

# Redesigning Federal Student Aid in Higher Education\*

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## Abstract

In this paper, we study the equilibrium impact of student aid in the United States market for sub-baccalaureate higher education and consider the implications of alternative aid policies. We document that the current federal aid system, by subsidizing marginal price increases, incentivizes private for-profit colleges to charge high tuition prices. We also present new descriptive evidence on the importance of advertising in the demand for higher education. Using these facts, we estimate a structural model of supply and demand in this market. We then derive an optimal voucher policy that maximizes educational quality, holding the quality of schools fixed. We measure quality by estimating the value-added in earnings generated by each sub-baccalaureate college. Counterfactual results show that the optimal voucher system improves the overall quality provided by 8.8%. Our optimal voucher policy highlights the fact that for-profit colleges, despite being lower quality on average, are more effective at increasing enrollment than public community colleges. Consequently, these schools play an important role in improving the educational outcomes of students.

**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

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# 1 Introduction

Across the world, government student aid programs play an important role in shaping higher education policy. In 2017, among the Organisation for Economic Co-operation and Development (OECD) countries for which data were available, student aid accounted for 19% of public higher education spending on average [OECD, 2021], and 52% of students on average received financial support for postsecondary education [OECD, 2020].<sup>1</sup> Moreover, these programs are most impactful for low-income students in encouraging postsecondary educational attainment OECD [2020]. Given the magnitude and coverage of these programs, how student aid is designed may have important welfare consequences for students.

The federal student aid program in the United States has some concerning features. Previous studies [Cellini and Goldin, 2014, Turner, 2014, Lucca et al., 2019] have documented that the design of federal aid incentivizes colleges to raise prices (known as the Bennett Hypothesis), reducing the savings passed on to students from public funds. Moreover, the largest beneficiaries of federal student aid (in terms of subsidy amount per student) are for-profit colleges, which have been shown to provide a low return on investment to students [Cellini and Turner, 2019]. Considering that the stated mission of federal student aid is to promote student achievement by ensuring equal access and a high quality of education,<sup>2</sup> policymakers are concerned by these outcomes.<sup>3</sup> Despite this interest, there is limited evidence on the equilibrium effects of the current aid system on both college and student decisions, and only a handful of studies (e.g., Colas et al. [2021]) have investigated alternative aid designs.

In this paper, we fill these gaps in the literature by studying the equilibrium impact of student aid in the market for sub-baccalaureate higher education and consider the implications of alternative aid policies. To do so, we first provide some new descriptive facts on this market. Using novel instrumental variables, we describe how enrollment responds to both price and advertising in this market. We show that advertising is an important input in the demand for for-profit colleges. These findings suggest that failing to account for the advertising choices of these schools under a new aid design may lead to erroneous welfare conclusions. We then estimate the value-added in long-run earnings of over 4,700 non-selective colleges in the United States, as a measure of school quality, and show that although for-profits produce worse outcomes on average according to this metric, there is significant heterogeneity across schools. This finding suggests that some for-profits are important contributors to quality in this market. We use these facts to build a structural model of supply and demand in the sub-baccalaureate market, accounting for the role of federal aid on both sides of the market.

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<sup>1</sup>The reported average percentage for % of public higher education spending comes from 34 OECD countries reporting these statistics. The reported average percentage for % of students receiving federal aid comes from 13 OECD countries.

<sup>2</sup>Source: <https://www2.ed.gov/about/landing.jhtml?src=ft>

<sup>3</sup>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/>

Finally, we consider the potential gains in student outcomes from alternative aid policies by simulating the equilibrium choices of students and colleges. These range from policies actively debated and discussed in the public sphere to an aid policy we derive to maximize quality in this market.

Sub-baccalaureate education consists of degrees below (in terms of completion time) the traditional 4-year bachelor’s degree. The two dominant types of institutions in this market are community colleges (CCs), which are public enterprises that charge students subsidized tuition, and private for-profit institutions (FPIs), which are typically more specialized in their educational services. For-profit colleges are unique in that their business model centers around marketing and advertising to attract students. Of their total budget for student services, 40% is invested in advertising [Cellini and Chaudhary, 2020]. Schools that offer sub-baccalaureate degrees are typically *non-selective*, meaning they admit all students that apply. This market comprises about 35% of both undergraduate enrollment and federal aid spending, and students in this market have historically been those on the margin between work and higher education, while also coming from more disadvantaged backgrounds [Kane and Rouse, 1999].

Students are currently allocated federal aid depending on their *financial need*: whether the cost of attending a particular institution exceeds their ability to pay for college out-of-pocket. In principle, this aid design allows aid to be disbursed efficiently, allocating grants and loans only to students who need it to attend their preferred higher education institution. However, one feature of this design is that the amount of aid a student receives is increasing in the price (tuition) a school sets. Depending on the extent to which colleges exploit this feature, this aid design can result in higher markups for colleges instead of increased access to higher education.

We use enrollment and institutional characteristics data for the universe of schools eligible for federal student aid, along with data on advertising and student labor market outcomes, to measure the key determinants of how students and colleges behave in this market. Our primary dataset is the Integrated Postsecondary Education Data System survey, conducted annually by the U.S. Department of Education (USDOE). We complement this source with Kanta Media data on the advertising of higher education institutions, as well as 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 to estimate the quality of each institution.

We provide evidence on how prices and advertising affect student choice in this market. The effect of these strategic inputs on demand differs by public/for-profit status. We estimate the enrollment elasticity to both tuition and advertising using three novel instrumental variables. Our tuition instruments utilize policy variation relevant for each type of college. For for-profits, we construct a simulated instrument capturing changes in generosity to the federal Pell grant program. For community colleges, we construct a Hausman-style cost instrument to measure changes to state education funding. For college advertising, we construct a shift-share instrument based on variation in monthly political advertising [Sinkinson and Starc, 2019]. Our results indicate that the demand response differs across for-profit and community colleges, due to the differing incentives these col-

leges face when setting price and advertising. For example, we find students are unresponsive to CC advertising, yet highly elastic to FPI advertising. This suggests advertising is an important input into the demand for for-profit colleges and explains in part their significant market share in this sector.

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 of value-added with a model of potential student outcomes that assumes selection on observables. We document significant heterogeneity across institutions: for-profit colleges produce worse outcomes for students on average, consistent with prior literature [Cellini and Turner, 2019]. However, the public versus private designation only explains half of the quality variation across schools. We use these quality estimates to evaluate how the total quality of education provided by the sub-baccalaureate market changes under alternative aid policies.

In our demand model, students choose their most preferred school in their home county or to not attend school at all. We allow preferences to depend on a wide range of school characteristics and consumer demographics to account for the high degree of product differentiation between schools. Our model assumes student preferences over *net student price*: the net present value of payments for college, accounting for federal aid subsidies and student discounting of future loan payments. This allows us to disentangle the role federal aid plays in shaping student demand and evaluate how an alternative aid schedule would change college choice.

Our conduct model for colleges reflects the differing incentives that public and private colleges face in this higher education market. Public schools set tuition to satisfy a budget constraint, given their dependence on government subsidies to maintain operation. For-profit colleges choose prices and advertising to maximize profits. At the same time, we assume that schools are endowed with their quality and cannot adjust it.<sup>4</sup>

We identify the parameters in our model using instrumental variables for price and advertising, micromoments on demographic sorting across schools, and survey data from USDOE on student intertemporal preferences. Our model estimates imply that students are not very sensitive to changes in tuition but are relatively elastic to their net student price. The wedge between tuition and net price elasticity is driven by a low *passthrough* of tuition to net student price, in part explained by the federal student aid design. This discrepancy allows FPIs to set high markups. Our model estimates suggest that an alternative aid scheme, without marginal subsidies to price, may incentivize students to choose lower priced, higher quality CCs and may encourage FPIs to set lower prices. These changes would result in an increase in quality delivered to students as well as expanded access to higher education.

We then use our model to simulate how students and both types of schools would respond to alternative aid policies in equilibrium. Our primary welfare metric in these counterfactuals is the

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<sup>4</sup>This is due primarily to data limitations in estimating time-varying quality. We show in the paper that student preferences for quality are low in this market, so it is unlikely that colleges will adjust quality when it is not explicitly targeted. For policies where quality is an input to aid, we show via a robustness check that results are qualitatively similar if aid is indexed to the exogenous component of school quality attributable to school characteristics.

aggregate value-added provided by the sub-baccalaureate sector. We consider two broad sets of counterfactuals. The first are bans that have been proposed in national policy circles on certain institutions from federal aid, or banning advertising. We find that banning FPIs from accessing federal student aid actually decreases the total quality provided, despite FPIs being lower quality on average, because some students substitute away from medium-quality FPIs to not attending college. We also find that banning low quality schools from federal aid improves the total quality of the sector by only 1%.

These results lead us to consider alternative ways to disburse aid that may better improve quality. Specifically, we focus on changing federal aid to a voucher-based system [Epple et al., 2017], which pays low-income students a fixed amount of aid, regardless of tuition. Our results suggest that switching to a voucher program where low-income students receive a fixed cash transfer increases aggregate value-added by 2.3%, through the channel of increasing aggregate enrollment. We then, under some additional assumptions, derive an optimal aid policy from the perspective of a social planner who wishes to maximize the value-added delivered to low-income students. This policy disburses more voucher aid to schools that are both higher quality and more elastic to aid. Under this policy, aggregate value-added would increase by 8.8% in the sub-baccalaureate sector. Moreover, an approximation of the optimal policy, using only publicly available data on school characteristics and market demographics, can capture a substantial portion of these gains, increasing aggregate value-added by 6.7%. 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 and Koedel, 2017], our estimates imply that these schools have strong incentives to increase enrollment due to their profit motives. Consequently, if the federal government can design aid that incentivizes higher quality for-profits to enroll more students, as we propose under our optimal policy, the benefits in terms of total quality generated in this market are substantial.

Our paper relates to several literatures. The first is the body of work studying the demand and supply responses in higher education to federal student aid. This research has shown that access to federal student aid leads colleges, particularly private colleges, to increase prices [Lucca et al., 2019, Turner, 2014, Cellini and Goldin, 2014, Singell Jr and Stone, 2007]. Dynarski [2003] also documents that students respond to federal aid eligibility by increasing educational attainment. We add to this literature by explaining the role of federal aid in student decision-making under the current design, through both novel instrumental variables and our structural model. We also estimate the effects of policy shifts from the current aid design, both in terms of student outcomes (college attendance and quality of education) and college decisions (tuition and advertising).

We also connect to the literature on the U.S. for-profit college sector, summarized in Cellini [2021]. Prior research has shown: that FPI attendance leads to worse outcomes for students on average [Cellini and Turner, 2019, Armona et al., 2017], relative to public colleges; that FPIs are an important factor in the recent student loan default crisis Looney and Yannelis [2015]; and that FPIs invest substantially in marketing efforts [Deming et al., 2012, Cellini and Chaudhary,

2020]. Our contribution to this literature is twofold. First, we estimate the value-added of non-selective colleges and document significant heterogeneity across schools in the returns to education, demonstrating that not all FPIs provide a poor quality of education. Second, using an advertising cost shock instrument, we also provide the first causal estimates of the effect of college advertising on enrollment.

Finally, we contribute to the growing literature using structural econometric models to evaluate education policies [Neilson, 2013, Kapor, 2015, Singleton, 2019, Allende, 2019, Dinerstein and Smith, 2021, Barahona et al., 2021]. Most similar to our paper is the study by Lau [2020], who estimates the equilibrium effects of tuition-free community colleges in non-selective higher education in the United States. Our paper builds upon the tools developed in this literature to evaluate the effect of alternative student aid policies on student welfare in the United States.

The paper proceeds as follows. Section 2 describes the existing federal student aid design. Section 3 describes the data used in this paper. Section 4 provides evidence on how students respond to prices and advertising. Section 5 describes how we estimate quality in the non-selective higher education sector. Section 6 introduces the equilibrium model of sub-baccalaureate education. Section 7 describes how we estimate the model. Section 8 discusses our model estimates. Section 9 describes the counterfactual policies considered and equilibrium outcomes under each alternative policy. Section 10 concludes the paper.

## 2 Current Student Aid Design in U.S. Higher Education

In this section, we describe the main components of federal student aid design in the United States and how the design may lead to distortionary choices on both the demand and supply side of sub-baccalaureate higher education. While there are numerous student aid programs in the U.S., we focus on two programs that constitute 97% of all federal spending on student aid:<sup>5</sup> 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.

Two key factors determine the amount of federal aid student  $i$  receives to attend school  $j$ . The first is the expected family contribution of student  $i$ ,  $EFC_i$ , a measure constructed by the federal government of a household’s ability to pay for college out-of-pocket. This measure is a function of the household’s income (net of taxes), household structure, and the dependent status of the student applying for college aid. Details of the construction of this variable for our sample can be found in Appendix A. The second factor needed to understand federal aid allocation is the cost of attendance of the school,  $COA_{i,j}$ , which measures, in addition to a college’s tuition and fees, how much a student must pay to attend a college, and depends on the student’s living situation (living with family or living independently).

Given an  $EFC_i$  and cost of attendance  $COA_{i,j}$ , the federal government defines a student’s financial need as  $\text{Need}_{i,j} = \max(COA_{i,j} - EFC_i, 0)$ , which determines the amount of federal aid

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<sup>5</sup>Source: Table 4, <https://studentaid.gov/sites/default/files/FY-2016-Annual-Report.pdf>.

for which students are eligible.

If a student has sufficiently low EFC, they are eligible to receive Pell grants. The parameters governing the policy, the maximum EFC threshold  $\overline{EFC}_y$ , the maximum Pell grant  $\bar{\pi}_y$ , and the minimum Pell grant  $\underline{\pi}_y$ , are set each year  $y$  by the federal government. To receive a Pell grant, a student's  $EFC_i$  must be lower than  $\overline{EFC}_y$ .<sup>6</sup> Pell grants, denoted  $\pi_{i,j}$ , are then disbursed so long as the student has positive financial need, up to an individual cap of  $\bar{\pi}_y - EFC_i$ .

If a student still has financial need after a Pell grant, then they qualify for federal student loans. There are two tiers of Stafford federal student loans: subsidized and unsubsidized. These differ in that subsidized loans had lower interest rates before 2013.<sup>7</sup> The federal government determines the limits for each tier annually.

Figure 1 plots the policy parameters governing federal student aid during our sample period (2008-2016). Panel (a) plots  $\overline{EFC}_y, \bar{\pi}_y$  over academic years in CPI-adjusted 2017 dollars, the parameters governing the Pell grant program.<sup>8</sup> In most years, the lowest income students can expect to receive around \$6,000 in Pell grants, though there is significant variation in the generosity of the program before 2012. Panels (b) and (c) plot the parameters over time determining the design of the federal student loan program: the loan limits and federal loan interest rates, in addition to private loan interest rates.<sup>9</sup> Interest rates on federal and private loans are declining over time during our sample. There is a sizeable gap between federal and private loans, from 3% to 7% APR, suggesting federal loan interest rates reflect a significant subsidy for students.<sup>10</sup> Loan limits did not change in nominal terms during our sample (2008-2016) but declined in real terms.

One of the hallmarks of the existing federal student aid program is that aid is mechanically increasing in the cost of attendance of the postsecondary institution the student chooses to attend. Figure 2 plots an example subsidy schedule for a dependent student attending college during the 2016-2017 academic year with an EFC of \$2,000, as a function of the cost of attendance of the school they choose to attend. For schools with COA below the student's EFC, the student receives no federal aid. Starting at  $COA_{i,j} = EFC_i + \underline{\pi}_y$ , they can receive Pell grants and the government matches the rising cost of attendance up to  $\bar{\pi}_y - EFC_i$ . After this, the student is eligible for federally subsidized loans, whose subsidy is calculated as the difference in total payments on a 10-year loan from the federal government and payments on an equivalent loan from the private

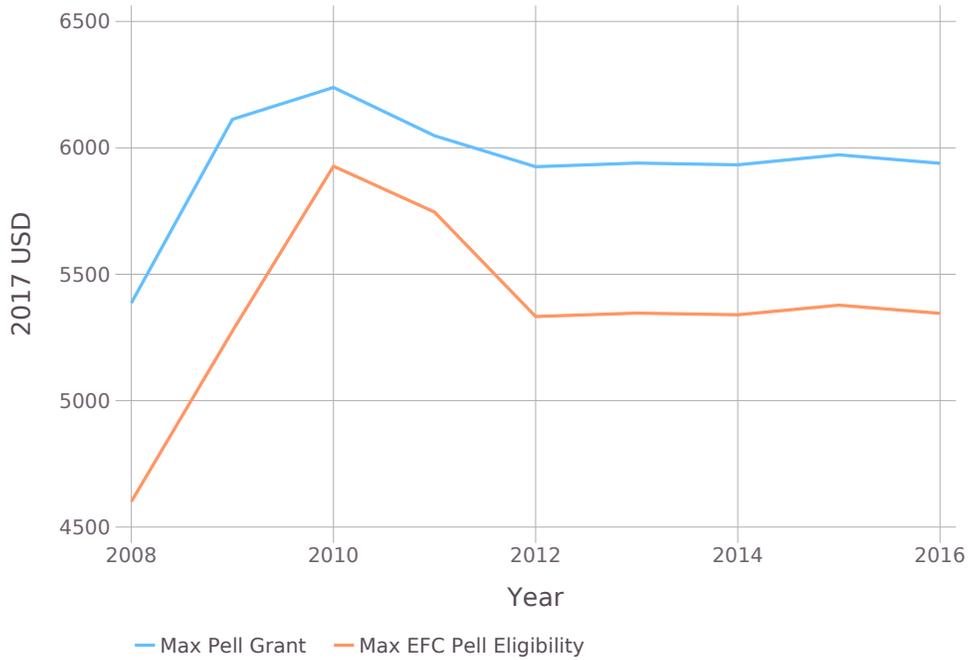
<sup>6</sup>They must also have sufficient financial need such that  $Need_{i,j} > \underline{\pi}_y$ . In practice, due to the secular rise in higher education costs, the minimum aid constraint  $\underline{\pi}_y$  does not bind for the vast majority of students attending college.

<sup>7</sup>Subsidized loans also differ from unsubsidized loans in that interest payments are covered by the federal government as long as the student is enrolled in an education program. In contrast, unsubsidized loans begin accruing interest as soon as the loan is disbursed. Because we do not observe the length of student enrollment in our data, and the sub-baccalaureate programs we consider are relatively short in length, we abstract from the deferment of interest payments for federally subsidized loans and treat them as identical to unsubsidized loans (with the exception of possibly lower interest rates).

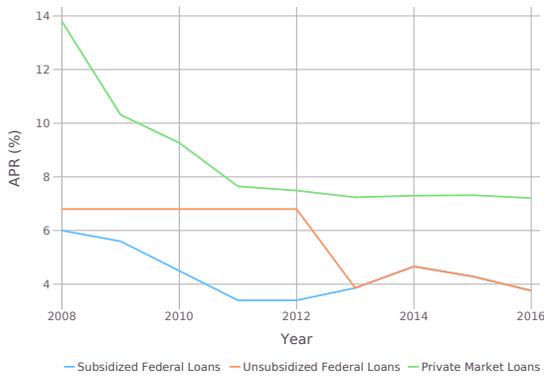
<sup>8</sup>Because most programs in our sample are 1-year programs, we use the Pell grant policy for students in their first year of education. In practice, students receive less aid in later years of education. We abstract from this in our analysis.

<sup>9</sup>See Section 3 for details on how this private student loan interest rate is calculated.

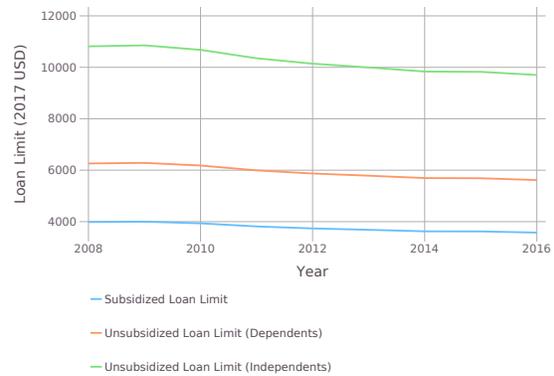
<sup>10</sup>Note that loan limits on unsubsidized federal student loans reflect limits on total (subsidized + unsubsidized) loans.



(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 1: 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 loan limits in 2017 USD for both subsidized (blue) and unsubsidized loans, where the limits differ for dependents (orange) and independents (green).

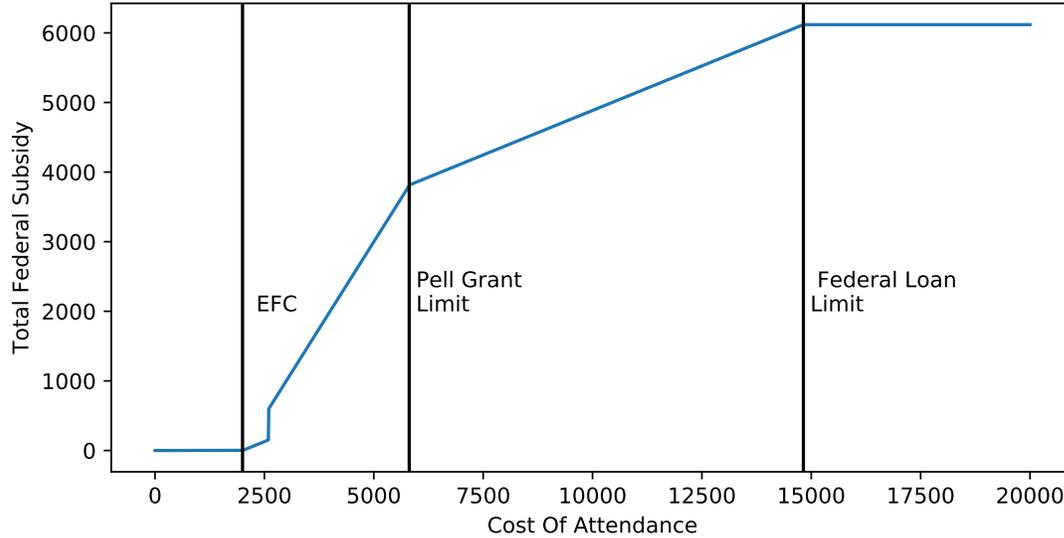


Figure shows the subsidy amount for an example student based on the aid policy in 2016, as a function of cost of attendance. We calculate the subsidy for loans as the difference in total interest payments between federal and private students loans.

Figure 2: Example Subsidy Schedule for Dependent Student in 2016 with  $EFC_i = 2000$

sector, as measured in Panel (b) of Figure 1.

A consequence of this aid structure is that the differences in prices across schools are “compressed”, because high-cost schools are subsidized more than low-cost schools. This may distort student choice and cause them to overenroll in high-price schools, all else equal. Additionally, if a school has a sufficiently low cost of attendance, marginal price increases will be partially absorbed by further student aid subsidies, which incentivizes schools to increase prices. This feature of federal student aid relates to the so-called Bennett Hypothesis that has been studied in past education research documenting a connection between increased student aid and rising college prices [Cellini and Goldin, 2014, Singell Jr and Stone, 2007, Lucca et al., 2019]. We examine this hypothesis in the context of federal aid design by incorporating these distortionary channels into our model of supply and demand in U.S. sub-baccalaureate education.

### 3 Data

We use enrollment and institutional characteristics data on the universe of schools eligible for federal student aid, along with auxiliary data on advertising and student labor market outcomes, to measure the key determinants of how colleges and students behave in this market.

### 3.1 IPEDS

Our main dataset is the Integrated Postsecondary Education Data System (IPEDS) database managed by the USDOE.<sup>11</sup> Each year the USDOE mandates completion of a detailed set of surveys on all aid-eligible postsecondary institutions and keeps the results under the IPEDS system.<sup>12</sup> IPEDS reports data at the campus/branch level. Each observation is a school campus by academic year (July 1st to June 30th the following year). Our sample covers academic years 2008 through 2016. We use the following key surveys from IPEDS.

**Institutional Characteristics** The institutional characteristics survey reports the location of each campus (FIPS county), and its ownership affiliations identified by a 6-digit OPEID. The OPEID helps us identify multiple campus that belong to the same chain. This survey also reports the types of degrees offered by award level (e.g., associate’s degrees, less-than-one-year certificates, etc.), student services offered by the school, tuition, and estimated cost of attendance.

**Fall Enrollment** We collect from the fall enrollment survey the number of first-time students who enroll in each campus,<sup>13</sup> as well as total campus enrollment. We observe both full-time and part-time enrollment, and construct a full-time equivalent (FTE) measure which treats each part-time enrollment as one-third of a full-time student. We observe gender and race composition of each incoming cohort, and the states of residence for every other cohort.

**Completions** We use the completions survey to identify the types of programs offered at each school. The survey reports the number of degrees/certificated awarded each year at the 6-digit CIP code level. We aggregate this to 26 types of student majors according the taxonomy used by the USDOE.<sup>14</sup> For simplicity, we aggregate all academic majors into one “academic” group,<sup>15</sup> since these majors are not commonly offered by FPIs. We also aggregate the marketing, business support, and business management majors into a single “business” major. That leaves us with 11 different majors to differentiate schools in their degree offerings: academic, agriculture, business, communication, computer and information services, consumer services, education, engineering, health sciences, protective services, public services, and manufacturing/construction.

**Student Financial Aid** We collect information on the fraction of full-time first-time students who receive a Pell grant or federal student loans in each academic year. This gives us a measure of

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<sup>11</sup>Link: <https://nces.ed.gov/ipeds/use-the-data>

<sup>12</sup>There do exist some postsecondary education, mostly small FPIs, that do not qualify for federal financial aid program (see e.g 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.

<sup>13</sup>We only consider first-time students who have not attended any other postsecondary institutions in the past as part of each year’s incoming cohort, omitting transfer students. Since transfer students only account for 12% of a school’s annual enrollment on average, we consider our enrollment measure reasonably accurate in capturing the incoming cohort sizes.

<sup>14</sup>Link: [https://nces.ed.gov/surveys/ctes/tables/postsec\\_tax.asp](https://nces.ed.gov/surveys/ctes/tables/postsec_tax.asp)

<sup>15</sup>Academic majors denote visual and performing arts, humanities, interdisciplinary studies, English, natural sciences and mathematics, social sciences, and history.

the proclivity of each school to use the federal student aid programs. We also measure the fraction of aid recipients who live with their parents off-campus, as a measure of students being a dependent.

**Finance** We collect information on the breakdown of revenue and expenses at each school.

## 3.2 Auxiliary Data Sets

We use a number of other datasets to complement our IPEDS data, described below.

**Labor Market Outcomes** We collect information on students' labor market outcomes from College Scorecard Data (CSD), provided by the USDOE. Outcomes are measured for students who received any form of Title IV federal student aid (Pell grants and student loans). Outcomes are reported at the pooled cohort (2 years of entering students) level for each school chain (6-digit OPEID). For each school chain with pooled cohort size 30 or above, we observe average 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.

**Market Demographics** We define a market as a county-year, which is consistent with past market definitions for studies that consider a similar sample of schools, such as Cellini [2009, 2010].<sup>16</sup> We define the potential student population in a county as those who are between 18 and 50 years old and whose highest educational attainment is a high school diploma or equivalent (e.g., GED). We use data from the Census Bureau's American Community Survey (ACS) by the Census to measure the demographics of potential students in each market. For each ACS participant, we observe standard demographic data such as race, income, and gender. We impute the dependent status of each ACS survey participant following the criteria used by the Federal Student Aid Office.<sup>17</sup> We use archives of the simplified EFC formulas provided by the Federal Student Aid Office to impute the EFC of each ACS survey participant and determine their eligibility for federal financial aid, since rules for calculating EFC change over time. (See Appendix A for details.)

**Advertising** We use the AdSpender database by Kantar Media to measure advertising activities by each college chain in each year. AdSpender tracks advertising activities across 17 media platforms (e.g., network TV, spot TV, newspaper). We observe both advertising expenditures and units of ads placed (e.g., # of spot TV slots purchased) by month in each of the top 101 Designated Market Areas (DMA).<sup>18</sup> For television advertising, we also observe the part of the day (e.g. daytime, prime

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<sup>16</sup>According to the 2012 National Postsecondary Student Aid Survey, the median distance for students in sub-baccalaureate colleges to their institution is only 9 miles. We therefore consider it reasonable to assume that people only consider sub-baccalaureate colleges in their counties.

<sup>17</sup>Specifically, we classify someone as a dependent if they meet all of the following criteria: less than 24 years old, not married, has no children, lives with either their mother or father, and is not a veteran or in active military duty.

<sup>18</sup>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.

time), known as daypart, of ads within each month.<sup>19</sup> We manually match the “brand name” in AdSpender to the institution names reported in IPEDS. 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 aggregate advertising activities to the college-chain-by-DMA level.

**Student Intertemporal Preferences** We use data from the USDOE’s Beginning Postsecondary Survey (BPS) survey of students entering college in the 2011-2012 academic year to measure how students discount the future. Respondents were asked whether they preferred \$250 today or  $X \leq 250$  dollars in one year, for varying  $X$ . We use this survey to better understand student preferences towards loans, which are paid back in the future.

**Aid/Student Loan Interest Rates** We collect information on federal loan and Pell grant policy from the Federal Student Aid website. We use the CFPB’s report on private student loans<sup>20</sup> to obtain private loan interest rates. This provides the annual median interest rate for private undergraduate student loans from 2004 to 2011. We impute the private loan interest rate for 2012-2016 by assuming a constant margin (equal to the median 2011 margin) over the 3-month Q3 LIBOR index, the typical risk-free interest rate to which private student loan interest rates are indexed.

### 3.3 Sample Criteria

We now describe how we designate schools to be in the local sub-baccalaureate education market, our sample of interest. We start with all colleges covered by the IPEDS data from 2008 to 2016, for a total of 62,593 school-year observations. 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.<sup>21</sup> Second, we limit our sample to “non-selective” colleges, whose only admissions requirements are a secondary school record, TOEFL score, or other general competency test.<sup>22</sup> Third, we exclude schools that ever offer their programs entirely online or that have over 20% out-of-state enrollment on average. These restrictions limit our sample to schools that service their local market. Finally,

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<sup>19</sup>AdSpender uses the following daypart definitions: daytime is 5am-4pm during the work week (Monday-Friday), early fringe/news is defined as 4pm-8pm during the work week, and 6pm-8pm during the weekend, late news / fringe is defined as 11pm-5am each day, prime time is defined as 8pm-11pm each day, and weekend daytime is 5am-6pm during the weekend.

<sup>20</sup>Source:<https://www.consumerfinance.gov/data-research/research-reports/private-student-loans-report/>

<sup>21</sup>For <1-year and 1-year certificates, we assign a degree-year of 1. For associate’s degrees and 2-year certificates, we assign a degree-year of 2, and for bachelor’s degrees, we assign 4 degree-years. This correction accounts for the fact that students spend more time in longer programs, so that even if the degree takes longer, schools are spending more time educating students in those programs.

<sup>22</sup>Since 2014, IPEDS has explicitly stated in its survey that if schools only are selective on the secondary school record and other test criteria, they are formally open enrollment / nonselective. We view the inclusion of schools that require TOEFL scores as non-restrictive: inspection of the data reveals that these schools are similar in characteristics to schools that do not require this test for admission.

we drop schools outside the top 101 DMAs, where we do not observe advertising. Our final sample consists of 26,367 school-years from IPEDS.

According to our criterion, 60% of counties within the top 101 DMAs have no sub-baccalaureate schools that are eligible for Title-IV aid. Appendix Figure A1 (Panel a) plots the average number of schools during our sample across our markets (U.S. counties). Panel (b) plots the average fraction of schools in a market that are for-profit colleges. 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.

### 3.4 Summary Statistics

Colleges in our sample differ both in their price and advertising decisions, as well as in student demographics. Table 1 shows the key summary statistics for CCs and FPIs in our sample.<sup>23</sup> For comparison, we also include the characteristics of 4-year selective colleges. FPIs account for 68% of colleges in our sample and around 20% of enrolled students.

We highlight a few important stylized facts that motivate our empirical analysis. On average, FPIs charge 4.2 times more in annual tuition than CCs and their students earn 15% less on average 10 years after entering college. Students who attend FPIs are more likely to be female, ethnic minorities, and from low-income households. Many students in the sub-baccalaureate sector use federal aid. At the same time, other forms of aid are sparse in sub-baccalaureate education: students receive an average of \$330 in state aid, and \$158 in institution aid (e.g., scholarships).

FPIs on average spend 4.9 times more than CCs on advertising, and 35.6 times more if we compare advertising per new student. However, not all FPIs invest equally in advertising. Figure 3 shows a binscatter of tuition prices versus advertising per new student by institution type.<sup>24</sup> FPIs that spend more on advertising per student also tend to charge higher tuitions, while there appears to be no relationship between price and advertising for CCs. These patterns are consistent with anecdotal evidence that advertising and marketing help FPIs attract students despite charging high prices. Appendix Figure A3 displays a boxplot of the types of advertising that institution types engage in, among those with positive advertising spending. While CCs use an assortment of media to advertise, FPIs invest the vast majority of their advertising spending (80%) in spot television ads, which are ads that air only in a single DMA.

These colleges also differ in both their funding and spending patterns. CCs on average receive 19% of their revenue from tuition and 70% from government appropriations, which are direct subsidies for operating expenses. In contrast, FPIs on average receive 81% of their revenue from tuition income. CCs on average allocate a larger fraction of their expenses to instruction than student services (46% versus 34%, respectively), while the reverse is true for FPIs (42% versus 46%, respectively). Among those with positive advertising, 6% of FPI spending is invested in

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<sup>23</sup>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.

<sup>24</sup>The number of bins is chosen using the Cattaneo et al. [2019] data-driven method.

Table 1: Summary Statistics

	In Sample		Out of Sample
	(1) Community Colleges	(2) For-Profit Colleges	(3) Selective 4-year Colleges
<b>Panel A: Prices</b>			
Tuition + Fees (2017 \$)	3,767.77 (2,664.47)	15,880.33 (5,352.59)	22,899.30 (12,964.05)
Cost Of Attendance (Living with Family) (2017 \$)	9,395.73 (3,448.83)	21,865.16 (6,886.34)	27,466.69 (12,675.69)
Cost Of Attendance (Living Off-Campus) (2017 \$)	18,219.11 (5,545.26)	32,911.47 (10,580.61)	35,337.46 (13,525.35)
<b>Panel B: School Characteristics</b>			
% Offering Associate's Degree	78.62 (41.00)	30.06 (45.86)	37.03 (48.29)
Number of Majors Offered	11.01 (4.59)	1.85 (1.54)	11.66 (5.25)
Student/Teacher Ratio	19.16 (7.09)	17.22 (8.26)	14.10 (4.76)
% Offering Job placement services	83.41 (37.20)	92.86 (25.75)	81.69 (38.67)
Ad Expenditures in Local Market (2017 \$)	46,888.90 (128,835.34)	228,697.13 (547,845.21)	. (.)
Ad Expenditures/Student in Local Market (2017 \$)	71.95 (283.16)	2,568.83 (9,108.97)	. (.)
Number of TV Ads Aired in Local Market	106.88 (336.14)	1,508.05 (3,017.10)	. (.)
<b>Panel C: Student Composition</b>			
FTE Cohort Size	856.41 (1,007.79)	79.46 (144.11)	886.23 (1,215.73)
% Male	47.82 (12.32)	23.77 (26.79)	46.36 (18.07)
% Black/Hispanic	30.37 (22.91)	44.72 (30.42)	22.53 (21.08)
% Living Off-Campus with Family (Dependents)	48.99 (22.94)	34.22 (22.74)	16.34 (20.53)
% Family Income < \$30,000	66.02 (19.05)	77.75 (19.58)	29.79 (18.82)
% Receiving Pell Grant	54.50 (17.61)	74.31 (18.25)	36.91 (18.87)
% Receiving Federal Loans	20.89 (23.04)	72.16 (26.15)	60.00 (23.71)
<b>Panel D: Outcomes</b>			
Avg Earnings 10 Years After Entry	29,005.48 (5,414.55)	23,763.14 (7,932.13)	47,410.60 (14,066.78)
% Graduating in 150% Normal Time	32.53 (24.18)	64.14 (19.25)	55.36 (19.24)
Observations	7,624	16,651	12,034
Entering Students/Year	1,454,397	589,972	1,171,890

Table displays means for each variable. Standard errors reported in parentheses. Column (1) displays the means for in-sample community colleges. Column (2) displays the mean for in-sample for-profit colleges. Column (3) displays the mean for out-of-sample selective 4-year colleges that are also located in the top 101 DMAs, the geographic sample we use in this paper.

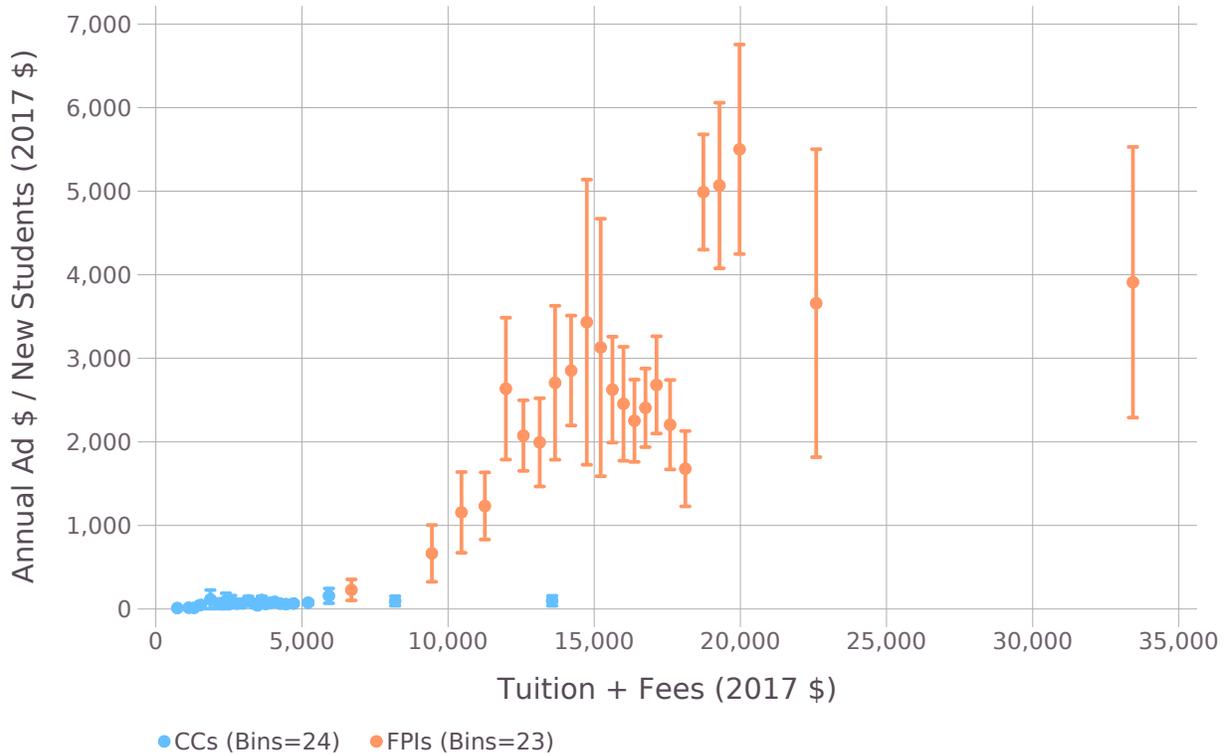


Figure shows a binscatter of the relationship between advertising per new student (defined as total ad expenditures divided by the total number of FTE first-time students) and tuition. The number of bins is chosen using the data-driven optimal bin selection method from the [Cattaneo et al., 2019] package.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

Figure 3: Relationship between Tuition and Advertising Investment by Schools

advertising on average. Note that this measure excludes other FPI marketing activities, such as call centers. Appendix Figure A2 displays a boxplot of spending and expense patterns across these colleges, using the IPEDS financial data. These patterns highlight a key distinction between these two types of colleges. CCs are public service oriented and seek to provide affordable education, but depend on government appropriations for funding. In contrast, FPIs rely on tuition income for revenue and invest in advertising to attract students.

## 4 Price and Advertising Elasticities

We now provide descriptive evidence on how the demand for colleges responds to prices and advertising. We focus on advertising as an additional supply-side input because of its prominence in the FPI business model. To isolate the demand response, we introduce instruments that provide exogenous variation in prices and advertising. In this section, We use these instruments to estimate the price and ad elasticities in the sub-baccalaureate market, in order to understand how college

decisions regarding these inputs influence the demand for higher education. In Section 7, we use these same instruments to estimate preferences for price and advertising in our structural model.

## 4.1 Price Elasticity

To measure the demand response to prices, we estimate the enrollment elasticity with respect to tuition: the sticker price of each college. This sticker price measure differs from the price students actually pay to attend college, due to both auxiliary costs in COA and aid from the federal government, as outlined in Section 2. However, colleges receive revenue from tuition, so it is the relevant price measure for supply-side decision making. Because of the different incentives CCs and FPIs face (broadening college access versus maximizing profits), we expect these schools to set tuition at different parts of the demand curve. Consequently, the tuition elasticities of CCs and FPIs should differ. Tuition may be correlated with unobservable demand shocks, which would bias an ordinary regression estimate of the tuition demand response. Therefore, we estimate the tuition elasticity for each college type (CCs, FPIs) using the following IV regression:

$$\log(q_{j,t}) = \delta_j + \alpha \log(p_{j,t}) + \gamma X_{j,t} + \epsilon_{j,t} \quad (1)$$

$$\log(p_{j,t}) = \delta_{j,1} + \phi Z_{j,t} + \gamma_1 X_{j,t} + \epsilon_{1,j,t} \quad (2)$$

where  $Z_{j,t}$  is an instrument for tuition  $p_{j,t}$ ;  $q_{j,t}$  denotes first-time FTE enrollment at school  $j$  in market  $t$ ; and  $\alpha$  denotes the tuition elasticity of demand. We include as controls  $X_{j,t}$  market-level demographics<sup>25</sup> and school characteristics,<sup>26</sup> in addition to school fixed effects  $\delta_j$ . To construct instruments for CC and FPI tuition, we use policy variation that exploit the institutional characteristics of these colleges in terms the types of aid each college type relies on for revenue.

### 4.1.1 For-Profit College Tuition Instrument

To instrument for FPI tuition, we leverage politically motivated changes to the Pell grant program that FPIs depend on for student subsidies. Given that FPIs receive 76% of their revenue on average from federal aid programs,<sup>27</sup> these schools may be particularly responsive to aid when setting prices. This conjecture is borne out in the data: the correlation between average (weighted by enrollment) FPI tuition over time and the annual maximum Pell grant is 0.75, while the correlation is only 0.36 for community colleges. (See Appendix Figure A4 for the time series.)

Our instrument for FPI prices exploits variation in the national Pell grant policy during our sample, generated by changes in political power in Washington. Two noteworthy policy shifts occur

<sup>25</sup> Defined as the fraction of students in the market (ages 18-50, high school education, same county) that are male, dependent, Black, Hispanic, unemployed, and the logged market size.

<sup>26</sup> 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).

<sup>27</sup>Source: Author's calculations using data from <https://studentaid.gov/data-center/school/proprietary>

in the maximum Pell grant in our sample period. In Panel (a) of Figure 1, the spike in Pell grant aid between 2008 and 2010 represents increases in student aid prioritized by the newly minted left-leaning Obama administration. The decline from 2010 to 2012 follows the 2010 midterms, when Republicans retook the House of Representatives and controlled federal budgeting. After 2012, Republicans maintained control of budgeting.

FPIs in poorer (low EFC) markets should be more exposed to changes in Pell grant policy, since their potential students are more eligible for aid. However, temporal changes in EFC may be correlated with demand for education, which is countercyclical to economic growth [Dellas and Sakellaris, 2003]. To leverage only geographical differences in exposure, we construct a “simulated instrument” [Gruber and Saez, 2002, Biasi, 2019], the expected maximum Pell grant in market  $t$ , conditional on the *pre-period* (2006) distribution of EFC.<sup>28</sup> Let  $m(t), y(t)$  denote the county  $m$  and year  $y$  of market  $t$ , respectively. The simulated Pell grant instrument is defined as follows:

$$Z_t^\pi = E_F[\bar{\pi}|m(t), y^{\text{Pell}} = y(t), y^{\text{EFC}} = 2006] = \int_e \bar{\pi}(e, y(t)) \partial F(e|m(t), y(t) = 2006) \quad (3)$$

$$\bar{\pi}(e, y) = \mathbb{1}\{e \leq \overline{EFC}_y - \underline{\pi}_y\} \times \max\{\bar{\pi}_y - e, 0\} \quad (4)$$

where  $F(e|m, y)$  denotes the distribution of EFC in year  $y$  and county  $m$  among potential students, and  $\bar{\pi}(e, y)$  is the maximum Pell grant award in year  $y$  for a student with EFC  $e$ . In other words, our instrument is the expected maximum Pell grant in a county  $m$  in 2006, if the market had been exposed to the Pell grant policy in year  $y$ . Two factors provide variation to this instrument: annual changes to the national Pell grant policy (governed by  $\underline{\pi}_y, \bar{\pi}_y, \overline{EFC}_y$ ) and the pre-period EFC distribution in  $t$ . Within year  $y$ , shifts in  $Z_t^\pi$  from an increase in Pell grant generosity are larger for colleges located in counties that had a larger share of low-income students in 2006. This shift-share design is similar in spirit to the instrument used by Lucca et al. [2019] to identify the effect of federal aid on tuition prices. Appendix Figure A5 plots the expected maximum Pell grant by market in 2006. The standard deviation of the pre-period expected Pell grant across U.S. counties is \$1500, roughly 25% of the maximum Pell grant in later periods, so there is significant geographical variation in aid eligibility in the pre-period. Because we include school fixed effects, we remove variation in  $Z_t^\pi$  solely attributable to cross-sectional variation in EFC across counties. Doing so allows us to isolate changes in the instrument used to identify the tuition elasticity to changes in national policy.

**Validity of Instrument** Our exclusion restriction relies on the assumption that the policy variation in the Pell grant program captured in our simulated instrument only affects demand through the changes induced to tuition, and this policy variation is uncorrelated with local demand shocks. One obvious violation of this exclusion restriction is that when Pell generosity increases, student aid increases, which would increase demand for education independent of the tuition price (since

<sup>28</sup>2006 is the first year available in the ACS with the demographic information required to measure a student’s EFC. In each year, we index both the distribution of  $EFC$  and the maximum Pell  $\bar{\pi}(e, y)$  to the CPI so that across years, values are understood in terms of 2017 USD.

students now have to pay a lower price to attend college). To address this concern, we limit our estimation of the FPI tuition elasticity for descriptive purposes to enrollment of students who do not receive Pell grants. Due to the high price of FPIs, this restriction effectively corresponds to students whose EFC is above the national limit  $\overline{EFC}_y$ .<sup>29</sup> We interpret the tuition elasticity estimated for this group as the tuition elasticity for high-income students (25% of students at FPIs). This elasticity may differ from the tuition elasticity of low-income students; however, without detailed microdata on student net prices, or imposing more structure that accounts for the net aid each student receives, we cannot reliably estimate the tuition elasticity for Pell-eligible students at FPIs. In our structural model (Section 6), we explicitly account for this channel by specifying student preferences to be over their net price after receiving both federal aid and loans.

Thus, our identification strategy is as follows: policy variation from the Pell grant program leads to further aid for Pell-eligible students, which FPIs capture by increasing tuition. For ineligible students, there is no corresponding increase in aid. Consequently, the enrollment response to tuition changes generated by the Pell grant policy reflects a demand response for ineligible students.

#### 4.1.2 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 policy. The binding constraint for most community colleges in terms of how tuition is set is the level of aid they receive from state and local governments. 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 from it, as an instrument for community college tuition. 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 of student (e.g., higher ability students) and where students reside. Our instrument for CC tuition is defined as the average tuition of 4-year public colleges in the same state, at least 100 miles away.<sup>30</sup> We denote this instrument as  $\bar{p}_{j,t,100}^{4yr}$  in the paper.

**Validity of Instrument** Our exclusion restriction relies on the assumption that demand shocks for community colleges are uncorrelated with the shifts in tuition of geographically distant public 4-year colleges in the same state. By choosing prices of 4-year public colleges, rather than other

<sup>29</sup>According to the 2012 National Postsecondary Student Aid Survey (NPSAS), a nationally representative survey of federal student aid recipients, only 15% of students below the national EFC limit do not receive a Pell grant when attending a sub-baccalaureate FPI.

<sup>30</sup>For 95% of community colleges, there is at least one public 4-year institution in the same state at least 100 miles away. For those CCs that do not meet this condition, we use the tuition of the farthest public four-year institution in the state as our instrument.

two-year colleges, we ensure that prices are taken from colleges that are unlikely to attract similar students, that rely on similar funding sources. For example, 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.

By choosing to include prices of schools 100 miles away, we ensure CCs and public 4-year colleges are not subject to similar local demand shocks for education. According to the 2012 NPSAS, 100 miles is the 79th percentile of distance for students attending a 4-year public college and the 95th percentile for community college attendees. In Appendix Figure A6, we explore whether the distance chosen for our tuition instrument is an important factor. Specifically, we regress CC tuition on the average tuition for 4-year public schools in the same state greater than 0 to 200 miles.<sup>31</sup> The figure documents that the effect of 4-year tuition does not vary over distance. This result suggests that the relevant variation from 4-year tuition used to instrument for CC tuition comes from centralized changes to education policy at the state level, rather than from local demand shocks.

## 4.2 Advertising Elasticity

We measure advertising in terms of television<sup>32</sup> ad units (number of commercials placed in the local television market) over a year.<sup>33</sup> We treat our measure of advertising units as a proxy for the number of ad views or impressions, which is unavailable in AdSpender. To better approximate impressions, we normalize the number of ads placed by each college to the equivalent number of viewers it would reach during the daytime daypart.<sup>34</sup> Though there is little prior literature on FPI advertising, investigative reports suggests FPI advertising is qualitatively different, and more persuasive, than traditional college advertising [GAO, 2010]. For this reason, we estimate the advertising elasticity separately by institution type (CC vs. FPI). Analogously to Equation 2, we estimating the advertising elasticity via an IV regression of log enrollment  $\log(q_{j,t})$  on logged advertising  $\log(a_{j,t} + 1)$ , with the same set of controls. We now describe the instrument used to generate exogenous variation in college advertising.

<sup>31</sup>We restrict the sample to schools with at least one 4-year school 200 miles away, the 90th percentile of distance from a student’s home and college, conditional on attending a selective 4-year public college (Source: NPSAS 2012 survey). This maintains sample consistency for each estimate. We only include school fixed effects in these regressions.

<sup>32</sup>Television advertising constitutes 73% of local advertising spending by FPIs in our sample

<sup>33</sup>The relevant advertising year is defined from November of year  $y - 1$  to October of year  $y$ . IPEDS’ fall enrollment measures are counts as of October 15th for academic calendar schools, and between August and October for non-academic schools, so this timeframe captures the total advertising that a new student may have been exposed to.

<sup>34</sup>For example, a television ad placed during primetime is likely to reach more viewers than an ad in the middle of the day. We perform this normalization by using the American Time Use Survey (ATUS), for which respondents keep a diary of their activities throughout the day. For each daypart, we calculate the average probability that respondents are watching television. We convert non-daytime ads to the equivalent number of daytime ads by multiplying by the likelihood an individual is watching television in each daypart. These weights are as follows: Daytime=1, Early News/Fringe=3.1, Late News/Fringe = 0.8, Primetime = 5.9, and Weekend Daytime = 1.9. We note that our results are qualitatively similar when we do not weight ads by daypart reach.

### 4.2.1 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 et al. [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 challenge we face 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 A7 plots the average number of spot TV ads placed by political advertisers<sup>35</sup> 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 estimate the month-level effect of political advertising on colleges. Second, we aggregate these effects to an annual level using each college’s propensity to advertise in a given month.

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

$$\log(a_{f,d,y,m} + 1) = \alpha_{f,d} + \delta_y + g_c\left(\log(P_{d,y,m} + 1)\right) + \bar{\gamma} \log(\bar{n}_{f,y,m} + 1) + \beta \log(p_{N,m,y}) + \epsilon_{f,d,m,y} \quad (5)$$

where  $a_{f,d,y,m}$  is college firm  $f$ ’s television advertising in the local DMA  $d$  in year-month  $y, m$ .  $\alpha_{f,d}$  denotes firm (OPEID×DMA) fixed effects. Year fixed effects  $\delta_y$  capture common level differences across election (and non-election) years in advertising.<sup>36</sup> We specify  $g_c$  as a 3rd-degree orthogonal polynomial [Golub and Van Loan, 2013] to capture the non-linear effect of political advertising.<sup>37</sup> For controls, we include national (cable, syndication, and network television) TV ads placed in month-year  $m, y$  by firm  $f$ , denoted  $\bar{n}_{f,m,y}$ , as well as the average price of national network television advertising across all advertisers  $p_{N,m,y}$ . 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 5 is the set of year-months of our sample of colleges, starting in the first month a school chain begins advertising in a DMA.

Appendix Figure A8 plots the estimated linear and nonlinear effect of political advertising on college advertising. Across CCs and FPIs, we generally see a decline in college advertising when political advertising increases. The linear specification masks an increased effect from large amounts of political advertising for CCs.

<sup>35</sup>We define political advertising, as in Moshary et al. [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”.

<sup>36</sup>We deviate from Moshary et al. [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).

<sup>37</sup>Our instrument works using a simple linear specification in logged political advertising but has less power.

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

$$Z_{f,d,t}^A = \sum_{m=1}^{12} w_{f,d,m} \times \hat{g}_c(\log(P_{d,m,t}) + 1) \quad (6)$$

To construct our weights  $w_{f,d,m}$ , we use a firm’s advertising likelihood during non-election (odd-numbered) years to estimate the advertising propensity of each college chain in a month. We calculate the average share of firm  $f, d$  purchasing ads in month  $m$  as follows:

$$w_{f,d,m} = \frac{1}{N_{\text{NE},f,d}} \sum_{y:\text{mod}(y,2)\neq 0} \frac{a_{f,d,m,y}}{\sum_{n=1}^{12} a_{f,d,n,y}} \quad (7)$$

where  $N_{\text{NE},f,d}$  denotes the number of non-election years we observe positive advertising.<sup>38</sup> 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.

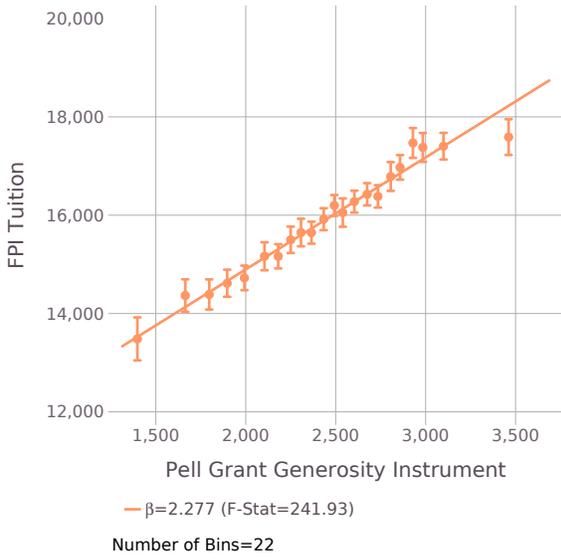
**Validity of Instrument** In terms of the exclusion restriction, Moshary et al. [2021] highlight three major threats in our context. First, demand shocks in education may change the equilibrium amount of local advertising. The product categories in which our schools fall account for 2.8% of non-cable TV commercials on average in a given month-DMA, suggesting little scope for this market affecting aggregate advertising in a DMA. Second, education markets may be “pivotal” to an election. While education is a political topic, historically it has not been a top priority for voters. Using data from Gallup’s Most Important Problem question,<sup>39</sup> only 2.6% of respondents from 2008 to 2016 reported education to be the most important issue, and the average rank of education being the most important issue ranges from 11 to 13, suggesting it is not a primary motivator when Americans make voting decisions. Third, colleges may substitute to national advertising. Our controls for national advertising in Equation 5 alleviate this concern, and in practice national advertising is relatively infrequent.

### 4.3 Elasticity Estimates

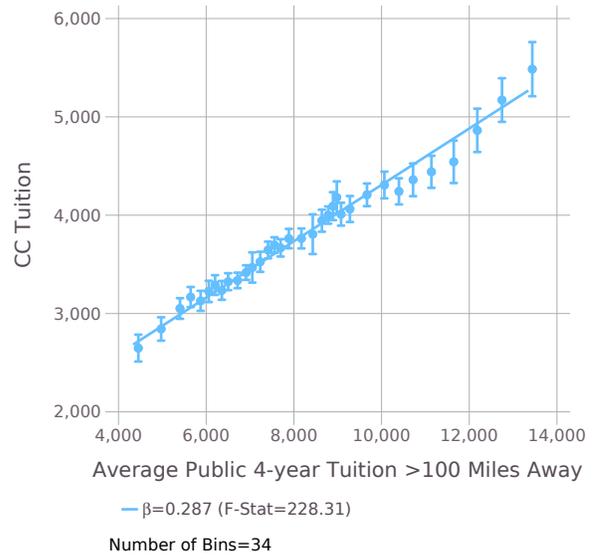
Figure 4 plots a (residualized) binscatter for tuition and advertising, by college type, against each relevant instrument. Each regression in the figure includes as controls school fixed effects, market-level demographics, and school characteristics. The coefficient from regressing for-profit tuition on the simulated Pell grant instrument is 2.3 (Panel (a)). In Appendix B, we show via an IV regression

<sup>38</sup>We observe advertising for 94% of firms in non-election years. For the remaining 5%, we use the leave-one-out share, the average propensity  $s_{f,d,t,m}$  in all other years besides  $t$ . Less than 1% of firms only advertise in one year, for which we simply use observed contemporaneous shares.

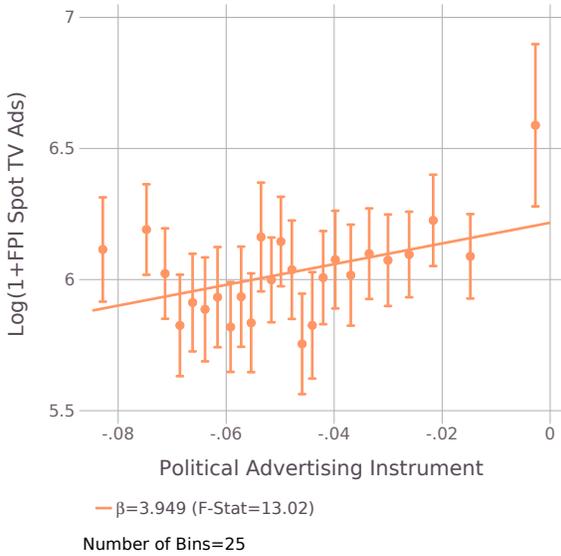
<sup>39</sup>Downloaded from the Comparative Agendas Project:  
[https://www.comparativeagendas.net/datasets\\_codebooks](https://www.comparativeagendas.net/datasets_codebooks)



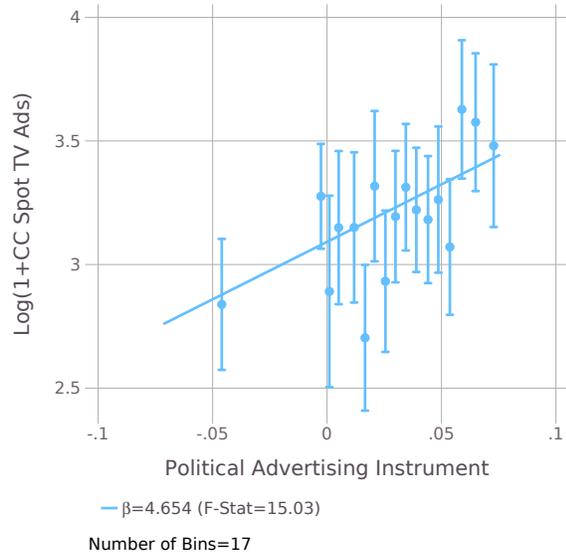
(a) For-Profit College Tuition



(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 characteristics. Market demographics and school characteristics are defined in footnotes 25 and 26, 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 4: Binscatter of Endogenous Variables (Tuition and Advertising) on Instruments, by College Type

Table 2: Price Elasticities, by College Type

	FPIs	CCs	
	(1) Log(FT Non-Pell)	(2) Log(FTE Enrollment)	(3) Log(FT Non-Pell)
Log(Tuition)	-2.549*** (0.378)	-0.437*** (0.066)	-0.809*** (0.085)
Observations	15,714	7,829	7,689
School FE	Yes	Yes	Yes
School Characteristics	Yes	Yes	Yes
Market Demographics	Yes	Yes	Yes
First Stage F-Stat	319.52	354.69	423.70
Endogeneity Test p-value	0.000	0.000	0.000

Table displays IV estimates of the relationship between first-time enrollment and tuition. Regressions are done separately for community colleges and for-profit colleges. Standard errors reported in parentheses are clustered at the school level. Log(FT Non-Pell) denotes the logged full-time, first-time enrollment of students who do not receive a Pell grant. Log(FTE Enrollment) denotes the logged full-time equivalent, first-time enrollment at each school. Market demographics and school characteristics are defined in footnotes 25 and 26, respectively. First-stage F-statistic denotes the F-statistic for the excluded instruments (tuition instruments) in the first-stage regression with log tuition as the dependent variable. Endogeneity Test p-value denotes the p-value from comparing the Sargan-Hansen statistics of two regressions where tuition is treated as exogenous and endogenous, respectively. \* $p < .1$ , \*\*  $p < .05$ , \*\*\*  $p < .01$

that the first-stage coefficient translates to a \$0.79 increase in FPI tuition for each additional federal aid dollar received by students, while CC tuition does not change when federal aid per student is increased. Panel (b) displays a binscatter regressing geographically distant 4-year tuition on CC prices. A \$1 increase in  $\bar{p}_{j,t,100}^{4yr}$  translates to a \$0.29 increase in CC prices in the same state-year. Both instruments have large F-statistics, confirming they provide relevant variation in prices. Panels (c) and (d) plot the relationship between TV ads purchased by colleges and the political advertising instrument, by college type.<sup>40</sup> Because the monthly effect  $g_c$  from political advertising is negative, we expect a positive relationship between college advertising and our instrument  $Z_{f,d,t}^A$ . The F-statistic is in both cases weaker than our price instruments, but reasonably high.

Table 2 displays our estimated price elasticities for FPIs and CCs.<sup>41</sup> In Column (1), we estimate a price elasticity of -2.5 for higher income, Pell-ineligible students at FPIs. This result suggests that non-Pell students are fairly price elastic. However, these students are also those that are least likely to qualify for student aid, so this may not be reflective of the overall market price elasticity at these schools. In Column (2), we estimate a price elasticity of -0.43 for CC FTE first-time enrollment. This estimate suggests CCs are not maximizing profits, since prices are set in the inelastic portion of the demand curve. In Column (3), we show the effect of CC prices on non-Pell enrollment at these schools, as in Column (1), to provide a comparable estimate to the

<sup>40</sup>These binscatters are done on the subset of colleges for which we ever observe advertise in our sample, that have the weights necessary to construct the political advertising instrument.

<sup>41</sup>IPEDS does not provide data on part-time non-Pell students.

Table 3: Advertising Elasticities, by College Type

Outcome: Logged FTE First-time Enrollment	CCs		FPIs	
	(1)		(2)	
	Log(TV Ads + 1)	0.018 (0.034)	0.381** (0.150)	
Observations	7,828	17,601		
School FE	Yes	Yes		
School Characteristics	Yes	Yes		
Market Demographics	Yes	Yes		
First Stage F-Stat	14.38	10.74		
Endogeneity Test p-value	0.556	0.000		

Table displays IV estimates of the relationship between first-time enrollment and television advertising. Regressions are done separately for community colleges and for-profit colleges. 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 and school characteristics are defined in footnotes 25 and 26, respectively. 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. Endogeneity Test p-value denotes the p-value from comparing the Sargan-Hansen statistics of two regressions where tuition is treated as exogenous and endogenous, respectively.

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

FPI price elasticity we show. The price elasticity is larger in magnitude, suggesting higher income students are more price elastic, but is still significantly below our estimate for FPI price elasticity, suggesting CCs and FPIs face different price elasticities in this market. However, the results in this column should be interpreted with caution since the outcome variable is the logged 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.<sup>42</sup>

Table 3 displays our estimated advertising elasticities by college type. We estimate an advertising elasticity of 0.38 at FPIs, while the CC advertising elasticity is 0.02 and insignificantly different from zero, despite the fact that we estimate a comparable first stage in terms of instrument strength. This large ad elasticity for FPIs is consistent with the anecdotal and empirical evidence that for-profit college advertising is highly persuasive [GAO, 2010]. An endogeneity test of CC advertising suggests that CCs are not strategic with respect to demand when advertising.<sup>43</sup> These results suggest FPI advertising is an important component of student demand, while CC advertising is negligible for student choice.

We also investigate how the advertising response differs by consumer demographic. Appendix Table A1 shows differences in advertising response in terms of FTE enrollment by gender, race,

<sup>42</sup>According to the 2012 NPSAS, about 35% of Pell-eligible students do not receive Pell grants when they attend a community college.

<sup>43</sup>This test is done by comparing the Sargan-Hansen statistics robust to heteroskedasticity from two regressions where price and advertising are treated as exogenous and endogenous.

Pell status,<sup>44</sup> and age of student.<sup>45</sup> Because some schools contain a zero cell count for some of these demographics (e.g., no white students are enrolled), we use the inverse hyperbolic sine (IHS) transformation in place of the log [Burbidge et al., 1988], which approximates the log but incorporates zero values. The only statistically significant differences are for gender ( $p = 0.043$ ) and Pell status ( $p = 0.075$ ), and the only sub-group with a statistically insignificant effect are non-Pell students. These findings suggest that a broad set of demographic subgroups are responsive to FPI advertising.

## 5 Estimating Quality of Sub-Baccalaureate Colleges

Three-quarters of sub-baccalaureate awards issued in our sample are in vocational education, which focuses on training students to obtain higher quality jobs. With this in mind, we measure school quality as the *value-added* of schools in terms of the long-run<sup>46</sup> labor market earnings they generate for students, measured as earnings ten years after initial enrollment.

We must address three challenges in estimating the value-added of colleges. First, as is typical in research estimating the value-added of colleges [Cunha and Miller, 2014, Carrell and Kurlaender, 2016, Hoxby, 2018, Mountjoy and Hickman, 2020], student characteristics affecting earnings may be correlated with college choice. Second, unlike in prior work on value-added in higher education, the relative differences across schools are insufficient in order to answer our policy questions of interest. The *level* of value-added, relative to no higher education, is key to understanding whether the sub-baccalaureate education sector is productive and policymakers should incentivize more participation. Third, our outcomes data are at the cohort (college chain  $\times$  year) level, which means that existing methods in the value-added literature that rely on student microdata [Chetty et al., 2011, Mountjoy and Hickman, 2020] are infeasible in our setting. In this section, we describe a model of potential student outcomes that attempts to overcome these challenges and provide us with a method to consistently estimate the value-added of each college.

We assume the following linear model for the outcome of student  $i$  in labor market (commuting zone  $\times$  year)  $l$ <sup>47</sup> attending school chain  $j$ , where  $j = 0$  denotes the option of not attending college:

$$\underbrace{Y_{i,j,l}}_{\text{Student Outcome}} = \underbrace{\delta_{i,l}}_{\text{Labor Market Shock}} + \underbrace{\eta_i}_{\text{Student Ability}} + \underbrace{\psi_j}_{\text{Value-Added}} \quad (8)$$

where  $\delta_{i,l}$  represents a labor market shock;  $\eta_i$  reflects the individual’s effect on outcomes unrelated to labor market conditions; and  $\psi_j$  denotes value-added. We normalize  $\psi_0 = 0$ , so that value-

<sup>44</sup>As before, for this measure, we only use full-time students since part-time data is unavailable

<sup>45</sup>Age of students is only reported at the total undergraduate level and only required to be reported every 2 years, so the sample size is smaller for these regressions

<sup>46</sup>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

<sup>47</sup>This definition of labor market allows us to use a larger sample of local no-college workers to achieve covariate balance during estimation, but results are very similar if we restrict our definition of labor market to county  $\times$  year.

added is relative to no college.  $\delta_{i,l}$  captures the relevant conditions in labor market  $l$  that shift a student’s earnings. For example, this variable could capture a local unemployment shock that has a differential effect on older versus younger workers.  $\eta_i$  captures the component of outcomes related to student ability. For example,  $\eta_i$  could capture a student’s effort/motivation to earn high wages. The two student-specific terms,  $\delta_{i,l}$  and  $\eta_i$ , underscore the fact that we must consider both the labor market conditions relevant for the potential outcome associated with no higher education, as well individual student ability. These factors may be correlated with college choice.

Let  $D_{i,j,l}$  be an indicator for individual  $i$  choosing school chain  $j$  in market  $l$ . In the College Scorecard dataset, we observe the mean outcome of each college cohort,  $\bar{Y}_{j,l} = \frac{1}{N_{j,l}} \sum_{i:D_{i,j,l}=1} Y_{i,j,l}$ . In terms of our outcomes model, the mean outcome has the following expected value:

$$E[\bar{Y}_{j,l}] = E[Y_{i,j,l}|D_{i,j,l} = 1] = E[\eta_i|D_{i,j,l} = 1] + E[\delta_{i,l}|D_{i,j,l} = 1] + \psi_j \quad (9)$$

Equation 9 reveals that if we only used the observed outcomes to estimate value-added, our estimates may be biased due to selection. For example, students that know the local economy is booming (e.g., high  $\delta_{i,l}$ ) may choose to enter the labor market directly out of high school. At the same time, there may be positive selection between  $\eta_i$  and  $\psi_j$  (e.g., high ability students choose high quality schools). We deal with these unobserved outcome shifters using a two-step approach.

**Measuring Outside Option Earnings** First, we construct a measure of cohort earnings under the outside option of no college,  $E[Y_{i,0,l}|D_{i,j,l} = 1]$ . To do so, we use ACS microdata to create a matched sample of no-college individuals who are the same labor market  $l$  who are demographically identical to enrollees at school  $j$  in market  $l$ . Let  $\mathbf{X}_i^0$  denote a set of demographics observable for both college and non-college individuals. This set of data includes race-gender cells, age-gender cells, and the veteran status of students. Our first identification assumption is that the labor market shock  $\delta_{i,l}$  is independent of enrollment decisions, conditional on labor market  $l$  and demographics  $\mathbf{X}_i^0$ :

$$E[\delta_{i,l}|l, \mathbf{X}_i^0, D_{i,j,l}] = E[\delta_{i,l}|l, \mathbf{X}_i^0] \quad (10)$$

We also assume that  $\eta_i$  is independent of the decision to not attend college, conditional on  $\mathbf{X}_i^0$ :<sup>48</sup>

$$E[\eta_i|X_i^0, D_{i,0,l} = 1, l] = \beta_0 \mathbf{X}_i^0 \quad (11)$$

The intuition for our identification assumptions is that labor market, age, gender, race, and veteran status are sufficient controls for selection bias related to earnings on the *extensive* margin: whether or not to pursue non-selective higher education. By additionally conditioning on the labor market  $l$ , we implicitly control for market-level differences relevant for the decision to not attend college, such as local college market structure. Our identification assumptions in Equations 10 and 11 allow us to recover a consistent estimate of  $E[Y_{i,0,l}|D_{i,j,l} = 1]$  from the ACS data.

<sup>48</sup>If  $\eta_i$  is non-linear in these characteristics, our identification assumption in Equation 11 is equivalent to assuming the residual of a linear projection of  $\eta_i$  on observables  $\mathbf{X}_i^0$  is independent of the decision to not attend college.

Our empirical approach is to construct a matched sample of high school graduates for each cohort using the entropy-balancing routine of Hainmueller [2012]. Details are given in Appendix D. This estimator is particularly well-suited to achieving balance on covariates  $\mathbf{X}_i^0$ , while remaining compatible with the College Scorecard data, which only reports cohort-level moments. This yields an estimate of the cohort-level earnings under no college education, denoted  $\tilde{Y}_{j,l}$ .

**Selection Between Colleges** Second, we control for a rich set of observable characteristics to partial out selection bias among college students. While we use a set of basic, pre-determined characteristics  $\mathbf{X}_i^0$  to control for selection bias in the decision to not attend college, these characteristics may be insufficient controls to capture student selection between schools, the *intensive* margin of education selection. For example, Denice [2015] studies both the extensive and intensive margin of selection for students in the for-profit sector and finds that selection bias is more likely when comparing students at different types of schools, relative to comparing students attending FPIs to high school graduates.

Let  $\mathbf{X}_i^1$  be an expanded set of student characteristics such that  $\mathbf{X}_i^0 \in \mathbf{X}_i^1$ . We include in  $\mathbf{X}_i^1$  the full set of observables available in the College Scorecard. Details can be found in Appendix D. This includes number of schools applied to, parental education level, and prior earnings. By controlling for prior earnings, we follow the previous literature that has used prior outcomes as a control for estimating value-added [Chetty et al., 2011]. Our third identification assumption is that student ability is independent of school choice within the higher education sector, conditional on  $\mathbf{X}_i^1$ :

$$E[\eta_i | X_i^1, D_{i,j,l} = 1, j \neq 0] = \beta_1 \mathbf{X}_i^1 \quad (12)$$

Assumptions 10-12, imply the following expected value of the cohort mean, net the matched high school cohort mean:

$$E[\bar{Y}_{j,l} - \tilde{Y}_{j,l}] = \psi_j + \beta_1 \bar{\mathbf{X}}_{j,l}^1 - \beta_0 \bar{\mathbf{X}}_{j,l}^0 \quad (13)$$

This equation suggests that we can recover a consistent estimate of value-added by regressing  $\bar{Y}_{j,l} - \tilde{Y}_{j,l}$  on  $\bar{\mathbf{X}}_{j,l}^1$  and school fixed effects. To estimate value-added, we run a weighted least squares regression of Equation 13, weighting by the variance of  $\bar{Y}_{j,l} - \tilde{Y}_{j,l}$ . Because some cohorts in the College Scorecard Dataset are small, our initial estimates of  $\psi_j$  from the school fixed effects may be noisy. Following the procedure in Chandra et al. [2013], we apply an empirical Bayes shrinkage estimator to our value-added estimates, to “shrink” these estimates toward a prior mean. Our empirically-based prior is  $\psi_j \sim N(W_j \zeta, \sigma_\psi^2)$ , where  $W_j$  are school chain characteristics.<sup>49</sup> Details are given in Appendix D. We treat the empirical Bayes estimate of  $\psi_j$  as the true value-added  $\psi_j$  of each chain.<sup>50</sup>

<sup>49</sup>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  $\bar{W}_j$  of a chain across campuses for our prior.

<sup>50</sup>The College Scorecard data suppress the average 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

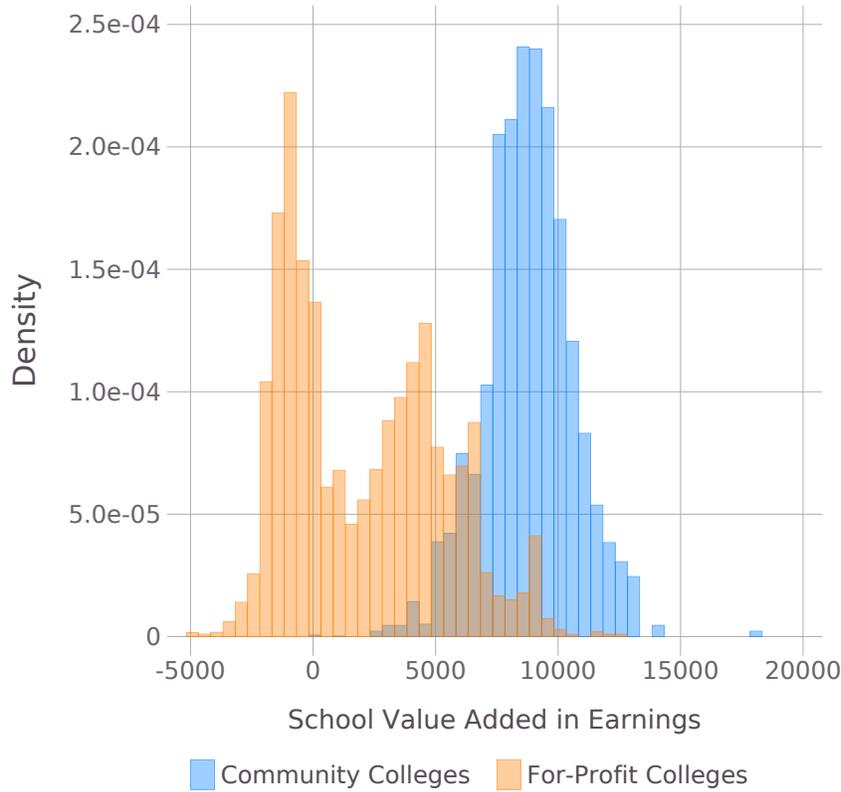


Figure shows the value-added of each school, measured in terms of the earnings generated by each institution ten years after enrolling in the institution for the first time. Though we estimate value-added at the school chain level, we plot the figure at the school (campus) level, since this is the unit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

Figure 5: Distribution of Value-Added Across Schools, By College Type

**Quality Estimates** Figure 5 shows the distributions of estimated value-added in terms of 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 in value-added across community colleges and for-profits are comparable to findings of Cellini and Turner [2019]. 37% of FPI chains have negative value-added, implying education at these schools is worth less than one or two years of experience in the labor market, at least in terms of earnings. Quality varies considerably across FPIs. The standard deviation of value-added is \$3,200 for FPIs and \$1,800 for CCs, and some FPIs possess value-added that compare well to CCs.

Table A2 displays the estimates of  $\zeta$ , which tells us how school characteristics are related to value-added. School characteristics explain a large fraction of the variation in value-added across schools. In particular, schools that offer majors in consumer services, business, and shorter degrees have lower value-added, while schools offering majors in health sciences, engineering, and associate’s by enrollment. For these schools, we estimate their quality using the prior mean  $VA_j = W_j\zeta$ .

degrees have higher value-added. Appendix Figure A9 decomposes the value-added estimates in terms of employment probability, and annual earnings conditional on employment by estimating the value-added of each school for these outcomes. The results indicate that while FPIs help students obtain employment, they tend to place students in low-paying jobs.

We also explore the correlates between quality and the strategic inputs of colleges. Figure 6 shows that among FPIs, schools with higher value-added tend to charge higher tuition and spend more on advertising per entering student. The positive correlation between quality and price may reflect higher costs to providing higher quality education. The positive correlation between advertising and quality also suggests that advertising by FPIs may inform prospective students about the quality of the college. On the other hand, some schools with the worst value-added also charge high tuition and invest heavily in advertising.

## 6 Model

In this section, we describe the structural model we use to estimate supply and demand in the sub-baccalaureate education market. On the demand side, consumers (potential students) have heterogeneous preferences over school characteristics, and their price preferences depend on net student prices, the net present value of student payments accounting for aid and loan payments. On the supply side, we use two conduct models that account for the differing incentives private and public colleges face. Later, in Section 9, we use our equilibrium model to understand the outcomes generated by new aid designs in equilibrium.

### 6.1 Student Choice

Given that sub-baccalaureate schools are non-selective, we model college demand as a discrete choice problem, as in Berry et al. [1995]. We define the geographic market for each college as the county it is located in, as in Cellini [2010]. Our market definition in a county is all individuals aged 18-50 with only a high school education in a given year. The utility derived from consumer  $i$  attending school  $j$  in market  $t$  is defined as:

$$u_{i,j,t} = -\alpha_i p_{i,j,t} + \lambda_i \log(a_{f(j),t} + 1) \times \mathbb{1}\{\text{FPI}_j\} + \gamma_i X_{j,t} + \delta_j + \xi_{j,t} + \epsilon_{i,j,t} \quad (14)$$

$$p_{i,j,t} = OOP_{i,j,t} + \beta_i L_{i,j,t} \quad (15)$$

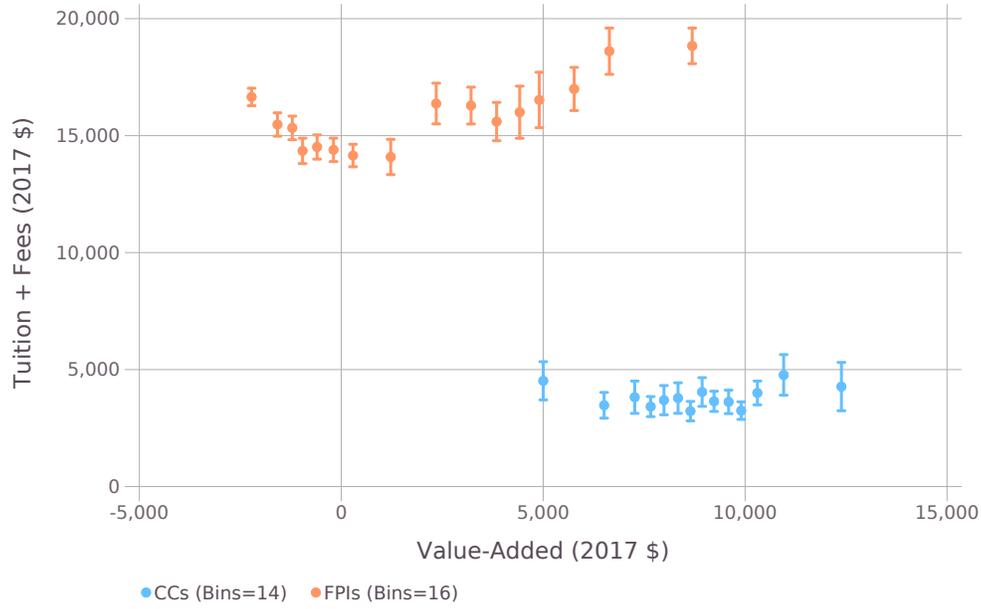
$$\alpha_i = \exp(\alpha + \Pi'_\alpha D_i + \sigma_\alpha v_{i,\alpha}) \quad (16)$$

$$\beta_i = \frac{\exp(\beta + \Pi'_\beta D_i + \sigma_\beta v_{i,\beta})}{1 + \exp(\beta + \Pi'_\beta D_i + \sigma_\beta v_{i,\beta})} \quad (17)$$

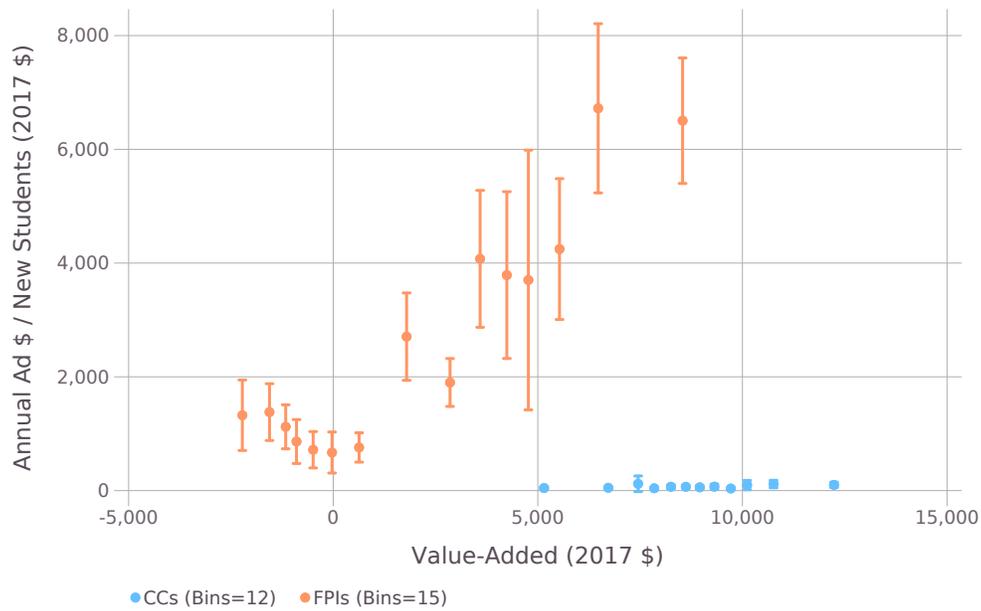
$$\lambda_i = \lambda + \Pi'_\lambda D_i + \sigma_\lambda v_{i,\lambda} \quad (18)$$

$$\gamma_i = \gamma + \Pi'_\gamma D_i + \Sigma \bar{v}_i \quad (19)$$

where  $p_{i,j,t}$  is the net price *paid* by students. This is a function of a college's tuition, auxiliary costs in the cost of attendance, federal financial aid policy, and a student's EFC and dependency status.



(a) Value-Added and Tuition



(b) Value-Added and Advertising

Each panel shows a binscatter of the relationship between a variable and value-added. 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 6: Relationship between Value-Added and Endogenous Variables

In Appendix C, we explain in detail the construction of the net price measure. If students cannot pay for college out-of-pocket due to low  $EFC_i$ , they must take out student loans and pay them back with interest. Our measure of net student price is split into two components: the out-of-pocket cost  $OOP_{i,j,t}$ , and the total payment (including interest) on federal and private loans,  $L_{i,j,t}$ . We allow heterogeneous discount factors  $\beta_i$  on total payments to loans.

Advertising, denoted  $a_{f(j),t}$ , is the total number of daypart-adjusted spot television ads purchased by firm  $f$  owning school  $j$  broadcast to market  $t$ . We define a firm as the collection of schools having the same 6-digit OPEID in a DMA, since this is the level at which television advertising decisions are made for colleges. We only model the consumer response to for-profit college advertising. As shown in Section 4, community college advertising has an insignificant effect on student demand and represents a small fraction of spending by community colleges. FPI advertising may be persuasive in nature [GAO, 2010], so we assume that advertising enters the utility of students directly, changing a student’s taste for the school [Bagwell, 2007].<sup>51</sup>

School characteristics, denoted  $X_{j,t}$ , are a  $K \times 1$  vector, and assumed to be exogenous. This vector includes the following characteristics: four vertically differentiated degree types (e.g., offering 1 year certificates), our 11 horizontally differentiated major definitions, eight student services, value-added  $\psi_j$ , an indicator for being an FPI, and an indicator for being a historically Black college or university (HBCU).

We model preferences as linear in school characteristics, allowing for preferences over these characteristics to depend on both observed and unobserved consumer characteristics. Students’ preferences over price, loan payments (relative to out-of-pocket), advertising, and school characteristics are denoted  $\alpha_i, \beta_i, \lambda_i, \tilde{\gamma}_i$ , respectively.  $D_i$  is a  $D \times 1$  vector of consumer characteristics. These are indicators for the following five demographic characteristics: is a dependent, gender is male, ethnicity is Black, ethnicity is Hispanic, and  $EFC_i \leq \overline{EFC}_t$  (e.g., the student is eligible for Pell-grants), which is a proxy for the student being low-income. We allow preferences to vary by demographic through  $\Pi_\alpha, \Pi_\beta, \Pi_\lambda$ , and  $\Pi_\gamma$ . We allow for random unobserved heterogeneity  $v_{i,k} \sim N(0, 1)$  for each characteristic  $k$ . Parameters  $\sigma_\alpha, \sigma_\beta, \sigma_\lambda$ , and  $\Sigma$  determine the importance of random heterogeneity for each characteristic. We assume  $\Sigma$  is a diagonal matrix.

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

Each student  $i$  in market  $t$  may choose from all schools in their choice set  $J_t$ . This includes all sub-baccalaureate, non-selective colleges located in the same market  $t$ , as well as the outside option of attending no college, denoted  $j = 0$ , whose mean utility is normalized to  $u_{i,0,t} = \epsilon_{i,0,t}$ . Students choose the option  $j \in J_t$  that maximizes their individual utility as expressed in Equation 14.

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 model. Let  $F(i|t)$  denote the joint distribution of demographics  $D_i$  and unobserved heterogeneity  $v_i$  in market

<sup>51</sup>If advertising were purely informative, we could alternatively model advertising as influencing students’ choice set, rather than utility, as in Hastings et al. [2013]

$t$ . Given the above specification of demand, 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

$$s_{j,t}(\Theta) = \int_i \frac{\exp(-\alpha_i p_{i,j,t} + \lambda_i \log(a_{f(j),t} + 1) \times \mathbb{1}\{\text{FPI}_j\} + \gamma_i X_{j,t} + \delta_j + \xi_{j,t})}{1 + \sum_{k \in J_t} \exp(-\alpha_i p_{i,k,t} + \lambda_i \log(a_{f(k),t} + 1) \times \mathbb{1}\{j \in J_{\text{FPI}}\} + \gamma_i X_{k,t} + \delta_k + \xi_{k,t})} dF(i|t) \quad (20)$$

## 6.2 Supply

We also model how colleges choose tuition  $p_{j,t}$  and advertising  $a_{f,t}$ . Because CCs and FPIs face different objectives and constraints, we specify different conduct models for each institution type.

### 6.2.1 For-Profit Colleges

We assume for-profit colleges set both their advertising and their tuition to maximize static (annual) profits. Because spot television advertising is broadcast at the DMA level, which includes multiple markets per year, we model the firm profit maximization problem at the DMA-year level, denoted  $d$ .<sup>52</sup> 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 firm  $f$  in market  $t$ , and  $J_{f,d} = \cup_{t \in \mathcal{M}_d} J_{f,t}$ . Consistent with the literature, we assume that for-profit firms engage in Bertrand-Nash competition [Nevo, 2000a]:

$$a_{f,t} \geq 0, \{p_{j,t} : j \in J_{f,d}\} \left( \sum_{t \in \mathcal{M}_d} M_t \sum_{j \in J_{f,t}} s_{j,t}(\vec{p}_t, \vec{a}_t) (p_{j,t} - c_{j,t}) \right) - \kappa_{f,d} a_{f,d} \quad (21)$$

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

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

$$c_{j,t} = c_j + \nu'_c \vec{X}_{j,t} + \omega_{j,t} \quad (22)$$

where  $\nu_c$  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 in school characteristics:<sup>53</sup>

$$\log(\kappa_{f,d}) = \kappa_f + \nu'_\kappa \bar{X}_{f,d} + \iota_{f,d} \quad (23)$$

where  $\nu_\kappa$  is the  $K \times 1$  vector mapping average characteristics  $\bar{X}_{f,d}$ <sup>54</sup> to the cost of advertising;  $\kappa_f$  is a time invariant component of advertising costs; and  $\iota_{f,d}$  is an advertising cost shock.

<sup>52</sup>We abuse notation and let  $d$  denote a DMA  $\times$  year in our structural model, whereas it represents a geographic DMA over time in Section 4.

<sup>53</sup>We parametrize the advertising cost as log-linear rather than linear because advertising costs in the data are distributed according to a power law.

<sup>54</sup>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.

To solve the firm profit maximization problem, we make use of the first order conditions that are satisfied by firms at their profit maximization point. For prices this is, in matrix notation:

$$\vec{c}_{j,t} = \vec{p}_{j,t} + O_t^{-1} \vec{s}_t \quad (24)$$

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

$$O_{t,j,k} = \begin{cases} \frac{\partial s_{j,t}}{\partial p_{k,t}} & \text{if } k \in J_{f(j),t} \\ 0 & \text{else} \end{cases} \quad (25)$$

Given  $\Theta$  and observed tuition  $p_{j,t}$ , we can recover the marginal costs of each FPI in our sample.

Because colleges receive revenue via tuition in our model, but students pay a net price  $p_{i,j,t}$  that depends not only on tuition but also on other factors such as federal financial aid policy, the derivative of market shares with respect to prices takes a non-standard form. In our setting,  $\frac{\partial s_{j,t}}{\partial p_{k,t}}$  is :

$$\frac{\partial s_{j,t}}{\partial p_{k,t}} = \int_i \frac{\partial s_{i,j,t}}{\partial p_{i,k,t}} \frac{\partial p_{i,k,t}}{\partial p_{k,t}} \partial F(i|t) \quad (26)$$

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. However, we also need to account for the pass-through from a marginal increase in tuition to an increase in net student prices,  $\frac{\partial p_{i,k,t}}{\partial p_{k,t}}$ . This will depend on the means through which a student is marginally paying for their education at  $j, t$ . Explicitly, it takes the following form:

$$\frac{\partial p_{i,k,t}}{\partial p_{k,t}} = \begin{cases} 1 & \text{if } i \text{ ineligible for more Pell grants and } COA_{i,j,t} \leq EFC_i \\ 0 & \text{if } i \text{ eligible for more Pell grants} \\ \beta_i \frac{120r_{p,t}}{1-(1+r_{p,t})^{-120}} & \text{if } i \text{ eligible for loans of type } p \end{cases} \quad (27)$$

The third case, students paying for the marginal dollar with federal/private student loans, applies to the vast majority of students in our sample. If  $\beta_i$  is lower than the interest rate multiplier, then  $\frac{\partial p_{i,k,t}}{\partial p_{k,t}} < 1$ , making them less sensitive to tuition than net price and increasing FPI incentives to charge high prices.

To recover the advertising cost, we use the advertising first-order condition in DMA-year  $d$  for FPI firm  $f$ . The advertising first order condition is as follows:

$$\kappa_{f,d} = \sum_{t \in \mathcal{M}_d} M_t \sum_{j \in J_{f,t}} \frac{\partial s_{j,t}}{\partial a_{f(j),t}} (p_{j,t} - c_{j,t}) \quad (28)$$

Due to the constraint  $a_{f,d} \geq 0$ , we cannot identify the marginal cost of advertising for FPI firms whose optimal advertising amount is zero, since the first-order condition need not hold. We assume that these firms are unable to advertise.

### 6.2.2 Community Colleges

Community colleges are unlikely to behave in a profit-maximizing fashion, as most have an explicit egalitarian mission to “expand access to higher education” [Mullin, 2010]. Community colleges are also known to have non-negligible capacity constraints due to limited seats and inelastic supply [Mullin and Phillippe, 2009, Deming et al., 2013]. Because IPEDS does not report the number of available seats at colleges, we do not explicitly include capacity constraints in our conduct model. Instead, we include budgetary constraints that capture similar forces. Community colleges depend on government appropriations for funding, receiving 80% of their revenue on average from these government subsidies. 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:

$$\max_{p_{j,t}} W_{j,t}(\vec{p}_t, \vec{a}_t) \quad (29)$$

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

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 the amount of appropriations received from federal, state, and local governments, as reported in the IPEDS Finance Survey.<sup>55</sup> We assume that community colleges use the budget  $B_{j,t}$  to subsidize the tuition  $p_{j,t}$  to be below the marginal cost  $c_{j,t}$ .

Community college choose one variable, tuition  $p_{j,t}$ , and face one constraint. So as long as the budget constraint holds, we can solve for the marginal cost of community colleges:

$$c_{j,t} = p_{j,t} + \frac{B_{j,t}}{M_t s_{j,t}} \quad (30)$$

For the budget constraint to bind, we require that  $\frac{\partial W_{j,t}}{\partial p_{j,t}} < 0 \quad \forall (\vec{p}_t, \vec{a}_t)$ , e.g., community colleges prefer students to pay lower prices. For example, if  $W_{j,t} = s_{j,t}$  (e.g., maximize enrollment subject to a budget constraint) or  $W_{j,t} = E[u_{i,j,t} | i \text{ chooses } j]$ , this condition holds because students always prefer lower prices.

Under alternative policy environments, community colleges may experience a surge in enrollment. For example, in Section 9, we simulate outcomes if all sub-baccalaureate for-profit colleges were banned from receiving federal aid, which will lead to some substitution toward community colleges. Given a constant budget  $B_{j,t}$ , this will require CCs to increase tuition, in order to balance the budget constraint. This price increase will then lead some students to not attend the community college, 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 prevents community colleges from inelastically subsidizing at current levels.

<sup>55</sup>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.

## 7 Estimation

We estimate our equilibrium model in sub-baccalaureate education using the canonical “BLP” model [Berry et al., 1995] of discrete choice in differentiated product markets. To solve for the market share equation in Equation 20, we follow previous work [Nevo, 2000a] 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, which is fixed during optimization and our counterfactuals, to approximate the integral in Equation 20. We use data from the 2008-2016 1-year ACS surveys from the Census Bureau to determine the distribution of demographics in each market  $F(i|t)$ .<sup>56</sup>

We use five sets of moments to identify the model’s parameters. The first two are the classic moments used in discrete choice models to jointly estimate demand and supply using market-level data: exogeneity of the demand and marginal cost shocks with respect to a set of instruments. Our third set of moments similarly concern the exogeneity of advertising cost shocks. We complement this with two sets of micromoments that use demographic school-level reporting data from IPEDS and data from the BPS survey on students’ intertemporal preferences. We now describe how each these moments are formulated and calculated.

### 7.1 Demand-Side Moments

We assume that the unobserved demand shock  $\xi_{j,t}$  is orthogonal to a vector of instruments  $\vec{Z}_{j,t}^\xi$  characterizing exogenous variables associated with school  $j$  in market  $t$  (see Section 7.5 for details):

$$g^\xi(\Theta) = E_{j,t}[\xi_{j,t}(\Theta)|\vec{Z}_{j,t}^\xi] = 0 \quad (31)$$

To estimate these demand shocks, let

$$\delta_{j,t} = \gamma X_{j,t} + \delta_j + \xi_{j,t} \quad (32)$$

$$\mu_{i,j,t} = -\alpha_i p_{i,j,t} + \lambda_i \log(a_{f,t} + 1) \times \mathbb{1}\{\text{FPI}_j\} + (\gamma_i - \gamma) X_{j,t} \quad (33)$$

so that  $u_{i,j,t} = \delta_{j,t} + \mu_{i,j,t} + \epsilon_{i,j,t}$ . For a given value of  $\Theta$ , we can calculate  $\mu_{i,j,t}$  directly  $\forall i, t$ . We then solve for  $\delta_{j,t}$  via a contraction mapping [Berry et al., 1995].

After recovering the implied  $\delta_{j,t}$ , we estimate Equation 32 via an OLS regression with school fixed effects to recover the linear preference parameters  $\gamma$ , as well as the demand shocks  $\xi_{j,t}$ . To estimate the level of preferences for characteristics colinear with school fixed effects, we follow Nevo [2000b] and project the estimated school fixed effects  $\hat{\delta}_j$  onto the time-invariant characteristics,

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<sup>56</sup>Because publicly available ACS data reports geolocation in terms of public use microdata areas (PUMAs), we make use of a publicly available 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.

weighting by the covariance matrix of the fixed effects.<sup>57</sup>

Given the recovered demand shock,  $\xi_{j,t}$  from Equation 32, we approximate the moment in Equation 31 with an empirical analogue, using linear functions of a vector of instruments  $\vec{Z}_{j,t}^\xi$ :

$$\vec{g}_\xi(\Theta) = \frac{1}{N} \sum_{j,t} (\xi_{j,t} \otimes \vec{Z}_{j,t}^\xi) = 0 \quad (34)$$

where  $N$  is the number of school-years in our sample, and  $\otimes$  is the Kronecker product. These moments help identify the preferences of consumers towards endogenous characteristics (price and advertising), as well as substitution patterns.

## 7.2 Supply-Side Moments

We recover the marginal costs  $c_{j,t}$  of CCs by solving the budget constraint in Equation 30. Because these marginal costs do not depend on the model parameters, we exclude CC marginal costs from our supply-side moments. We recover the marginal cost  $c_{j,t}$  of FPIs by solving the first-order pricing condition given in Equation 24 at each guess  $\Theta$ . Our supply-side moments state that the supply cost shocks  $\omega_{j,t}, \iota_{f,d}$  for FPIs are orthogonal to a vector of instruments  $\vec{Z}_{j,t}^\omega, \vec{Z}_{f,d}^\iota$ , respectively:

$$g^\omega(\Theta) = E_{j,t}[\omega_{j,t}(\Theta) | \vec{Z}_{j,t}^\omega] = 0 \quad (35)$$

$$g^\iota(\Theta) = E_{f,d}[\iota_{f,d}(\Theta) | \vec{Z}_{f,d}^\iota] = 0 \quad (36)$$

We recover  $\nu_c$  as well as the supply shock  $\omega_{j,t}$  for each FPI by estimating Equation 22 via a linear regression with school fixed effects. We follow the approach used to estimate preferences for time-invariant characteristics to recover the effect of value-added on marginal costs. Given the recovered supply shock,  $\omega_{j,t}$ , we approximate the moment in Equation 35 with an empirical analogue, using linear functions of  $\vec{Z}_{j,t}^\omega$ , analogous to equation 34.

Similarly, we take the advertising cost  $\kappa_{f,d}$  recovered from the advertising first order condition given by Equation 28, and estimate Equation 23 with a linear regression with firm-DMA fixed effects to recover  $\nu_\kappa$ , and the cost shock  $\iota_{f,d}$ . We approximate the moment in Equation 36 with an empirical analogue, using linear functions of  $\vec{Z}_{f,d}^\iota$ .

## 7.3 Demographic Micromoments

We make use of five sets of demographic micromoments from IPEDS, which reports demographic data on the first-time (entering) student body each year. We use these moments to match our model's predictions to the observed demographic sorting across schools with differing characteristics. We use the following statistics on the incoming cohort at each school-market  $j, t$  for each demographic  $h$ , denoted  $\hat{f}_{j,t,h}$ : % Black, % Hispanic, % Male, % Dependent Status,<sup>58</sup> and %

<sup>57</sup>These time-invariant characteristics consist of a constant term (value of inside good), value-added  $\psi$ , FPI status, and HBCU status.

<sup>58</sup>This is measured as the % of first-time, full time students receiving aid living off campus with their family.

Receiving Pell grants.<sup>59</sup> The model-implied fractions  $f_{j,t,d}$  are:

$$f_{j,t,h}(\Theta) = Pr(D_{i,h} = 1 | i \text{ choose } j) = \frac{Pr(D_{i,h} = 1 \ \& \ i \text{ choose } j)}{Pr(i \text{ choose } j)} = \frac{\int_i s_{i,j,t}(\Theta) \mathbb{1}\{D_{i,h} = 1\} \partial F(i|t)}{\int_i s_{i,j,t}(\Theta) \partial F(i|t)} \quad (37)$$

To construct our moments, we assume the prediction error between the IPEDS reported value and the value implied by the model is orthogonal to a vector of instruments:

$$g^{f,h}(\Theta) = E_{j,t}[(\hat{f}_{j,t,h} - f_{j,t,h}(\Theta)) | \vec{Z}_{j,t}^f] = 0 \quad (38)$$

Similar to previous moments, we construct an empirical analogue to Equation 38 via a linear interaction of the vector of instruments with the prediction error for each demographic  $d$ .

In terms of identification, these micromoments most directly aid us in identifying the parameters  $\Pi_\alpha$ ,  $\Pi_\gamma$ , and  $\Pi_\lambda$  that characterize heterogeneous preferences depending on consumer demographics. For example, one of our instruments  $X_{j,t,k} \in Z_{j,t}$ , is a dummy for whether a school offers engineering degrees. The corresponding moment tells the model to match the average fraction of students of demographic  $d$ , conditional on the school offering engineering programs, to the average reported in IPEDS. If males are much more likely to enroll in schools with engineering programs in the data, this tendency will load onto the parameter in  $\Pi_\gamma$  that governs the male consumer taste for engineering programs.

## 7.4 Discount Factor Micromoments

On average, 56% of students attending a school in our sample take out loans to attend college. For many consumers in our model, there is no variation in whether they take loans to attend a school in their choice set. Exogenous variation in school prices alone will then be insufficient to identify the discount factor  $\beta_i$  separately from sensitivity to net student price  $\alpha_i$ .

To separately identify the discount factor, we use data from the 2012 Beginning Postsecondary Survey (BPS), described in Section 3. Each respondent is iteratively asked to trade off a payment of \$250 and \$X in one year, from \$250 to \$500 in increments of \$50. Using this survey question, we construct the cumulative distribution function (CDF) of annual discount factors at five points of the distribution, for each unique  $D_i$  in our model.<sup>60</sup> Figure A10 plots the distribution of discount factors from the survey data. We then convert these to the implied discount factors on 10-year loans, assuming monthly exponential discounting. We match the empirical probabilities of discount factors reported in the BPS to those implied by the model, conditional on attending college. The

<sup>59</sup>% 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 % with positive  $\pi_{i,j,t}$  implied by the model.

<sup>60</sup>We downloaded demographic cell-level data on this BPS question from the NCES's DataLab tool. We only include respondents who attend a sub-baccalaureate (less than 2-year or 2-year) college in the survey.

theoretical probability of interest is

$$Pr(\beta_i \leq \beta^{BPS}(p) | j \neq 0, \Theta, d, y(t) = 2011) \quad (39)$$

$\beta^{BPS}(p)$  denotes one of the five points along the CDF of discount factors we observe in the survey.  $d$  denotes either all students or a demographic indicator corresponding to the demographics for which we allow preference heterogeneity. The probability is calculated for students entering school at the same time as BPS respondents, where  $y(t)$  denotes the year corresponding to a market. Our discount factor micromoments are

$$g_{p,d}^\beta(\Theta) = Pr(\beta_i \leq \beta^{BPS}(p) | j \neq 0, \Theta, d, y(i) = 2011) - \hat{Pr}_{BPS}(\beta_i \leq \beta^{BPS}(p), d) = 0$$

where  $\hat{Pr}_{BPS}(\beta_i \leq \beta^{BPS}(p), d)$  denotes the corresponding empirical probability derived from the BPS survey data. We describe how we compute this moment in greater detail in Appendix E.

These moments help identify both the mean discount rate parameter  $\beta$ , the parameter governing demographic heterogeneity in intertemporal preferences,  $\Pi_\beta$ , and the dispersion parameter governing unobserved heterogeneity in discount factors,  $\sigma_\beta$ . Given our six demographics, and five observed points for each CDF, this translates to 30 discount factor micromoments.

## 7.5 Instruments

We use the following variables as instruments for our moment conditions: school characteristics  $X_{j,t}$ ;  $\bar{p}_{j,t,100}^{Ayr} \times \mathbb{1}\{\text{CC}_j\}$ , the price of public colleges  $\geq 100$  miles away;  $Z_t^\pi \times \mathbb{1}\{\text{FPI}_j\}$ , the simulated Pell grant instrument;  $Z_{j,t}^A \times \mathbb{1}\{\text{FPI}_j\} \times \mathbb{1}\{\sum_t a_{f(j),t} > 0\}$ , the advertising instrument, interacted with an indicator for whether the school is an FPI and ever advertises in our sample. (See Section 4 for details on the price/advertising instruments.) Note that the moments with respect to school characteristics  $X_{j,t}$  are automatically satisfied because they are a condition of the solution to the linear regression used to recover  $\gamma, \nu_c, \nu_\kappa$ . For the demand and supply shock moments  $g^\xi(\Theta), g^\omega(\Theta)$ , and  $g^l(\Theta)$ , we also interact the structural shocks with the rival quadratic differentiation instruments,  $Z_{j,t,c}^d$ , introduced in Gandhi and Houde [2019]. These instruments measure the level of differentiation along a single characteristic  $X_{j,t,c}$  a college has with respect to its rivals (colleges not owned by the same firm, but in the same market):

$$Z_{j,t,c}^d = \sum_{k \in J_t, f(k) \neq f(j)} (X_{j,t,c} - X_{k,t,c})^2 \quad (40)$$

The intuition behind using these instruments is that the level of market power a school has depend on the characteristics of all other colleges in the same market. Accounting for this would require including all relevant functions of the  $J_t \times K$  matrix of product characteristics in a market, which introduces a curse of dimensionality problem. This is the original motivation for the ‘‘BLP instruments’’ [Berry et al., 1995] (sums of other product characteristics) that have been used in other discrete choice settings. Differentiation instruments are a low-dimensional way to capture

the relevant variation in the product characteristic matrix with respect to identifying the demand function. They have been shown to assist in identifying substitution patterns between products, particularly for the parameters governing random heterogeneity,  $\Sigma$ .

Let  $\vec{g}_f(\Theta)$  denote the stacked vector of demographic micromoments for each demographic  $h$ , and let  $\vec{g}^\beta(\Theta)$  denote the vector of moments for each demographic  $d$  and CDF point  $\beta^{BPS}(p)$ . Our full set of  $G = 265$  moments included in our model estimation are as follows:

$$\vec{g}(\theta) = \left[ \vec{g}^\xi(\Theta), \vec{g}^\omega(\Theta), \vec{g}^\pi(\Theta), \vec{g}^f(\Theta), \vec{g}^\beta(\Theta) \right] \quad (41)$$

We estimate the model using the two-step General Method of Moments (GMM) [Hansen, 1982], solving for the parameters that set the moments in Equation 41 to zero. Details can be found in Appendix F.

## 8 Results

In this section, we discuss the results from our model estimation. Our demand side estimates suggest that students are very responsive to advertising when choosing schools, while being unresponsive to quality. We estimate that students are less elastic to tuition than to their net price, which increases the scope for FPIs to charge high markups. Our supply-side estimates suggest that the costs across CCs and FPIs are quite similar. Consequently, our findings suggest that a combination of market power by FPIs and subsidized education by CCs explains most of the price differences across public and private colleges.

**Preferences** Table A3 displays the parameter estimates governing consumer preferences in sub-baccalaureate education, both the baseline linear parameters, as well as the non-linear heterogeneity parameters indexed by demographic characteristics  $D_i$  and random unobserved heterogeneity  $\vec{v}_i$ . The parameter estimates are sensible in the heterogenous preferences they capture; for example, men have lower preferences for schools with consumer service programs (which mostly offer cosmetology degrees) and stronger preferences for engineering and production programs. Similarly, Black individuals receive higher utility from attending historically Black colleges/universities (HBCUs). Dependents, who are more traditional students, have stronger preferences for schools offering associate’s degrees and academic programs.

We estimate that potential students who are low-income have a lower price coefficient on average (0.94 utils versus 1.15 utils for high-income students). This finding runs counter to typical demand estimates that suggest low-income individuals are more price elastic. Most explanations for high-income consumers being price inelastic involve their access to greater wealth / income, which makes prices less impactful on their household budget [Berry et al., 2004]. Our net student price measure already accounts for this mechanism by requiring students to take out loans when they attend a school whose cost of attendance is beyond their ability to pay out-of-pocket. Instead, we interpret the lower price sensitivity of low-income consumers as attributable to potential information frictions

or financial illiteracy, which has been documented in the higher education literature [Chen and Volpe, 1998]. Appendix Figure A11 plots the distribution of consumer price preferences (in utils)  $\alpha_i$  across markets for net student prices  $p_{i,j,t}$  (Equation 15), both overall and by income and race.

Our average estimated discount factors on 10-year loans in the consumer population is 0.62, which is equivalent to about 9.9% annual discounting. Low-income consumers in the potential student population discount the future slightly less: their discount factor is 0.64 on average (9.3% annual discounting) versus 0.59 for high-income consumers (11% annual discounting). Appendix Figure A12 plots the distribution of discount factors  $\beta_i$  in the consumer population. However, there is significant negative selection on discount factors associated with choosing to enroll in higher education. If we weight the discount factors by the likelihood of attending a college in the sub-baccalaureate market, the average discount factor is on ten-year loans is 0.44 (17.7% annual discounting), and low income students discount the future more (19.3% versus 15.8% annually for high income students). Essentially, we find that students who value the future less, and thus weight future payments on student loans less, are more likely to participate in sub-baccalaureate education. Moreover, the negative selection is stronger for low-income students, due to their greater likelihood to attend high-priced FPIs.

We estimate that advertising influences student choice; our utility model implies that a 10% increase in advertising is on average equivalent to a \$80 reduction in out-of-pocket payments (standard deviation = \$21).<sup>61</sup> For-profit advertising is more influential on low-income consumers, for whom a 10% increase is equivalent to a \$86 decrease in net student price, compared to high-income students, for whom this is \$69 on average. These dollar equivalents are relatively large, but not outside the range of prior studies: Murry [2017], which studies the effect of advertising on automobile purchases, another high-priced durable good, estimates that a 10% increase in advertising to be valued at \$74. We estimate the average school-level ad elasticity to be 0.63 among advertising FPIs, which is larger than what the literature has typically found [Shapiro et al., 2019]. Some prior work suggests that FPI’s marketing targets low-income students,<sup>62</sup> including an investigative report [GAO, 2010] documenting that advertising of large FPI chains is predatory in nature. Our results provide additional evidence that FPI advertising is highly persuasive and influential in student college choice. Appendix Figure A13 plots the distribution of consumer preferences given a 10% increase in FPI advertising (0.1 units of  $\log(a_{f,t} + 1)$ ).

In contrast, we do not observe strong preferences for the value-added of institutions on the demand side (Figure A14). Our utility model implies a \$1,000 increase in *annual* labor market earnings is equivalent to just \$34 on average (standard deviation = \$113), much lower than what one might expect from a \$1,000 increase in one’s stream of wages after college. In essence, our model estimates imply that students do not value quality when choosing schools. One explanation

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<sup>61</sup>We convert preferences to out-of-pocket dollars by dividing the coefficient on characteristic  $c$ ,  $\gamma_{i,c}$ , by each consumer’s price sensitivity  $\alpha_i$ .

<sup>62</sup>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

is that these preferences for value-added are conditional on all other characteristics. Because characteristics explain a majority of the variation in value-added (Table A2), taste for quality may be loading onto other school characteristics.<sup>63</sup> It may be the case that students lack information on college quality unrelated to observable characteristics, such as the types of degrees, so it is not a significant input when they choose a college. The undervaluation of school quality suggests that relying on welfare estimates implied from revealed preferences may not fully capture outcomes relevant for policymakers.

**Price Elasticities** We now discuss the price elasticities implied by the model. Due to different prices students and colleges face (net student price versus tuition), the price elasticities relevant for the demand and supply side differ. Colleges set tuition as a function of the tuition elasticity, which is defined as

$$\varepsilon_{j,t}^{\text{Tuition}} = \frac{\partial \log(s_{j,t})}{\partial \log(p_{j,t})} = \frac{\partial s_{j,t} p_{j,t}}{\partial p_{j,t} s_{j,t}} = \frac{p_{j,t}}{s_{j,t}} \int \frac{\partial s_{i,j,t}}{\partial p_{i,j,t}} \frac{\partial p_{i,j,t}}{\partial p_{j,t}} \partial F(i|t) \quad (42)$$

Note the term  $\frac{\partial p_{i,j,t}}{\partial p_{j,t}}$  capturing the pass-through of tuition to net student prices due to student liquidity / federal aid. In contrast, students make choices on where to enroll based on their net student price.

Figure 7 plots the tuition elasticities faced by schools in the model. For-profit colleges face a median tuition elasticity of -3.06, while community colleges face a median elasticity of -0.83. These estimates are consistent with the range of price elasticities found in previous studies of higher education [Gallet, 2007], as well with as our descriptive results in Section 4. The tuition elasticity for most CCs is  $> -1$ , consistent with these schools not maximizing profits.

To analyze the differences between the net price and tuition elasticities, we consider the student-level price elasticities of each consumer  $i$ , which are, respectively:

$$\varepsilon_{i,j,t}^{\text{Net Price}} = \frac{\partial s_{i,j,t} p_{i,j,t}}{\partial p_{i,j,t} s_{i,j,t}}, \quad \text{and} \quad \varepsilon_{i,j,t}^{\text{Tuition}} = \frac{\partial s_{i,j,t}}{p_{i,j,t}} \frac{\partial p_{i,j,t}}{\partial p_{j,t}} \frac{p_{j,t}}{s_{i,j,t}} \quad (43)$$

Figure 8 displays the distribution of tuition elasticities versus the student price elasticities at the student level, by college type.<sup>64</sup> The average net student price elasticity of a college in our sample is -3.23, relative to an average tuition elasticity of -1.18. At both types of institutions, students are less elastic to tuition prices relative to their net student price. This result is consistent with the mechanisms used to fund student enrollment in colleges (loans and federal cash transfers) shielding students from fully internalizing tuition price increases. This difference in tuition and net student price elasticities gives colleges an opportunity to charge higher tuition prices while still retaining a significant market share of students.

Among students, price elasticities differ significantly by income, particularly at for profit colleges,

<sup>63</sup>The raw correlation between the logged enrollment of institutions and value-added is 0.66, suggesting that controlling for other school characteristics has partialled out the taste students have for higher-quality institutions.

<sup>64</sup>By student level, we mean those enrolled at college. Each consumer's elasticity is weighted by the probability of enrolling in college  $j$ . We apply these weights to be consistent with school-level elasticities, which can be derived by a weighted average of individual-level elasticities, where the weights are choice probabilities.

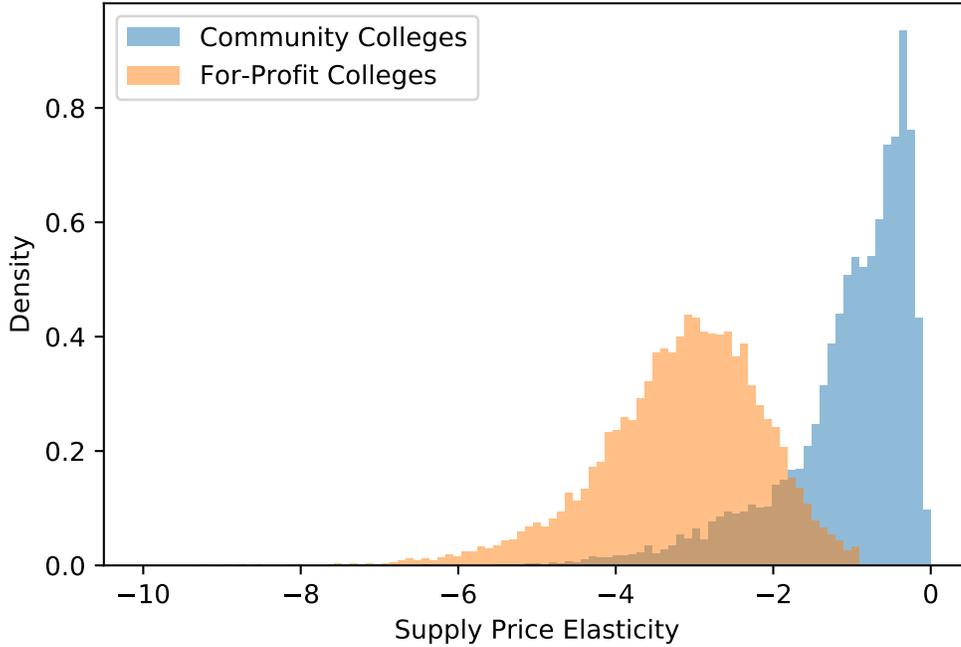


Figure displays the distribution of school-level tuition elasticities elasticities, by college type.

Figure 7: Distribution of College-level Tuition Elasticities by College Type

where aid and loans make up a more substantial portion of how students pay for college. Figure 9 shows that low-income students are less sensitive to both net price and tuition. The difference is particularly large between net student prices elasticities of low and high income students. In Appendix G, we show via a decomposition that lower net prices explain low-income students' lower net price elasticity, and lower tuition passthrough  $\frac{\partial p_{i,j,t}}{\partial p_{j,t}}$  explains their lower tuition elasticity. Figure 10 plots the passthrough rate of an additional dollar of tuition's effect on net student prices at for-profit colleges, by income. A large fraction of high-income students have a passthrough of 1, meaning no distortion in prices. These students are paying the marginal dollar out of pocket. For low-income students, the passthrough is lower due to marginal subsidies and greater temporal discounting.

**Supply-Side Costs** We now turn to the estimates of supply-side parameters from our model. Figure 11 plots the estimated costs recovered from the profit maximization condition of for-profit colleges, versus the budget-balance condition of community colleges. For-profit marginal costs are slightly lower on average, \$10,329, compared to \$10,930 at community colleges. In red, we plot the average cost of for-profits, accounting for advertising costs. This estimate is \$11,935 on average across FPIs. Although these estimates come from entirely different data sources/ conduct assumptions, the distribution of estimated costs is relatively similar across public and private

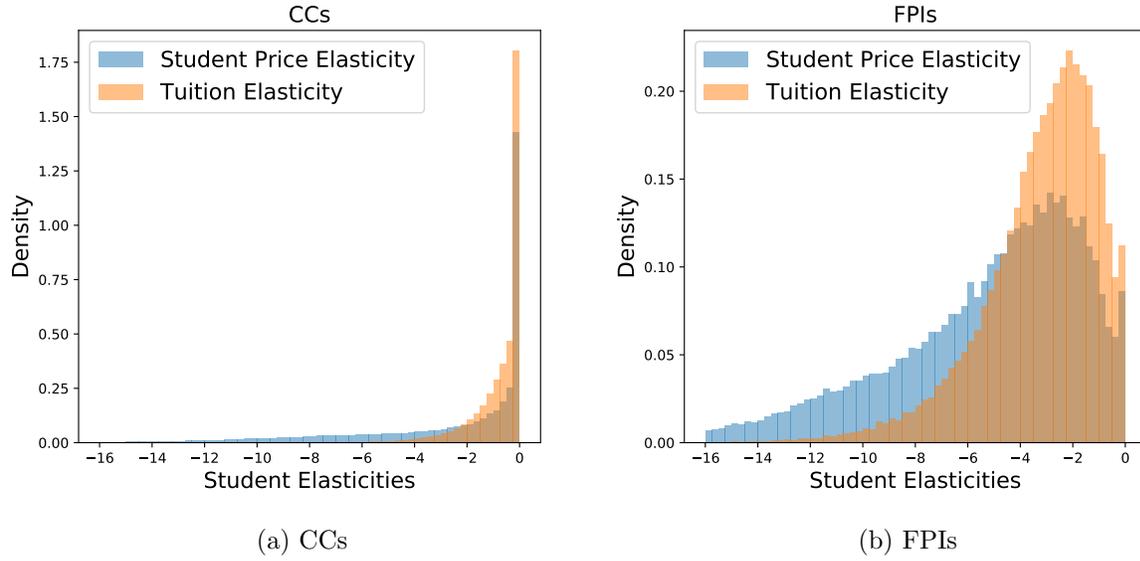


Figure displays the distribution of individual-school pair price elasticities, weighted by the probability of attending each school times the market size (so that each weight represents an effective number of students),  $s_{i,j,t} \times M_t$ , for community colleges and for-profit colleges.

Figure 8: Distribution of Student-level Net Price & Tuition Price Elasticities

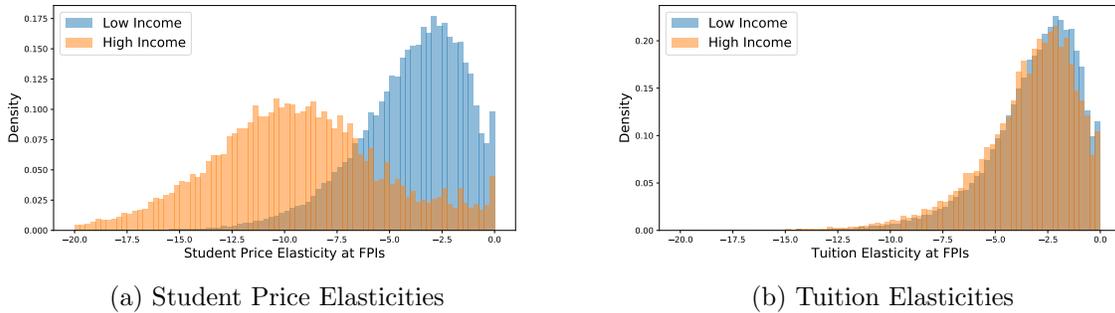


Figure displays the distribution of individual-school pair price elasticities, weighted by the probability of attending each school times the market size (so that each weight represents an effective number of students), for for-profit colleges. Within each subfigure, we plot the distribution by whether the student is eligible for Pell grants ( $EFC_i \leq \overline{EFC}_t$ )

Figure 9: Distribution of Student-level FPI Price Elasticities by Income

colleges. Appendix Table A4 displays the estimates of the effects of characteristics on the marginal cost of for-profit colleges,  $\nu_c$ . Our estimates imply that a \$1,000 increase in value-added increases the marginal cost of FPIs by \$259, suggesting it is costly to provide higher quality education.

We estimate FPI markups in our sample to be large, on average \$5,552. On average, markups account for 35% of the tuition price of FPIs. We evaluate how much of these markups are attributable to the low tuition passthrough documented above, by recalculating markups as if there

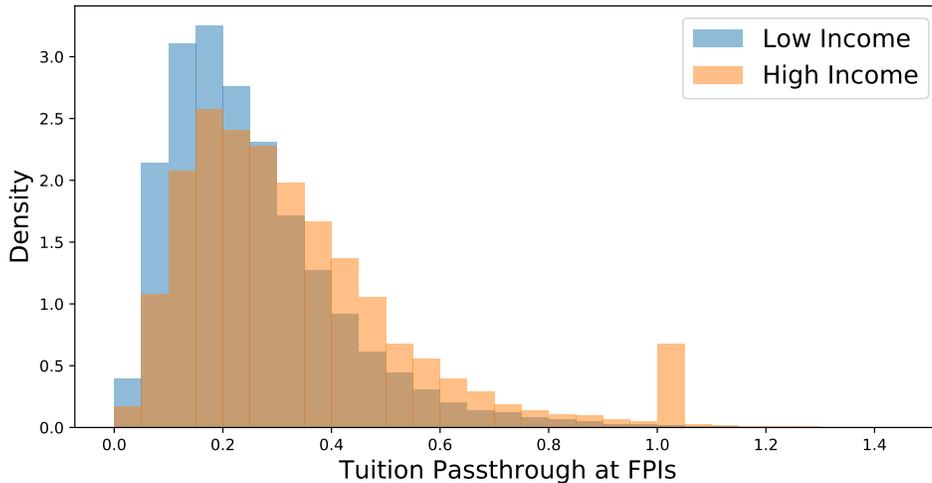


Figure displays the distribution of individual-school pair tuition passthroughs  $\partial p_{i,j,t}/p_{j,t}$ , weighted by the probability of attending each school times the market size (so that each weight represents an effective number of students), for for-profit colleges. Within each subfigure, we plot the distribution by whether the student is eligible for Pell grants ( $EFC_i \leq \overline{EFC}_t$ )

Figure 10: Distribution of FPI Tuition Passthrough Rates By Income

is no passthrough wedge between tuition and net price, such that  $\frac{\partial p_{i,j,t}}{\partial p_{j,t}} = 1$ , holding everything else fixed. Under this scenario, FPI markups would be \$1,255 on average, a 78% decrease. This estimate suggests that FPIs are able to charge high prices due to the asymmetry between the prices they receive (tuition) and the prices students pay (net student price). Appendix Figure A15 plots the distribution of markups (how much price is above marginal cost) for FPIs, along with the markdowns (how much price is below marginal cost) for CCs. The median tuition of FPIs is 49% above marginal cost, while the median tuition of CCs is 64% below marginal cost. Our model suggests that the large price differences documented in Table 1 across these two types of institutions stem from differential conduct. For profits charge prices above cost due to imperfect competition, and community colleges charging below cost due to government appropriations. These findings highlight another way in which government intervention distorts the market for higher education. If markets were sufficiently competitive and government intervention was absent, such that institutions priced near their costs, prices across these institution types would look fairly similar.

Appendix Table A5 displays our estimates of the effect of school characteristics on the fixed cost of advertising,  $\nu_\kappa$ . The median advertising cost of a spot television ad among for-profit firms in our sample is an estimated \$94. This is similar to the median estimate for FPIs running spot television ads in a DMA in the AdSpender accounting data (\$106).

Three stylized facts emerge from the analysis of our demand and supply estimates. First, we estimate a large advertising elasticity, suggesting FPI advertising is an important input into student choice. Second, we find that our differential supply models for community colleges and for-profits

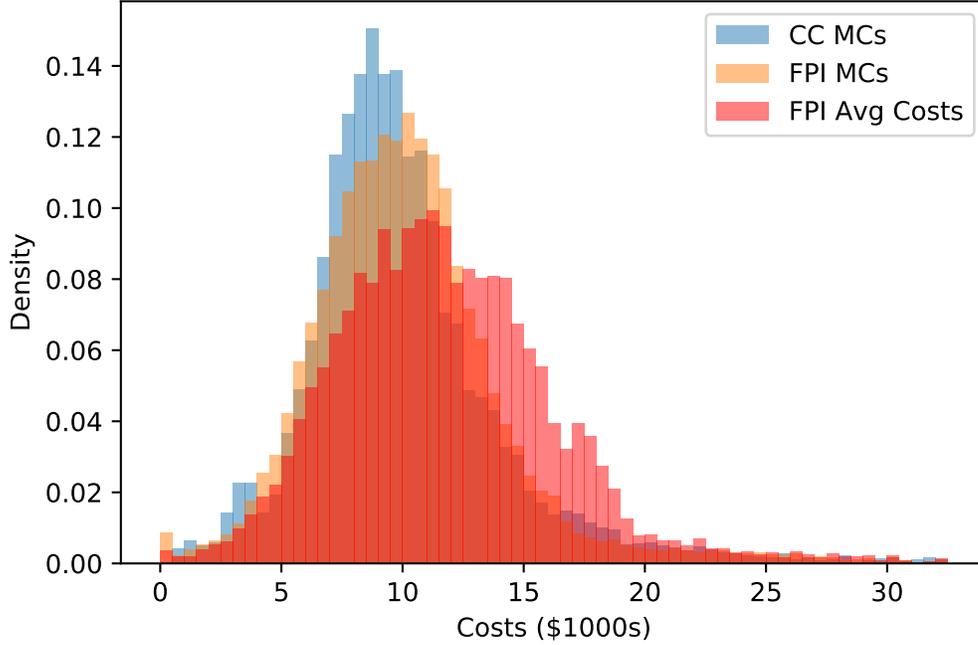


Figure displays the distribution of school-level marginal costs  $c_{j,t}$  estimated from the model, along with the average costs for FPIs, constructed at the firm-DMA level. Average costs are defined as  $(\kappa_{f,d}a_{f,d} + \sum_{j \in J_{f,d}} M_t s_{j,t} c_{j,t}) / (\sum_{j \in J_{f,d}} M_t s_{j,t})$ , the total marginal cost and advertising cost divided by the number of students. Average costs are weighted by the number of campuses within firm-DMA to be comparable to the school-level marginal cost estimates.

Figure 11: Distribution of Education Costs by College Type

explain the majority of price differences across these institutions. Third, we document a large difference in the relevant supply (tuition) and demand (net student price) price elasticities in this market, due an asymmetric passthrough from tuition to net prices students pay. This is attributable in part to federal student aid. These findings suggest that federal aid design contributes to the sizeable markups we estimate for FPIs and that outcomes would change considerably if aid were no longer tied to price. However, to fully evaluate a change in policy, we must consider how both colleges and students would respond. With this in mind, we next discuss the counterfactual policies considered in this paper, which more directly shed light on whether alternative student aid design would improve student outcomes.

## 9 Counterfactuals

We now consider alternative policies the federal government could introduce to improve student welfare. Our counterfactual analysis primarily evaluates policies by three metrics: consumer welfare as implied by the demand model, consumer welfare excluding advertising, and the aggregate value-

added provided in this market. Let  $\mathcal{P}$  denote a policy set by the federal government. Consumer welfare is defined in its usual logit form:

$$CS(\mathcal{P}) = \sum_t \sum_{i \in t} \frac{1}{\alpha_i} E_{\epsilon_{i,j,t}} [u_{i,j,t} | \mathcal{P}] = \sum_t \sum_{i \in t} \frac{1}{\alpha_i} \log(1 + \sum_{j \in J_t} \exp(\delta_{j,t}(\mathcal{P}) + \mu_{i,j,t}(\mathcal{P}))) \quad (44)$$

Due to the importance of advertising in consumer demand, which likely contains both informative and persuasive components, policymakers may be skeptical of this metric to evaluate consumer gains from new policies. Following Allcott [2013], we construct a measure of the *experience utility* for students, which excludes FPI advertising:

$$CS(\mathcal{P})^{\text{No Ads}} = CS(\mathcal{P}) - \sum_t \sum_{i \in t} s_{i,j,t} \cdot \frac{\lambda_i}{\alpha_i} \cdot a_{j,t}(\mathcal{P}) \quad (45)$$

In addition, high quality education is an explicit mission of the federal government. For these reasons, we use a measure of total quality of education provided in this market (in terms of future earnings) as our main benchmark for evaluating the benefits of alternative policies. The aggregate value-added  $\Psi$  is defined as follows:

$$\begin{aligned} \Psi(\mathcal{P}) &= \sum_t M_t \int E[\psi_j | \mathcal{P}, i] \partial F(i | t) \\ &= \sum_t M_t \frac{1}{B} \sum_i \sum_{j \in J_t} s_{i,j,t}(\mathcal{P}) \times \psi_j \end{aligned} \quad (46)$$

One limitation of this measure is that it ignores compensating differentials. Students may receive non-pecuniary benefits from working in certain professions. In the context of our demand model, this is captured by our consumer welfare measures from attending college. For this reason, though we focus on aggregate value-added, we consider our consumer welfare measures as well when evaluating alternative policies.

In our counterfactuals, we hold the quality of institutions  $\psi_j$  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, because we cannot estimate the advertising cost of schools that do not advertise in our data, we assume that these schools do not have access to advertising technology, and fix their advertising to  $a_{j,t} = 0$  in all counterfactuals.

Under each alternative policy  $\mathcal{P}$ , we allow students to respond by changing which schools they attend and colleges to change their tuition/advertising in response to the new policy, in order to balance their budget (CCs) or maximize profits (FPIs). To evaluate the policies comparably, we restrict attention to policies  $\mathcal{P}$  that spend the same amount of federal money as under the current observed equilibrium, denoted  $G_0$  (approximately \$33.8 billion in our sample).<sup>65</sup> With this in mind,

<sup>65</sup>Current government spending is calculated as the total Pell grants distributed to students in all markets in our

we define an equilibrium  $\mathcal{E}(\mathcal{P})$  under policy  $\mathcal{P}$  as satisfying the following four conditions: consumers residing in market  $t$  select schools to maximize utility  $u_{i,j,t}$  (Equation 14); CCs set tuition  $p_{j,t}$  to balance their budget (Equation 30); FPIs set tuition  $p_{j,t}$  and advertising  $a_{f,t}$  to maximize profits (Equation 21); 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 involve bans that have been actively pursued by policymakers in higher education. The second set of policies center on distributing aid to students through a voucher program that does not tie aid amount to cost of attendance. Details on equilibrium computation for both types of policies are given in Appendix H.

## 9.1 Proposed Ban Policies

We consider first a set of counterfactuals similar to those that have been proposed by policymakers to address systemic issues among FPIs. The first is to ban for-profit colleges from receiving federal aid. By banning FPIs, we may induce students to pick higher quality institutions. The second proposal we consider is to simply ban advertising by for-profit colleges. The third proposal is to ban low quality schools from receiving federal aid. These are exclusively for-profit colleges.

Under these bans, the for-profit sector is likely to shrink in size, reducing federal student aid spending. To obtain an equilibrium  $\mathcal{E}$  where federal government spending is constant, we allow the federal government to change the generosity of the federal student aid system in our counterfactuals. Because we are interested in policies targeting low-income, Pell-eligible students, we focus on counterfactual ban policies that hold fixed the structure of federal student loans, but change the generosity of the Pell grant program, indexed by a parameter  $g$  set for each policy. We allow Pell grants to be more or less generous using the following formula:

$$\bar{\pi}_y(\mathcal{P}) = g \times \bar{\pi}_{y,\text{Observed}} \quad (47)$$

where  $\bar{\pi}_{y,\text{Observed}}$  is the maximum Pell grant award under current student aid in year  $y$ .

**Banning For-Profit Colleges** We first consider a policy of banning for-profit colleges from receiving federal student aid. FPIs were banned from receiving federal student aid until 1972, when the law was amended to allow these institutions to have access to federal funds [McGuire, 2012]. The for-profit sector has been criticized by policymakers in recent years due to its reputation of low quality and over-priced education. Bills have been considered as recently as 2019 to re-ban FPIs from federal aid,<sup>66</sup> This policy would mean that students wishing to attend a for-profit must pay the full cost of attendance, without pell grants or subsidized federal loans. If students do not have sufficient EFC to pay for college, they must take out private student loans. Demand

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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.

<sup>66</sup>See the “Students Not Profits Act of 2019” <https://www.republicreport.org/wp-content/uploads/2019/10/Students-Not-Profits-Act.pdf>

and supply is otherwise exactly as modeled before, where students choose their utility-maximizing choice from  $J_t$ , for-profit colleges maximize profits, and community colleges set tuition to balance their budget.

**Banning For-Profit College Advertising** We also consider a policy where for-profit college advertising  $a_{f,t}$  is banned by the government.<sup>67</sup> Because advertising by for-profit colleges has been documented to be predatory in nature [GAO, 2010], policymakers are concerned this specific mechanism causes poor choices by students in how they select colleges.

**Banning Low-Quality Colleges** Finally, our last ban concerns the treatment of low-quality colleges. We define a low-quality college as one with  $\psi_j < 0$ , or negative value-added. This accounts for 23% of colleges but only 3% of enrollment, since these are mostly small for-profits. This ban is in the spirit of the gainful employment regulations proposed by the Obama administration [Heller, 2011], which sought to ban schools producing poor outcomes for students from receiving federal aid, and were repealed by the Trump administration before they went into effect. To estimate the equilibrium in this counterfactual, we assume that students wishing to attend a school with negative value-added must pay for the cost of attendance out of pocket or with private student loans, as in the case of the FPI ban.

## 9.2 Targeted Vouchers

In Section 2, we document some of the distortionary components of the current federal aid design. We examine the role of this design in impairing student outcomes by simulating a policy where federal aid is disbursed in the form of a voucher whose generosity is independent of price. Vouchers have been implemented in education markets across the world. While results on the effects of vouchers on educational outcomes are mixed, they have typically improved competition between schools and student access to quality education [Epple et al., 2017]. We consider an aid design that issues a voucher  $\tau_{i,j,t}$  only to low-income students because most (89%) of federal student aid spending in the sub-baccalaureate market is directed towards Pell-eligible students. Thus,  $\tau_{i,j,t} = 0$  if  $EFC_i > \overline{EFC}_t$  in all counterfactuals. Federal loans are discontinued. Students who can no longer afford college net their voucher, e.g.,  $COA_{i,j,t} - \tau_{i,j,t} > EFC_i$ , must take out loans in the private market.<sup>68</sup> Net student prices are as follows in the voucher counterfactuals:

$$p_{i,j,t} = \begin{cases} COA_{i,j,t} - \tau_{i,j,t} & \text{if } COA_{i,j,t} - \tau_{i,j,t} \leq EFC_i \\ EFC_i + \beta_i(COA_{i,j,t} - \tau_{i,j,t} - EFC_i) \frac{120r_{\text{private},t}}{1-(1+r_{\text{private},t})^{120}} & \text{if } COA_{i,j,t} - \tau_{i,j,t} > EFC_i \end{cases} \quad (48)$$

<sup>67</sup>This is similar to a recent bill proposed by Senator Sherrod Brown in the United States, who introduced a bill to ban for-profit colleges from spending federal financial aid on marketing. Source: <https://www.brown.senate.gov/newsroom/press/release/sen-brown-introduces-bill-to-ban-colleges-from-spending-federal-financial-aid-dollars-on-marketing-and-recruiting>

<sup>68</sup>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 attendance.

Under this counterfactual, FPIs solve the profit equation in Equation 21, and CCs satisfy their budget constraint, replacing the federal aid prices in Equation 15 with Equation 48.

**Lump-Sum Voucher** The first voucher policy we consider is switching the existing federal student aid policy of price-dependent loan/transfer subsidies to 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. This proposed voucher removes the distortionary component of federal student aid, since students do not receive more aid to attend a higher price institution. Explicitly, lump-sum vouchers take the following form in this policy:

$$\tau_{i,j,t}^{\text{Lump-Sum}} = g \quad (49)$$

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

**Quality Vouchers** Tying federal student aid to the quality of an institution's education, as measured by earnings after enrollment, has been attempted in the past in the United States, most recently by the gainful employment regulations of the Obama administration [Guida Jr and Figuli, 2012]. To evaluate the benefits of delivering more aid to higher quality schools, we consider a voucher design tied to the quality of institutions  $\psi_j$ . The voucher takes the following form:

$$\tau_{i,j,t}^{\psi} = g \times \psi_j \quad (50)$$

where  $g$  determines the weight given to the quality of the institution.

**Optimal Voucher** We consider what an optimal voucher design would look like if the social planner only cares about maximizing the aggregate value-added  $\Psi$  provided to targeted (low-income) students, holding federal government spending fixed. We assume the social planner can perfectly observe demand, the quality of each institution, and each college's cost structure. We also assume that state and local subsidies  $B_{j,t}$  of community colleges cannot be adjusted; the planner can only control federal student aid. The social planner's optimization problem is specified as follows:

$$\begin{aligned} \max_{\{\tau_{j,t}\}} & \sum_t M_{t,L} \sum_{j \in \mathcal{J}_t} s_{j,t,L} \cdot \psi_j \\ \text{s.t.} & \sum_t M_{t,L} \sum_{j \in \mathcal{J}_t} s_{j,t,L} \cdot \tau_{j,t} \leq G_0 \end{aligned} \quad (51)$$

where  $s_{j,t,L}$  denotes the market share of school  $j$  in market  $t$  among low-income consumers;  $M_{t,L}$  is the number of low-income consumers in the market;  $\psi_j$  is the quality of school  $j$ ; and  $\tau_{j,t}$  is a school-specific voucher amount. Besides the quality of the school, the key to understanding the optimal allocation across schools is the *voucher elasticity*:  $\varepsilon_{k,j,t}^{\tau} = \frac{\partial \log(s_{j,t,L})}{\partial \log(\tau_{k,t})} = \frac{\partial s_{j,t,L}}{\partial \tau_{k,t}} \frac{\tau_{k,t}}{s_{j,t,L}}$ . This measure is the increase in 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. The derivative of shares with respect to the voucher can be decomposed into the following terms:

$$\frac{\partial s_{j,t,L}}{\partial \tau_{k,t}} = -\frac{\partial s_{j,t,L}}{\partial p_{k,t}} \left(1 - \frac{\partial p_{k,t}}{\partial \tau_{k,t}}\right) + \frac{\partial s_{j,t,L}}{a_{f(k),t}} \frac{\partial a_{f(k),t}}{\partial \tau_{k,t}} \quad (52)$$

The first term captures the increased enrollment effect from lower prices, due to increased voucher aid, but this effect is dampened by  $(1 - \frac{\partial p_{k,t}}{\partial \tau_{k,t}})$ , which captures the fact that colleges may respond to an increase in their voucher  $\tau_{j,t}$  by increasing tuition. The second term accounts for for-profit colleges responding to changes in government aid by changing advertising. We use a simplified solution to the social planner problem for our counterfactual analysis. In Appendix I, we provide the full solution to the social planner problem, which is qualitatively similar in formulation.

*Proposition 1.* Suppose the social planner optimizes Equation 51, and  $\varepsilon_{j,k,t}^\tau \approx 0$  if  $j \neq k$ . The optimal voucher for school  $j$  in market  $t$  is

$$\tau_{j,t}^* \approx \underbrace{\frac{1}{\lambda}}_{\text{Shadow Price of Budget Constraint}} \times \underbrace{\frac{\varepsilon_{j,j,t}^\tau}{1 + \varepsilon_{j,j,t}^\tau}}_{\text{Voucher Elasticity Distortion Term}} \times \underbrace{\psi_j}_{\text{Quality}} \quad (53)$$

*Proof.* See Appendix I. □

The intuition for allocation under this formulation is as follows. First, conditional on  $\varepsilon_{j,j,t}^\tau$ , give schools with higher quality more aid. Second, conditional on  $\psi_j$ , gives more aid to schools whose enrollment is more responsive to voucher aid. In practice, we find that because community colleges are budget constrained and must increase prices proportionally to enrollment increases, for-profit enrollment is more elastic to voucher aid. This is particularly true for advertising for-profit colleges, since we estimate that demand is highly elastic to advertising. Thus, conditional on quality, this aid scheme implies that it is optimal for the government to allocate more aid to for-profits. In Figure 12, we plot the estimated voucher elasticity distortion term (See Appendix H for details on computation) under Proposition 1, by college type. For our counterfactuals, we estimate an approximation of the optimal voucher presented in Proposition 1. Using plug-in estimates of the voucher elasticities,  $\hat{\varepsilon}_{j,j,t}^\tau$  (see Appendix H for details), our implementation of the optimal voucher is:

$$\tau_{i,j,t}^* = g \times \frac{\hat{\varepsilon}_{j,j,t}^\tau}{\hat{\varepsilon}_{j,j,t}^\tau + 1} \times \psi_j \quad (54)$$

where  $g$  is substituted for the shadow price of the federal government budget constraint.

### 9.3 Counterfactual Results

Table 4 displays aggregate statistics from the new equilibrium under each of the six counterfactual policies considered. In terms of the aggregate value-added  $\Psi$  delivered to students, the for-profit col-

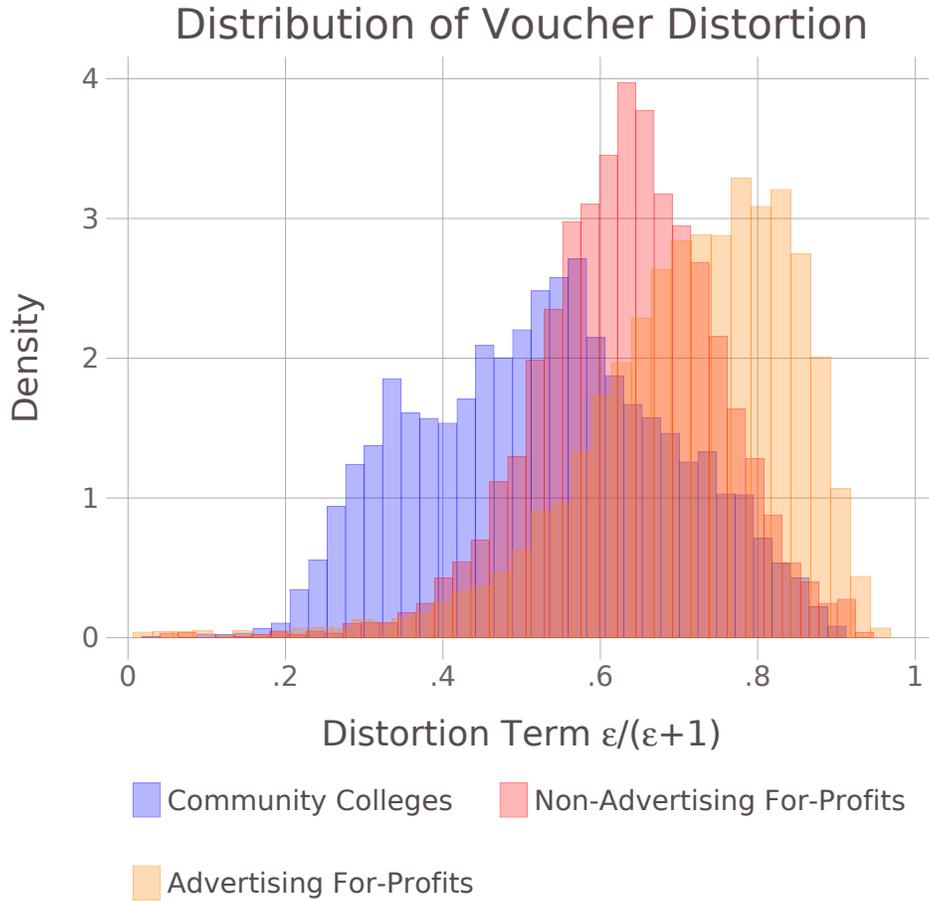


Figure displays the distribution of school-level estimated distortion terms  $\frac{\varepsilon_{j,j,t}^{\tau}}{\varepsilon_{j,j,t+1}^{\tau}}$  used for the optimal voucher policy. Non-advertising for-profits denote for-profit colleges whose observed advertising is zero, while advertising for-profits denote for-profit colleges whose observed advertising is greater than zero. See Appendix H.3 for details on estimation.

Figure 12: Distribution of Estimated Distortion Terms  $\frac{\varepsilon_{j,j,t}^{\tau}}{\varepsilon_{j,j,t+1}^{\tau}}$  for Optimal Voucher, by College Type

lege aid ban (combined with a 21.8% increase in the generosity of the Pell grant program to balance the federal budget) slightly increases total value-added, by 1%, relative to the current equilibrium. While there is a large decline in the for-profit sector, and for-profit institutions are on average of significantly lower quality in terms of value-added, there is significant quality heterogeneity in the for-profit sector. In particular, 65% of for-profit colleges are estimated to have positive value-added. By limiting federal aid to all for-profit schools, many students exit medium-quality private institutions to the outside option, as indicated by the 5.6% decrease in total enrollment. For profits respond to this ban on aid by increasing markups and decreasing advertising substantially, to essentially cater to the smaller but non-trivial price inelastic portion of the demand curve, consistent

with results from Hastings et al. [2013], where private firms respond to a lower priced competitor by raising prices. Consumer welfare, as measured by our demand model increases slightly by 0.6%. Because FPI advertising decreases substantially, consumer surplus excluding advertising increases by 13.7%.

Under the advertising ban, which is accompanied by an 10.9% increase in the generosity of the Pell grant program, total quality declines by 2%. This policy is ineffective at improving quality provision largely because the problems associated with a for-profit college ban are exacerbated under the advertising ban. For-profit schools that engage in advertising are typically higher quality than their non-advertising private counterparts, as documented in Figure 6; on average, 81% of for-profits that advertise have positive value-added, while only 52% of non-advertising for-profits have positive value-added. Thus, the advertising ban specifically targets those for-profits that are relatively high in quality.

The final ban policy considers the equilibrium outcomes from directly targeting low-quality schools by banning those with negative value-added. This ban would be accompanied by a 1.8% increase in Pell grant generosity to balance the federal budget. Here, we see an increase in total value-added of 1.6%. In addition, consumer surplus is effectively unchanged. Among the bans we consider, directly targeting these low-quality schools appears to be the most effective at improving quality. However, all three bans are relatively ineffective at improving quality in the sub-baccalaureate education sector.

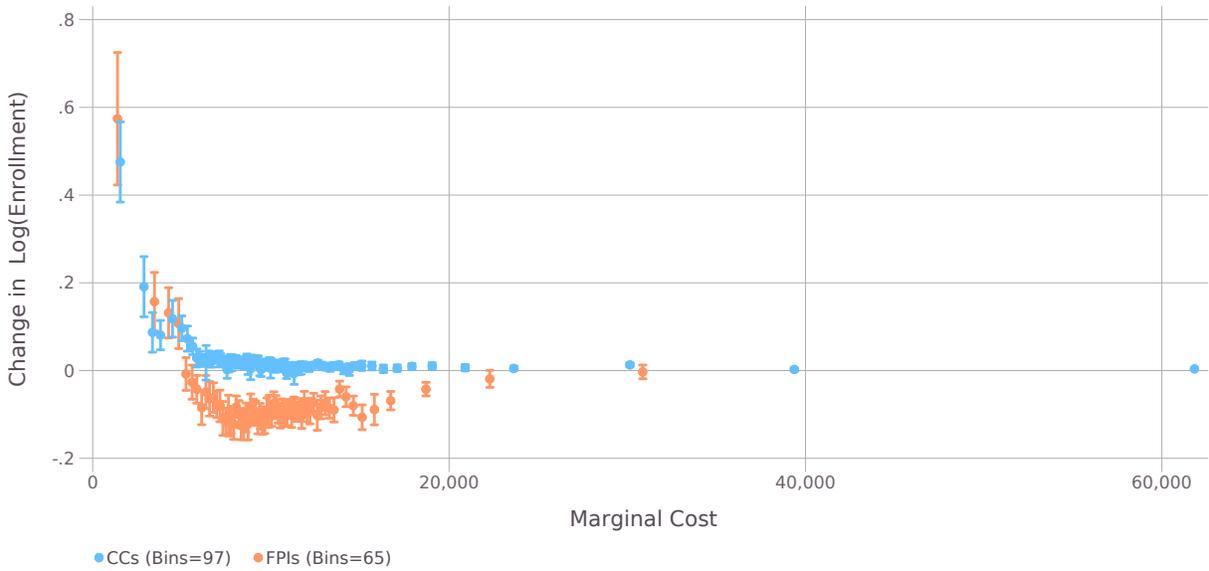
We now move to discussing results from our voucher policies. We solve for a lump-sum voucher of \$6,830 in 2017 USD to balance the federal budget. Under a lump-sum voucher, there is a 2.3% increase in total value-added, and a 10% increase in quality for low-income consumers. This increase is driven by the proportional increase in the number of consumers who choose to attend college. Consumer surplus both with and without advertising increases under the lump-sum voucher system. Although markups increase by 3.4% for FPIs, students pay an average net student price 7.4% lower on average, which confirms that transitioning to a voucher system results in more savings for students. These savings occurs primarily through student re-sorting into lower-cost institutions. Figure 13 plots a binscatter of the logged change in outcomes for FPIs, relative to the observed equilibrium under current federal aid design, grouped by their marginal cost  $c_{j,t}$ . Error bars denote 95% confidence intervals from robust standard errors of the mean of each bin. Panel (a) shows the change in logged enrollment at the school level by marginal cost bin. There is a downward sloping relationship between enrollment changes under the lump-sum voucher and marginal cost for both FPIs and CCs. We interpret this as evidence that decoupling price from aid incentivizes students to choose lower price schools. Panels (b) and (c) show the change in logged tuition and logged advertising, respectively. Low-cost FPIs increase their advertising, and decrease tuition, in response to the policy. CCs increase prices across the board due to the influx in enrollment.

We now consider how a linear quality voucher ( $g = 0.793$ ) performs in comparison. Aggregate value-added under the linear quality voucher increases by 5.3% relative the current equilibrium, despite the fact that total enrollment actually *decreases* by 2.6%. Under this policy, the for-profit

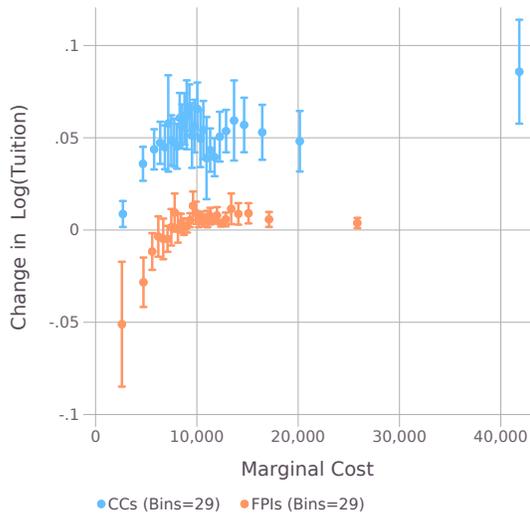
Table 4: Counterfactual Results

Policy	Level	% Change From Current					
		Current Aid Regime	For-Profit Ban	Advertising Ban	Low Quality Ban	Lump-Sum	Voucher
Aggregate Value Added	64.66B\$	+0.98%	-1.94%	+1.51%	+2.30%	+5.33%	+8.77%
Aggregate Value-Added (Low-Income)	35.85B\$	+7.32%	+0.79%	+2.70%	+10.50%	+19.63%	+23.62%
Average Value-Added	8,234\$	+7.09%	+4.65%	+1.75%	+0.29%	+8.09%	+8.34%
Average Value-Added (Low-Income)	7,903\$	+11.07%	+6.48%	+2.78%	+0.70%	+14.79%	+15.31%
Students	7.85M	-5.70%	-6.29%	-0.23%	+2.00%	-2.55%	+0.40%
Low-Income Students	4.54M	-3.37%	-5.34%	-0.08%	+9.74%	+4.22%	+7.21%
Avg. Net Student Price	7,576\$	-4.86%	-3.71%	-0.35%	-7.42%	-9.96%	-12.75%
Avg. Net Student Price (Low-Income)	7,313\$	-5.59%	-3.95%	-0.42%	-8.14%	-12.50%	-20.66%
Consumer Surplus	37.08B\$	+0.55%	-1.65%	+0.18%	+1.93%	+2.08%	-0.41%
Consumer Surplus (Low-Income)	20.91B\$	+5.38%	+0.52%	+0.56%	+8.52%	+10.55%	+3.55%
Consumer Surplus (No Ads)	31.47B\$	+13.62%	+15.86%	-0.53%	+3.03%	+10.78%	+2.71%
Consumer Surplus (Low-Income, No Ads)	16.63B\$	+26.75%	+26.37%	-0.30%	+10.53%	+25.64%	+7.71%
% FPI	16.85%	-10.44%	-8.48%	-0.55%	-0.47%	-7.28%	-4.80%
% FPI (Low-Income)	22.13%	-15.54%	-11.19%	-0.97%	-1.08%	-11.14%	-7.24%
FPI Profits	5.00B\$	-40.72%	-24.63%	-4.01%	-1.96%	-26.77%	-21.37%
Avg. Community College Markup	7,162\$	-4.36%	-2.35%	-0.34%	-1.65%	-2.52%	+0.36%
Avg. For-Profit College Markup	5,552\$	+35.55%	+16.54%	+11.93%	+3.51%	+28.61%	+26.71%
Avg. FPI Profits/Student	3,998\$	+33.20%	+56.63%	+14.72%	+3.10%	+30.15%	+28.63%
FPI Advertising	2.74B\$	-57.39%	-100.00%	-1.88%	-4.02%	-35.73%	-22.95%
Total Welfare	42.08B\$	-4.35%	-4.38%	-0.32%	+1.47%	-1.35%	-2.90%
Federal Govt Spending	33.99B\$	-0.01%	-0.01%	+0.02%	+0.03%	+0.07%	-0.10%
Community College Subsidies	40.50B\$	-0.00%	+0.00%	+0.00%	+0.00%	+0.00%	+0.00%
Government Spending	74.49B\$	-0.00%	-0.00%	+0.01%	+0.01%	+0.03%	-0.04%

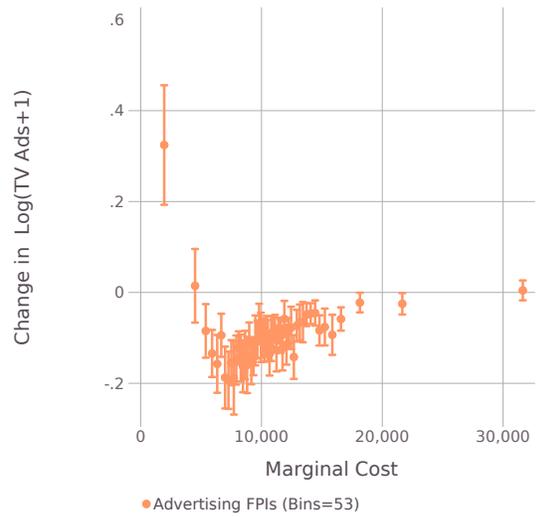
Table displays results from counterfactual analysis of alternative policies in equilibrium. Aggregate value-added denotes the sum of quality  $\psi_j$  multiplied by the number of students at each school. Students denotes total enrollment in the market. Average value-added denotes aggregate value-added 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 markup 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.



(a) Enrollment



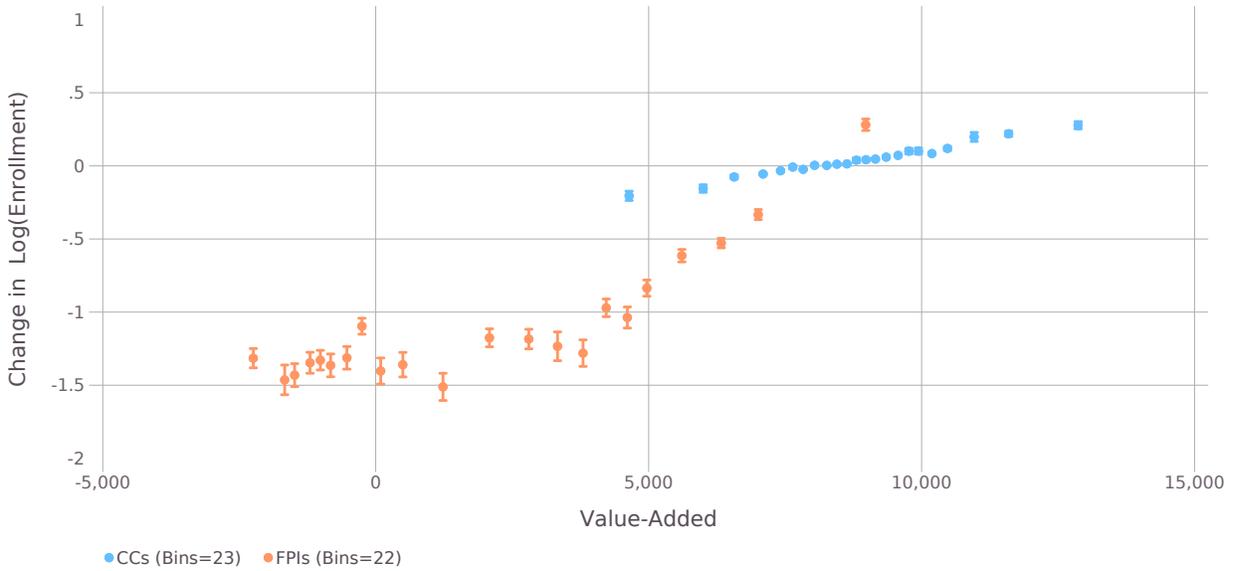
(b) Tuition



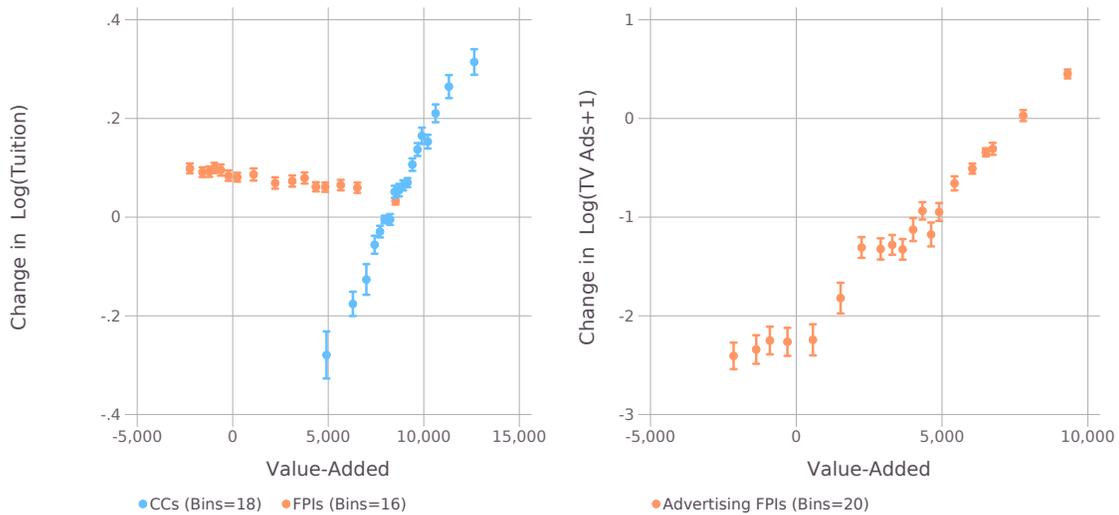
(c) Advertising

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



(a) Enrollment

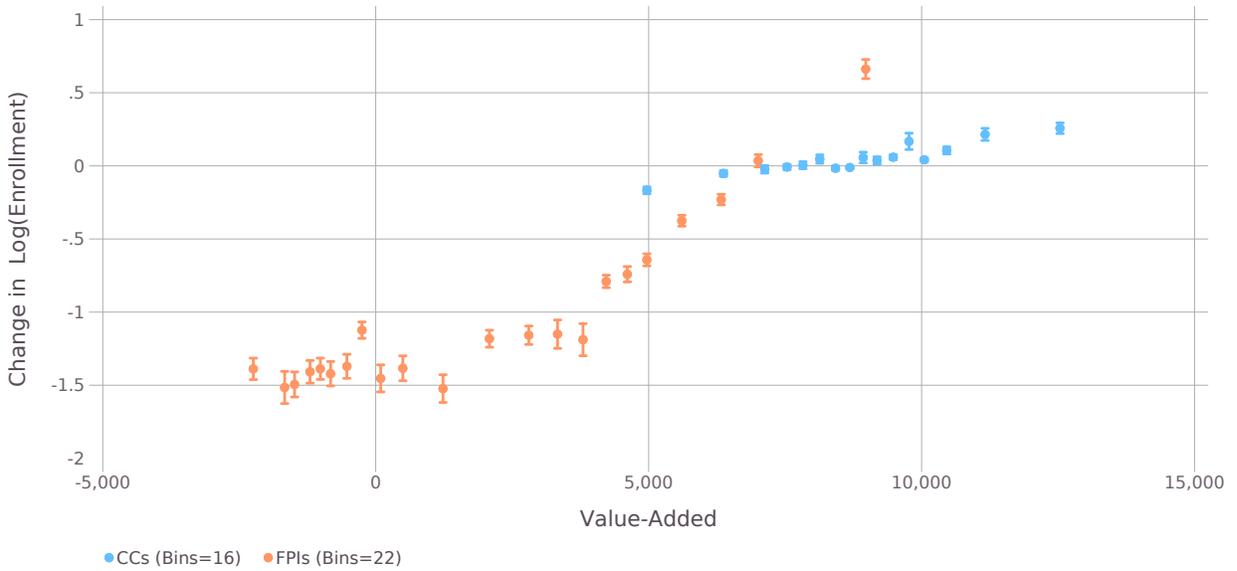


(b) Tuition

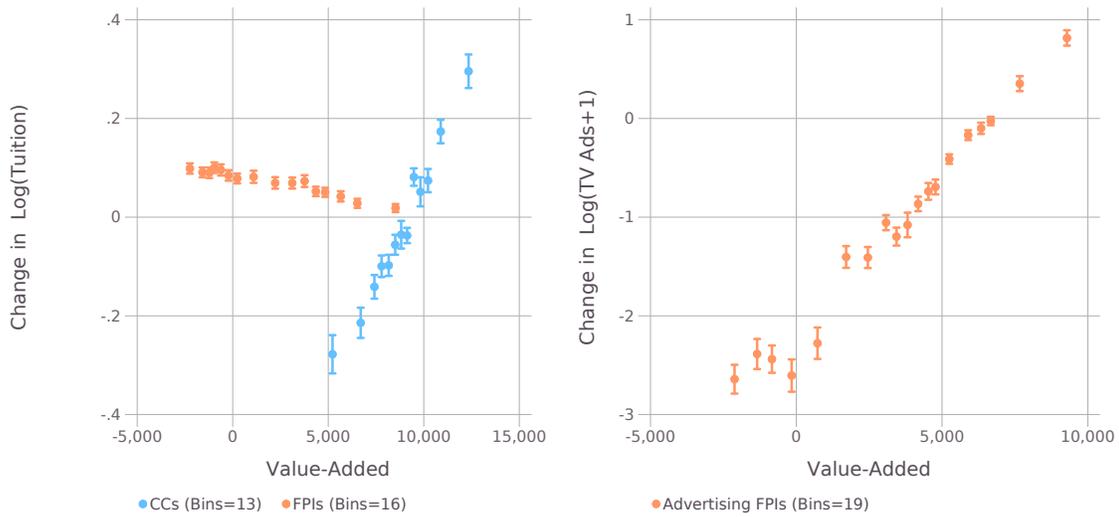
(c) Advertising

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



(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 15: Change in Supply and Demand Under Optimal Voucher, by Value-Added

sector experiences a large enrollment decline, to only 9.5% of enrollment. This suggests the policy is effective at inducing consumers to substitute away from for-profit education, since for-profits are lower quality on average. Consumer surplus increases moreso under the quality voucher, particularly when excluding advertising, since advertising spending by FPIs declines by 36% under the linear quality voucher policy. Panel (a) of Figure 14 plots binscatters of the change in logged enrollment across institutions, as a function of their value-added. The change in enrollment from the observed equilibrium increases as a function of the school’s value-added across all institution types. However, the response to the voucher program is heterogenous across school types, with the for-profit sector able to more aggressively responding to the quality voucher scheme. This outcome is largely due to the budget constraint community colleges face, since they must increase prices in order to balance their budgets when enrollment increases. This requires higher quality CCs to increase tuition when they increase enrollment (Panel (b)). In contrast, though for-profits of all quality increase tuition on average, higher quality for-profits increase tuition to a lesser amount. For-profits with access to advertising technology are able to further respond to the quality voucher policy, due to the increase (decrease) in advertising for higher-quality (lower-quality) schools (Panel (c)).

Under the optimal quality voucher policy ( $g=1.328$ ), we find that the aggregate value-added increases substantially, by 8.8% among all consumers and 23.6% for low-income consumers. The number of students enrolled in sub-baccalaureate education increases slightly by 0.4%. This is driven by a smaller decline in the for-profit sector. For-profit advertising, which is explicitly incentivized under this voucher policy for high-quality schools, also declines to a lesser amount, decreasing by only 22.9%. Consumer surplus measured without advertising also increases by 2.7% under the optimal voucher policy, despite not being a target of the voucher design.

In Figure 15, we display the same supply and demand responses as in Figure 14, but under the optimal quality voucher design. Compared to the linear quality voucher, we see in Panel (a) that more medium quality for-profits increase enrollment, which reflects increased subsidies to these schools due to their higher voucher elasticity. The advertising response function (Panel (c)) is also larger, with more medium-quality FPIs increasing advertising.

Though we assume quality is fixed, there is concern that schools may adjust quality in response to government policies. In particular, schools may invest in higher quality education to receive more government aid. Another concern is that quality is difficult for the government to observe, and assigning aid based on a school-specific quality index is infeasible. Similarly, it may be challenging for the government to estimate the voucher elasticities used to construct our optimal quality voucher. As a robustness check, we re-run our quality-indexed aid policies by assuming the government assigns aid based more plausibly exogenous<sup>69</sup> and easily observable school characteristics.

Explicitly, to approximate value-added  $\psi_j$ , we substitute  $\psi_j$  in Equations 50 and 54 with the prior mean of value-added  $W_j\zeta$  based on school characteristics.<sup>70</sup> To approximate the optimal voucher using only exogeneous variables, we use the random forest algorithm [Athey and Imbens,

<sup>69</sup>For example, the degrees offered by schools must be accredited to have access to federal financial aid, and this accreditation process can take years to complete.

<sup>70</sup>Estimates of  $\zeta$  can be found in Table A2.

2019] to predict a school’s response to voucher aid. Because a college’s response to aid may depend not only on their own characteristics, but also market structure, we predict the distortion term  $\hat{\varepsilon}_{j,j,t}^\tau / (\hat{\varepsilon}_{j,j,t}^\tau + 1)$  with the following variables: school characteristics  $X_{j,t}$ ; the fraction of consumers within each market belonging to each of the 5 demographic groups we include in our structural model  $\bar{D}_t$ ; and the differentiation instruments  $Z_{j,t,c}^d$  expressed in Equation 40. The differentiation instruments serve to approximate the level of competition a school faces in their market. The random forest algorithm allows us to recover non-linear relationships between these input variables using a relatively simple specification of decision trees. We perform cross-validation to determine the complexity of the random forest.<sup>71</sup> We then train the random forest algorithm using the selected hyperparameters on our full sample, and substitute the predicted distortion term based on these exogenous inputs in place of the distortion term in Equation 54.

Table A6 shows the results from a feasible implementation of our voucher policies indexed to quality. We obtain qualitatively similar, though quantitatively smaller, increases to aggregate value-added when aid is indexed to school characteristics: aggregate value-added increases by 4.0% under the feasible linear quality voucher, and 6.7% under the feasible optimal quality voucher. Thus, we find that a viable version of our proposed policies, that only relies on publicly available data on market demographics and school characteristics, are able to capture a substantial portion of the theoretical gains from indexing aid to quality in an optimal fashion.

In order to quantify the role that the supply-side response plays in our results, we present counterfactual outcomes in which only students are allowed to respond in Table A7. We hold the advertising and tuition of colleges fixed (except in the case of the advertising ban). Because tuition prices at community colleges are subsidized, we estimate these counterfactuals by balancing the *total* government aid budget, which includes federal aid and subsidies given to community colleges  $\sum_{j,t} B_{j,t}$  by local governments. Without this, we cannot make a lateral comparison of alternative aid policies, since only equalizing the federal budget would lead to large increases in overall government spending (from the state and local level). Under this counterfactual exercise, we find in general that the benefits of our considered policies are over-stated. Under the for-profit ban on federal aid, aggregate quality actually increases by a sizeable 3% when the supply side is held fixed. This is because we do not allow for-profits to respond to a ban on federal aid by increasing prices and decreasing advertising. Thus, failing to account for the supply side may lead a policymaker to believe that the for-profit ban is a significantly more effective method to improving quality than is true in equilibrium. In addition, the gains from the quality voucher are much higher with only a demand-side response, and indistinguishable from the optimal voucher policy. This is because high quality CCs no longer have to increase tuition, since state subsidies are able to increase by 7.1%, making these schools even more attractive to students. These estimates highlight that the supply-side response is key to understanding student outcomes under alternative student

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<sup>71</sup>We perform 5-fold cross validation over the depth of the tree and the number of features used for each decision tree, stratifying the cross-validation scheme by market. Under the random forest specification chosen by cross-validation, we obtain a R-squared of 0.56 out of sample, and 0.91 insample, indicating a good fit from the exogenous variables used in this prediction task.

aid policies.

One of the key ways that for-profit colleges contribute to quality provision is through their advertising response to quality-indexed voucher policies. In Table A8, we report equilibrium outcomes for our voucher policies, under the assumption that for-profits cannot adjust their advertising, to quantify the importance of for-profit advertising in quality provision. We find that in terms of aggregate value-added, there are lower returns in terms of quality across our voucher policies. In particular, aggregate value-added increases by only 6.8% instead of 8.8% under the optimal policy voucher when we assume no advertising decision is made.<sup>72</sup> This is because high-quality for-profits are no longer able to attract students by increasing advertising. Moreover, around 40% of FPIs under these policies receive negative profits, due to their large fixed advertising costs, which makes these counterfactuals unrealistic.

Our results suggest that by simply indexing aid to quality, we can achieve 60% of the gains from an optimal voucher, in terms of aggregate value-added. However, to fully unlock the potential of the sub-baccalaureate sector in terms of quality provision, our results suggest the government should incentivize schools that are more responsive to aid *and* high quality to expand their market share. We show that by using publicly available information on school characteristics and market structure, a feasible version of the optimal voucher achieves 75% of the potential gains to aggregate value-added. 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 allocates aid to the right (high-quality, aid-elastic) schools.

## 10 Conclusion

In this paper, we assess the impact of federal student aid design on student and college decisions 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. Quality increases further under a voucher design linear in quality. 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. Finally, we find that a feasible version of our optimal voucher policy, based on publicly available data, is able to capture most of the gains from this design.

This paper is not without its limitations. We cannot accurately assess the effect that redesigning aid would have on the 4-year selective college sector, due to the ability for these schools to screen students. Additionally, we do not model the quality decision, nor the entry and 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 the equilibrium outcomes from alternative aid policies at a large scale in the U.S. higher

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<sup>72</sup>For this counterfactual, we recalculate the voucher elasticity used for the optimal voucher as if there is no advertising response for FPIs (e.g.  $\partial\tau_{j,t}/\partial a_{j,t} = 0$ ).

education sector. Consequently, our results can still be used to inform policymakers, particularly those interested in the outcomes of sub-baccalaureate students.

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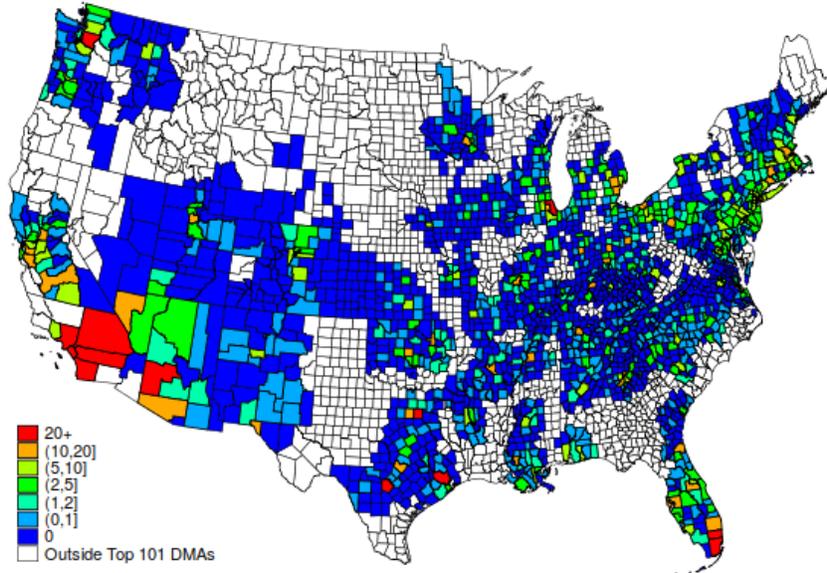
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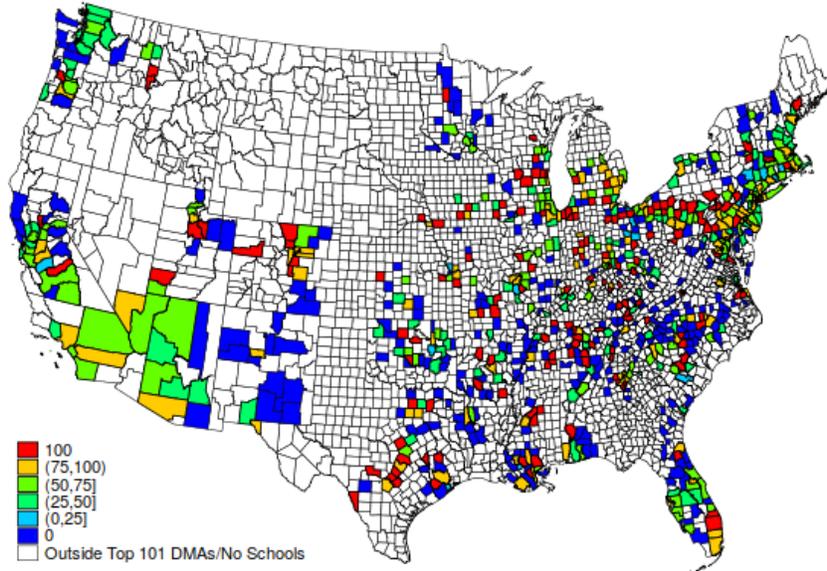
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### Mean Number of Schools Per County



(a) Number of Schools in County

### Mean Percent FPI Schools In County



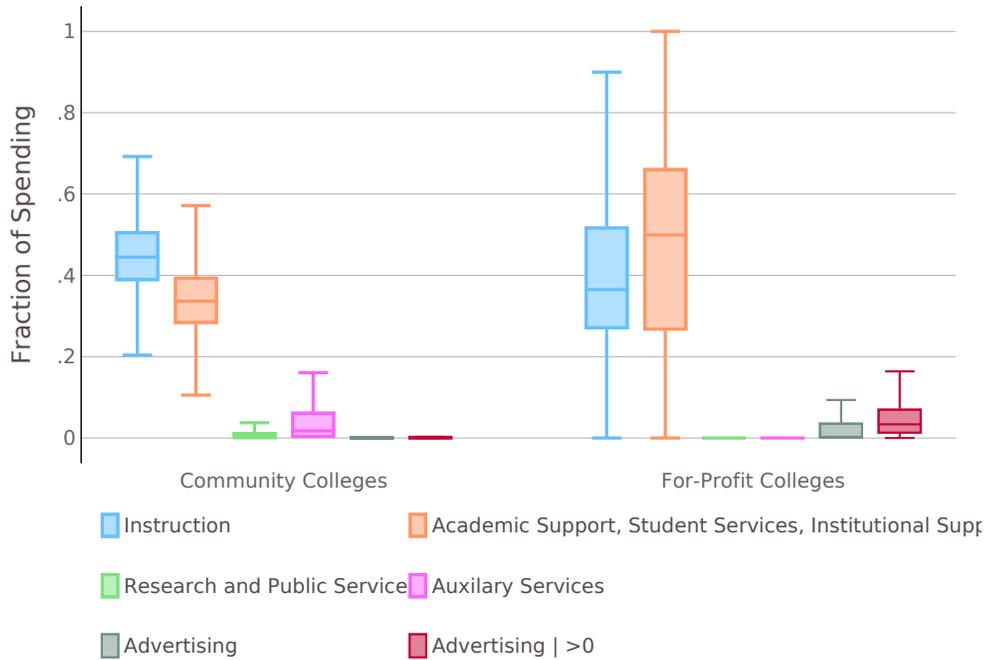
(b) Fraction of Sub-Baccalaureate Schools that are For-Profit

Figure A1: 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) Revenue Sources



(b) Expense Sources

Figure A2: Financial Data of Colleges, by College Type

Panel (a) of figure shows a boxplot of the fraction of revenue coming from tuition, government appropriations, and auxiliary services (e.g. student bookstores), separately by whether the school is a for-profit college or community college. Panel (b) of figure shows a boxplot of the fraction of expenses coming from instruction, research and public services, academic support / student services / institution support, auxiliary services, advertising (as calculated from AdSpender), and advertising among schools for which we observe positive advertising.

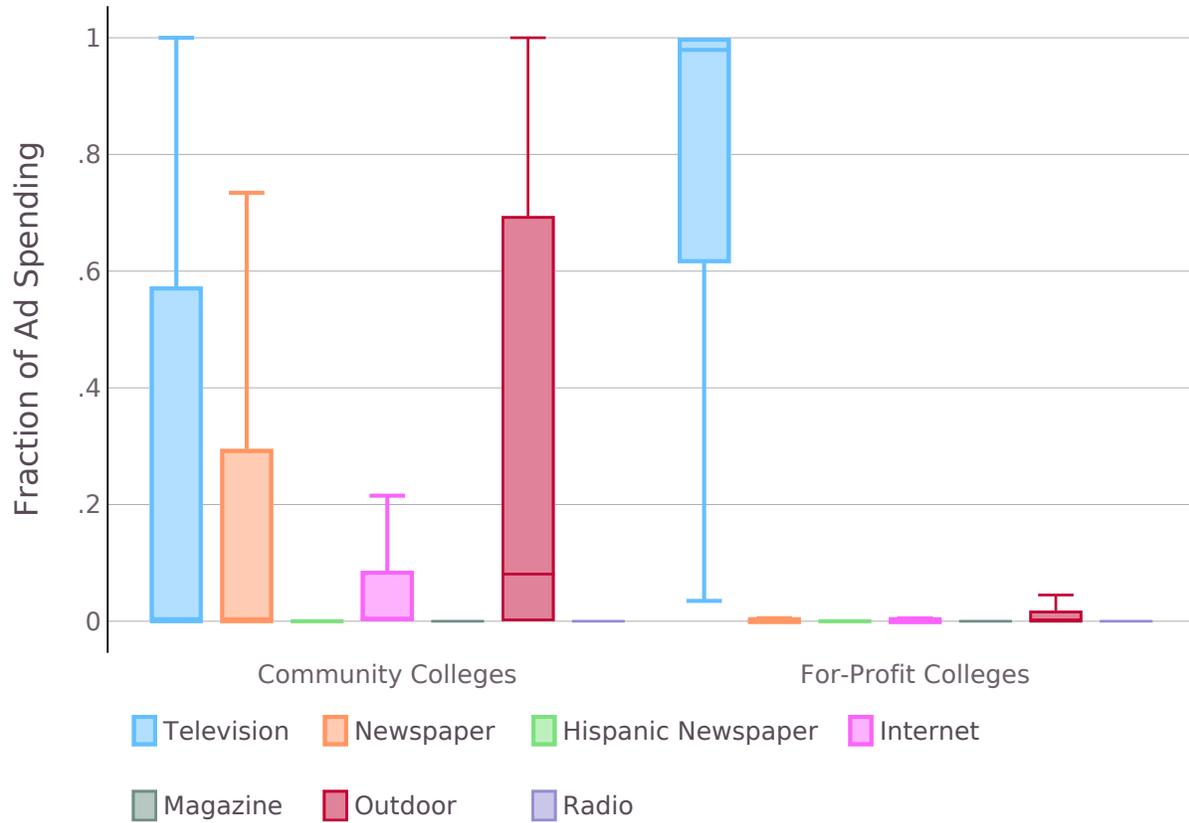
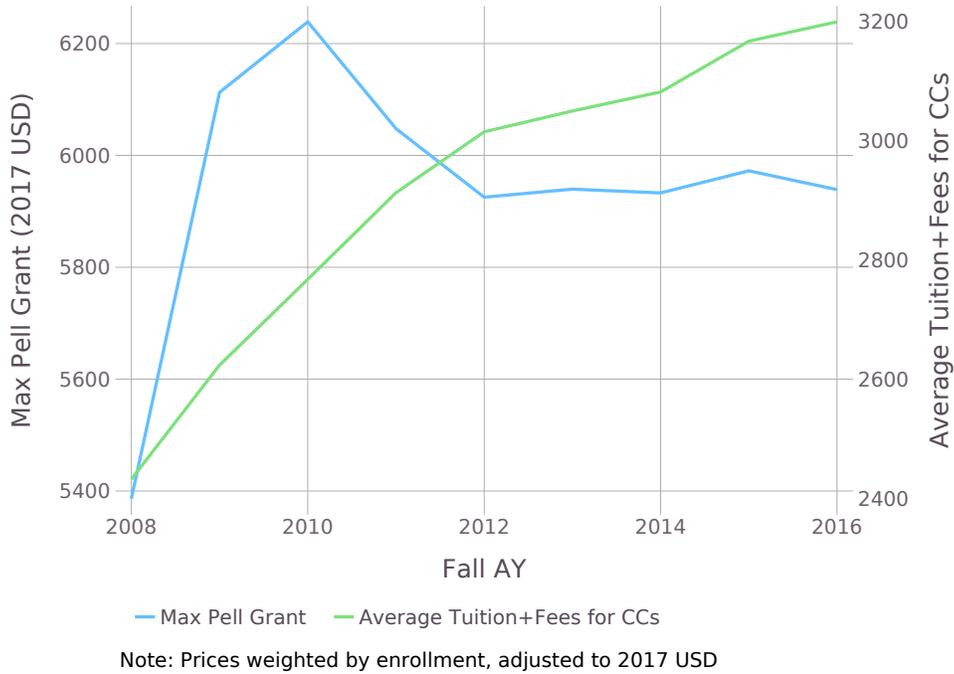
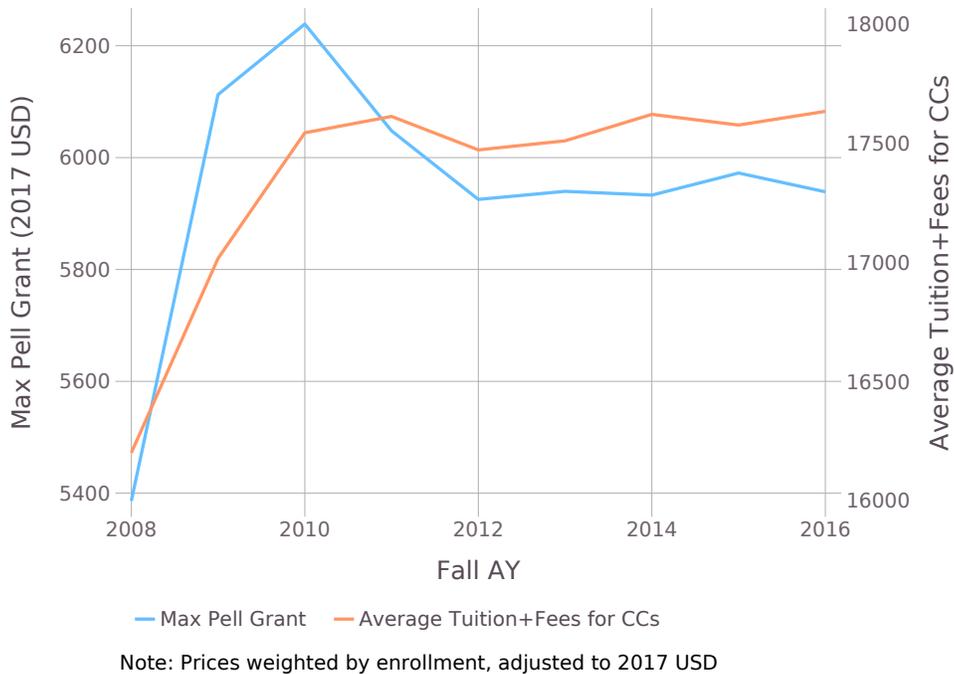


Figure A3: Types of Advertising in by College Type

Figure shows boxplot the fraction of advertising spending done in local markets (DMA) by type of advertising, separately by community colleges and for-profit colleges.



(a) Community Colleges



(b) For-Profit Colleges

Figure A4: Time Series of Tuition versus Maximum Pell Grant Amount, by College Type

Figure shows the average tuition at for-profit and community colleges, weighted by total FTE enrollment, by academic year, against the maximum Pell grant award in each year. Tuition numbers are adjusted to 2017 \$ using the CPI.

### Expected Max Pell Grant In 2006 (Preperiod)

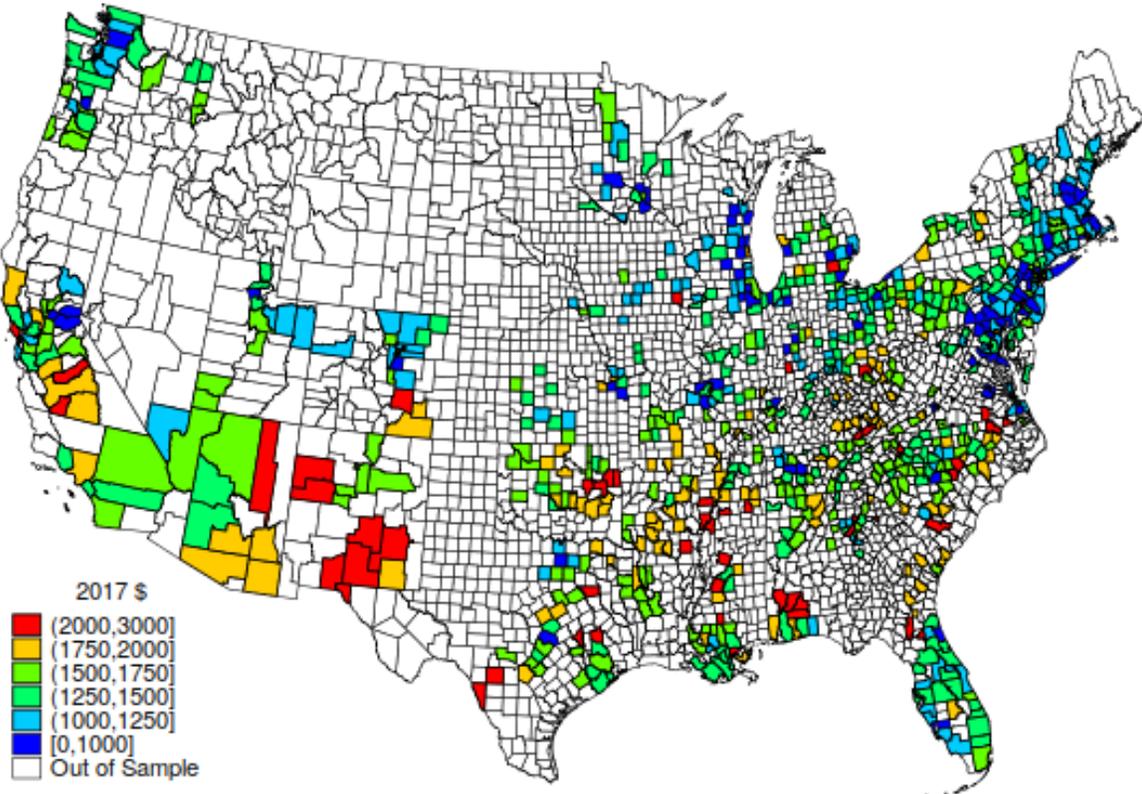


Figure A5: Expected Maximum Pell Grant in U.S. Counties, 2006

Figure shows, by county, the expected maximum Pell grant award among potential students in 2006. This is equal to our simulated instrument (See Section 4.1.1 for details) for the year 2006, the pre-period base year.

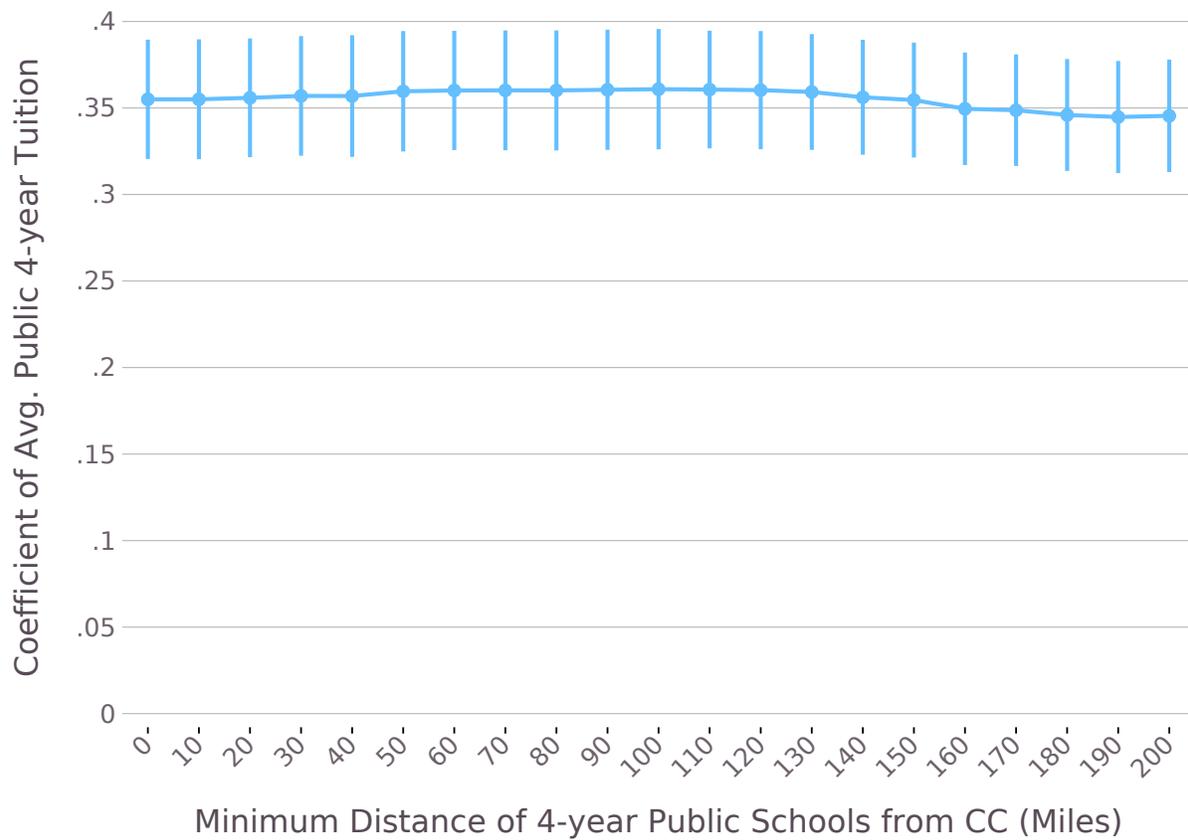


Figure A6: Correlation between Community College Tuition and 4-year Tuition, by Distance

Figure shows the output of a regression of community college tuition on the average tuition of 4-year public colleges in the same state at least  $d$  miles away, varying  $d$  from 0 miles to 200 miles. Regression includes school fixed effects. 95% confidence intervals displayed in the plot come from standard errors clustered at the school level.

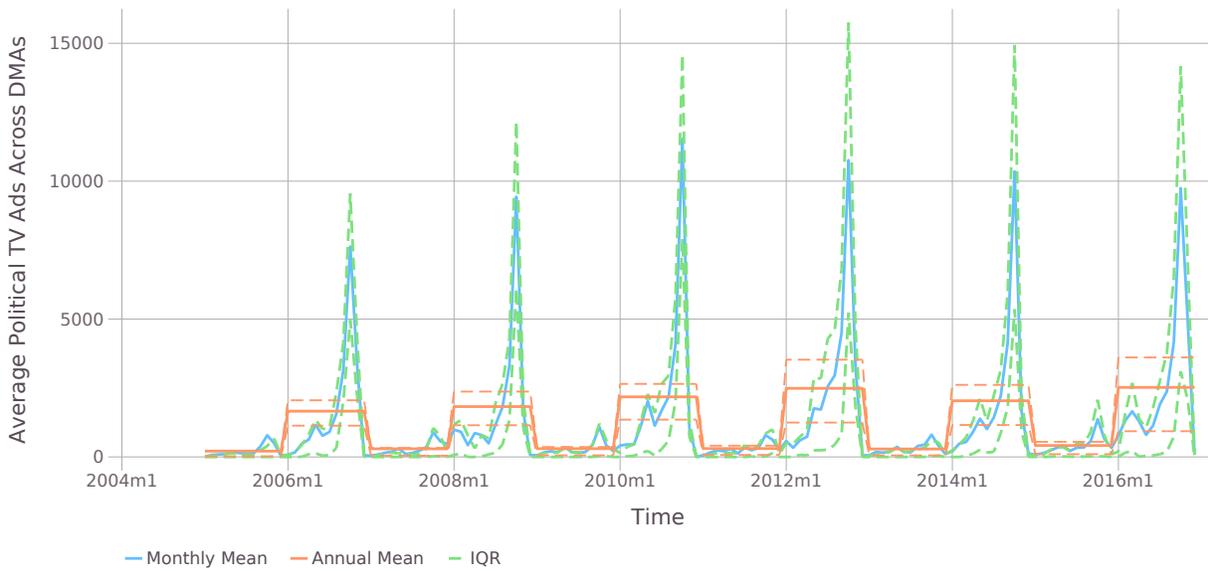
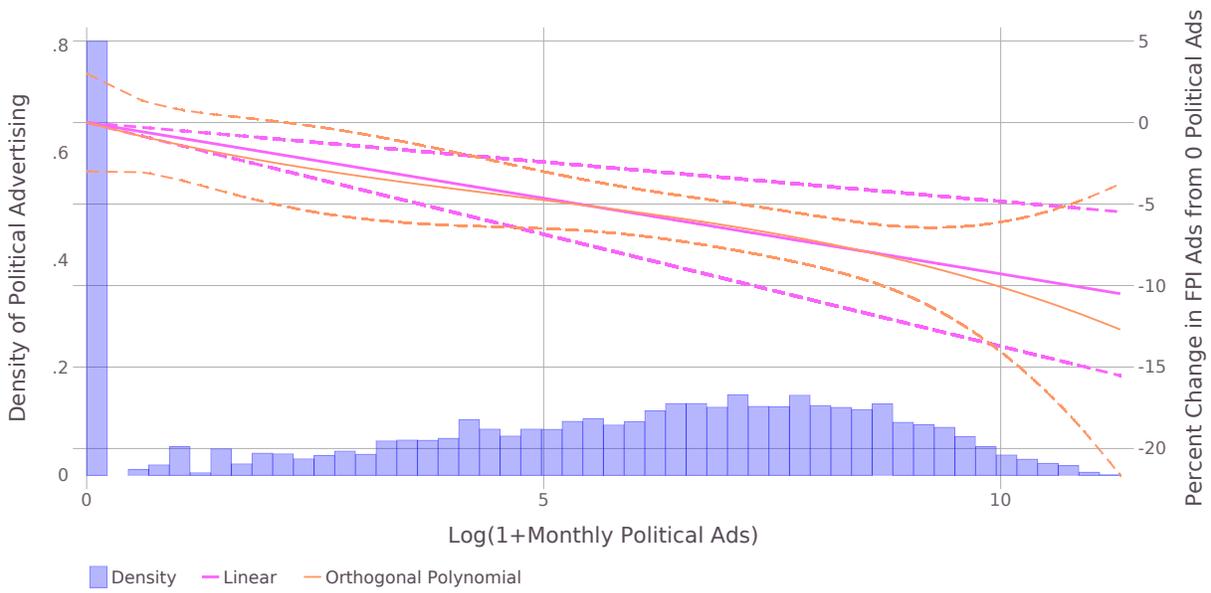
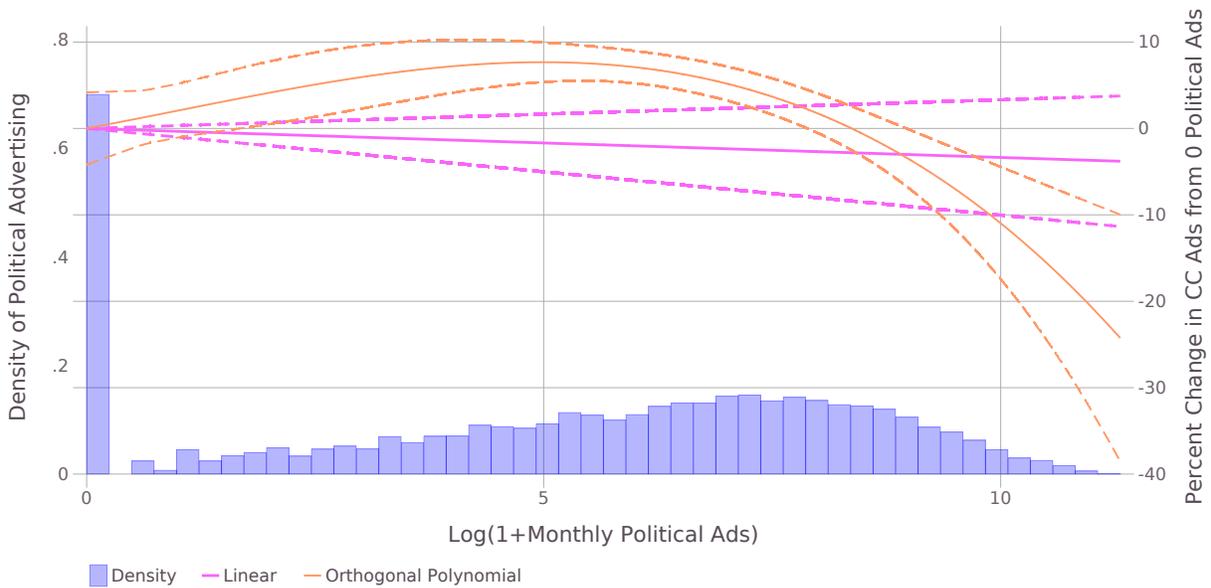


Figure A7: Monthly Time Series of Average Political Advertising within DMA

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.



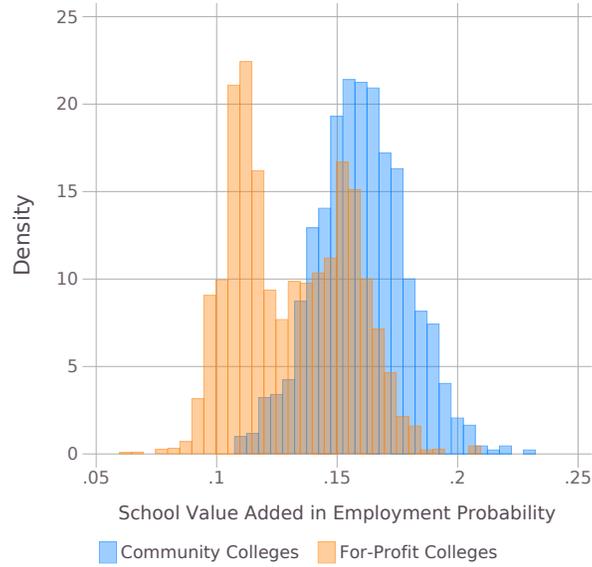
(a) For-Profit Colleges



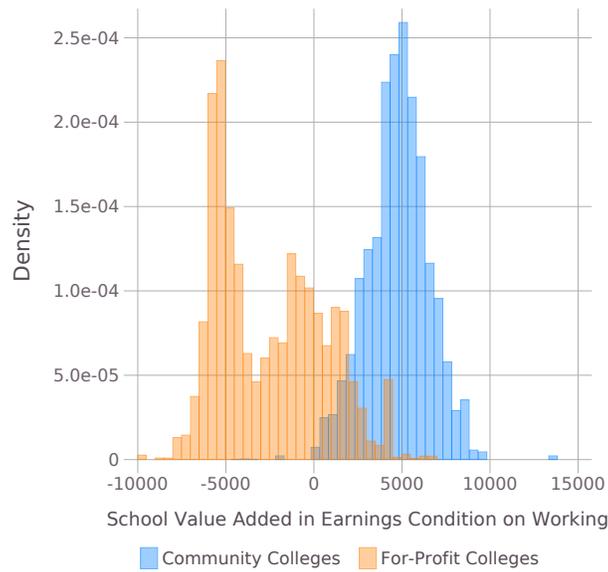
(b) Community Colleges

Figure A8: 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  $\log(1+\text{political monthly ads})$ , 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.



(a) Probability of Employment



(b) Earnings Conditional on Employment

Figure A9: 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.

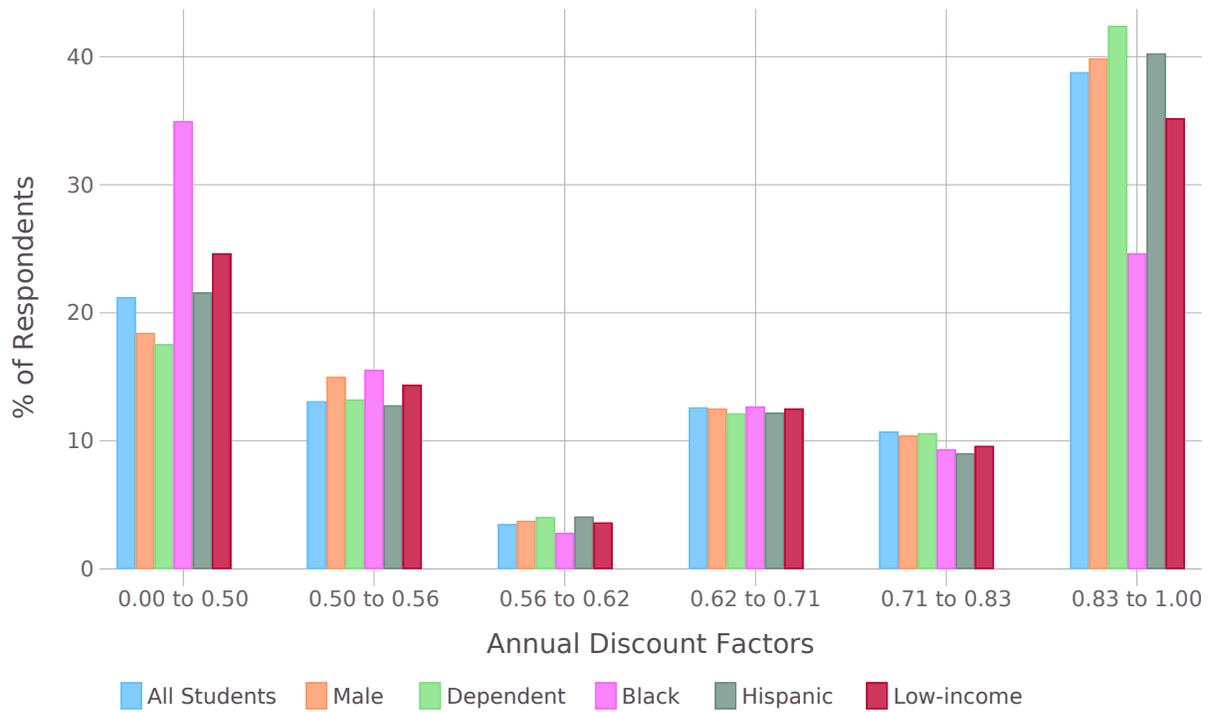
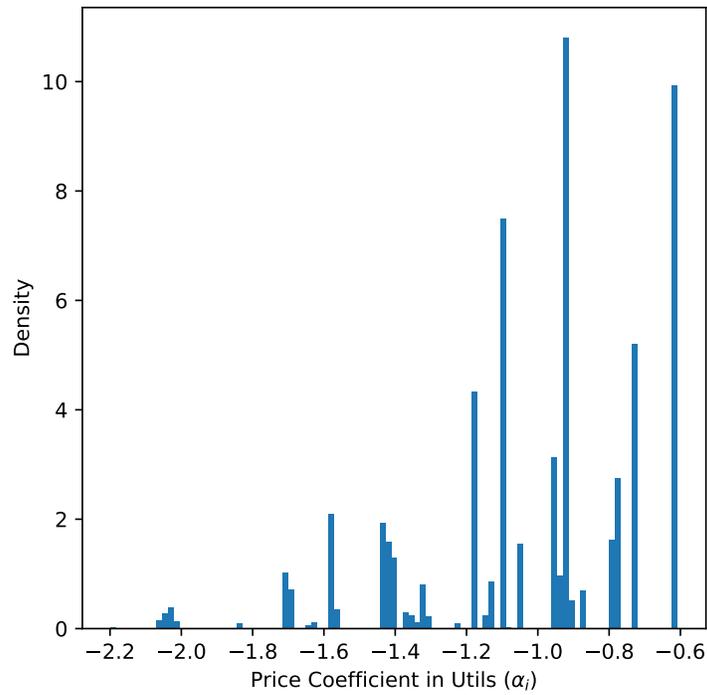
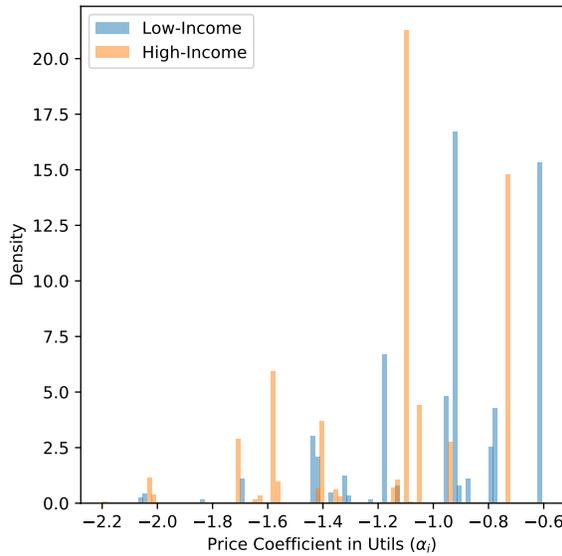


Figure A10: Distribution of Discount Factor Micromoments

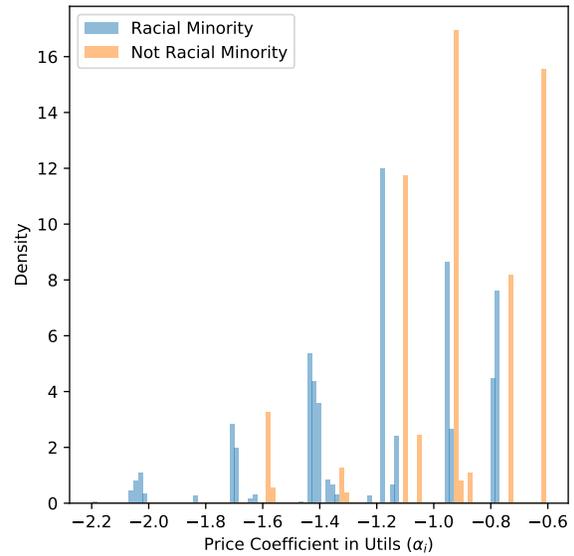
Table shows the distribution of discount factors from student responses to the 2012 Beginning Postsecondary Survey. Discount factors are expressed as the value of a dollar in one year. We plot the distribution for all sub-baccalaureate students in the BPS, as well as by each of the 5 demographics used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



(a) All Consumers



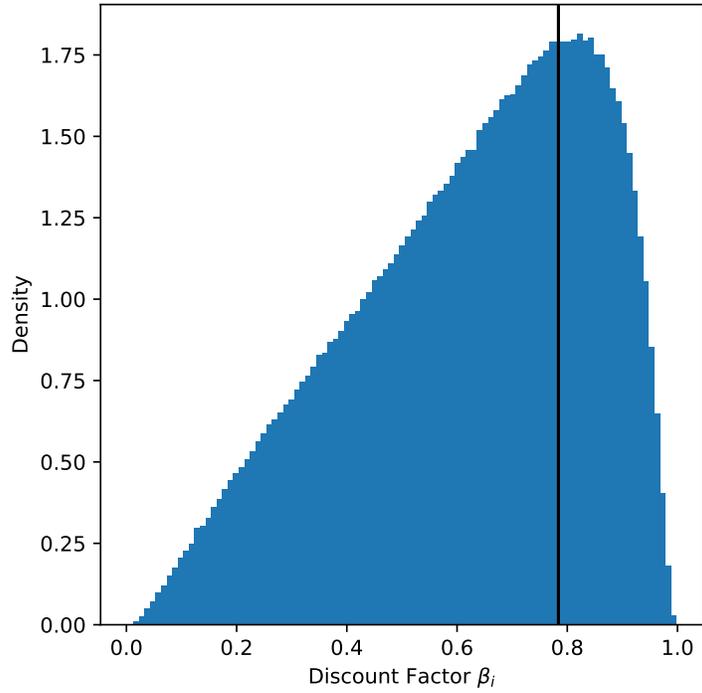
(b) By Income



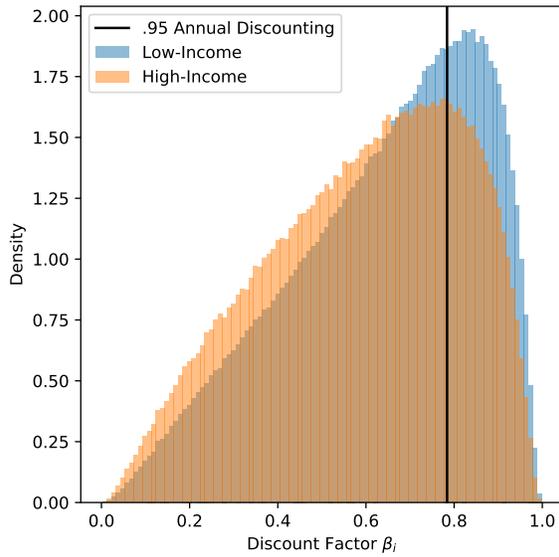
(c) By Race

Figure A11: Distribution of Price Preferences  $\alpha_i$

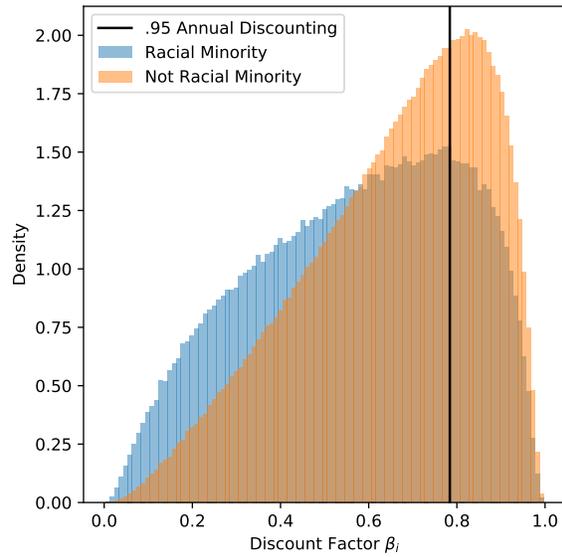
Figure shows the distribution of the estimated price coefficient  $\alpha_i$ , in terms of utility. Each consumer is weighted by the market size, so that each point represents the density relative to the total number of effective students. Panel (b) shows the distribution broken out by whether the potential student's EFC falls below the Pell grant eligibility threshold ( $EFC_i \leq EFC_y$ ). Panel (c) shows the distribution broken out by whether the student is a racial minority (Black or Hispanic).



(a) All Consumers



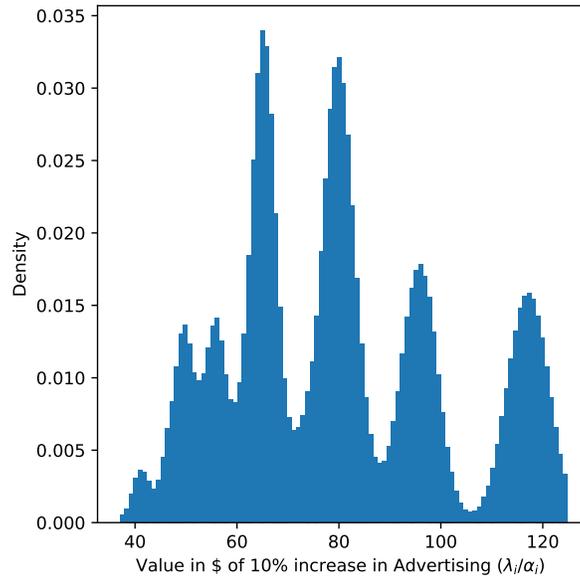
(b) By Income



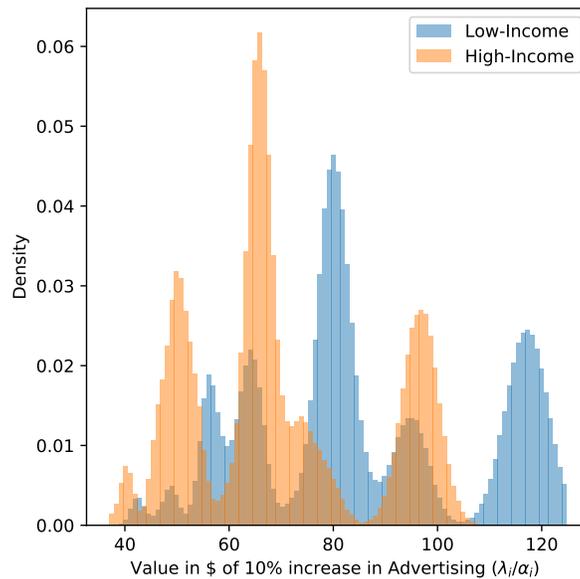
(c) By Race

Figure A12: Distribution of Discount Factors  $\beta_i$

Figure shows the distribution of the estimated discount factor  $\beta_i$  on 10-year student loans. Each consumer is weighted by the market size, so that each point represents the density relative to the total number of effective students. Panel (b) shows the distribution broken out by whether the potential student's EFC falls below the Pell grant eligibility threshold ( $EFC_i \leq \bar{EFC}_y$ ). Panel (c) shows the distribution broken out by whether the student is a racial minority (Black or Hispanic). The solid black line denotes the equivalent discounting on ten-year loans for an individual with 5% annual discounting.



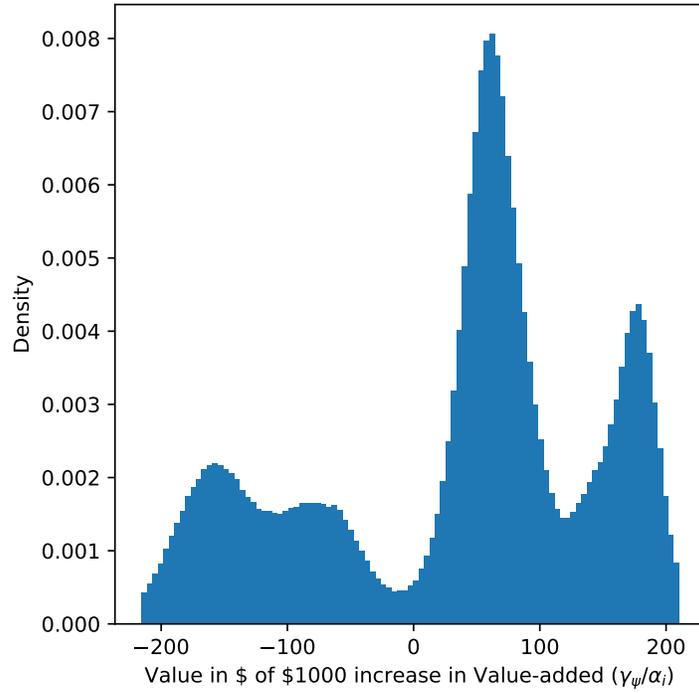
(a) All Consumers



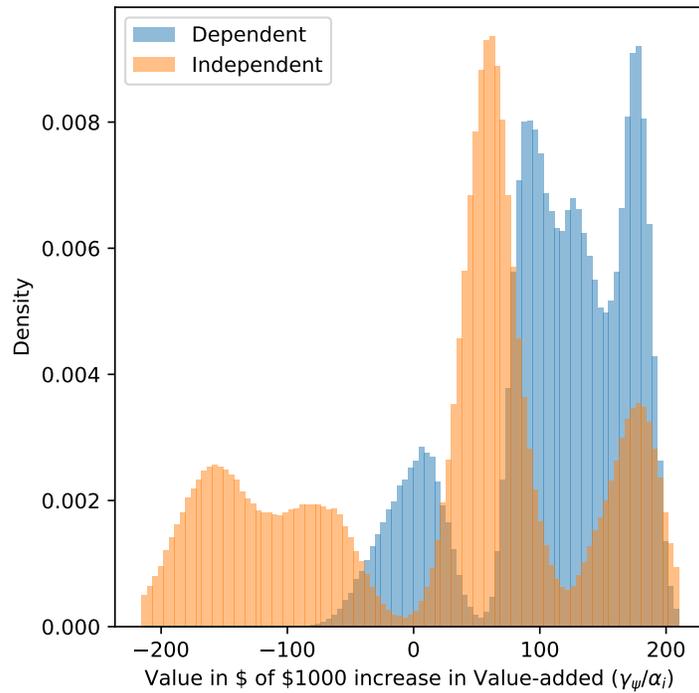
(b) By Income

Figure A13: Distribution of Monetary Valuations of Advertising  $\lambda_i/\alpha_i$

Figure shows the distribution of the estimated value in \$ terms ( $\lambda_i/\alpha_i$ ) of a 10% increase in FPI television advertising (.1 units of  $\log(a_{j,t} + 1)$ ). Each consumer is weighted by the market size, so that each point represents the density relative to the total number of effective students. Panel (b) shows the distribution broken out by whether the potential student's EFC falls below the Pell grant eligibility threshold ( $EFC_i \leq EFC_y$ ).



(a) All Consumers



(b) By Dependency Status

Figure A14: Distribution of Monetary Valuations of Value-Added  $\gamma_{\psi,i}/\alpha_i$

Figure shows the distribution of the estimated value in \$ terms ( $\gamma_{\psi,i}/\alpha_i$ ) of a \$1,000 increase in value-added. Each consumer is weighted by the market size, so that each point represents the density relative to the total number of effective students. Panel (b) shows the distribution broken out by whether the potential student is a dependent or independent.

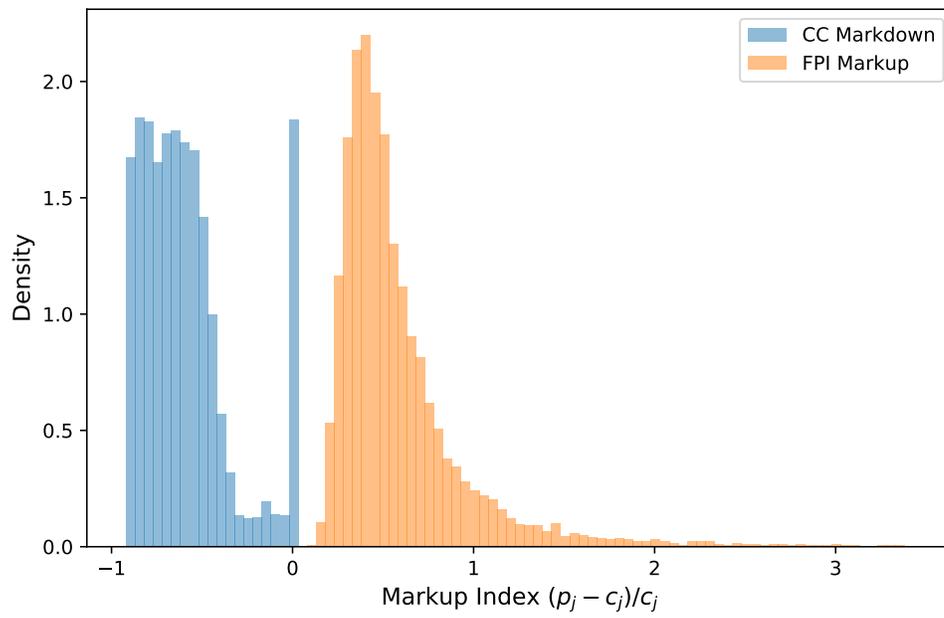


Figure A15: Distribution of Markups/Markdowns by College Type

Figure shows the distribution of community college markdowns (the price as % below cost) and for-profit college markups (the price as % above cost), calculated as  $(p_{j,t} - c_{j,t})/c_{j,t}$ .

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)	0.377** (0.149)	0.500*** (0.189)	0.250* (0.129)	0.351** (0.157)	0.425** (0.172)	0.551*** (0.205)	0.234 (0.169)	0.404** (0.176)	0.536** (0.217)
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	10.74	10.74	10.74	10.74	10.74	9.08	9.08	6.79	6.79

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: Empirical Bayes Estimates of Quality Prior Mean

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

Table A3: Demand Estimates: Preferences for College Characteristics

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

Standard errors reported in parentheses. Standard errors for linear parameters (baseline coefficients) recovered from an OLS regression on  $\delta_{j,t}$  on  $X_{j,t}$ . Standard errors for linear parameters on time-invariant variables (For-Profit College, Value-Added, HBCU) recovered from a GLS regression of fixed effects  $\delta_j$  recovered from Equation 32 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 A4: 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\$. 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 24 on  $X_{j,t}$ . Standard errors for linear parameters on time-invariant variables (Value-Added) recovered from an OLS regression of fixed effects  $c_j$  recovered from Equation 22 on colinear variables.

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

Table A5: 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\$. 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 24 on  $\bar{X}_{f,d}$ . \* $p < .1$ , \*\* $p < .05$ , \*\*\* $p < .01$

Table A6: Counterfactual Results (Feasible Quality Vouchers)

Voucher Indexed to:	Level	% Change From Current			
	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  $\psi_j$  and estimated voucher elasticities  $\hat{\epsilon}_{j,j,t}$ . 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  $\psi_j$ . 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  $\hat{\epsilon}_{j,j,t}$ . Aggregate value-added denotes the sum of quality  $\psi_j$  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)

Policy	Level	% Change From Current						
		Current Aid Regime	For-Profit Ban	Advertising Ban	Low Quality Ban	Lump-Sum	Low-Income Voucher	Optimal
Aggregate Value Added	64.66B\$		+3.02%	-1.32%	+1.32%	+2.76%	+8.20%	+8.31%
Aggregate Value-Added (Low-Income)	35.85B\$		+6.01%	-0.59%	+2.29%	+9.27%	+19.09%	+19.28%
Average Value-Added	8,234\$		+5.51%	+4.50%	+1.66%	+0.84%	+8.55%	+9.41%
Average Value-Added (Low-Income)	7,903\$		+8.97%	+6.22%	+2.69%	+1.32%	+14.52%	+16.02%
Students	7.85M		-2.36%	-5.56%	-0.34%	+1.90%	-0.33%	-1.01%
Low-Income Students	4.54M		-2.72%	-6.41%	-0.38%	+7.85%	+3.99%	+2.81%
Avg. Net Student Price	7,576\$		-3.27%	-2.99%	-0.38%	-7.19%	-9.52%	-13.00%
Avg. Net Student Price (Low-Income)	7,313\$		-3.67%	-3.08%	-0.40%	-7.69%	-12.07%	-21.79%
Consumer Surplus	37.08B\$		+1.84%	-1.45%	+0.27%	+1.91%	+2.87%	-1.60%
Consumer Surplus (Low-Income)	20.91B\$		+3.88%	-0.92%	+0.56%	+7.07%	+8.77%	+0.85%
Consumer Surplus (No Ads)	31.47B\$		+10.75%	+16.10%	+0.61%	+3.60%	+9.24%	+4.61%
Consumer Surplus (Low-Income, No Ads)	16.63B\$		+19.44%	+24.57%	+1.21%	+9.84%	+20.53%	+11.75%
% FPI	16.85%		-8.02%	-8.28%	-1.03%	-1.47%	-6.03%	-6.43%
% FPI (Low-Income)	22.13%		-12.52%	-10.87%	-1.58%	-2.20%	-9.60%	-10.25%
FPI Profits	5.00B\$		-67.31%	-29.70%	-9.37%	-9.42%	-48.41%	-54.41%
Avg. FPI Profits/Student	3,998\$		-40.10%	+37.56%	-9.90%	-2.81%	-26.35%	-28.26%
Total Welfare	42.08B\$		-6.38%	-4.80%	-0.88%	+0.56%	-3.23%	-7.88%
Federal Govt Spending	33.99B\$		-8.18%	-4.34%	-1.05%	-5.06%	-8.54%	-13.88%
Community College Subsidies	40.50B\$		+6.87%	+3.64%	+0.88%	+4.25%	+7.16%	+9.44%
Government Spending	74.49B\$		-0.00%	-0.00%	-0.00%	-0.00%	-0.00%	-1.20%

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 Advertising Response)

Policy	Level	% Change From Current		
	Current Aid Regime	Lump-Sum	Quality	Optimal
Aggregate Value Added	64.66B\$	+2.14%	+5.21%	+6.83%
Aggregate Value-Added (Low-Income)	35.85B\$	+10.33%	+19.38%	+22.17%
Average Value-Added	8,234\$	+0.30%	+6.88%	+7.32%
Average Value-Added (Low-Income)	7,903\$	+0.71%	+13.25%	+14.06%
Students	7.85M	+1.83%	-1.56%	-0.45%
Low-Income Students	4.54M	+9.55%	+5.41%	+7.12%
Avg. Net Student Price	7,576\$	-7.11%	-9.45%	-12.91%
Avg. Net Student Price (Low-Income)	7,313\$	-7.75%	-11.88%	-20.66%
Consumer Surplus	37.08B\$	+1.94%	+2.59%	+0.41%
Consumer Surplus (Low-Income)	20.91B\$	+8.59%	+11.20%	+5.96%
Consumer Surplus (No Ads)	31.47B\$	+3.16%	+9.45%	+7.30%
Consumer Surplus (Low-Income, No Ads)	16.63B\$	+10.85%	+24.11%	+18.30%
% FPI	16.85%	-0.68%	-6.38%	-6.73%
% FPI (Low-Income)	22.13%	-1.35%	-10.20%	-10.75%
FPI Profits	5.00B\$	-5.21%	-40.57%	-44.91%
Avg. Community College Markdown	7,162\$	-1.69%	-2.52%	-2.60%
Avg. For-Profit College Markup	5,552\$	+1.90%	+22.73%	+23.85%
Avg. FPI Profits/Student	3,998\$	-13020.44%	-40417.82%	-44794.91%
FPI Advertising	2.74B\$	0.00%	0.00%	0.00%
Total Welfare	42.08B\$	+1.09%	-2.54%	-4.98%
Federal Govt Spending	33.99B\$	-0.01%	-0.02%	-0.02%
Community College Subsidies	40.50B\$	+0.00%	-0.00%	-0.00%
Government Spending	74.49B\$	-0.01%	-0.01%	-0.01%

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  $\psi_j$  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.

## A EFC Construction

In this section, we describe the construction of the Expected Family Contribution (EFC) for each individual we observe in the market (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<sup>73</sup> to construct the measure for each year.<sup>74</sup> We use the simplified EFC formulas, which does not consider household asset contributions and so can be inferred from 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 when attempting to qualify for federal financial aid. Because our model considers only the tuition from full-time annual enrollment, we calculate the EFC for annual or  $\geq 9$  months, and do not prorate EFC for students entering shorter-term programs.

Within the EFC calculation, there are three worksheets (A,B,C) that contain differing formulas depending on whether the student is a dependent, an independent without other dependents, or an independent with dependents, respectively. We classify individuals as dependents in line with 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. All of this information is available in the ACS microdata.

Students who are dependents and their parent's income falls below a threshold (\$25,000 in 2015), or independents with children from whom their + their spouse's income falls below an income threshold (\$25,000) are classified as having  $EFC = 0$ . This is analogous to the requirements on the actual EFC worksheet, except we do not also condition on the household filing a 2015 IRS Form 1040, 1040A, 1040EZ, since this is unobserved in the ACS. Students that 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 outcome. 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 the household and the number of students currently enrolled in college; and an employment expense allowance, which gives the maximum of 35% of the minimum working parent's income, or \$4,000. Allowances are subtracted from income to determine the amount of available income a dependent student's parents have. The parents' available income is converted to a contribution from available income using a formula from the worksheet, which ranges from 22-47% of available income depending on how much available parent income is calculated. This is then divided by the number of students in college attached

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<sup>73</sup>Example: <https://studentaid.gov/sites/default/files/2017-18-efc-formula.pdf>

<sup>74</sup>Archived handbooks can be found here: <https://ifap.ed.gov/ilibrary/document-types/federal-student-aid-handbook?archive=1>

to the household to determine the parent's contribution. If the dependent student is working as well, 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 how negative it was). We subtract student allowances from their income to calculate their available income, then divide this by two to get the student's 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 households' social security tax allowance, which is also provided by the worksheet; an income protection allowance, which depends on the marital status of the independent and whether the student is enrolled at least 1/2 time <sup>75</sup>; and an employment expense allowance, which is zero if the student is not working unless both the student and their spouse are working, in which case it is the maximum of 35% of the minimum of the independent and their spouse's income, or \$4,000. Allowances are subtracted from 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 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 households' social security tax allowance, which is also provided by the worksheet; an income protection allowance, which depends on the number of members in the household and the number of students currently enrolled in college; and an employment expense allowance, which gives the maximum of 35% of the minimum working parent's income, or \$4,000, if all heads of household are working. 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 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.

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<sup>75</sup>Since we calculate the EFC for full-time enrollment, we use the income protection allowance corresponding to at least half time enrollment

## B Tuition Passthrough

In this section, we describe the effects of increased federal aid on college prices. In Section 2, we highlighted that federal student aid generosity increases with cost. This may incentivize colleges to increase tuition prices to capture the additional aid students may receive (the so-called Bennett Hypothesis). To test this hypothesis, we estimate the following linear relationship between price  $p_{j,t}$  of a college  $j$  in market  $t$  (county  $\times$  year) and federal aid:

$$p_{j,t} = \alpha_j + \beta \text{Federal Aid Per Student}_{j,t} + \gamma X_{j,t} + \epsilon_{j,t} \quad (55)$$

Where  $p_{j,t}$  denotes a measure of price,  $\alpha_j$  is a school fixed effect,  $\text{Federal Aid Per Student}_{j,t}$  is the average amount of federal aid issued to each student attending college  $j$  in year  $t$ , and  $X_{j,t}$  includes school controls. Because public and private colleges may have differential responses to federal aid, we run this regression separately by institution type (Community Colleges and For-Profits). We measure federal aid per student using the Financial aid portion of the IPEDS survey, which reports the gross amount of Pell grants, federal grants, and federal loans received by full-time, first-time students at each school. We normalize this gross amount by the cohort size of full-time, first-time students reported to produce our measure of federal aid per student. Our set of controls  $X_{j,t}$  include the set of student services offered, the majors offered at each school, the level of degrees offered at each school, the HEPI cost index,<sup>76</sup> as well as market demographics.<sup>77</sup> We index all \$ measures to 2017\$ using the CPI.  $\beta$  measures the effect on price (e.g., tuition) from each student receiving an additional dollar of aid.

Because students at higher price institutions are mechanically eligible for more federal aid, there will be reverse causality in Equation 55. Therefore, to estimate the causal effect of aid on prices, we follow an instrumental variables (IV) approach, using the instrument for Pell grant generosity described in Section 4.1.1,  $Z_t^\pi$ :

$$\begin{aligned} \text{Federal Aid Per Student}_{j,t} &= \delta_j + \alpha Z_t^\pi + \gamma_1 X_{j,t} + \epsilon_{j,t} \\ p_{j,t} &= \delta_j + \beta \widehat{\text{Federal Aid Per Student}}_{j,t} + \gamma X_{j,t} + \epsilon_{j,t} \end{aligned}$$

Table B1 displays OLS first stage estimates of the effect of our Pell grant instrument on aid per student. Similar effects of the instrument are obtained for both community colleges and for-profits in terms of the federal grant \$ per student, which is unsurprising given that the Pell grant program makes up most of federal grants. If we look at the effect on federal loans per student, there is also a positive effect at both types of institutions, though it is marginally significant at community

<sup>76</sup>Source: <https://www.commonfund.org/higher-education-price-index>

<sup>77</sup>We define market demographics as demographic data among the population of individuals with a high school degree and ages 18-50 (the set of “potential students”) residing in the same county each school is located in. The market demographics we include are the following: Average EFC, Average Income, % Male, % Hispanic, % Black, % White, % Dependents, their average EFC, and the (logged) size of the market.

colleges. This is in line with the fact that a low fraction of students need to take federal loans to afford community colleges. In our preferred measure of aid, the number of grants and loans in \$ terms per student, there are significant effects at both types of institutions.

Table B2 plots the OLS and IV estimates of the effect of aid on tuition. The OLS estimates suggest a very similar effect of federal aid on tuition across institution types, around \$.08 per dollar increase of aid. This is due in large part to the mechanical increase in aid with price/cost. If we move to the IV estimates, we see that the effects across institutions diverge. The effect is estimated to be insignificantly different from zero, around \$.02 per dollar, at community colleges (column 2), while the causal effect of aid on FPI prices is substantially increased: for each \$ increase in federal aid induced by federal policy, tuition at FPIs increases by \$.80, suggesting an 80% passthrough from aid to prices at these colleges. This is similar in magnitude with the evidence presented in Lucca et al. [2019], which finds that for-profits have a 62% passthrough in tuition from changes to the generosity of federal student loans, the other major federal student aid program. We also note that the first-stage F-stat is large at both sets of institutions, suggesting our instrument is sufficiently strong to capture this effect.

While the previous table provides evidence that tuition does increase at for-profit colleges when aid is increased, another question of policy interest is whether federal aid is counterproductive and translates to increased costs of students to obtain higher education. To test this, we regress federal aid per student on a variety of net student price measures from IPEDS. Our first measure is the cost of attendance, which is calculated using tuition, books and supplies, and a weighted average of the “other expenses” cost of attendance category in IPEDS.<sup>78</sup> Notably, we exclude the component of cost-of-attendance coming from room + board, since this may be driven by local housing prices and are unlikely to be absorbed by the college providing education services, since on average the vast majority of students (98.8%) attending a school live off-campus. We subtract the average amount of federal grants per student from this COA measure, to measure the effect of federal aid on prices a student would need to pay through a combination of loans and out-of-pocket. Finally, we subtract federal grants and federal loans, which measures the cost in terms of what a student needs to pay out of pocket, or through other loan providers, to attend a college.

Table B3 displays estimates of these effects by institution type. For cost of attendance, our estimates suggest a modest (but statistically insignificant at 95% confidence levels) increase in prices at community colleges, and a 1.1\$ increase in cost at for-profits, which is statistically indistinguishable from a 1:1 passthrough, and similar in level to the effect on tuition. However, the increased effect size suggests scope for colleges to increase costs on students through other means besides tuition in response to federal aid increases. In columns (3) and (4), we display estimates on cost of attendance, minus federal grants. Under this metric, we see that federal aid works at community colleges, in the sense that it provides large decreases in the amount they need to finance through out-of-pocket

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<sup>78</sup>This is weighted by the composition in the full-time, first-time, aid-receiving cohort of individuals living off-campus with their family (dependents) those living on-campus, and those living off-campus without their family (independents), since other expenses differ across these groups. Data on the living situation of the entire cohort is unavailable in IPEDS.

payments and loans. At for-profits, there is still a positive pass-through on this net price measure of .50\$ per dollar, though the effect is lower than the effect on tuition. Finally, in columns (5) and (6) we provide estimates of the effect of cost of attendance netting out federally subsidized student loans and federal grants. For this net price measure, the effect is now statistically insignificant in differing from zero. Whether this translates into a perceived increase in costs, however, will depend on how students internalize future payments on federal loans. In our structural model presented in Section 6, we quantify this by estimating discount rates on loan payments. To fully evaluate the pass-through effects would require additional modeling assumptions. Finally, we note that this net student price is constructed as an average across the entire cohort, including those not receiving any federal aid. Thus, among aid-receiving students, the net student price would be lower, and the effect of federal aid on net prices for this population would be smaller.

Finally, we also examine the effect of federal aid on advertising, the other endogenous school input considered in this paper. Table B4 displays the results. For easier interpretation, both federal aid and advertising are logged, so that we can understand the impact of federal aid on advertising in terms of an aid elasticity. Community colleges do not increase advertising in a statistically significant manner when aid is increased. For-profits, on the other hand, have an estimated elasticity of 1.57, suggesting a 10% increase in federal aid per student leads to a 15.7% increase in advertising. Note advertising is not in per student terms. The elasticity may be greater than 1 because further student aid increases the total pool of students that attend a college, which incentivizes further advertising by for-profit colleges.

Table B1: Effect of Simulated Pell Grant Instrument on Federal Aid Per Student

	Grants Per Student		Loans Per Student		Grants+Loans Per Student	
	CCs (1)	FPIs (2)	CCs (3)	FPIs (4)	CCs (5)	FPIs (6)
Simulated Pell Instrument	1.743*** (0.126)	1.508*** (0.131)	0.255** (0.105)	0.841*** (0.207)	1.998*** (0.187)	2.349*** (0.283)
Observations	7159	16881	7159	16881	7159	16881
R-Squared	0.801	0.617	0.867	0.752	0.830	0.707
School FE	Yes	Yes	Yes	Yes	Yes	Yes
School Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Market Demographics	Yes	Yes	Yes	Yes	Yes	Yes

Table displays OLS estimates of the relationship between federal aid per student and our Pell grant instrument. Standard errors reported in parentheses are clustered at the school level. Grants per student denotes the average \$ of federal grants per first-time, full-time student, while loans per student denote the average \$ of federal loans per first-time, full-time student. Market Demographics denote the fraction of students in the market (18-50, high school education, same county) that are male, dependent, Black, Hispanic, unemployed, and the logged market size, as well as the average EFC. 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). All regressions also include controls for the HEPI cost index. Regressions for CCs include the logged appropriations as an additional control variable.

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

Table B2: Effect of Federal Aid Per Student on Tuition

Outcome: Tuition (\$)	CCs		FPIs	
	(1)	(2)	(3)	(4)
Federal Aid (Grants+Loans) Per Student	0.0853*** (0.0275)	0.0206 (0.0445)	0.0786*** (0.00871)	0.793*** (0.122)
Observations	7157	7157	16402	16402
Estimation Method	OLS	IV	OLS	IV
School FE	Yes	Yes	Yes	Yes
School Characteristics	Yes	Yes	Yes	Yes
Market Demographics	Yes	Yes	Yes	Yes
First-Stage F-stat	-	114.390	-	69.744

Table displays OLS and IV estimates of the relationship between federal aid per student and tuition prices. Standard errors reported in parentheses are clustered at the school level. Market Demographics denote the fraction of students in the market (18-50, high school education, same county) that are male, dependent, Black, Hispanic, unemployed, and the logged market size, as well as the average EFC. 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). All regressions also include controls for the HEPI cost index. Regressions for CCs include the logged appropriations as an additional control variable. Regressions exclude schools in our sample that have above 2% of the within-school standard deviation in tuition, to remove the influence of outliers in our estimates.

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

Table B3: Effect of Federal Aid Per Student on Net Price Measures

	Cost Of Attendance (COA)		COA - Grants		COA - Grants - Loans	
	CCs (1)	FPIs (2)	CCs (3)	FPIs (4)	CCs (5)	FPIs (6)
Federal Aid (Grants+Loans) Per Student	0.234* (0.123)	1.105*** (0.161)	-0.590*** (0.134)	0.520*** (0.150)	-0.718*** (0.125)	0.153 (0.164)
Observations	6895	15533	6895	15533	6895	15533
Estimation Method	IV	IV	IV	IV	IV	IV
School FE	Yes	Yes	Yes	Yes	Yes	Yes
School Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Market Demographics	Yes	Yes	Yes	Yes	Yes	Yes

Table displays IV estimates of the relationship between federal aid per student and net student prices. Standard errors reported in parentheses are clustered at the school level. COA denotes the average cost of attendance excluding Room and Board, where average is taken based on the composition of on campus, off campus with family, and off campus without family students. COA - Grants denotes the average COA minus the average \$ of federal and state grants given to students in each cohort. COA - Grants - Loans denotes COA - Grants minus the average \$ of federal loans given to students in each cohort. Market Demographics denote the fraction of students in the market (18-50, high school education, same county) that are male, dependent, Black, Hispanic, unemployed, and the logged market size, as well as the average EFC. 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). All regressions also include controls for the HEPI cost index. Regressions for CCs include the logged appropriations as an additional control variable. Regressions exclude schools in our sample that have above 2% of the within-school standard deviation in net student price, to remove the influence of outliers in our estimates.

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

Table B4: Effect of Federal Aid Per Student on Advertising

Outcome: Log(TV Ads+1)		
	CCs	FPIs
	(1)	(2)
Log(Federal Aid Per Student)	0.301 (0.498)	1.574** (0.670)
Observations	7159	16881
Estimation Method	IV	IV
School FE	Yes	Yes
School Characteristics	Yes	Yes
Market Demographics	Yes	Yes
First-Stage F-stat	84.804	23.478

Table displays IV estimates of the relationship between logged federal aid per student and logged advertising \$ spent in the local market (in 2017 USD). Standard errors reported in parentheses are clustered at the school level. Market Demographics denote the fraction of students in the market (18-50, high school education, same county) that are male, dependent, Black, Hispanic, unemployed, and the logged market size, as well as the average EFC. 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). All regressions also include controls for the HEPI cost index. Regressions for CCs include the logged appropriations as an additional control variable.

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

## C Federal Student Aid and Net Student Price Construction

In this section, we describe the construction of net student prices  $p_{i,j,t}$  used to estimate student demand for college.

First, we describe the cost of attendance each student faces,  $COA_{i,j}$ . There are three types of cost of attendance, depending on whether they choose to live on campus, off campus with family, or off campus (living independently). In our sample, on average 1.2% of the students at each school live on-campus,<sup>79</sup> and only 7.62% of schools in our sample report providing any form of on-campus housing, since sub-baccalaureate schools are primarily commuter schools. Because of this, we ignore on-campus cost-of-attendance. The federal government determines the type of off-campus cost of attendance based on dependency status. We follow this rule and classify  $COA_{i,j}$  as being the off-campus with family cost of attendance if they are labeled as a dependent (< 24, live with family).

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  $\beta_i$ .

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

Students can only pay out of pocket up to their  $EFC_i$ , which measures their ability to pay for college themselves. The amount of Pell aid a student may receive,  $\pi_{i,j,t}$  is determined by the following formula:

$$\pi_{i,j,t} = \begin{cases} 0 & \text{if } \text{Need}_{i,j} < \underline{\pi}_t \\ \text{Need}_{i,j} & \text{if } \text{Need}_{i,j} \leq [\underline{\pi}_y, \bar{\pi}_y - EFC_i] \quad \& \quad EFC_i \leq \overline{EFC}_y \\ \bar{\pi}_y - EFC_i & \text{if } \text{Need}_{i,j} > \bar{\pi}_y \quad \& \quad EFC_i \leq \overline{EFC}_t \end{cases} \quad (56)$$

where  $\underline{\pi}_y$  determines the minimum amount of financial need required to receive a Pell grant, 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.

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

$$OOP_{i,j,t} = \begin{cases} COA_{i,j,t} - \pi_{i,j,t} & \text{if } COA_{i,j,t} - \pi_{i,j,t} \leq EFC_i \\ EFC_i & \text{else} \end{cases} \quad (57)$$

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

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<sup>79</sup>Source: IPEDS Financial Aid Survey

Subsidized loans. The amount of these loans taken is defined as follows:

$$A_{i,j,t,\text{Sub}} = \begin{cases} 0 & \text{if } COA_{i,j,t} - \pi_{i,j,t} - EFC_i \leq 0 \\ COA_{i,j,t} - \pi_{i,j,t} - EFC_i & \text{if } COA_{i,j,t} - \pi_{i,j,t} - EFC_i \in (0, \bar{A}_{y,\text{Sub}}) \\ \bar{A}_{y,\text{Sub}} & \text{if } COA_{i,j,t} - \pi_{i,j,t} - EFC_i \geq \bar{A}_{y,\text{Sub}} \end{cases} \quad (58)$$

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 1. 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  $\bar{A}_{i,t,\text{Unsub}}$  that depends on whether  $i$  is a dependent or independent. The origination amount of Unsubsidized federal student loans is defined as:

$$A_{i,j,t,\text{Unsub}} = \begin{cases} 0 & \text{if } COA_{i,j,t} - \pi_{i,j,t} - EFC_i - A_{i,j,t,\text{Sub}} \leq 0 \\ COA_{i,j,t} - \pi_{i,j,t} - EFC_i - A_{i,j,t,\text{Sub}} & \text{if } COA_{i,j,t} - \pi_{i,j,t} - EFC_i - A_{i,j,t,\text{Sub}} \in (0, \bar{A}_{i,t,\text{Unsub}}) \\ \bar{A}_{i,t,\text{Unsub}} & \text{if } COA_{i,j,t} - \pi_{i,j,t} - EFC_i - A_{i,j,t,\text{Sub}} \geq \bar{A}_{i,t,\text{Unsub}} \end{cases} \quad (59)$$

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

$$A_{i,j,t,\text{Private}} = \max(0, COA_{i,j,t} - \pi_{i,j,t} - EFC_i - A_{i,j,t,\text{Sub}} - A_{i,j,t,\text{Unsub}}) \quad (60)$$

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  $y$ .<sup>80</sup> The standard repayment plan length for federal student loans is 10 years<sup>81</sup> 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 61 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  $t$ .

$$L_{i,j,t} = \sum_p A_{i,j,t,p} \frac{i_{p,y}(1 + i_{p,y})^{120}}{(1 + i_{p,y})^{120} - 1}, \quad p \in \{\text{Sub, Fed. Unsub, Private}\} \quad (61)$$

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

<sup>80</sup>Calculated by dividing the annual interest rate reported by 12.

<sup>81</sup>Source: <https://studentaid.gov/manage-loans/repayment/plans>

## D Details on Estimating Quality

In this section, we give details on the entropy balancing procedure, the weighted regression used to estimate value-added, and the shrinkage performed in the estimation. We also explicitly list the observables controlled for in estimation.

### D.1 Entropy Balanced High School Cohorts

We estimate  $E[Y_{i,0,l} | D_{i,j,l} = 1]$ , the expected earnings of students who enroll in  $j, t$  had they entered the labor market with no college experience, by implementing the entropy balancing procedure described in Hainmueller [2012]. Given our observed-cohort level moments  $\bar{\mathbf{X}}_{j,l}^0$ , this procedure is defined as follows:

$$\max_{p_{i,j,l}} \sum_{i \in \mathcal{I}_{HS,l}} p_{i,j,l} \log(p_{i,j,l}) \quad (62)$$

$$\text{subject to } \sum_{i \in \mathcal{I}_{HS,l}} p_{i,j,l} \mathbf{X}_i^0 = \bar{\mathbf{X}}_{j,l}^0 \quad (63)$$

where  $\mathcal{I}_{HS,l}$  is the set of high school graduates in observed in the same year earnings are measured, and also reside in PUMAs (the most granular geographic measure in the ACS) that overlap with the commuting zone each school is located in. The first equation 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, we make the weights as close as possible to the uniform distribution, subject to achieving covariate balance. Our choice of observables we match on include the following:

- **Average Age:**  $\bar{\text{Age}}_{j,l}$ . The average age of the cohort at entry, observed in the College Scorecard. Because the baseline potential outcome is no college earnings at the time post-college 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:**  $\mathbb{1}\{\text{Age}_i \in a, \text{Gender}_i \in g\}$ , for  $a \in \{0 - 17, 18 - 19, 20 - 21, 22 - 24, 25 - 29, 30 - 34, 35 - 39, 40 - 49, 50 - 64, 65+\}$  and  $g \in \{\text{Male}, \text{Female}\}$ . 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 cohort of interest.
- **Race-Gender Distribution:**  $\mathbb{1}\{\text{Race}_i \in r, \text{Gender}_i \in g\}$ , for  $r \in \{\text{White}, \text{Asian}, \text{Native American}, \text{Black}, \text{Hispanic}, \text{Two or More Races}\}$  and  $g \in \{\text{Male}, \text{Female}\}$ . Race-gender cells are measured from the IPEDS Fall Enrollment Survey for first-time students.

- **Veteran Status:**  $\{\text{Veteran}_i = 1\}$ , 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:

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

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

$$E[\tilde{Y}_{j,l}] = E[Y_{i,0,l} | D_{i,0,l} = 1, \mathbf{X}_i^0 = \bar{\mathbf{X}}_{j,l}^0] = \psi_j + \beta_0 \bar{\mathbf{X}}_{j,l}^0 + E[\delta_{i,l} | t, \mathbf{X}_i^0 = \bar{\mathbf{X}}_{j,l}^0]$$

which is equal to  $E[Y_{i,0,l} | D_{i,j,l} = 1, \mathbf{X}_i^0 = \bar{\mathbf{X}}_{j,l}^0]$ , the counterfactual earnings of the observed cohort  $j, t$  had they attended no college.

## D.2 Value-Added Regression

We recover the value-added  $\psi_j$  described in Section 5 by regressing the difference in the observed and synthetic cohort earnings,  $\bar{Y}_{j,l} - \tilde{Y}_{j,l}$  on a set of controls  $\bar{\mathbf{X}}_{j,l}^1$  observed in the college scorecard, to control for selection bias among college students:

$$\bar{Y}_{j,l} - \tilde{Y}_{j,l} = \beta_1 \bar{\mathbf{X}}_{j,l}^1 + \psi_j \tag{64}$$

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:**  $\mathbb{1}\{\text{Married}_i = 1\}$ ,  $\mathbb{1}\{\text{Dependent}_i = 1\}$ ,  $\mathbb{1}\{\text{Female}_i = 1\}$ .
- **Average Age:**  $\text{Age}_i$ . Controls for students at different stages of earnings lifecycle selecting into different types of education (e.g., vocational versus academic).
- **Parent Education:**  $\mathbb{1}\{\text{ParEdu}_i \in PE\}$  for  $PE \in \{\text{Middle School}, \text{High School}, \text{Some College}+\}$ . This captures potential selection on education choice depending on family history with higher education.
- **Average Income:**  $\text{Inc}_i$ . 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.
- **Prior Income Distribution:**  $\mathbb{1}\{\text{Inc}_i \in I\}$  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).

- **Choice Set Size:**  $\mathbb{1}\{J_i \in k\}$  for  $k \in \{1, 2, 3, 4, 5+\}$ . This is measured as the number of schools a student sent their FAFSA. 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:**  $\mathbb{1}\{i \text{ received Pell Grant}\}, \mathbb{1}\{i \text{ received Federal Loan}\}$ . 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 size. For those cohorts, we include missing dummies for each missing characteristic. Note that, besides age, these controls are all indicator variables. Since we observe the mean cohort, we use the averages of these individual-level dummies in our value-added regression, as is reported in the college scorecard. For age, we use simply the average age. This consistent with the higher education shifter  $\eta_i$  being linear in these rich demographic indicator variables.

Conditional on  $\bar{\mathbf{X}}_{j,l}^1$ , our dependent variable,  $\bar{Y}_{j,l} - \tilde{Y}_{j,l}$  is an imperfect but consistent measure of  $E[Y_{i,j,l} - Y_{i,0,l} | D_{i,j} = 1]$ , due to sampling error. Moreover, 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 64 by using a weighted least squares regression. Our weights are proportional to the variance of the dependent variable. Assume that  $\text{Var}(Y_{i,j,l}) = \sigma_Y^2$ , that is, the variation in potential outcomes equals a constant across all individuals, regardless of characteristics and schooling decisions. Under this assumption,  $\text{Var}(\bar{Y}_{j,l}) = \sigma_Y^2 / N_{j,l}$ , and  $\text{Var}(\tilde{Y}_{j,l}) = \text{Var}(\sum_{i \in \mathcal{I}_{HS,l}} p_{i,j,l} Y_{i,0,l}) = \sigma_Y^2 \sum_{i \in \mathcal{I}_{HS,l}} p_{i,j,l}^2$ , taking weights  $p_{i,j,l}$  as given. Therefore,

$$\text{Var}(\bar{Y}_{j,l} - \tilde{Y}_{j,l}) = \frac{\sigma_Y^2}{N_{j,l}} + \sigma_Y^2 \sum_{i \in \mathcal{I}_{HS,l}} p_{i,j,l}^2 = \sigma_Y^2 \left( \frac{1}{N_{j,l}} + \sum_{i \in \mathcal{I}_{HS,l}} p_{i,j,l}^2 \right) \equiv \sigma_Y^2 V_{j,l}$$

Assuming  $\bar{Y}_{j,l}$  and  $\tilde{Y}_{j,l}$  are independent. We estimate the regression in Equation 64 using weights  $V_{j,l}^{-1}$  proportional to the inverse variance. This procedure accounts for the different level of information on value-added in each cohort observation, and is efficient. Because each observation included in this regression is a college cohort (net their synthetic high school mean), the fixed effects represent the relative value-added, denoted  $\hat{\psi}_j$ . In order to estimate the level of value-added, we shift these relative differences by mean of the dependent variable, so that  $\psi_j = \hat{\psi}_j + \hat{\beta}_1 E[\mathbf{X}_i^1 | j \neq 0]$ , which can be read from the data. This serves as our preliminary measure of value-added.

### D.3 Shrinkage

Because some cohorts in the College Scorecard Dataset are small, our initial estimates of  $\psi_j$  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  $\psi_j \sim N(W_j \zeta, \sigma_\psi^2)$ , where  $W_j$  are school chain characteristics.<sup>82</sup> Appendix Table A2 displays the estimates of  $\zeta$ , for each of the

<sup>82</sup>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,

three outcome variables considered. Our set of characteristics explain 47% of the variation of the estimated value-added in earnings (both unconditional and conditional on earnings). The empirical bayes estimate of  $\psi$  is defined as follows:

$$\psi_{j,EB} = (B_j)W_j\zeta + (1 - B_j)\psi_{j,\text{Prelim}}, \quad B_j = \frac{N_\psi - r - 2}{N_\psi - r} \frac{V(\hat{\psi}_j)}{V(\hat{\psi}_j) + \hat{\sigma}_\psi^2} \quad (65)$$

where  $N_\psi$  denotes the number of chains in our sample,  $V(\hat{\psi}_j)$  denotes the variance of the estimated fixed effect  $\hat{\psi}_j$ , and  $r$  is the dimension of  $\zeta$ .  $\psi_{j,EB}$  represent the reported value-added estimates in this paper.

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we use the average characteristic  $\bar{W}_f$  of a chain across campuses for our prior.

## 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 discounting, 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

Thus, for each respondent  $i$  in the 2012 survey, we observe bounds  $lb_i \leq \beta_i^{BPS} \leq ub_i$  of each individual's annual discount factor. Assuming that students discount the future at a monthly frequency, and discounting is exponential, and they are indifferent between \$250 today and  $\$X$  in one year, we convert the implied annual discount factor from the survey to the average monthly discount on 10-year loans,  $\beta_i$  in our model. The monthly discount factor implied by the annual discount factor reported in the survey, assuming exponential discounting, is  $\beta_{i,m} = (\frac{250}{X})^{1/12}$ . We then convert this to a 10-year average discount factor using the following formula:

$$\beta^{BPS}(X) = \frac{1}{120} \frac{(1 - \beta_{i,m})^{120}}{(1 - \beta_{i,m})} \quad (66)$$

Recall, however, we do not observe the indifference points of each student, but their bounds. so for each  $X \in \{300, 350, 400, 450, 500\}$ <sup>83</sup>, we observe the fraction of students with  $\beta_i \leq \beta_i(X)$ , 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  $d$ :

$$\hat{Pr}_{BPS}(\beta_i \leq \beta^{BPS}(X), d) = \frac{\sum_{i:D_{i,d}=1} \mathbb{1}\{ub_i \leq X\}}{\sum_{i:D_{i,d}=1} 1} \quad (67)$$

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

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<sup>83</sup>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.

probabilities is retrieved using the DataLab service from the USDOE’s website.<sup>84</sup> 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 probabilities reported in the BPS to those implied by the model. The model-implied moment CDF evaluation 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 consuming the inside good. The theoretical moments corresponding to the empirical moments in equation 67 are as follows, using Bayes rule’:

$$Pr(\beta_i \leq \beta^{BPS}(X)|j \neq 0, \Theta, d) = \frac{Pr(\beta_i \leq \beta^{BPS}(X)|\Theta, d)Pr(j \neq 0|\beta_i \leq \beta^{BPS}(X), \Theta, d)}{Pr(j \neq 0|\Theta, d)} \quad (68)$$

We discuss how we evaluate each of these probabilities on the right hand side of Equation 68.

with respect to  $Pr(\beta_i \leq \beta^{BPS}(X)|\Theta, d)$ , 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  $\Theta$ , 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 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:

$$E_{v_{i,\beta}}[\mathbb{1}\{\beta_i \leq \beta^{BPS}(X)\}] = \Phi\left(\frac{\log\left(\frac{\beta^{BPS}(X)}{1-\beta^{BPS}(X)}\right) - (\beta + \Pi_\beta D_i)}{\sigma_\beta}\right) \quad (69)$$

where  $\Phi$  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.

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.

The challenge arrives in calculating 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  $\Theta$ , the condition  $\beta_i \leq \beta_i \leq \beta^{BPS}(X)$  implies that the unobserved heterogeneity  $v_i$  is not above a certain value, depending on demographics, current estimates of  $\Theta$ , and  $\beta^{BPS}(X)$ . For a given consumer  $i$ , condi-

<sup>84</sup><https://nces.ed.gov/datalab/index.aspx>

tional 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  $\phi$  is the standard normal pdf. We note now that, conditional on  $v_i \leq X$ ,  $v_i$  follows the distribution of a truncated normal. To solve this integral, we sample from this distribution. We can do this using an inverse CDF transformation, since given  $v \sim [0, 1]$ , a truncated normal with upper bound  $X$  can be sampled as follows:  $v_i = \Phi^{-1}(p \cdot \Phi(X))$ . Therefore, we sample from the uniform<sup>85</sup> and perform monte carlo integration. We estimate this as follows, given  $V$  points of integration over  $v_i$ :

$$\begin{aligned} Pr_{v_i}(j_i \neq 0 | \tilde{\beta}_i \leq \beta^{BPS}(X)) &= \frac{1}{V} \sum_{v=1}^V \frac{1}{1 + \sum_{j \in J_t} \exp(\alpha_i(OOP_{i,j,t} + \beta_i(p_v)L_{i,j,t}) + \delta_{i,j,t}))} \\ \beta_i(p_v) &= \frac{\exp\left(\beta + \Pi_\beta D_i + \sigma \Phi^{-1}\left(p_v \cdot \Phi\left(\frac{\tilde{X} - \beta - \Pi_\beta D_i}{\sigma}\right)\right)\right)}{1 + \exp\left(\beta + \Pi_\beta D_i + \sigma \Phi^{-1}\left(p_v \cdot \Phi\left(\frac{\tilde{X} - \beta - \Pi_\beta D_i}{\sigma}\right)\right)\right)} \\ p_v &\sim U[0, 1] \end{aligned}$$

To be consistent, we similarly use this sampling procedure from the (non-truncated) normal distribution to calculate the denominator inside good share. Let  $s_{i,0}(X)$  denote the implied outside good share when  $v_i = X$ . We can now construct the moment as follows:

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

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<sup>85</sup>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.

## F Model Optimization

We estimate the model using 2-step GMM [Hansen, 1982]. We also incorporate the nonlinear constraints implied by the supply side of the model in terms of FPI firms maximizing profits. These are that marginal costs are positive, and the second-order condition of the firm with respect to advertising  $a_{f,t}$  is satisfied.<sup>86</sup> This is similar to the approach of Romeo [2016], as 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 AdSpender data, denoted  $\widehat{\text{AdSpending}}$  (2.44 billion USD).<sup>87</sup> 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:

$$\begin{aligned}
 \min_{\Theta} G(\Theta) &= \min_{\Theta} \vec{g}(\Theta)^T \mathbf{W}(\Theta_0) \vec{g}(\Theta) & (70) \\
 \text{s.t.} & \\
 c_{j,t}(\Theta) &\geq 0 \quad \forall j, t \text{ where FPI}_j = 1 \\
 \frac{\partial^2 \Pi_{f,d}(\Theta)}{\partial^2 a_{f,d}} &\leq 0 \quad \forall f, d \text{ where } a_{f,d} > 0 \\
 \sum_{f,d} a_{f,d} \kappa_{f,d} &= \widehat{\text{AdSpending}} & (71)
 \end{aligned}$$

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  $\Theta_0$  denotes an estimate of  $\Theta$  for the model fixed during each estimation step. Given an estimate of  $\Theta$ , we can construct the optimal weight matrix as the inverse covariance of all  $G$  moments:

$$\mathbf{W}(\Theta_0) = \text{Cov}(\vec{g}(\Theta_0), \vec{g}(\Theta_0)^T)^{-1} \quad (72)$$

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 method 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 ( $\xi$ ), the moments on supply marginal cost shocks ( $\omega$ ), the moments on advertising cost shocks ( $\iota$ ), the moments on matching demographic shares ( $\vec{g}^f(\Theta)$ ), and the moments on discount micromoments ( $g^\beta(\Theta)$ ).

<sup>86</sup>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 constraints bind.

<sup>87</sup>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 AdSpender data (\$88).

We begin optimization by estimating the diagonal of the weighting matrix at an initial starting value  $\Theta_0$  with no preference heterogeneity, to optimize over the first GMM step (e.g., no covariance is used in the first step). Given an estimate  $\Theta_1^*$  from this optimization, we then estimate the 2nd step of the GMM optimization using the full weighting matrix  $\mathbf{W}(\Theta_1^*)$  to obtain our final solution  $\Theta_2^*$  for the model. The estimated parameters from this second step are asymptotically both efficient and consistent with respect to the true value of  $\Theta$  [Hansen, 1982]. We estimate the optimization problem using the `knitro` optimization software within MATLAB.

## G Price Elasticity Decomposition

We formalize the role passthrough plays in tuition elasticity being lower than the net student price elasticity by performing the following decomposition in log differences of the two elasticities:

$$\log(\varepsilon_{i,j,t}^{\text{Tuition}}) - \log(\varepsilon_{i,j,t}^{\text{Net Price}}) = \log(p_{j,t}/p_{i,j,t}) + \log\left(\frac{\partial p_{i,j,t}}{\partial p_{j,t}}\right) \quad (73)$$

The first term is the ratio between tuition and net price. If  $p_{i,j,t} < p_{j,t}$ , due to federal aid or student discounting on loans, this will be positive. The second term is the logged passthrough rate of tuition from net student prices (Equation 27). Figure B1 plots the average across students of the components in Equation 73, by college type. For both college types, the passthrough effect is negative and large, driving the lower average 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.

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

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

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:

$$\Delta^{\text{Inc}} \log(\varepsilon_{i,j,t}^{\text{Tuition Elasticity}}) = \underbrace{\Delta^{\text{Inc}} \log(\alpha_i)}_{\text{Price Sensitivity}} + \underbrace{\Delta^{\text{Inc}} \log(p_{j,t})}_{\text{Tuition}} + \underbrace{\Delta^{\text{Inc}} \log(1 - s_{i,j,t})}_{\text{Pr(Do Not Enroll in } j)}} + \underbrace{\Delta^{\text{Inc}} \log\left(\frac{\partial p_{i,j,t}}{\partial p_{j,t}}\right)}_{\text{Tuition Pass-Through}} \quad (74)$$

$$\Delta^{\text{Inc}} \log(\varepsilon_{i,j,t}^{\text{Net Price Elasticity}}) = \underbrace{\Delta^{\text{Inc}} \log(\alpha_i)}_{\text{Price Sensitivity}} + \underbrace{\Delta^{\text{Inc}} \log(p_{i,j,t})}_{\text{Net Price}} + \underbrace{\Delta^{\text{Inc}} \log(1 - s_{i,j,t})}_{\text{Pr(Do Not Enroll in } j)}} \quad (75)$$

Figure B2 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 more inelastic to net price by 0.98 units. This is driven by the lower net student price low-income students have to pay to attend these schools, through both federal aid and increased discounting. In other words, because their net prices are lower, low-income students are less sensitive to price changes on this margin. Figure B3 shows the decomposition of the factors leading to differences in FPI tuition elasticities between income groups. Low-income students are more inelastic to tuition by 0.1 units. While low-income FPI students are 12% more sensitive to net price, they have a tuition passthrough 27% lower than that of high-income students, which explains the lower tuition elasticity. We interpret this result as implying that lower passthrough largely explains for-profit colleges' ability to charge high prices and still attract low-income students.

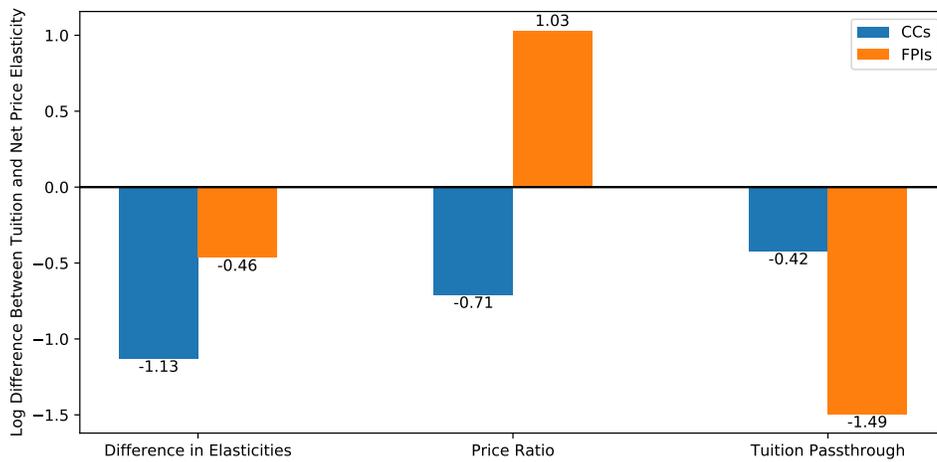


Figure B1: Decomposition of Tuition And Net Student Price Elasticity Difference by Institution Type

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 73. 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,  $\log(\frac{\partial p_{i,j,t}}{\partial p_{j,t}})$ .

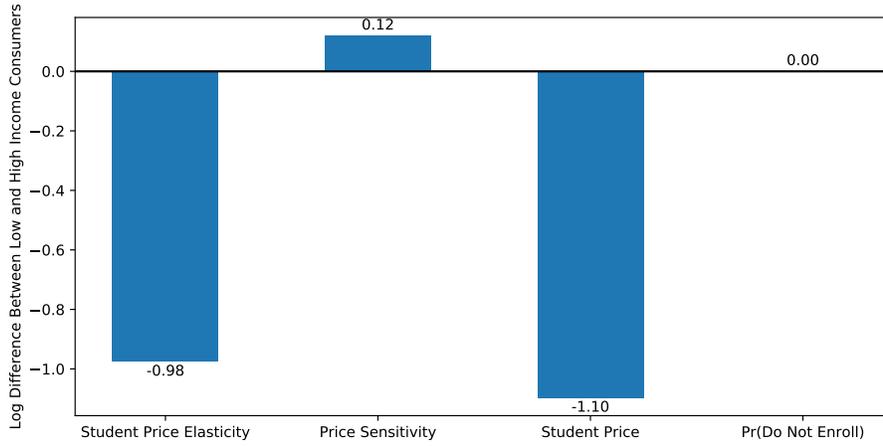


Figure B2: Decomposition of Net Student Price Elasticity Difference by Income at FPIs

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  $\alpha_i$  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.

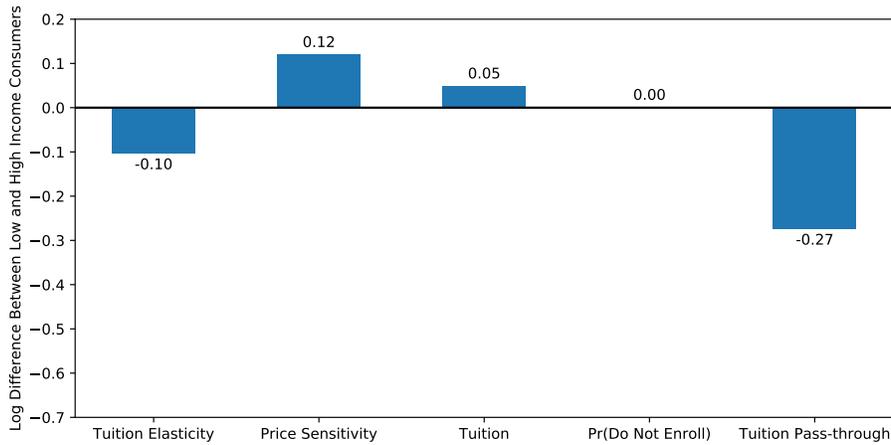


Figure B3: Decomposition of Tuition Elasticity Difference by Income at FPIs

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 expressed in Equation 74. 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 Equilibriums

### H.1 Voucher Equilibrium

In this section, we describe the method we use to solve for equilibrium when firms can respond by changing both prices and advertising. 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 vouchers we consider are solvable up to a generosity parameter  $g$ .

The standard approach to solve for an equilibrium is to simultaneously solve the system of pricing and advertising first order conditions. However, because advertising is constrained to be non-negative, the first order condition for advertising will not necessarily hold at the zero bound. This is particularly important for our counterfactual quality voucher policy, where many schools with low value-added effectively find it optimal to invest in zero advertising. To accomodate this scenario, we solve for an equilibrium using an iterated best response algorithm. We solve for the equilibrium under a voucher aid regime by guessing a generosity  $g$  of aid to give low income students, followed by solving Algorithm 1 given  $g$ , calculating the amount of federal student aid allocated under the new equilibrium we solve for, and terminating when  $g$  is found to balance the federal budget in our sample.

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#### Algorithm 1: Voucher Equilibrium

---

```

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

```

---

### H.2 Ban Equilibrium

Our set of existing policy proposals constitute either changes access of federal aid by certain schools, or a ban on for-profit advertising. For the advertising ban, in addition to the counterfactuals where

there is no advertising response (Table A8), the remaining endogeneous variables constitute only prices. Under this policies, we solve for the equilibrium as follows. Given a generosity parameter  $g$  on Pell grants, we solve in each market the system of  $|J_t|$  equations, denoted  $\vec{F}_t$  for each college in a market, that yield the balance budget conditions of community colleges/first-order price conditions if FPIs:

$$\vec{0} = \vec{F}_t(\mathcal{P}) = \begin{cases} M_t \cdot s_{j,t}(\vec{p}_t, \vec{0}, g) \cdot (c_{j,t} - p_{j,t}) - B_{j,t} & \text{if } j \neq \text{For-Profit College} \\ M_t \left( s_{j,t}(\vec{p}_t, \vec{0}, g) + \sum_{k \in J_{f,t}} (p_{k,t} - c_{k,t}) \frac{\partial s_{k,t}(\vec{p}_t, \vec{0}, g)}{\partial p_{j,t}} \right) & \text{if } j = \text{For-Profit College} \end{cases} \quad (76)$$

where  $g$  is included in the function of market shares to explicitly indicate that the community college budget constraint is impacted via government aid, due to its impact on student prices. After solving for the equilibrium in each market, we then calculate the amount of federal government spending across markets, and search over  $g$  until an equilibrium is found with spending approximately equal to the amount of federal spending under current aid.

For the ban on for-profit and low-quality schools, FPIs can still advertise. For these institutions, we solve for equilibrium as in Algorithm 1, using an iterated best response approach, but instead of inputting voucher prices in Equation 48, we input the net student price implied by no federal aid and only access to private loans for the banned schools, and the net student price under the current federal aid system (scaled up by increases in generosity to the Pell grant program) for non banned schools.

### H.3 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 9.2. 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  $d^{88}$ , 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, these are 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  $J_{i,j} = \frac{\partial \vec{F}_i(\mathcal{E})}{\partial S_j}$ . Then by the implicit function theorem, the passthrough of prices/ads with respect to the vouchers are:

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

we can 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 equilibrium

<sup>88</sup>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.

$\varepsilon$ .

## 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 51. The optimal voucher in market  $t$  is:

$$\bar{\tau}_t^* = \underbrace{(I + \mathbf{E}_t)^{-1} \mathbf{E}_t}_{\text{Voucher Elasticity Distortion Term}} \times \underbrace{\frac{1}{\lambda}}_{\text{Shadow Price of Budget Constraint}} \times \underbrace{\vec{\psi}_t}_{\text{Quality}} \quad (77)$$

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 9.2 is as follows:

$$\begin{aligned} \max_{\{\tau_{k,t}\}} \quad & \sum_t \sum_{k \in \mathcal{J}_t} q_{k,t,L} \psi_k \\ \text{s.t.} \quad & \sum_t \sum_{k \in \mathcal{J}_t} q_{k,t,L} \tau_{k,t} \leq G \end{aligned}$$

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

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

where  $M$  is market size,  $f_{m,L}$  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 77

The lagrangian of this problem is simply:

$$\mathcal{L} = \sum_m \sum_{k \in \mathcal{J}_m} q_{k,t,L} \psi_k - \lambda \left( \sum_t \sum_{k \in \mathcal{J}_t} q_{k,t,L} \tau_{k,t} - G \right)$$

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

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial \tau_{j,t}} &= \left( \sum_{k \in \mathcal{J}_m} \frac{\partial q_{k,t,L}}{\partial \tau_{j,t}} (\psi_k - \lambda \tau_{k,t}) \right) - \lambda q_{j,t,L} = 0 \\ \Rightarrow q_{j,t,L} &= \sum_{k \in \mathcal{J}_m} \frac{\partial q_{k,t,L}}{\partial \tau_{j,t}} \left( \frac{\psi_k}{\lambda} - \tau_{k,t} \right) \end{aligned}$$

we will want to express the voucher in terms of the voucher enrollment elasticity of school  $k$  w.r.t.  $\tau_{j,t}$ :

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

Which can be done doing the following:

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

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

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

□

The optimal solution takes on three parts: the quality of the school  $\psi_j$ , the lagrange multiplier on the budget constraint,  $\lambda$ , 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  $\epsilon_{k,j,t} = 0$  if  $k \neq j$ . We can think of this as effects 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.* This is a direct consequence of Proposition 2. Assuming  $\epsilon_{j,k,t}^\tau = 0$  if  $k \neq j$ ,

then we note  $\mathbf{E}_t$  is a diagonal matrix, with elements  $\epsilon_{j,j,t}^\tau$  along the diagonal, which implies:

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

□

Intuitively, we find a form similar to the linear quality voucher scheme. the difference is we “distort” the subsidy by  $\frac{\epsilon_{j,j,t}}{(1 + \epsilon_{j,j,t})}$ , which is analogous to the pricing condition of a monopolist facing a downward sloping demand curve. Thus, if enrollment increases greatly due to increased voucher (either due to elastic demand, low passthroughs to price, or elastic 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.