Redesigning Federal Student Aid in Sub-baccalaureate Higher Education

Luis Armona, Shengmao Cao*

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Abstract

We evaluate the design of student aid in the US market for sub-baccalaureate higher education. We estimate each college's value-added and an equilibrium model determining choices in this market. We use this model to evaluate alternative aid policies, including a targeted voucher policy aimed at maximizing quality of education. This policy highlights that despite having lower quality, for-profit colleges are more effective at increasing enrollment than public community colleges. Consequently, these schools could play an important role in improving student outcomes under a well-targeted aid design.

JEL Codes: H52, H75, I2, L10, L5, L88.

Keywords: Education, College, Optimal Policy, For-profit Colleges, Community Colleges, Federal Student Aid, Advertising, Student choice, Vouchers

*Armona: Post-Doctoral Fellow, NBER, larmona@hks.harvard.edu. Cao: Assistant Professor, Department of Economics, Strategy Department, Kellogg School of Management at Northwestern University, shengmao.cao@kellogg.northwestern.edu. We are thankful to Liran Einav, Neale Mahoney, Frank Wolak, Heidi Williams, Mark Shepard, Nano Barahona, Sebastian Otero, Diego Jimenez, Melanie Wallskog, and Franklin Qian for their helpful comments and feedback on this paper. We are particularly thankful to the generous advising by Matthew Gentzkow, Caroline Hoxby, and Paulo Somaini.

Across the world, government student aid programs play an important role in higher education. In 2017, student aid accounted for 19% of public higher education spending across OECD countries on average, and 52% of students received financial support for postsecondary education OECD (2020).[1] Moreover, these programs are particularly important in helping low-income students attain postsecondary education OECD (2020). Given the scope and impact of these programs, the design of student aid may have significant welfare consequences for students.

The federal student aid program in the United States has some concerning features. Previous studies (e.g., Lucca, Nadauld and Shen (2019)) show that the design of federal aid incentivizes colleges to raise prices, reducing the savings passed on to students from public funds. Moreover, the most heavily subsidized colleges by federal aid are for-profit institutions (FPIs), which have been shown to provide a low return on investment to students (Cellini and Turner, 2019). Considering that the mission of federal student aid is to promote achievement by ensuring equal access to high-quality education,[2] policymakers are concerned by these outcomes.[3] Despite these high stakes, there is limited evidence on the equilibrium effects of the current aid system, and only a handful of studies (e.g., Colas, Findeisen and Sachs (2021)) have investigated alternative aid designs.

To fill these gaps in the literature, we study the equilibrium impact of student aid in the market for sub-baccalaureate higher education and consider the implications of alternative aid policies. Using novel instrumental variables, we estimate how enrollment responds to price and advertising in this market, providing the first causal estimates of the effects of advertising on college choice. We show that advertising is an important driver of demand for FPIs. We also estimate the quality of each college, using value-added in terms of long-run earnings as our quality metric. We show that FPIs have low value-added on average, but there is significant heterogeneity across schools. Building on these findings, we develop a structural model of supply and demand for the sub-baccalaureate market, accounting for the role of federal aid and FPIs' advertising activities. We use the model to simulate student outcomes under alternative aid policies. The set of policies we consider range from policies actively debated in the public sphere, such as bans on FPIs receiving federal aid, to a novel voucher-based policy we derive to maximize quality provision in this market.

[1]The reported average percentage for % of public higher education spending comes from 34 OECD countries reporting these statistics, retrieved from OECD data warhouse `https://stats.oecd.org/index.aspx?lang=en`. The reported average percentage for % of students receiving financial aid comes from 13 OECD countries for which data was available.

[2]Source: `https://www2.ed.gov/about/landing.jhtml?src=ft`

[3]Source: `http://web.archive.org/web/20161119195007/https://www.washingtonpost.com/news/grade-point/wp/2016/11/17/when-it-comes-to-career-training-programs-for-profit-schools-dont-measure-up-feds-say/`

Our counterfactual results suggest that redesigning student aid can significantly improve the quality of education students receive, particularly if aid is targeted towards high-quality schools that respond to government aid by expanding enrollment.

Sub-baccalaureate education consists of degrees below (in terms of completion time) the traditional 4-year bachelor's degree. Schools that offer sub-baccalaureate degrees are typically *non-selective*, meaning they admit all students that apply. This market comprises about one-third of both undergraduate enrollment and federal aid spending. Sub-baccalaureate students have historically been more disadvantaged and are often on the margin of work and higher education (Kane and Rouse, 1999). The two primary types of sub-baccalaureate institutions are community colleges (CCs) and FPIS. CCs are public institutions that provide subsidized education, while FPIs are private enterprises that typically specialize in vocational education. FPIs also invest significantly more in marketing and advertising to attract students. On average, 40% of FPI spending on student services is directed towards advertising (Cellini and Chaudhary, 2020).

Students receive federal aid in the United States based on their *financial need*: the difference between the cost of attending an institution and their ability to pay for college out-of-pocket, up to certain limits. In principle, if markets are sufficiently competitive, this design allows aid to be disbursed efficiently, so that only students who actually need aid to attend college receive public funds. However, if market power exists, colleges may charge higher prices to capture additional government subsidies, limiting the program's intended impact of making college more affordable.

Our empirical analysis leverages detailed institution-level data from the universe of schools eligible for federal student aid, along with data on advertising and student labor market outcomes. Our primary dataset is the Integrated Postsecondary Education Data System (IPEDS) survey conducted annually by the U.S. Department of Education (USDOE). This dataset provides price and demographic-level enrollment data at U.S. colleges. We complement this with college advertising data from Kantar Media and post-college labor market outcomes of students from the USDOE's College Scorecard dataset. These data allow us to measure the student response to advertising and estimate the quality of each institution.

We begin our empirical analysis by estimating the enrollment elasticity to both tuition and advertising using three novel instrumental variables. Our tuition instruments utilize shocks to funding sources for each type of college, while our college advertising instrument exploits shocks from local political advertising (Sinkinson and Starc, 2019). We estimate that FPIs set prices on the elastic portion of the demand curve, while CCs set prices on the inelastic portion. We also show that students are unresponsive to CC advertising, but highly elastic to FPI advertising, consistent with prior studies that have found FPI marketing to be persuasive in nature GAO (2010). These results show that CCs and FPIs differ in their market conduct and that advertising is an important driver of demand for FPIs.

To estimate school quality, we follow the education literature by estimating the *value-added* of institutions (Cunha and Miller, 2014) in terms of annual earnings after college. We microfound our estimation procedure with a model of potential student outcomes that accounts for selection of students into different colleges depending on their observable attributes. We find significant heterogeneity across institutions: FPIs produce worse outcomes on average, but a non-trivial fraction of FPIs have a value-added comparable to CCs. These value-added measures provide us with a metric to evaluate alternative aid policies.

Building on these findings, we develop an equilibrium model of demand and supply for colleges. On the demand side, we allow preferences to depend on a wide range of school characteristics and consumer demographics, which help capture the importance of product differentiation between schools. We explicitly model the role of federal aid in driving a wedge between tuition price and the net price that students pay. This allows us to describe the effects of federal aid on students' demand and colleges' pricing decisions. On the supply side, CCs set tuition to satisfy a budget constraint, while FPIs choose prices and advertising to maximize profits.

We identify the parameters in our model using instrumental variables for price and advertising, micromoments concerning student demographics, and survey data on students' intertemporal preferences towards loans. Our estimates imply that student demand is elastic to changes in the net prices they pay, but relatively inelastic to changes in tuition, because part of the tuition changes are absorbed by additional federal aid. This low *passthrough* from tuition to net student price allows FPIs to charge high markups. These findings suggest that an alternative aid scheme that decouples aid from tuition prices may incentivize students to choose lower-priced, higher-quality CCs while encouraging FPIs to set lower prices.

We then use our model to simulate how students and colleges would respond to alternative aid policies in equilibrium. Our primary welfare metric in these counterfactuals is the aggregate value-added provided by the sub-baccalaureate sector. We first consider a simple voucher-based system that pays low-income students a fixed amount of aid not tied to tuition. We show that switching to a simple voucher program increases aggregate value-added by 2.3%, primarily through the channel of increasing aggregate enrollment and re-sorting students into lower-priced schools. We compare this to various policies that have been actively debated in national policy circles, such as FPI bans and gainful employment regulations. These policies lead to smaller increases in aggregate value-added of 1%-1.5%. Their benefits are limited because they cause many students to forgo higher education instead of substituting to higher-quality colleges.

We then, under some additional assumptions, derive a "optimal" voucher aid policy that maximizes the value-added delivered to low-income students. This policy disburses more voucher aid to high-quality schools whose enrollment is more elastic to aid. Under this policy, aggregate value-added would increase by 8.8% in the sub-baccalaureate sector. Moreover, an implementable version of this policy, which ties vouchers to an observable set of school characteristics, can capture a substantial portion of these gains. Central to the benefits of the optimal policy is that it encourages high-quality FPIs to expand their investment in advertising to attract new students. While for-profit colleges have been criticized in the higher education literature for their practices (Cellini, 2021), our estimates imply that these schools have strong incentives to increase enrollment due to their profit motives. Consequently, we find in our counterfactual analysis that subsidizing high-quality FPIs is an effective way to increase the total quality of education provided in this market.

Our paper relates to several literatures. The first is a body of work studying the demand and supply responses to federal student aid in higher education. Earlier studies have shown that federal student aid leads colleges, particularly private colleges, to increase prices (Cellini and Goldin, 2014; Turner, 2014; Lucca, Nadauld and Shen, 2019). We add to this literature by quantifying the effects of federal aid on students' college choices through novel instrumental variables and a structural model. We also estimate the effects of alternative federal aid designs on college decisions and student outcomes.

We also connect to the literature on the U.S. for-profit college sector, summarized in Cellini (2021). Prior research has shown that FPIs invest heavily in marketing efforts (Cellini and Chaudhary, 2020), lead to worse student outcomes (Cellini and Turner, 2019; Armona, Chakrabarti and Lovenheim, 2017), and played an important role in the recent student loan default crisis Looney and Yannelis (2015). Our contribution to this literature is twofold. First, we estimate the value-added at the college level and document significant heterogeneity across schools in the returns to education. Second, we show that FPIs' incentives to expand enrollment as federal aid increases make them a potentially effective tool to expand access to high-quality education.

Finally, we contribute to the growing literature using structural econometric models to evaluate education policies (Neilson, 2013; Fu, 2014; Allende, 2019; Barahona, Dobbin and Otero, 2021). Most similar to our paper is Lau (2020), who estimates the equilibrium effects of tuition-free community colleges. We build on this literature by applying similar methods to evaluate the welfare impact of alternative student aid policies in the United States, while also being the first to consider the role of market and advertising in the supply side response to education policy.

1 Current Student Aid Design in US Higher Education

In this section, we describe the federal student aid system in the United States and discuss how its design may lead to choice distortions on both the demand and the supply side of sub-baccalaureate higher education. We focus on two programs that constitute 97% of all federal spending on student aid:[4] the Pell Grant program, which is a cash transfer for low-income students, and the Stafford Loan Program, which offers subsidized loans to students who cannot afford to pay for college out-of-pocket.

The amount of federal aid a student could receive to attend a college depends on her financial need, which is the difference between the cost of attendance (COA) and her expected family contribution (EFC). COA includes tuition and fees, plus estimated living expenses. EFC is an estimate of the student's ability to pay for college out-of-pocket. It is a function of household income, household structure, and whether the student is a dependent.

Students with sufficiently low EFC are eligible for the Pell Grant. The federal government sets the maximum Pell Grant at around \$6,000 in most years, though the cap fluctuated substantially before 2012. An eligible student receives an amount approximately equal to the difference between the maximum Pell grant and her EFC.[5]

If a student still has financial need after Pell Grant disbursion, she can take out Stafford federal students loans up to an annual limit of around \$6,000 (dependents) or \$10,000 (independents).[6] Interest rates on Stafford loans are significantly lower than the rates on private loans: the gap ranges from 3% to 7% APR between 2008 and 2016. The full formula to calculate federal aid amounts and students' EFC is provided in Appendix A. Figure A1 shows changes to federal student aid over time.

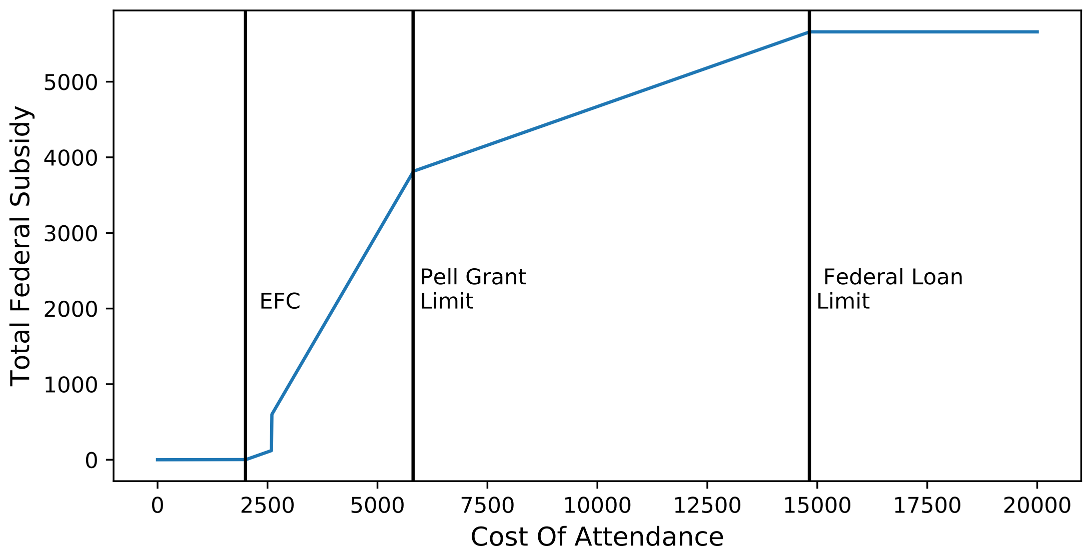
One hallmark of the existing federal student aid program is that aid is mechanically increasing in COA. Figure 1 shows how subsidy changes with COA in an example where a student attends college during the 2016-2017 academic year with an EFC of \$2,000. When COA is below her EFC, the student receives no federal aid. Between her EFC and the maximum Pell Grant, each incremental dollar of COA is covered entirely by the Pell Grant. For COA above the maximum grant, up to the limit for Stafford loans, the difference is subsidized by the difference in expected interest payments between Stafford loans and private

[4]Source: Table 4, `https://studentaid.gov/sites/default/files/FY-2016-Annual-Report.pdf`.

[5]Consider an example in which the maximum Pell grant is \$6,000. A student with an EFC of 0 could receive the full \$6,000 to cover her financial need. A student with an EFC of \$2,000 could receive up to \$4,000 and needs to pay \$2,000 out-of-pocket.

[6]There are two tiers of Stafford loans: subsidized and unsubsidized. Subsidized loans had lower interest rates before 2013, and the federal government covers their interest payments as long as the student is enrolled in an education program. Because the sub-baccalaureate programs we consider are relatively short in length, we abstract from the deferment of interest payments for federally subsidized loans.

loans.



Note: Figure shows shows how subsidy changes with the cost of attendance in an example where a student attends college during the 2016-2017 academic year with an EFC of $2,000. We calculate the subsidy for loans as the difference in total interest payments between federal and private student loans.

Figure 1: Subsidy Schedule for A Student in 2016 with an EFC of $2,000

Such an aid structure, where marginal price increases are partially absorbed by increases in student aid subsidies, creates a perverse incentive for colleges to increase prices. This feature relates to the so-called Bennett Hypothesis on the connection between increased student aid and rising college prices (Cellini and Goldin, 2014). We examine this hypothesis in the context of sub-baccalaureate higher education in the US and quantify the effects of the federal aid design on tuition levels, college choices, and student outcomes.

2 Data

2.1 IPEDS

Our main dataset is the Integrated Postsecondary Education Data System (IPEDS) managed by the USDOE.[7] Each year the USDOE mandates the completion of a detailed set of surveys by all aid-eligible postsecondary institutions and keeps the results under the IPEDS

[7]Link: `https://nces.ed.gov/ipeds/use-the-data`

database.[8] IPEDS reports data at the campus level. Each observation is a school campus by academic year (July 1st to June 30th the following year). Our sample covers the academic years 2008 through 2016.

For each campus–year, we observe the full–time equivalent (FTE) fall enrollment of first–time students, as well as total campus enrollment.[9] We also observe each incoming cohort's gender and race composition and the states of residence for every other cohort. On the supply side, we observe annual tuition and COA, in addition to a rich set of college characteristics such as degrees offered by award level, student services offered, majors offered, and breakdown of revenue and expenses. Finally, IPEDS reports the location of each campus and an OPEID that identifies multiple campuses that belong to the same chain/firm.

2.2 Auxiliary Data Sets

We complement the IPEDS data with auxiliary data on labor market outcomes, college advertising, student aid, and a national student survey. We collect information on students' labor market outcomes from the College Scorecard Dataset (CSD) provided by the USDOE. Outcomes are reported at the pooled cohort level (2 years of entering students) for each school chain. We observe labor market outcomes based on IRS tax data, such as the fraction employed and average annual income of those employed, 6 to 10 years after students began enrolling in an institution. In addition, we use Census Bureau's American Community Survey (ACS) to measure the demographics of potential students in each county where the colleges are located.

We use the Ad$pender database by Kantar Media to measure advertising activities by each school chain each year. Ad$pender tracks advertising activities across 17 media platforms (e.g., network TV, spot TV, newspaper). We observe monthly advertising expenditures and units of ads placed (e.g., # of spot TV slots purchased) in each of the top 101 Designated Market Areas (DMA).[10] For television, we also observe the daypart of each advertisement (time slot the ad is aired). We are able to match 71% of college-years in our sample to the AdSpender data. Unmatched schools tend to be smaller institutions that are either not advertising or not tracked by AdSpender.

We also collect terms for Pell Grant and Stafford Loan programs from the Federal Student

[8]There do exist some postsecondary education, mostly small FPIs, that do not qualify for federal financial aid program (See Cellini (2010)). Since we focus on the design of federal student aid in this study, we consider those schools outside the scope of our empirical analysis.

[9]We use a standard measure that treats each part-time enrollment as one-third of a full-time student. We focus on first-time students and omit transfer students who account for 12% of annual enrollment on average.

[10]A DMA is an aggregation of U.S. counties based on historical differences in FCC television licensing regions. The top 101 DMAs cover approximately 86% of the U.S. population in 2015.

Aid website. We obtain private loan interest rates from Consumer Financial Protection Bureau (CFPB) reports.[11] Finally, to better understand students' preferences towards loans, we use USDOE's Beginning Postsecondary Survey (BPS) in the 2011-2012 academic year. Respondents were asked whether they preferred \$250 today or $X \geq 250$ dollars in one year, for varying X. This survey help us calibrate students' intertemporal preferences.

2.3 Sample Criteria

Our sample of interest includes schools in the local sub-baccalaureate education market. We start with all colleges covered by the IPEDS data from 2008 to 2016. First, we retain schools that never offer graduate programs and issue at least 50% of their degrees, weighted by completion time, at the sub-baccalaureate level. Second, we limit our sample to "non-selective" colleges, whose only admissions requirements are a secondary school record, TOEFL score, or other general competency tests. Third, we exclude schools that ever offer their programs entirely online or have over 20% out-of-state enrollments on average. These restrictions limit our sample to schools that serve their local market. Finally, we drop schools outside the top 101 DMAs, where we do not observe advertising. Our final sample consists of 26,367 school–years.

According to our sample criterion, 40% of counties have at least one sub-baccalaureate college (Appendix Figure A2). While some rural counties are only serviced by FPIs or CCs, most urban and suburban counties have a mixture of public and private providers of sub-baccalaureate education.

2.4 Summary Statistics

FPIs account for 68% of colleges in our sample and around 20% of enrollment.[12] Our data reveal many stark contrasts between CCs and FPIs. Table 1 shows such differences in school characteristics, student demographics, and labor market outcomes.

We highlight three salient facts. First, FPIs on average charge 4.2 times the tuition as CCs do. FPI students are more likely to take out both federal grants and loans. Second, despite the higher price tag, FPI students have worse labor-market outcomes, earning 15% less on average 10 years after entering college. Part of this gap could be driven by selection:

[11] Source:`https://www.consumerfinance.gov/data-research/research-reports/private-student-loans-report/`. We use the annual median interest rate for private undergraduate loans from 2004 to 2011. For 2012-2016, We impute the private loan interest rate by assuming the median 2011 margin over the 3-month Q3 LIBOR index, the typical risk-free interest rate to which these loans are indexed.

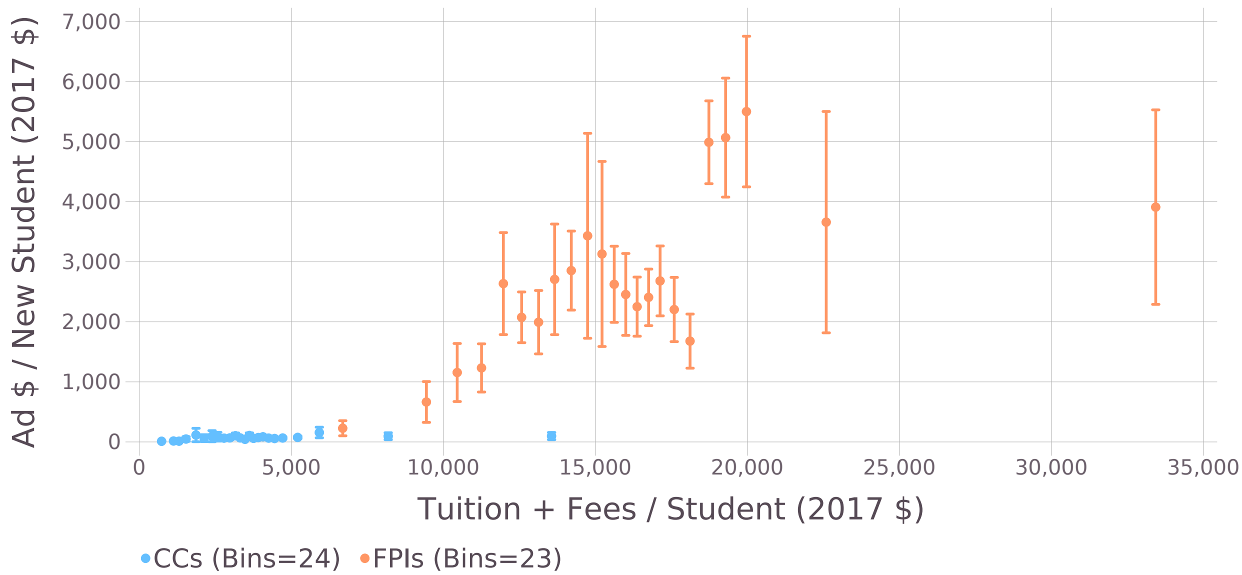
[12] We classify the 3.5% of schools in our sample that are private not-for-profits as FPIs. Many not-for-profits (NFPs) are subsidiaries of FPI chains, and some FPIs switch between FPI and NFP status. Moreover, Lau (2020) estimates that these non-selective NFPs behave as if they are profit maximizers.

Table 1: Summary Statistics

	(1) Community Colleges	(2) For-Profit Colleges
Panel A: Prices		
Tuition + Fees (2017 $)	3,767.77	15,880.33
	(2,664.47)	(5,352.59)
Cost Of Attendance (No Room/Board) (2017 $)	9,395.73	21,865.16
	(3,448.83)	(6,886.34)
Panel B: School Characteristics		
% Offering Associate's Degree	78.62	30.06
	(41.00)	(45.86)
Number of Majors Offered	11.01	1.85
	(4.59)	(1.54)
% Offering Job placement services	83.41	92.86
	(37.20)	(25.75)
Ad Expenditures in Local Market (2017 $)	46,888.90	228,697.13
	(128,835.34)	(547,845.21)
Ad Expenditures/Student in Local Market (2017 $)	71.95	2,568.83
	(283.16)	(9,108.97)
Panel C: Student Composition		
FTE Cohort Size	856.41	79.46
	(1,007.79)	(144.11)
% Male	47.82	23.77
	(12.32)	(26.79)
% Black/Hispanic	30.37	44.72
	(22.91)	(30.42)
% Family Income < $30,000	66.02	77.75
	(19.05)	(19.58)
% Receiving Pell Grant	54.50	74.31
	(17.61)	(18.25)
% Receiving Federal Loans	20.89	72.16
	(23.04)	(26.15)
Panel D: Outcomes		
Avg Earnings 10 Years After Entry	29,005.48	23,763.14
	(5,414.55)	(7,932.13)
% Graduating in 150% Normal Time	32.53	64.14
	(24.18)	(19.25)
Observations	7,624	16,651
Entering Students/Year	1,454,397	589,972

Table shows summary statistics for CCs and FPIs in our sample, with 4-year colleges as an additional comparison group. Standard errors reported in parentheses.

students who attend FPIs are more likely to be female, ethnic minorities, and from low-income households. Third, FPIs on average spend 4.9 times more than CCs on advertising, and 35.6 times more if we compare advertising per new student. Figure 2 shows that FPIs



Note: Figure shows a binscatter of the relationship between advertising per new student (defined as total ad expenditures divided by the total number of FTE first-time students) and tuition. The number of bins is chosen using the data-driven optimal bin selection method from the (Cattaneo et al., 2019) package. Each bin mean is displayed along with a 95% confidence interval, using standard errors clustered at the school level.

Figure 2: Relationship between Tuition and Advertising Investment by Schools

that spend more on advertising per student also tend to charge higher tuitions, while no such relationship exists among CCs. These patterns are consistent with anecdotal evidence that advertising and marketing help FPIs attract students despite high prices.

Altogether, we see that FPIs appear to offer lower returns to investment in education. The federal aid system and FPIs' advertising efforts are potential reasons why many students still choose them over CCs. In the next section, we provide more formal estimates of the value-added of different colleges and evaluate the roles of price and advertising on students' college choices.

3 Descriptive Evidence

We now provide descriptive evidence on the effects of prices and advertising on college choices, the effects of federal aid on these strategic inputs. We focus on advertising as an additional supply-side input because of its prominence in the FPI business model. Our empirical strategy utilizes instruments that provide exogenous variation in college prices and advertising. We also estimate the quality of each school via a value-added model to better understand the differences in returns to education across institutions.

3.1 Price Elasticity and Passthrough

We estimate the enrollment elasticity to tuition: the sticker price of each college. Tuition differs from the actual price students pay to attend college but is the relevant metric for supply-side price-setting. Because CCs and FPIs have different objectives, we estimate price elasticities separately for these two types of colleges, using differing sources of exogeneous variation. Our instrument for CC tuition utilizes variations in the prices of colleges that rely on the same state funding but operate in different markets. Our instrument for FPI tuition leverages variation in federal student aid policy. This instrument allows us to estimate the price elasticities and measure the passthrough of federal aid to tuition prices. Our empirical strategy for the FPI price elasticity is to estimate how tuition changes driven by the Pell grant program affect the demand of students who are ineligible for Pell grant aid and consequently experience no change in their federal aid amount.

For-Profit College Tuition Instrument To instrument for FPI tuition, we leverage changes to the generosity of Pell grant over time. Given that FPIs receive 76% of their revenue on average from federal aid programs, they can be particularly responsive to Pell grant generosity when setting prices.

There were two major changes to the maximum Pell grant in our sample period: from 2008 to 2010, it increased after the election of the left-leaning Obama administration, and from 2010 to 2012, it declined after Republicans retook the House of Representatives and controlled federal budgeting. Republicans maintained control of budgeting after 2012, and the maximum pell grant did not change during this period.

FPIs in poorer markets are more exposed to changes in Pell grant policy because a larger fraction of potential students are eligible to federal aid. A threat to identification of the price elasticity is that education demand is negatively correlated with income shocks. To remove variation in income potentially correlated with demand, we construct a "simulated instrument" (Gruber and Saez, 2002): the expected maximum Pell grant $\bar{\pi}$ in a county m in 2006, if the market t had been exposed to the Pell grant policy in year y: [13]

$$Z_t^{\pi} = E_F[\bar{\pi}|m(t), y^{\text{Pell}} = y(t), y^{\text{EFC}} = 2006] = \int_e \bar{\pi}(e, y(t)) \partial F(e|m(t), y(t) = 2006) \quad (1)$$

where $F(e|m, y)$ denotes the EFC distribution among potential students, and $\bar{\pi}(e, y)$ is the

[13] 2006 is the first year available in the ACS with the demographic information required to measure EFC. In each year, we index the distribution of EFC and the maximum Pell $\bar{\pi}(e, y)$ to the 2017 CPI.

maximum Pell grant award in year y for a student with EFC e. Within year y, shifts in Z_t^{π} from Pell grant policy changes are larger for colleges located in counties that were poorer in 2006. Our empirical strategy includes school fixed effects, so that variation is driven solely by policy changes and their interaction with pre-period exposure. The standard deviation of the instrument across U.S. counties is \$1500 in the baseline period, suggesting significant geographic variation in aid eligibility. This shift-share design is similar to that used by Lucca, Nadauld and Shen (2019) to identify the effect of federal aid on tuition prices.

Our exclusion restriction for estimating the tuition enrollment elasticity assumes that the variation in the simulated Pell grant instrument only affects demand through the changes induced to tuition, and this policy variation is uncorrelated with local demand shocks. One obvious violation is that when Pell generosity increases, student aid for eligible students increases, which would increase demand for education independent of the tuition price (since students now have to pay a lower price to attend college). For this reason, we estimate the FPI tuition price elasticity only for Pell-ineligible students, who receive no aid increase from Pell grant policy changes. Thus, our estimate may not capture the overall market price elasticity at FPIs to the extent that price sensitivity differs by income. In our structural model (Section 4), we use a similar identification strategy but address this shortcoming by specifying student preferences to depend on their net price after receiving both federal aid and loans. This allows us to estimate price elasticities for both Pell eligible and Pell ineligible students with some additional assumptions.

Community College Tuition Instrument To instrument for community college tuition, we use the prices of public colleges in the same state that operate in different markets, as a proxy for state-level changes in education funding. According to IPEDS, state appropriations are the largest source of funding for these schools: on average, community colleges receive 33% of their total revenue from state appropriations in our sample. Similarly, 4-year public state colleges receive 25% of their revenue from state appropriations. Both types of schools are constrained by state funding when setting tuition, yet cater to different segments of the higher education market.

We use variation in the tuition set by 4-year public colleges in the same state as a community college, but geographically distant (at least 100 miles away), as our instrument for community college tuition.[14] This instrument is a variant of the "prices in other markets" instrument introduced in Hausman (1996). Geographically distant 4-year colleges reside in different markets in two senses: demand for 4-year college differs both in terms of the type

[14]For the 5% of CCs without at least one public 4-year institution in the same state 100 miles away, we use the tuition of the farthest public four-year institution in the state as our instrument.

Table 2: Price Elasticities and Passthrough, by College Type

Outcome:	Log(FT Non-Pell)	Log(FTE Enrollment)	Log(FT Non-Pell)	Tuition ($)	
College Type:	FPIs	CCs	CCs	FPIs	CCs
	(1)	(2)	(3)	(4)	(5)
Log(Tuition)	-2.629***	-0.357***	-0.735***		
	(0.389)	(0.068)	(0.086)		
Federal Aid ($) Per Student				0.803***	0.323***
				(0.064)	(0.025)
Observations	15,714	7,829	7,689	16,870	7,739
School FE	Yes	Yes	Yes	Yes	Yes
School Characteristics	Yes	Yes	Yes	Yes	Yes
Market Demographics	Yes	Yes	Yes	Yes	Yes
First Stage F-Stat	310.92	323.92	385.67	317.81	559.23
Sargen-Hansen Test p-value	0.000	0.005	0.000	0.000	0.000

Table displays IV estimates of the tuition elasticity and passthrough of federal aid to tuition, separately for community and for-profit colleges. Standard errors clustered at the school level. FT Non-Pell denotes entering full-time students who do not receive a Pell grant, while FTE denotes the full-time equivalent entering students at each school. In Columns (1),(4), and (5), the excluded instrument is the simulated pell grant instrument, while in Columns (2) and (3), the excluded instrument is the price of distant 4-year public colleges in the same state. Market demographics and school characteristics are defined in footnotes 16 and 17, respectively. F-statistics refer to excluded instruments in the first-stage regression. Sargan-Hansen test p-value refers to test statistics of two regressions where tuition is treated as exogenous and endogenous, respectively. $^{*}p < .1,^{**} p < .05,^{***} p < .01$

of students (e.g., higher ability students) and where students reside. As a result, CCs and these 4-year public colleges are unlikely to experience common shocks to their target student population or their local economy.[15]

Estimates Columns (1)-(3) of Table 2 displays our estimated price elasticities for FPIs and CCs. We include as controls school fixed effects, market-level demographics,[16] and time-varying school characteristics.[17] We estimate a tuition elasticity of -2.6 for higher income, Pell-ineligible students at FPIs, suggesting they are fairly price elastic. In contrast, we estimate a tuition elasticity of -0.35 for CC FTE first-time enrollment, implying prices are set at

[15]According to the NCES's 2009 High School Longitudinal Study, among students who enrolled in a community college after high school graduation in 2012, only 23% applied to a public 4-year institution. According to the 2012 NPSAS, 100 miles is the 95th percentile in terms of distance from home for community college attendees.

[16] Defined as the fraction of students in the market (ages 18-50, high school education, same county) that are male, dependent, Black, Hispanic, the logged market size, along with the average age, EFC, and household income in the market.

[17] Defined as dummies for student services (offering remedial services, academic/career counseling, employment services, placement services, on-campus day care, ROTC, study abroad, weekend/evening college, teacher certification, and distance learning opportunities) degree majors (offering an academic degree, as well as dummies for offering each of the 14 occupational majors as defined by NCES), and degree levels (offering < 1-year certificate, 1-year certificate, 2-4 year certificate, and an associate's degree).

the inelastic portion of the demand curve. For non-Pell students at CCs, the tuition elasticity is -0.7, significantly below the price elasticity of these higher-income students at FPIs.[18] These results suggest that tuition is an important factor when students consider enrolling in FPIs, but less so when they consider CCs. Appendix Figure A3 plots a (residualized) binscatter of the first stage for the instruments by college type. The first-stage F-statistics shown in Table 2 demonstrate that our chosen instruments are not weak.

Columns (4) and (5) show the passthrough of federal aid to tuition prices. We regress the tuition set by each college on federal aid per student, instrumenting for federal aid using the simulated pell grant. We find evidence of positive passthrough at both types of colleges. Passthrough at FPIs is significantly higher than at CCs, consistent with results from the prior literature (Singell Jr and Stone, 2003; Turner, 2014; Lucca, Nadauld and Shen, 2019). A $1 increase in federal aid per student increases FPI tuition by $0.8. This result shows that the current federal aid design incentivizes FPIs to raise prices and limits the savings passed on to students. It also highlights the importance of accounting for supply-side responses in evaluating the equilibrium effects of federal aid designs.

3.2 Advertising Elasticity and Passthrough

We measure advertising using ad units placed in the local spot TV markets, which account for 73% of advertising expenditures by FPIs in our sample. We weigh ads placed in different dayparts differently to better approximate the impressions that the ads create.[19] Government reports have shown that FPI advertising tends to be more aggressive and persuasive than traditional college advertising (GAO, 2010). For this reason, we estimate the advertising elasticities separately by FPIs and CCs. We also estimate the passthrough of additional federal aid to advertising to see if colleges respond to federal policy through strategic inputs beyond prices.

College Advertising Instrument Estimating advertising elasticities is challenging because advertising decisions depend on both unobserved market characteristics and competitors' actions. To address such endogeneity concerns, we follow Sinkinson and Starc (2019)

[18] However, this result should be interpreted with caution since the outcome variable is the number of incoming students *receiving* Pell grants. While receiving Pell grants is a good proxy for overall Pell eligibility at high priced FPIs, this is not the case for CCs. According to the 2012 NPSAS, about 35% of Pell-eligible students do not receive Pell grants when they attend a community college. This is the same reason we choose to not instrument for CC tuition with the simulated pell grant instrument to estimate an enrollment price elasticity, despite using the simulated pell grant instrument to estimate tuition passthrough for CCs.

[19] We construct the weights using the American Time Use Survey (ATUS), which tracks how often households watch TV during different parts of the day. For example, we treat a prime-time ad as 5.9 day-time ads. Our results are qualitatively similar when we do not weigh ads by daypart reach.

and use political advertising as an instrument for college advertising, which relies on large swings in political advertising "crowding-out" the advertising of other entities.

The crowding-out effects of political ads create two plausibly exogenous sources of variations in college advertising. First, political advertising in election years tends to be concentrated in "swing states" where elections are most competitive. Second, within a DMA, different colleges that usually advertise in different months would have different exposures to shocks from political advertising. To capture such variations, we first estimate the monthly effects of political advertising on college advertising and then aggregate these effects to the annual level, weighted by each college's propensity to advertise each month. We describe full details of how we construct this instrument in Appendix B. This shift-share design creates within-market variation in political advertising shocks. Schools that have a higher propensity to advertise in months with high political advertising (e.g., right before an election) will be more affected than a school in the same DMA that never advertises in those months.

We consider some threats to the exclusion restriction of our instrument, as discussed in Moshary, Shapiro and Song (2021). One concern is that education markets may be "pivotal" to elections. While education can be a political topic, it has historically not been a top priority for voters. Gallup surveys show that only 2.6% of respondents between 2008 and 2016 considered education the most important issue, and the average rank of education as a priority issue ranges from 11 to 13.[20] It is unlikely that political advertising would respond to demand shocks specific to education markets. Another concern is that colleges may substitute for national advertising. Our data show that national advertising by sub-baccalaureate colleges is relatively infrequent. We also directly control national advertising when we construct our instrument.

Estimates Columns (1) and (2) of Table 3 displays our estimated advertising elasticities by college type. We estimate an advertising elasticity of 0.38 for FPIs, while the CC advertising elasticity is 0.03 and not significantly different from zero. This large ad elasticity for FPIs is consistent with existing evidence that for-profit college advertising is highly persuasive (GAO, 2010). A Sargen-Hansen endogeneity test of CC advertising suggests that we cannot rule out that CCs are non-strategic with respect to demand when advertising. These results suggest that advertising is an important driver of demand for FPIs but not CCs.[21]

Columns (3) and (4) show the effects of additional federal aid per student on advertis-

[20] Downloaded from the Comparative Agendas Project:
`https://www.comparativeagendas.net/datasets_codebooks`

[21] We also investigate how the advertising response differs by demographics. Appendix Table A1 shows differences in advertising responses by gender, race, income level, and age group. We find that a broad set of demographic subgroups are responsive to FPI advertising. Male students, older students and low-income students respond relatively more.

Table 3: Advertising Elasticities, by College Type

Outcome:	Log(FTE Enrollment)		#TV Ads	
College Type:	FPIs	CCs	FPIs	CCs
	(1)	(2)	(3)	(4)
Log(TV Ads + 1)	0.383**	0.032		
	(0.151)	(0.035)		
Federal Aid ($) Per Student			0.216***	0.021
			(0.054)	(0.016)
Observations	17,601	7,828	16,879	7,739
School FE	Yes	Yes	Yes	Yes
School Characteristics	Yes	Yes	Yes	Yes
Market Demographics	Yes	Yes	Yes	Yes
First Stage F-Stat	10.57	13.89	282.60	550.33
Sargen-Hansen Test p-value	0.000	0.333	0.000	0.099

Table displays IV estimates of the television advertising elasticity and passthrough of federal aid to television advertising, separately for community colleges and for-profit colleges. Standard errors are clustered at both the school level and the OPEID6-DMA-year level. FTE Enrollment is the full-time equivalent entering students at each school, while TV Ads denotes the number of spot television ads run by each school chain, adjusted by the daypart the ad airs. In Columns (1) and (2), the excluded instrument is the political advertising instrument, while in Columns (3) and (4), the excluded instrument is the simulated pell grant instrument. Market demographics and school characteristics are defined in footnotes 16 and 17, respectively. First-stage F-stat denotes the F-statistic for the excluded instrument (political advertising) in the first-stage regression with log television advertising as the dependent variable. Sargan-Hansen Test p-value refers to test statistics of two regressions where advertising is treated as exogenous and endogenous, respectively. $^{*}p < .1,^{**} p < .05,^{***} p < .01$

ing, instrumenting for federal aid using the simulated pell grant instrument. FPIs air 0.22 additional television ads per dollar increase in federal aid per student, while we do not find appreciable responses by CCs. A back-of-the-envelope calculation suggests that for the median advertising FPI, 15% of aid increases are reinvested in advertising spending.[22] These results suggest one potential benefit of providing federal aid to FPI students: because college demand is highly responsive to FPI advertising, federal aid reinvested in advertising could significantly expand participation in higher education. The effects of expanded participation on student outcomes depend on the quality of the advertising FPIs, which we turn to in the next section.

[22] We multiply the coefficient in Column (4) in Table 3 by the average price paid per TV ad by each FPI, divide by the number of students at each FPI, and then calculate the median of this value across FPIs with positive advertising.

3.3 Estimating Quality of Sub-Baccalaureate Colleges

We measure school quality as the *value-added* of schools in terms of the long-run[23] labor market earnings they generate for students ten years after initial enrollment. Unlike prior work on value-added in higher education, the relative differences across schools are insufficient to answer our policy questions of interest. Critical to our policy recommendations will be how productive the entire sector is on average, and whether more sub-baccalaureate attainment should be encouraged. Thus, we estimate the value-added of colleges relative to no higher education. Because we observe student outcomes at the cohort level, workhorse methods in the value-added literature that rely on student microdata (Chetty, Friedman and Rockoff, 2011; Mountjoy and Hickman, 2020) are not feasible in our setting. Our estimation approach addresses these challenges using a micro-founded model of student outcomes consistent with our aggregated data. Outcomes for student i attending college chain j (where $j = 0$ is no college) in labor market l are defined as follows:

$$\underbrace{Y_{i,j,l}}_{\text{Student Outcome}} = \underbrace{\eta_{i,l}}_{\text{Student/Labor Market Shifter}} + \underbrace{\psi_j}_{\text{Value-Added}} \tag{2}$$

We normalize $\psi_0 = 0$, so that value-added is relative to no college. $\eta_{i,l}$ captures the component of outcomes related to student ability, such as effort/motivation, as well as labor market conditions, such as unemployment shocks. $\eta_{i,l}$ may be correlated with college choice, so we deal with this unobserved outcome shifter using a two-step approach. Both steps account for selection bias by controlling for observable student characteristics, as is standard when estimating value-added in higher education settings (Cunha and Miller, 2014).

Estimation First, we estimate each cohort's earnings under the outside option of no college. To do so, we use ACS microdata to create a matched sample of no-college individuals in the same labor market l (defined as commuting zone) that are demographically identical on a set of observables $\mathbf{X}_i^0$ to enrollees at school j in market l, using the entropy balancing procedure of Hainmueller (2012). We include in $\mathbf{X}_i^0$ all observable demographics in both the College Scorecard and the ACS datasets: race-gender cells, age-gender cells, and the veteran status of students. We assume that $\eta_{i,l}$ is independent of the decision to not attend college, conditional on l and $\mathbf{X}_i^0$. We interpret this assumption as partialling out selection bias related to earnings on the extensive margin: whether or not to pursue non-selective higher education. Under this assumption, we are able to recover a consistent estimate of

[23] For example, Chetty et al. (2017) find that after age 28, the youngest possible age for entry cohorts ten years after enrollment, the correlation between current and long-run earnings is $\geq$0.95, and the correlation is even greater for those attending two-year colleges, our sample of interest

cohort earnings under no college, denoted $\widetilde{Y}_{j,l}$, from the earnings of local ACS participants with no college education.

Second, we estimate value-added by running the following weighted least squares regression, weighting by the variance of $\bar{Y}_{j,l} - \widetilde{Y}_{j,l}$:

$$\bar{Y}_{j,l} - \widetilde{Y}_{j,l} = \psi_j + \beta_1 \bar{\mathbf{X}}^1_{j,l} \tag{3}$$

where $\bar{\mathbf{X}}^1_{j,l}$ are cohort-level averages of a set of individual-level demographics $\mathbf{X}^1_i$. We include in $\bar{\mathbf{X}}^1_{j,l}$ the full set of cohort observables available in the College Scorecard. This includes the number of schools applied to, parental education level, and prior earnings. In particular, by including prior earnings, we partial out selection bias related to time-invariant differences in earnings potential across students, as these would be reflected in the past earnings of students. We interpret our controls $\mathbf{X}^1_i$ as partialling out for selection on the intensive margin, across colleges. In order to identify value-added, we assume that, conditional on $\mathbf{X}^1_i$ and $j \neq 0$, $\eta_{i,l}$ is independent of school choice.

Following Chandra et al. (2013), we posit an empirical Bayes prior on value-added, $\psi_j \sim N(W_j\zeta, \sigma^2_\psi)$, where W_j are school chain characteristics, to "shrink" our value-added estimates towards a prior mean. We provide full implementation details in Appendix C.[24]

Estimates Figure 3 shows the distributions of estimated value-added in annual earnings ten years after entering college. CCs on average have value-added of \$8,800, compared to \$2,100 for FPIs. These aggregate differences across CCs and FPIs are comparable to findings of Cellini and Turner (2019). However, quality varies considerably across FPIs. The standard deviation of value-added is \$3,200 for FPIs and \$1,800 for CCs. 37% of FPIs have negative value-added, while many others have value-added that compare well to CCs. Appendix Figure A4 decomposes the value-added estimates in terms of employment probability, and earnings conditional on employment, by estimating the value-added of each school in terms of these outcomes. The results indicate that while FPIs help students obtain employment, they tend to place students in low-paying jobs.

Appendix Table D1 shows estimates of ζ, the relationship between value-added and exogeneous school characteristics. School characteristics explain a large fraction of the variation in value-added across schools. With respect to college's strategic inputs, we find that value-added is positively associated with both tuition (correlation = .20) and advertising spending

[24]The College Scorecard data suppresses earnings outcomes for school chains with 2-year cohorts smaller than 30 students, for privacy-related concerns. Therefore, we are unable to estimate the quality of schools that have very small cohorts. These account for 32% of unique school chains in our sample, but only 3.7% of schools weighted by enrollment. For these schools, we impute their quality using their prior mean $W_j\zeta$.

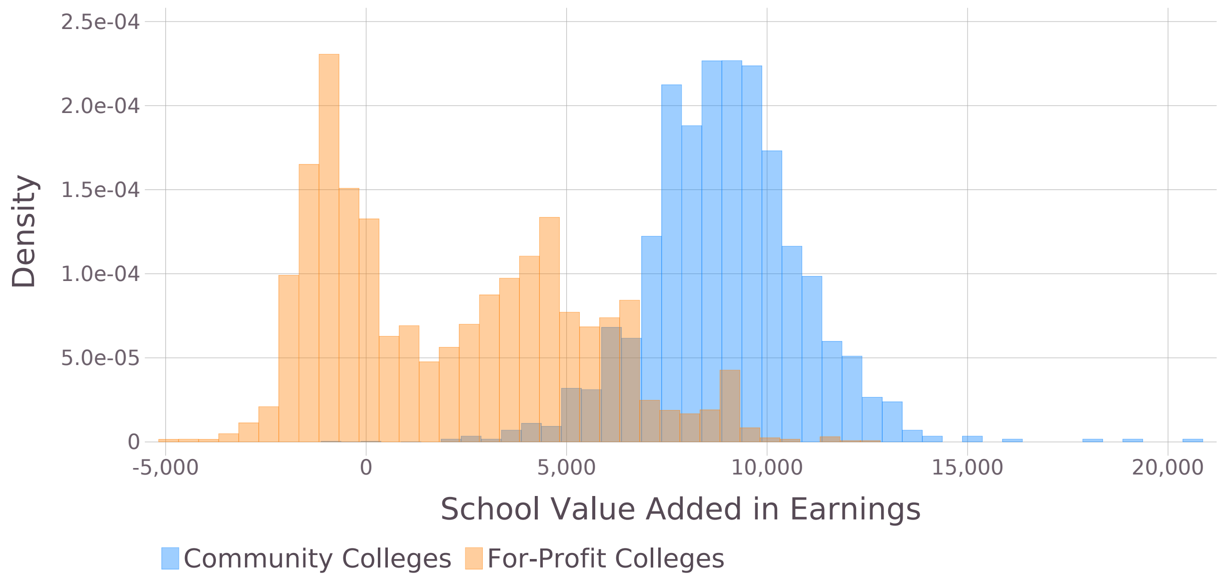


Figure shows the value-added of each school, measured in terms of the earnings generated by each institution ten years after enrolling in the institution for the first time. Though we estimate value-added at the school chain level, we plot the figure at the school (campus) level, since this is the unit of analysis for most of the paper.

Figure 3: Distribution of Value-Added Across Schools, By College Type

(correlation = 0.33) among FPIs. The latter correlation suggests FPIs may use marketing to inform prospective students about quality. This is less so the case at CCs: the correlation is .03 for tuition, and .12 for advertising.

4 Model

In this section, we develop a structural model we use to estimate supply and demand in the sub-baccalaureate education market. On the demand side, we model consumers (potential students) as solving a discrete choice problem among colleges in their market. On the supply side, we use two conduct models that account for the different incentives of FPIs and CCs.

4.1 Student Choice

Given that sub-baccalaureate schools are non-selective, we model college demand as a discrete choice problem in the tradition of Berry, Levinsohn and Pakes (1995). We define the geographic market for each college as the county it is located in, as in Cellini (2010), and a market t as a county-year. Potential students in a market include all individuals aged 18-50 with only a high school education. The utility derived for consumer i attending school j in market t is defined as:

$$u_{i,j,t} = -\alpha_i p_{i,j,t} + \lambda_i \log(a_{f(j),t} + 1) \cdot \mathbb{1}\{\text{FPI}_j\} + \vec{\gamma}_i' \vec{X}_{j,t} + \delta_j + \xi_{j,t} + \epsilon_{i,j,t} \tag{4}$$

$$p_{i,j,t} = OOP_{i,j,t} + \beta_i L_{i,j,t} \tag{5}$$

$$\alpha_i = \exp(\alpha + \Pi_\alpha' D_i + \sigma_\alpha v_{i,\alpha}) \tag{6}$$

$$\beta_i = \exp(\beta + \Pi_\beta' D_i + \sigma_\beta v_{i,\beta}) / \Big(1 + \exp(\beta + \Pi_\beta' D_i + \sigma_\beta v_{i,\beta})\Big) \tag{7}$$

$$\lambda_i = \lambda + \Pi_\lambda' D_i + \sigma_\lambda v_{i,\lambda} \tag{8}$$

$$\vec{\gamma}_i = \gamma + \Pi_\gamma' D_i + \Sigma \vec{v}_i \tag{9}$$

Utility depends on price, FPI advertising, school characteristics, and unobserved demand shocks. Price preferences are specified over the net price *paid* by students, denoted $p_{i,j,t}$. Net price is a function of cost of attendance, federal financial aid policy, as well as student characteristics such as EFC. It is split into two components: the out-of-pocket cost $OOP_{i,j,t}$, and the total payment on loans (including interest) $L_{i,j,t}$ that students take out if they are liquidity constrained. We allow heterogenous discount factors β_i on total payments to loans. In Appendix D, we explain in detail the construction of the net price measure.

Advertising, denoted $a_{f(j),t}$, is the total number of daypart-adjusted spot TV ads purchased by firm f in market t. We define a firm as the collection of schools having the same 6-digit OPEID in a DMA. As shown in Section 3.2, CC advertising has an insignificant effect on student demand and represents a small fraction of their total spending. Therefore, we only model the consumer responses to FPI advertising. We assume that advertising enters consumers' utility directly and changes their taste for the school, based on the evidence that FPI advertising is often persuasive in nature (GAO, 2010).[25]

Other school characteristics, denoted $X_{j,t}$, are assumed to be exogenous. This vector includes the following K attributes: four vertically differentiated degree levels (e.g., offering 1 year certificates), 11 horizontally differentiated majors, eight types of student services, value-added ψ_j, an indicator for being an FPI, and an indicator for being an HBCU.[26]

Students' preferences over price, loan payments (relative to out-of-pocket), advertising, and school characteristics are denoted $\alpha_i, \beta_i, \lambda_i, \vec{\gamma}_i$, respectively. We model preferences as linear in school characteristics, allowing preferences to depend on both observed (D_i) and

[25] If advertising were purely informative, we could alternatively model advertising as influencing students' choice set, rather than utilty, as in Hastings, Hortaçsu and Syverson (2013)

[26] The average preference for value-added, FPIs, and HBCUs are subsumed by the school dummy δ_j. We include them in X_j to measure heterogeneous preferences by different demographic groups. We partial out the baseline taste for these collinear preferences using the approach outlined in the appendix of Nevo (2000).

unobserved (v_i) consumer characteristics. Observed consumer characteristics are indicators for the following five demographics: student is a dependent, gender is male, ethnicity is Black, ethnicity is Hispanic, and student is low-income, measured by whether they have sufficiently low EFC to qualify for Pell grants. The parameters Π_α,Π_β,Π_λ, and Π_γ control how these observed demographics alter preferences over college characteristics. We additionally allow for random unobserved heterogeneity $v_{i,k} \sim N(0,1)$ for each characteristic k. Parameters $\sigma_\alpha, \sigma_\beta, \sigma_\lambda$, and Σ determine the importance of random heterogeneity for each characteristic.

We also account for characteristics observable to students but not the econometrician. δ_j captures time-invariant tastes for school j. $\xi_{j,t}$ is a time-varying demand shock. $\epsilon_{i,j,t}$ is an i.i.d idiosyncratic demand shock, assumed to follow a standard Gumbel distribution.

The choice set J_t of each student includes all sub-baccalaureate, non-selective colleges located in the same market t, as well as the outside option of attending no college, denoted $j = 0$. We normalize the mean utility of the outside option to 0. Students choose the option $j \in J_t$ that maximizes their individual utility as expressed in Equation 4.

Let $\Theta = \{\alpha, \beta, \lambda, \gamma, \Pi_\alpha, \Pi_\beta, \Pi_\lambda, \Pi_\gamma, \sigma_\alpha, \sigma_\beta, \sigma_\lambda, \Sigma\}$ denote the parameters of the demand model. Let $F(i|t)$ denote the joint distribution of demographics D_i and unobserved heterogeneity v_i in market t. By integrating over the idiosyncratic shock $\epsilon_{i,j,t}$ and consumers i, the market share of school j in market t can be expressed as:

$$s_{j,t}(\Theta) = \int_i \frac{\exp(-\alpha_i p_{i,j,t} + \lambda_i \log(a_{f(j),t} + 1) \times \mathbb{1}\{\text{FPI}_j\} + \vec{\gamma}_i' X_{j,t} + \delta_j + \xi_{j,t})}{1 + \sum_{k \in J_t} \exp(-\alpha_i p_{i,k,t} + \lambda_i \log(a_{f(k),t} + 1) \times \mathbb{1}\{\text{FPI}_j\} + \vec{\gamma}_i' X_{k,t} + \delta_k + \xi_{k,t})} dF(i|t) \tag{10}$$

4.2 Supply

We model how colleges choose tuition $p_{j,t}$ and advertising $a_{f,t}$. We specify different conduct models for CCs and FPIs to capture the different objectives of each institution type.

For-Profit Colleges We assume FPI firms set both their tuition and advertising to maximize static (annual) profits. Because spot television advertising is broadcast at the DMA level, which includes multiple counties (markets), we model the firm profit maximization problem at the DMA-year level, denoted d. Let $\mathcal{M}_d$ denote the set of markets t in each DMA-year d, $J_{f,t}$ denote the set of schools owned by FPI firm f in market t, and $J_{f,d} = \cup_{t \in \mathcal{M}_d} J_{f,t}$. We assume that FPI firms engage in Bertrand-Nash competition as in Nevo (2000):

$$\max_{\{p_{j,t} : j \in J_{f,d}\}, a_{f,d} \geq 0} \Big(\sum_{t \in \mathcal{M}_d} M_t \sum_{j \in J_{f,t}} s_{j,t}(\vec{p}_t, \vec{a}_t)(p_{j,t} - c_{j,t}) \Big) - \kappa_{f,d} \cdot a_{f,d} \tag{11}$$

where $c_{j,t}$ denotes the constant marginal cost of providing education; $p_{j,t}$ is the annual tuition+fees set by each school; M_t is the size of market t; $\kappa_{f,d}$ is the cost of a spot TV ad; and $\vec{p}_t, \vec{a}_t$ are $|J_t| \times 1$ vectors of prices and advertising of schools in market t.

We parametrize the marginal cost $c_{j,t}$ as a linear function of school characteristics $X_{j,t}$, a time-invariant component of costs, c_j, and a supply cost shock $\omega_{j,t}$:

$$c_{j,t} = c_j + \nu_c' \vec{X}_{j,t} + \omega_{j,t} \tag{12}$$

where ν_c is the $K \times 1$ vector mapping school characteristics to the marginal cost to supply education. Similarly, we parametrize the fixed cost per unit of advertising as log-linear[27] in school characteristics, a time-invariant component κ_f and an advertising cost shock $\iota_{f,d}$:

$$\log(\kappa_{f,d}) = \kappa_f + \nu_\kappa' \bar{X}_{f,d} + \iota_{f,d} \tag{13}$$

where ν_κ is the $K \times 1$ vector mapping average characteristics $\bar{X}_{f,d}$[28] to the cost of advertising.

To recover the cost structure of FPIs, we make use of the first order conditions satisfied by firms at their profit maximization point. For tuition this is, in matrix notation:

$$\vec{c}_{j,t} = \vec{p}_{j,t} + O_t^{-1} \vec{s}_t \tag{14}$$

where O_t is the $|J_t| \times |J_t|$ ownership matrix of cross-price derivatives, whose (j,k) entry is

$$O_{t,j,k} = \begin{cases} \frac{\partial s_{j,t}}{\partial p_{k,t}} & \text{if } k \in J_{f(j),t} \\ 0 & \text{else} \end{cases} \tag{15}$$

Because colleges receive revenue via tuition, but students pay a net price $p_{i,j,t}$ after federal aid, the derivative of market shares with respect to tuition takes the following form:

$$\frac{\partial s_{j,t}}{\partial p_{k,t}} = \int_i \frac{\partial s_{i,j,t}}{\partial p_{i,k,t}} \frac{\partial p_{i,k,t}}{\partial p_{k,t}} \partial F(i|t) \tag{16}$$

The first component of the integrand, $\frac{\partial s_{i,j,t}}{\partial p_{i,k,t}}$, follows the standard form from a logit choice model. The second component, $\frac{\partial p_{i,k,t}}{\partial p_{k,t}}$, accounts for the pass-through from a marginal increase in tuition to an increase in net student prices. This passthrough depends on the means

[27] We parametrize the advertising cost as log-linear rather than linear because advertising costs in the data are distributed according to a power law.

[28] We take a simple average across all schools within a DMA owned by the firm. We also include $|J_{f,d}|$, the number of campuses in DMA-year d, as an additional school characteristic.

through which a student is paying for their education at j,t on the margin.

$$\frac{\partial p_{i,k,t}}{\partial p_{k,t}} = \begin{cases} 1 & \text{if } i \text{ ineligible for more Pell grants and } COA_{i,j,t} \leq EFC_i \\ 0 & \text{if } i \text{ eligible for more Pell grants} \\ \beta_i \frac{120 r_{p,t}}{1-(1+r_{p,t})^{-120}} & \text{if } i \text{ eligible for loans of type } p \end{cases} \tag{17}$$

Where $r_{p,t}$ denotes the monthly interest rate associated with loan of type p (e.g. federal subsidized). The third case in which students pay for the marginal dollar with student loans applies to the vast majority of our sample. If β_i is lower than the interest rate multiplier for an amortized 10-year student loan, then $\frac{\partial p_{i,k,t}}{\partial p_{k,t}} < 1$, implying these students are less sensitive to tuition increases then net price increases, which in turn may incentivize FPIs to charge high prices.

Finally, we recover advertising costs $\kappa_{f,d}$ with the following first-order condition:

$$\kappa_{f,d} = \sum_{t \in \mathcal{M}_d} M_t \sum_{j \in J_{f,t}} \frac{\partial s_{j,t}}{\partial a_{f(j),t}} (p_{j,t} - c_{j,t}) \tag{18}$$

We cannot identify the advertising cost for FPI firms whose observed advertising level is zero. We assume that these firms are unable to advertise in all of our counterfactual scenarios.

Community Colleges Instead of maximizing profits, CCs have an egalitarian mission to expand access to higher education. Community colleges receive 80% of their revenue from government appropriations and depend on these subsidies for funding. With this in mind, we assume that community colleges set tuition $p_{j,t}$ to maximize a social welfare function $W_{j,t}(\vec{p}_t, \vec{a}_t)$, subject to a budget constraint:

$$\max_{p_{j,t}} W_{j,t}(\vec{p}_t, \vec{a}_t) \tag{19}$$

$$\text{subject to: } M_t s_{j,t}(c_{j,t} - p_{j,t}) \leq B_{j,t}$$

where $B_{j,t}$ is the total dollar amount of government subsidies received by community college j in market t. We infer $B_{j,t}$ from appropriations received from federal, state, and local governments reported in the IPEDS Finance Survey.[29] We assume that CCs use their budgets to set tuition $p_{j,t}$ below marginal cost $c_{j,t}$. If the budget constraint holds, the marginal cost

[29] We multiply the amount reported in IPEDS by $FTE_{j,t,\text{Incoming Cohort}}/FTE_{j,t,\text{Total}}$, the ratio of first-time FTE students to total FTE enrollment, to get the effective budget for new students.

of community colleges can be expressed as follows:

$$c_{j,t} = p_{j,t} + \frac{B_{j,t}}{M_t s_{j,t}} \tag{20}$$

For the budget constraint to bind, we assume that $\partial W_{j,t}/\partial p_{j,t} < 0 \quad \forall(\vec{p}_t, \vec{a}_t)$, which means community colleges always prefer students to pay lower prices. Otherwise, we remain agnostic about the welfare function of community colleges. Some examples of compatible welfare functions include maximizing total enrollment or student utility, since students always prefer lower prices.

Our conduct model also captures CCs' capacity constraints due to limited seats and inelastic supply (Mullin and Phillippe, 2009).[30] Under our model, a CC's ability to expand their enrollment is limited by their budget constraints. For a fixed budget $B_{j,t}$, enrollment increases requires CCs to increase tuition. This price increase will turn some students away, disciplining our counterfactual simulations so that enrollment at community colleges does not reach implausible levels. Thus, we interpret the budget constraint as a "soft" capacity constraint since it rules out an unconstrained supply of subsidized education.

4.3 Estimation and Identification

We estimate our equilibrium model following the approach in Berry, Levinsohn and Pakes (1995). To solve for the college market shares, we follow previous work (Nevo, 2000) and take a single draw of $B = 1,000$ consumers in each market t from $F(i|t)$, the distribution of consumers in a market, to approximate the integral in Equation 10. We use data from the 2008-2016 1-year ACS surveys from the Census Bureau to determine the distribution of demographics in each market.[31]

We use three sets of moments to identify the model's parameters. The first three concern independence of the demand and cost shocks with respect to a set of instruments. We complement this with two sets of micromoments that use cohort-level demographics data from IPEDS and data from the BPS survey on students' intertemporal preferences.

[30] Because IPEDS does not report the number of available seats at colleges, we do not explicitly include capacity constraints in our conduct model.

[31] Because ACS data reports geolocation in terms of public use microdata areas (PUMAs), we make use of a crosswalk from the Missouri Census Data Center `http://mcdc.missouri.edu/applications/geocorr.html` that reports what fraction of the population in each PUMA resides in a U.S. county in the 2000 and 2010 census. We sample consumers for county-year t from the ACS, weighting PUMAs according to the fraction of the market relevant population (18-50, HS education). For 2008-2011, we use population weights based on the 2000 census, and for 2012-2016, we use population weights based on the 2010 census. An implicit assumption of this sampling is that conditional on PUMA, consumers are spatially distributed i.i.d.

Structural Shock Moments We assume that the unobserved demand shocks $\xi_{j,t}$, as well as the supply cost shocks $\omega_{j,t}$, $\iota_{f,d}$ for FPIs, are orthogonal to a vector of instruments $\vec{Z}_{j,t}$:

$$g^{\xi}(\Theta) = E_{j,t}[\xi_{j,t}(\Theta)|\vec{Z}^{\xi}_{j,t}] = 0 \tag{21}$$

$$g^{\omega}(\Theta) = E_{j,t}[\omega_{j,t}(\Theta) \otimes \vec{Z}^{\omega}_{j,t}] = 0 \tag{22}$$

$$g^{\iota}(\Theta) = E_{f,d}[\iota_{f,d}(\Theta) \otimes \vec{Z}^{\iota}_{f,d}] = 0 \tag{23}$$

We use as instruments school characteristics $\vec{X}_{j,t}$ and the price and advertising instruments introduced in Section 3: the simulated Pell grant instrument for FPI prices, the price of public 4-year colleges $\geq$ 100 miles away for CC prices, and the political advertising instrument for FPI advertising. These identify the price and FPI advertising preferences of consumers. We also interact the unobserved demand and supply shocks with the rival quadratic differentiation instruments introduced in Gandhi and Houde (2019). These instruments capture differentiation a college has with respect to its rivals along a particular dimension c of $\vec{X}_{j,t}$:

$$Z^{d}_{j,t,c} = \sum_{k \in J_t, f(k) \neq f(j)} (X_{j,t,c} - X_{k,t,c})^2 \tag{24}$$

These instruments are a low-dimensional way to capture the relevant variation of product characteristics in a market with respect to identifying the demand function, as shown in Gandhi and Houde (2019). They are particularly useful for identifying the parameters governing random heterogeneity, Σ.

Demographic Micromoments We use annual demographic data from IPEDS on the first-time (entering) student body at each school in order to match our model's predictions to the observed demographic sorting across schools. For each school j, t, we observe the % Black, % Hispanic, % Male, % Dependent Status,[32] and % Receiving Pell grants.[33] We then introduce a set of micromoments that minimize the difference between the model's prediction of the fraction of students in each cohort belonging to demographic h, denoted $f_{j,t,h}(\Theta)$, and the observed fraction of students from the demographic in IPEDS, denoted $\hat{f}_{j,t,h}$, conditional on instruments $\vec{Z}^{f}_{j.t}$, which consist of school characteristics and our price/advertising

[32] This is measured as the % of first-time, full time students receiving aid living off campus with their family.

[33] % Receiving Pell grants is measured only for first-time, full-time students. Note this differs from the fraction of Pell-eligible students, the corresponding student demographic in our model. In practice, 97% of schools in our sample have a sufficiently high cost-of-attendance that any Pell-eligible student would take out Pell grants. For this micromoment, we match the % of Pell-receiving students observed in IPEDS to the % receiving a positive Pell grant amount as implied by the model.

instruments:

$$g^{f,h}(\Theta) = E_{j,t}[\Big(\hat{f}_{j,t,h} - f_{j,t,h}(\Theta)\Big) \otimes \vec{Z}^{f}_{j.t}] = 0 \tag{25}$$

Equivalently, we assume the prediction error between the reported IPEDS value and the model implied value is orthogonal to a vector of instruments. These micromoments most directly aid us in identifying the parameters that characterize heterogeneous demographic preferences. For example, the fraction of males in schools that offer engineering degrees helps recover male students' preferences for engineering programs.

Discount Factor Micromoments Due to liquidity constraints, many consumers in our sample need to take out loans to attend any college in their choice set. Exogenous variation in school prices alone will then be insufficient to identify their discount factor β_i separately from sensitivity to net student price α_i. To estimate the discount factor, we use data from the 2012 Beginning Postsecondary Survey (BPS). Survey respondents are asked to incrementally trade off cash payments today versus in one year, which we use to construct the cumulative distribution function (CDF) of annual discount factors at five points of the distribution. Figure A5 plots the distribution of discount factors from the survey data across demographics. For each observed point p of the BPS CDF, and demographic h, we match the empirical probabilities of discount factors reported in the BPS, denoted $\hat{Pr}_{BPS}(\beta_i \leq p|h)$, to those implied by the model, conditional on attending college, denoted $Pr(\beta_i \leq p|j \neq 0, , h, \Theta)$. Appendix E provides details on how we compute this probability.

$$g^{\beta}_{p,h}(\Theta) = Pr(\beta_i \leq p|j \neq 0, h, \Theta) - \hat{Pr}_{BPS}(\beta_i \leq p|h) = 0 \tag{26}$$

Optimization We estimate demand and supply jointly using a modified version of the two-step General Method of Moments (GMM). We provide additional details on moment construction and estimation in Appendix F.

5 Model Results

Price Preferences The price elasticities relevant to the demand and the supply side differ. Students choose where to enroll based on the net student price. In contrast, colleges set tuition as a function of the tuition elasticity, which depends on the passthrough from tuition to the net price. FPIs face a median tuition elasticity of -3.06, while CCs face a median elasticity of -0.83. The tuition elasticity for 59% of CCs is > -1, consistent with these schools not maximizing profits.

Table 4: Student Preferences

	All Students		Income		School Type	
	Mean	SD	Low-Inc	High-Inc	CC	FPI
Net Student Price ($)	7,576	5,092	5,153	10,891	7,587	7,521
Net Price Elasticity	-3.23	3.93	-2.23	-4.61	-2.80	-5.35
Tuition Elasticity	-1.18	1.63	-1.20	-1.16	-0.76	-3.25
Tuition Passthrough ($\partial p_{i,j,t}/\partial p_{j,t}$)	0.66	0.34	0.54	0.83	0.74	0.27
Discount Factor (β_i)	0.44	0.24	0.41	0.48	0.50	0.18
10% Increase in Ads (λ_i/α_i)	73.16	21.64	76.51	68.57	71.47	81.48
$1000 Increase in VA ($\gamma_\psi/\alpha_i$)	56.26	98.71	0.45	132.59	65.96	8.38

Table reports summary statistics from a student-school level dataset of preferences. All summary statistics are weighted by the probability of attendance ($w_{i,j,t} = q_{i,j,t} = M_t \cdot s_{i,j,t}$), such that the statistics are as if sampled from the population of enrolled students. Cells under Income and School Type are weighted means.

To compare net price and tuition elasticities, we consider the *student-level* price elasticities of each consumer i,[34] which are, respectively:

$$\varepsilon_{i,j,t}^{\text{Net Price}} = \frac{\partial s_{i,j,t}}{\partial p_{i,j,t}} \frac{p_{i,j,t}}{s_{i,j,t}}, \qquad \text{and} \qquad \varepsilon_{i,j,t}^{\text{Tuition}} = \frac{\partial s_{i,j,t}}{p_{i,j,t}} \frac{\partial p_{i,j,t}}{\partial p_{j,t}} \frac{p_{j,t}}{s_{i,j,t}} \tag{27}$$

Table 4 reports summary statistics on student-level preferences. The average net student price elasticity is -3.23, while the average tuition elasticity of -1.18. We show via a decomposition in Appendix G that this large wedge is driven primarily by a low tuition passthrough ($0.66 for each tuition dollar) to net price at both CCs and FPIs. These low passthrough estimates are driven by both marginal federal subsidies on price, and the low discount factors estimated (on average 0.44, equivalent to 17.7% annual discounting).

We estimate FPI markups in our sample to be large, on average $5,552. To evaluate the contribution of low tuition passthrough to markups, we recalculate markups assuming a perfect passthrough from tuition and net price, holding everything else fixed. Under this scenario, FPI markups would be $1,255 on average, a 78% decrease. This result suggests that the federal aid design incentivizes FPIs to charge high prices.

We estimate that low-income students have an average net price elasticity of -2.23, while high-income students' elasticity is -4.61. Low-income students are less price elastic partly due to their lower discount factors (19.3% annually versus 15.8% for high income students). We interpret the lower price sensitivity of low-income consumers as attributable to poten-

[34]By student level, we mean those enrolled in a college. Throughout this section, consumers' price elasticities are weighted by the probability of enrolling in college j, to be consistent with school-level elasticities traditionally used.

tial information frictions or financial illiteracy, which have been documented in the higher education literature (Chen and Volpe, 1998). In Appendix G, we show formally via a decomposition that lower net price levels, due to larger subsidies and temporal discounting, explain low-income students' lower net price elasticity.

Advertising Preferences Advertising influences student choice: our utility model implies that a 10% increase in advertising is equivalent to a $73 reduction in out-of-pocket payments.[35] This dollar equivalent is relatively large but not outside the range of results from prior studies (Murry, 2017). The average school-level FPI ad elasticity is 0.63, also somewhat larger than what the literature has typically found (Shapiro, Hitsch and Tuchman, 2019). Prior work suggests that FPI's marketing targets low-income students,[36] and an investigative report (GAO, 2010) shows that advertising by large FPI chains is often predatory. Our results provide additional evidence that FPI advertising is highly persuasive.

Quality Preferences In contrast, we do not observe strong preferences for the value-added of institutions. Our utility model implies a $1,000 increase in *annual* labor market earnings is valued at just $56 on average. This may be explained by a lack of information on college quality when students choose schools. Additionally, other characteristics students do have strong preferences over (such as type of degree) are correlated with quality, so the taste for quality may be captured by these characteristics.

Heterogeneous Preferences Table A2 displays the full set of parameter estimates Θ governing consumer preferences. The parameter estimates are sensible in the heterogeneous preferences they capture. For example, men have weaker preferences for schools with consumer service programs and stronger preferences for engineering programs. This preference heterogeneity leads to differential substitution patterns. For example, when we calculate the diversion ratios (Conlon and Mortimer, 2018) across colleges, which capture where students switch to after marginal price increases at their enrolled college, we find that 27% of switchers go to schools of the same type (CC vs. FPI), a sizeable 68% drop out of higher education entirely, and only 4.6% go to schools of a different type. Similarly, in Figure A6, we show that diversion ratios are significantly higher for schools that offer the same programs, suggesting students are unwilling to switch across majors.

[35] We convert preferences to out-of-pocket dollars by dividing the coefficient on characteristic c, $\gamma_{i,c}$, by each consumer's price sensitivity α_i.

[36] For example, in this complaint filed by the State of California against a major for-profit college chain in 2013 (`https://oag.ca.gov/news/press-releases/attorney-general-kamala-d-harris-files-suit-alleged-profit-college-predatory`), the document notes that the chain explicitly targeted students near the poverty line in their advertising messaging

Table 5: Supply-side Estimates

	Mean	SD	Median
CC Marginal Cost	\$10,930	\$7,440	\$9,526
FPI Marginal Cost	\$10,329	\$4,469	\$9,895
Avg. FPI Costs	\$11,935	\$5,146	\$11,397
CC Markdown	\$7,162	\$7,428	\$6,019
FPI Markup	\$5,552	\$2,600	\$5,034
Cost of FPI Spot TV Ad	\$1,824	\$32,950	\$108

Table reports summary statistics on supply side estimates of the model at the college level. Average costs are defined as $(\kappa_{f,d}a_{f,d} + \sum_{j \in J_{f,d}} M_t s_{j,t} c_{j,t})/(\sum_{j \in J_{f,d}} M_t s_{j,t})$, the total marginal cost and advertising cost divided by the number of students.

Supply-Side Costs Table 5 reports summary statistics on college supply-side parameters, and Appendix Tables A3 and A4 report the effects of characteristics on the marginal cost and fixed cost of advertising at for-profit colleges, respectively. The median advertising cost of a spot television ad among for-profit firms is \$108, which is similar to the median estimate in the AdSpender accounting data (\$106).

Our model estimates suggest that prices differences across CCs and FPIs stem from the differential conduct of these institutions. Despite the large tuition differences documented in Table 1, the distribution of estimated costs across public and private colleges is relatively similar. The median CC markdown is 64% below marginal cost, while the median FPI markup of is 49% above marginal cost. For profits are able to charge prices above cost due to local market power and a low tuition passthrough, while community colleges are able to charge below cost due to government appropriations.

These results suggest that college conduct and student outcomes would change considerably if student aid were no longer tied to price. To fully evaluate a change in policy, we must consider how both colleges and students would respond in equilibrium. With this in mind, we now turn to various counterfactual policies.

6 Counterfactuals

Expanding access to high quality education is an explicit mission of the federal student aid program. We use a measure of total quality of education provided in this market (in terms of future earnings) as our main metric for evaluating alternative policies. Let $\mathcal{P}$ denote a policy set by the federal government. The aggregate value-added Ψ is defined as follows:

$$\Psi(\mathcal{P}) = \sum_{t} \sum_{i \in t} \sum_{j \in J_t} Pr(i \text{ chooses } j \text{ in market } t | \mathcal{P}) \times \psi_j \tag{28}$$

One limitation of this measure is that it ignores compensating differentials. Students may receive non-pecuniary benefits from attending certain schools, or working in certain professions. These are captured by the revealed preference consumer welfare measures from our demand model, and so we also consider these metrics when evaluating alternative policies. Because advertising likely contains informative and persuasive components, policymakers may be skeptical of using it to evaluate consumer gains from new policies. Following Allcott (2013), we construct a measure of student *experience utility*, which excludes FPI advertising, in addition to the standard consumer surplus measure:

$$CS(\mathcal{P}) = \sum_{t} \sum_{i \in t} \frac{1}{\alpha_i} E_{\epsilon_{i,j,t}}[u_{i,j,t} | \mathcal{P}], \quad CS(\mathcal{P})^{\text{No Ads}} = \sum_{t} \sum_{i \in t} \frac{1}{\alpha_i} E_{\epsilon_{i,j,t}}[u_{i,j,t} - \lambda_i a_{j,t} | \mathcal{P}] \tag{29}$$

In our counterfactuals, we hold the quality of institutions ψ_j fixed. For counterfactuals where quality is an input to aid, this is a substantial limitation. In these cases, we expect our results to be lower bounds of the gains from such policies, since schools would likely increase investment in quality if the federal government rewarded them with more student aid. Additionally, we assume that colleges with zero observed advertising do not have access to advertising technology, and fix their advertising to $a_{j,t} = 0$ in all counterfactuals.

Under each policy $\mathcal{P}$, students respond by changing their enrollment choice and colleges change their tuition/advertising, in order to balance their budget (CCs) or maximize profits (FPIs). To evaluate the policies comparably, we restrict attention to policies that spend the same amount of federal money as the current observed equilibrium, denoted G_0 (approximately \$33.8 billion).[37] We define an equilibrium $\mathcal{E}(\mathcal{P})$ under a policy as satisfying the following four conditions: consumers select schools to maximize utility $u_{i,j,t}$ (Equation 4); CCs set tuition $p_{j,t}$ to balance their budget (Equation 20); FPIs set tuition $p_{j,t}$ and advertising $a_{f,t}$ to maximize profits (Equation 11); and government spending $G(\mathcal{P}) = G_0$.

Broadly, we consider two types of counterfactual policies the federal government may pursue. The first set of policies center on distributing aid to students through a voucher program that does not tie aid amount to cost of attendance. The second set of policies

[37] Current government spending is calculated as the total Pell grants distributed to students in all markets in our sample, plus the total amount of federal student loans distributed to students in all markets in our sample, multiplied by the difference in federal and private student loan interest rates. Thus, we assume that the private student loan market is sufficiently competitive that interest rates are set at a level such that real profits are zero on private loans.

involve bans that have been actively considered by policymakers in higher education. Details on equilibrium computation for both types of policies are given in Appendix H.

6.1 Targeted Vouchers

The main distortionary feature of the current aid system is that aid marginally increases with the price that colleges charge students. We now explore the extent to which voucher systems, consisting of cash transfers to students whose generosity is independent of tuition price, may yield welfare gains by eliminating this distortion. While results on the effects of vouchers on educational outcomes are mixed, they have typically improved competition between schools and expand access to quality education (Epple, Romano and Urquiola, 2017). In these counterfactuals, we only permit low income students to receive vouchers, denoted $\tau_{j,t}$, since most (89%) of federal student aid spending in the sub-baccalaureate market is directed towards Pell-eligible students. Federal loans are discontinued, so students who can no longer afford college net their voucher must take out loans in the private market to enroll.[38] We consider three separate voucher designs.

Lump-Sum Voucher The first voucher policy we consider is a lump-sum voucher program for low-income students. Under this policy, low-income (Pell-eligible) students receive a fixed amount of aid regardless of their school choice. Explicitly, lump-sum vouchers take the following form:

$$\tau_{i,j,t}^{\text{Lump-Sum}} = g \tag{30}$$

where g determines the generosity of the low-income voucher program.

Quality Vouchers To evaluate the benefits of delivering more aid to higher quality schools, we consider a voucher design tied to the quality of institutions ψ_j. The voucher takes the following form:

$$\tau_{i,j,t}^{\psi} = g \times \psi_j, \tag{31}$$

Optimal Voucher Finally, we consider what an optimal voucher design would look like if the social planner only cares about maximizing the aggregate value-added Ψ provided to targeted (low-income) students. We assume the social planner can perfectly observe demand, the quality of each institution, and each college's cost structure. We also assume the planner can only control federal student aid and not the budgets $B_{j,t}$ of CCs, and that the policy space

[38]Because not all students may be approved for private student loans, we interpret this assumption as requiring the federal government to offer loans at non-subsidized rates (e.g., the prevailing interest rates in the private student loan market at the time of the enrollment decision) to cover the cost of attedance.

consists of school-specific vouchers $\{\tau_{j,t}\}$ that may differ in amount. The social planner's optimization problem is specified as follows:

$$\max_{\{\tau_{j,t}\}} \Big\{ \sum_t M_t \sum_{j \in \mathcal{J}_t} s_{j,t,L} \cdot \psi_j \Big\} \qquad \text{s.t.} \qquad \sum_t M_t \sum_{j \in \mathcal{J}_t} s_{j,t,L} \cdot \tau_{j,t} \leq G_0, \tag{32}$$

where $s_{j,t,L}$ is the market share of j in t among low-income students. Besides the quality of the school, the key to understanding the optimal aid allocation across schools under this social planner problem is the *voucher elasticity*: $\varepsilon^{\tau}_{k,j,t} = \partial \log(s_{j,t,L})/\partial \log(\tau_{k,t})$. This represents the increase in low-income enrollment at school j from increased voucher aid to school k. It depends on both the demand side elasticity to price changes and the supply-side response to the voucher: the tuition or advertising response. More aid translates to lower prices for students, which increases demand, but it may also provide incentives for colleges to increase tuition, dampening this effect. Furthermore, FPIs may respond to aid changes through advertising. In Appendix I, we provide the full solution to the social planner's problem. For our counterfactual analysis, we use a simplified solution to the social planner's problem, which is qualitatively similar in formulation.

Proposition 1. Suppose the social planner optimizes Equation 32, and $\varepsilon^{\tau}_{j,k,t} \approx 0$ if $j \neq k$. The optimal voucher for school j in market t is

$$\tau^*_{j,t} \approx \underbrace{\frac{1}{\lambda}}_{\substack{\text{Shadow Price} \\ \text{of Budget Constraint}}} \times \underbrace{\frac{\varepsilon^{\tau}_{j,j,t}}{1 + \varepsilon^{\tau}_{j,j,t}}}_{\substack{\text{Own-Voucher Elasticity} \\ \text{Distortion Term}}} \times \underbrace{\psi_j}_{\text{Quality}} \tag{33}$$

Proof. See Appendix I. □

The intuition for this solution is as follows. First, conditional on $\varepsilon^{\tau}_{j,j,t}$, give higher quality schools more aid. Second, conditional on ψ_j, give more aid to schools whose enrollment is more responsive to increases in voucher aid. Using plug-in estimates of the elasticities, $\hat{\varepsilon}^{\tau}_{j,j,t}$ (see Appendix H for estimation details), our implementation of the optimal voucher is:

$$\tau^*_{i,j,t} = g \times \frac{\hat{\varepsilon}^{\tau}_{j,j,t}}{\hat{\varepsilon}^{\tau}_{j,j,t} + 1} \times \psi_j \tag{34}$$

where g is substituted for the shadow price of the planner's budget constraint.

We estimate that FPI enrollment is more elastic to aid than CC enrollment. This is for a few reasons. As we saw in our descriptive evidence and model results, CC demand is significantly more price inelastic, meaning prices are worse shifters of student choices at these schools. Because CCs are budget constrained, they must increase prices proportionally to enrollment, further dampening the effects of additional aid. Additionally, we estimate that FPIs respond to further voucher aid by increasing advertising, and given the importance of FPI advertising in college demand, this is another manner in which FPIs can attract more students. The average voucher elasticity $\varepsilon^{\tau}_{j,j,t}$ is 1.4 for CCs in our sample, and 2.7 for FPIs (3.4 for advertising FPIs). Thus, conditional on quality, this aid scheme implies that it is optimal for the government to allocate more voucher aid to for-profits.

6.2 Proposed Ban Policies

We also consider a set of counterfactuals similar to those that have been proposed by policy-makers to address systemic issues that involve banning certain institutions from federal aid. To balance the federal budget, we change the generosity of the Pell grant program, indexed by a parameter g set for each policy: $\bar{\pi}_y(\mathcal{P}) = g \times \bar{\pi}_{y,\text{Observed}}$, where $\bar{\pi}_{y,\text{Observed}}$ is the current maximum Pell grant award in year y.

Banning For-Profit Colleges We consider a policy of banning for-profit colleges from receiving federal student aid. Bills have been considered as recently as 2019 to ban FPIs from federal aid due to their reputation of low quality and over-priced education.[39] Under this policy, students wishing to attend a for-profit must pay the full cost of attendance, without access to Pell grants or subsidized federal loans.

Banning Low-Quality Colleges We also consider a more targeted policy of banning low-quality colleges from receiving federal aid, similar to the gainful employment regulations proposed by the Obama administration. We define a college as low-quality if value-added ψ_j is negative. These low-quality colleges account for 23% of institutions but only 3% of enrollment, since these are mostly small FPIs.

6.3 Counterfactual Results

Table 6 displays aggregate statistics from the new equilibrium under each of the five counterfactual policies considered, for our main outcomes of interest. Appendix Table A5 displays auxiliary outcomes of interest as well. We solve for a lump-sum voucher of \$6,830 in 2017 USD to balance the federal budget. Under a lump-sum voucher, there is a 2.3% increase in total value-added (10% for low-income consumers). This is driven by the proportional increase in the number of consumers who choose to attend college. In addition, consumer surplus increases by 2% when we include advertising as part of welfare calculations, and 3%

[39] See the "Students Not Profits Act of 2019" `https://www.republicreport.org/wp-content/uploads/2019/10/Students-Not-Profits-Act.pdf`

Table 6: Counterfactual Equilibrium Results

	Level	% Change From Current				
Policy:	Current Aid	Low-Income Voucher			Federal Aid Ban	
	Regime	Lump-Sum	Quality	Optimal	FPI	Low Quality
Panel A: All Students						
Aggregate Value Added	64.66B$	+2.30%	+5.33%	+8.77%	+0.98%	+1.51%
Students	7.85M	+2.00%	-2.55%	+0.40%	-5.70%	-0.23%
Avg. Net Student Price	7,576$	-7.42%	-9.96%	-12.75%	-4.86%	-0.35%
Consumer Surplus	37.08B$	+1.93%	+2.08%	-0.41%	+0.55%	+0.18%
Consumer Surplus (No Ads)	31.47B$	+3.03%	+10.78%	+2.71%	+13.62%	-0.53%
% FPI	16.85%	-0.47%	-7.28%	-4.80%	-10.44%	-0.55%
Panel B: Low-Inc Students						
Aggregate Value Added	35.85B$	+10.50%	+19.63%	+23.62%	+7.32%	+2.70%
Students	4.54M	+9.74%	+4.22%	+7.21%	-3.37%	-0.08%
Avg. Net Student Price	7,313$	-8.14%	-12.50%	-20.66%	-5.59%	-0.42%
Consumer Surplus	20.91B$	+8.52%	+10.55%	+3.55%	+5.38%	+0.56%
Consumer Surplus (No Ads)	16.63B$	+10.53%	+25.64%	+7.71%	+26.75%	-0.30%
% FPI	22.13%	-1.08%	-11.14%	-7.24%	-15.54%	-0.97%
Panel C: College Outcomes						
FPI Profits	5.00B$	-1.96%	-26.77%	-21.37%	-40.72%	-4.01%
Avg. CC Markdown	7,162$	-1.65%	-2.52%	+0.36%	-4.36%	-0.34%
Avg. FPI Markup	5,552$	+3.51%	+28.61%	+26.71%	+35.55%	+11.93%
FPI Advertising	2.74B$	-4.02%	-35.73%	-22.95%	-57.39%	-1.88%

Table displays results from counterfactual analysis of alternative policies in equilibrium. Aggregate value-added denotes the sum of quality ψ_j multiplied by the number of students at each school. Students denotes total enrollment in the market. Avg. Net student price is the average net student price paid, weighted by the individual-level market shares multiplied by market size (so that each weight represents an effective number of students). Consumer Surplus denotes revealed preference utility, in units of out-of-pocket payments. Consumer Surplus (No Ads) is Consumer surplus without the component attributable to FPI advertising. Average FPI markup denotes the average difference of tuition and marginal cost across for-profit campuses. Average CC markdown denotes the average difference between marginal cost and tuition across community college campuses. FPI advertising denotes the total spending on advertising as measured by the estimated advertising costs $\kappa_{f,d}$. Current aid regime denotes values at the current observed equilibrium, as implied by our model.

when we exclude advertising. The larger increase in consumer surplus without ads is driven by a decrease in total FPI advertising. Although markups increase by 3.4% for FPIs across schools, students pay a net student price 7.4% lower on average. These savings occur primarily through student re-sorting into lower-cost institutions. In particular, more students choose CCs, and within FPIs, students enroll in schools that have tuition \$670 lower on average, a 4% decrease. We interpret this as evidence that decoupling price from aid lowers prices in higher education.

Under the linear quality voucher, aggregate value-added increases by 5.3%, despite a reduction in total enrollment. Under this policy, the for-profit sector experiences a large decline, with their share of total enrollment decreasing from 16.9% to 9.5%. This suggests the policy is effective at inducing consumers to substitute away from low-quality FPIs. Advertising spending declines by 36% under this policy, making advertising a less important input into student choice. Consequently, consumer surplus (excluding advertising) increases by 10.8%.

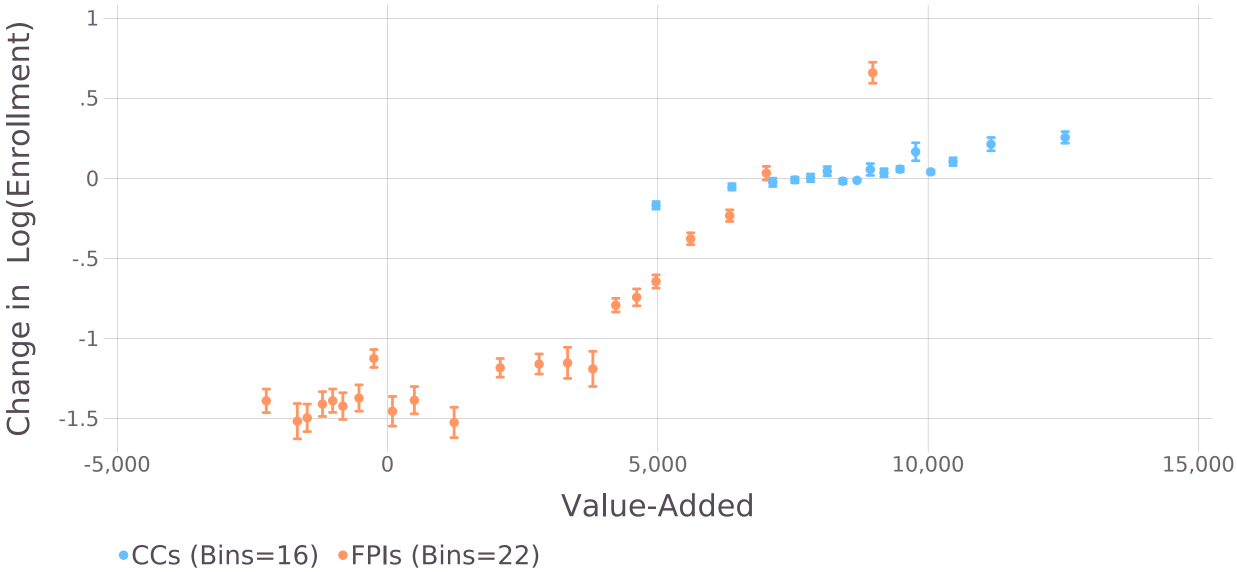
To better understand how the optimal voucher policy works, we plot in Figure 4 its equilibrium effects on enrollment, tuition, and advertising expenditure for CCs and FPIs at different levels of value-added. The optimal voucher program redirects students to higher-quality schools. Most notably, responses to the program are heterogeneous across school types: FPIs respond more aggressively than CCs to increased aid, as indicated by the steeper slope in FPI enrollment with respect to value-added. This pattern is consistent with the higher voucher elasticities we estimate for FPIs. High-quality CCs must increase prices when demand increases due to budget constraints (Panel (b)). In contrast, higher-quality FPIs increase tuition less than low-quality FPIs. High (low)–quality FPIs also increase (decrease) advertising in response to the policy, amplifying its impact on enrollment.

As a result of these channels, we find that the aggregate value-added increases substantially under the optimal voucher program, by 8.8% among all consumers and 23.6% for low-income consumers. At the same time, total sub-baccalaureate enrollment is effectively unchanged. For-profit advertising decreases by 22.9%, a smaller decline than under the linear quality voucher case because high-quality FPIs are incentivised under this system to increase advertising. Additionally, consumer surplus excluding advertising increases by 2.7% under the optimal voucher policy.

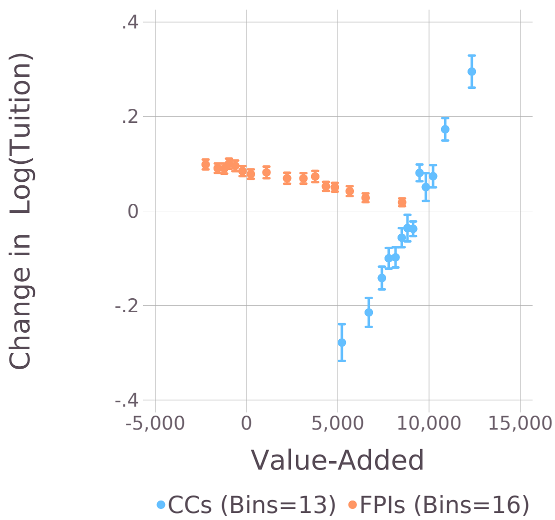
In comparison, bans are not as effective as vouchers at improving quality provision. The FPI aid ban, coupled with a 22% increase in Pell grants to balance the budget, slightly increases total value-added by 1%, relative to the current equilibrium. This ban is not effective primarily because it punishes both medium and low-quality FPIs equally. Moreover, because CCs and FPIs are not close substitutes, many students exit from the FPIs to the outside option, resulting in a 5.7% decrease in total enrollment. When we ban low-quality schools from student aid, total value-added increases by 1.5%, making it slightly more effective. Importantly, compared to our quality-based voucher policies, these bans are ineffective primarily because they do not impact the choice of the infra-marginal consumer: even under the low-quality ban, students are not incentivized by aid design to choose a high instead of medium quality school.

6.4 Robustness Checks

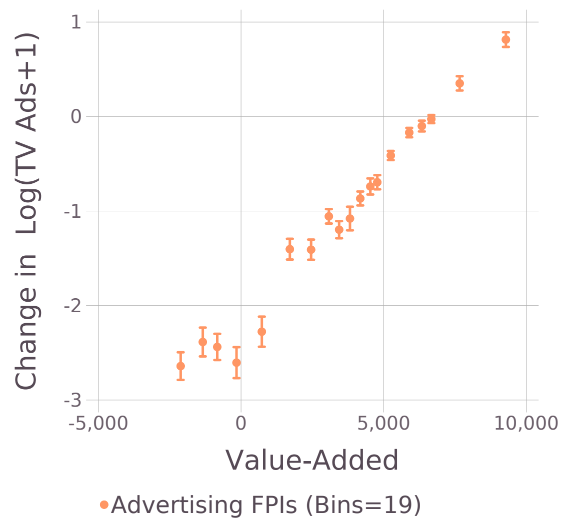
We now investigate whether the results of our proposed voucher policies hinge on certain assumptions made during our counterfactual analysis. The optimal voucher we consider



(a) Enrollment



(b) Tuition



(c) Advertising

Figure displays a binscatter, separately by community and for-profit colleges, of the school-level logged change of each variable from the observed equilibrium to the optimal quality voucher equilibrium, versus a school's value-added. The number of bins is chosen using the Cattaneo et al. (2019) data-driven optimal bin selection method. 95% confidence intervals reflect within-bin means, and are clustered at the school level.

Figure 4: Change in Supply and Demand Under Optimal Voucher, by Value-Added

may not be feasible in practice for two reasons. First, assigning aids based on school-specific voucher elasticities and value-added can be politically and logistically challenging. Second, schools may adjust their quality in response to the policy. As a robustness check, we consider a feasible version of the optimal voucher system under which the government assigns aid based on a set of observable and plausibly exogenous school characteristics.[40] We replace our value-added measures ψ_j in Equation 34 with their prior mean based on school characteristics and use the random forest algorithm to predict voucher elasticities as a function of school characteristics.[41] Table A6 shows the equilibrium outcomes under this feasible voucher design. We find that aggregate value-added would increase by 6.7%, capturing a large share of the gains from the optimal voucher design.

Our conduct model assumes that CCs must increase tuition to balance the budget when demand increases under alternative federal aid systems. We try relaxing this assumption by shutting down CCs' pricing responses in the counterfactuals.[42] CCs are no longer "penalized" by the optimal voucher policy due to their budget constraints and have voucher elasticities comparable to those of the FPIs.[43] Table A8 shows that we obtain qualitatively results under this assumption. In Table A7, we shut down the supply side completely, and also obtain similar aggregate results. At the same time, low-income students, the targets of vouchers, benefit from these policy changes less when there is only a demand response: their aggregate value-added increases by 3% less under the optimal voucher. Thouh CCs expand greatly in these counterfactuals due to increased state subsidies, this benefits high-income students moreso, since low-income students prefer many of the characteristics of for-profit schools.

Finally, we examine the role of advertising in our counterfactual welfare results by shutting down FPIs' advertising responses in the counterfactuals. Table A9 shows that our voucher policies generate a smaller increase in value-added under this restriction. Aggregate value-added increases by 0.8% less under the optimal voucher design, translating to a \$540-million reduction in annual post-college income.[44] Value-added is lost when high-

[40]For example, changing the degrees offered could take years because of the federal accreditation process.

[41]The prior mean of value-added is $W_j\zeta$. Estimates of ζ can be found in Table D1. We predict the distortion term $\hat{\varepsilon}^{\tau}_{j,j,t}/(\hat{\varepsilon}^{\tau}_{j,j,t}+1)$ using school characteristics, the average consumer demographics in each market, and the differentiation instruments expressed in Equation 24. To tune hyperparameters, we perform 5-fold cross-validation over the depth of the tree and the number of features used for each decision tree. We obtain an R-squared of 0.56 out-of-sample and 0.91 in-sample, indicating a good fit.

[42]Because tuition prices at CCs are subsidized, we estimate these counterfactuals by balancing the *total* government budget, which includes both federal aid and subsidies given to community colleges $\sum_{j,t} B_{j,t}$ by local governments. We assume CCs continue to subsidize tuition at the same rate per student as the observed equilibrium.

[43]For-profits still have a larger voucher elasticity on average, though the difference is smaller. The reason is two-fold: CCs often price at the inelastic portion of the demand curve, meaning vouchers are less effective at shifting student choice, and CCs do not respond to additional voucher aid with advertising.

[44]19% of FPIs receive negative profits due to fixed costs in advertising, which makes these counterfactuals

quality FPIs can no longer use additional voucher aid to increase advertising and expand enrollment. This result shows the importance of advertising in this market and in assessing potential reforms.

7 Conclusion

In this paper, we assess the equilibrium impact of federal student aid design in the U.S. sub-baccalaureate market. Existing policy proposals, such as banning for-profits from federal student aid, do little to improve aggregate quality. In contrast, switching to a voucher design of federal student aid, where aid schedules are independent of price, has large, positive effects on student enrollment and aggregate quality provision. Moreover, if the government can incentivize high-quality private colleges to expand enrollment, we show under our optimal voucher design that further gains could be realized. Thus, private enterprises, due to their strong profit motives, can be a useful tool for policymakers to increase quality provision, as long as the government can allocate aid to the proper (high-quality, aid-elastic) schools.

This paper is not without its limitations. Our results may not generalize to the 4-year selective college sector, due to the ability for these schools to screen students. Additionally, we do not model the endogenous quality choices nor the entry/exit decisions of colleges. Future work should be undertaken to better understand the full equilibrium outcomes that may arise from an overhaul of federal student aid. At the same time, our paper is the first to estimate equilibrium outcomes from alternative aid policies at a large scale in the U.S. higher education sector. Consequently, our results are useful to inform policymakers, particularly those interested in the outcomes of sub-baccalaureate students.

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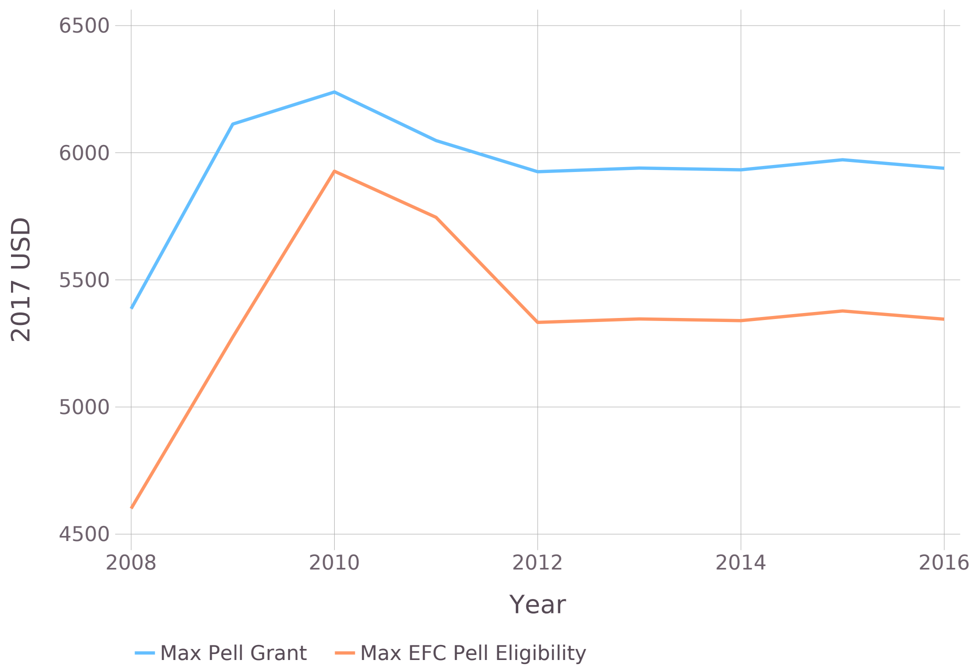
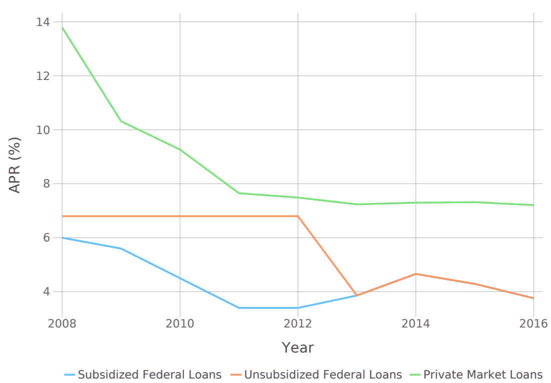
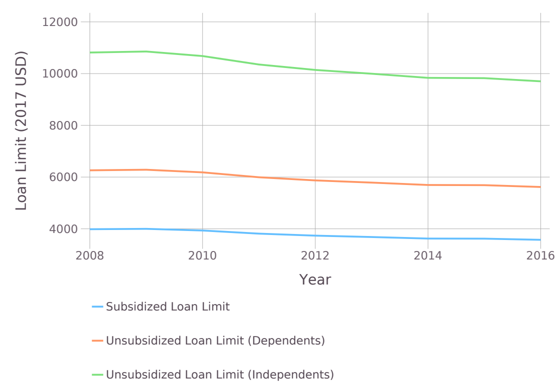


(a) Maximum EFC Eligibility $\overline{EFC}_y$ and Maximum Pell Grant $\bar{\pi}_y$ Over Time



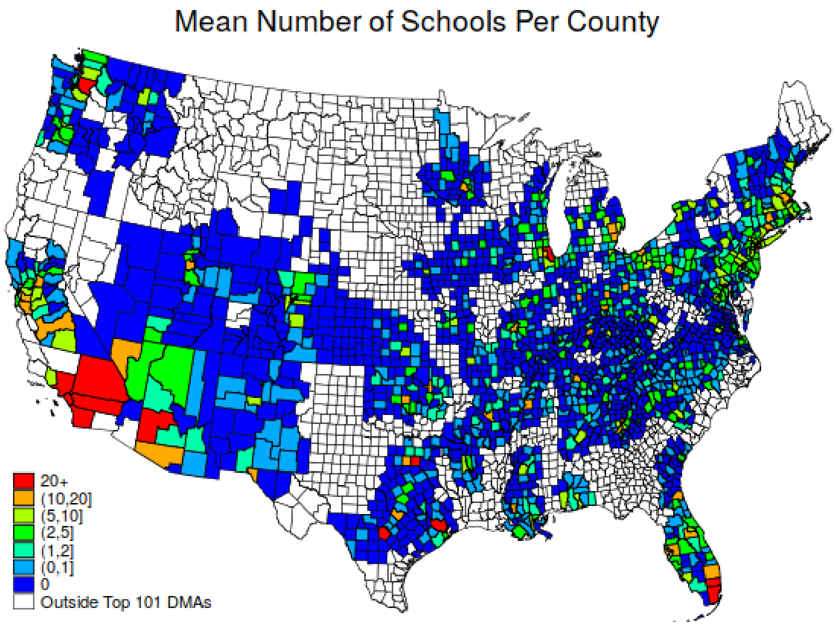
(b) Interest Rates on Student Loans



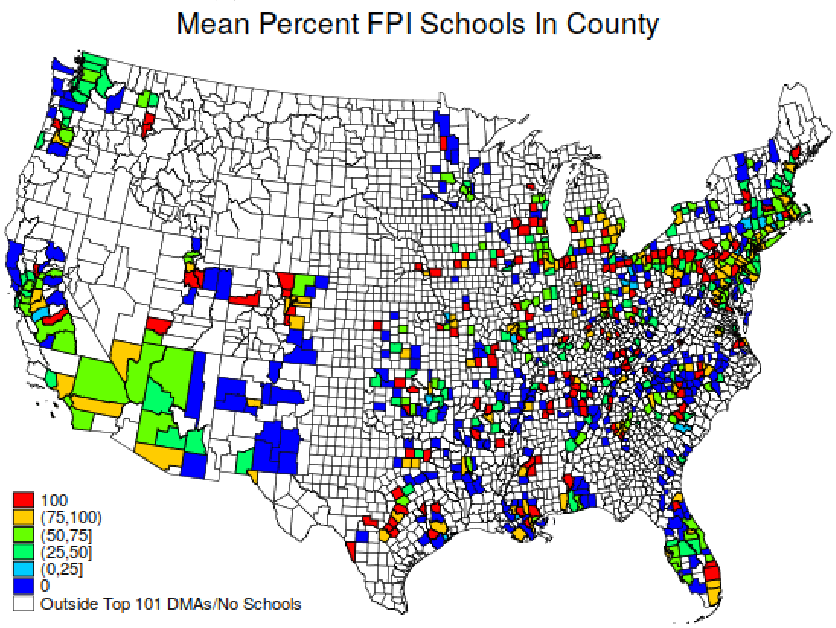
(c) Limits on Federal Student Loans

Figure A1: Federal Aid Policy Over Time

Figure shows the changes to federal student aid at the national level from 2008-2016. Panel (a) plots $\overline{EFC}_y$ (orange) and $\bar{\pi}_y$ (blue) in real 2017 USD. Panel (b) plots the subsidized federal student loan interest rate (blue), the unsubsidized federal student loan interest rate (orange), and the average private student loan interest rate (green). For private market interest rates before 2011, we use the average median interest rate for undergraduates reported by the CFPB. for years after 2011, we use the 3-month Q3 LIBOR index, plus the median 2011 margin on private student loans. Panel (c) plots the the loam limits in 2017 USD for both subsidized (blue) and unsubsidized loans, where the limits differ for dependents (orange) and independents (green).



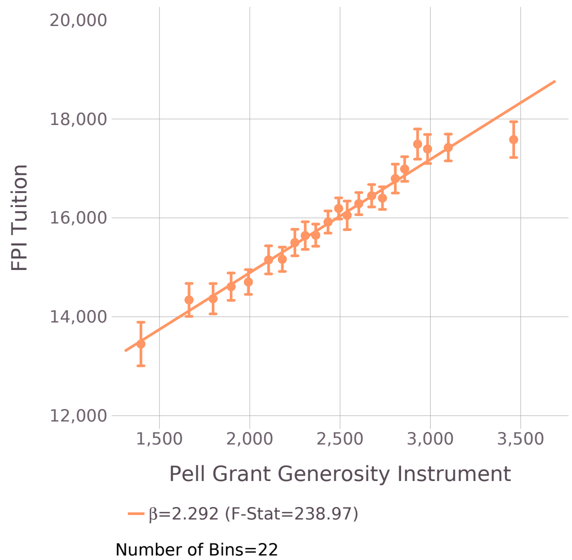
(a) Number of Schools in County



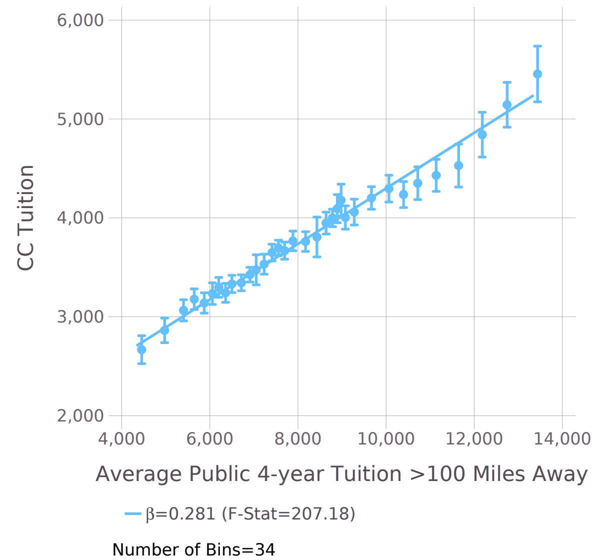
(b) Fraction of Sub-Baccalaureate Schools that are For-Profit

Figure A2: Map of Counties covered in Sample

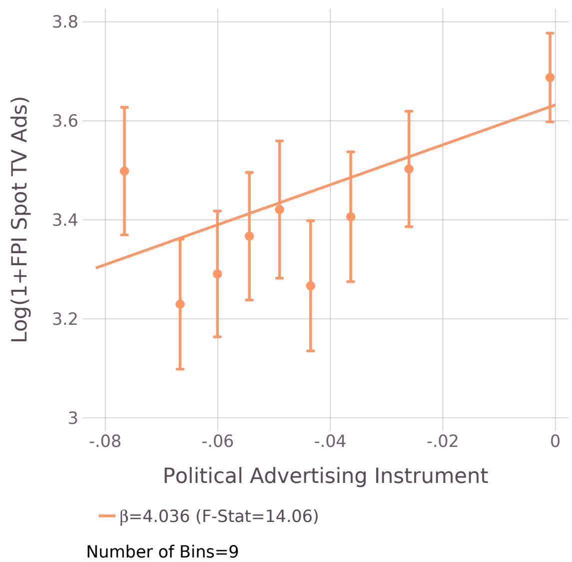
Panel (a) of figure shows the average number of schools per county across the 101 DMAs in the continental United States. Panel (b) of figure shows the average fraction of schools per county across the 101 DMAs in the continental United States that are for-profit colleges.



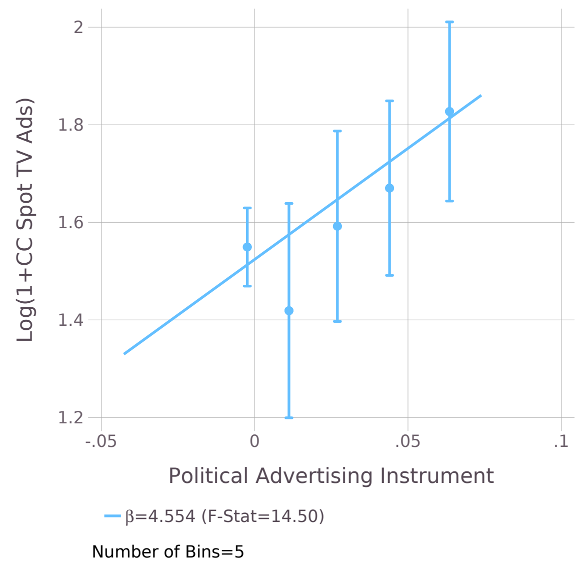
(a) For-Profit College Tuition



(b) Community College Tuition



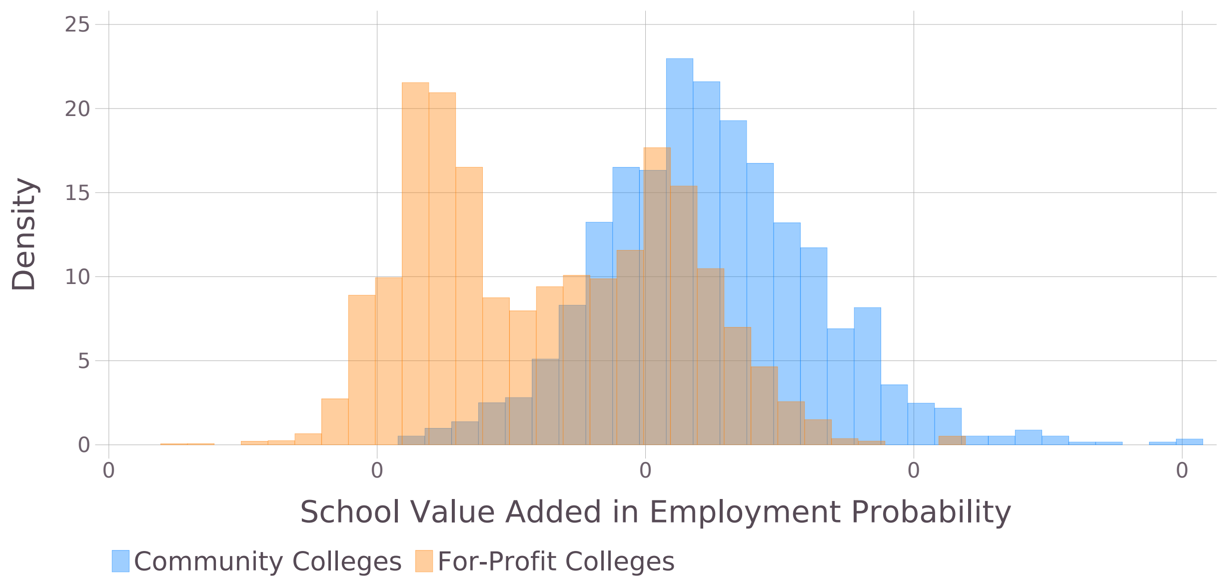
(c) For-Profit College Advertising



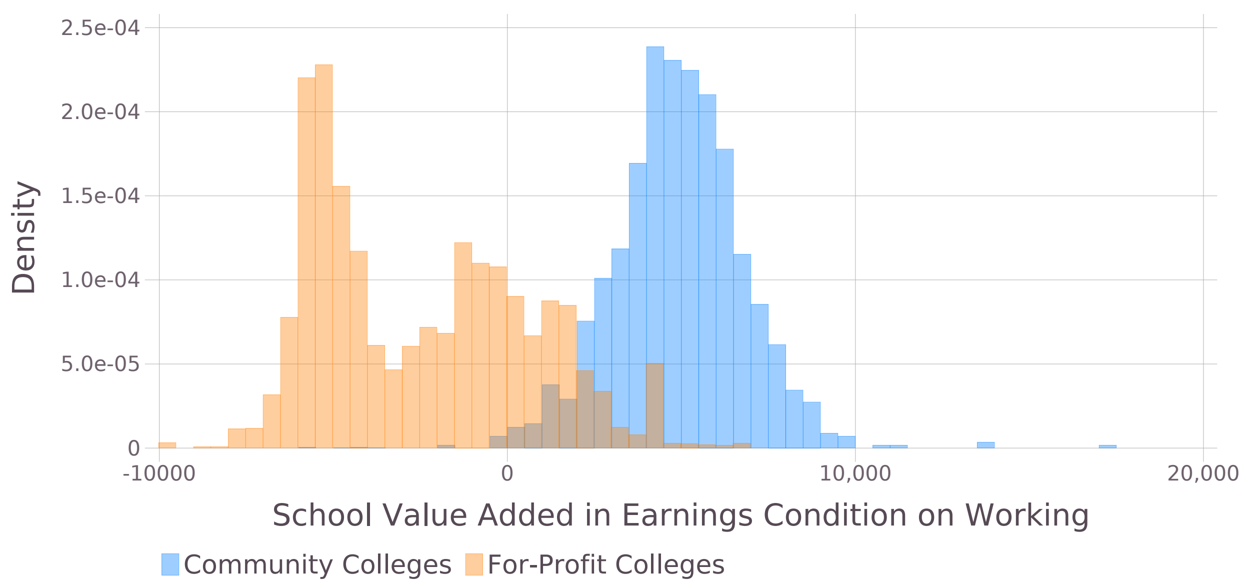
(d) Community College Advertising

Each panel shows a binscatter of the relationship between a variable and its instrument. The number of bins is chosen using the rule-of-thumb implementation from the (Cattaneo et al., 2019) package. Each bin mean is displayed along with a 95% confidence interval, using standard errors clustered at the school level. Controls include school fixed effects, market demographics, and school characterstics. Market demographics and school characteristics are defined in footnotes 16 and 17, respectively. Binscatter effect sizes are reported at the mean of control variables. We superimpose the relationship recovered from a linear regression, using the same controls. Advertising binscatters are estimated on the sample of schools which we ever observe advertise in our data.

Figure A3: Binscatter of Endogenous Variables (Tuition and Advertising) on Instruments, by College Type



(a) Probability of Employment



(b) Earnings Conditional on Employment

Figure A4: Decomposition of Value-Added Earnings Estimates

Panel (a) of figure shows the estimated value-added of each college, where the outcome is the average cohort employment rate ten years after entry. Panel (b) of figure shows the estimated value-added of each college, where the outcome is the average cohort earnings, conditional on employment, ten years after entry.

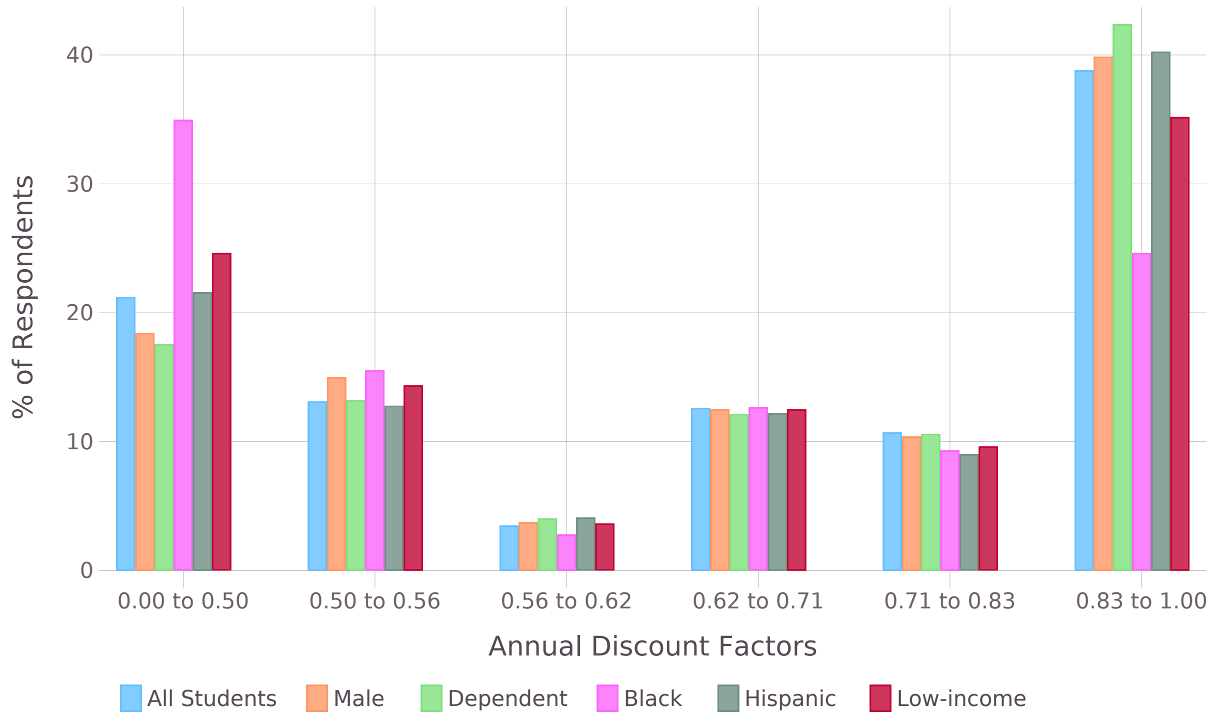


Figure A5: Distribution of Discount Factor Micromoments

Table shows the distribution of discount factors from student responses to the 2012 Beginning Postsecondary Survey. Discount factors are expressed as the value of a dollar in one year. We plot the distribution for all sub-baccalaureate students in the BPS, as well as by each of the 5 demographics used in our model.

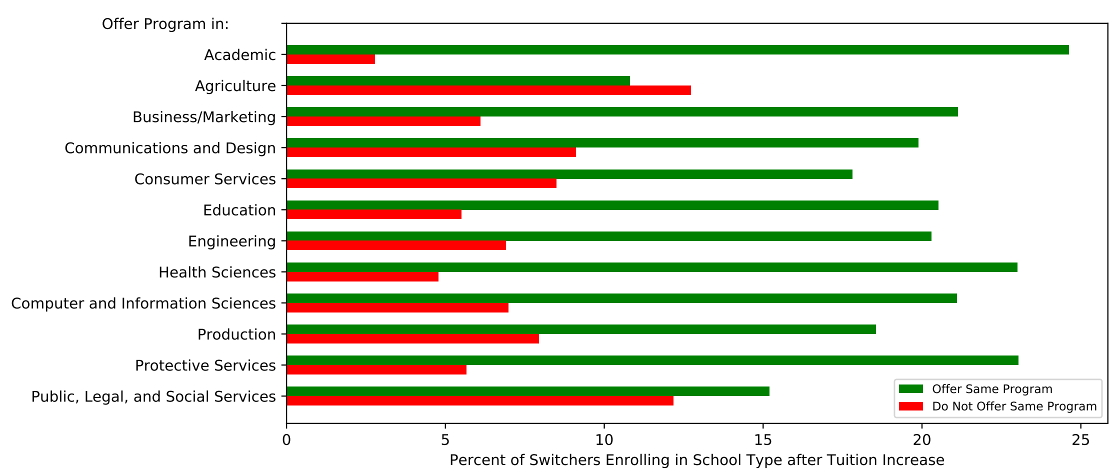
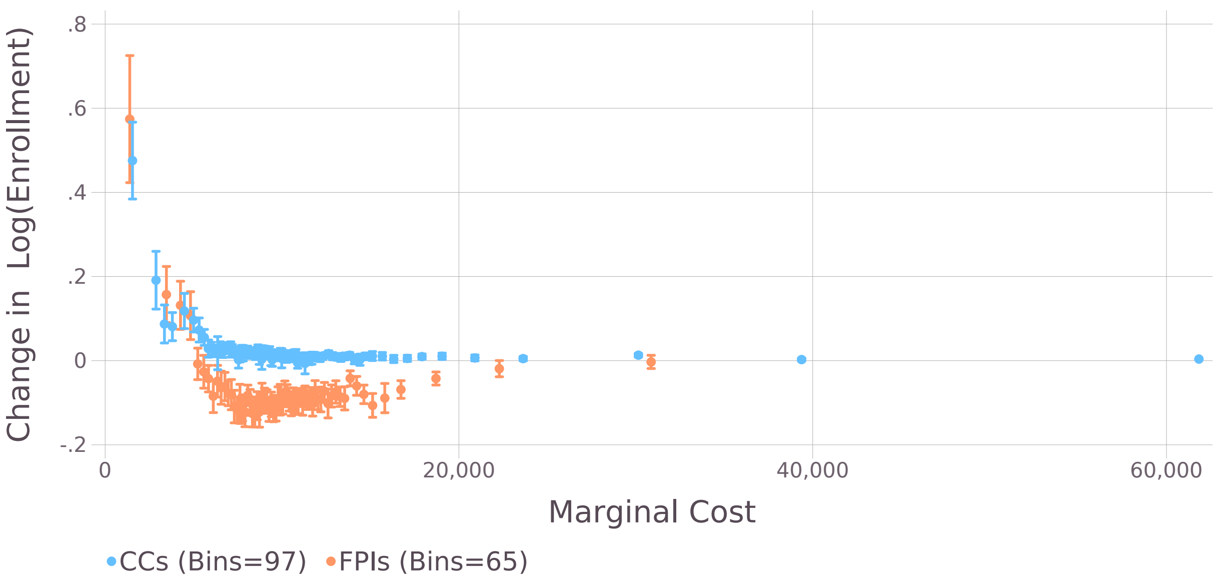
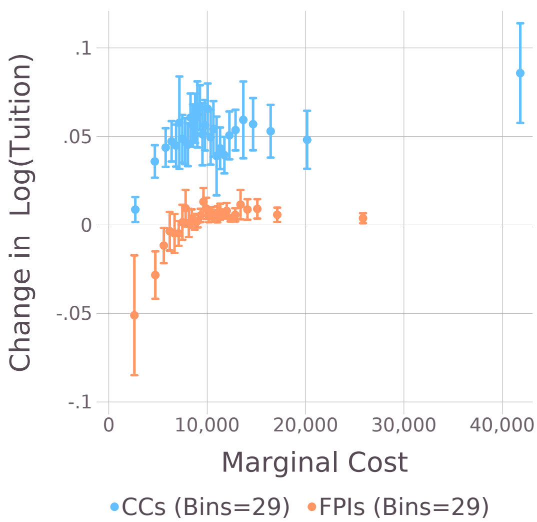


Figure displays the average diversion ratios across colleges. For each college, we sum the diversion ratios across colleges with and without the same program offered, then take averages.

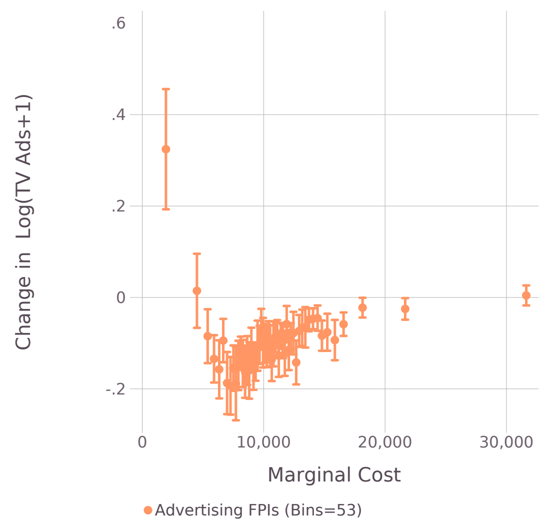
Figure A6: Distribution of Education Costs by College Type



(a) Enrollment



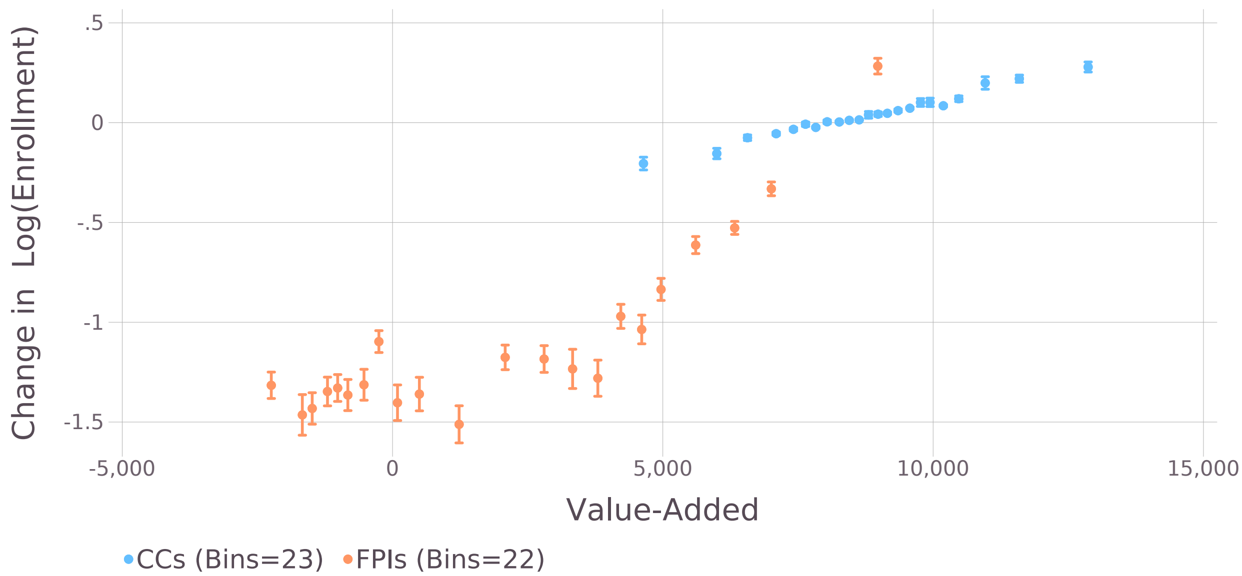
(b) Tuition



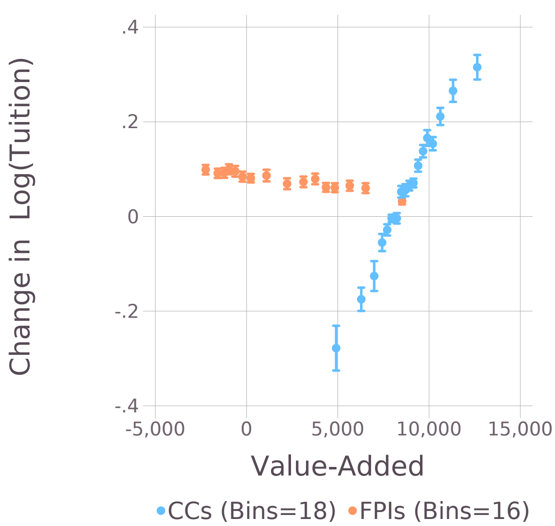
(c) Advertising

Figure displays a binscatter, separately by community and for-profit colleges, of the school-level logged change of each variable from the observed equilibrium to the lump-sum voucher equilibrium, versus a school's marginal cost. The number of bins is chosen using the Cattaneo et al. (2019) data-driven optimal bin selection method. 95% confidence intervals reflect within-bin means, and are clustered at the school level.

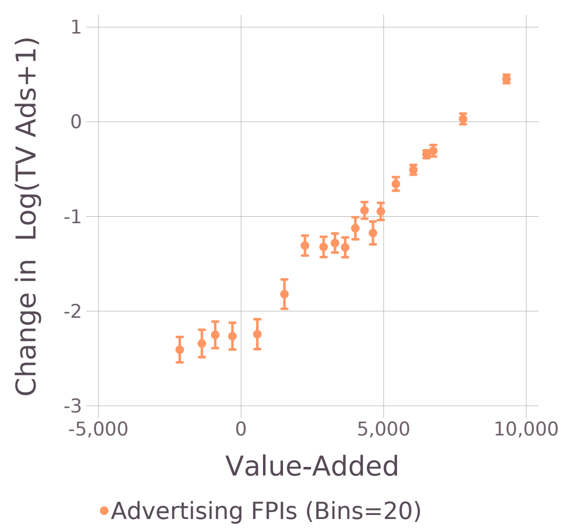
Figure A7: Change in Supply and Demand Under Lump-Sum Voucher, by Marginal Cost



(a) Enrollment



(b) Tuition



(c) Advertising

Figure displays a binscatter, separately by community and for-profit colleges, of the school-level logged change of each variable from the observed equilibrium to the linear quality voucher equilibrium, versus a school's value-added. The number of bins is chosen using the Cattaneo et al. (2019) data-driven optimal bin selection method. 95% confidence intervals reflect within-bin means, and are clustered at the school level.

Figure A8: Change in Supply and Demand Under Quality Voucher, by Value-Added

Table A1: FPI Advertising Elasticity, by Demographic

Outcome: IHS First-time Enrollment	All	Gender		Race		Income		Age	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All	Men	Women	Minority	White	Pell	No Pell	Age < 25	Age ≥ 25
Log(TV Ads + 1)	0.380**	0.506***	0.253*	0.372**	0.426**	0.561***	0.246	0.384**	0.515**
	(0.150)	(0.192)	(0.130)	(0.163)	(0.173)	(0.210)	(0.172)	(0.168)	(0.208)
Observations	17,601	17,601	17,601	17,601	17,601	16,879	16,879	10,987	10,987
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First Stage F-Stat	10.57	10.57	10.57	10.57	10.57	8.92	8.92	6.91	6.91

Table displays IV estimates of the relationship between first-time enrollment and television advertising. Standard errors reported in parentheses are clustered at both the school level and the OPEID6-DMA-year level, the level at which advertising purchases occur. Dependent variable is the logged full-time equivalent, first-time enrollment at each school. Market Demographics denote the fraction of students in the market (18-50, high school education, same county) that are male, dependent, Black, Hispanic, the average EFC, and the logged market size. School Characteristics denote dummies for student services (offering remedial services, academic/career counseling, employment services, placement services, on-campus day care, ROTC, study abroad, weekend/evening college, teacher certification, and distance learning opportunities), degree majors (offering an academic degree, as well as dummies for offering each of the 14 occupational majors as defined by NCES) and degree levels(offering < 1-year certificate, 1-year certificate, 2-4 year certificate, and an associate's degree). First-stage F-stat denotes the F-statistic for the excluded instruments (political advertising) in the first-stage regression with log tuition as the dependent variable.
$^{*}p < .1, ^{**}p < .05, ^{***}p < .01$

Table A2: Demand Estimates: Preferences for College Characteristics

Characteristic	Baseline Coefficients	Heterogenous Coefficients: Men	Low-Income	Black	Hispanic	Dependent	σ_v
Inside Good	4.197	-0.009	-5.671	-1.666	-1.160	-0.727	0.406
	(0.119)	(0.887)	(1.224)	(0.711)	(0.704)	(0.643)	(1.271)
Multiplier on Price Coefficient	-0.315	0.407	-0.179	0.444	0.251	0.363	-0.002
	(0.165)	(0.181)	(0.164)	(0.199)	(0.169)	(0.120)	(0.120)
Discount Factor (Log Odds)	0.725	0.055	0.240	-1.070	-0.018	-0.771	1.043
	(0.060)	(0.069)	(0.056)	(0.083)	(0.055)	(0.061)	(0.020)
Academic Programs	-1.009	-0.235	0.034	0.498	0.423	0.911	0.319
	(0.173)	(0.179)	(0.208)	(0.218)	(0.243)	(0.266)	(2.212)
Business Programs	-0.466	-0.274	0.447	0.441	0.319	-0.061	0.792
	(0.105)	(0.133)	(0.118)	(0.170)	(0.163)	(0.162)	(1.262)
Communications and Design Programs	0.580	0.732	-0.763	-0.078	0.024	-0.257	0.097
	(0.101)	(0.172)	(0.172)	(0.160)	(0.173)	(0.154)	(2.495)
Consumer Services Programs	0.132	-0.839	-0.034	0.249	-0.033	0.510	-0.426
	(0.119)	(0.090)	(0.173)	(0.130)	(0.141)	(0.134)	(1.358)
Education Programs	-1.285	-0.248	0.156	0.281	0.771	-0.038	-2.527
	(0.096)	(0.152)	(0.115)	(0.231)	(0.363)	(0.630)	(1.888)
Computer and Information Sciences Programs	0.321	0.285	-0.011	0.046	-0.086	-0.041	-0.192
	(0.091)	(0.113)	(0.093)	(0.103)	(0.108)	(0.119)	(1.425)
Engineering Programs	-0.446	0.766	0.026	-0.226	-0.159	0.449	-0.666
	(0.094)	(0.209)	(0.190)	(0.165)	(0.135)	(0.191)	(1.771)
Health Sciences Programs	-0.121	-1.464	0.533	0.098	0.202	-0.547	0.179
	(0.144)	(0.193)	(0.235)	(0.110)	(0.152)	(0.120)	(0.972)
Production Programs	-0.735	2.098	-0.683	0.331	0.279	-0.106	-0.328
	(0.112)	(0.232)	(0.292)	(0.127)	(0.127)	(0.142)	(1.945)
Protective Services Programs	-1.764	0.167	-0.020	-0.071	0.068	0.667	2.761
	(0.124)	(0.244)	(0.198)	(0.209)	(0.262)	(0.515)	(1.493)
Public, Legal, and Social Services Programs	0.288	-0.254	0.028	0.166	0.000	-0.079	0.530
	(0.096)	(0.117)	(0.113)	(0.112)	(0.140)	(0.189)	(2.074)
<1yr Certificates	0.409	-0.014	-0.318	0.181	0.236	0.095	0.007
	(0.065)	(0.076)	(0.063)	(0.064)	(0.086)	(0.065)	(1.397)
1yr Certificates	-0.404	-0.685	0.313	0.351	0.336	-0.178	0.395
	(0.086)	(0.102)	(0.145)	(0.112)	(0.121)	(0.099)	(0.944)
Associate's Degrees	-0.916	0.259	0.083	-0.485	-0.430	0.578	1.482
	(0.137)	(0.188)	(0.136)	(0.141)	(0.153)	(0.254)	(1.102)
2-4yr Certificates	0.276	0.181	-0.182	-0.300	-0.055	-0.428	-0.511
	(0.074)	(0.125)	(0.133)	(0.135)	(0.125)	(0.125)	(2.266)
Tuition Payment Plan	-0.423	-0.165	-0.268	-0.184	0.158	0.248	0.631
	(0.072)	(0.095)	(0.099)	(0.091)	(0.098)	(0.085)	(0.836)
Online Classes	-0.612	-0.046	0.096	0.052	0.010	0.212	-0.863
	(0.079)	(0.104)	(0.113)	(0.129)	(0.126)	(0.215)	(1.358)
Weekend/Evening college	-0.106	0.066	-0.467	-0.152	0.061	-0.050	-0.520
	(0.061)	(0.112)	(0.127)	(0.091)	(0.108)	(0.083)	(1.477)
Remedial Services	0.090	0.305	-0.173	0.098	0.052	-0.163	0.165
	(0.094)	(0.116)	(0.087)	(0.093)	(0.078)	(0.082)	(1.427)
Academic/Career counseling Service	0.220	0.245	-0.035	-0.180	0.095	-0.379	0.139
	(0.094)	(0.084)	(0.085)	(0.102)	(0.082)	(0.075)	(1.251)
Post-College Placement Services	0.585	0.332	-0.329	-0.019	0.098	-0.256	-0.168
	(0.101)	(0.137)	(0.137)	(0.132)	(0.121)	(0.090)	(1.151)
Childcare	-24.374	-1.271	-1.365	4.178	1.251	9.197	-16.522
	(0.131)	(0.836)	(0.619)	(1.083)	(0.700)	(2.552)	(2.882)
Sports Teams	-0.944	-0.222	-0.077	0.931	0.189	2.011	0.561
	(0.152)	(0.138)	(0.137)	(0.206)	(0.207)	(0.468)	(3.279)
Log(1+For-ProfitSpot TV Ads)	0.706	0.014	0.009	0.074	0.031	0.066	0.025
	(0.096)	(0.018)	(0.026)	(0.021)	(0.021)	(0.018)	(0.177)
For-Profit College	-0.964	0.856	-0.998	0.486	1.362	0.920	0.193
	(0.079)	(0.343)	(0.406)	(0.422)	(0.450)	(0.299)	(0.988)
HBCU	-7.318			7.612			-5.323
	(0.251)			(2.074)			(2.234)
Value-Added ($1000s)	0.055	0.144	-0.151	0.042	0.025	0.080	-0.018
	(0.008)	(0.032)	(0.034)	(0.024)	(0.022)	(0.022)	(0.177)

Standard errors reported in parentheses. Standard errors for linear parameters (baseline coefficients) recovered from an OLS regression on $\delta_{j,t}$ on $\vec{X}_{j,t}$. Standard errors for linear parameters on time-invariant variables (For-Profit College, Value-Added, HBCU) recovered from a GLS regression of fixed effects δ_j on colinear variables, weighted by the covariance matrix of the estimated fixed effects. Standard errors for non-linear parameters (coefficients on consumer characteristics) recovered from the GMM estimates of asymptotic variance with the optimal weighting matrix.

$^{*}p < .1, ^{**}p < .05, ^{***}p < .01$

Table A3: Cost Estimates: Marginal Cost $c_{j,t}$ of Education and College Characteristics

Characteristic	Estimate
Inside Good	8.864***
	(0.105)
Academic Programs	-0.540*
	(0.285)
Business Programs	-0.107
	(0.137)
Communications and Design Programs	0.869***
	(0.193)
Consumer Services Programs	-0.197
	(0.190)
Education Programs	-0.013
	(0.186)
Computer and Information Sciences Programs	0.305**
	(0.133)
Engineering Programs	0.249*
	(0.149)
Health Sciences Programs	-0.701***
	(0.178)
Production Programs	-0.184
	(0.172)
Protective Services Programs	0.101
	(0.194)
Public, Legal, and Social Services Programs	0.138
	(0.153)
<1yr Certificates	-0.017
	(0.081)
1yr Certificates	0.021
	(0.101)
Associate's Degrees	0.387**
	(0.160)
2-4yr Certificates	-0.045
	(0.117)
Tuition Payment Plan	0.335***
	(0.106)
Online Classes	0.394***
	(0.102)
Weekend/Evening college	0.230***
	(0.083)
Remedial Services	-0.092
	(0.112)
Academic/Career counseling Service	-0.133
	(0.110)
Post-College Placement Services	0.223
	(0.165)
Value-Added ($1000s)	0.259***
	(0.012)

Marginal cost estimates reported in terms of 1,000$s. Standard errors reported in parentheses. Standard errors for linear parameters (baseline coefficients) recovered from an OLS regression on marginal costs $c_{j,t}$ of for-profit colleges from Equation 14 on $\vec{X}_{j,t}$. Standard errors for linear parameters on time-invariant variables (Value-Added) recovered from an OLS regression of fixed effects c_j recovered from Equation 12 on colinear variables.
$^{*}p < .1,^{**} p < .05,^{***} p < .01$

Table A4: Cost Estimates: Logged Advertising Cost $\kappa_{f,d}$ of Education and College Characteristics

Characteristic	Estimate
Academic Programs	-0.491***
	(0.161)
Business Programs	0.217***
	(0.080)
Communications and Design Programs	-0.023
	(0.104)
Consumer Services Programs	0.239**
	(0.113)
Education Programs	0.113
	(0.202)
Computer and Information Sciences Programs	0.109
	(0.083)
Engineering Programs	-0.019
	(0.086)
Health Sciences Programs	0.133
	(0.120)
Production Programs	-0.190*
	(0.099)
Protective Services Programs	-0.152
	(0.103)
Public, Legal, and Social Services Programs	-0.043
	(0.084)
<1yr Certificates	0.099**
	(0.050)
1yr Certificates	0.005
	(0.063)
Associate's Degrees	-0.187**
	(0.095)
2-4yr Certificates	0.190***
	(0.071)
Tuition Payment Plan	-0.209***
	(0.071)
Online Classes	-0.257***
	(0.057)
Weekend/Evening college	-0.296***
	(0.055)
Remedial Services	0.029
	(0.065)
Academic/Career counseling Service	0.043
	(0.070)
Post-College Placement Services	0.139
	(0.163)
Number of Campuses in DMA	0.132**
	(0.055)

Advertising cost estimates reported in terms of 1,000$s. Standard errors reported in parentheses. Standard errors for linear parameters (baseline coefficients) recovered from an OLS regression on logged advertising costs $\log(\kappa_{f,d})$ of for-profit college firms from Equation 14 on $\bar{X}_{f,d}$. $^{*}p < .1, ^{**} p < .05, ^{***} p < .01$

Table A5: Counterfactual Equilibrium Results (All Outcomes)

	Level	% Change From Current				
Policy:	Current Aid Regime	Low-Income Voucher			Federal Aid Ban	
		Lump-Sum	Quality	Optimal	FPI	Low Quality
Aggregate Value Added	64.66B$	+2.30%	+5.33%	+8.77%	+0.98%	+1.51%
Aggregate Value-Added (Low-Income)	35.85B$	+10.50%	+19.63%	+23.62%	+7.32%	+2.70%
Average Value-Added	8,234$	+0.29%	+8.09%	+8.34%	+7.09%	+1.75%
Average Value-Added (Low-Income)	7,903$	+0.70%	+14.79%	+15.31%	+11.07%	+2.78%
Students	7.85M	+2.00%	-2.55%	+0.40%	-5.70%	-0.23%
Low-Income Students	4.54M	+9.74%	+4.22%	+7.21%	-3.37%	-0.08%
Avg. Net Student Price	7,576$	-7.42%	-9.96%	-12.75%	-4.86%	-0.35%
Avg. Net Student Price (Low-Income)	7,313$	-8.14%	-12.50%	-20.66%	-5.59%	-0.42%
Consumer Surplus	37.08B$	+1.93%	+2.08%	-0.41%	+0.55%	+0.18%
Consumer Surplus (Low-Income)	20.91B$	+8.52%	+10.55%	+3.55%	+5.38%	+0.56%
Consumer Surplus (No Ads)	31.47B$	+3.03%	+10.78%	+2.71%	+13.62%	-0.53%
Consumer Surplus (Low-Income, No Ads)	16.63B$	+10.53%	+25.64%	+7.71%	+26.75%	-0.30%
% FPI	16.85%	-0.47%	-7.28%	-4.80%	-10.44%	-0.55%
% FPI (Low-Income)	22.13%	-1.08%	-11.14%	-7.24%	-15.54%	-0.97%
FPI Profits	5.00B$	-1.96%	-26.77%	-21.37%	-40.72%	-4.01%
Avg. Community College Markdown	7,162$	-1.65%	-2.52%	+0.36%	-4.36%	-0.34%
Avg. For-Profit College Markup	5,552$	+3.51%	+28.61%	+26.71%	+35.55%	+11.93%
Avg. FPI Profits/Student	3,998$	+3.10%	+30.15%	+28.63%	+33.20%	+14.72%
FPI Advertising	2.74B$	-4.02%	-35.73%	-22.95%	-57.39%	-1.88%
Total Welfare	42.08B$	+1.47%	-1.35%	-2.90%	-4.35%	-0.32%
Federal Govt Spending	33.99B$	+0.03%	+0.07%	-0.10%	-0.01%	+0.02%
Community College Subsidies	40.50B$	+0.00%	+0.00%	+0.00%	-0.00%	+0.00%
Government Spending	74.49B$	+0.01%	+0.03%	-0.04%	-0.00%	+0.01%

Table displays results from counterfactual analysis of alternative policies in equilibrium. Aggregate value-added denotes the sum of quality ψ_j multiplied by the number of students at each school. Students denotes total enrollment in the market. Average value-added denotes aggregate value-added divided by the total enrollment. Avg. Net student price is the average net student price paid, weighted by the individual-level market shares multiplied by market size (so that each weight represents an effective number of students). Average for-profit college markup denotes the average difference of tuition and marginal cost across for-profit campuses. Average community college markdown denotes the average difference between marginal cost and tuition across community college campuses. FPI advertising denotes the total spending on advertising as measured by the estimated advertising costs $\kappa_{f,d}$. Total welfare denotes the sum of FPI profits and consumer surplus. Federal government spending is calculated as the sum of Pell grants disbursed, plus the total difference in interest payments between federal student loans and equivalent loans acquired on the private student loan market. Current aid regime denotes values at the current observed equilibrium, as implied by our model.

Table A6: Counterfactual Results (Feasible Quality Vouchers)

	Level	% Change From Current			
Voucher Indexed to:	Current Aid	True Values		School Characteristics	
Voucher Type:	Regime	Quality	Optimal	Quality	Optimal
Aggregate Value Added	64.66B$	+5.33%	+8.77%	+4.03%	+6.70%
Aggregate Value-Added (Low-Income)	35.85B$	+19.63%	+23.62%	+16.64%	+20.14%
Average Value-Added	8,234$	+8.09%	+8.34%	+6.75%	+6.46%
Average Value-Added (Low-Income)	7,903$	+14.79%	+15.31%	+11.31%	+10.91%
Students	7.85M	-2.55%	+0.40%	-2.55%	+0.23%
Low-Income Students	4.54M	+4.22%	+7.21%	+4.79%	+8.33%
Avg. Net Student Price	7,576$	-9.96%	-12.75%	-10.19%	-13.78%
Avg. Net Student Price (Low-Income)	7,313$	-12.50%	-20.66%	-12.07%	-20.40%
Consumer Surplus	37.08B$	+2.08%	-0.41%	+2.22%	+0.14%
Consumer Surplus (Low-Income)	20.91B$	+10.55%	+3.55%	+11.13%	+5.55%
Consumer Surplus (No Ads)	31.47B$	+10.78%	+2.71%	+11.99%	+7.21%
Consumer Surplus (Low-Income, No Ads)	16.63B$	+25.64%	+7.71%	+28.25%	+17.28%
% FPI	16.85%	-7.28%	-4.80%	-7.83%	-6.58%
% FPI (Low-Income)	22.13%	-11.14%	-7.24%	-12.07%	-10.20%
FPI Profits	5.00B$	-26.77%	-21.37%	-29.07%	-27.22%
Avg. Community College Markdown	7,162$	-2.52%	+0.36%	-3.50%	-1.22%
Avg. For-Profit College Markup	5,552$	+28.61%	+26.71%	+28.27%	+26.47%
Avg. FPI Profits/Student	3,998$	+30.15%	+28.63%	+29.06%	+27.97%
FPI Advertising	2.74B$	-35.73%	-22.95%	-39.70%	-31.75%
Total Welfare	42.08B$	-1.35%	-2.90%	-1.50%	-3.11%
Federal Govt Spending	33.99B$	+0.07%	-0.10%	-0.14%	-0.13%
Community College Subsidies	40.50B$	+0.00%	+0.00%	+0.00%	+0.00%
Government Spending	74.49B$	+0.03%	-0.04%	-0.06%	-0.06%

Table displays counterfactual analysis of alternative policies in equilibrium. Vouchers indexed to true values denotes quality vouchers indexed to ψ_j and estimated voucher elasticities $\hat{\varepsilon}_{j,j,t}$. Voucher indexed to school characteristics indicates using $W_j\zeta$, the expected quality of each school chain according to the empirical bayes prior mean based on school chain characteristics W_j, in place of true quality ψ_j. For the optimal quality voucher indexed to school characteristics, we use the predicted distortion term of each school from a random forest based on school characteristics, differentiation instruments, and market demographics, in place of the distortion term based on $\hat{\varepsilon}_{j,j,t}$. Aggregate value-added denotes the sum of quality ψ_j multiplied by the number of students at each school. Students denotes total enrollment in the market. Average value-added denotes aggregate value-added divided by the total enrollment. Avg. Net student price is the average net student price paid, weighted by the individual-level market shares multiplied by market size (so that each weight represents an effective number of students). Average for-profit college markup denotes the average difference of tuition and marginal cost across for-profit campuses. Average community college markdown denotes the average difference between marginal cost and tuition across community college campuses. FPI advertising denotes the total spending on advertising as measured by the estimated advertising costs $\kappa_{f,d}$. Total welfare denotes the sum of FPI profits and consumer surplus. Federal government spending is calculated as the sum of Pell grants disbursed, plus the total difference in interest payments between federal student loans and equivalent loans acquired on the private student loan market. Current aid regime denotes values at the current observed equilibrium, as implied by our model.

Table A7: Counterfactual Results (Demand Response Only)

	Level	% Change From Current				
Policy:	Current Aid	Low-Income Voucher			Federal Aid Ban	
	Regime	Lump-Sum	Quality	Optimal	FPI	Low Quality
Aggregate Value Added	64.66B$	+2.76%	+8.20%	+9.03%	+3.02%	+1.32%
Aggregate Value-Added (Low-Income)	35.85B$	+9.27%	+19.09%	+20.59%	+6.01%	+2.29%
Average Value-Added	8,234$	+0.84%	+8.55%	+9.51%	+5.51%	+1.66%
Average Value-Added (Low-Income)	7,903$	+1.32%	+14.52%	+16.18%	+8.97%	+2.69%
Students	7.85M	+1.90%	-0.33%	-0.43%	-2.36%	-0.34%
Low-Income Students	4.54M	+7.85%	+3.99%	+3.80%	-2.72%	-0.38%
Avg. Net Student Price	7,576$	-7.19%	-9.52%	-13.82%	-3.27%	-0.38%
Avg. Net Student Price (Low-Income)	7,313$	-7.69%	-12.07%	-23.02%	-3.67%	-0.40%
Consumer Surplus	37.08B$	+1.91%	+2.87%	-1.22%	+1.84%	+0.27%
Consumer Surplus (Low-Income)	20.91B$	+7.07%	+8.77%	+1.53%	+3.88%	+0.56%
Consumer Surplus (No Ads)	31.47B$	+3.60%	+9.24%	+5.03%	+10.75%	+0.61%
Consumer Surplus (Low-Income, No Ads)	16.63B$	+9.84%	+20.53%	+12.54%	+19.44%	+1.21%
% FPI	16.85%	-1.47%	-6.03%	-6.44%	-8.02%	-1.03%
% FPI (Low-Income)	22.13%	-2.20%	-9.60%	-10.29%	-12.52%	-1.58%
FPI Profits	5.00B$	-9.42%	-48.41%	-54.41%	-67.31%	-9.37%
Avg. FPI Profits/Student	3,998$	-2.81%	-26.35%	-28.34%	-40.10%	-9.90%
Total Welfare	42.08B$	+0.56%	-3.23%	-7.54%	-6.38%	-0.88%
Federal Govt Spending	33.99B$	-5.06%	-8.54%	-12.18%	-8.18%	-1.05%
Community College Subsidies	40.50B$	+4.25%	+7.16%	+10.22%	+6.87%	+0.88%
Government Spending	74.49B$	-0.00%	-0.00%	-0.00%	-0.00%	-0.00%

Table displays results from counterfactual analysis of alternative policies, accounting only for the demand response to a new policy. Students denotes total enrollment in the market. Average value-added denotes aggregate value-added divided by the total enrollment. Avg. Net student price is the average net student price paid, weighted by the individual-level market shares multiplied by market size (so that each weight represents an effective number of students). Average for-profit college markup denotes the average difference of tuition and marginal cost across for-profit campuses. Average community college markdown denotes the average difference between marginal cost and tuition across community college campuses. Total welfare denotes the sum of FPI profits and consumer surplus. Federal government spending is calculated as the sum of Pell grants disbursed, plus the total difference in interest payments between federal student loans and equivalent loans acquired on the private student loan market. Current aid regime denotes values at the current observed equilibrium, as implied by our model.

Table A8: Counterfactual Results (No Community College Response)

	Level	% Change From Current		
Policy:	Current Aid Regime	Low-Income Voucher		
		Lump-Sum	Quality	Optimal
Aggregate Value Added	64.66B$	+2.80%	+7.84%	+9.02%
Aggregate Value-Added (Low-Income)	35.85B$	+9.34%	+18.68%	+20.72%
Average Value-Added	8,234$	+0.94%	+10.35%	+11.21%
Average Value-Added (Low-Income)	7,903$	+1.45%	+16.80%	+18.32%
Students	7.85M	+1.84%	-2.27%	-1.98%
Low-Income Students	4.54M	+7.78%	+1.61%	+2.03%
Avg. Net Student Price	7,576$	-7.65%	-10.10%	-14.26%
Avg. Net Student Price (Low-Income)	7,313$	-8.30%	-12.82%	-23.59%
Consumer Surplus	37.08B$	+1.79%	+1.95%	-2.09%
Consumer Surplus (Low-Income)	20.91B$	+6.92%	+7.66%	+0.47%
Consumer Surplus (No Ads)	31.47B$	+4.09%	+11.53%	+5.80%
Consumer Surplus (Low-Income, No Ads)	16.63B$	+10.55%	+23.51%	+12.82%
% FPI	16.85%	-1.51%	-7.93%	-7.49%
% FPI (Low-Income)	22.13%	-2.26%	-11.78%	-11.15%
FPI Profits	5.00B$	-4.39%	-28.82%	-31.07%
Avg. Community College Markdown	7,162$	0.00%	0.00%	0.00%
Avg. For-Profit College Markup	5,552$	+6.07%	+29.21%	+28.80%
Avg. FPI Profits/Student	3,998$	+5.79%	+30.60%	+29.98%
FPI Advertising	2.74B$	-7.72%	-39.02%	-37.35%
Total Welfare	42.08B$	+1.05%	-1.71%	-5.53%
Federal Govt Spending	33.99B$	-5.07%	-8.87%	-11.51%
Community College Subsidies	40.50B$	+4.25%	+7.28%	+9.68%
Government Spending	74.49B$	-0.00%	-0.09%	+0.01%

Table displays counterfactual analysis of alternative policies in equilibrium, assuming CCs are able to inelastically supply additional seats at observed tuition prices. Aggregate value-added denotes the sum of quality ψ_j multiplied by the number of students at each school. Students denotes total enrollment in the market. Average value-added denotes aggregate value-added divided by the total enrollment. Avg. Net student price is the average net student price paid, weighted by the individual-level market shares multiplied by market size (so that each weight represents an effective number of students). Average for-profit college markup denotes the average difference of tuition and marginal cost across for-profit campuses. Average community college markdown denotes the average difference between marginal cost and tuition across community college campuses. FPI advertising denotes the total spending on advertising as measured by the estimated advertising costs $\kappa_{f,d}$. Total welfare denotes the sum of FPI profits and consumer surplus. Federal government spending is calculated as the sum of Pell grants disbursed, plus the total difference in interest payments between federal student loans and equivalent loans acquired on the private student loan market. Current aid regime denotes values at the current observed equilibrium, as implied by our model.

Table A9: Counterfactual Results (No Advertising Response)

	Level	% Change From Current		
Policy:	Current Aid Regime	Low-Income Voucher Lump-Sum	Quality	Optimal
Aggregate Value Added	64.66B$	+2.14%	+5.21%	+7.95%
Aggregate Value-Added (Low-Income)	35.85B$	+10.33%	+19.38%	+22.95%
Average Value-Added	8,234$	+0.30%	+6.88%	+7.07%
Average Value-Added (Low-Income)	7,903$	+0.71%	+13.25%	+13.70%
Students	7.85M	+1.83%	-1.56%	+0.82%
Low-Income Students	4.54M	+9.55%	+5.41%	+8.14%
Avg. Net Student Price	7,576$	-7.11%	-9.45%	-13.81%
Avg. Net Student Price (Low-Income)	7,313$	-7.75%	-11.88%	-22.13%
Consumer Surplus	37.08B$	+1.94%	+2.59%	+0.42%
Consumer Surplus (Low-Income)	20.91B$	+8.59%	+11.20%	+5.28%
Consumer Surplus (No Ads)	31.47B$	+3.16%	+9.45%	+6.26%
Consumer Surplus (Low-Income, No Ads)	16.63B$	+10.85%	+24.11%	+15.67%
% FPI	16.85%	-0.68%	-6.38%	-5.89%
% FPI (Low-Income)	22.13%	-1.35%	-10.20%	-9.45%
FPI Profits	5.00B$	-5.21%	-40.57%	-38.52%
Avg. Community College Markdown	7,162$	-1.69%	-2.52%	-0.30%
Avg. For-Profit College Markup	5,552$	+1.90%	+22.73%	+25.66%
Avg. FPI Profits/Student	3,998$	-13020.44%	-40417.82%	+1.40%
FPI Advertising	2.74B$	0.00%	0.00%	0.00%
Total Welfare	42.08B$	+1.09%	-2.54%	-4.21%
Federal Govt Spending	33.99B$	-0.01%	-0.02%	-0.00%
Community College Subsidies	40.50B$	+0.00%	-0.00%	+0.00%
Government Spending	74.49B$	-0.01%	-0.01%	-0.00%

Table displays counterfactual analysis of alternative policies in equilibrium, assuming no advertising adjustment is allowed by for-profit colleges. Aggregate value-added denotes the sum of quality ψ_j multiplied by the number of students at each school. Students denotes total enrollment in the market. Average value-added denotes aggregate value-added divided by the total enrollment. Avg. Net student price is the average net student price paid, weighted by the individual-level market shares multiplied by market size (so that each weight represents an effective number of students). Average for-profit college markup denotes the average difference of tuition and marginal cost across for-profit campuses. Average community college markdown denotes the average difference between marginal cost and tuition across community college campuses. FPI advertising denotes the total spending on advertising as measured by the estimated advertising costs $\kappa_{f,d}$. Total welfare denotes the sum of FPI profits and consumer surplus. Federal government spending is calculated as the sum of Pell grants disbursed, plus the total difference in interest payments between federal student loans and equivalent loans acquired on the private student loan market. Current aid regime denotes values at the current observed equilibrium, as implied by our model.

Appendix - For Online Publication

A EFC Construction

In this section, we describe the construction of the Expected Family Contribution (EFC) for each individual defined to be in our market of potential students (18-50, high school educational attainment) in the ACS Census data. We use the archived federal student aid handbooks, in addition to the EFC worksheets from the federal student aid website[45] to construct the measure for each year.[46] We use the simplified EFC formulas, which does not consider household asset contributions, so that we can reconstruct EFC with only the ACS data. Students qualify for the simplified EFC if they are considered low-income, but this is also often the first EFC calculation sent to schools in applications for federal financial aid. Because our model considers only the tuition from full-time annual enrollment, we calculate the EFC for students enrolled for 9 months or longer and do not prorate EFC for students entering shorter programs.

Within the EFC calculation, there are three worksheets (A,B,C) that contain different formulas depending on whether the student is a dependent, an independent without other dependents, or an independent with dependents, respectively. We classify an individual as a dependent using the federal aid criteria, which require students to be under the age of 24, not married, have no children, live with either their mother or father, and is not a veteran or in active military duty.

Students who are dependents with parental income below a threshold ($25,000 in 2015), or independents with children and a household income below $25,000 are classified as having $EFC = 0$ automatically. This step follows requirements on the actual EFC worksheet, except that we do not also condition on the household filing an IRS Form 1040, 1040A, 1040EZ, which we do not observe. Students who do not automatically qualify for zero EFC must fill out the full simplified EFC formula.

For dependents, we calculate their EFC using simplified worksheet A. We begin by calculating the parent's total income, then subtracting the total allowances against the parent's income. Allowances include the U.S. federal taxes paid by the parent's (imputed using the U.S. income tax schedule for the year, depending on their household structure); state tax allowances (provided by the worksheet, calculated as a % of parent income varying by state); each parent's social security tax allowance, which is also provided and depends on their individual income; an income protection allowance, which depends on the number of member's in

[45]Example: `https://studentaid.gov/sites/default/files/2017-18-efc-formula.pdf`

[46]Archived handbooks can be found here: `https://ifap.ed.gov/ilibrary/document-types/federal-student-aid-handbook?archive=1`

the household and the number of students currently enrolled in college; and an employment expense allowance, which is given if dependents have all their parents currently working. The employment expense allowance is 35% of the income of lowest earner of the dependent's parents, up to a cap ($4,000 in 2015). Allowances are subtracted from parental income to determine the amount of available income relevant for a dependent student. The parents' available income is converted to a contribution from available income using a formula from the EFC worksheet, which ranges from 22-47% of available income depending on how much available parent income is present. This is then divided by the number of students in college attached to the household to determine the parent's contribution.

If the dependent student is working, we calculate their personal income, their federal and state income tax allowance (state tax allowances differ for the student's income and is generally lower in generosity), their social security tax allowance (identical to parent's), a fixed income protection allowance for working students, and an allowance if their parent's income was negative (proportional to the magnitude of negative income). We subtract student allowances from their income to calculate their available income, then divide this by two to get the students contribution. We add the parents' and student's contribution to calculate a dependent student's EFC.

For independents without children, we calculate their EFC using worksheet B. We begin by calculating the student's and their spouse's (if applicable) total income, then subtracting their total allowances against their income. Allowances include the U.S. federal taxes paid by the independent (and their spouse); state tax allowances (provided by the worksheet, calculated as a % of head of household income varying by state); the head of housholds' social security tax allowance, which is also provided by the worksheet; an income protection allowance, which depends on the maritual status of the independent and whether the student is enroll at least half-time [47]; and an employment expense allowance, which is zero unless both the student and their spouse are working. In that case, the employment expense allowance is 35% of the income of lowest earner between the spouse and student, up to a cap ($4,000 in 2015).

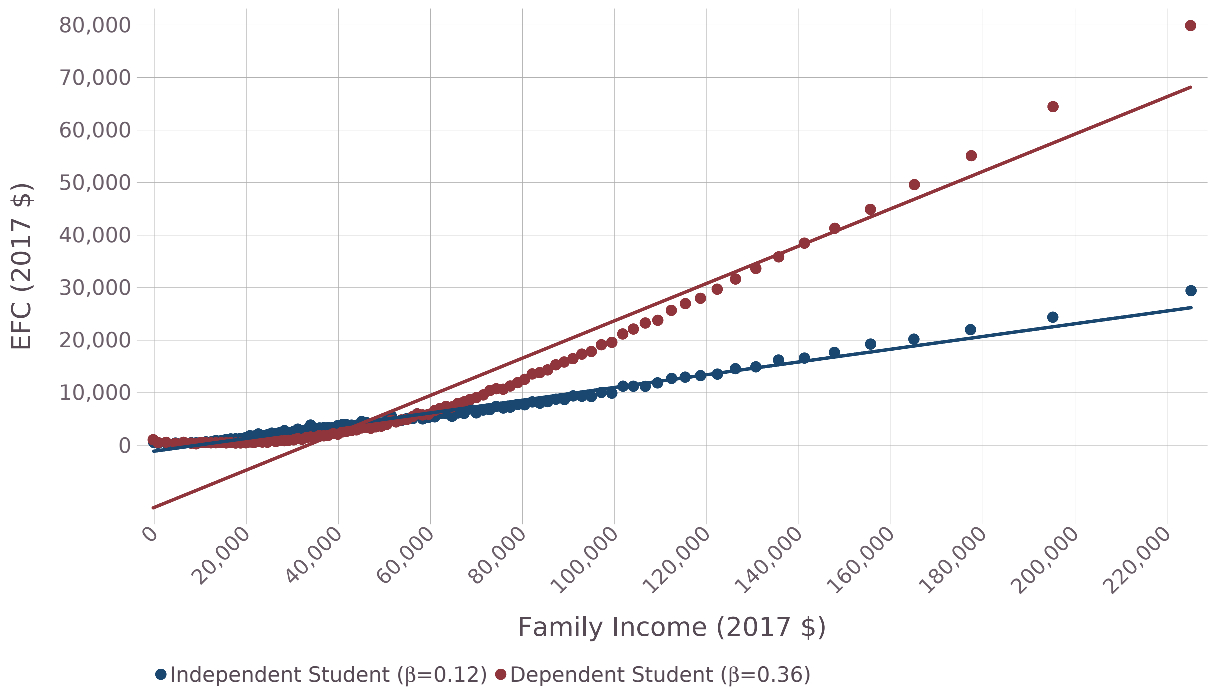
Allowances are subtracted from own and spousal income to determine the amount of available income the independent student has. This is then divided by the number of students in college in the household to determine the expected family contribution.

For independents with children, we calculate their EFC using worksheet C. We begin by calculating the student's and their spouse's (if applicable) total income, then subtracting their total allowances against their joint income. Allowances include the U.S. federal taxes

[47] Since we calculate the EFC for full-time enrollment, we use the income protection allowance corresponding to at least half time enrollment

paid by the independent (and their spouse); state tax allowances (provided by the worksheet, calculated as a % of head of household income varying by state); the head of housholds' social security tax allowance, which is also provided by the worksheet; an income protection allowance, which depends on the number of member's in the household and the number of students currently enrolled in college; and an employment expense allowance. In that case, the employment expense allowance is 35% of the income of lowest earner between the spouse and student, up to a cap ($4,000 in 2015). Allowances are subtracted from income to determine the amount of available income the independent student has. This is converted to a contribution from available income using a formula from the worksheet, which is ranges from 22-47% of available income depending on how much available income is calculated. This is then divided by the number of students in college in the household to determine the expected family contribution.

Figure A9 plots the relationship between observed family income and calculated EFC in our sample of potential students from the ACS. Dependents' EFC increases by $0.36 for each $ increase in parental income. Independents' EFC increases by $0.12 for each dollar increase in their own income and spousal income.



Figures displays, for each centile of family income, the average EFC, by dependent status. Excludes households with family income greater than $250,000. β denotes the regression line from regressing EFC on family income. EFC and income are deflated by the CPI to be in 2017 $.

Figure A9: Mapping of Family Income to EFC, by Dependent Status

B Details on Political Advertising Instrument

To instrument for college advertising, we use political advertising (Sinkinson and Starc, 2019) as a cost shock to each college's advertising decision. Moshary, Shapiro and Song (2021) find that political advertising has a first-stage F-statistic of 71.9 for the advertising of "schools, camps, and seminars," which includes colleges, suggesting it is a relevant cost shifter in our setting.

One feature of our setting is that while our enrollment and price data are annual, political advertising is heterogenous throughout the year due to the timing of elections and primaries. Figure C1 plots the average number of spot TV ads placed by political advertisers[48] across the 101 DMAs in our sample. The monthly time series shows significant variation within election years (even-numbered years) across DMAs. To aggregate this monthly data to an annual instrument, we follow a two-step approach to construct our political advertising instrument: First, we follow the prior literature and estimate the month-level effect of political advertising on college advertising. Second, we aggregate these effects to an annual level using each college's propensity to advertise in a given month of the year. This second step also creates within-market variation in our instrument.

Monthly Political Advertising Effect We estimate the following linear regression to recover the monthly college advertising response to political advertising by institution type $c \in \{FPI, CC\}$:

$$\log(a_{f,d,y,m}+1) = \alpha_{f,d}+\delta_{y,c}+g_c\Big(\log(P_{d,y,m}+1)\Big)+\vec{\gamma}_c\log(\vec{n}_{f,y,m}+1)+\beta_c\log(p_{N,y,m})+\epsilon_{f,d,m,y} \tag{35}$$

where $a_{f,d,y,m}$ is firm (defined as a 6-digit OPEID) f's television advertising in the local DMA d in year y and month of year m. $\alpha_{f,d}$ denotes firm by advertising market (OPEID6$\times$DMA) fixed effects. Year fixed effects $\delta_{y,c}$ capture common level differences across election (and non-election) years in advertising.[49] We specify g_c as a 3rd-degree orthogonal polynomial to capture the non-linear effect of political advertising.[50] For controls, we include national (cable, syndication, and network television) TV ads placed in month-year m, y by firm f,

[48]We define political advertising, as in Moshary, Shapiro and Song (2021), as advertising done by brands in the following categories: "Unions," "Political Organizations," "Ballot Issues," "National-Campaigns (Non-Presidential)," "Presidential Campaigns," "State & Local Campaigns,", and "Political & Political Parties: Combined & Not Elsewhere Classified".

[49]We deviate from Moshary, Shapiro and Song (2021) by only including year fixed effects. When we include month-year fixed effects, we obtain a qualitatively similar but much noisier estimate for the effect of political advertising (for FPIs).

[50]Our instrument also works using a simple linear specification of logged political advertising, however the linear specification is under-powered relative to the orthogonal polynomial specification.

denoted $\vec{n}_{f,m,y}$, as well as the average price of national network television advertising across all advertisers in a given month-year, $p_{N,y,m}$. These variables capture potential substitution by colleges to national advertising as well as changes to TV prices as a whole across year-months. Our sample for estimating Equation 35 is the set of year-months of our sample of colleges, starting in the first month a school chain begins advertising in a DMA.

Figure C2 plots the estimated linear and nonlinear effect of political advertising on college advertising. We see that choosing a cubic spline or a orthogonal polynomial as our non-linear specification, both of which are used by Moshary, Shapiro and Song (2021) to estimate the effect of political advertising, produces qualitatively very similar results. Across CCs and FPIs, we generally see a decline in college advertising when political advertising increases. The linear specification masks convexity in the crowding out effects of political advertising for both CC and FPI advertising.

Annual Aggregation To construct an instrument for annual college advertising, denoted $Z^{A}_{f,d,y}$, we use a weighted sum of the estimated monthly effects $\{\hat{g}_c\Big(\log(P_{d,y,m})+1)\Big)\}_{m=1}^{12}$ from the previous step:

$$Z^{A}_{f,d,y} = \sum_{m=1}^{12} w_{f,d,m} \times \hat{g}_c\Big(\log(P_{d,m,t})+1)\Big) \tag{36}$$

To construct our weights $w_{f,d,m}$, we use a college firm's advertising likelihood in each month of the year during non-election (odd-numbered) years. We choose this measure because it reflects advertising propensities that are not influenced by political advertising. We calculate the weight of month m for firm f, d as follows:

$$w_{f,d,m} = \frac{1}{N_{\text{NE},f,d}} \sum_{y:\text{mod}(y,2)\neq 0} \frac{a_{f,d,y,m}}{\sum_{k=1}^{12} a_{f,d,y,k}} \tag{37}$$

where $N_{\text{NE},f,d}$ denotes the number of non-election years we observe positive advertising of a given firm in a DMA d.[51] These weights create within-market heterogeneity in the effect of political advertising on a particular college's annual advertising amount. One major driver of differences in weights between college is differences in enrollment periods: some schools only enroll new students during particular periods of the year (e.g. the beginning of a semester) , so they focus their advertising investments in the months right before their enrollment

[51] We observe advertising for 94% of firm-DMA observations with any positive advertising in our sample during non-election years. For the remaining 5%, we use the leave-one-out share, the average propensity to advertise in a given month in all other years besides y. Less than 1% of firms only advertise in one year, for which we simply use observed contemporaneous shares.

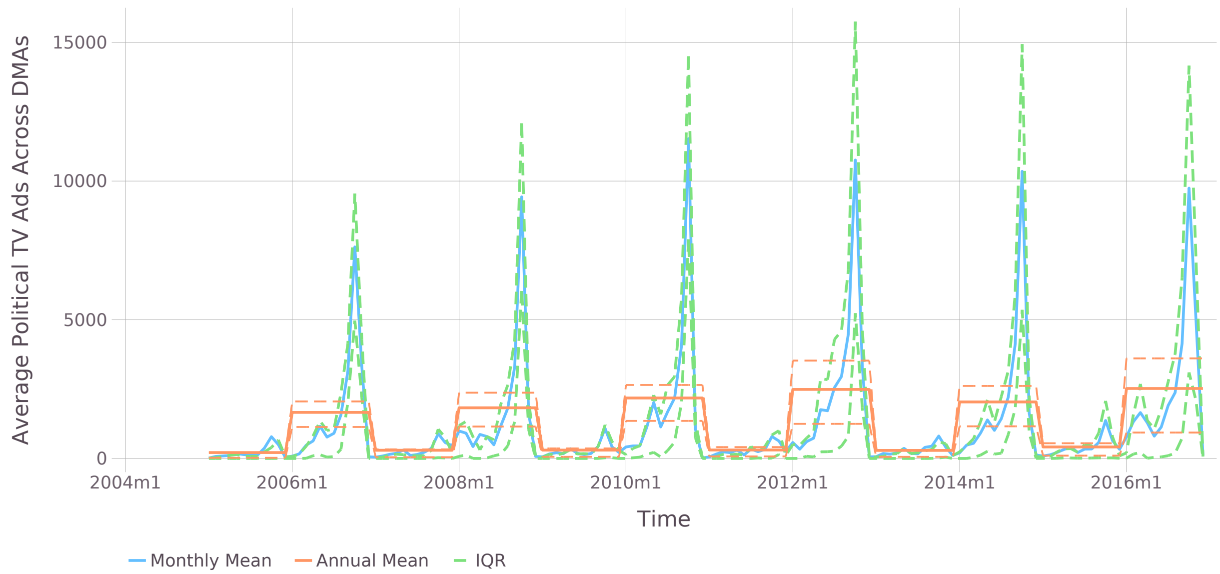
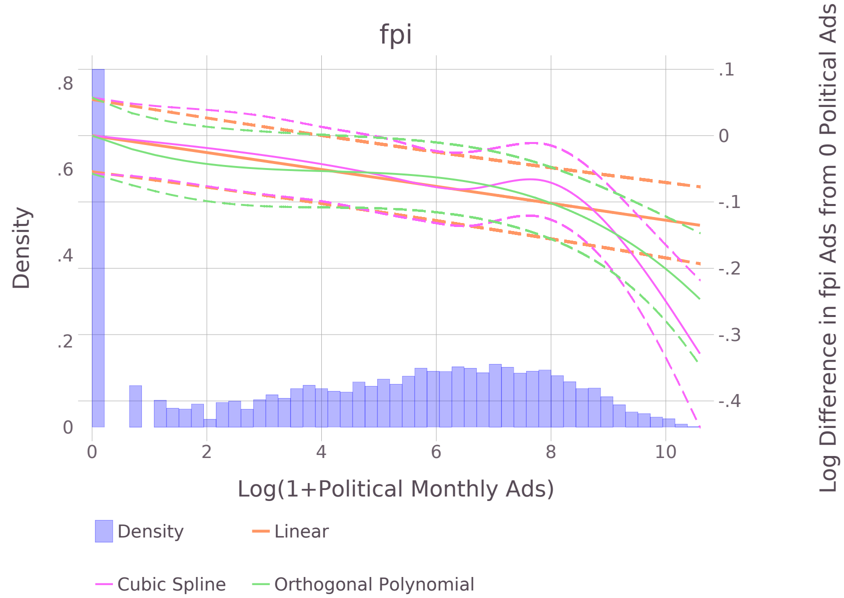


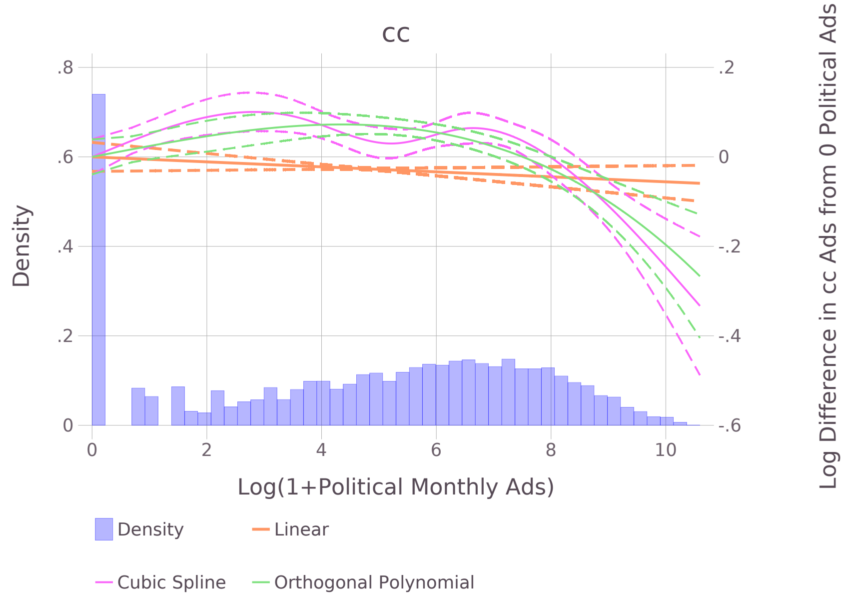
Figure C1: Monthly Time Series of Average Political Advertising within DMA

Figure shows, in blue, the average monthly level of a political advertising across the 101 DMAs in our sample. In green/dashed, we plot the inter-quartile range (IQR) of advertising across DMAs for each month-year. In solid orange, we plot the mean advertising, averaged across both months and DMAs in a given year. In dashed orange, we plot the IQR across DMAs of the average (by year) monthly political advertising.

period. Schools that have a higher propensity to advertise in months with high political advertising (e.g., right before an election) will be more affected than a school in the same DMA that never advertises in those months. Because we include school fixed effects in all specifications, our instrument's variation is not driven by these time invariant weights. Instead, the variation in $Z^A_{f,d,t}$ comes from the interaction of these weights and the estimated monthly political advertising effects.



(a) For-Profit Colleges



(b) Community Colleges

Figure C2: Effect of Monthly Political Advertising on Monthly College Advertising

Figure shows the estimated response to monthly political advertising by in college advertising, relative to zero political advertising. The histogram shows the distribution of political advertising intensity by college-year-month. The orange line plots the estimated linear effect by college. The pink line plots the estimated non-linear effect, recovered from a third-degree orthogonal polynomial in log(1+political monthly ads), as calculated by the `orthpoly` command in STATA. 95% confidence intervals shown in dashed lines for each. Each subfigure plots the response by institution type.

C Details on Estimating Quality

In this section, we give details on the estimation procedure we use to recover value-added from the College Scorecard dataset. This includes the entropy balancing procedure used in the first step to recover expected wages from the outside option of not going to college, the weighted regression used in the second step to estimate value-added, and the shrinkage performed in the estimation.

C.1 Entropy Balanced High School Cohorts

We first estimate $E[Y_{i,0,l}|i \text{ chooses } j \text{ in } l]$, the expected earnings of students who enroll in college j in labor market l, had they entered the labor market with no college experience. We do so by implementing the entropy balancing procedure described in Hainmueller (2012). Given a set of observed cohort level demographic characteristics $\bar{\mathbf{X}}^0_{j,l}$, we perform the following optimization routine for each cohort j, l:

$$\max_{p_{i,j,l}} \sum_{i \in \mathcal{I}_{HS,l}} p_{i,j,l} \log(p_{i,j,l}) \tag{38}$$

$$\text{subject to} \sum_{i \in \mathcal{I}_{HS,l}} p_{i,j,l} \mathbf{X}^0_i = \bar{\mathbf{X}}^0_{j,l} \tag{39}$$

where $\mathcal{I}_{HS,l}$ is the set of high school graduates observed in the same year earnings are measured, that also reside in PUMAs (the most granular geographic measure in the ACS) that overlap with the commuting zone l each school is located in. The first equation (38) maximizes the entropy or dispersion of the weights $\{p_{i,j,l}\}_{i \in \mathcal{I}_{HS,l}}$. Without constraints, the solution to this problem is to assign uniform weights $p_{i,j,l} = 1/|\mathcal{I}_{HS,l}|$ to each ACS participant. By adding the constraints in Equation 39, we make the weights as close as possible to the uniform distribution, subject to achieving covariate balance. Our choice of observables in $\bar{\mathbf{X}}^0_{j,l}$ include all characteristics observed both in the ACS and the our cohort-level college datasets. These include the following:

- **Average Age:** $\bar{\text{Age}}_{j,l}$. The average age of the cohort at entry, observed in the College Scorecard. Since earnings are measured 10 years after entry, we subtract the age of high school graduates in the ACS by 10 to match the entry age of each earnings cohort.

- **Age-Gender Distribution:** $Pr(\text{Age}_i \in a, \text{Gender}_i \in g)$, for $a \in \{0-17, 18-19, 20-21, 22-24, 25-29, 30-34, 35-39, 40-49, 50-64, 65+\}$ and $g \in \{\text{Male,Female}\}$.

  Age-gender cells are measured from the IPEDS Fall Enrollment Survey for the undergraduate population. Because this question is only required in IPEDS to be completed every two years, some years of data are missing. For a missing year y, we take the age-gender IPEDS distribution for all undergraduates from year $y+1$, since this would include second-year students who correspond to the pooled cohort measured in $\bar{\mathbf{X}}^0_{j,l}$. Since earnings are measured 10 years after entry, we subtract the age of high school graduates in the ACS by 10 to match the age cell of each earnings cohort.

- **Race-Gender Distribution:** $Pr(\text{Race}_i \in r, \text{Gender}_i \in g)$,

  for $r \in$ {White, Asian, Native American, Black, Hispanic, Two or More Races} and $g \in$ {Male,Female}. Race-gender cells are measured from the IPEDS Fall Enrollment Survey for first-time students.

- **Veteran Status**: $Pr(\text{Veteran}_i = 1)$, the fraction of veterans in each cohort. This is observed in the College Scorecard.

Given estimated weights $\{p_{i,j,l}\}_{i\in\mathcal{I}_{HS,l}}$, the estimated cohort mean outcome under no college is defined as:

$$\widetilde{Y}_{j,l} = \sum_{i\in\mathcal{I}_{HS,l}} p_{i,j,l} Y_{i,0,l}$$

The expected value of $\widetilde{Y}_{j,l}$ is:

$$\begin{aligned}
E[\widetilde{Y}_{j,l}] &= E[Y_{i,0,l} | i \text{ chooses no college}, \mathbf{X}^0_i = \bar{\mathbf{X}}^0_{j,l}] \\
&= \psi_0 + E[\eta_{i,l} | i \text{ chooses no college}, \mathbf{X}^0_i = \bar{\mathbf{X}}^0_{j,l}] \\
&= E[\eta_{i,l} | i \text{ chooses college } j \text{ in } l, \mathbf{X}^0_i = \bar{\mathbf{X}}^0_{j,l}] \\
&= E[Y_{i,0,l} | i \text{ chooses college } j \text{ in } l]
\end{aligned}$$

where the second equality comes from the normalization $\psi_0 = 0$, while the third equality comes from the assumption that $\eta_{i,l}$ is independent of each student's extensive margin choice of attending a college or no college, conditional on the labor market l and $\mathbf{X}^0_i$. Therefore, on expectation, $\widetilde{Y}_{j,l}$ is equal the counterfactual earnings of the observed cohort j, l had they attended no college.

C.2 Value-Added Regression

We recover the value-added ψ_j described in Section 3.3 by regressing the difference in the observed and synthetic cohort earnings, $\bar{Y}_{j,l} - \widetilde{Y}_{j,l}$ on a set of controls $\bar{\mathbf{X}}^1_{j,l}$ observed in the College Scorecard dataset. We do this to control for the selection bias associated with the intensive margin choice of choosing which college to attend, conditional on attending any college:

$$\bar{Y}_{j,l} - \widetilde{Y}_{j,l} = \beta_1 \bar{\mathbf{X}}_{j,l} + \psi_j \tag{40}$$

We include in as our measures of $\mathbf{X}_i^1$, in addition to the controls for high school graduates $\mathbf{X}_i^0$, the following variables in the college scorecard, expressed in terms of their individual-level equivalent:

- **Demographics**: $Pr(\text{Married}_i = 1), Pr(\text{Dependent}_i = 1), Pr(\text{Female}_i = 1)$.
- **Average Age**: $\bar{\text{Age}}_i$. Controls for students at different stages of earnings lifecycle selecting into different types of education (e.g., vocational versus academic).
- **Parent Education**: $Pr(\text{ParEdu}_i \in PE)$ for $PE \in \{\text{Middle School ,High School, Some College+}\}$. This captures potential selection on education choice depending on family history with higher education.
- **Average Income**: $\bar{\text{Inc}}_i$. This amounts to controlling for average income prior entry. It is measured at the time of FAFSA completion. For dependent students, this is family income. For independent students, this is their own earnings. This controls for potential selection between schools and high potential outcomes in earnings without college. We allow this control to vary depending on dependency status.
- **Prior Income Distribution**: $Pr(\text{Inc}_i \in I)$ for $I \in \{0{-}\$30,000, \$30,000{-}\$48,000, \$48,000{-}\$75,000, \$75,000 - 110,000, \$110,000{+}\}$. We use income cells to control for higher-order moments of the distribution of earnings within cohort (e.g., a non-linear effect on potential outcomes for very low income individuals making $< \$30,000$ prior to entry). We also allow this to affect earnings heterogenously on dependency status.
- **Choice Set Size:** $Pr(J_i \in k)$ for $k \in \{1, 2, 3, 4, 5+\}$. This is measured as the number of schools a student sent their FAFSA application for federal student aid. It controls for selection between schools that may occur for students who invest more time in the college search process by considering multiple schools.
- **Pell, Loan Receipt**: $Pr(i \text{ received Pell Grant}), Pr(i \text{ received Federal Loan})$. This further controls for student liquidity and low-income status.

In rare cases, some of these controls are missing for certain college cohorts due to small sample sizes. For those cohorts, we include missing dummies for each missing characteristic. Note that, because all of our cohort-level controls are averages of either continuous (prior income, age) or indicator variables, our empirical approach is consistent with the individual-level student shifter $\eta_{i,l}$ being linear in these rich demographic variables, plus a residual that is independent of student choice.

Conditional on $\bar{\mathbf{X}}^1_{j,l}$, our dependent variable, $\bar{Y}_{j,l} - \widetilde{Y}_{j,l}$ is an consistent measure of $E[Y_{i,j,l} - Y_{i,0,l} | i \text{ choose } j \text{ in } l]$, though imperfect due to sampling error. The precision of this measure from cohort-to-cohort varies by the effective sample size. To adjust for this, we estimate the regression in Equation 40 by using a weighted least squares regression. Our weights are proportional to the variance of the dependent variable. Assume that $Var(Y_{i,j,l}) = \sigma^2_Y$, that is, the variation in potential outcomes is constant across all individuals, regardless of characteristics and schooling decisions. Under this assumption, $Var(\bar{Y}_{j,l}) = \sigma^2_Y / N_{j,l}$, where $N_{j,l}$ is the number of students in the earnings cohort, and $Var(\widetilde{Y}_{j,l}) = Var(\sum_{i \in \mathcal{I}_{HS,l}} p_{i,j,l} Y_{i,0,l}) = \sigma^2_Y \sum_{i \in \mathcal{I}_{HS,l}} p^2_{i,j,l}$, taking weights $p_{i,j,l}$ as given. Therefore,

$$Var(\bar{Y}_{j,l} - \widetilde{Y}_{j,l}) = \frac{\sigma^2_Y}{N_{j,l}} + \sigma^2_Y \sum_{i \in \mathcal{I}_{HS,l}} p^2_{i,j,l} = \sigma^2_Y (\frac{1}{N_{j,l}} + \sum_{i \in \mathcal{I}_{HS,l}} p^2_{i,j,l}) \equiv \sigma^2_Y V_{j,l}$$

Assuming $\bar{Y}_{j,l}$ and $\widetilde{Y}_{j,l}$ are independent. We estimate the regression in Equation 40 using weights $V^{-1}_{j,l}$ proportional to the inverse variance. This weighting accounts for the different level of information on value-added in each cohort observation, and is efficient.

The fixed effects output from the regression represent the relative value-added among inside goods, denoted $\hat{\psi}_j$. In order to estimate the level of value-added, relative to the outside option of no college, we shift these relative differences by mean of the dependent variable, which will capture the earnings premium from attending any college versus no college. Denote $\psi_{j,\text{Prelim}} = \hat{\psi}_j + \hat{\beta}_1 E[\mathbf{X}^1_i | j \neq 0]$. The expectation can be read from the college scorecard data. This serves as our preliminary measure of value-added.

C.3 Shrinkage

Because some cohorts in the College Scorecard Dataset are small, our initial estimates of ψ_j may be noisy due to small sample sizes. For this reason, we apply an empirical Bayes shrinkage estimator to our value-added estimates, following the procedure in Chandra et al. (2013), to "shrink" these estimates towards a prior mean. Our empirically-based prior is $\psi_j \sim N(W_j \zeta, \sigma^2_\psi)$, where W_j are school chain characteristics.[52] Appendix Table D1 displays the estimates of ζ, for each of the three outcome variables considered. Our set of characteristics explain 47% of the variation of the estimated value-added in earnings (both unconditional

[52]These characteristics are: degrees offered, services offered, public/private status of institution, and whether the school chain is a multi-campus institution. Because the degrees/services offered at each campus of a chain may differ, we use the average characteristic $\bar{W}_f$ of a chain across campuses for our prior.

and conditional on earnings). The empirical bayes estimate of ψ is defined as follows:

$$\psi_{j,EB} = (B_j)W_j\zeta + (1 - B_j)\psi_{j,\text{Prelim}}, \qquad \text{where} \quad B_j = \frac{N_\psi - |\zeta| - 2}{N_\psi - |\zeta|}\frac{V(\hat{\psi}_j)}{V(\hat{\psi}_j) + \hat{\sigma}^2_\psi} \tag{41}$$

where N_ψ denotes the number of chains in our sample, $V(\hat{\psi}_j)$ denotes the variance of the estimated fixed effect $\hat{\psi}_j$, and $|\zeta|$ is the dimension of ζ. $\psi_{j,EB}$ represent the value-added estimates we use throughout the paper.

Table D1: Empirical Bayes Estimates of Quality Prior Mean

	(1) Earnings	(2) Earnings | Working	(3) Employment
Avg. Offer Program in Agriculture and natural resources	-245.9	24.43	-0.492*
	(243.0)	(250.6)	(0.00285)
Avg. Offer Program in Communications and design	218.4	12.80	-0.464
	(244.4)	(252.8)	(0.00290)
Avg. Offer Program in Consumer services	-2630.5***	-2657.4***	-1.100***
	(250.4)	(259.8)	(0.00300)
Avg. Offer Program in Education	-488.9*	-363.6	-0.375
	(267.7)	(276.2)	(0.00315)
Avg. Offer Program in Engineering, architecture and science technologies	1231.8***	1445.9***	-0.0155
	(341.4)	(353.9)	(0.00410)
Avg. Offer Program in Health sciences	2382.7***	2028.2***	2.828***
	(304.1)	(316.5)	(0.00369)
Avg. Offer Program in Computer and information sciences	-598.6*	-435.0	-1.018**
	(339.6)	(352.8)	(0.00410)
Avg. Offer Program in Manufacturing, construction, repair, and transportation	-187.1	207.8	-0.174
	(274.8)	(284.2)	(0.00326)
Avg. Offer Program in Protective services	81.15	-155.9	0.551
	(291.4)	(302.1)	(0.00349)
Avg. Offer Program in Public, legal, and social services	-175.3	-132.5	-0.563**
	(235.7)	(243.4)	(0.00279)
Avg. Offer Program in Academic Field	811.3*	216.4	1.209**
	(451.7)	(469.3)	(0.00546)
Avg. Offer Program in Business	-1112.0***	-897.0**	-0.611
	(361.3)	(375.5)	(0.00438)
Avg. Less than one year certificate	-1144.7***	-1265.0***	-0.405
	(247.6)	(257.3)	(0.00296)
Avg. One but less than two years certificate	-901.2**	-974.9**	-0.603
	(366.6)	(381.1)	(0.00441)
Avg. Associate's degree	1537.5***	1379.9***	1.632***
	(337.9)	(351.0)	(0.00409)
Avg. Two but less than 4 years certificate	760.1***	954.5***	-0.0544
	(231.7)	(240.2)	(0.00275)
Avg. Bachelor's degree	558.4	687.4*	0.126
	(397.5)	(410.5)	(0.00469)
Avg. Tuition payment plan	77.99	482.5**	-0.933***
	(213.1)	(220.6)	(0.00254)
Avg. Offer Distance learning opportunities	-70.00	304.8	-0.192
	(383.3)	(398.3)	(0.00466)
Avg. Offer Weekend/evening college	-77.27	-221.8	-0.0175
	(193.7)	(200.4)	(0.00231)
Avg. Remedial services	744.4**	761.2**	0.288
	(315.8)	(328.4)	(0.00382)
Avg. Academic/career counseling service	-36.34	-1.710	-0.823*
	(368.7)	(384.9)	(0.00447)
Avg. Placement services for completers	129.2	185.7	0.208
	(307.1)	(317.7)	(0.00361)
Avg. On-campus day care for students' children	-90.14	-322.6	-0.787***
	(233.0)	(240.6)	(0.00274)
Avg. Athletic Program	814.8***	424.1*	1.480***
	(237.6)	(245.0)	(0.00278)
Avg. Has Library	85.24	-19.55	-0.0252
	(401.6)	(418.9)	(0.00484)
HBCU	-1360.4	-1243.9	1.386
	(1049.5)	(1099.9)	(0.0125)
FPI	-4965.8***	-5718.9***	-1.819***
	(504.0)	(524.4)	(0.00608)
FPI Chain	-514.8*	-413.3	-0.239
	(265.6)	(277.0)	(0.00322)
Avg. Offer Any Program	-207.3	112.9	-1.000
	(891.4)	(937.4)	(0.0111)
Constant	8618.3***	4322.4***	17.19***
	(1105.5)	(1158.9)	(0.0136)
Observations	2114	2114	2326
Adjusted R-Squared	0.519	0.527	0.172

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Table displays OLS estimates of the relationship between quality and school characteristics. Observations are weighted by the inverse variance of the value-added measure as in Chandra et al. (2013). Because value-added is taken at the firm level, we take the average of school characteristics for a given firm and use these as explanatory variables. Standard errors reported in parentheses. $^{*}p < .1,^{**}p < .05,^{***}p < .01$

D Federal Student Aid and Net Student Price Construction

In this section, we describe the construction of net student prices $p_{i,j,t}$ used in our demand model to estimate student price preferences.

First, we describe the cost of attendance each student i faces at college j, $COA_{i,j}$. There are three types of cost of attendance, depending on whether a student chooses to live on campus, off campus with family, or off campus (living independently). Sub-baccalaureate schools are primarily commuter schools. In our sample, on average 1.2% of the students at each school live on-campus,[53] and only 7.62% of schools in our sample report providing any form of on-campus housing. Because of this, we ignore on-campus cost-of-attendance. The federal government determines the type of off-campus cost of attendance based on a student's dependency status. We follow this rule and classify $COA_{i,j}$ for student i as being the off-campus with family cost of attendance if they are labeled as a dependent (< 24, live with family), and the off campus living independently cost of attendance if they are labeled as independents.

The individual student price is defined as the out-of-pocket payment $OOP_{i,j,t}$, plus the amount of loans a student i must take to attend school j, $L_{i,j,t}$, which are discounted by the 10-year loan discount factor β_i.

$$p_{i,j,t} = OOP_{i,j,t} + \beta_i L_{i,j,t}$$

Students can only pay out of pocket up to their EFC_i, which measures their ability to pay for college themselves. Any further cost of attedance beyond EFC must be paid via Pell grants or loans. Let $\text{Need}_{i,j} = COA_{i,j} - EFC_i$ denote a student's financial need. The amount of Pell aid a student may receive, denoted $\pi_{i,j,t}$, is determined by the following formula:

$$\pi_{i,j,t} = \begin{cases} 0 & \text{if Need}_{i,j} < \underline{\pi}_y \\ \text{Need}_{i,j} & \text{if Need}_{i,j} \leq [\underline{\pi}_y, \bar{\pi}_y - EFC_i] \quad \& \quad EFC_i \leq \overline{EFC}_y \\ \bar{\pi}_y - EFC_i & \text{if Need}_{i,j} > \bar{\pi}_y \quad \& \quad EFC_i \leq \overline{EFC}_t \end{cases} \tag{42}$$

where $\underline{\pi}_y$ determines the minimum amount of financial need required to receive a Pell grant in year y, and $\bar{\pi}_y$ is the maximum aid from Pell grants a student who has 0 EFC may receive. Thus, students are personally eligible for financial aid up to $\bar{\pi}_y - EFC_i$ from the Pell-grant program.

[53]Source: IPEDS Financial Aid Survey

The out-of-pocket cost a student pays is defined as follows:

$$OOP_{i,j,t} = \begin{cases} COA_{i,j,t} - \pi_{i,j,t} & \text{if} \quad COA_{i,j,t} - \pi_{i,j,t} \leq EFC_i \\ EFC_i & \text{else} \end{cases} \tag{43}$$

If $OOP_{i,j,t} < COA_{i,j,t} - \pi_{i,j,t}$, then students must also take out loans to pay for college. Let $A_{i,j,t,p}$ denote the origination amount taken out for a loan of type p, where $p \in \{\text{Subsidized, Unsubsidized, Private}\}$. Because all students who have financial need are eligible for Subsidized federal student loans, which have lower interest rates than Unsubsidized federal student loans, we assume they first take out Subsidized loans. The amount of these loans taken is defined as follows:

$$A_{i,j,t,\text{Sub}} = \begin{cases} 0 & \text{if} \quad COA_{i,j,t} - OOP_{i,j,t} \leq 0 \\ COA_{i,j,t} - OOP_{i,j,t} & \text{if} \quad COA_{i,j,t} - OOP_{i,j,t} \in (0, \bar{A}_{y,\text{Sub}}) \\ \bar{A}_{y,\text{Sub}} & \text{if} \quad COA_{i,j,t} - OOP_{i,j,t} \geq \bar{A}_{y,\text{Sub}} \end{cases} \tag{44}$$

Where $\bar{A}_{y,\text{Sub}}$ is the maximum amount of subsidized federal student loans allowed to be taken by students each year, shown in Figure A1. If students fall into the third case, they still have financial need after receiving the maximum amount of Subsidized loans. They are then allowed to receive Unsubsidized federal loans, up to a maximum $\bar{A}_{i,y,\text{Unsub}}$ that depends on both the year y and whether i is a dependent or independent. The origination amount of Unsubsidized federal student loans is defined as:

$$A_{i,j,t,\text{Unsub}} = \begin{cases} 0 & \text{if} \quad COA_{i,j,t} - OOP_{i,j,t} - A_{i,j,t,\text{Sub}} \leq 0 \\ OOP_{i,j,t} - A_{i,j,t,\text{Sub}} & \text{if} \quad COA_{i,j,t} - OOP_{i,j,t} - A_{i,j,t,\text{Sub}} \in (0, \bar{A}_{i,y,\text{Unsub}}) \\ \bar{A}_{i,y,\text{Unsub}} & \text{if} \quad COA_{i,j,t} - OOP_{i,j,t} - A_{i,j,t,\text{Sub}} \geq \bar{A}_{i,y,\text{Unsub}} \end{cases} \tag{45}$$

Finally, if students still have financial need, we assume they take out private student loans at the prevailing market annual interest rate to pay the cost of attendance for institution j:

$$A_{i,j,t,\text{Private}} = \max(0, COA_{i,j,t} - OOP_{i,j,t} - A_{i,j,t,\text{Sub}} - A_{i,j,t,\text{Unsub}}) \tag{46}$$

Once the origination amounts for each loan type are determined, we must calculate the total payments associated with each loan origination. Let $r_{p,y}$ denote the monthly interest rate associated with a loan of type p in year y.[54] The standard repayment plan length for

[54]Calculated by dividing the annual interest rate reported by 12.

federal student loans is 10 years[55] and the loans are paid back monthly. We assume each loan is amortized to be paid back monthly in 10 years with equal monthly payments. Equation 47 below shows how to convert a loan of origination size $A_{i,j,t,p}$ into its total payments. This leads to the following expression of total loan payments for student i attending school j in market t.

$$L_{i,j,t} = \sum_{p} A_{i,j,t,p} \frac{r_{p,y}(1+r_{p,y})^{120}}{(1+r_{p,y})^{120}-1}, \quad p \in \{\text{Sub, Unsub, Private}\} \tag{47}$$

$L_{i,j,t}$ is then multiplied by the individual discount factor on loans, β_i, to obtain the net student price $p_{i,j,t}$.

[55]Source: `https://studentaid.gov/manage-loans/repayment/plans`

E Details on Discount Factor Micromoments

In this section, we describe the moments used in our structural model to recover the discount factor of consumers. To measure the empirical distribution of temporal discounting among students, we make use of the following question asked in the 2011-2012 BPS baseline survey, when students first enter college:

> *Now we have a series of quick "what-if" scenarios for you about money. Imagine you have a choice between receiving \$250 today or \$250 in one year. This gift is guaranteed whether you choose to take the \$250 today or \$250 in one year. Would you prefer...*
>
> 1. *\$250 today or \$250 in one year*
> 2. *[If prefer \$250 today] \$250 today or \$300 in one year*
> 3. *[If prefer \$300 today] \$250 today or \$350 in one year*
> 4. *[If prefer \$350 today] \$250 today or \$400 in one year*
> 5. *[If prefer \$400 today] \$250 today or \$450 in one year*
> 6. *[If prefer \$450 today] \$250 today or \$500 in one year*

Therefore, for each student i in the BPS respondents, we observe lower and upper bounds on their indifference point between \$250 today and \$$X_i$ in one year.

Consider for now the scenario that we observe the indifference point X_i. Assuming that students discount the future at a monthly frequency, and discounting is exponential, if a student is indifferent between \$250 today and \$$X_i$ in one year, we can convert the implied annual discount factor from the survey to the average monthly discount on 10-year loans, β_i in our model. The monthly discount factor implied by the annual discount factor reported in the survey, assuming exponential discounting, is:

$$\beta_m(X_i) = \left(\frac{250}{X_i}\right)^{1/12}$$

We then convert this to a 10-year average discount factor using the following formula:

$$\beta^{BPS}(X_i) = \beta_i^{BPS} = \frac{1}{120}\frac{(1-\beta_m(X_i))^{120}}{(1-\beta_m(X_i))} \tag{48}$$

And this could be used directly to fit the discount factors in our model. Recall, however, we do not observe the indifference points of each student, but their bounds. For each respondent i in the 2012 survey, we observe bounds lb_i, ub_i such that $lb_i \leq \beta_i^{BPS} \leq ub_i$. For each

$X \in \{300, 350, 400, 450, 500\}$[56], we observe the fraction of students with $\beta_i \leq \beta^B PS(X)$. From this we are able to construct the following observed points of the CDF of discount factors of the student population responding to the discount factor survey question, for a particular demographic group d:

$$\hat{Pr}_{BPS}(\beta_i \leq \beta^{BPS}(X)|d) = \frac{\sum_{i:D_{i,d}=1} \mathbb{1}\{X_i \leq X\}}{\sum_{i:D_{i,d}=1} 1} \tag{49}$$

where i indexes BPS respondents. Thus, although we do not observe any individual's indifference point, we can use the upper bounds reported on discount factors to obtain an empirical cumulative distribution function of students' discount factors in the survey. Data on these cumulative probabilities is retrieved using the DataLab service from the USDOE's website.[57] We collect these statistics on set of students who claim to attend a sub-baccalaureate (less than 2-year, 2-year) college in the survey, since these students are most similar to those in our sample. We also obtain the cumulative distribution of discount factors for students conditional on each of our 5 demographic characteristics for which we allow preferences to be heterogenous: Male, Black, Hispanic, Dependent, and Pell-eligible.

We match the empirical CDF probabilities reported in the BPS to those implied by the model. The model-implied moment must be taken for consumers *conditional* on enrollment, since the BPS only surveys enrolled students, not potential students. This corresponds to consumers in our demand model choosing the inside good. The theoretical moments corresponding to the empirical moments in equation 49 are as follows, using Bayes rule':

$$Pr(\beta_i \leq \beta^{BPS}(X)|j \neq 0, \Theta, d) = \frac{Pr(\beta_i \leq \beta^{BPS}(X)|\Theta, d)Pr(j \neq 0|\beta_i \leq \beta^{BPS}(X), \Theta, d)}{Pr(j \neq 0|\Theta, d)} \tag{50}$$

We discuss how we evaluate each of these probabilities on the right hand side of Equation 50.

First, for $Pr(\beta_i \leq \beta^{BPS}(X)|\Theta, d)$, one could take for any guess of the parameters a simple average of the binary indicators $\mathbb{1}\{\beta_i(\Theta) \leq \beta^{BPS}(X)\}$. An issue with this is that the gradient of the indicator function $\mathbb{1}\{\beta_i \leq \beta^{BPS}(X)\}$ with respect to Θ, in particular the parameters $\beta, \sigma_\beta, \Pi_\beta$ governing the distribution of discount factors in the market, is zero. Thus, the moments will not directly shift the estimates of the discount factor parameters, but instead sort students with higher/lower discount factors into consuming the inside good if the model

[56] We do not include the indifference point of \$250 in one year vs today because it implied a discount factor of $\beta_i = 1$, which is impossible under our logit specification of the discount factor. However, we still include the mass of students reporting $\beta_i = 1$ when calculating our CDFs.

[57] Retrieved from `https://nces.ed.gov/datalab/index.aspx`.

currently under/over-predicts the empirical moments. To address this computational issue, we instead integrate over the random unobserved heterogeneity $v_{i,\beta}$ on the discount factor, which is normally distributed. By applying the inverse logit equation, and using the fact that the (inversed) discount factor is linear in the unobserved heterogeneity, we can express this probability in terms of the normal CDF:

$$E_{v_{i,\beta}}[\mathbb{1}\{\beta_i \leq \beta^{BPS}(X)\}] = \Phi\Big(\frac{\log(\frac{\beta^{BPS}(X)}{1-\beta^{BPS}(X)}) - (\beta + \Pi_\beta D_i)}{\sigma_\beta}\Big), \tag{51}$$

where Φ is the CDF of the standard normal distribution. The expected value of the indicator $\mathbb{1}\{\beta_i \leq \beta^{BPS}(X)\}$, with expectation taken over the normally-distributed unobserved heterogeneity, has a non-zero gradient with respect to $\beta, \sigma_\beta, \Pi_\beta$, which allows us to shift the discount factor parameters directly to match the empirical micromoments collected from the BPS survey.

Second we have the probability that the consumer enrolls in a school, *conditional* on $\beta_i \leq \beta_i \leq \beta^{BPS}(X)$, $Pr(j \neq 0|\beta_i \leq \beta^{BPS}(X), \Theta, d)$. At a given Θ, the condition $\beta_i \leq \beta^{BPS}(X)$ implies that the unobserved heterogeneity v_i is not above a certain value, depending on demographics, current estimates of Θ, and $\beta^{BPS}(X)$. For a given consumer i, conditional on v_i, the probability has a closed form solution. This can be expressed in integral form:

$$Pr(j_i \neq 0|\tilde{\beta}_i \leq \beta^{BPS}(X)) = \int_{v_i} (1 - s_{i,0,t}(v_i))\phi(v_i|v_i \leq \frac{\tilde{X} - \beta - \Pi_\beta D_i}{\sigma})\partial v_i,$$

where $\tilde{X} = \log(\frac{\beta^{BPS}(X)}{1-\beta^{BPS}(X)})$, and ϕ is the standard normal pdf. Conditional on $v_i \leq X$, v_i follows the distribution of a truncated normal. We sample from this distribution using an inverse CDF transformation. Given a random variable $p \sim U[0,1]$, the transformation $v_i = \Phi^{-1}(p \cdot \Phi(X))$ follows a truncated normal distribution with upper bound X. Therefore, we sample from the uniform[58] and perform Monte Carlo integration. We estimate this as

[58]rather than randomly sample, since it is a uniform, we construct a grid of equally spaced points along $[0, 1]$, which captures the equiprobable nature of the uniform, but guarantees we cover the entire probability space.

follows, given V points of integration over v_i:

$$Pr_{v_i}(j_i \neq 0|\tilde{\beta}_i \leq \beta^{BPS}(X)) = \frac{1}{V}\sum_{v=1}^{V} \frac{1}{1+\sum_{j\in J_t}\exp(\alpha_i(OOP_{i,j,t}+\beta_i(p_v)L_{i,j,t})+\delta_{i,j,t}))}$$

$$\beta_i(p_v) = \frac{\exp\left(\beta+\Pi_\beta D_i+\sigma\Phi^{-1}(p_v\cdot\Phi(\frac{\tilde{X}-\beta-\Pi_\beta D_i}{\sigma}))\right)}{1+\exp\left(\beta+\Pi_\beta D_i+\sigma\Phi^{-1}(p_v\cdot\Phi(\frac{\tilde{X}-\beta-\Pi_\beta D_i}{\sigma}))\right)}$$

$$p_v \sim U[0,1]$$

Where $\delta_{i,j,t}$ denotes the components of utility unrelated to price or the logit shock $\epsilon_{i,j,t}$. To be consistent in our evaluation of the theoretical moment, we use this sampling procedure from the (non-truncated) normal distribution to calculate the inside good share in the denominator. Let $s_{i,0}(X)$ denote the implied outside good share when $v_i = X$. We can now construct the moment as follows:

$$\begin{aligned}\hat{g}^{\beta}_{X,d}(\Theta) &= Pr(\tilde{\beta}_i \leq \beta^{BPS}(X)|j\neq 0,\Theta,y(t)=2011,d) - \hat{P}r_{BPS}(\beta_i \leq \beta^{BPS}(X)|d)\\ &= \frac{\sum_{t:y(t)=2011} M_t \sum_{i:D_{i,d}=1}\Phi(\frac{\tilde{X}-\beta-\Pi_\beta D_i}{\sigma})\frac{1}{V}\sum_v\left(1-s_{i,0,t}(\Phi^{-1}(p_v\cdot\Phi(\frac{\tilde{X}_{f,BPS}-\beta-\Pi_\beta D_i}{\sigma})))\right)}{\sum_{t:y(t)=2011} M_t \sum_{i:D_{i,d}=1}\frac{1}{V}\sum_v\left(1-s_{i,0,t}(\Phi^{-1}(p_v))\right)}\\ &\quad - \hat{P}r_{BPS}(\beta_i \leq \beta^{BPS}(X)|d)\end{aligned}$$

Finally, the denominator $Pr(j\neq 0|\Theta,d)$ corresponds to the probability that a consumer enrolls in any school, $1-s_{i,0,t}$. This is relatively simple to compute.

F Model Optimization

We estimate the model using 2-step GMM, while incorporating the nonlinear constraints implied by the supply side of the model in terms of FPI firms maximizing profits. These constraints are that marginal costs are positive, and the second-order condition of the FPI firm with respect to advertising $a_{f,t}$ is satisfied.[59] This is similar to the approach of Romeo (2016), in that we incorporate economic theory on the supply-side conduct in this market as prior constraints when estimating our demand system. Finally, we also impose a constraint that the total advertising spending implied by the model by FPIs is equal to the amount observed in the Ad$pender data, denoted $\widehat{\text{AdSpending}}$ (2.44 billion USD).[60] This is to ensure that counterfactual advertising quantities can be understood in nominal terms. Explicitly, we solve the following constrained optimization problem at each GMM step:

$$\min_{\Theta} G(\Theta) = \min_{\Theta} \vec{g}(\Theta)^T \mathbf{W}(\Theta_0)\vec{g}(\Theta) \tag{52}$$

$$\begin{aligned} &\text{s.t.} \\ c_{j,t}(\Theta) &\geq 0 \quad \forall j,t \text{ where FPI}_j = 1 \\ \frac{\partial^2 \Pi_{f,d}(\Theta)}{\partial^2 a_{f,d}} &\leq 0 \quad \forall f,d \text{ where } a_{f,d} > 0 \\ \sum_{f,d} a_{f,d}\kappa_{f,d} &= \widehat{\text{AdSpending}}, \end{aligned} \tag{53}$$

where $\mathbf{W}(\Theta_0)$ is the $G \times G$ weighting matrix determining the importance of each moment included in the model estimation routine, and Θ_0 denotes an estimate of Θ for the model fixed during each estimation step. Given an estimate of Θ, we can construct the optimal weight matrix as the inverse covariance of all G moments:

$$\mathbf{W}(\Theta_0) = Cov(\vec{g}(\Theta_0), \vec{g}(\Theta_0)^T)^{-1} \tag{54}$$

Note that the covariance is calculated over the relevant schools j,t for the demand, supply, and demographic moments, while the covariance matrix for discount micromoments taken from the BPS survey are calculated using the covariance implied in the survey data, as

[59] Without these constraints, we sometimes estimate negative marginal costs, or ad costs that imply negative profits at the observed advertising choices. At our solution, only 59 of the 22,946 nonlinear constraints bind.

[60] In practice, we implement this equality constraint as two inequality constraints for feasibility, namely that the advertising-weighted average advertising cost of the model, $(\sum_{f,d} \kappa_{f,d} a_{f,d})/(\sum_{f,d} a_{f,d})$, is within \$10 of the value in the Ad$pender data (\$88).

described in the appendix of Petrin (2002). We estimate the covariance matrix as a block diagonal matrix of the five types of moments in our model: the moments on demand shocks (ξ), the moments on supply marginal cost shocks (ω), the moments on advertising cost shocks (ι), the moments on matching demographic shares ($\vec{g}^f(\Theta)$), and the moments on discount micromoments ($g^\beta(\Theta)$).

We begin optimization by estimating the diagonal of the weighting matrix at an initial starting value Θ_0 with no preference heterogeneity, to optimize over the first GMM step (e.g., no covariance is used in the first step). Given an estimate Θ_1^* from this optimization, we then estimate the second step of the GMM optimization using the full block diagonal weighting matrix $\mathbf{W}(\Theta_1^*)$ to obtain our final solution Θ_2^* for the model. We estimate Θ using the `knitro` optimization software within MATLAB.

G Price Elasticity Decomposition

We formalize the role passthrough plays in the wedge between students' tuition and net price elasticity by performing the following decomposition in log differences of the two elasticities:

$$\log(\varepsilon_{i,j,t}^{\text{Tuition}}) - \log(\varepsilon_{i,j,t}^{\text{Net Price}}) = \log(p_{j,t}/p_{i,j,t}) + \log(\frac{\partial p_{i,j,t}}{\partial p_{j,t}}) \tag{55}$$

The first term is the ratio between tuition and net price. If $p_{i,j,t} < p_{j,t}$, which may be due to federal subsidies or temporal discounting on loans, this will be positive. The second term is the logged passthrough rate of tuition to net student prices (Equation 17). Because the decomposition in in log terms, we can interpret the differences as percentage points. Figure D1 plots the average value, weighted by the enrollment probabilities of each student, of each component in Equation 55, by college type. For both college types, the passthrough effect is negative and large, contributing to the low tuition elasticity. However, because for-profit colleges receive more aid, and loans are a bigger portion of how students pay, the price ratio has a positive effect for these schools, dampening the difference in price elasticities. In other words, because FPI net prices are much lower than tuition, students are less sensitive to this variable when choosing colleges.

Among students, price elasticities differ significantly by income, particularly at for profit colleges, where aid and loans are a more substantial portion of how students pay for college. To quantify the factors leading to a lower price sensitivity for low income students, we decompose the difference in tuition and net price elasticities between high and low-income students at FPIs. Let

$$\Delta^{\text{Inc}} x = \frac{\sum_{j:FPI_j=1}\sum_{i:i\in\text{low}} s_{i,j}x_i}{\sum_{j:FPI_j=1}\sum_{i:i\in\text{low}} s_{i,j}} - \frac{\sum_{j:FPI_j=1}\sum_{i:i\in\text{high}} s_{i,j}x_i}{\sum_{j:FPI_j=1}\sum_{i:i\in\text{high}} s_{i,j}}$$

denote the average difference in x among low and high income students. Using the logit formulation of shares, we can express the difference in elasticities across groups as follows:

$$\Delta^{\text{Inc}} \log(\varepsilon_{i,j,t}^{\text{Net Price Elasticity}}) = \underbrace{\Delta^{\text{Inc}} \log(\alpha_i)}_{\text{Price Sensitivity}} + \underbrace{\Delta^{\text{Inc}} \log(p_{i,j,t})}_{\text{Net Price}} + \underbrace{\Delta^{\text{Inc}} \log(1 - s_{i,j,t})}_{\text{Pr(Do Not Enroll in } j)} \tag{56}$$

$$\Delta^{\text{Inc}} \log(\varepsilon_{i,j,t}^{\text{Tuition Elasticity}}) = \underbrace{\Delta^{\text{Inc}} \log(\alpha_i)}_{\text{Price Sensitivity}} + \underbrace{\Delta^{\text{Inc}} \log(p_{j,t})}_{\text{Tuition}} + \underbrace{\Delta^{\text{Inc}} \log(1 - s_{i,j,t})}_{\text{Pr(Do Not Enroll in } j)} + \underbrace{\Delta^{\text{Inc}} \log(\frac{\partial p_{i,j,t}}{\partial p_{j,t}})}_{\text{Tuition Pass-Through}} \tag{57}$$

Figure D2 shows the decomposition of the of student-level net price elasticities by high and low income status of students, at for-profit colleges. Low income students are less elastic than high income studentsto net price by 0.98 units. This is driven entirely by the lower net student price low income students have to pay to attend these schools, through both federal aid and increased discounting. Figure D3 shows the decomposition of the factors leading to differences in FPI tuition elasticities between income groups. Low-income students are less elastic to tuition by 0.1 log units. While low income FPI students are 12% more sensitive to net price, in terms of their price coefficient, they have a tuition passthrough 27% lower than that of high income students, which explains their lower tuition elasticity. This low passthrough is a key facilitator of the high tuition prices FPIs charge, while still being able to attract low income students to enroll in their institutions.

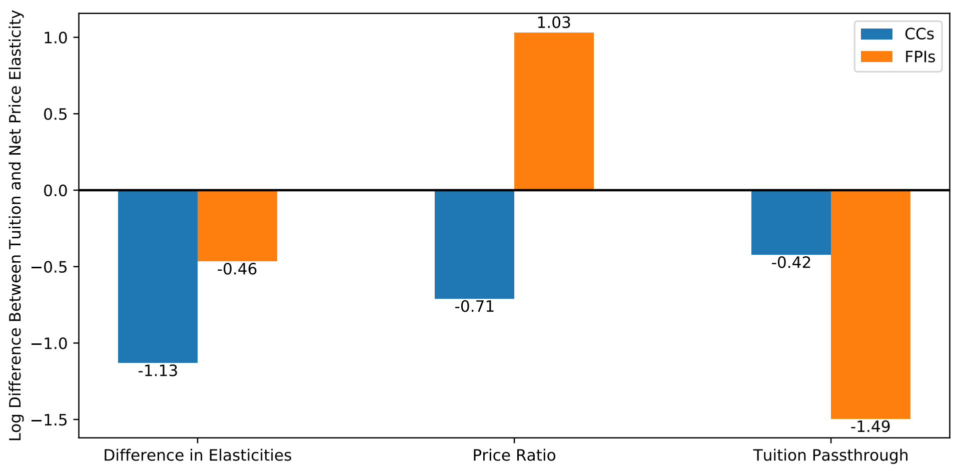


Figure D1: Decomposition of Tuition And Net Student Price Elasticity Difference by Institution Type

Figure plots the decomposition of the log difference between the tuition and net price elasticity, $\log(\varepsilon_{i,j,t}^{\text{Tuition Elasticity}}) - \log(\varepsilon_{i,j,t}^{\text{Net Price}})$ displayed in Equation 55. Each bar represents the average value of each component, weighted by the probability of consumer i enrolling in an institution j, multiplied by the market size M_t, so that weights are proportional to the effective number of students. Averages are calculated separately for for-profit colleges and community colleges. Price ratio denotes the log ratio between tuition and net student price, $\log(p_{j,t}/p_{i,j,t})$. Tuition passthrough denotes the logged marginal increase in net price from an increase in tuition, $\log(\frac{\partial p_{i,j,t}}{\partial p_{j,t}})$.

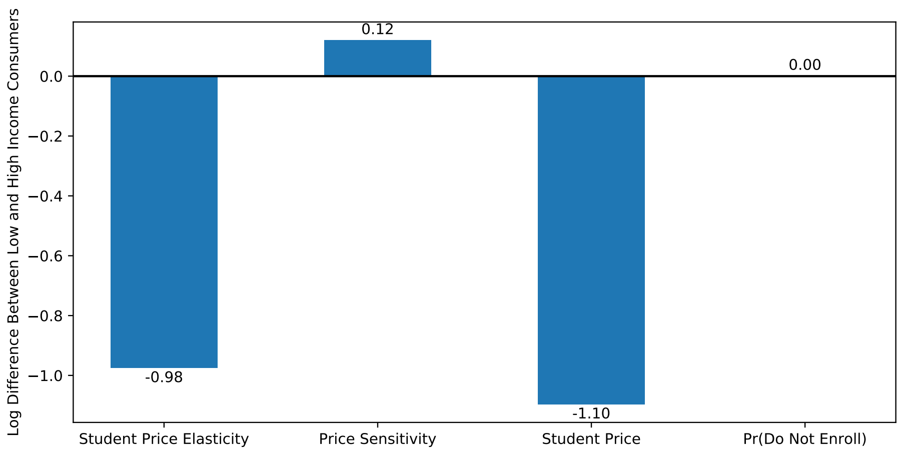


Figure D2: Decomposition of Net Student Price Elasticity Difference by Income at FPIs

Figure plots the decomposition of the difference in the average net student price elasticity, $\varepsilon_{i,j,t}^{\text{Net Price}}$, at for-profit colleges, by income (whether or not the student is eligible for Pell grants). Each bar represents the average difference in each component between low and high income students, weighted by the probability of consumer i enrolling in an institution j, multiplied by the market size M_t, so that weights are proportional to the effective number of students. Price sensitivity denotes the average difference in α_i between low and high income groups. Student price denotes the average difference in net student price $p_{i,j,t}$ between low and high income groups. Pr(Do Not Enroll) denotes the average difference in net student price $(1 - s_{i,j,t})$ between low and high income groups.

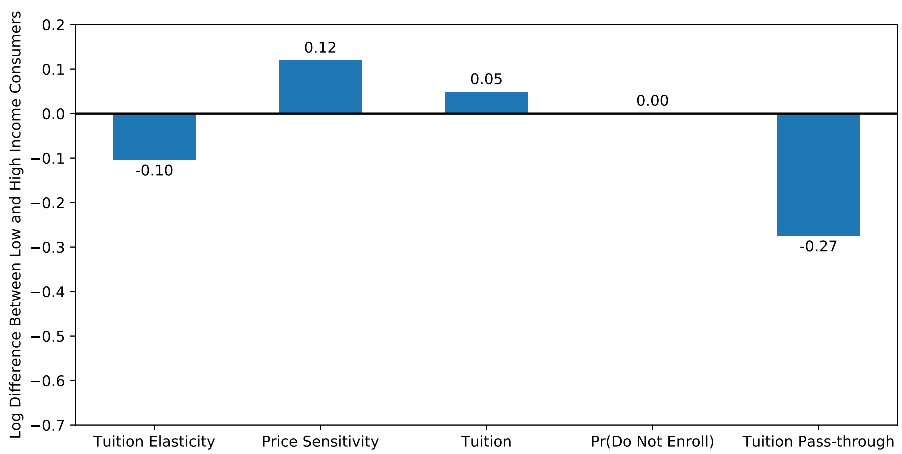


Figure D3: Decomposition of Tuition Elasticity Difference by Income at FPIs

Figure plots the decomposition of the difference in the average tuition elasticity, $\varepsilon_{i,j,t}^{\text{Tuition Elasticity}}$, at for-profit colleges, by income (whether or not the student is eligible for Pell grants), as as expressed in Equation 57. Each bar represents the average difference in each component between low and high income students, weighted by the probability of consumer i enrolling in an institution j, multiplied by the market size M_t, so that weights are proportional to the effective number of students.

H Solving Counterfactual Equlibriums

H.1 Best Response Equilibrium Estimation

In this section, we describe the method we use to solve for equilibrium under our counterfactual policies. Let $\mathcal{F}_d$ denote the set of firms f located in DMA-year d. We treat each community college campus as a separate firm, optimizing their individual budget constraint, while for-profit firms jointly maximize profits across all their campuses in a given DMA-year. Note that all voucher designs we consider during counterfactuals are solvable up to a generosity parameter g.

The standard approach to solve for an equilibrium in a Nash-Bertrand framework is to simultaneously solve the system of pricing and advertising first order conditions for the supply side. However, because advertising is constrained to be non-negative, the first order condition for advertising will not necessarily hold in equilibrium if the optimal advertising amount of an FPI firm is zero. This is particularly important for our counterfactual quality-based voucher policies, where many schools with low value-added effectively find it optimal to invest in zero advertising. To accomodate this scenario, we solve for each equilibrium using an iterated best response algorithm. We solve for the equilibrium under a voucher aid regime by first guessing a generosity g of aid to give low income students. Then, given g, we implement Algorithm 1 to obtain the equilibrium price and advertising amounts under the counterfactual policy. Then, we calculate the amount of federal student aid allocated under the equilibrium we solve for, and terminate when g is found to balance the federal budget in our sample.

Algorithm 1: Voucher Equilibrium

for $d = 1, \dots D$ **do**
  Initialize set of endogenous objects $E_{0,d} = \{p_{j,t}, a_{f,t} \quad \forall j \in J_d\}$ to those observed in current federal aid equilibrium.
  for $s = 1, \dots, S$ **do**
    Randomize the order f of colleges. **for** $f \in \{f : f \in \mathcal{F}_d\}$ **do**
      if f =Community College **then**
        Solve budget constraint of community college f to get best response price $p^*_{f,t,s}$ given endogenous objects E_s.
      else if f =For-Profit College **then**
        Maximize profits of firm f to get best response prices and ads $\{p^*_{j,t,s} : j \in J_{f,d}\}.a^*_{f,d,s}$ given endogenous objects E_s.
      Update components of E_s corresponding to firm f to be $\{p^*_{j,t,s} : j \in J_{f,d}\}, a^*_{f,d,s}$.
    if $\max(|E_s - E_{s-1}|) < \epsilon$ **then**
      Break out of s loop.

H.2 Solving for Optimal Voucher

In order to estimate the voucher elasticities, we must choose an equilibrium $\mathcal{E}$ at which to estimate the voucher elasticities. We choose the equilibrium solved for in the lump-sum voucher presented in Section 6.1. At that equilibrium, we can estimate $\frac{\partial s_{j,t,L}}{p_{j,t}}, \frac{\partial s_{j,t,L}}{a_{j,t}}$ directly. A challenge comes in estimating the passthrough rates on tuition and advertising, $\frac{\partial p_{j,t}}{\tau_{j,t}}, \frac{\partial a_{f(j),t}}{\tau_{j,t}}$. To do so, we note that the optimal prices and (non-zero) ads are the solution to a set of first order conditions in each DMA-year d[61], denoted $F(\vec{a}_d, \vec{p}_d, \tau_d)$, where $\vec{p}_d$ is the vector of prices charged by schools in DMA d, and $\vec{a}_d, \vec{\tau}_d$ are defined analogously. Namely, F is comprised of the profit-maximizing first order conditions of FPI firms, and the budget constraint of community colleges. Let $S = [\vec{p}_d, \vec{a}_d]$ denote the endogenous supply-side objects in each market, and J be the $|F| \times |S|$ Jacobian matrix whose elements are $J_{i,j} = \frac{\partial \vec{F}_i}{\partial S_j}$. Then by the implicit function theorem, the passthrough of prices/ads with respect to the vouchers are:

$$\frac{d\vec{S}}{d\tau_{j,d}} = -J^{-1} \frac{d\vec{F}}{d\tau_{j,d}}$$

[61]We perform this estimation at the DMA-year level because advertising is purchased at the DMA-level, so the effect of increased advertising in one market may spillover to another market (county) in the same DMA.

We calculate $\frac{d\vec{F}(\mathcal{E})}{d\tau_{j,d}}$ directly from the first order conditions, to estimate the passthrough rates. Having recovered the passthrough rates, we can solve for the voucher elasticities at the lump-sum voucher equilibrium, which we use as our plug-in estimates for the optimal voucher policy.

I Proofs of Optimal Aid Policy

In this section, the solution to the social planner problem, both in its simplified formulation used in counterfactuals, and it's full solution, are shown here:

Proposition 2. Suppose the social planner optimizes Equation 32. The optimal voucher in market t is:

$$\vec{\tau}_t^* = \underbrace{(I + \mathbf{E_t})^{-1}\mathbf{E_t}}_{\substack{\text{Voucher Elasticity} \\ \text{Distortion Term}}} \times \underbrace{\frac{1}{\lambda}}_{\substack{\text{Shadow Price} \\ \text{of Budget Constraint}}} \times \underbrace{\vec{\psi}_t}_{\text{Quality}}, \tag{58}$$

where $\mathbf{E_t}$ is a $\mathcal{J}_t \times \mathcal{J}_t$ matrix with elements:

$$\mathbf{E}_{t,k,j} = \varepsilon_{k,j,t} \times \frac{s_{k,t,L}}{s_{j,t,L}}$$

Proof. The social planner problem presented in Section 6.1 is as follows:

$$\max_{\{\tau_{k,t}\}} \sum_t \sum_{k \in J_t} q_{k,t,L}\psi_k$$

$$\text{s.t.} \sum_t \sum_{k \in J_t} q_{k,t,L}\tau_{k,t} \leq G$$

where, $q_{k,t,L}$ is:

$$q_{k,t,L} = M_t f_{t,L} s_{k,L} = M_t f_{t,L} \int_i s_{i,k,t} \partial F(i|L),$$

where M is market size, $f_{t,L}$ is the fraction of the market that is low-income, and $F(i|L)$ is the distribution of consumers that are low-income. We now describe the proof for deriving the optimal aid policy presented in Equation 58.

The lagrangian of this problem is simply:

$$\mathcal{L} = \sum_m \sum_{k \in J_m} q_{k,t,L}\psi_k - \lambda(\sum_t \sum_{k \in J_t} q_{k,t,L}\tau_{k,t} - G),$$

where λ denotes the lagrange multiplier. Taking derivatives of the lagrangian with respect to a particular $\tau_{j,t}$, we have:

$$\frac{\partial \mathcal{L}}{\partial \tau_{j,t}} = \Big(\sum_{k \in J_m} \frac{\partial q_{k,t,L}}{\partial \tau_{j,t}}(\psi_k - \lambda\tau_{k,t})\Big) - \lambda q_{j,t.L} = 0$$

$$\Rightarrow q_{j,t,L} = \sum_{k \in J_m} \frac{\partial q_{k,t,L}}{\partial \tau_{j,t}}(\frac{\psi_k}{\lambda} - \tau_{k,t})$$

The voucher enrollment elasticity of school k w.r.t. $\tau_{j,t}$ is:

$$\varepsilon_{k,j,t} = \frac{\partial \log(q_{k,t,L})}{\partial \log(\tau_{j,t,L})} = \frac{\partial q_{k,t,L}}{\partial \tau_{j,t}} \frac{\tau_{j,t}}{q_{k,t,L}}$$

We can express the solution to the social planner problem in terms of voucher elasticities through the following rearrangement:

$$\begin{aligned}
\Rightarrow q_{j,t,L} &= \sum_{k \in J_t} \frac{\partial q_{k,t,L}}{\partial \tau_{j,t}} \frac{\tau_{j,t}}{\tau_{j,t}} \frac{q_{k,t,L}}{q_{k,t,L}} (\frac{\psi_k}{\lambda} - \tau_{k,t}) \\
\Rightarrow q_{j,t,L} &= \sum_{k \in J_t} \varepsilon_{k,j,t} \frac{q_{k,t,L}}{\tau_{j,t}} (\frac{\psi_k}{\lambda} - \tau_{k,t}) \\
\Rightarrow \tau_{j,t} &= \sum_{k \in J_t} \varepsilon_{k,j,t} \frac{q_{k,t,L}}{q_{j,t,L}} (\frac{\psi_k}{\lambda} - \tau_{k,t})
\end{aligned}$$

Let $\mathbf{E_t}$ be a $|J_t| \times |J_t|$ such that $\mathbf{E_{t,k,j}} = \varepsilon_{k,j} \frac{q_{k,t,L}}{q_{j,t,L}}$. Then , in vector/matrix notation, we can express the market-level system of equations as:

$$\begin{aligned}
\vec{\tau}_t &= \mathbf{E_t}(\frac{1}{\lambda}\vec{\psi}_t - \vec{\tau}_t) \\
(I + \mathbf{E_t})\vec{\tau}_t &= \frac{1}{\lambda}\mathbf{E_t}\vec{\psi}_t \\
\vec{\tau}_t &= \frac{1}{\lambda}(I + \mathbf{E_t})^{-1}\mathbf{E}\vec{\psi}_t
\end{aligned}$$

□

The optimal solution takes on three parts: the quality of the school ψ_j, the lagrange multiplier on the budget constraint, λ, that is constant across schools, and a term that depends on the responsiveness of enrollment in market t to voucher aid. Because the voucher depends on not only the own-voucher elasticity, but the effect of all other vouchers in a market on a school's demand/supply response, this term is difficult to interpret. Moreover, it depends on the ratio of enrollment across schools, which itself is an equilibrium object. With this in mind, we also derive a simpler expression for the optimal voucher, in Proposition 1, under some additional assumptions. Consider the case where $\varepsilon_{k,j,t} = 0$ if $k \neq j$. We can think of this as the effect of changing the tax/subsidy on school j having a negligible effect on demand for school k. This is exactly the case when j is a monopolist in their local market. The proof of the optimal voucher formulation used in our counterfactuals is provided below:

Proof of Proposition 1. Assuming $\varepsilon^{\tau}_{j,k,t} = 0$ if $k \neq j$, then we note $\mathbf{E_t}$ is a diagonal matrix, with elements $\varepsilon^{\tau}_{j,j,t}$ along the diagonal. Following Proposition 2, we have:

$$\begin{aligned}
\tau_{j,t} &= \sum_{k \in J_t} \varepsilon_{k,j,t}(\frac{\psi_k}{\lambda} - \tau_{j,t}) \\
\Rightarrow \tau_{j,t} &= \varepsilon_{j,j,t}(\frac{\psi_j}{\lambda} - \tau_{j,t}) \\
\tau_{j,t}(1 + \varepsilon_{j,j,t}) &= \varepsilon_{j,j,t}\frac{\psi_j}{\lambda} \\
\tau^*_{j,t} &= \frac{\varepsilon_{j,j,t}}{(1 + \varepsilon_{j,j,t})}\frac{\psi_j}{\lambda}
\end{aligned}$$

□

We find a formulation similar to the linear quality voucher scheme. The difference is we "distort" the subsidy by $\frac{\varepsilon_{j,j,t}}{(1+\varepsilon_{j,j,t})}$, which is analogous to the pricing condition of a monopolist facing a downward sloping demand curve. Thus, if enrollment increases significantly in response to additional voucher aid (either due to price elastic demand, low passthroughs to price, or an ad response to subsidies), then conditional on value-added, the subsidy is greater. Note that this formulation only depends on quality and the own-voucher elasticity, which is more likely to be approximately constant under different equilibriums.