PRICE REGULATION IN CENTRALIZED COLLEGE ADMISSION SYSTEMS

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Abstract

The rising demand for higher education in developing countries is increasingly met by private supply. There is a dearth of empirical evidence on how government regulation of private higher education providers, specifically direct price intervention, affects market structure, competitive incentives, and the welfare of students. I examine a government price setting policy in an Indian engineering college market which raised tuition prices by an average of 20%, leaving subsidies unchanged for poor students. 80% of students face higher out-of-pocket expenses on college tuition as a result of the policy. Using a dynamic difference-in-difference empirical design, I find that the policy led to significant declines in enrollment among colleges with an above-median price change. The decline in enrollment is driven by wealthy, high-ability students. As a result of the policy, I also find suggestive evidence that above-median price change colleges experience significant teacher turnover. New hires at these colleges are less experienced and less likely to have a PhD. Jointly these results suggest that the policy decreased enrollment, increased segregation in the student body, lowered peer-quality in programs, and lowered education quality supplied by colleges. To quantify the welfare consequences of the policy I set up structural demand and supply side estimation models examining student and college responses under current and counterfactual regulatory frameworks.

1 Introduction

An effective tertiary education system augments human capital, facilitates upward social mobility, and is essential for economic development. In the last few decades developing countries have seen a rapid rise in demand for higher education. Given that public higher education institutions in these countries face capacity and funding constraints, the demand has been met with an expansion in private provision of higher education.[1] Private provision poses an important puzzle for academics and policymakers studying higher education in developing country settings. On one hand, unregulated private colleges can provide high-quality education at high prices, potentially worsening social stratification as poor and marginalized students are priced out of the market (Muralidharan, 2019; Otero et al., 2021). In contrast, regulations that aim to promote equity and increase access for marginalized students, can have unintended consequences. Excessive regulation can incentivize an adverse selection of profit-motivated entrants in higher education markets, who have the the ability to manipulate regulations and exploit red tape (Kapur and Mehta, 2007). Profit-maximizing private providers in developing countries often enjoy unchecked market power, which further incentivizes them to *optimally* markdown quality, relative to a competitive benchmark (Neilson, 2013).

A burgeoning literature demonstrates that government policies can be effectively designed to balance the policymaker's dual objectives. Namely, creating access for marginalized students while ensuring that educational institutions are incentivized to compete along price and quality dimensions. Existing literature has analyzed policies like vouchers and subsidies for poor students (Neilson 2013; Allende 2019) and affirmative action (Bertrand et al. 2010; Bagde et al. 2016; Otero et al. 2021). However, there remains a gap in our understanding of how direct government price intervention will affect private higher education markets on the whole. Importantly, we are unsure of the impact this will have on marginalized student groups, who often represent the poorest sections of society, and therefore have the most to gain from access to quality higher education.

This paper endeavours to bridge this gap by investigating demand and supply side responses and quantifying the welfare effects of government price setting in higher education markets. To this end, I study the engineering college market in a prominent Indian state (hereafter State X) from 2015-16 to 2020-21. I investigate the effects of a 2019-20 government policy that raised tuition prices by an average of 20% (with a range of 0-100%), while leaving tuition subsidies unchanged for 80% of students. There are approximately 150 colleges in this market, with around 95% of them being private, self-financed institutions. Every three years, all colleges in this market are required to submit their financial information to a State Fee Fixation Committee, that sets a tuition price for each individual college. I combine administrative data from different sources to create panel datasets that contain student and college level information over the period from 2015-16 to 2020-21. There are two main steps to estimate the impact of State X's price setting policy. First, I employ a reduced form approach using a difference-in-difference empirical design to causally estimate the policy impact on the demand and supply side of State X's engineering college market. Following the estimation of some informative causal descriptive

[1] Examples of recent expansion in private higher education supply are documented in India (Kapur and Mehta, 2007), China (Mok, 2000), Bangladesh (Quddus and Rashid, 2000), Mexico (Lloyd, 2005), and Kenya (Kapur and Crowley, 2008). See Kapur and Crowley (2008) for a comprehensive overview of supply and demand behavior in higher education markets in developing countries.

statistics, I proceed to structurally estimate college choice and competitive profit maximization models for students and colleges respectively. Structural estimation in this context allows us to examine the market-wide welfare consequences of the price-setting policy.

To operationalize the first step in the estimation process, I use a difference-in-difference approach (Stevenson and Wolfers, 2006; Finkelstein, 2007). I exploit the plausibly exogenous variation in tuition prices created by the price setting policy, to show that colleges with above-median price increases saw significant enrollment declines, particularly among wealthier, high-ability students who potentially have better, more expensive outside options (Otero et al., 2021). This trend resembles *white flight*, signaling increased student segregation and lowered peer quality in the market (Idoux, 2022). Ultimately, these changes can affect the educational attainment of the disadvantaged students (Backward Caste, Scheduled Castes and Tribes) who stay back in this market as they have worse outside options. As a preliminary examination of supply side responses, I examine changes in colleges' faculty composition before and after the price increase. I find evidence that indicates colleges with an above-median price increase experience significant teacher turnover, with new hires being more inexperienced and less likely to have PhD degrees. Faculty qualification is well known to be an important determinant of education quality (Chetty et al., 2014). Jointly these results suggest significant changes in students' program preferences and enrollment behavior as well as colleges' resource allocation decisions and education quality.

In order to quantify the market-wide welfare implications of the price-setting policy, I set up structural demand and supply side estimation models. On the demand side, I model the utility from students' college choice using their rank-ordered list of program preferences submitted to the centralized admissions mechanism[2]. The centralized admissions process in State X's engineering college market follows a Deferred Acceptance mechanism with serial dictatorship, that incentivizes truthful reporting of program preferences by students.[3] The demand estimation model enables the estimation of students' price elasticities in addition to other parameters that affect the utility of a student like the utility from the college and program a student enrolls in as well as other college inputs and features.

I posit three primary mechanisms that can affect student welfare through their college choice. First, the price mechanism, whereby students dislike out-of-pocket expenditure and therefore experience a decrease in welfare stemming from the increased tuition prices. Second, the sorting mechanism, where as a result of the price increase, students sort themselves into cheaper colleges which also have a lower mean utility. Third, the exit mechanism, where students choose their respective outside option instead of enrolling in this market. This mechanism is important because it embeds heterogeneity in welfare for students from different socioeconomic or caste backgrounds. Wealthier students can choose expensive outside options with higher utility while poorer affirmative action students may be forced to choose a lower-utility program or not attend college altogether. Delineating these mechanisms will allow us to quantify the change in welfare for students while highlighting equity and redistributive welfare considerations for poorer, affirmative action students.

On the supply side, I aim to use administrative data on college inputs and the median salary of graduates from a program to model the *optimal education quality* decision made by profit-maximizing

[2]A program is defined as a choice of college and major. Students can rank up to 600 programs offered by the 150 colleges in this market.

[3]See Gale and Shapley (1962) for a comprehensive overview of matching mechanisms and Otero et al. (2021) or Fack et al. (2019) for contemporary applications in the education literature.

colleges. Private colleges cannot choose their prices in this market and can only choose their individual inputs and education quality. I identify two channels through which the tuition price increase can affect quality. First, the direct effect, namely an increase in price should translate to an increase in the competitive provision of quality by all colleges, since marginal costs are a function of quality. Second, the indirect effect, may be more ambiguous. On one hand, if students have a large positive quality elasticity of demand, then colleges will not be incentivized to markdown this quality relative to a competitive benchmark. On the other hand, if students' quality elasticity of demand is not large or is fixed, then colleges can exploit their market power and significantly markdown quality relative to the competitive level of education quality that should be provided. Essentially, colleges with higher market share of enrollment have a greater incentive to markdown quality relative to the competitive benchmark and may choose to do so if students are sufficiently inelastic to quality changes.

This paper contributes to two primary strands of literature. First, it adds to the literature examining the welfare consequences of government policies in education markets (Neilson, 2013; Allende, 2019; Otero et al., 2021; Idoux, 2022; Corradini, 2023). Second, it augments the growing literature examining the interaction between government regulations and market structure in the developing world, with a focus on quantifying redistribution and potential welfare changes for the poor (Sahai, 2023; Garg and Saxena, 2022, 2023).

The rest of the paper is organized as follows: Section 2 provides details about the institutional context in this engineering college market, the specific price regulation being investigated, and sources of data. Section 3 outlines the empirical design and identification strategy used to generate causal estimates of the policy impact. Section 4 presents some descriptive findings showing the impact of the policy on important demand and supply side variables. Section 5 proposes a college choice model and college profit-maximization model to investigate the welfare consequences of government price regulation and highlights the mechanisms through which welfare is affected. It also provides the next steps in the estimation process. Section 6 concludes.

2 Institutional context and regulation

2.1 Engineering college market and admissions

Like most Indian states, State X provides an ideal setting to study the impact of price regulation on higher education markets for three reasons. First, both the central and state governments in India regulate nearly all aspects of private college decision-making, including tuition prices, admissions, affirmative action, entry and exit, capacity, and faculty hiring Varghese and Khare (2020). Second, private engineering colleges in State X account for nearly 95% of the supply and 85% of engineering enrollment. Marginalized castes represent an overwhelming majority (70%) of enrollment in private colleges (approximately 50% Backward Caste and 20% Scheduled Castes and Tribes). All engineering colleges in this market follow a centralized admissions process that uses a Deferred Acceptance Mechanism (Gale and Shapley, 1962) to match students and programs based on a common entrance exam.[4] Analyzing candidates' rank-ordered program

[4] The centralized mechanism in this context eliminates the need to model *selection* by colleges. Students are ranked objectively, based on their exam performance (i.e. serial dictatorship), rank programs by preference, and are matched to their most preferred feasible program. The mechanism incentivizes truthful reporting of preferences and produces stable,

preferences offers insights into how students choose programs and how price interventions affect choices, revealed preferences, and welfare. Third, the quality, skills, and employability of Indian engineering graduates have been declining for at least two decades. This trend is documented by news articles (BBI, 2020), employer surveys (The New Indian Express 2011; Muralidharan 2019; Aggarwal et al. 2019), World Bank reports (Blom and Saeki, 2011), and recent Indian government publications (Varghese and Khare, 2020). The decline in college quality underscores the need for closer scrutiny of higher education market design and government policy interventions.

There are government mandated affirmative action policies in place typically based on gender and caste categories. There are three main caste groups in this market namely General (GEN), Backward Caste (BC), and Scheduled Caste/ Scheduled Tribes (SC/ST). Correspondingly there are three admission categories under which students can be matched to their most preferred feasible program. 50% of seats in a program are classified as open competition (OC). Students from all castes are eligible to compete for these seats, however students from the GEN caste can compete only for OC seats, i.e. the unreserved admissions category. BC and SC/ST caste groups have 30% and 20% of seats reserved respectively. These are the historically marginalized castes that college admission affirmative action policies target. They are each eligible to compete for OC seats or the seats reserved for their caste category. GEN, BC, and SC/ST make up approximately 30%, 50%, and 20% of the student body respectively.

2.2 Data

There are four main types of administrative data culled together for this paper. First, the centralized admissions system in State X yields students' high school and entrance exam scores in addition to demographic details like their gender, caste category, and affirmative action status. I also have access to students' rank-ordered list of program (college-major combination) preferences, the student-program matches generated by the mechanism, and the out-of-pocket expense faced by each student, i.e. the voucher amount they receive. Second, I obtain the sticker prices for each college in the pre and post period relative to the 2019-20 price policy from the state's Government Order registry. Jointly these two datasets will facilitate an examination of demand side changes in response to policy.

Third, I prepare a college level panel dataset of infrastructure features, physical inputs, faculty information, and financial outlays using the All India Survey of Higher Education (AISHE) and the National Institute Ranking Framework (NIRF). Finally, I obtain data on students' median salary upon graduation in addition to the number of students who graduate within the minimum time (4 years). The latter two datasets will enable an examination of the supply side responses to the price setting policy. Education quality will serve as the equilibriating variable that students can "observe" about a college when they prepare their rank-ordered list and that colleges can optimally "choose" in response to the policy.

2.3 Price regulation policy

I study the engineering college market in Indian State X, between the academic years 2015-16 and 2020-21. There are approximately 150 colleges in this market, with around 95% of them being private,

optimal matches (Fack et al. 2019; Otero et al. 2021).

self-financed institutions. Every three years, all colleges in this market are required to submit their financial information to a State Fee Fixation Committee, that sets a tuition price for each individual college. Colleges typically do not charge a price lower than this amount and it is illegal to charge any additional fees beyond the sticker price fixed by the government. The government published new tuition prices for each college in 2019-20 yielding 4 pre-policy years and 2 post-policy years. The policy led to increased tuition prices (approximately 20% on average) across the entire private market but affected different colleges to varying degrees.

Table 1: Out-of-pocket Expense by Student Type

Ethnic Group: Caste	**% of enrolled students**	**% AA seats**	**OOP**
Sched. Caste/Tribe [SC/ST]	20%	20%	$\approx$ Rs. 0
Backward Caste [BC]	50%	30%	Rs. P_j - 35k $\uparrow$
General [GEN]	30%	NA	Rs. P_j $\uparrow$

Table 1 summarizes the *out-of-pocket expenditure* (OOP) of the three main ethnic groups comprising the student body and explains how government price intervention affected each group. GEN and BC students are directly affected by the government imposed increase in tuition price P_j. As P_j increased on average by about 20% in the market, with no change in the subsidy offered to BC students, GEN and BC students face a significantly higher OOP in the post period relative to pre-policy years. SC/ST students are federally funded and attend college for (almost) free in the pre and post periods. We see therefore that government price intervention cause a rise in sticker prices that potentially affects up to 80% of the student body with no changes in subsidies for the eligible BC group. SC/ST students are federally funded and attend college for (almost) free in the pre and post periods. Figure 1 shows the variation in the percent price change across colleges in this market that forms the basis for the DiD empirical strategy. We observe that while the average college receives a price change of about 20%, there is significant variability around this mean with a range of 0-100% price change.

3 Empirical strategy

As the government imposed price increase affected different colleges to varying degrees, the policy introduces *plausibly exogenous* variation in prices. I leverage this variation using a difference-in-difference (DiD) (Stevenson and Wolfers, 2006; Finkelstein, 2007) empirical design to causally estimate the impact of this policy on sticker prices, out-of-pocket expenditure of different students, and changes in college demand (student) and supply of quality (college). I categorize colleges that received a price increase above the median as *high-change* colleges and those that received a price increase below the median as *low-change* colleges. Therefore high-change colleges form the *treated* group and low-change colleges form the *control* group for the DiD design although in reality all colleges in the market were affected by the policy and the binary classification represents the *intensity* of policy-impact. The main identifying assumption is that in the absence of the increased sticker price policy, enrollment and other outcomes of

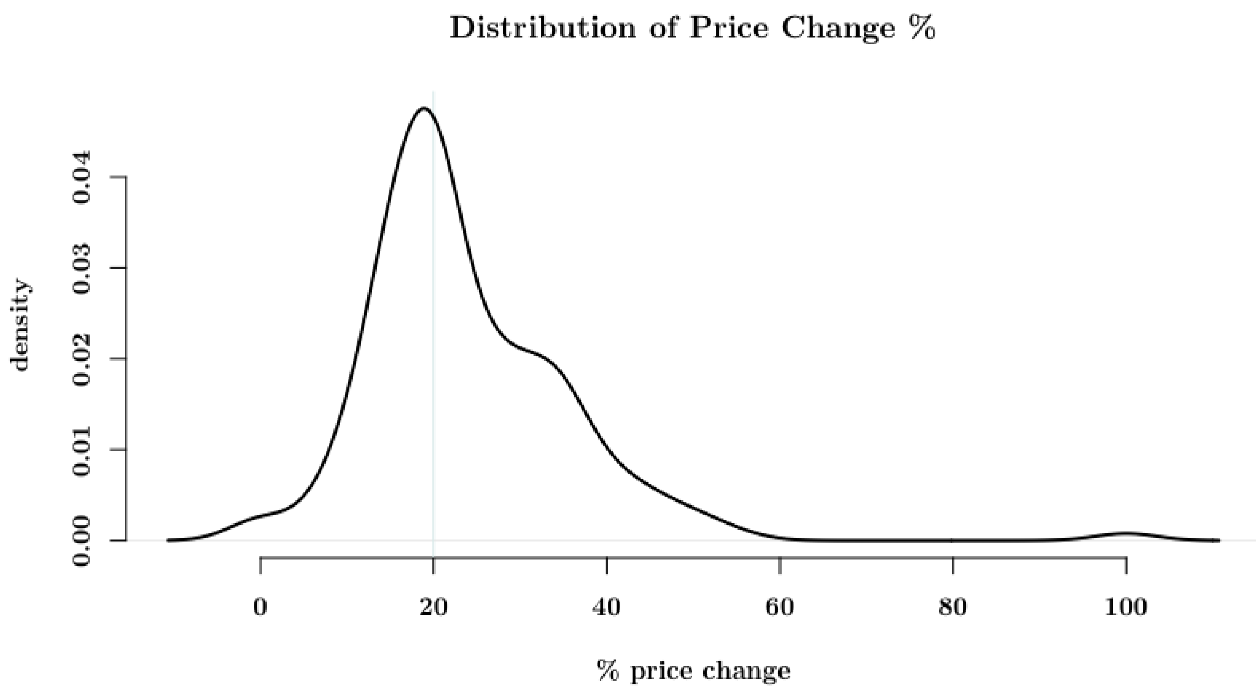

Figure 1: ***Variation in % price change as a result of 2019-20 policy.*** *The horizontal axis represents the percentage price change as a result of the 2019-20 government policy. The vertical axis represents the density of the distribution. The solid black line shows the density distribution of percent price changes.*

interest would proceed along parallel trends. The primary DiD specification is as follows:

$$y_{mjt} = \alpha_j + \alpha_t + \sum_{k=2015;k\neq 2018}^{2020} \beta_k \{D_j \times \mathbb{I}[k=t]\} + \gamma X_{mjt} + \epsilon_{mjt}$$

y_{mjt} is outcome of interest in program m, college j, time t. $D_j = 1$ for a high-change college and 0 otherwise. X_{mjt} is a vector of relevant controls like program capacity. The specification includes college (α_j) and year (α_t) fixed effects with standard errors clustered at the college level. β measures the relative difference in y_{mjt} between high-change and low-change colleges and is the coefficient of interest.

4 Causal descriptive statistics

4.1 Tuition prices and out-of-pocket expenditure

Figure 2 shows the mechanical impact of the policy on high and low changes colleges. We see that the parallel trends assumption holds in prices before the policy is implemented in 2019-20 and the policy clearly increases prices on average. The high-change group has an average price change of about 30% while the low-change group has an average price change of 16%.

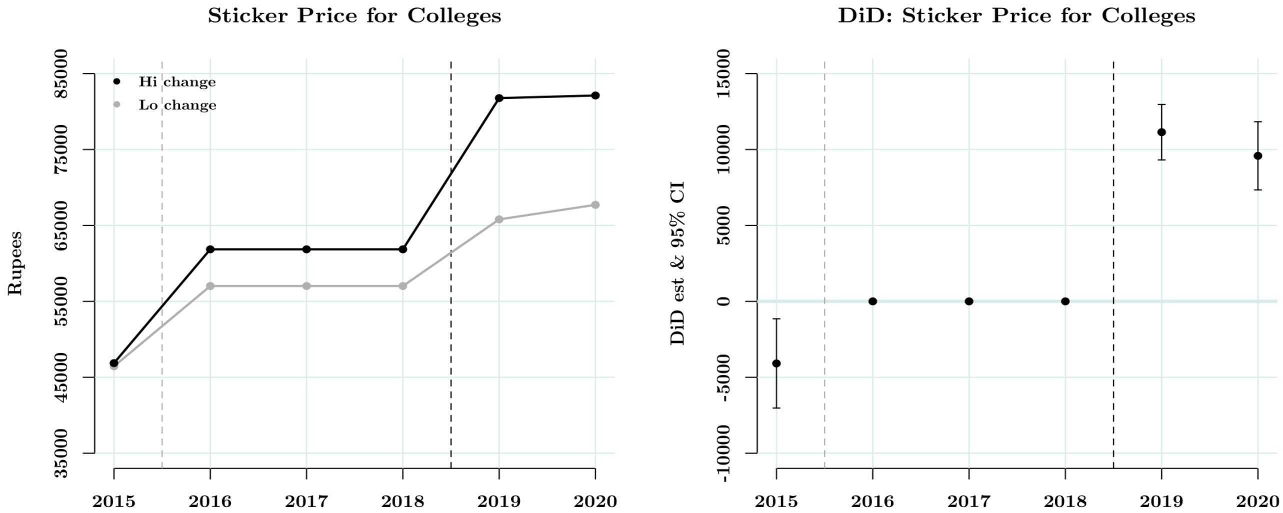

Figure 2: ***Policy impact on sticker prices for high and low-change colleges.*** *The horizontal axes represents the academic years. Left: the vertical axis represents the sticker price in rupees. The black and gray trend lines represent the average price of high and low-change colleges respectively. Right: the vertical axis represents the policy impact on sticker prices. Black dots indicate the DiD estimate and the error bars correspond to the 95% interval. The dotted vertical line separates the pre and post-policy periods.*

Figure 3 further showcases the impact of increased sticker prices owing to government price setting on students' out-of-pocket expenditure (OOP). There are two main takeaways from this plot. First, we see in the first column, that SC/ST students are not impacted by the policy. As they are federally funded, their OOP is unchanged by the state level government price setting policy. Second, we see that despite parallel pre-trends in OOP, BC and GEN groups both experience a substantial increase in the amount they are expected to pay for the same programs. The average OOP increased by 50% and 23% at high and low-change colleges respectively.

4.2 Enrollment and cohort composition

Figure 4 shows the policy impact of increased tuition price and subsequently student OOP on enrollment. There are four main takeways in this plot. First, we see that the parallel trends assumption holds in the pre-policy period, and there is a larger decline in overall enrollment at high-change colleges relative to low-change colleges. Second, we see that SC/ST students whose OOP was unaffected by the price increase do not significantly alter their enrollment pattern after the policy. In fact, they appear to increase enrollment at more expensive programs. This suggests that expensive programs are typically more desirable and given there are more vacant seats at high-change colleges, SC/ST students are able to enroll there in higher numbers than previous years.

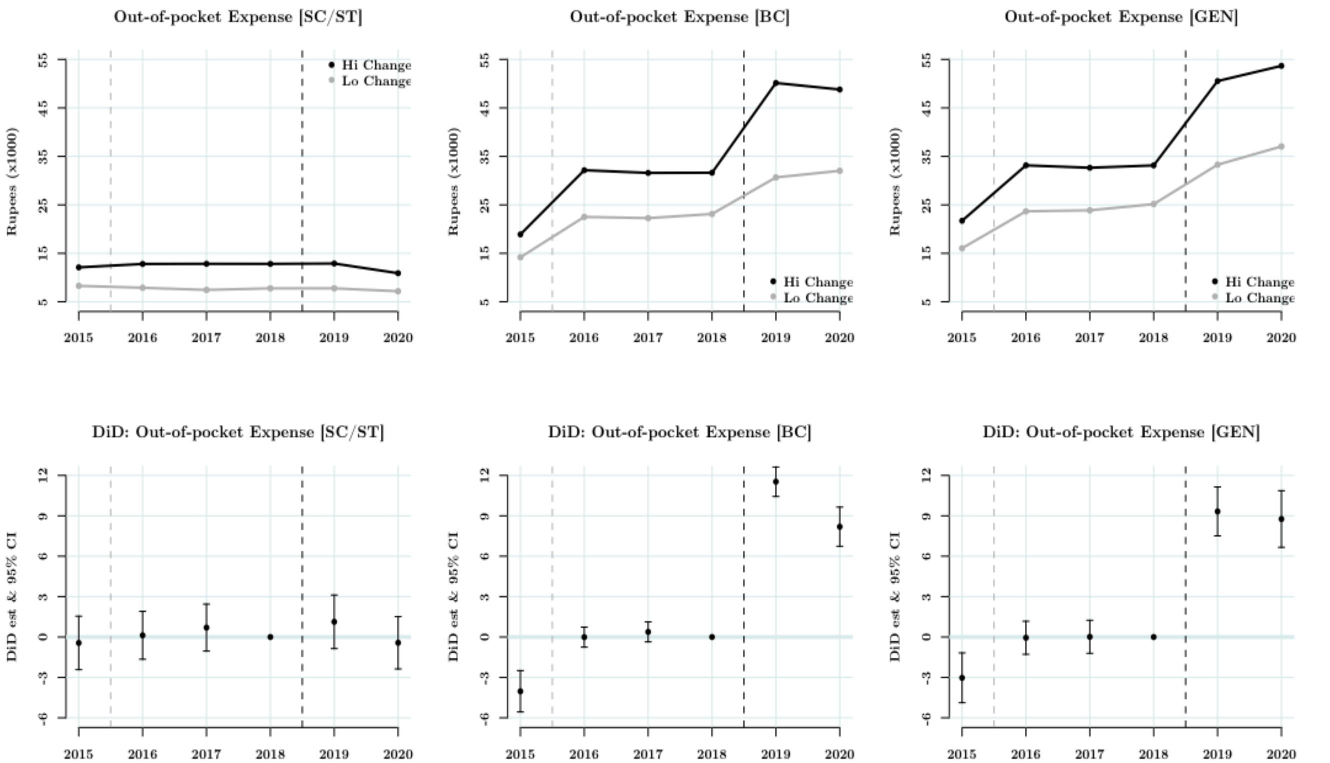

Figure 3: ***Policy impact on students' out-of-pocket expenditure.*** *The horizontal axes represents the academic years. Top row: vertical axes represents students' OOP in thousands of rupees. The black and gray trend lines represent the average student OOP at high and low-change colleges respectively. Bottom row: vertical axes represent the policy impact on students' OOP. Black dots indicate the DiD estimate and the error bars correspond to the 95% interval. The dotted vertical line separates the pre and post-policy periods.*

Third, the decline in enrollment is driven by the groups of students who are directly affected by the increased out-of-pocket expenditure (GEN and BC). Despite parallel pre-trends, on average by the year 2020-21, there are around 3 less BC students and 4 less GEN students in a high-change college program relative to their low-change counterparts. Considering that there are over 600 programs in this market corresponding to around 150 colleges, this is a sizeable decline in the number of students enrolled in the market. Fourth, the differential pattern in enrollment decline between BC and GEN can be explained by the availability of outside options and affirmative action rules. BC students sacrifice their affirmative action status and subsidy eligibility if they leave their home state. They would be treated as GEN students in any other engineering college market. Additionally, private universities which are not part of this market typically are up to 8 times more expensive than the most expensive college in this market and do not have affirmative action rules in place. Therefore, GEN and BC students have very different outside options. GEN students can afford to leave this market and go to another state or potentially enroll in expensive private universities within or outside the state.

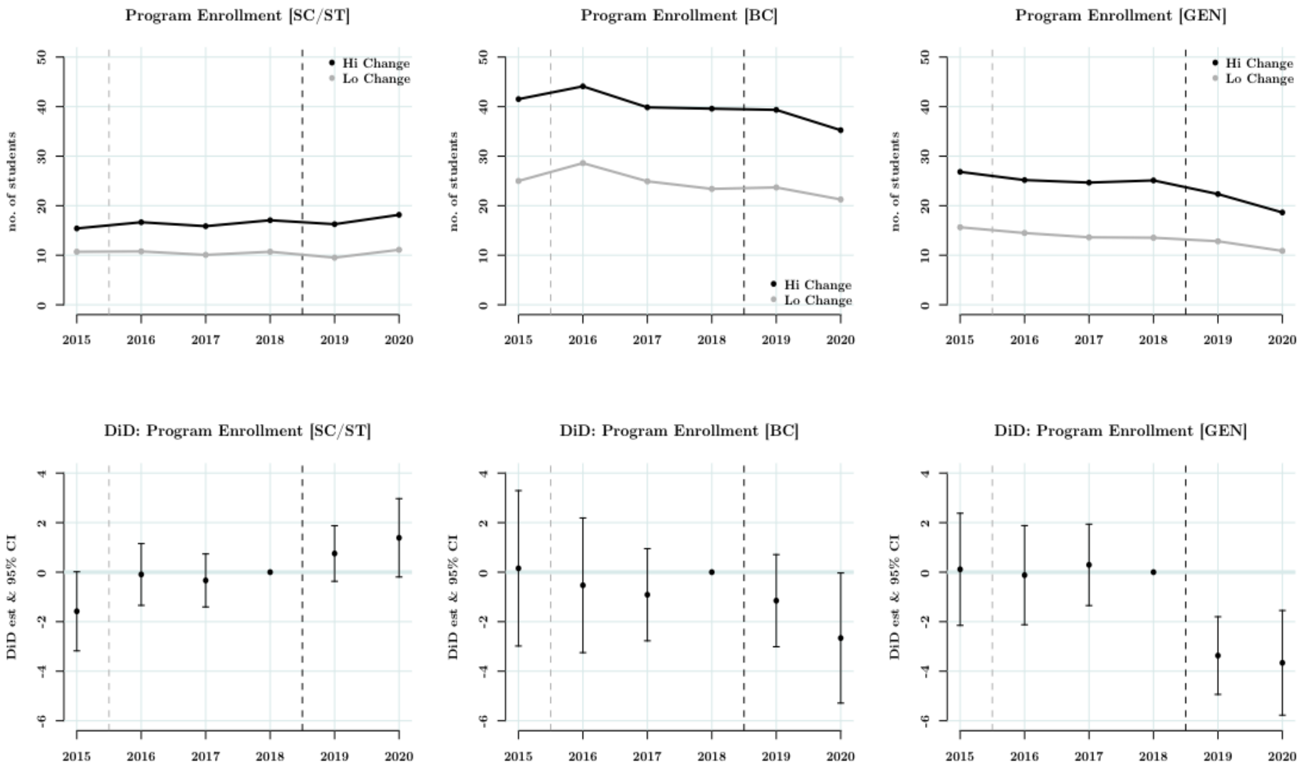

Figure 4: ***Policy impact on students' enrollment.*** *The horizontal axes represents the academic years. Top row: vertical axes represents the average number of students in a program. The black and gray trend lines represent the average program enrollment at high and low-change colleges respectively. Bottom row: vertical axes represent the policy impact on enrollment. Black dots indicate the DiD estimate and the error bars correspond to the 95% interval. The dotted vertical line separates the pre and post-policy periods.*

Figure 5 shows the density distributions of students' ability at the time of matriculation, for each caste group. We see a clear pattern emerge where GEN students have the highest incoming ability and the students who are targeted by affirmative action policies, namely BC and SC/ST have lower ability as measured by a composite of their high school graduation exam and the entrance exam score. Figure 6 shows the changes in the average quality of matriculating students as measured by their performance on a common state-wide high school graduation exam. There are three main takeaways from this plot. First, we see that the incoming quality of unaffected SC/ST students does not significantly change as a result of the price increase. There appears to be a preexisting trend of increasing student quality that continues after the policy is implemented. Second, BC students demonstrate a reversal in the quality of incoming students where matriculating students in the post-policy period are lower quality than previous years at both high and low-change colleges. This suggests that the best BC students are no longer enrolling in this market and quality is lowered across the board, not differentially between high and low change colleges. Third, GEN students react similarly to BC students and the top achievers no longer enroll in this market however the trend is (imprecisely) different between high and low-change colleges.

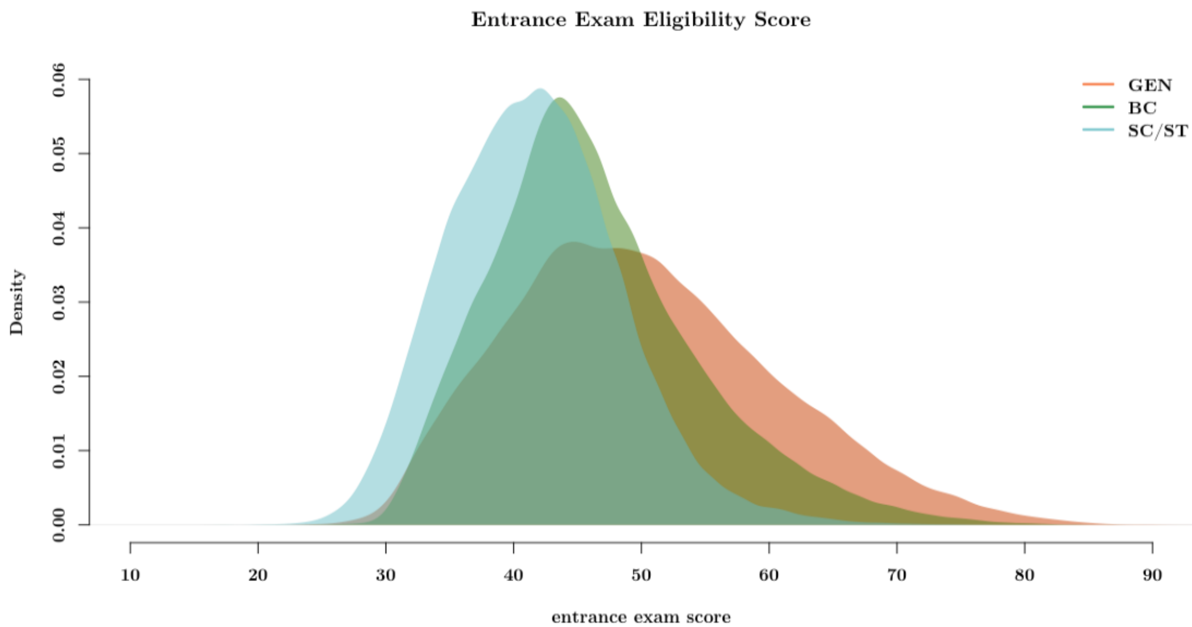

Figure 5: ***Ability of incoming students by caste.*** *The horizontal axis represents students' ability measured as by a composite of their high school graduation and entrance exam scores. The vertical axis represents the density of the distributions. The blue, green, and orange distributions correspond to SC/ST, BC, and GEN caste groups respectively.*

Jointly these patterns suggest that the average BC and GEN students who stay back in this market have lower incoming ability. This implies that average peer quality is lowered in programs. Peer quality is an important determinant of the education quality received by a student (Ladant et al., 2022). When taken together with the ability distributions in Figure 5, the results indicate that the altered cohort composition could have implications for students' returns from a college education.

Figure 7 shows that in the pre-policy period, GEN category students occupied around 30% of a program on average. This measure is in line with historic trends in the market as well as relative to other engineering college markets in India. However, in the post policy period we see there is a decline in the percentage of GEN students who are typically wealthier and high-ability students across the board. High-change colleges show a stronger declining pattern with almost a 3 p.p. faster decline relative to the low-change colleges. This departure of students is not unlike the *white flight* documented by Idoux (2022) in the New York City public school market. This result begins to suggest that there was a significant change in cohort composition as the student body became more segregated as students who could afford to leave do so, and students who are potentially more demand inelastic because of their affirmative action status or tuition subsidies (BC and SC/ST) stay back in the market. Further, the decline in enrollment can have an impact of colleges' decision making (e.g. investments, expenditure on inputs, faculty hired and fired) as a smaller student body could translate to lower revenue.

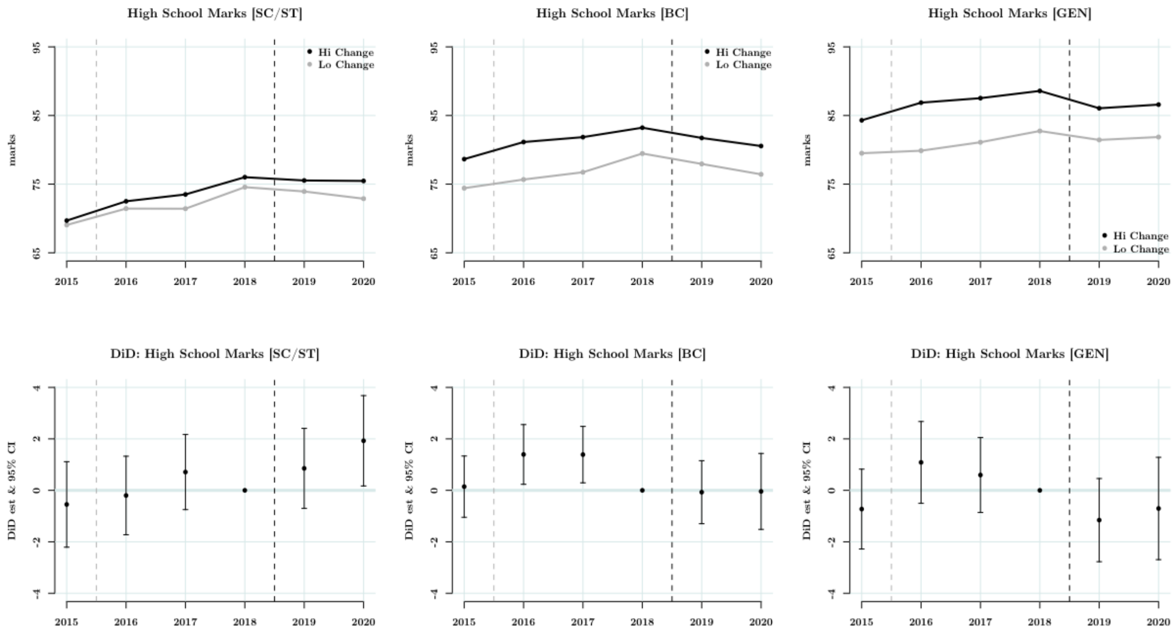

Figure 6: ***Policy impact on incoming student quality.*** *The horizontal axes represents the academic years. Top row: vertical axes represents the average high school grades of matriculating students. The black and gray trend lines represent the average high school grades at high and low-change colleges respectively. Bottom row: vertical axes represent the policy impact on enrollment. Black dots indicate the DiD estimate and the error bars correspond to the 95% interval. The dotted vertical line separates the pre and post-policy periods.*

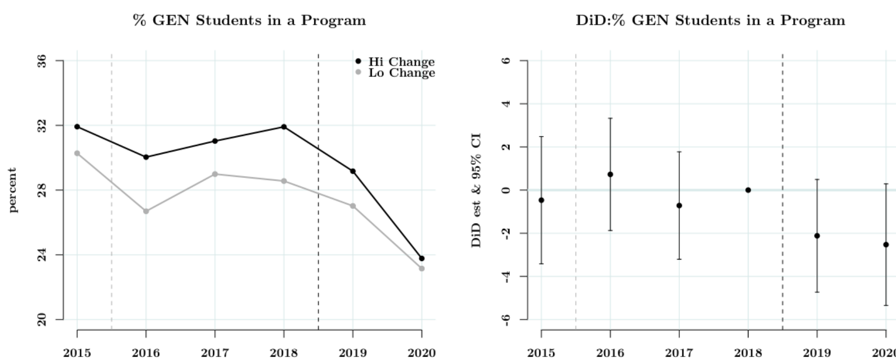

Figure 7: ***Policy impact on cohort caste composition*** *The horizontal axes represents the academic years. Left: the vertical axis represents the % of GEN category students in a program. The black and gray trend lines represent the average price of high and low-change colleges respectively. Right: the vertical axis represents the policy impact on % GEN students in a program. Black dots indicate the DiD estimate and the error bars correspond to the 95% interval. The dotted vertical line separates the pre and post-policy periods.*

4.3 College resource allocation: faculty composition

Given the demand side changes associated with the 2019-20 government price setting policy it follows that I investigate possible changes on the supply side. I.e. do colleges respond to the increased tuition prices? On one hand, if the fixed prices are close to the marginal cost of quality, colleges could have more leeway to improve their education quality at higher prices. On the other hand, if the prices are significantly lower than the competitive price that colleges would have chosen in the absence of regulations, they may choose to decrease education quality in order to manage costs. Due to data limitations, at present, I have detailed data on faculty composition for the year immediately before and the year after the policy. Using this data I set up a two-period pre-post analysis to evaluate supply side changes in response to the policy. Table 2 shows the results of this reduced form analysis. I find that the above-median price change colleges have a significant number of new hires and also have a significant number of teachers leaving. We also see imprecise estimates suggesting that there is a small decline in the number of years of experience that teachers have and the number of new teachers with a PhD.[5] This could suggest that more expensive colleges are experiencing teacher turnover or are choosing to hire less experienced teachers without PhDs in a bid to pay them less as per government mandated pay scales. A restructuring of the faculty body could lower colleges' marginal cost of quality per student and therefore increase their profits.

Table 2: Changes in Faculty 2018-19 to 2019-20

	# teachers	# new hires	yrs exp.	# PhD	# left	# new PhD	new yrs exp.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treat × *Post*	7.34	4.97*	−0.08	0.69	6.88*	−1.51	0.01
	(5.08)	(2.93)	(0.10)	(1.43)	(4.14)	(1.01)	(0.52)
Treat = 1	191.16***	37.70*	−2.32***	48.17***	−15.71	9.68	−4.91
	(38.61)	(22.31)	(0.76)	(10.84)	(31.46)	(7.74)	(4.02)
Post = 1	−5.37	−1.67	0.70***	2.72***	2.16	0.32	0.02
	(3.51)	(2.03)	(0.07)	(0.99)	(2.86)	(0.69)	(0.36)
College FE	✓	✓	✓	✓	✓	✓	✓
N	281	281	281	281	281	266	266
R^2	0.973	0.832	0.989	0.973	0.863	0.789	0.815

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

[5] Estimates in columns 3 and 6, while interesting, are imprecise. One reason for this could be the smaller dataset containing only two years worth of data. I am currently assembling a comprehensive supply side panel dataset with colleges' financial information including their revenues and categorized expenditures. This dataset will also include median salary of graduating cohorts over time.

5 Modeling college choice and optimal quality

Based on previous results we have evidence to suggest that the demand and supply side of State X's engineering college market responded to the 2019-20 government price setting policy. In this section, I aim to explain the changes in student and college responses using structural demand and supply estimation models. Modeling the decision making process of utility maximizing students and competitively profit-maximizing colleges will give us insight into their objective functions and optimization process. Further it allows us to identify the mechanisms through which these decisions will be altered by direct government price intervention, thereby facilitating welfare calculations under the current and counterfactual regulatory scenarios.[6]

5.1 Demand: college choice model

5.1.1 Conceptual framework

On the demand side we observed an overall decline in enrollment and in particular a stronger response in the GEN caste group relative to the BC caste group. SC/ST on the other hand demonstrates no change in their enrollment. Using data containing students' rank ordered list (ROL) of program preferences submitted to the centralized admissions system in State X we can understand how students form their preferences about programs and in particular how these preferences change in response to the tuition price increase. I set up a college choice model that estimates the probability of a student submitting a particular rank-ordered list.

Consider the utility for student i ranking a program that is a combination of college j and major m to be given by the following equation,

$$\begin{aligned}
v_{ijmt} &= \mu_{ijmt} + \epsilon_{ijmt} \\
&= \alpha \log(\mathbf{oop}_{ijt}) + \delta_{jm} + \epsilon_{ijmt} \qquad (1)\\
\epsilon_{ijmt} &\sim EVT1(0,1) \\
\alpha &= \sum_K \mathbb{1}[k(i) = k]\alpha_k \ \forall k \in K = \{GEN, BC, SC/ST\}
\end{aligned}$$

$\mathbf{oop}_{ij}$ denotes the out-of-pocket expense that a student i faces at college j depending on their voucher eligibility status. α captures the students' heterogeneous sensitivity to price, and from this setup we can obtain separate coefficients for the GEN, BC, and SC/ST caste individually. Therefore we can draw inferences about their heterogeneous price elasticity. δ_{jm} measures the mean indirect utility from a program. These terms subsume all observed and unobserved preferences for a given college j and major m. Finally ϵ_{ijm} captures the unobserved idiosyncratic preference that student i has for college j and major m. As we assume that ϵ follows an extreme value type-1 distribution, and given that the Deferred Acceptance Mechanism in this setting incentivizes truth-telling, we can use maximum likelihood estimation (MLE) to obtain a closed form expression for the probability any student i submits a particular ranking of programs

[6] The structural models and parameter estimates laid out in this section represent the theoretical framework for estimation of preferences. While the general framework and related welfare mechanisms will remain the same, the college choice model is currently being extended and the college profit maximization model is yet to be estimated following the preparation of a supply side panel dataset.

R_i as follows (see Agarwal and Somaini (2020)) for an overview of estimating parameters from school choice models).

The probability that a student i will submit the ROL $R_i = (R_{i1}, ..., R_{iK_i})$, where R_{ik} is the school ranked k and K_i is the length of student i's ROL. X denotes all data available and Θ denotes the vector of parameters to be estimated.

$$P(i \text{ submits } R_i|X,\Theta) = \prod_{k=1}^{K_i} \frac{\exp\{\mu_{ik}\}}{1 + \sum_j 1\{j \neq R_{ik'}\ \forall\ k' < k\} \exp\{\mu_{ij}\}}$$

MLE estimation enables us to recover the preference parameters $\Theta = \{\alpha, \delta\}$. Using these estimates we will compute each individual students' utility using the expression for v_{ijmt} based on the college they are actually allotted.[7] Student i's utility from college j and major m in time t is affected by the vector of preference parameters Θ. All elements of Θ are time-invariant. For example, students' price elasticity α or a program's perceived mean utility δ does not change over time. The primary mechanism through any welfare change will operate in this framework is owing to changes (in this case a policy induced increase) in OOP. I set the utility of one randomly chosen program to be 0 and all other mean utility parameters are interpreted relative to this.[8]

5.1.2 Preference parameter estimates

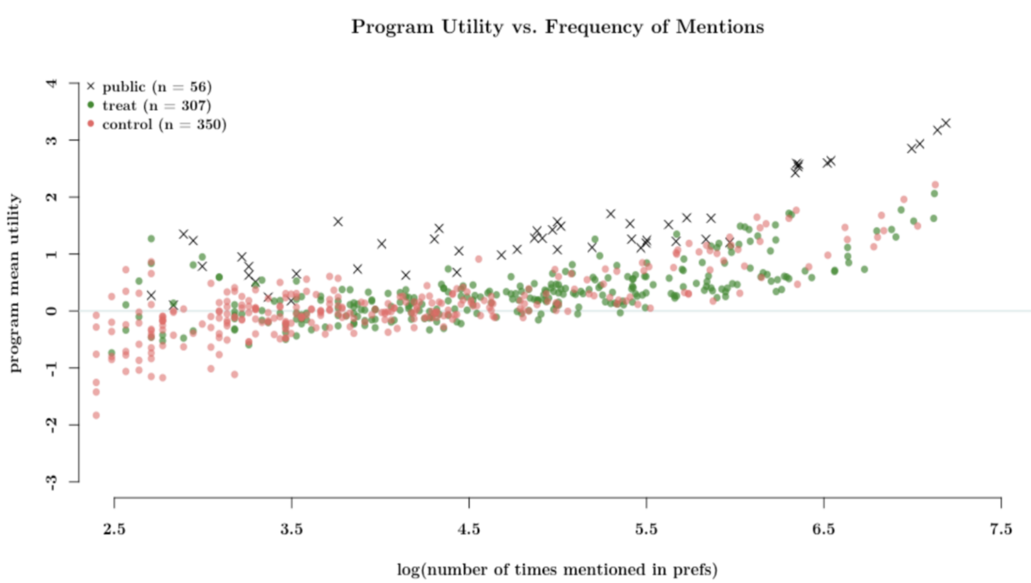

Figure 8: ***Program mean utility parameters*** δ_{jm}. *The horizontal axis represents the number of times a program is mentioned in students' preferences. The vertical axis represents the estimated value of* δ_{jm} *for a program. Black X's, green dots, and red dots correspond the mean utility of public, treated or high-change colleges, and control or low-change colleges respectively.*

[7] It is important to caveat that at present, students form their preferences based on prices and mean utility from a college and a major. Further extensions of this model will include a term quality term q, that corresponds to median salary of graduates from a particular program.

[8] As there are over 600 programs I use a minorization technique to implement the demand estimation model with high dimensional fixed effects. Please refer to Appendix A for additional details.

Figure 8 and Table 3 report the MLE estimates of students' preference parameters $\Theta = \{\alpha, \delta\}$ that explain their submitted ROL. Figure 8 shows the estimates of δ_{jm} or the mean utility of each program in this market as captured by the college choice model. There are three main takeaways from this plot. First, programs at public colleges, which subscribe to the same centralized admissions process, represent 8.5% of all available programs and are the most desirable by students. Second, the colleges which were *treated* by the policy, which we refer to as high-change colleges are generally more expensive but also offer a higher mean indirect utility on average. Third, the *control* or low-change colleges are generally cheaper and offer on average a lower mean indirect utility as revealed by the students' ROL data across all years. Since these parameters are time-invariant, we learn that students generally prefer high-change colleges to low-change colleges, but by increasing tuition prices, poorer students could be priced out of high-change colleges where they would rather go and instead have to go to lower mean utility low-change colleges.

Table 3: Students' price elasticity: α

Parameter	Estimate
α_{GEN}	-0.13
α_{BC}	-0.18
$\alpha_{SC/ST}$	-0.21

In Table 3 we see that the price elasticities of students track their income and ability distributions with SC/ST being the most price elastic, followed by BC and the wealthiest group of students, namely GEN, are the least price elastic. I highlight three mechanisms that govern changes and potentially redistribution in students' welfare from their college choice. First, the *price* mechanism. We see that students receive negative utility from out-of-pocket expenditure oop_{ij}. An increase in OOP results in a decrease in utility. Second, the *sorting* mechanism. Students have, on average, historically preferred the treated or high-change colleges which offer a higher mean utility δ. However, when the tuition price at these colleges increases, we might see poorer students rank these colleges lower in their ROL effectively *sorting* into lower δ colleges because they are unable to afford them in the post-policy period, when they would have been able to do so in the pre-policy period conditional on ability. Third, the *exit* mechanism at the external margin, where certain groups of students choose to exit the market altogether. Although this is not a feature of the current demand estimation setup, we can extend the model to include different outside options for students who are and aren't targeted by affirmative action policies. Since BC and SC/ST students would typically have worse outside options than GEN students (Otero et al., 2021), we might see an overall decrease in welfare if poorer students end up leaving the market altogether.

5.2 Supply: college profit-maximization model

In this section I explain the objective function of a profit-maximizing college in this market.

5.2.1 Conceptual framework

Since colleges cannot choose their price in this setting, the can only decide their optimal quality in order to maximize profits. The college's profit maximization problem is given by the following equation:

$$\arg\max_{q_j} \Pi_j = \Big[\bar{p_j} - MC(q_j)\Big] \sum_{k \in K} n_{j,k}(\mathbf{q}_j, \mathbf{oop}_{j,k}) - F_j \tag{2}$$
$$MC(q_j) = c_0 + c_q q_j$$

Where $j \in J = \{1, .., N_J\}$ indexes colleges. $k \in K = \{GEN, BC, SC/ST\}$ indicates each individual student group based on caste category. $\bar{p_j}$ is the **fixed** sticker price at college j. $MC(q_j)$ is the marginal cost at college j as a linear function of quality q_j. F_j are fixed costs at college j. $n_j(\mathbf{q}, \mathbf{oop}) = \sum_{k \in K} n_{jk}(q_j, oop_{j,k})$. Where $n_{jk}(q_j, oop_{j,k})$ is the number of students from caste k who enroll at college j. $n_{jk}(.)$ is a function of college quality q_j and price p_j operating through the out of pocket expense $oop_{j,k}$ a student from community $k \in K$ has to pay at college j.[9]

Optimal quality q_j^*computed by setting $\frac{\partial \Pi_j}{\partial q_j} = 0$

$$q_j^* = \underbrace{\frac{\bar{p_j} - c_0}{c_q}}_{\textbf{competitive quality}} \underbrace{- n_j(\mathbf{q}, \mathbf{oop}) \left[\frac{\partial n_j(\mathbf{q}, \mathbf{oop})}{\partial q_j}\right]^{-1}}_{\textbf{quality markdown}} \tag{3}$$

Equation 3 shows the two factors affecting a college's optimal quality decision. Each of the terms in this equation highlights a mechanism through which the government mandated price increase can affect optimal quality, and therefore students' welfare as they incorporate college quality into their ROL preparation. The first term represents the *direct effect* of the price increase. An increase in tuition prices $\bar{p_j}$ should lead to an overall increase in education quality in the market which will naturally benefit students, if costs remain unchanged. The second term represents the *indirect effect* of the price increase, namely the quality markdown. This term is a product of two positive terms if students have a positive preference for quality and college enrollment responds positively to an increase in quality. Therefore the higher the market share of a college n_j, the greater its ability to markdown quality relative to the competitive benchmark.

5.2.2 Foreshadowing changes in quality

We saw suggestive evidence in Table 2 that high-change colleges potentially made changes in their faculty composition that led them to hire lesser qualified teachers in the post-policy period. In Figure 9 we see that high-change colleges historically have higher market shares than low-change colleges. This indicates that all other factors being equal, these colleges would have a higher ability to markdown quality and still maximize profits relative to their low-change counterparts. It is possible that this difference in market

[9]Note that in the proposed college profit-maximization model, students' demand enters through the share of students from each caste category k that enroll in a college. The term capturing demand, $n_j(\mathbf{q}, \mathbf{oop})$ is a function of OOP and college quality. At present college quality is not included in Equation 1 however the college choice model will be extended to include this term following the preparation of supply side data.

share enables above-median price change colleges to decrease their education quality as measured by faculty composition and experience.

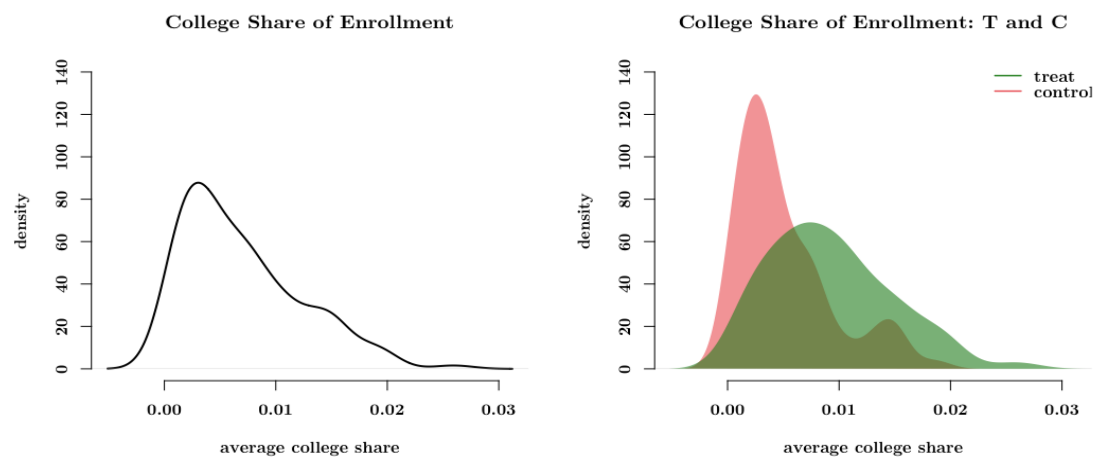

Figure 9: ***Density distribution of college market shares*** n_j

5.3 Next steps

I propose two next steps in order to evaluate the impact of direct government price intervention in a college market with centralized admissions. First, I will prepare a comprehensive supply side dataset that includes two main indicators of college and education quality in this market, namely, the *median salary of graduating cohorts* and information on college *incomes* and *expenditures* over time. This will allow me to model a college's optimal quality decision q_j in the profit-maximization model and define equilibrium in this market. Colleges will receive a fixed sticker price $\bar{p}_j$ from the government and choose their optimal quality q_j^* to maximize profits. Students prepare their ROL reflecting program preferences based on $\{\mathbf{q}_j, \mathbf{oop}_{ij}\}$, i.e. quality and their anticipated OOP at a college. Thereafter, I can leverage the exogenous change in prices to quantify the effect of direct government price intervention on students' welfare and highlight how the welfare of poor students is affected by the 2019-20 price increase. Second, I can use the preference parameters and the centralized admissions mechanism to predict students' ROLs under counterfactual price regulation policies. Important counterfactuals will include an estimation of optimal college prices and welfare under alternate subsidy schemes for affirmative action students which increase the subsidy amount to compensate students a percentage of the tuition expenditure rather than a fixed voucher.

6 Conclusion

In this paper I examine the impacts of direct government price intervention in higher education markets with centralized admission systems. I examine the engineering college market in an Indian state which uses a Deferred Acceptance mechanism, with serial dictatorship to match students and programs. Private colleges in this market account for over 90% of education supply in this market and have their tuition prices fixed by the state government. In 2019-20 the state government updated individual college tuition prices leading to a 20% increase, on average, in prices without any changes in vouchers or subsidies for poor, affirmative action students. Leveraging the plausibly exogenous variation in prices created by the policy, I use a dynamic difference-in-differences approach to causally estimate the policy impact on the demand and supply side of the market. On the demand side I find that colleges with above-median price increases saw significant enrollment declines, lower incoming student quality, and increased segregation as wealthy and high-ability students leave these colleges. On the supply side I find that above-median price increase colleges experience significantly more teacher turnover with new hires being less experienced and less likely to have a PhD. In order to quantify the market-wide welfare consequences of the price change I estimate a college choice or demand estimation model, propose an extension of this model, and outline the college profit-maximization model. I highlight the primary mechanisms through which government price intervention can affect student and college decisions, and in turn welfare.

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A Minorization to estimate high-dimensional fixed effects

Consider the utility for student i ranking a program that is a combination of college j and major m to be given by the following equation,

$$\begin{aligned} v_{ijmt} &= \mu_{ijmt} + \epsilon_{ijmt} \\ &= \alpha \log(\mathbf{oop}_{ijt}) + \delta_{jm} + \epsilon_{ijmt} \\ \epsilon_{ijmt} &\sim EVT1(0,1) \\ \alpha &= \sum_{K} \mathbb{1}[k(i) = k]\alpha_k \ \forall k \in K = \{GEN, BC, SC/ST\} \end{aligned}$$

$\mathbf{oop}_{ijt}$ denotes the out-of-pocket expense that a student i faces at college j depending on their voucher eligibility status. α captures the students' heterogeneous sensitivity to price. δ_{jm} measures the mean indirect utility from a program. ϵ_{ijmt} captures the unobserved idiosyncratic preference that student i has for college j and major m.

Student i submits a rank ordered list (ROL) of college preferences, $R_i = \{R_{i1}, ..., R_{iK_i}\}$ of student specific length K_i where each item in the list R_i corresponds to a college. For instance, college R_{i1} is the most preferred college and college R_{iK_i} is the least preferred college.

The probability that student i submits an ROL R_i is given by the following expression

$$L_i = P(i \text{ submits } R_i|\alpha, \delta) = \prod_{k=1}^{K_i} \frac{\exp\{\mu_{ik}\}}{\sum_{k'=1}^{K_i} y_{ik'} \exp\{\mu_{ik'}\}}$$

Where $y_{ik'} = 1$ if $k' \geq k$ and 0 otherwise. i.e. it is the product of K_i discrete choice probabilities where the denominator of the k^{th} term is the sum of utilities of the college ranked in position k and all colleges ranked worse than it.

Therefore the log-likelihood for a given student is obtained by taking the log of the previous expression,

$$LL_i = \sum_{k=1}^{K_i} \left[\mu_{ik} - \log\left(\sum_{k'=1}^{K_i} y_{ik'} \exp\{\mu_{ik'}\}\right)\right]$$

Using this expression, we can write the joint log-likelihood for all students as follows:

$$LL = \sum_{i=1}^{N} LL_i$$

In order to estimate the high dimensional vector, $\vec{\delta} = \{\delta_1, ..., \delta_J\}$ of college fixed effects, I use a computational trick involving the first order condition (FOC), by computing the derivative of the joint likelihood LL, with respect to each δ_j. The first order partial derivative takes the following form

$$\frac{\partial LL}{\partial \delta_j} = \sum_{i=1}^{N} \mathbb{1}[j \in R_i] - \sum_{i=1}^{N} \sum_{k=1}^{Y_{ij}} \frac{\exp\{\mu_{ij}\}}{\sum_{k'=1}^{K_i} y_{ik'} \exp\{\mu_{ik'}\}}$$

Where $N_j \sum_{i=1}^{N} \mathbb{1}[j \in R_i]$, is the total number of students who ever list college j in their rank ordered list. Therefore $N_j \leq N$ (the total number of students). Additionally Y_{ij} denotes the "numeric position" of college j in student i's rank ordered list. Say college j is ranked in the fourth position of a students ROL, then $R_{i4} = j$ and $Y_{ij} = 4$.

Taking the partial derivative $\frac{\partial LL}{\partial \delta_j}$ and setting it equal to zero, we obtain the FOC

$$N_j = \sum_{i=1}^{N} \sum_{k=1}^{Y_{ij}} \frac{\exp\{\mu_{ij}\}}{\sum_{k'=1}^{K_i} y_{ik'} \exp\{\mu_{ik'}\}}$$

Where $\mu_{ij} = \alpha \log(\mathbf{oop}_{ij}) + \delta_j$. I simplify $\log(\mathbf{oop}_{ij}) = p_{ij}$ for ease of notation.

By the properties of the exponential function we can simplify this further as follows

$$\begin{aligned} N_j = & \exp\{\delta_j\} \sum_{i=1}^{N} \sum_{k=1}^{Y_{ij}} \frac{\exp\{\alpha p_{ij}\}}{\sum_{k'=1}^{K_i} y_{ik'} \exp\{\alpha p_{ik'} + \delta_{k'}\}} \\ \implies \exp\{\delta_j\} = & N_j \left[\sum_{i=1}^{N} \sum_{k=1}^{Y_{ij}} \frac{\exp\{\alpha p_{ij}\}}{\sum_{k'=1}^{K_i} y_{ik'} \exp\{\alpha p_{ik'} + \delta_{k'}\}} \right]^{-1} \\ \implies \delta_j = & \log\left(N_j \left[\sum_{i=1}^{N} \sum_{k=1}^{Y_{ij}} \frac{\exp\{\alpha p_{ij}\}}{\sum_{k'=1}^{K_i} y_{ik'} \exp\{\alpha p_{ik'} + \delta_{k'}\}} \right]^{-1} \right) \end{aligned}$$

Consider the RHS in the above equation to be a function of δ defined as $\Omega(\delta)$. We can write the following expression

$$\delta^{(n+1)} = \Omega(\delta^{(n)})$$

Therefore given a trial vector $\delta^{(n)}$ one can iteratively compute $\delta^{(n+1)}$ until some prespecified tolerance criterion is met on the difference between $\delta^{(n+1)}$ and $\Omega(\delta^{(n)})$.