Differential Pricing in Undergraduate Education: Effects on Degree Production by Field

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Abstract

In the face of declining state support, many universities have introduced differential pricing by undergraduate program as an alternative to across-the-board tuition increases. This practice aligns price more closely with instructional costs and students' ability to pay postgraduation. Exploiting the staggered adoption of these policies across universities, this paper finds that differential pricing does alter the share of students studying engineering and possibly business. There is some evidence that student groups already underrepresented in certain fields are particularly affected by the new pricing policies. Price does appear to be a policy lever through which state governments can alter the allocation of students to majors and thus the field composition of the workforce.

INTRODUCTION

The provision of higher education is one of the most important functions of state governments in the United States, accounting for $170 billion of direct state spending in 2011 (National Association of State Budget Officers [NASBO], 2012). Historically states have attempted to provide their residents with access to high-quality postsecondary education by providing large subsidies directly to public institutions with few directives for how the money was used. Public institutions, in turn, charged all students a price well below cost, with very little price variation between in-state undergraduate students within institutions.[1] The implicit assumption is that all college degrees—regardless of field—generate comparable private and social benefits, such as enhanced workforce productivity, civic participation, and other externalities.

However, escalating tuition and tight state budgets have placed higher education institutions under recent scrutiny, as lawmakers debate what type of education government should be promoting and who should pay for it. One of the more high-profile proposals stemming from these debates is the recent effort by Florida Governor Rick Scott to nudge more students into majors in "strategic areas" like engineering and biotechnology by freezing tuition rates in these fields, while increasing rates for students in liberal arts (Alvarez, 2012). An alternative approach was taken at public universities in Texas following deregulation in 2004. Many institutions increased overall tuition rates and began charging higher rates for specific

[1] Public institutions do charge different prices to in-state and out-of-state students and lower prices to students that attend part-time, but other forms of price differentiation within institutions are less pronounced historically.

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programs, at least partially in an attempt to improve the quality of these specific programs by generating additional resources (Kim & Stange, 2014). Michigan and Ohio recently followed the trend of many other states by making appropriations conditional on various measures of institutional performance, including the production of degrees in high-need fields (Jesse, 2012; Plant, 2012). At the national level, calls to increase the number of bachelor's degrees awarded in engineering and nursing (Executive Office of the President, 2012; Institute of Medicine, 2011) motivated the SMART Grant program and various workforce provisions of the Affordable Care Act.[2] In short, policymakers at many levels are attempting to alter the mix of undergraduate degrees to achieve the greatest return on the public's substantial investment in higher education, explicitly acknowledging social cost or benefit differences between fields.

The efficacy of many of these efforts depends on the responses of students and institutions to changes in major-specific prices, a topic about which little is known. This question is the focus of this paper. The situations in Texas and Florida are not atypical, as institutions across the country are increasingly charging students higher prices for upper division coursework and for certain high-cost majors such as engineering, business, and nursing. This reverses the historical convention of universities charging all undergraduates the same price regardless of field. A recent survey found that 42 percent of public doctoral institutions now charge differentially either by field or level, with field-based differentials much more common (Ehrenberg, 2012). Given the heightened scrutiny and financial pressure faced by institutions, differential pricing may very well become the new standard practice in undergraduate education, as it is in graduate education. Since differential pricing could induce both demand and supply responses, the combined effect on the sorting of students into majors is theoretically ambiguous and thus an important and unanswered empirical question.

In this paper, the effect of differential pricing is estimated using data on the mix of degrees awarded by 142 large public research universities from 1990 to 2010. Fifty of these universities established higher prices (differential pricing) for engineering, business, or nursing during this time period. These three fields are the most common targets for differential pricing and also account for a sizable share of all undergraduate students. Employing a difference-in-differences and event-study strategy, I compare changes in the share of degrees awarded in certain fields at these universities to changes at schools that did not alter their tuition policy during the same time period. Several different plausible control groups—colleges that adopt differential pricing at different times, colleges that considered adopting (but did not), nonadopters in the same region, and selectivity category—are used to estimate the counterfactual time trend that adopters would have experienced had they not enacted price differentials. The event-study model finds no evidence that schools adopting differential pricing policies were trending differently than control schools prior to adoption.

The results indicate that differential pricing for engineering is associated with a statistically significant 1.1 percentage point decrease in the share of degrees awarded in engineering after three years (on a base of 14.7 percent). The analogous figure for business is an (imprecise) 0.8 percentage point decrease in the business share within three years (on a base of 19.5 percent). Differential pricing for nursing is actually associated with a 0.8 percentage point *increase* in the nursing share (on a base of 4.4 percent), though this estimate is very imprecise and not significantly different from zero. However, these patterns for all three majors are generally robust across a

[2] See Evans (2012) for a discussion of the recently discontinued SMART Grant program and Morgan (2010) for discussion of the nursing and other health workforce provisions in the Affordable Care Act.

number of specifications, covariate adjustments, different control groups, and samples. Women and minorities have comparable reductions in the likelihood of majoring in engineering as male and white students, but due to smaller rates of engineering participation at baseline, this response leads to a decrease in the share of engineering students that are female or minority. Higher tuition for engineering thus appears to undercut efforts to increase female and minority representation in engineering. Using individual-level data, I find no evidence that additional institutional grant aid offsets the increased tuition for impacted majors.

Since the effects I uncover combine both a demand and supply response, different responses across fields may reflect differences in demand parameters, that the supply response differs across fields, or that fields are in different initial equilibrium states. It is possible that additional revenue enables an expansion in the supply of oversubscribed nursing positions while any quality and capacity enhancement of engineering programs is not sufficient to overcome the price impact on demand. While existing data are not rich enough to distinguish these channels, the fact that observed effects are weaker (and possibly positive) for institutions that are more selective overall suggests that supply or capacity may be an important mediating factor, as these are the institutions likely to be most supply constrained.

This paper provides the first evidence on the consequence of a new model for pricing in higher education, which has grown significantly and is likely to become the norm in the near future. Graduate training has long differentiated price based on instructional cost and students' willingness (or ability) to pay, but this has become widespread in undergraduate education only recently. Price does appear to be a policy lever through which state governments can alter the field composition of the workforce they are training with the public higher education system.

This paper proceeds as follows. The following section provides a brief background on differential pricing. A framework for interpreting the empirical results is presented in the next section. Previous literature is then discussed, followed by a description of the data used in the analysis and the empirical strategy. Results and robustness are then examined, and the last section concludes.

BACKGROUND ON DIFFERENTIAL PRICING

A few large public universities, such as the University of Illinois and the University of Michigan, have charged more for upper division coursework and for high-cost majors for quite some time (Yanikoski & Wilson, 1984). However, many more universities have recently implemented explicit differential prices by level and program as an alternative to across-the-board tuition and fee increases. In a broad survey of 165 public research universities, Nelson (2008) found that 45 percent of schools had at least one undergraduate program with differential tuition or fees in 2008, with most implementing them in the past decade. This share was up to 57 percent by 2011 (Reed, 2011). Many more, such as the University of California System, have recently considered and rejected such a scheme (Gordon, 2009; University of California Office of the President, 2009) or have commissioned studies of pricing practices at other institutions as a possible first step to considering such schemes (University of Washington Office of Planning and Budgeting, 2011). Differential pricing by level, independent of major program, is rarer, but still present at some institutions (Ehrenberg, 2012; Simone, 2010). A recent survey found a continuation of this trend: 42 percent of all public doctoral institutions had some form of tuition differential in 2010 to 2011, as did many public masters and bachelor's-level public institutions (18 and 30 percent, respectively; Ehrenberg, 2012). The enactment of these practices has grown steadily since the mid-1990s with no sign of slowing down (Cornell Higher Education Research Institute, 2012).

Since responsibility for tuition setting varies tremendously across institutions and states, the ability and decision to adopt differential pricing does as well. Primary tuition authority is centrally controlled by state legislators or a statewide coordinating agency in 14 states, while governing boards and institutional leadership sets tuition policy at the others (State Higher Education Executive Officers [SHEEO], 2011). In Texas, a shift of tuition-setting authority from state legislators to individual institutions in 2003 facilitated the adoption of differential pricing at several institutions in the state (Kim & Stange, 2014). Institutions' administration and governing boards were the most active participants in the decision to adopt differential pricing among those institutions that did, but faculty and students also played active roles at many (Nelson, 2008).

Proponents of differential pricing cite two primary rationales (Hoenack & Weiler, 1975; Nelson, 2008; Siegfried & Round, 1997). First, differentials make the price students experience align more closely with actual instructional costs, eliminating the implicit cross-subsidy across major fields that results from the conventional practice of charging similar prices. The cost of instruction differs tremendously between upper and lower division coursework and across programs even within institutions. For instance, recent analysis of cost data from four large state postsecondary systems (Florida, Illinois, New York-SUNY, and Ohio) indicated that upper division instruction costs approximately 40 percent more per credit hour than lower division instruction, and that upper division engineering, physical science, and visual/performing art was approximately 40 percent more costly than the least costly majors (SHEEO, 2010). In fact, an earlier but more extensive cost study found that more than three-fourths of the variance in instructional cost across institutions is explained by the disciplinary mix within an institution (U.S. Department of Education, 2003). The consequence is that lower division students subsidize upper division students and students in costly majors are subsidized by those in less-expensive ones. Of course, institutions also benefit from the reputation and donations of graduating alumni, which may offset these cost differences at many of these schools.

Second, tuition differentials better align prices with students' ability to pay post-graduation. Lower division includes many students who eventually drop out, while students that have advanced to upper division are more likely to graduate and earn more. Engineering, science, and business majors tend to earn more and have higher returns than education and humanities majors, even after controlling for differential selection of major by ability (Arcidiacono, 2004). Higher earnings upon graduation mean that graduates with these degrees are thus in a better position to finance higher tuition fees with loans. Again, nondifferentiated pricing implicitly creates cross-subsidization that runs counter to differences in postschooling earnings and ability to pay. In addition to being regressive, this pattern of cross-subsidization is highly unusual; profit-maximizing firms in other markets are predicted to charge based on marginal cost and willingness to pay.

Some opponents of the changes worry that tuition differentials will adversely affect student choice, particularly for low-income students (Nelson, 2008). A related concern is that differential tuition practices will make it even more difficult to increase participation in STEM fields and in health professions such as nursing, as some of these fields are often the target of tuition differentials. Others worry that differential tuition will discourage student exploration (Redden, 2007), undermining the liberal arts goals of institutions and resulting in worse matches between students and majors or occupations.

The consequences of differential pricing likely depends on how any additional revenue is allocated and spent. Though no systematic data on within-institution resource allocation exists, Nelson (2008) surveyed and interviewed administrators at 31 institutions with differential pricing. He found that most institutions either explicitly or implicitly cited a desire to maintain or improve program quality in the face of high costs and declining state support as a reason for implementing differential pricing. Furthermore, when asked where and how any additional revenue from differential pricing will be used, the majority of institutions (58 percent) said that all of the additional revenue would stay with the college or department housing the major or program. One-quarter indicated that revenues would go to the General Fund and the remainder indicated a cost-sharing relationship, with majority of funds going to the impacted college. Furthermore, the funds are primarily used for "Teaching," "Equipment," and "Technology," though these terms are not defined precisely nor are amounts quantified. It is interesting that few institutions earmarked the additional revenue for financial aid, research, service, or student services.

POSSIBLE DEMAND AND SUPPLY CHANNELS

The introduction of differential pricing by program could induce both a demand and supply response, so the combined effect on the sorting of students into majors is theoretically ambiguous. This section discusses the possible demand and supply channels to help interpret the reduced form effects uncovered in the empirical analysis. Throughout I assume that program-specific price at each institution is set externally (e.g., by a board of trustees or legislature), so that individual departments and students act as price-takers and price does not necessarily equate supply and demand.

On the demand side, individuals weigh the long-term expected benefits of studying a particular program against the short-term costs of doing so, as is typical in the human capital framework (Becker, 1964). First suppose that supply is perfectly elastic. Individuals are thus free to choose the major for which the difference between expected benefit and cost is the greatest. The financial return is one salient benefit, which varies by program and could also depend on program quality (e.g., class size, faculty prestige, and classroom technology). Benefits also include the nonfinancial aspects of careers associated with each major and the consumption value during college. In most previous analysis of major choice, costs consist of the individual-specific nonfinancial effort costs stemming from the difficulty of completing each major. For instance, large differences in effort cost and study requirements exist between majors (Babcock & Marks, 2011; Stinebrickner & Stinebrickner, 2008).[3] A differential tuition policy creates financial cost differences by program that may also influence demand.

A program-specific price increase will affect the share of students choosing that major through a number of channels. First, there is the direct demand effect, which is likely negative since higher prices should discourage students from entering impacted fields, holding all else constant. However, price changes can also induce at least two supply responses that could also alter students' major decisions. First, programs likely use some of the additional revenue to improve quality. If students value earnings and there are positive returns to program quality, then demand may improve due to quality improvements. If the quality improvement is substantial, demand for a given program could actually increase when its price is raised. The key mediator is how much colleges reinvest additional revenue to improve the quality of impacted majors.[4]

[3] Differences in required study time between majors could also be thought of as differences in the opportunity cost of time not available for work, given that many students combine work and schooling.
[4] This discussion simplifies things by assuming that the effort costs and nonfinancial benefits of a given major are not altered when its price increases.

Expanded capacity is a second supply response. Now suppose that department-level capacity is not perfectly elastic, but rather upward sloping with price. Higher prices may enable units to teach more students without altering program quality (e.g., class size) by offering more course sections and hiring more faculty. If the initial price (set externally) is too low, demand will exceed supply creating capacity constraints and individual programs will ration slots with non-price mechanisms (e.g., waiting lists, GPA cutoffs, separate application processes). In this case, an increase in price will enable a department to expand capacity, which could increase equilibrium quantity. If a department initially has excess supply (more slots available than students demand at the externally set initial price), then demand effects will dominate and equilibrium quantity will decline as price increases (assuming no quality response).

To summarize, demand theory is unambiguous in predicting that higher prices via differential pricing should discourage students from entering the impacted fields, holding all else constant. However, if impacted programs use the additional revenue to improve quality, the net effect on demand will be ambiguous since quality improvements will increase demand. Furthermore, if the equilibrium at initial prices is one of overdemand (a shortage of available seats), then higher prices may permit oversubscribed departments to expand supply and increase the total number of students.

Thus, we may expect to see a range of effects across majors and institutions, depending on the major-specific elasticity of demand, the extent to which additional revenue is used to improve instructional quality, the elasticity of supply, and the nature of the equilibrium point at initial prices. The average combined effect of all these mechanisms across all institutions is thus an empirical question. While the data do not permit the separate identification of these various channels, it is important to keep in mind that the reduced form effects I estimate are a combination of responses by students (demand) and institutions (supply). This may be, however, the effect most relevant to policymakers who often set prices without dictating what individual departments do with any additional revenue.

PREVIOUS LITERATURE

There is a large body of evidence showing that students' enrollment, persistence, and college choices are influenced by net college price. A consensus estimate is that a $1,000 change in college price (1990 dollars) is associated with an approximately 3 to 5 percentage point difference in enrollment rates (Kane, 2006). Evidence on the effect of college price on persistence and degree completion is rarer, but most studies suggest that persistence and completion are modestly responsive to prices for at least some groups (Bettinger, 2004; DesJardins & McCall, 2010; Dynarski, 2008; Goldrick-Rab, Harris, Benson, & Kelchen, 2011; Turner, 2004). Price also appears to be a strong predictor of the specific college students choose to attend (Jacob, McCall, & Stange, 2013; Long, 2004). All of this work exploits variation that affects prices of all majors simultaneously, so it sheds little light on the independent price effects across majors.

Previous research on the determinants of major choice has focused on expected earnings, student tastes or preferences, and student ability. Berger (1988) finds that students respond to predicted lifetime earnings across majors, rather than starting salaries, consistent with a standard economic life-cycle model. Montmarquette, Cannings, and Mahseredjian (2002) extend this approach by including uncertainty about successful completion for each major. Arcidiacono (2004) estimates a dynamic structural model to control for selection into major and finds that student ability, preferences, and earnings all impact student choice of major. Exploiting differences in major-specific returns over the business cycle to eliminate selection bias, Beffy, Fougere, and Maurel (2012) find that the elasticity of major choice to expected earnings is significant, but low. They conclude that nonpecuniary factors are a primary determinant of major choices.[5] Griffith (2010) finds that academic background, grade performance, and the educational focus of the institution explain a great deal of the higher exit rate of women and minorities from STEM fields.

There has been almost no research on how major-specific prices affect students' major choice. One exception is a recent working paper by Evans (2012), who finds that eligibility for the National SMART Grant had little impact on students' likelihood of pursing a STEM major at public institutions in Ohio.[6] Given the stringent eligibility requirements, low program participation, and specific setting of the study, these findings may not generalize to other forms of major-specific pricing. Furthermore, students' responses to earnings differences by major (for which there is evidence) may provide a poor guide to the likely effects of differential tuition. Students may weigh short-term and long-term financial considerations differently (Rothstein & Rouse, 2011), so price and earnings responses may be very different. I add to this literature by explicitly estimating the price response of major choice for a broad set of institutions using variation in their normal pricing practices, rather than through a specialized program.[7]

Evidence on the response of institutions to price (or resources more generally) is also limited, though the research that does exist has found that institutions reallocate resources when faced with changes in their budgets and that these reallocations have real impacts on students. For instance, Brown, Dimmock, Kang, and Weisbenner (2010) found that negative endowment shocks lead universities to reduce hiring (or accelerate the firing) of both faculty and support personnel (but not university administrators), but positive endowment shocks have no effect on these measures of real resources. Using changes in per-student funding arising from exogenous variation in cohort size across states over time, Bound and Turner (2007) conclude that funding for public universities has a large impact on both the quantity and the quality of college graduates because supply is far from perfectly elastic. A reduction in per-student state appropriations thus reduces collegiate attainment and the production of college-educated workers, though which mediating factors (reduced quality of instruction, fewer support services, less generous institutional aid) explain this relationship is not assessed. In one of the few studies that examined resource allocation within institutions, Johnson and Turner (2009) find that faculty salary differences across fields do correlate with student–faculty ratios, suggesting that economic factors (such as price) could cause institutions to reallocate instructional resources such as faculty. I am not aware of any evidence on the reallocation of resources across departments within institutions in response to greater revenue

[5] Very recently, researchers have begun to collect subjective expectations of earnings in each major in an attempt to isolate the effect of earnings expectations while relying on fewer assumptions about expectations (Arcidiacono, Hotz, & Kang, 2012; Stinebrickner & Stinebrickner, 2011; Wiswall & Zafar, 2011). These papers all conclude that future earnings are an important consideration in students' major choice, though preferences and ability/background may be even more important.

[6] Evans (2012) exploits variation in exposure to SMART due to the discontinuous threshold for financial eligibility: students with an expected family contribution (EFC) below a certain threshold were eligible for Pell and thus also eligible for SMART. Using various regression discontinuity approaches and administrative data for all students at public universities in Ohio from 2006 to 2010, he finds no evidence that the grant altered freshmen- or junior-year major choices.

[7] Hoenack and Weiler (1975) and Berg and Hoenack (1988) discuss the implementation of cost-related tuition (an earlier name for "differential tuition") at the University of Minnesota and also present simulation results of the likely consequences. Neither of these papers directly assesses the impact of the policy, however. Hoenack and Weiler (1975) simulate major-specific price responses using the enrollment response to distance to approximate the enrollment response to differential tuition.

generated by specific departments. Though if institution-level evidence is any guide, we would expect departments to increase both program quality and quantity (number of students) in response to differential pricing.

EMPIRICAL IMPLEMENTATION

Data and Sample

Information on differential tuition prices by undergraduate major or program is not readily available from any standard data source. The most common source for tuition information, the Integrated Postsecondary Education Data System (IPEDS), only publishes differentials by in-state status.[8] I have obtained data on tuition differentials by program compiled by Nelson (2008). This data set contains the incremental tuition or fees charged to different majors above base tuition (in percentage terms) for the 2007 to 2008 academic year at 161 public research universities.[9] Seventy-four of these institutions had differential tuition for at least one program in 2007 to 2008. The data set also contains information on the year of differential enactment and which schools considered (but did not implement) differential pricing. Of the 161 institutions, the precise timing of differential adoption was unavailable for 19 institutions, so my study concentrates on the 142 remaining institutions (55 that adopted differential pricing for at least one program). My analysis focuses on the 50 institutions that had implemented differentials for engineering, business, and nursing majors as of the 2007 to 2008 academic year. These three fields are the most common fields in which differentials were enacted that also affect a sizable number of students. Though differentials for architecture and fine arts are also common, these impact a very small number of students and are ignored in my analysis. Table A1 in the appendix lists the schools that adopted differential tuition policies for these three majors, along with the magnitude and timing of adoption.[10] The differential is positive (higher price for these majors) in all cases. One limitation of the data is that the timing of field-specific differentials was not obtained, so I have assumed that differentials for all majors at a school were adopted at the same time. If schools enacted differentials for different fields during different years, then the timing may be misclassified, creating bias in my estimates. Depending on the nature of the misclassification, estimates could be attenuated or shifted temporally and could differ between fields if certain fields are more likely to be enacted before others.

The primary outcome I examine is the share of undergraduate degrees awarded by field, which is assessed using the IPEDS Degrees and Certificates Conferred (Completions) module.[11] The raw data include the number of students who complete a

[8] IPEDS does currently collect program-specific tuition prices for some institutions, but these are vocational-oriented institutions and programs, not bachelors-granting undergraduate institutions. IPEDS did collect differential information for a few select years in the 1980s, but the reliability and completeness of this information is not clear.

[9] Nelson (2008) collected information on differential pricing from a variety of sources, including a survey of chief business officers, a review of institutional Web sites, and interviews with selected chief business officers at the institutions. His sample includes the 165 public research intensive and extensive institutions defined by 2000 Carnegie Classification categories 15 and 16. In my analysis I exclude UCSF, CUNY-Graduate, and University of Maryland-Baltimore because they had specialized undergraduate programs and University of Puerto Rico because it is not included in the IPEDS universe.

[10] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's Web site and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi-bin/jhome/34787.

[11] I also estimate models with the logarithm of the number of degrees awarded in each field as the outcome variable and the results are qualitatively and quantitatively similar.

postsecondary program by Classification of Instructional Programs (CIP) code and level by sex and race. From this data I calculate the fraction of bachelor's degrees awarded in engineering, business, and nursing for each institution in each year from 1990 to 2008 overall and by sex and race. The full data set thus contains 2,698 observations (142 institutions × 19 years), though several specifications restrict this sample in different ways. Most importantly, many specifications restrict the sample to include only four years before and after the implementation of differential pricing for those institutions that adopt such policies so that baseline major shares for these institutions are estimated with observations close to the time of adoption. The resulting sample size is smaller (2,304 for engineering, 2,234 for business, and 2,489 for nursing). This outcome data were supplemented with year-specific freshmen enrollment, tuition (in-state and out-of-state differential), resources (full-time faculty, state appropriations, and spending per full-time-equivalent students [FTE]), and student attributes (percent full-time, percent in-state, Pell grant amount per FTE). Institutions are grouped into three selectivity categories, using the Barron's taxonomy (most or highly competitive, very competitive, competitive, or less competitive).

Table 1 presents summary statistics of my analysis sample. Institutions that adopt differential pricing tend to be better resourced, have fewer Pell-eligible students, and draw more students from out-of-state. Across all schools and years, business majors represent 18 percent of the sample, engineering 8 percent, and nursing 3 percent. Though the fraction of students choosing nursing is comparable across the three groups, institutions with differentials tend to have more engineering and business majors than colleges without differentials. Given these apparent differences between institutions with and without differentials, it will be important to control for observed (and unobserved) differences between colleges that may correlate with both major choice and the adoption of differential pricing.

To analyze how differential pricing affects the composition and financial aid of students in impacted fields, I also analyze individual-level data from the 1996, 2000, 2004, and 2008 waves of the National Postsecondary Student Aid Study (NPSAS).[12] My NPSAS analysis sample consists of undergraduate students who attended one of these 142 universities, excluding students attending multiple institutions during the survey year, a few whose undergraduate level is missing, and any students whose major field is either missing or undecided/undeclared. I also restrict attention to full-time, full-year students so that financial aid differences do not reflect enrollment intensity. Across all four years, the NPSAS student sample contains approximately 18,000 students attending one of 141 universities.[13]

Identification Strategy

Institutions adopted differential pricing for these programs at different times throughout the past two decades. Using this staggered adoption, my basic empirical strategy is to compare changes in major shares at universities that have

[12] An earlier version of this paper also used the NPSAS to assess major choice, but estimates from this analysis (which found no statistically significant effects of differential pricing) were extremely imprecise and thus abandoned in favor of using the IPEDS completions data. Using IPEDS completions, data generate confidence intervals that are three to five times narrower and also permit the testing for pretreatment balance using an event-study approach.

[13] One of my 142 analysis institutions does not appear in the NPSAS. I have rounded the number of students to the nearest 500. Missing information on SAT score reduces this sample to 12,000 for analysis that relies on non-missing SAT scores. Using a balanced sample of institutions that appear in all waves of the NPSAS generates qualitatively similar estimates.

Table 1. Summary statistics of institutional sample.

	All schools	Never had differential	Had at least one differential	Difference in 2008 (p-value)	Had at least one differential: Timing known	Had at least one differential: Timing unknown
Pricing differential						
Has differential in engineering during year	0.11	0.00	0.29		0.29	n/a
Has differential in business during year	0.12	0.00	0.30		0.30	n/a
Has differential in nursing during year	0.04	0.00	0.11		0.11	n/a
College characteristics						
Total BA degrees granted (1,000)	2.97	2.92	3.02	0.74	3.09	2.81
Current freshmen enrollment (1,000)	2.75	2.62	2.89	0.28	2.96	2.69
In-state tuition + fees (sticker price) ($1,000)	4.76	4.72	4.81	0.10	4.90	4.54
Out-of-state differential (percent over in-state)	1.89	1.95	1.82	0.16	1.84	1.76
Full-time faculty per 100 FTE	6.34	6.10	6.63	0.02	6.55	6.88
State appropriations per FTE ($1,000)	10.00	10.30	9.66	0.03	9.57	9.91
Instructional spending per FTE ($1,000)	9.10	9.06	9.16	0.65	9.17	9.12
Academic support spending per FTE ($1,000)	2.34	2.34	2.35	0.98	2.31	2.46
Undergraduates percent full-time	0.80	0.80	0.79	0.52	0.80	0.77
Pell grant amount per FTE ($1,000)	0.62	0.66	0.58	0.01	0.56	0.63
Freshmen enrollment percent in-state	0.81	0.84	0.77	0.00	0.78	0.76
Most/highly competitive	0.17	0.20	0.15	0.63	0.16	0.11
Very competitive	0.30	0.24	0.36	0.13	0.36	0.37
Competitive/less/noncompetitive	0.53	0.56	0.49	0.30	0.47	0.53
Share of bachelor's degrees awarded in						
Engineering	0.08	0.07	0.10	0.24	0.10	0.07
Business	0.18	0.17	0.19	0.34	0.19	0.18
Nursing	0.03	0.03	0.03	0.97	0.03	0.06
Observations	3,059	1,653	1,406	161	1,045	361
Number of colleges	161	87	74	161	55	19

Notes: Full sample includes observations for 161 public research universities for 19 years (1990 to 2008). Analysis sample includes the 87 nondifferential schools and the 55 differential schools for which precise information about the timing of adoption of differential pricing was obtained. Data on differential pricing come from Nelson (2008), college characteristics come from IPEDS and the Delta Cost Project, and share of bachelor's degrees awarded by category comes from IPEDS. p-Values depicted in column (4) are for a two-sided test of difference in means between institutions that never had differential pricing and those that had at least one. Given the strong serial correlation of these variables, only observations from 2008 were used in performing the test.

recently adopted differential tuition pricing to changes at universities that did not alter their tuition policy during the same time period. To implement this difference-in-differences strategy, I estimate regressions of the form:

$$EngShare_{jt} = \beta EngDiff_{jt} + \alpha X_{jt} + \delta_t + \lambda_j + \varepsilon_{jt} \quad (1)$$

In this specification, *EngShare* is the fraction of degrees awarded in engineering at university j during year t. *EngDiff* is an indicator for whether j charges differential tuition for engineering during year t, X is a vector of time-varying institutional controls, δ is a set of year fixed effects, λ is a full set of school fixed effects, and ε is an error term.[14] Aggregate time trends in major choice across all institutions (e.g., changes in the popularity of the business major) are accounted for by year fixed effects. School fixed effects control for average differences in field prevalence across institutions that may be related to the adoption of differential tuition policies. Some specifications include time-varying school characteristics to control for any changes in student population or school resources at the institution level that may correlate with adoption of differential tuition.[15] This specification is conceptually equivalent to estimating a separate difference-in-differences model for each school that implemented differential tuition, then pooling these school-specific estimates. The coefficient of interest (β) is the change in share of degrees granted in engineering following the adoption of differential pricing for engineering. I estimate equation (1) separately for the three majors that have differential tuition most frequently—engineering, business, and nursing—and that also represent a sizeable share of all college students. Standard errors are clustered by institution, to address the possibility that errors within schools are not independent.

The simple difference-in-differences specification assumes that outcomes for treatment and control schools would trend similarly in the absence of treatment. While this assumption is inherently not testable, the panel data approach does allow one to test whether treatment and control schools were trending similarly in the years leading up to the adoption of differential pricing by the former. To do so, I estimate an event-study specification:

$$EngShare_{jt} = \sum_{k=-3}^{k=4^+} \beta^k StartEngDiff_{jt+k} + \alpha X_{jt} + \delta_t + \lambda_j + \varepsilon_{jt} \quad (2)$$

In the event-study specification, $StartEngDiff_{j,t+k}$ indicates that institution j adopted differential pricing for engineering k years before year t. The parameter β^k is the change in share of degrees granted in engineering k years after the adoption of differential pricing relative to the omitted category ($k = -4$ or earlier). For instance, β^{-3} is the change in share three years before adoption, β^0 is the share change in the year of adoption, and β^{4+} is the share change four or more years after adoption (all relative to four or more years before adoption). A suggestive test of the common trends assumption is that all the pretreatment coefficients are equal to

[14] In all cases I have examined, the differential policy applies to all students in the first year it is enacted. For instance, juniors that are already majoring in engineering when the policy is adopted will have to pay the higher price if they continue in engineering the following year and are not "grandfathered" by the policy. Thus treatment is defined to occur the first year the policy is enacted rather than several years later. The event-study approach explicitly lets treatment effects vary with time since policy adoption.
[15] To better reflect the characteristics of institutions when students were making their major decisions and also confront the possibility that these characteristics are endogenous to differential pricing, I use values from four years prior to outcome measurement in the estimation. Results using contemporaneous values for these institutional characteristics are quite similar.

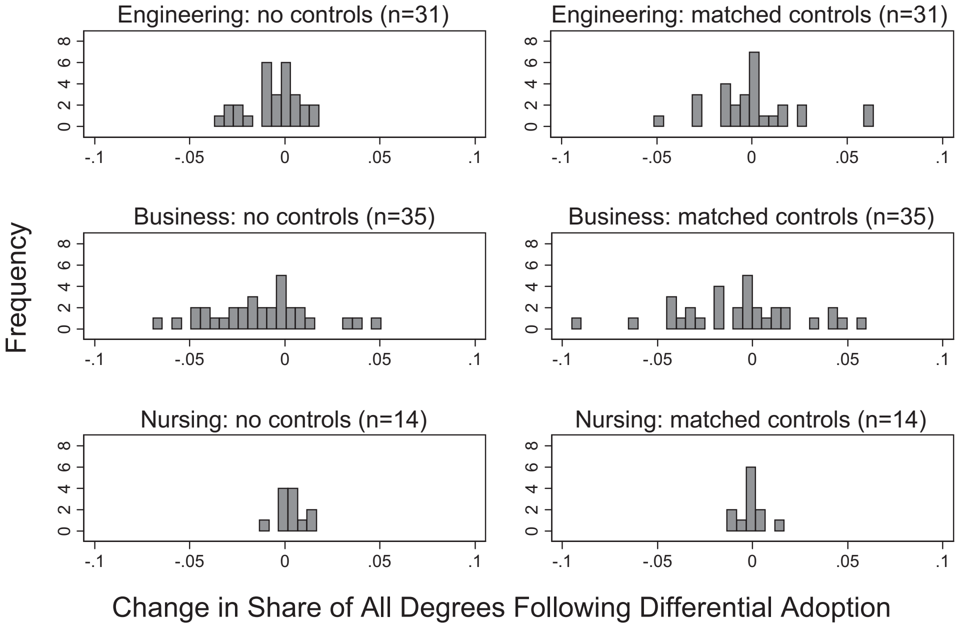
zero. Another limitation of the simple difference-in-differences specification is that a new pricing policy may take a few years before affecting degree production, but it is not obvious how quickly this will happen. The event-study specification has the additional benefit of quantifying how quickly policy effects develop.

Since major-specific price differentials are not experimentally assigned, there are several threats to identification that confound estimates of β. First, lifetime earnings differences across majors and unobserved student preferences for majors (or the jobs that certain majors lead to) cannot be directly entered as time-varying controls. If differential tuition is implemented for specific majors precisely when they become more desirable or lucrative at specific schools, β will suffer from omitted variable bias. It thus may appear that students actually prefer to pay higher prices. My first way of addressing this is to only include schools that considered (but did not implement) differential tuition as controls. Presumably demand for impacted majors was sufficiently high at these latter institutions to warrant a formal consideration of differential tuition. My second strategy is to compare schools within the same region or state by replacing the year fixed effects in equations (1) and (2) with unrestricted region- or state-specific year fixed effects as a robustness check. This specification controls for any time-varying determinants of major share that are common to all institutions in the same geographic area, such as labor market conditions or K-12 preparation. For instance, the relative desirability of majoring in engineering at the University of Oregon (no differential tuition for engineering) will serve as a counterfactual for the relative desirability of majoring in engineering at Oregon State and Portland State Universities (both enacted differential tuition for engineering in 1994) in each year. Since the models also control for institution fixed effects, any time-invariant differences across institutions will not confound estimates. A third strategy for addressing this concern is to test for pretreatment trend differences between schools that do and do not adopt differential pricing. A lack of trend differences between adopting and nonadopting universities immediately before treatment occurs would also suggest policy adoption is not correlated with unobserved factors. Given the many political and legislative hurdles to adopting differential pricing, it is unlikely that institutions are able to control policy adoption with yearly precision.

Another possible confounder is financial aid. The vast majority of financial aid is based on need or general merit and is independent of program of study, so will not bias estimates of β.[16] The only Federal financial aid program that specifically considers major is the SMART Grant, which provided large grants to Pell upperclassmen majoring in STEM fields or a critical foreign language from 2006 to 2010. Since this program was available to students at all institutions, regardless of differential pricing, its existence should not bias my estimates. However, it is possible that institutions may redirect some of the additional revenue collected from differential tuition to financial aid for students in affected majors. I explicitly examine whether schools with differential tuition provide more institutional aid to students in affected majors conditional on merit and income.

Finally, I cannot rule out the possibility that institutions happen to implement other policies coincident with differential tuition. For instance, if differential tuition accompanied changes in the entry requirements for different majors or outreach by impacted departments, then my estimates will confound the pricing effect

[16] Institutions typically use the average or base tuition when determining cost of attendance, which determines financial aid eligibility. Students in impacted majors can petition to adjust cost of attendance, but this is unlikely to impact aid amounts much as most Pell-eligible students receive the maximum at large research universities.



Notes: Left comun plots the distribution of changes in major share of degrees granted following the introduction of differential tuition at each school. Right column plots distribution of school-specific estimates from regression with one treatment school matched with control schools in same Barrons's category and census region.

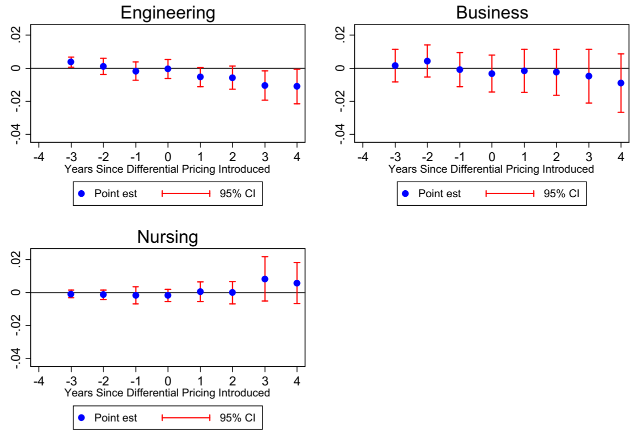
Figure 1. Distribution of Treatment Effects at Individual Universities.

with these other policies as well. It should be reiterated that my estimates may combine a demand price response, a quality response, and changes in supply resulting from major-specific price differentials. Separately distinguishing demand and supply would require a different setting in which price was altered for only one side of the market in isolation.

RESULTS

Case Study Evidence

I first document how the major share changes following each school's adoption of differential tuition. For each university that implemented differential pricing for engineering, business, or nursing between 1990 and 2008, I calculate the change in the fraction in each major following the policy change. The left panel of Figure 1 plots the distribution of these school-specific changes for the three majors. While there is substantial heterogeneity in schools' experience following the introduction of differential pricing, the majority of schools experienced a decrease in the fraction of students majoring in engineering and business. In contrast, a majority of schools experienced an *increase* in the fraction of students majoring in nursing when differential pricing for nursing was introduced. Since many things could be determining time trends in major choice at individual colleges and also be correlated with differential pricing, one should not necessarily interpret these raw estimates as causal



Notes: Graphs plot the point estimates from the event study model in equation (2) using the restricted (+/- 4 year window) sample. Institution sample includes 142 institutions with known adoption dates for differential pricing. Dependent variable is the share of degrees awarded in the specified field.

Figure 2. Event-Study Estimates of Effect of Differential Pricing on Major Share.

effects. For instance, changes in the demand for certain fields within states that happen to correlate with changes in pricing policy may cause the simple change over time to not equal the causal effect of differential pricing on major share. The right column of Figure 1 plots the distribution of these school-specific changes after controlling for major-specific time trends using colleges in the same region and Barron's selectivity group as controls.[17] This method controls for any time trends in the popularity of certain majors within regions and selectivity category. Though the distribution of estimates changes somewhat, the original pattern remains. This general pattern—negative effects of differential pricing on the fraction of degrees awarded in engineering or business and positive or minimal effects on the fraction awarded in nursing—persists throughout a number of different identification strategies and robustness checks.

Main Results

Figure 2 presents estimates of the event-study model separately by field using the restricted (± four year window) sample.[18] The figure plots the point estimates and

[17] The histograms plot the distribution of treatment effects estimated by school-specific difference-in-differences models. For each college that enacted differential tuition, I estimate a separate regression of $MAJORSHARE_{tj}$ on $DIFF_{tj}$ (=1 if the college had differential tuition during year t), $SWITCHER_j$ (a dummy for the college under study), and year dummies on a sample that includes the *SWITCHER* college and any other control colleges in the same census division and Barron's category (most/highly competitive, very competitive, competitive/less/noncompetitive). The histograms plot the distribution of estimated coefficients on $DIFF_{tj}$.

[18] Event-study estimates using the full balanced panel (not restricted to an eight-year window around policy adoption) are qualitatively very similar, though larger in magnitude. Estimates permitting longer lags are also qualitatively similar, though less precise. Appendix Figure A1 presents estimates of the effect of differential pricing ten years after adoption using the sample of observations four years prior to ten years after policy adoption. (All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's Web site and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi-bin/jhome/34787.)

95 percent confidence interval for the β^k coefficients in equation (2). Consistent with the assumption that differential pricing was not implemented when these three majors were trending differently at treatment and control schools, the point estimates on the pretreatment years are close to zero and insignificant. This finding gives some credibility to the key difference-in-differences assumption that treatment and control schools would have trended similarly if not for the adoption of differential pricing. However, the share of degrees awarded in engineering or business eventually drops following the enactment of differential pricing, while the nursing share increases. These event-study estimates also suggest that any treatment effects may take three to four years to emerge, as the point estimates experience their most notable change three years after differential pricing was enacted. To gain precision and facilitate the comparison of many specifications, my preferred specification is a difference-in-differences model that permits separate effects for the immediate (zero, one, and two years after the policy was enacted) and medium-run (three and four years after) time periods. Table 2 presents these difference-in-differences results.

Columns (1), (5), and (9) present the raw correlation between differential tuition policies and major share. University-year observations in which differentials are in place for engineering and nursing are coincident with greater number of degrees awarded in these majors. The raw correlation for business majors is small, negative, and insignificant. This raw correlation may overstate the positive effect of tuition differentials (or, rather, understate the negative effect) if differentials are implemented by universities whose students are predisposed to choose impacted majors, as a simple revenue-maximization goal would suggest universities should do. For instance, students with high SAT math scores are more likely to major in engineering and business and thus colleges with high SAT students may be more likely to implement tuition differentials. To address some of these concerns, columns (2), (6), and (10) control for year and university fixed effects. In these models, the effect of differential pricing on major share is identified by changes in major share within universities following the introduction of price differentials, relative to the time path of major share predicted by other (nontreatment) colleges. In all three cases, the point estimate becomes more negative and, in the case of engineering, becomes statistically significant (engineering p-value = 0.03; business p-value = 0.13). Specifications (3), (7), and (11) separate the posttreatment observations into two periods (zero to two years after adoption vs. 3+ years). Consistent with the event-study estimates, the effect of differential pricing on the major shares are larger three years after enactment than immediately following. The final specifications restrict the analysis sample to include observations for treatment schools only within an eight-year window; around the year differential pricing was enacted. In this specification, only observations close to the time of the policy change are used to identify the pre- or postperiod school averages that identify the treatment effects. This restriction has the effect of diminishing the estimated effect for engineering and business share. This final (preferred) specification indicates that differential pricing for engineering is associated with a statistically significant 1.1 percentage point decrease in the share of degrees awarded in engineering within three years (on a base of 14.7 percent). The analogous figure for business is an (imprecise) 0.8 percentage point decrease in the business share within three years (on a base of 19.5 percent). Differential pricing for nursing is actually associated with a 0.8 percentage point *increase* in the nursing share (on a base of 4.4 percent), though this is imprecise and

Table 2. Effect of differential tuition on composition of degrees awarded, main results.

	Dependent variable: share engineering				Dependent variable: share business				Dependent variable: share nursing			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Have differential in year	0.059**	−0.011**			−0.001	−0.008			0.015**	−0.001		
	(0.028)	(0.005)			(0.015)	(0.005)			(0.006)	(0.002)		
Adopted differential zero to two years earlier			−0.004	−0.004**			−0.004	−0.004			−0.003	0.000
			(0.004)	(0.002)			(0.004)	(0.004)			(0.002)	(0.002)
Adopted differential 3+ years earlier			−0.017**	−0.011***			−0.012	−0.008			0.004	0.008
			(0.007)	(0.004)			(0.009)	(0.007)			(0.003)	(0.006)
Constant	0.079***	0.097***	0.097***	0.088***	0.181***	0.213***	0.213***	0.210***	0.027***	0.023***	0.023***	0.021***
	(0.009)	(0.002)	(0.002)	(0.002)	(0.007)	(0.003)	(0.003)	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)
Sample	All years	All years	All years	±4 years	All years	All years	All years	±4 years	All years	All years	All years	±4 years
Controls	None	Year FE School FE	Year FE School FE	Year FE School FE	None	Year FE School FE	Year FE School FE	Year FE School FE	None	Year FE School FE	Year FE School FE	Year FE School FE
Observations	2,698	2,698	2,698	2,304	2,698	2,698	2,698	2,234	2,698	2,698	2,698	2,489
R-squared	0.027	0.979	0.979	0.978	0.000	0.906	0.906	0.913	0.008	0.903	0.903	0.918
Outcome mean	0.147	0.147	0.147	0.147	0.195	0.195	0.195	0.195	0.044	0.044	0.044	0.044

Notes: Robust standard errors clustered by school in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. All specifications include 142 schools, though the number of schools that adopted a differential tuition policy varies between fields. Model is estimated using ordinary least squares (OLS). Outcome mean is for colleges that eventually adopted tuition differentials in the predifferential period.

not significantly different from zero. The 95 percent confidence interval permits me to rule out negative effects larger than 0.37 percentage points.[19]

Given the magnitude of the price increase associated with these policies (the average increase in price of engineering relative to base tuition is by 14.5 percent, business by 13.7 percent, and nursing by 18.9 percent.), these represent fairly large elasticities. For engineering and business, the implied elasticities are negative 0.51 and 0.30, respectively. For nursing, the elasticity is positive and almost unity (elasticity = 1.0).[20]

Robustness of Main Results

The key untestable assumption of the difference-in-differences approach is that the time path for the outcome experienced by control schools provides a valid counterfactual for the time path of treatment schools in absence of the treatment. That is, the time trend in fraction of students graduating with a degree in engineering at schools that did not adopt differential tuition is what adopters would have experienced had they not implemented differential pricing. Given the centrality of this counterfactual time path to the validity of difference-in-differences estimates, the choice of control group is critical. My base model uses all nonadopters to form the control group, both schools that had differential tuition policies in place throughout the time period and those that never implemented one. Table 3 examines the robustness of the main findings to the choice of control group used to estimate the counterfactual time trends. The first column reports the base model, taken from columns (4), (8), and (12) from Table 2.

Column (2) controls for lagged observable time-varying differences in prices, resources, and student characteristics between treatment and controls that may happen to correlate with both degree mix and the adoption of differential pricing (time-invariant differences are absorbed by the school fixed effects). Estimates are similar to the baseline specification, though stronger for business. Column (3) includes controls for the simultaneous adoption of differential pricing in related fields.[21] The presence of differentials for other (related) fields is relatively uncommon and has no impact on the point estimates. Column (4) controls for the simultaneous adoption of price differentials for the other two fields. Though magnitudes change modestly, the qualitative relationship is unchanged. Column (5) controls for the number of

[19] Table A2 in the Appendix repeats this analysis using the logarithm of number of degrees granted as the outcome (rather than the share), both with and without controlling for the log of total number of degrees (in any field). The implied proportionate change in the share of degrees awarded in each field is similar with this specification. The log specifications (not controlling for total degrees awarded) also suggest that differential pricing is associated with an absolute decline in number of degrees awarded in engineering, not just as a share of the total. (All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's Web site and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi-bin/jhome/34787.)

[20] These elasticities are only approximate as they are calculated based on the response to a binary policy change and the average amount of the differential in 2008, rather than from correlations between the share change and the differential amount at the institution level. I find no correlation between institution-specific treatment effect size and the differential amount in 2008, as depicted in Appendix Figure A2, suggesting that the size of the differential is less important than whether one is present. This result should be interpreted with caution, however, since differential amount is only available in a single year, which may not reflect the amount at the time it was introduced. (All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's Web site and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi-bin/jhome/34787.)

[21] I include controls for differential pricing for architecture, computer science, or physical science when examining engineering share, liberal arts when examining business share, and other health professions and physical therapy when studying nursing share.

Table 3. Robustness of main results to choice of control group and other covariates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Sample	Base model: all colleges	All colleges	All colleges	All colleges	All colleges	Adopted any differential by 2008	Adopted differential in this major	Adopted differential in this major + considered any differential	All colleges with graduates in program in all years	All colleges	All colleges	All colleges
Controls	None	Institutional control variables	Differential in related field	Differential in other two fields	Number of different majors in broad field	None	None	None		Census division × year FE	State × year FE	Barrons × census division × year FE
Panel A: Engineering (mean = 0.147)												
Adopted differential zero to two years earlier	−0.004**	−0.005*	−0.003	−0.004	−0.004**	−0.004*	0.000	−0.004*	−0.003	−0.004*	−0.005**	−0.005*
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Adopted differential 3+ years earlier	−0.011***	−0.012***	−0.010*	−0.012**	−0.011***	−0.011***	−0.003	−0.011**	−0.010**	−0.010***	−0.011***	−0.008*
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	2,304	1,804	2,304	2,304	2,304	651	252	708	1,683	2,304	2,304	2,304
Panel B: Business (mean = 0.195)												
Adopted differential zero to two years earlier	−0.004	−0.008*	−0.003	−0.010*	−0.004	−0.004	−0.003	−0.003	−0.003	−0.005	−0.007	−0.007
	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)
Adopted differential 3+ years earlier	−0.008	−0.014*	−0.008	−0.019*	−0.008	−0.010	−0.009	−0.006	−0.006	−0.011	−0.016	−0.014*
	(0.007)	(0.008)	(0.007)	(0.011)	(0.007)	(0.008)	(0.009)	(0.008)	(0.007)	(0.007)	(0.010)	(0.007)
Observations	2,234	1,754	2,234	2,235	2,234	600	277	733	2,054	2,234	2,234	2,234
Panel C: Nursing (mean = 0.044)												
Adopted differential zero to two years earlier	0.000	0.001	−0.000	0.001	0.001	0.000	0.002	−0.001	0.000	−0.000	0.001	−0.000
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)
Adopted differential 3+ years earlier	0.008	0.009	0.007	0.009	0.008	0.008	0.012	0.007	0.008	0.007	0.012	0.008
	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.008)	(0.006)	(0.007)	(0.006)	(0.008)	(0.006)
Observations	2,489	1,951	2,489	2,490	2,489	855	114	570	1,330	2,489	2,489	2,489

Notes: All specifications include year fixed effects, college fixed effects, and are restricted to four years before and after the adoption of a price differential for each school. Column (2) includes in-state list tuition price, out-of-state tuition differential, full-time faculty to student ratio, state appropriations per student, instructional and academic support spending per student, fraction of students that are full-time, fraction in-state, and the average Pell grant per student, all measured four years prior to outcome. Column (3) includes controls for differential pricing for architecture, computer science, or physical science (panel A), liberal arts (panel B), or other health professions and physical therapy (panel C). Robust standard errors clustered by school in parentheses. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. Outcome mean is for colleges that eventually adopted tuition differentials in the predifferential period.

different majors offered (as indicated by a six-digit CIP code) within the broad field. Differential pricing could be introduced simultaneously with the introduction (or closure) of specific majors within engineering, business, and nursing. If the diversity of major offerings impacts total field enrollment, then this could be a source of omitted variable bias. Results are unchanged by this control.

Columns (6) to (9) alter the control group by restricting the sample to only students attending schools that either adopted differential tuition during the analysis period or that are arguably more similar to adopters than a typical nonadopter school. These control groups include schools that have adopted some form of differential by the 2007/2008 academic year in any field (column 6), only universities that adopted a differential in the given field (column 7), the 16 schools that considered (but did not adopt) tuition differentials in any field (column 8), and only institutions that had graduates in the specific field throughout the sample period (column 9).[22] The main qualitative results are generally robust to these various control groups, though the magnitudes of the point estimates do change somewhat. In columns (6) and (8), engineering differentials are associated with a 1.1 percentage point drop in the engineering share after three years. Specification (7) is the only anomaly, with a much smaller, but negative, and insignificant coefficient for engineering. It should be noted that this specification has a substantially smaller sample size than the others so I cannot reject that coefficients are different.[23] The coefficients for business and nursing change only slightly, remaining negative for business and positive for nursing, but insignificant for both.

Columns (10) through (12) alter the control group used to generate counterfactual time trends by estimating year effects that are specific to various college characteristics. These models permit unrestricted year effects to vary by census division (10), institution state (11), and the interaction between division and Barron's category (12). For instance, if there was an increased demand for engineers from selective colleges on the west coast that happened to coincide with the adoption of differential tuition policies at some west coast schools, then specification (12) would control for this source of omitted variable bias. Identification comes from comparisons between the time path in degree share of adopters and nonadopters among similarly selective schools in the same region. Specification (11) permits time paths to vary by institution state, exploiting within-state variation in the adoption of differential tuition. The base results are robust to all these alternative control groups. The point estimates for engineering share are remarkably stable and those for business and nursing only become larger in magnitude, though are still insignificant.[24]

Heterogeneity and Student Sorting

A primary concern voiced by opponents of differential pricing is that certain groups would be particularly affected. For instance, if minority or low-income students are particularly price-sensitive, then they may be dissuaded from entering more high-priced fields. Differential responses would be worrisome given that these fields are

[22] The base case specification includes some schools that do not have engineering, business, and nursing programs throughout. Program openings may be a sign of aggregate demand that control schools should pick up. Excluding program openings (or closings), as done in specification (9), thus ignores this aspect of demand.
[23] The results for specification (7) in Table 3 using longer time lags (i.e., all observations) are very similar to the base specification. Thus it appears that this result is confined to this one specification and sample. These results are available from the author.
[24] Estimates that account for institution-specific linear time trends are directionally similar, though smaller in magnitude (and insignificant) for engineering and larger in magnitude for business. Estimates for nursing are unchanged, though still insignificant. These results are available from the author.

Table 4. Response heterogeneity by gender and race.

	Women (1)	Men (2)	Black (3)	White (4)	Hispanic (5)	Asian (6)	Other race (7)
Panel A: Engineering							
Outcome mean	0.074	0.215	0.095	0.128	0.121	0.196	0.200
Adopted differential zero to two years earlier	−0.003**	−0.006*	−0.013*	−0.004	−0.009	−0.031**	−0.002
	(0.001)	(0.003)	(0.007)	(0.003)	(0.013)	(0.014)	(0.009)
Adopted differential 3+ years earlier	−0.010**	−0.012**	−0.015	−0.012***	−0.014	−0.050**	−0.012
	(0.004)	(0.005)	(0.011)	(0.004)	(0.018)	(0.019)	(0.016)
3+ year coefficient/mean	−0.135	−0.056	−0.158	−0.094	−0.116	−0.255	−0.060
Observations	2,304	2,304	1,709	1,712	1,695	1,707	1,705
Panel B: Business							
Outcome mean	0.163	0.234	0.165	0.183	0.170	0.246	0.244
Adopted differential zero to two years earlier	−0.003	−0.005	−0.002	−0.004	0.001	−0.017	−0.018
	(0.004)	(0.005)	(0.011)	(0.004)	(0.013)	(0.017)	(0.012)
Adopted differential 3+ years earlier	−0.008	−0.009	−0.006	−0.009	0.015	−0.026	−0.030*
	(0.006)	(0.008)	(0.013)	(0.006)	(0.016)	(0.022)	(0.016)
3+ year coefficient/mean	−0.049	−0.038	−0.036	−0.049	0.088	−0.106	−0.123
Observations	2,234	2,234	1,665	1,668	1,651	1,663	1,661
Panel C: Nursing							
Outcome mean	0.070	0.011	0.037	0.049	0.037	0.033	0.022
Adopted differential zero to two years earlier	−0.001	0.002**	0.010	0.000	0.005	0.004	0.003
	(0.003)	(0.001)	(0.011)	(0.002)	(0.006)	(0.004)	(0.004)
Adopted differential 3+ years earlier	0.008	0.006**	0.009	0.001	0.004	0.008	0.019*
	(0.009)	(0.003)	(0.012)	(0.009)	(0.012)	(0.013)	(0.010)
3+ year coefficient/mean	0.114	0.545	0.243	0.020	0.108	0.242	0.864
Observations	2,489	2,489	1,847	1,850	1,833	1,845	1,843

Notes: All specifications include year fixed effects, college fixed effects, and are restricted to four years before and after the adoption of a price differential for each school. Regressions for race groups are limited to 1995 to 2008. Robust standard errors clustered by school in parentheses. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. Outcome mean is for the specified group at colleges that eventually adopted tuition differentials in the predifferential period.

particularly lucrative and that there is already concern about underrepresented minority and female representation in many fields. To test for response heterogeneity, I reestimate the base model separately by gender and race. The outcome variables are the share of all degrees awarded to individuals in each group at time t that were in engineering, business, and nursing. Table 4 presents these results. The point estimate for the three-year impact on engineering share is similar for most gender and racial groups, but given the large differences in initial major share across groups, the percent reduction is much larger for women than for men and for underrepresented minorities than for white students. Interestingly, the absolute and proportional response is greatest for Asian students, despite their high initial share in engineering. For business, there is less variation across gender and race in the baseline degree share, so similar absolute effects across groups result in similar proportionate effects for men and women and for black and white students. As for engineering, the effect for Asian students is large both absolutely and proportionately. Contrary to the pattern for these other racial or ethnic groups is the experience of Hispanic students, for which the point estimate is positive (but statistically insignificant). Lastly, panel C presents the results for nursing. Differences across groups are more difficult to interpret as the estimates are much less precise relative to the initial major share than for engineering and business. But the point estimates are positive (though not statistically significant) for all gender and racial groups. For men, the point estimate is significant and implies an extremely large proportionate increase in the share of men majoring in nursing following the introduction of differential pricing for nursing.

Table 5 presents additional evidence on whether differential pricing altered the characteristics of students who enter impacted fields using individual-level data from the NPSAS. A benefit of the individual data is that I can test for changes in characteristics not available in the aggregate IPEDS data, such as test scores and socioeconomic status. I regress each student characteristic on dummies for being in each impacted major, indicators for whether the institution charged differentially for the majors during the survey year, and interactions between major and differential pricing.[25] In this difference-in-differences specification, coefficients on the interactions test whether the characteristic changed more for the impacted fields than other fields following the introduction of differential pricing. For instance, if women were driven from studying engineering when differential pricing was introduced, the coefficient on the engineering interaction should be negative in column (1). Though the coefficients on the main field dummies indicate substantial differences in student characteristics across fields (men and higher SAT math students are more likely to enter engineering, higher income students are more likely to enter business), there are few significant changes in student characteristics following the introduction of differential pricing. There is some evidence that differential pricing for engineering students is associated with fewer Pell recipients entering engineering and a shift toward students with higher SAT scores (relative to other students at their institution), but no other changes are significant.

Table 5 also provides suggestive evidence on the extent that students sort across institutions in response to differential pricing. The coefficients on the indicators for differential pricing during the survey year quantify the change in enrolled student characteristics across all other (nonimpacted) fields following differential pricing. The overall student body enters with lower SAT scores when differential pricing for engineering is introduced, but there are no other observed changes in student characteristics. Taken at face value, this could suggest that one mechanism through which differential pricing for engineering reduces the number of engineering graduates is by shifting the enrollment of higher SAT freshmen (who are disproportionately more likely to enter engineering) to other universities.[26] It should be noted

[25] The models also include a full set of year and institution fixed effects. Qualitative results do not change if I include the major indicator, differential pricing indicator, and interaction for each field one at a time.
[26] At the institution level, I find that the share of students that are full-time, the share of students that are in-state, and the Pell amount per full-time equivalent student (a proxy for socioeconomic disadvantage) also do not change following the introduction of differential pricing. Thus it does not appear that differential pricing alters these characteristics of students, nor does it shift students to part-time status. Institution-level evidence on whether differential pricing alters total enrollment is mixed, with first-time freshmen enrollment declining following the adoption of differential pricing but total undergraduate enrollment potentially increasing. These enrollment effects should be interpreted with caution, however, as they are quite imprecise and cannot distinguish enrollment shifts between sectors, institutions, or from nonenrollment. Results for this institution-level analysis can be found in Appendix Table A3. (All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's Web site and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi-bin/jhome/34787.)

Table 5. Effect of differential pricing on student composition in impacted fields using NPSAS microdata.

	Outcomes (sample mean)						
	Female (0.518) (1)	Minority (0.175) (2)	Pell (0.228) (3)	SAT math (0.098) (4)	SAT verbal (0.056) (5)	Income, \$1,000 (81.71) (6)	EFC, \$1,000 (14.42) (7)
Engineering major	−0.373***	−0.001	−0.007	0.520***	−0.031	7.116	0.308
	(0.016)	(0.013)	(0.017)	(0.037)	(0.037)	(6.038)	(0.728)
Have engineering differential	−0.013	−0.003	0.020	−0.214**	−0.158*	0.620	0.495
	(0.029)	(0.019)	(0.017)	(0.093)	(0.094)	(4.661)	(0.896)
(Engineering major) × (have engineering differential)	0.013	−0.015	−0.043*	0.198**	0.243***	−2.959	1.363
	(0.028)	(0.028)	(0.023)	(0.081)	(0.071)	(7.722)	(1.339)
Business major	−0.129***	0.011	−0.040***	0.103***	−0.208***	10.164***	2.738***
	(0.016)	(0.011)	(0.011)	(0.029)	(0.031)	(2.008)	(0.529)
Have business differential	−0.008	−0.018	−0.029	0.052	0.168	5.543	0.463
	(0.034)	(0.023)	(0.025)	(0.072)	(0.112)	(5.260)	(1.193)
(Business major) × (have business differential)	0.025	−0.015	−0.005	−0.033	0.029	−4.886	−1.146
	(0.031)	(0.024)	(0.023)	(0.054)	(0.057)	(4.343)	(1.208)
Health major	0.194***	0.008	−0.008	−0.178***	−0.282***	−2.968	−0.686
	(0.018)	(0.012)	(0.013)	(0.045)	(0.042)	(1.870)	(0.464)
Have health differential	−0.000	−0.027	0.060**	0.073	−0.120	−3.457	−0.490
	(0.042)	(0.029)	(0.030)	(0.127)	(0.156)	(6.241)	(1.666)
(Health major) × (have health differential)	0.099*	−0.016	0.041	−0.023	−0.012	0.202	0.392
	(0.054)	(0.036)	(0.075)	(0.093)	(0.135)	(8.019)	(2.178)
Observations	18,105	18,105	18,105	12,202	12,202	18,105	18,105
R-squared	0.096	0.125	0.054	0.232	0.177	0.051	0.054

Notes: All specifications include year fixed and institution fixed effects. Sample includes only full-time, full-year students attending one of 142 institutions with complete differential pricing information. SAT math and verbal scores are converted to z-scores including students that were not full-time, full-year so mean is greater than zero for the analysis sample. Family income and expected family contribution (EFC) are in 2009 dollars. Specifications (4) and (5) have fewer observations due to missing SAT information for some students. Robust standard errors clustered by school in parentheses. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

that due to the relatively few students in each major and at each institution, these estimates are imprecise and I cannot rule out modest changes in student characteristics at institutions and in impacted majors following the introduction of differential pricing.

The possibility of reallocation between institutions influences whether my negative results for institutions translates to fewer engineers at a more aggregate level (e.g., states). If differential pricing causes students to shift to nondifferential universities, then the base estimates will overstate the impact of differential pricing on aggregate degree production in states. However, estimates from the base specification that include state-specific year fixed effects are similar, suggesting this reallocation is small. Estimates would be greater in the within-state specification if cross-institution reallocation was large because many students would likely shift between public institutions within states.

Mechanisms: Financial Aid, Resources, Supply, and Major Substitutability

One way that institutions can use revenue generated by differential pricing is to provide additional financial aid to students in impacted majors, partially offsetting the tuition increase. George-Jackson, Rincon, and Garcia (2012) found that minorities studying engineering at two universities received financial aid packages that offset differential tuition. Table 6 presents estimates of the effect of differential pricing on the share of list price covered by institutional grant aid using the same difference-in-differences model used to examine student characteristics. Institutional grant aid covers 15 percent of the tuition list price across our entire sample. Coefficients on the interactions test whether institutional grant aid changed more for the impacted fields than other fields following the introduction of differential pricing. For instance, if business schools redirected the revenue generated from differential pricing to more grant aid for undergraduate business students, the coefficient on the business interaction should be positive. I find no evidence that differential pricing leads to a reallocation of institutional grant aid across majors. Whether controlling for an extensive set of individual controls (SAT score, female, minority, undergraduate level, EFC) or looking at specific student subgroups, the interaction coefficients are never significant.

A full accounting of changes in resource levels and allocation following the introduction of differential pricing is not feasible due to the absence of within-institution, department-specific resource measures over time for a large sample of universities. However, using university-level measures, I do find that the introduction of differential pricing is associated with higher overall sticker price, more net tuition revenue per student, and lower state appropriations, but no noticeable change in spending on instruction or academic support at the university level. It should be noted that these aggregate university-level measures may provide a poor approximation for the price and resource changes occurring in specific departments or schools within universities.[27]

To assess whether capacity constraints can explain differences across institutions and fields, Table 7 examines effect heterogeneity by institution-level selectivity. Institutions that are more selective overall will likely also be more selective (and thus capacity constrained) for these particular majors. For instance, the University of Wisconsin-Madison is highly selective overall (has many applications for a small

[27] These results are presented in Appendix Table A3. (All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's Web site and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi-bin/jhome/34787.)

Table 6. Effect of differential pricing on institutional aid to students in impacted fields.

	Dependent variable: (institutional grants) / (list tuition + fees)					
	All students		In-state	Lower division	Upper division	Fourth year
	(1)	(2)	(3)	(4)	(5)	(6)
Engineering major	0.042**	0.033**	0.048***	0.027	0.045**	0.037
	(0.016)	(0.016)	(0.018)	(0.025)	(0.021)	(0.024)
Have engineering differential	−0.020	−0.013	−0.028	−0.034	−0.004	−0.002
	(0.033)	(0.033)	(0.032)	(0.046)	(0.038)	(0.034)
(Engineering major) × (have engineering differential)	−0.012	−0.016	0.001	0.014	−0.031	−0.009
	(0.019)	(0.019)	(0.022)	(0.035)	(0.026)	(0.038)
Business major	−0.019**	−0.011	−0.019*	−0.023	−0.017	−0.018
	(0.009)	(0.009)	(0.011)	(0.014)	(0.013)	(0.020)
Have business differential	0.018	0.006	0.022	0.059	−0.009	0.021
	(0.041)	(0.043)	(0.036)	(0.038)	(0.057)	(0.051)
(Business major) × (have business differential)	0.014	0.015	0.021	0.034	−0.008	0.033
	(0.018)	(0.017)	(0.016)	(0.028)	(0.026)	(0.043)
Health major	−0.013	−0.009	−0.019	−0.014	−0.012	−0.011
	(0.012)	(0.012)	(0.012)	(0.018)	(0.014)	(0.018)
Have health differential	−0.016	−0.009	−0.023	−0.000	−0.041	−0.081
	(0.044)	(0.046)	(0.043)	(0.065)	(0.059)	(0.053)
(Health major) × (have health differential)	0.009	0.006	−0.003	−0.019	0.028	0.024
	(0.025)	(0.025)	(0.026)	(0.025)	(0.046)	(0.068)
Additional controls	No	Yes	No	No	No	No
Observations	18,039	18,039	15,693	7,010	11,029	7,369
R-squared	0.062	0.089	0.071	0.090	0.070	0.087
Outcome mean	0.150	0.150	0.151	0.165	0.138	0.144

Notes: All specifications include year fixed and institution fixed effects. Sample includes only full-time, full-year students attending one of 142 institutions with complete differential pricing information. Additional controls in specification (2) include female, minority, normalized SAT math and verbal score, dummy for missing SAT score, undergraduate level, in-state, and expected family contribution. Robust standard errors clustered by school in parentheses. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

number of spots), so its business program is likely to have excess demand too. Thus, its business program should be able to raise tuition without decreasing degrees awarded more than the University of Wisconsin-Milwaukee, which is much less selective. The effect of differential pricing for engineering and business is actually positive for "Most/highly competitive" institutions and consistently negative for "Competitive and less competitive" institutions (the omitted category). For institutions in the middle (Very competitive), the results differ between engineering and business. For nursing, very competitive institutions have a positive effect of differential pricing and less-competitive institutions have a zero effect. The heterogeneity analysis is thus roughly consistent with the importance of capacity constraints as a mediating factor.[28]

[28] The negative result for "Most/highly competitive" should be ignored, as this is estimated from only one institution adopting differential pricing and the standard errors are likely unreliable because clustering works poorly with so few treated schools. The table also reports heterogeneity by average tuition level,

Table 7. Effect of differential tuition on composition of degrees awarded, heterogeneity.

	Engineering share		Business share		Nursing share	
	(1)	(2)	(3)	(4)	(5)	(6)
Adopted differential zero to two years earlier	−0.001	−0.003	−0.008	−0.008	0.001	−0.001
	(0.003)	(0.002)	(0.006)	(0.005)	(0.003)	(0.002)
× very competitive	−0.008**		0.006		0.005	
	(0.004)		(0.008)		(0.008)	
× most/highly competitive	0.001		0.013		−0.003	
	(0.004)		(0.009)		(0.004)	
× high tuition		−0.004		0.009		0.007
		(0.004)		(0.008)		(0.005)
Adopted differential 3+ years earlier	−0.008	−0.009**	−0.019*	−0.008	−0.001	0.003
	(0.006)	(0.004)	(0.010)	(0.009)	(0.003)	(0.007)
× very competitive	−0.012		0.016		0.018*	
	(0.008)		(0.014)		(0.009)	
× most/highly competitive	0.012*		0.034**		−0.007	
	(0.007)		(0.015)		(0.009)	
× high tuition		−0.005		0.000		0.016
		(0.008)		(0.015)		(0.014)
Outcome mean	0.147	0.147	0.195	0.195	0.0442	0.0442
Observations	2,304	2,304	2,234	2,234	2,489	2,489

Notes: All specifications include year fixed effects and college fixed effects and are restricted to four years before and after the adoption of a price differential for each school. Omitted category for (1), (3), and (5) are institutions classified by Barrons as “Competitive,” “Less Competitive,” and “Not Competitive.” High tuition is indicator for having mean tuition rate across all years of sample that is higher than the median. Robust standard errors clustered by school in parentheses. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. Outcome mean is for colleges that eventually adopted tuition differentials in the predifferential period.

To further uncover the channels through which my main results operate, I also examined the effect of differential pricing on the degree share of all other fields. There are no clear and robust patterns of substitution between fields following the adoption of differential pricing.[29] For instance, I find no evidence that differential pricing for engineering shifts students toward computer science, math, or other obviously closely related fields; many estimates are imprecise and depend on the specification. Overall, I do find that differential pricing does shift degree production toward fields that earn less on average, though the magnitude is small (a reduction in average earnings of 0.7 percent following differential pricing for business) and the estimate is imprecise and not robust.

IMPLICATIONS AND CONCLUSIONS

This paper provides the first evidence on the consequences of differential pricing by undergraduate program in postsecondary education. Given the differences in instructional costs and earnings premiums across majors, some view this practice as an equitable and politically feasible alternative to across-the-board tuition and fees increases. I find that differential pricing is associated with a sizable reduction

but the results are mixed. Engineering share is more adversely affected by price differentials at high tuition schools, but business share is not.

[29] These results are presented in Appendix Table A4. (All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher’s Web site and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi-bin/jhome/34787.)

in the fraction of degrees granted in engineering. Business share is slightly less responsive, though this is not significant at conventional levels in most specifications. Differential pricing for nursing is actually associated with a large *increase* in the nursing share, though the estimate is very imprecise and not significantly different from zero. Encouragingly, these basic patterns across fields are robust to many different samples, specifications, and robustness checks. Consistent with the concern of some critics of this development, I also find that women and minorities have larger proportionate effects than male and white students. It does not appear that additional institutional grant aid offsets the increased tuition for impacted majors.

This study has relevance for a number of different policies. Most directly, the results inform the likely consequences of colleges' use of differential pricing for engineering and, with more uncertainty, business and nursing. Previous research on the effect of price on college enrollment or choice and the effect of expected earnings on major choice are unlikely to provide much guidance to the likely effects of differential pricing by program. My results suggest that implementing these differentials may indeed impact the fields that students pursue and have particularly large proportionate impacts on women and minorities. Institutions and policymakers should pay particular attention to these disparate effects by gender and race, as higher tuition may undercut efforts to increase female and minority representation in engineering. Revenue enhancement for institutions may thus come at a cost of greater inequality, given that differential pricing typically targets the most lucrative fields. Furthermore, since differentials may reduce demand, these policies may not raise as much revenue as expected. It is important for colleges to understand how the revenue and student impact of differential pricing compares to alternative pricing schemes such as across-the-board tuition increases or tuition increases for wealthier or out-of-state students. This paper informs one side of this calculation, albeit for a wide set of institutions overall rather than any one institution specifically.

The experience with differential pricing may also be informative about the likely impact of financial incentives designed to alter students' field of study, though with some caveats. The fact that potential engineering students appear to respond to differential pricing suggests that students' major choice could also respond to other financial incentives, such as subsidies for studying STEM. However, generalizing the response I uncover (from price increases) to the situation of price decreases should be done cautiously, as responses could be asymmetric due to demand- or supply-side factors. For instance, it may be easier for students to switch from engineering to a lower priced major when engineering becomes more expensive than the reverse, if an insufficient number of students are prepared for the rigor of engineering or if supply contracts when price is lowered. Knowledge of the contribution of demand and supply factors is necessary before my results can be applied to settings in which the weight of these two factors differs from the setting I examine. For instance, a price increase that does not alter the revenue received by a targeted program would likely be free of a supply response and thus could have a more negative effect than reported in this study.

This study also contributes to our understanding of how students respond to financial incentives at different stages of the college process. Students may respond to financial incentives differently before college entry, while enrolled in lower division coursework, or closer to graduation, though the timing of incentives has received little attention. Though it is difficult to pinpoint precisely when college major choices are made, these results suggest that even decisions made during college can be responsive to price. Understanding where financial incentives are strongest (or weakest) informs how they should best be targeted.

This study has a number of limitations that should be addressed in subsequent work. First, I study the experience of many large public research universities, 50 of which adopted differential tuition during the analysis period for engineering, business, or nursing. While these schools represent an important segment of the U.S. postsecondary landscape, their experience may not be typical of other segments, such as smaller public and private colleges, for-profits, and sub-baccalaureate institutions. Future data collection on differentials should target these institutions and examine the consequences.

Second, my data do not permit me to separate demand from supply factors, which combine to determine the sorting of students into majors. Different observed responses across fields could reflect differences in demand parameters, a supply or quality response that differs across fields, or reveal that fields are in different initial equilibrium states since the effects I uncover combine both a demand and supply response. It is possible that additional revenue enables an expansion in the supply of nursing positions while engineering revenue is used to improve quality and attract better (though fewer) students. Uncovering just how and whether programs reallocate resources or increase capacity in response to this new revenue stream would help to interpret my findings and apply them to other policy interventions, and would be a welcome complement to the present study.

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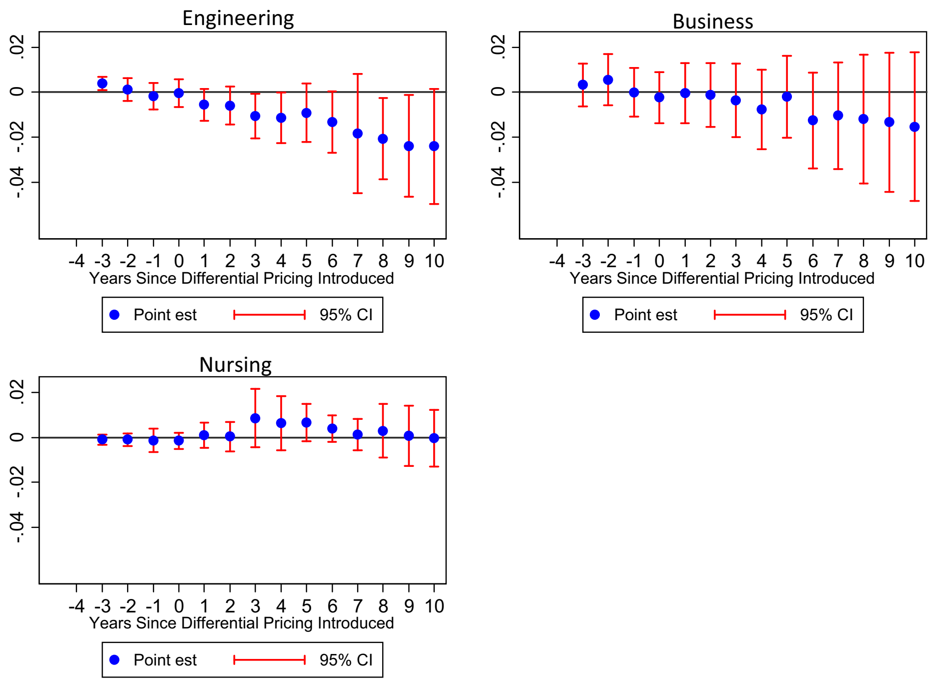
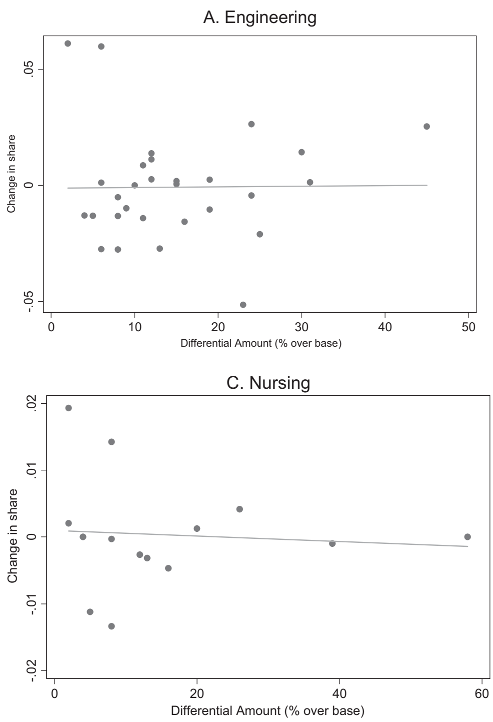
Figure A1. Event-study Estimates of Long-term Effect of Differential Pricing on Major Share.



Notes: Graphs plot the point estimates from the event study model in equation (2) using the sample that includes observations four years prior and ten years after the adoption of differential pricing. Institution sample includes 142 institutions with known adoption dates for differential pricing. Dependent variable is the share of degrees awarded in the specified field.

Figure A2. School-Specific Estimates by Differential Pricing Amount.



Notes: Each point corresponds to the treatment effect and amount of the price differential (in percent terms over base tuition) for a specific institution that adopted differential pricing for the specified field. Point estimates are from school-specific difference-in-difference estimates with one treatment school matched to control schools in the same Barrons selectivity category and census division. Fitted line is from a simple linear regression. Institution sample includes 142 institutions with known adoption dates for differential pricing. Dependent variable is the share of degrees awarded in the specified field.

Table A1. Institutions with differential pricing for engineering, business, and nursing in 2008

Institution	Year adopted	Amount of differential (% higher than base tuition)		
		Engineering	Business	Nursing
University of South Alabama	2008	8		
University of Arkansas Main Campus	2000	16	14	
University of Arkansas at Little Rock	2001		3	
University of Arizona	1993	12	16	
Colorado State University	2006	6	9	
University of Colorado Denver	1989	14	2	147
University of Colorado at Boulder	1984	38	59	
University of Northern Colorado	2006		7	5
University of Hawaii at Manoa	2007		12	39
Iowa State University	2007	19		
University of Iowa	2007	19		
University of Illinois at Chicago	1992	25	8	26
University of Illinois at Urbana-Champaign	1994	45	45	
Indiana University-Purdue University-Indianapolis	2008		10	16
Purdue University-Main Campus	1999	8	13	
Kansas State University	2003	15	8	
University of Kansas	1994	16	40	
University of Kentucky	2005		6	
University of Louisville	2004	3		
Louisiana Tech University	2006		3	4
Michigan Technological University	2004	11		
Oakland University	2005			2
University of Michigan-Ann Arbor	1989	7		
Missouri University of Science and Technology	1996	23	23	
Montana State University	2003	5	8	8
The University of Montana	2001		22	
North Dakota State University-Main Campus	1998	13		12
University of Nebraska-Lincoln	2004	24		
University of New Hampshire-Main Campus	1991	8	8	
Rutgers University-New Brunswick	1992	11	2	
Rutgers University-Newark	1993		4	
Miami University-Oxford	2007		7	
Oregon State University	1994	30		
Portland State University	1994	24	7	
University of Oregon	1999		10	
Pennsylvania State University-Main Campus	2008	6	6	20
Temple University	1989		2	21
Clemson University	2006		17	
University of South Dakota	2005		30	58
University of Memphis	2002	10	12	
The University of Texas at Arlington	2004	4	13	8

Institution	Year adopted	Amount of differential (% higher than base tuition) Engineering	Business	Nursing
The University of Texas at Austin	2003	12	16	8
The University of Texas at Dallas	2005	15		
The University of Texas at El Paso	2000			2
University of Houston	2005	6	6	
University of Utah	2007		35	
Utah State University	2003	2	31	
Virginia Commonwealth University	2008	31	6	
Virginia Polytechnic Institute and State University	2008	12		
University of Wisconsin-Madison	2008		16	
University of Wisconsin-Milwaukee	2005	9	9	13

Source: Glen Nelson. Blank indicates that no differential for this particular field.

Table A2. Effect of differential tuition on composition of degrees awarded, log results

	Log(eng degrees)		Log(bus degrees)		Log(nurse degrees)	
	(1)	(2)	(3)	(4)	(5)	(6)
Adopted differential 0–2 years earlier	−0.056**	−0.033	−0.059**	−0.024	−0.037	−0.038
	(0.026)	(0.025)	(0.024)	(0.022)	(0.039)	(0.039)
Adopted differential 3+ years earlier	−0.100***	−0.071*	−0.058	−0.035	0.066	0.055
	(0.037)	(0.039)	(0.038)	(0.038)	(0.088)	(0.097)
Log(Total Degrees)		1.169***		1.082***		0.874***
		(0.151)		(0.077)		(0.122)
Constant	5.062***	−3.949***	6.033***	−2.258***	4.282***	−2.507***
	(0.070)	(1.180)	(0.025)	(0.594)	(0.047)	(0.949)
Sample	+/− 4 years	+/− 4 years	+/− 4 years	+/− 4 years	+/− 4 years	+/− 4 years
Additional controls	Year FE School FE	Year FE School FE	Year FE School FE	Year FE School FE	Year FE School FE	Year FE School FE
Observations	1,804	1,804	2,127	2,127	1,425	1,425
R−squared	0.940	0.950	0.948	0.963	0.803	0.820
Outcome mean	5.709	5.709	6.280	6.280	4.784	4.784

Notes: Robust standard errors clustered by school in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. All specifications initially include 142 schools, though the number of schools that adopted a differential tuition policy varies between fields and school-year observations with zero degrees awarded in the specified field are dropped. Model is estimated using OLS. Outcome mean is for colleges that eventually adopted tuition differentials in the pre-differential period.

Table A3. Effects of differential pricing on institution-level student characteristics, enrollment, revenue and resources

	Student characteristics and enrollment					Price and resources				
	Share part-time (1)	Pell amount per FTE ($1,000) (2)	Share in-state (3)	First-time freshmen enrollment (4)	Total undergrad enrollment (5)	In-state sticker price ($1000) (6)	Net tuition revenue per FTE ($1000) (7)	State appropriations per FTE ($1000) (8)	Instructional spending per FTE ($1000) (9)	Academic support per FTE ($1000) (10)
Engineering differential										
Adopted differential 0 to 2 years earlier	0.002	0.009	0.003	−84.969	1,524	0.165*	0.161	−0.359	0.081	0.038
	(0.005)	(0.014)	(0.008)	(63.474)	(998)	(0.096)	(0.102)	(0.225)	(0.132)	(0.065)
Adopted differential 3+ years earlier	−0.003	−0.004	0.005	−64.523	2,388	0.385**	0.276*	−0.412*	0.156	0.002
	(0.007)	(0.025)	(0.014)	(62.554)	(1600)	(0.155)	(0.166)	(0.248)	(0.189)	(0.087)
Outcome mean	0.804	0.602	0.789	3240	33247	4.602	5.417	9.987	9.007	2.224
Observations	2,303	2,304	2,285	2,051	2,303	2,296	2,304	2,301	2,304	2,304
Business differential										
Adopted differential 0 to 2 years earlier	−0.005	0.032	0.008	−137.573**	775	−0.046	0.245*	−0.218	0.078	−0.024
	(0.005)	(0.020)	(0.008)	(59.899)	(775)	(0.145)	(0.126)	(0.210)	(0.122)	(0.059)
Adopted differential 3+ years earlier	−0.010	0.033	0.008	−127.174**	1,752	0.146	0.271*	−0.146	0.174	−0.046
	(0.007)	(0.033)	(0.014)	(61.701)	(1482)	(0.170)	(0.152)	(0.225)	(0.163)	(0.086)
Outcome mean	0.798	0.590	0.796	3139	27898	5.098	5.773	9.157	8.890	2.336
Observations	2,233	2,234	2,215	1,988	2,233	2,226	2,234	2,231	2,234	2,234
Nursing differential										
Adopted differential 0 to 2 years earlier	−0.007	0.031**	0.006	−111.565	3,122*	0.001	0.029	−0.183	−0.128	−0.125
	(0.009)	(0.014)	(0.006)	(114.953)	(1802)	(0.117)	(0.170)	(0.280)	(0.129)	(0.077)
Adopted differential 3+ years earlier	−0.008	0.053**	−0.001	−54.964	7,263**	0.380	0.085	−0.464	−0.057	−0.121
	(0.012)	(0.026)	(0.012)	(82.970)	(3569)	(0.261)	(0.163)	(0.311)	(0.178)	(0.101)
Outcome mean	0.783	0.671	0.821	2815	41929	4.994	5.563	8.713	9.520	2.360
Observations	2,488	2,489	2,470	2,215	2,488	2,481	2,489	2,483	2,489	2,489

Notes: All specifications include year fixed effects and college fixed effects and are restricted to 4 years before and after the adoption of a price differential for each school. Robust standard errors clustered by school in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Outcome mean is for colleges that eventually adopted tuition differentials in the pre-differential period.

Table A4. Effect of differential fricing on detailed composition of degrees awarded and average earnings

		Engineering diff 3+ years ago			Business diff 3+ years ago			Nursing diff 3+ years ago	
	Outcome mean	Coeff	SE	Outcome mean	Coeff	SE	Outcome mean	Coeff	SE
Panel A: No controls for simultaneous differential in other two fields									
Business	0.185	0.003	(0.006)	0.195	−0.008	(0.007)	0.194	−0.008	(0.010)
Computer science	0.031	0.001	(0.004)	0.025	0.002	(0.002)	0.022	0.005**	(0.002)
Education	0.054	0.010**	(0.005)	0.061	0.010*	(0.005)	0.068	0.006	(0.006)
Engineering	0.147	−0.011***	(0.004)	0.096	−0.008**	(0.003)	0.085	−0.012**	(0.006)
Health	0.041	0.001	(0.003)	0.048	−0.001	(0.003)	0.061	−0.001	(0.005)
Humanities	0.112	−0.000	(0.004)	0.133	−0.003	(0.004)	0.130	−0.003	(0.005)
Life science	0.079	0.002	(0.006)	0.079	0.002	(0.006)	0.085	0.012	(0.011)
Math	0.010	0.000	(0.001)	0.010	−0.000	(0.001)	0.009	−0.002	(0.002)
Nursing	0.027	−0.002	(0.002)	0.026	−0.001	(0.002)	0.044	0.008	(0.006)
Other professional	0.134	−0.002	(0.005)	0.121	0.006	(0.006)	0.131	−0.003	(0.006)
Physical science	0.016	0.000	(0.001)	0.017	0.001	(0.001)	0.016	0.000	(0.001)
Social science	0.151	−0.004	(0.003)	0.175	−0.001	(0.003)	0.146	−0.004	(0.005)
Vocational technical	0.014	0.001	(0.001)	0.014	0.001	(0.001)	0.011	0.000	(0.001)
Average earnings	76,453	−484**	(187)	75,291	−569***	(216)	74,486	−417*	(243)
Panel B: Controls for simultaneous differential in other two fields									
Business	0.185	0.029**	(0.013)	0.195	−0.019*	(0.011)	0.194	−0.005	(0.011)
Computer science	0.031	−0.002	(0.006)	0.025	0.003	(0.003)	0.022	0.005	(0.004)
Education	0.054	0.007	(0.009)	0.061	0.010	(0.009)	0.068	0.002	(0.007)
Engineering	0.147	−0.012**	(0.005)	0.096	0.000	(0.009)	0.085	−0.002	(0.008)
Health	0.041	0.006	(0.006)	0.048	−0.005	(0.005)	0.061	−0.001	(0.005)
Humanities	0.112	0.007	(0.006)	0.133	−0.002	(0.006)	0.130	−0.002	(0.006)
Life science	0.079	−0.005	(0.008)	0.079	−0.009	(0.008)	0.085	0.011	(0.010)
Math	0.010	0.000	(0.001)	0.010	−0.001	(0.001)	0.009	−0.003	(0.002)
Nursing	0.027	−0.002	(0.002)	0.026	−0.002	(0.002)	0.044	0.009	(0.007)
Other professional	0.134	−0.013	(0.008)	0.121	0.012	(0.008)	0.131	−0.008	(0.007)
Physical science	0.016	−0.001	(0.001)	0.017	0.000	(0.001)	0.016	−0.001	(0.001)
Social science	0.151	−0.012**	(0.006)	0.175	0.010*	(0.005)	0.146	−0.002	(0.006)
Vocational technical	0.014	−0.001	(0.001)	0.014	−0.002	(0.002)	0.011	−0.003	(0.002)
Average earnings	76,453	−214	(311)	75,291	−480	(359)	74,486	70	(231)

Notes: All specifications also include year fixed effects, college fixed effects, a dummy for 0 to 2 years post adoption of differential (not reported), and are restricted to 4 years before and after the adoption of a price differential for each school. Robust standard errors clustered by school in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. All specifications include 142 schools, though the number of schools that adopted a differential tuition policy varies between fields. Model is estimated using OLS. Outcome mean is for colleges that eventually adopted tuition differentials in the pre-differential period. Average earnings is computed for each institution and year using the 2009 and 2010 ACS to compute mean annual earnings for each undergraduate major nationally and then averaging across all majors using an institution's share of degrees granted in each major in each year as weights.