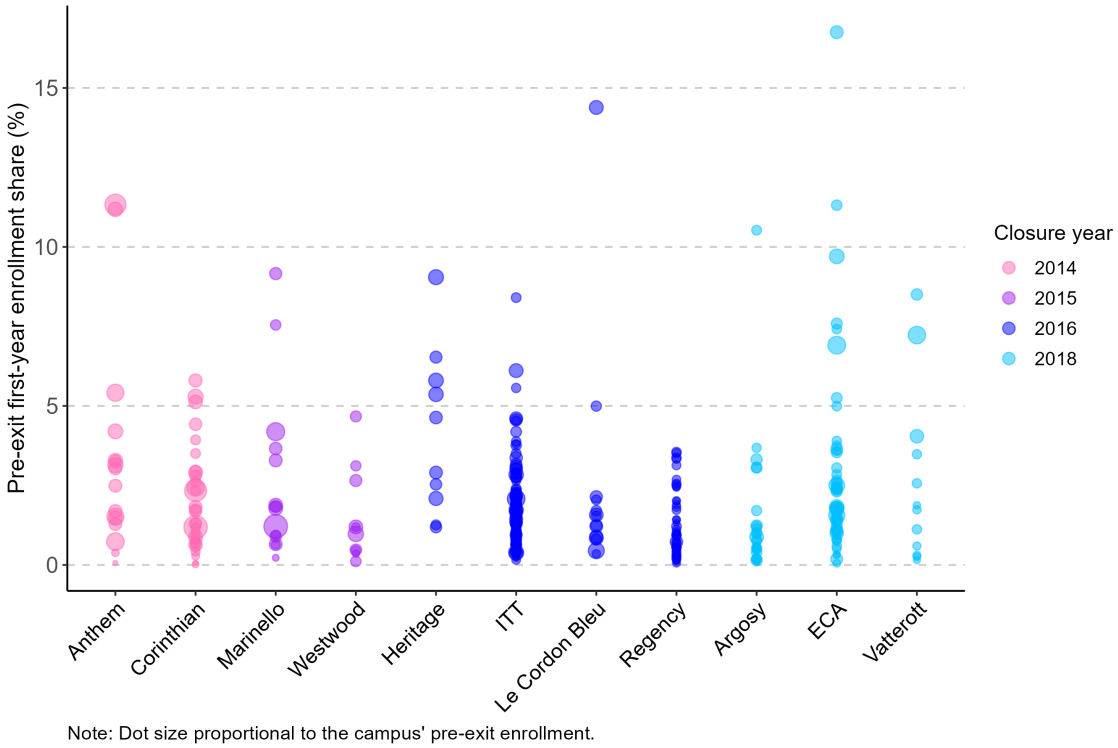
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Appendix

A For-Profit Closures

Figure A1 shows the intensive-margin variation in the share of closing chain campuses, for each of the 11 large chains in my sample. 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.

Figure A1: Pre-Exit Campus-Level Market Shares of the 11 Large Chains



Most of these chains closed as a result of federal regulatory pressure. Six of the largest chains, including ITT Tech, Corinthian Colleges, Education Corporation of America, Argosy, Marinello, and Vatterott, were all directly sanctioned by 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 Heritage – 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.

Table A1 describes the timing of each closure. Several chains stopped admitting new students shortly before announcing their complete shutdown. The effective closure date – the official date of the last campus closure – falls shortly after or even concurrently with the announcement date for most chains. Note that Marinello closed 56 campuses, but IPEDS only tracks enrollment at a subset of 22. In addition, Anthem's owner continued to operate its sister chain Florida Career College after Anthem shut down. Just 10 of all these chain campuses had more than 10% of students enrolled online, and I exclude these in my analysis.

Table A1: Timing of Chain Closures

Chain	Announcement date	Effective date[20]	# campuses
Anthem College	8/25/2014	8/28/2014	18
Corinthian College	4/26/2015	4/27/2015	50
Marinello School of Beauty	2/4/2016	2/5/2016	22
Westwood College	1/25/2016	3/8/2016	14
ITT Technical Institute	9/6/2016	9/6/2016	132
Le Cordon Bleu	12/16/2015	9/29/2017	16
Regency Beauty Institute	9/28/2016	9/28/2016	82
Heritage College	11/1/2016	11/1/2016	10
Argosy University	7/10/2018	3/8/2019	35
Education Corporation of America	12/5/2018	12/21/2018	70
Vatterott College	12/17/2018	12/17/2018	16

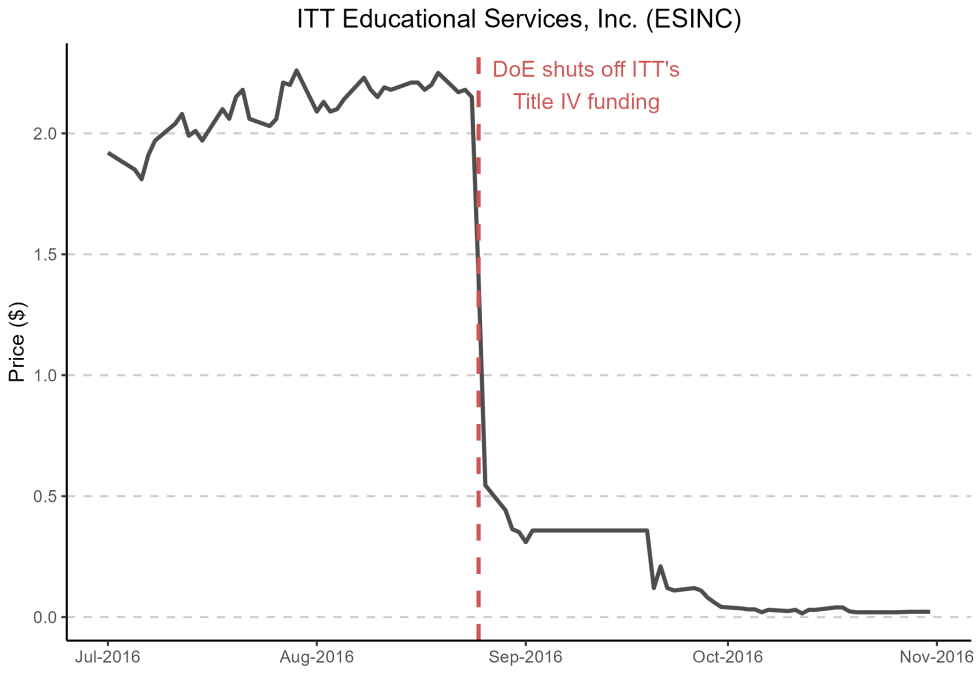
Note: Corinthian announced a portion of these closures on July 3, 2014. In some cases, Anthem operated as the Bryman School; Corinthian as Everest, Heald, and WyoTech; Heritage as Missouri College; Argosy as the Art Institute; Education Corporation of America as Brightwood College, Virginia College, Golf Academy of America, and the Ecotech Institute; and Vatterott as L'Ecole Culinaire.

Most chains were owned by private equity groups, but some were publicly traded or a subsidiary of a publicly traded company. Their stock price movements can shed light on the abruptness and unexpectedness of their closures. ITT Tech's case is particularly illuminating, as its parent company operated no other major enterprises. On August 25, 2016, the DoE

[20]Chains generally stopped admitting new students on or before the announcement date. The effective date is later in some cases as they continued to teach current students.

barred ITT Tech from accessing federal aid for new students, and its stock price dropped 75% by the following day (Figure A2). Within days, ITT Tech announced its nationwide closure. This case study shows both the abruptness of this largest chain closure, as well as the extent to which profitability depends on access to federal aid.

Figure A2



B Characteristics of For-Profit and Public Sectors

Figure A3: Enrollment and Net Entry by Sector, 2005-2019

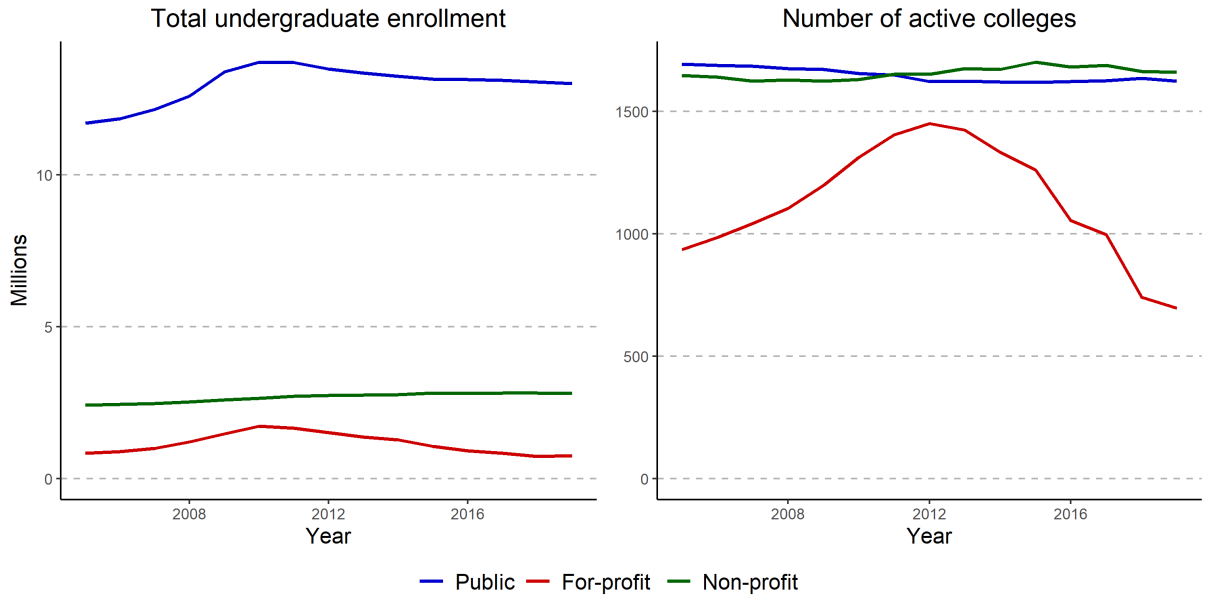


Figure A4



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

Table A2: 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).

Table A3: 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.

Table A4: For-Profit Students are Non-Traditional

	Public	Non-profit	For-profit
High school diploma (%)	84.6	83.9	79.8
Age at entry $\geq$ 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.

C TAACCCT Event Studies

Here I plot alternatives to Figure 7 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 A5: Effect of Similar TAA-Funded CC Program on Log For-Profit Enrollment

