PRICE REGULATION IN CENTRALIZED COLLEGE ADMISSION SYSTEMS

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Abstract

This paper studies the effects of government price regulation in a college market with centralized admissions. I analyze a policy change in a large Indian state that increased tuition ceilings at private engineering colleges by an average of 20%, leaving tuition subsidies for most marginalized students unchanged. Using administrative data on students' rank-ordered program preferences, enrollment outcomes, and college characteristics, I document that the policy raised out-of-pocket expenses for 80% of students, triggered enrollment declines among wealthier, high-ability students, and led to a deterioration in peer quality and increased socioeconomic segregation. Colleges with greater pre-policy market share passed through price increases with minimal quality improvements, while less dominant colleges upgraded quality more aggressively. To quantify equilibrium impacts, I estimate a structural model of student college choice and college quality investment under fixed prices. Structural estimates reveal substantial quality markdowns among colleges with greater historical market share and net welfare losses concentrated among students directly affected by the price-setting policy. Price and quality changes have opposing effects on enrollment but the price effect dominates causing overall enrollment declines. Compensating variation estimates indicate the policy caused net losses in welfare with modest redistribution of surplus to the poorest students. The findings highlight how government price setting interacts with market power and centralized admissions to reshape competition, access, and welfare in higher education markets.

Keywords: higher education, price regulation, centralized admissions, school choice, welfare

JEL Classification Codes: I23, I25, I28, O12, L11, L51

1. INTRODUCTION

An effective tertiary education system is vital for human capital accumulation, upward social mobility, and economic development. In recent decades, developing countries have witnessed a rapid expansion in demand for higher education. Faced with capacity and funding constraints in the public sector, much of this demand has been met by a growing private higher education market.[1] The rise of private colleges, however, presents a fundamental tension for policymakers and economists: how can systems expand access without exacerbating inequality or eroding quality? On one hand, private providers can offer high-quality education but at prices that often exclude poor and marginalized students (Muralidharan, 2019). On the other, government regulation designed to promote affordability and equity can distort market incentives, inviting entry by low-quality, profit-maximizing institutions and encouraging quality markdowns when providers possess market power (Kapur and Mehta, 2007; Neilson, 2013). Understanding how policy interventions shape both student access and institutional behavior is critical to designing effective higher education systems in developing countries.

This paper contributes to this broader debate by examining an understudied policy tool: *direct government price regulation*. Studies of targeted vouchers and subsidies highlight how financial assistance to poor students reshapes school incentives and market structures (Neilson, 2013; Allende, 2019). Other work explores affirmative action policies in centralized admissions systems (Bertrand et al., 2010; Bagde et al., 2016; Otero et al., 2021), while recent papers investigate how tuition-linked voucher designs can induce strategic pricing responses among private schools (Sahai, 2023). There is relatively little empirical evidence on how binding government price controls, without accompanying quality mandates, impact student enrollment, education quality, and welfare in private higher education markets. This paper addresses that gap by investigating both demand and supply side responses to government-imposed tuition prices, focusing particularly on the heterogeneous effects by market structure and student socioeconomic status.

I study the impact of direct government price regulation in the private engineering college market of a large Indian state (hereafter "State X") from 2015–2021. In 2019–20, the state government revised individual college tuition prices, resulting in an average price increase of about 20%, with considerable variation across colleges (ranging from 0% to 100%). Importantly, tuition subsidies for the majority of disadvantaged caste groups were left unchanged. The policy generates *plausibly exogenous* variation in prices and students' out-of-pocket costs while also creating differential exposure across institutions based on their pre-policy market share. Leveraging administrative datasets that link student demographics, ranked program preferences, entrance exam scores, tuition prices, and college characteristics, I use a combination of reduced form approaches to document both demand and supply-side responses to the price-setting policy. I report three main findings. First, the price setting policy led to an increase in tuition prices and out-of-pocket expenses (OOP) in the

[1] Examples include 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.

market as a whole. Price increases are directly associated with colleges' market share as colleges in the top two quartiles based on pre-period enrollment share experience a 27% increase in price relative to the bottom two quartiles which receive a 18% increase in prices. Second, on the demand side, I find that colleges experiencing larger price increases suffered significant enrollment declines, primarily driven by wealthier, high ability students. The decline was especially pronounced at high market share colleges, while some low market share colleges experienced modest enrollment gains driven by poorer students. Additionally, the exodus of high ability students lowered the average incoming student quality and increased socioeconomic segregation within programs. Third, on the supply side, I find that colleges' responses to the price-setting policy were highly heterogeneous. Colleges in the bottom quartiles of enrollment share improved educational quality substantially, as measured by *salary per teacher*. In contrast, top-quartile colleges, despite greater revenue potential, exhibited minimal quality improvements. A triple-difference design that jointly leverages variation in price changes, college market share, and time, confirms that high market share colleges exercised greater market power, passing through price increases with minimal quality upgrades, while colleges with lower market share responded competitively by raising quality and attracting some displaced students.

While these empirical results highlight important demand and supply-side responses they do not, by themselves, quantify the welfare consequences of price regulation or the strategic incentives faced by colleges under fixed pricing. I address this by developing a rank-ordered logit model of student college choice in a centralized admissions system (Agarwal and Somaini, 2020), and a competitive profit maximization model of college quality choice given fixed tuition prices. This structural framework allows me to separately identify students' heterogeneous price sensitivities by caste group, colleges' quality responses to policy shocks, and the extent of quality markdowns induced by market power. The structural estimates yield three primary findings. First, wealthier students, who aren't targeted by affirmative action (AA) policies are the most price elastic and poorer students targeted by AA and voucher policies are the least price elastic and therefore have the highest willingness-to-pay for quality improvements. Second, while the price-setting policy expanded revenue potential for colleges, it led to large quality markdowns at historically high-demand institutions, with bottom-quartile colleges passing through more of the intended quality improvements to students. Third, compensating variation estimates reveal substantial welfare losses for 80% of students, directly affected by the price-setting policy and increased OOP, with only modest welfare gains accruing to federal subsidy eligible students. Overall, the policy imposed large aggregate welfare losses on the market.

This paper is related to several strands of literature. First, a large body of work studies the welfare implications of government policy in education markets. In decentralized settings, Neilson (2013), Muralidharan and Sundararaman (2015), and Allende (2019) show how vouchers and school competition affect student achievement, market power, and educational inequality. More recently, in centralized admissions systems, policies like vouchers, affirmative action, and admission reforms have been shown to alter sorting patterns and access to quality education (Otero et al., 2021; Idoux, 2022; Sahai, 2023). This paper contributes by studying direct price regulation in a centralized college market, where tuition controls reshape both student demand and college supply. Unlike prior work, which focuses on price-sensitive school competition or affirmative action alone, I analyze how binding prices interact with market power in a centralized college market to shape enrollment behavior and quality incentives. I further provide evidence on the trade-offs between access, quality, and welfare under government intervention. Second, this paper contributes to a growing literature that examines development through the lens of industrial organization and market structure. Recent work has used structural models to study how market frictions, price controls, and government interventions reshape firm behavior and welfare outcomes in developing countries (Garg and Saxena, 2022, 2023). In particular, studies of price regulation in industrial markets (e.g., cement, agriculture) emphasize how supply-side responses to policy can drive long-run industry evolution and distributional impacts. This paper extends these insights to the higher education sector, modeling how price ceilings affect college quality choices, student demand, and market power under centralized admissions. Third, this paper relates to an extensive literature that examines school choice, preferences, and welfare using structural models in both decentralized (Ferreyra, 2007; Neilson, 2013; Angrist et al., 2013; Ferreyra, 2007; Allende, 2019; Dinerstein and Smith, 2021) and centralized (Abdulkadiroğlu and Sönmez, 2003; Abdulkadiroğlu et al., 2005; Pathak and Sönmez, 2008; Fack et al., 2019; Otero et al., 2021; Larroucau and Rios, 2022; Idoux, 2022; Corradini, 2023; Kapor, 2024) market settings.

The remainder of the paper is organized as follows. Section 2 describes the institutional setting and price-setting policy. Section 3 details the sources and types of available data. Section 4 presents empirical evidence on the impact of the price-setting policy on enrollment and college quality. Section 5 outlines the demand side college choice model and supply side profit maximization model. Section 6 analyzes equilibrium outcomes and welfare. Section 7 concludes.

2. INSTITUTIONAL CONTEXT AND PRICE REGULATION

2.1. Engineering College Market and Centralized Admissions

Like most Indian states, State X provides an ideal setting to study the impact of price regulation on higher education markets with centralized admission for three reasons. First, the central and state governments in India jointly regulate nearly all aspects of private college decision-making, including tuition prices, admissions, affirmative action, entry and exit, program capacity, and faculty compensation scales (Varghese and Khare, 2020). Second, private engineering colleges in State X account for nearly 95% of the supply and over 90% of enrollment in the engineering college market. Marginalized castes represent a majority (70%) of enrollment in private colleges (approximately 50% Backward Caste and 20% Scheduled Castes and Tribes). 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.

The engineering college market in State X admits between 40,000–45,000 students annually across 150 colleges offering around 650 programs. The 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 (college + major) based on a common entrance exam. Students submit unrestricted length rank-ordered lists of program preferences and are themselves ranked objectively, based on their exam performance (i.e. serial dictatorship). This property eliminates the need to model *selection* by colleges or the admissions decision. Based on government mandated program capacity and affirmative action rules, candidates are matched with their most preferred *feasible* program. Therefore, under reasonable assumptions, the mechanism incentivizes truthful reporting of preferences and produces stable, optimal matches (Fack et al., 2019; Agarwal and Somaini, 2020; Otero et al., 2021). Analyzing candidates' rank-ordered program preferences offers insights into how students choose programs and how price interventions affect choices, revealed preferences, and welfare. Aspiring engineering students in this system typically face three choices. First, they can take the common entrance test (CET) offered within their state and accept their allotted program. Second, they can choose to enroll in a private university outside this system or in a neighboring state. For the majority of students this can be either prohibitively expensive or requires extremely high academic ability to secure enrollment in a state that is not the candidate's *state of domicile*. Third, they can choose to leave this market altogether and either obtain another college degree (e.g. Bachelor of Science/Arts) or a technical diploma. This paper focuses on the students opting for the first option who give the in-state CET and submit their ROL preferences to the admissions mechanism.

2.2. Price-Setting Policy and Market Share

Private college tuition prices in this market are regulated by the state government and are reset approximately every three years. Colleges submit detailed financial information, including income and expenditure reports, to a state Fee Fixation Committee (FFC), which then assigns a fixed sticker price P_j to each college j. The price-setting process is input-based and aims to cover marginal costs per student while maintaining affordability. Program capacity is also set administratively and is not automatically revised without a specific request by a college. The capacity expansion cycle need not coincide with the price fixation cycle. Notably, the majority of private programs remain undersubscribed during the admissions process. At the start of academic year 2019–20, the government conducted a price review, leading to updated tuition prices for approximately 150 colleges. Figure 1 shows the variation in the percent price change across colleges in this market. We observe that while the median college receives a price change of about 20%, there is significant variability around this with a range of 0-100% price change.

The broad variation in price changes raises an important question, namely, which types of colleges receive smaller or larger price adjustments? Since colleges differ substantially in realized enrollment and market share, it is important to further examine how price changes varied with

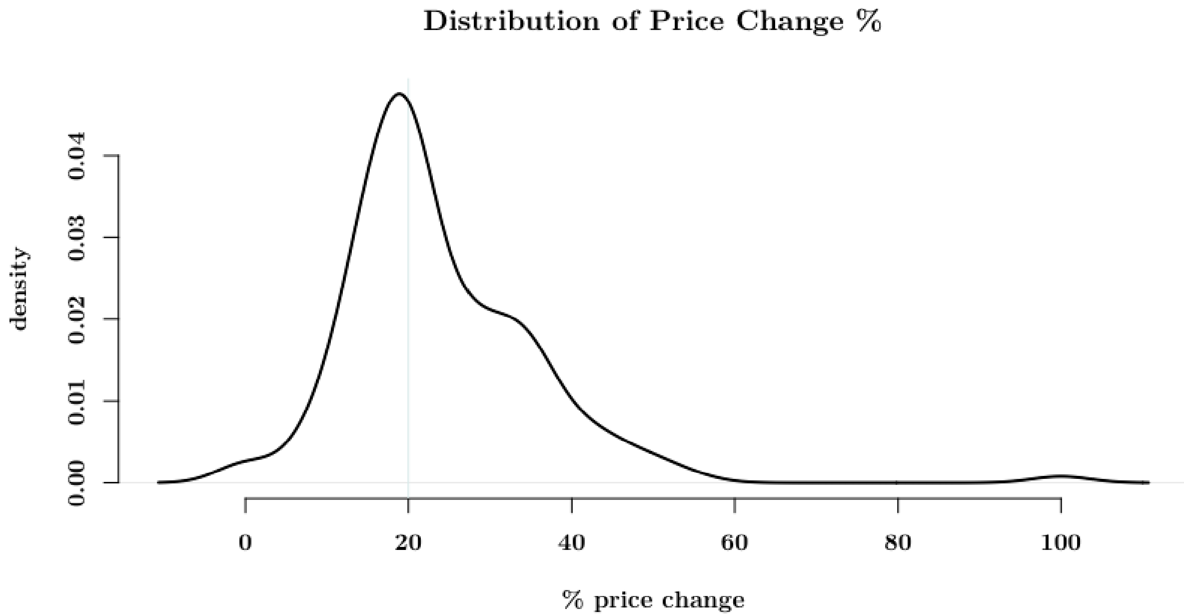

Figure 1: ***Variation in % price change as a result of 2019-20 policy.*** *The horizontal axis represents the percentage price change as a result of the 2019-20 government policy. The vertical axis represents the density of the distribution. The solid black line shows the density distribution of percent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

pre-policy enrollment share — a proxy for a college's pre-existing market power. To address this, I divide colleges into quartiles based on their pre-policy enrollment share, with Q1 colleges having the least enrollment share pre-policy and Q4 having the most, aggregating across all pre-policy years. Analyzing price changes across these market share quartiles reveals systematic patterns.

Figure 2 presents the average change in tuition prices (both in absolute rupees and percentage terms) across enrollment share quartiles. The primary takeaway is colleges with a greater enrollment share are typically more expensive in rupee terms but also receive the largest price increases as a percentage of their pre-policy price. For example colleges in Q1 and Q2 receive a price increase of $\approx 18\%$ whereas colleges in the top two quartiles receive a price increase of $\geq 25\%$. These patterns suggest that market share is an important dimension along which price regulation affected colleges differentially. Colleges with higher pre-policy enrollment shares, and hence greater market power, faced greater price increases. This motivates using both *price change exposure* and *market share quartile* as key sources of variation when evaluating the impact of price regulation on student and college behavior in the empirical analysis that follows.

2.3. Affirmative Action and Out-of-pocket Expense

In this section I explain how Affirmative Action (AA) policies work for admission into a program through the centralized admission system and relatedly how students' out-of-pocket expense (OOP)

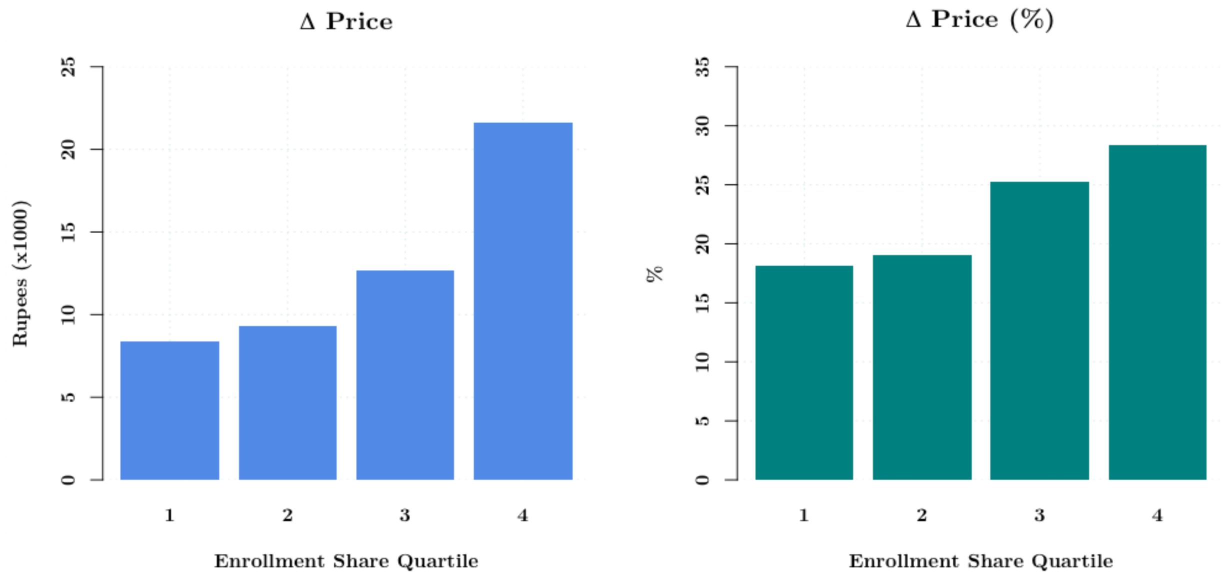

Figure 2: ***Change in Price by Market Share Quartile.*** *The horizontal axes in both panels represent the pre-period enrollment share quartile.* *Left:* *the vertical axis represents the actual price increase in ₹1k.* *Right:* *the vertical axis represents the percentage increase in price.*

changes as a result of the price-setting policy. There are three main student groups based on caste category, namely Scheduled Caste and Scheduled Tribe (SC/ST), Backward Caste (BC), and General (GEN). The first two groups of students are the ones targeted by AA policies, while GEN students are not. In terms of household income, SC/ST, BC, and GEN families earn an annual per capita income of approximately ₹234,000 ($2740), ₹276,000 ($3200), and ₹600,000 ($7020) respectively. Table 1 summarizes the AA status, OOP, and explains how government price intervention

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

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

affected each group. There are three main takeaways. First, SC/ST students who make up about 20% of the student body have 20% of seats reserved for them through AA policies. They are federally funded throughout this period and effectively attend college for free within this market. Second, BC students who constitute around 50% of the student body have 30% of seats reserved through AA policies. This group is eligible for a fixed state-sponsored subsidy of ₹35,000 throughout the period under study. Third, GEN students, who constitute 30% of the student body and are not targeted by AA policies have to compete for the remaining 50% of seats. They are ineligible for any federal or state subsidies throughout this period and always pay full price for a private engineering college in this market. We observe that with the average increase across the market in tuition price P_j and no change in subsidy policy, BC and GEN students, i.e. 80% of the student body face significantly higher OOP in the post period relative to pre-policy years.

3. DATA

The empirical analysis combines several administrative and survey datasets that together provide a detailed picture of student preferences, college characteristics, pricing, and educational outcomes across private engineering colleges in the state.

3.1. Demand: Student-Level Admissions Data

The primary source of student information comes from the centralized college admission test (CET) records between academic years 2015-16 and 2020-21. This dataset includes student level demographics like high school and entrance exam scores, gender and caste category (used to determine affirmative action eligibility). It also includes students' submitted rank-ordered lists (ROL) of program preferences, where each program is uniquely identified by a college-major pair (e.g. Bachelor of Computer Science Engineering at College X is a program). Further, I have access to final student-program matches as generated by the mechanism, a binary indicator for enrollment, and actual out-of-pocket expenses after accounting for caste-based subsidies or vouchers. This allows for the construction of student-level choice sets, preference rankings, and post-match enrollment outcomes, which are critical for estimating student demand and welfare outcomes.

3.2. Supply: College Prices and Features

College or supply side data is aggregated across several sources. College-level sticker prices are collected from the State Government's Order Registry. These administrative orders assign a government-mandated tuition price P_j to each college j following the 2019–20 price review. I observe both pre- and post-policy prices, allowing the measurement of variation in tuition changes across colleges, as discussed in Section 2.2. Data on college inputs and quality indicators come from multiple sources between 2017 and 2020. This includes the All India Survey of Higher Education (AISHE), National Institute Ranking Framework (NIRF), and individual college balance sheets available on the college website. From the All India Council for Technical Education (AICTE), I scrape information on *program capacity* associated with each college and program in the market under study. *Salary per teacher* is used a proxy measure of college quality throughout this paper. An examination of college-level financial data shows that the faculty wage-bill accounts for, on average, 70% of total expenditures by a college in an academic year. Further, the AICTE has strict guidelines for salaries to be paid to faculty members at each level of qualification and experience (e.g. Asst. Prof with x years of experience). Therefore using salary per teacher gives us an idea of not only the total wage-bill but also the faculty composition. I construct a panel data of college quality and infrastructure variables that tracks colleges for two years before the policy and two years after.

4. IMPACT OF PRICE SETTING POLICY

In this section I evaluate the impact of the price-setting policy on student enrollment and resorting as well as college quality. As demonstrated in Section 2.2, the government price setting policy affected different colleges to varying degrees introducing *plausibly exogenous* variation in tuition prices. I leverage this variation to study changes in enrollment and college quality using three empirical approaches. First, I use an event-study difference-in-differences (ESDiD) design (Stevenson and Wolfers, 2006; Finkelstein, 2007) to examine the impact of exposure to the price policy on out-of-pocket expense (OOP) and enrollment. Second, I examine heterogeneity in enrollment and college quality response by studying changes within market-share quartiles before and after the policy using a pre-post analysis. Third, I combine the first two empirical approaches in a triple difference design to understand the joint impact of exposure to the price setting policy and pre-period enrollment share.

4.1. Event Study Difference-in-Differences

In order to estimate the causal impact of the tuition price setting policy I use an ESDiD framework where treatment is defined based on the median price change percentage across all colleges in the market. I categorize colleges that received a price increase above the median (20%) as *high-change* colleges and those that received a price increase of 20% or below 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 interest would proceed along parallel trends. Equation 1 shows the primary ESDiD specification.

$$y_{mjt} = \alpha_m^M + \alpha_j^J + \alpha_t^T + \sum_{k=2015; k\neq 2018}^{2020} \beta_k \big\{ D_j^{price} \times \mathbb{1}[k=t] \big\} + \gamma X_{mjt} + \epsilon_{mjt} \tag{1}$$

y_{mjt} is outcome under consideration in program m, college j, time t. $D_j^{price} = 1$ for a high-change college and 0 otherwise. X_{mjt} is a vector of relevant controls like program capacity. The α coefficients represent fixed effects of majors, colleges, and time. The primary coefficient of interest is β which measures the relative difference in y_{mjt} between high-change and low-change colleges interpreted against $\beta_{2018} = 0$. Standard errors are clustered at the level of treatment, i.e. the college level.

4.1.1. Tuition Prices and Out-of-pocket Expenditure

Figure 3 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

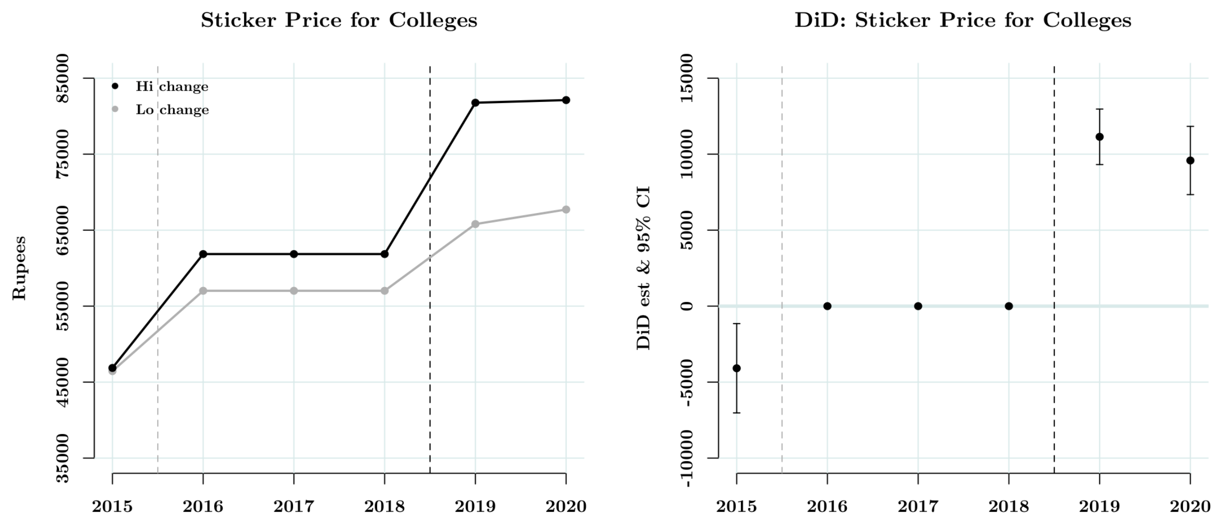

Figure 3: ***Policy impact on sticker prices for high and low-change colleges.*** *The horizontal axes represents the academic years.* *<u>Left:</u> the vertical axis represents the sticker price in rupees. The black and gray trend lines represent the average price of high and low-change colleges respectively.* *<u>Right:</u> 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.*

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 18%.

Figure 4 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.

4.1.2. Enrollment and Cohort Composition

Figure 5 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 weakly increase enrollment at high-change programs. This

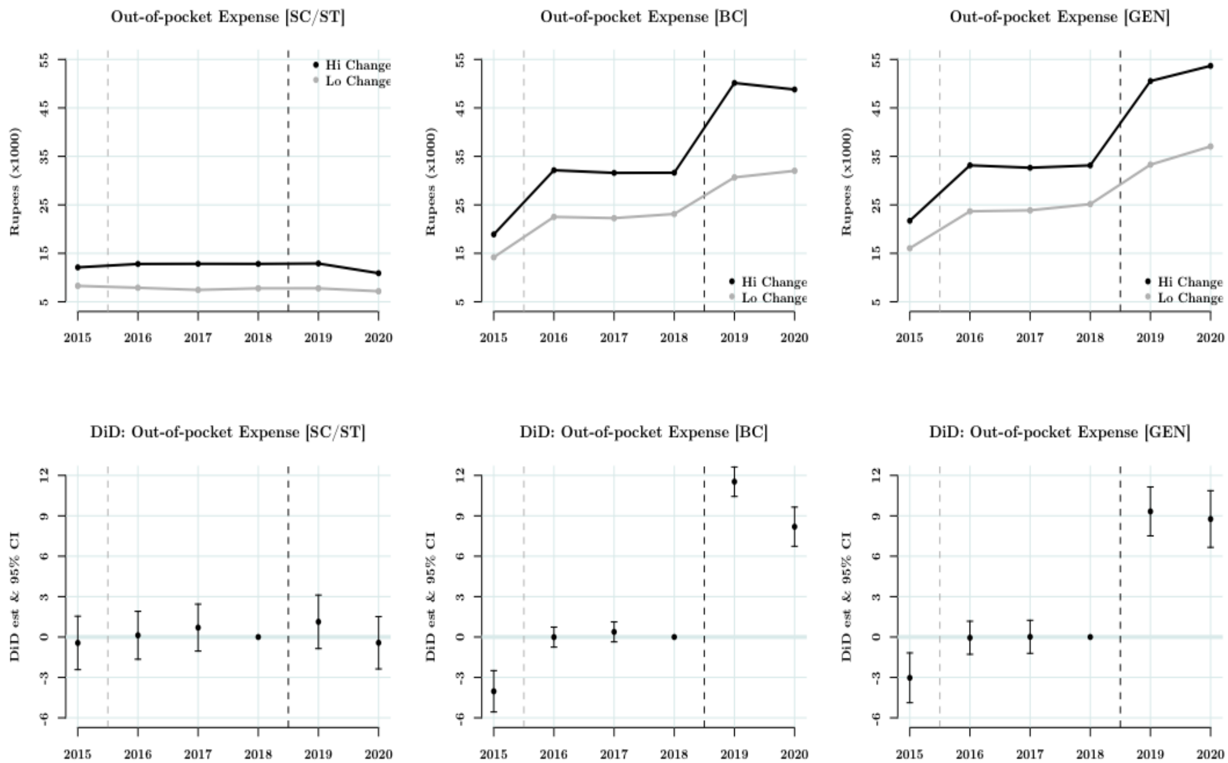

Figure 4: ***Policy impact on students' out-of-pocket expenditure.*** *The horizontal axes represents the academic years.* <u>*Top row:*</u> *vertical axes represents students' OOP in thousands of rupees. The black and gray trend lines represent the average student OOP at high and low-change colleges respectively.* <u>*Bottom row:*</u> *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.*

suggests that programs with higher price policy exposure 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. 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

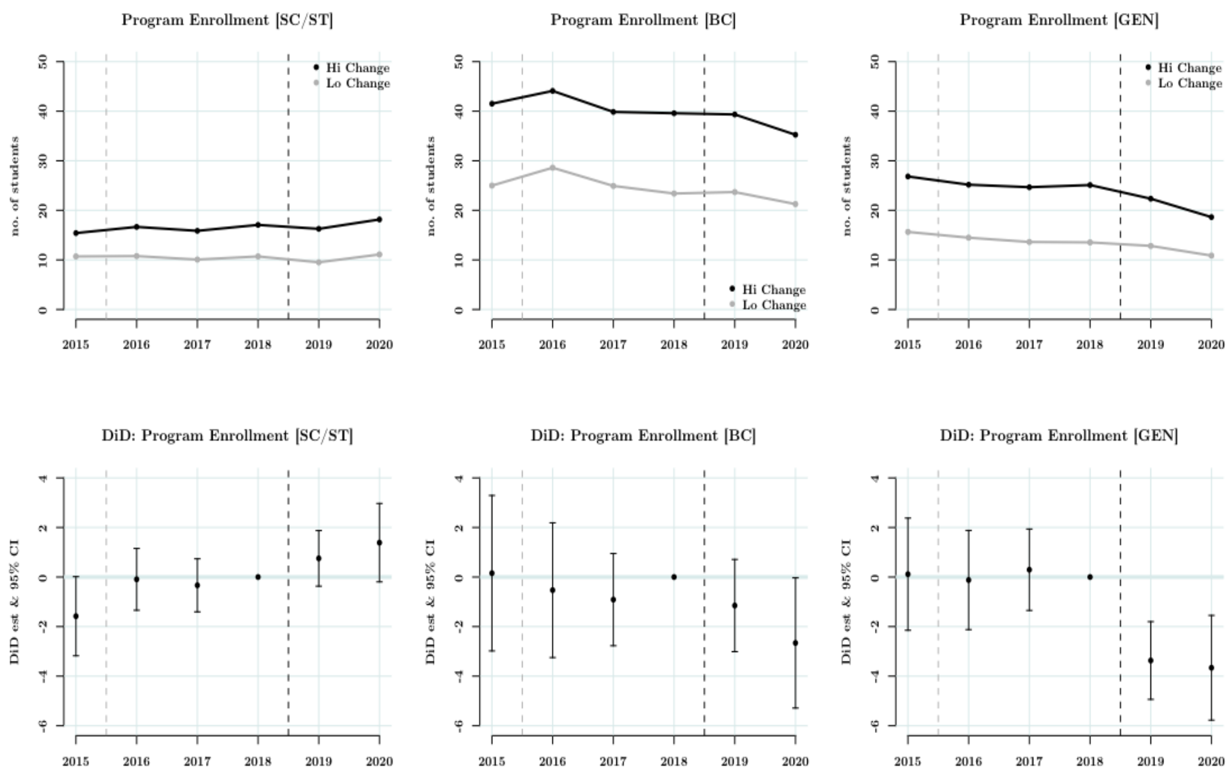

Figure 5: ***Policy impact on students' enrollment.*** *The horizontal axes represents the academic years.* <u>*Top row:*</u> *vertical axes represents the average number of students in a program. The black and gray trend lines represent the average program enrollment at high and low-change colleges respectively.* <u>*Bottom row:*</u> *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.*

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 6 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 7 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

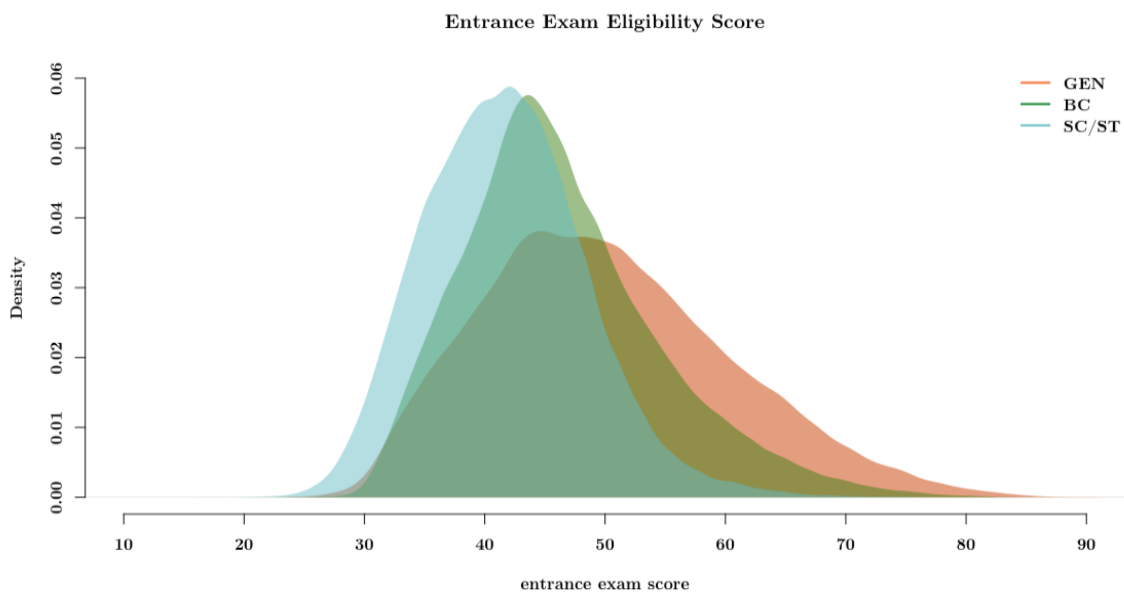

Figure 6: ***Ability of incoming students by caste.*** *The horizontal axis represents students' ability measured as by a composite of their high school graduation and entrance exam scores. The vertical axis represents the density of the distributions. The blue, green, and orange distributions correspond to SC/ST, BC, and GEN caste groups respectively.*

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. 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 6, the results indicate that the altered cohort composition could have implications for students' returns from a college education.

Figure 8 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

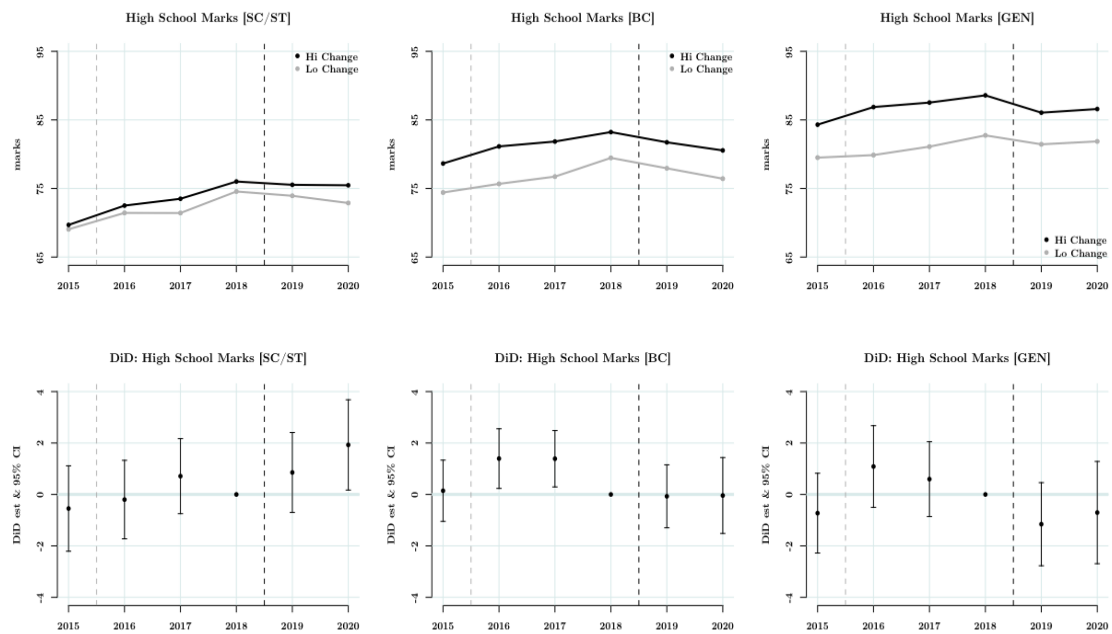

Figure 7: ***Policy impact on incoming student quality.*** *The horizontal axes represents the academic years.* <u>*Top row:*</u> *vertical axes represents the average high school grades of matriculating students. The black and gray trend lines represent the average high school grades at high and low-change colleges respectively.* <u>*Bottom row:*</u> *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.*

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.

4.1.3. 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, detailed data on faculty composition is available only for ± 1 year relative to the policy. Using this data I set up a two-period pre-post (i.e. a 2x2 special case of Equation 1) 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

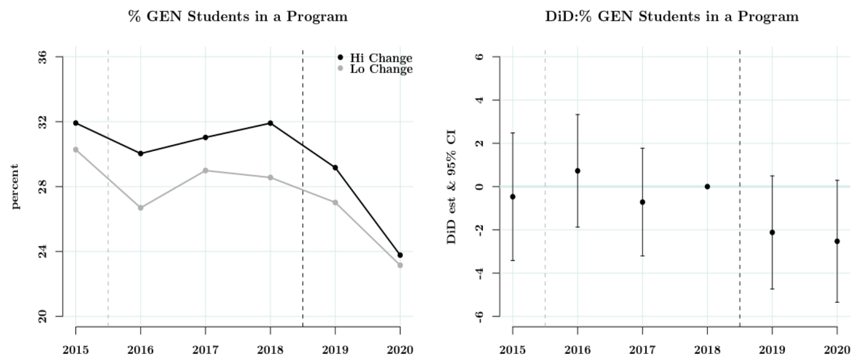

Figure 8: ***Policy impact on cohort caste composition*** *The horizontal axes represents the academic years. Left: the vertical axis represents the % of GEN category students in a program. The black and gray trend lines represent the average price of high and low-change colleges respectively. Right: 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.*

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.[2] 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' quality enhancing expenditures and therefore maintain or increase profits. Detailed regression results and tables based on the ESDiD approach can be found in Appendix A.1.

4.2. Quartile Split Pre-Post Analysis

In Section 4.1 I used an ESDiD to assess the impact of the price policy on OOP and enrollment. In this section I pivot to using a pre-post examination of enrollment and college quality through the lens market share quartiles, defined based on pre-policy enrollment. There are two primary reasons for adopting this approach. First, we are unable to examine heterogeneity in enrollment responses by market share, in particular, the binary treatment classification based on price policy exposure does not give us information about students resorting between colleges. Second, I have college quality data, namely *salary per teacher* only for ± 2 years relative to the policy (2017-2020).

[2]Estimates in columns 3 and 6, while interesting, are imprecise. The likely reason for this is the small dataset tracking approximately 140 colleges over 2 years. Given the dearth of administrative supply-side data, the estimates here are used to guide and inform possible patterns in college quality response rather than be interpreted as actual causal impacts. Section 5.2 attempts to build a more concrete approach to understanding college quality incentives and response.

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)
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

Given the sharp timing of the price policy in 2019-20 and its market-wide effect, using an approach that aggregates within the pre and post policy periods avoids over-interpreting year-specific noise and mitigates concerns about imprecise lead estimates, while still providing valuable insight into how outcomes of interest were affected by the policy. Equation 2 shows the primary specification used to examine heterogeneity in enrollment and quality response by pre-period enrollment share or quartile.

$$y_{jt} = \alpha_j^J + \sum_q \beta_q \left\{ D_t^{post} \times \mathbb{1}[\text{Quartile}_j = q] \right\} + \gamma \cdot X_{jt} + \epsilon_{jt} \tag{2}$$

y_{jt} is outcome under consideration in college j at time t. $D_t^{post} = 1$ for the academic years 2019-20 and 2020-21 and 0 otherwise. X_{jt} is a vector of relevant controls like college capacity or the number of teachers. α^J represents college fixed effects. The primary coefficient of interest is β which measures the change in y_{jt} within an enrollment quartile in the post-policy period, i.e. as a result of the price policy. Standard errors are clustered at the level of treatment, i.e. the college level.

Figure 9 shows program enrollment changes, within a market share quartile, for the total student body, as well as each caste group. We observe that enrollment declined most sharply in top-quartile (most popular) colleges, with the drop progressively dampening or even increasing in lower quartiles. Further, we see that declines in enrollment are driven by BC and GEN students. However SC/ST students increase their enrollment in bottom quartile programs. This suggests that students moved away from high-enrollment, high-price colleges post-policy, potentially toward less expensive but less selective institutions. Conversely, colleges in the bottom quartile saw modest increases in enrollment driven by poorer students groups.

Figure 10 shows the change in average high school academic performance of incoming students, within a market share quartile, for the total student body, as well as each caste group. There are three main takeaways. First, we see that average student quality, as measured by high school marks,

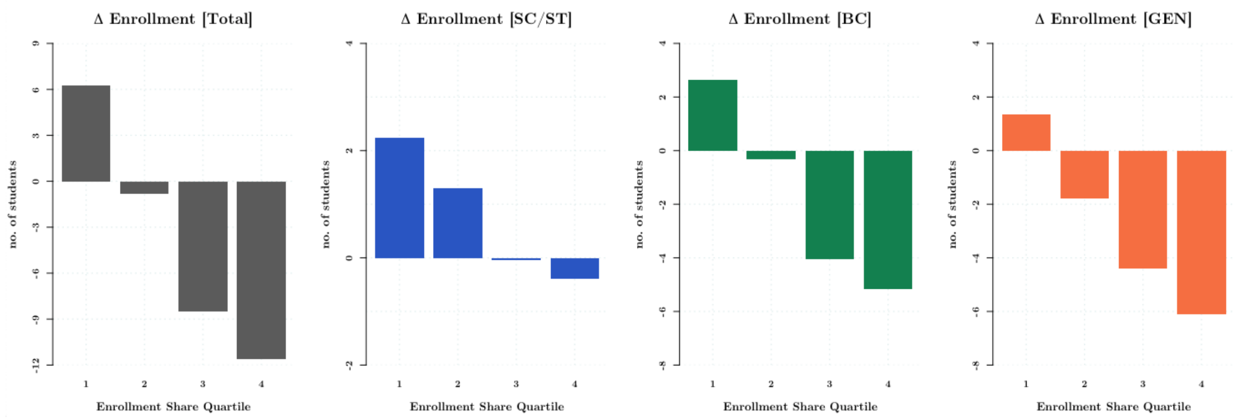

Figure 9: ***Change in Enrollment by Market Share Quartile.*** *The horizontal axes represent the pre-period enrollment share quartile. The vertical axes represent estimated change in program enrollment within a quartile, in the post-policy period relative to the pre-policy enrollment.*

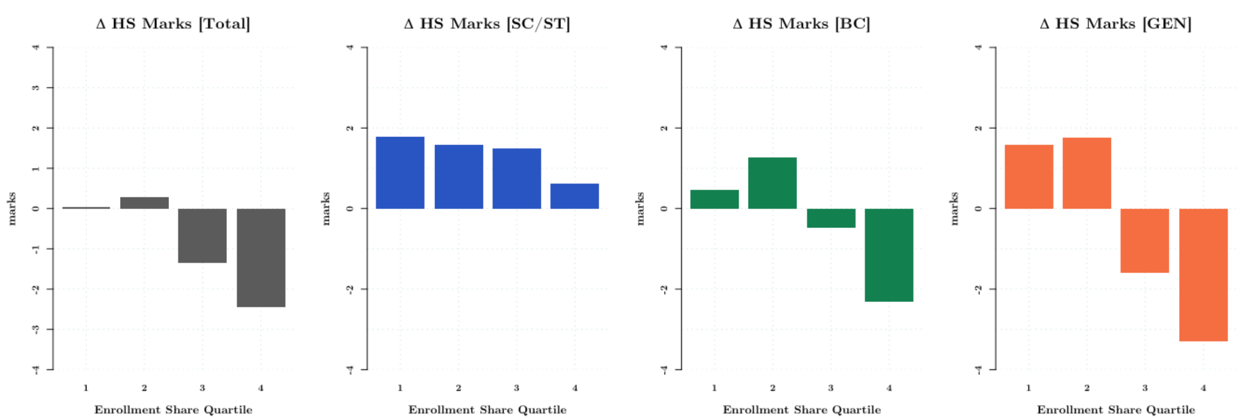

Figure 10: ***Change in High School Marks by Market Share Quartile.*** *The horizontal axes represent the pre-period enrollment share quartile. The vertical axes represent estimated change in high school marks within a quartile, in the post-policy period relative to the pre-policy enrollment.*

declined most sharply in the top two quartiles post-policy. This pattern is driven primarily by BC and GEN students, who show substantial drops in Quartile 4 and modest declines in Quartile 3, suggesting that higher-performing students from these groups exited top-tier colleges or re-sorted downward in response to price increases. Second, we see that SC/ST students, on average, are of higher academic ability across all quartiles in the post-period with largest improvements in the first three quartiles. Third, the bottom-two quartiles exhibit mild increases in student quality across all caste groups, indicating that lower-tier colleges attracted relatively better students post-policy, likely as a result of this re-sorting. Together, these patterns suggest that the policy reduced peer quality in high-demand programs while higher performing students enroll in the bottom quartile colleges.

Figure 11 examines changes in college quality (measured by salary per teacher) across market

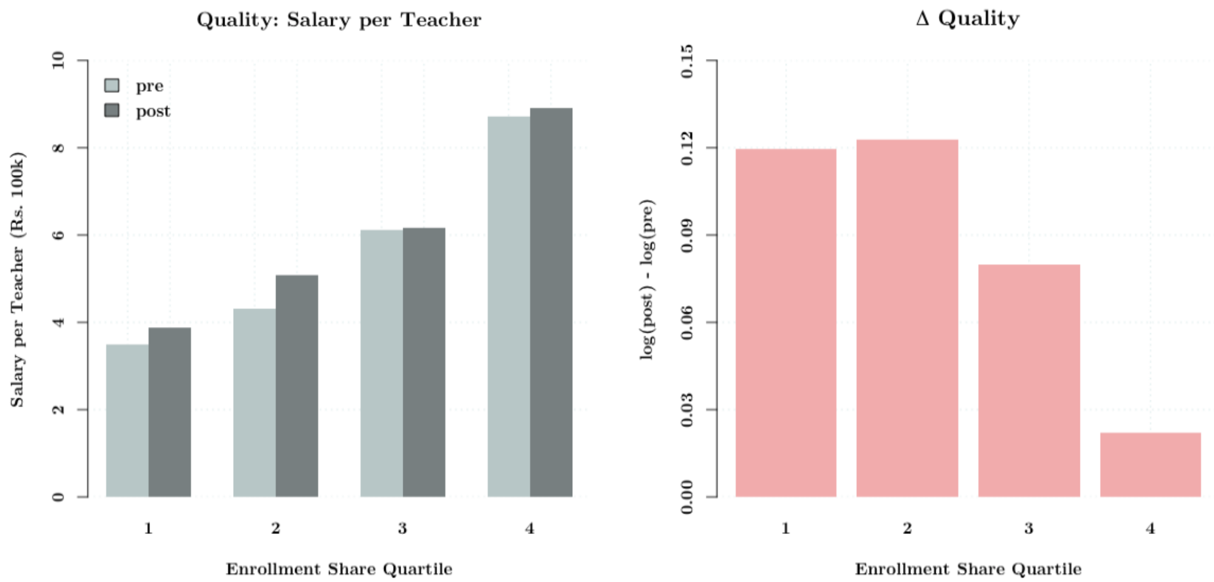

Figure 11: ***Change in College Quality by Market Share Quartile.*** *The horizontal axes in both panels represent the pre-period enrollment share quartile. Left: the vertical axis represents salary per teacher in ₹100k. Light and dark gray bars represent salary per teacher in the pre and post periods respectively. Right: the vertical axis represents the log difference in pre and post period salary per teacher. Pink bars represent the estimated change in salary per teacher within a quartile in the post-policy period relative to the pre-policy salary per teacher.*

share quartiles. The left panel shows levels pre and post; the right panel shows the log difference between pre and post averages within a quartile. There are three main takeaways from these results. First, we see that in level terms, bottom-quartile colleges pay teachers significantly less than top-quartile colleges. Second, we observe that while all quartiles improved quality post-policy, the bottom-quartiles exhibited the largest relative increase, with ≈12-13% increases in salary per teacher. Third, top-quartile colleges, despite receiving higher price increases (as observed in Figure 2) invest less in quality, which is consistent with them exercising greater market power and responding weakly to competitive pressure along the quality dimension. Together, these results highlight the asymmetric response across market share quartiles to the price-setting policy.

Overall, these results show that the price-setting policy had heterogeneous impacts across the college market. Enrollment fell most sharply in top-quartile programs, driven by BC and GEN students, while bottom-quartile colleges experienced gains in both enrollment and student quality. Additionally, although government mandated price increases led to improvement in quality across the market, bottom-quartile colleges show far greater passthrough to students. The combination of enrollment shifts, student re-sorting, and asymmetric quality responses underscores the role of market position in shaping institutional behavior under regulation. Detailed regression results based on the quartile split pre-post analysis can be found in Appendix A.2.

4.3. Triple Difference Design

In this section, I formally evaluate heterogeneity in key outcomes on the demand and supply side by implementing a triple-difference empirical design that incorporates variation created by price-treatment intensity, college market share, and time. In Section 4.1 we defined a binary treatment variable D_j^{Price} based on the price-change percent for college j, where $D_j^{Price} = 1$ if college j has a price increase of $> 20\%$ and is 0 otherwise. In this section, I define a binary treatment variable D_j^{Top} for college j such that $D_j^{Top} = 1$ if college j is in the top two market share quartiles and is 0 otherwise, defined based on pre-period enrollment. This approach allows me to isolate how the policy's effects vary both by baseline market position (pre-policy enrollment quartile) and exposure to the price increase. The design captures both direct price effects and how they interact with institutional market power to shape enrollment losses and supply-side responses.

$$\begin{aligned} y_{jt} = {} & \beta_1[D_j^{Price} \times D_t^{Post}] + \beta_2[D_j^{Top} \times D_t^{Post}] + \beta_3[D_j^{Price} \times D_j^{Top} \times D_t^{Post}] \\ & + \gamma \mathrm{X}_{jt} + \alpha_j^J + \alpha_t^T + \epsilon_{jt} \end{aligned} \tag{3}$$

Equation 3 shows the primary specification used in this section. y_{jt} represents the outcome of interest in college j at time t. D_j^{Price}, D_j^{Top} and D_j^{Post} indicate above-median price change colleges, colleges that belong to market share quartiles 3 and 4, and years $\geq$ 2019-20 respectively. The specification compares changes in enrollment and quality across four mutually exclusive groups: Bottom-Control, Bottom-Treated, Top-Control, and Top-Treated. β_1, β_2 and $\beta_1 + \beta_2 + \beta_3$ represent the effects for each of these groups, interpreted relative to the Bottom-Control group which serves as the baseline.

Table 3: Post-Policy Effects by College Group (Triple Difference)

Group	**Coeff.** (1)	**Enroll** (2)	**SC/ST** (3)	**BC** (4)	**GEN** (4)	**log(sal/teach)** (5)
Bottom-Control	Baseline	0.00	0.00	0.00	0.00	0.000
Bottom-Treated	β_1	+5.74	+3.26	+2.90	–0.419	+0.165
Top-Control	β_2	–9.59	–2.04	–4.33	–3.23	–0.031
Top-Treated	$\beta_1 + \beta_2 + \beta_3$	–10.14	–0.65	–3.27	–4.84	+0.060

Table 3 shows the estimated post-policy effects on enrollment and quality outcomes across the four college groups defined by price treatment status and pre-policy market position. Programs in the Bottom-Treated group (low market share, high price increase) experienced a positive enrollment response, gaining almost 6 students on average relative to the Bottom-Control group. This increase is driven by SC/ST and BC students, suggesting that the bottom-quartile colleges were able to absorb some displaced students from top-quartile institutions. These colleges also improved quality substantially, increasing salary per teacher by ≈17%, the largest improvement across all groups. Top-Treated (high market share, high price increase) and Top-Control (high market share, low price increase) programs, by contrast, lose approximately 10 students each, with effects driven by the GEN and BC groups. Finally, despite higher price increases, Top-Treated colleges invested less in quality than Bottom-Treated institutions (only 6% increase in teacher salary). Top-Control colleges, which did not receive an above-median price increase in percentage terms, but are still more expensive and have greater historic demand, even show an insignificant reduction in their quality investment. Detailed regression results based on the triple-difference approach can be found in Appendix A.3.

Overall, the triple difference estimates highlight an asymmetric institutional response to the price-setting policy. Bottom-Treated colleges gained enrollment and improved quality, consistent with competitive behavior. In contrast, top-quartile colleges lost students and passed through price changes with minimal quality upgrades, consistent with greater market power. These patterns motivate the structural supply model in the Section 5, where I examine student choice, quantify optimal college behavior, and estimate quality markdowns under price regulation.

5. MODELING COLLEGE CHOICE AND PROFIT MAXIMIZATION

5.1. Demand: College Choice Model

In this section I provide an overview of the centralized admissions mechanism and set-up a college choice model that enables us to recover the preference parameters governing a student's utility from a program. Consider a set of individual students, indexed by $i \in \mathcal{I} = \{1, \dots, I\}$, who apply to a finite set of engineering programs (college + major) through the state's centralized admission system. Programs are indexed by pairs $(j, m) \in \mathcal{J} \times \mathcal{M}$, where j represents the college and m the major (e.g., Computer Science or Electronics and Communication Engineering). All students take a common entrance exam and receive a numerical eligibility score $e_i \in [0, 100]$. Students are ranked based on these scores and this ranking is accepted as an objective priority ordering by all programs. Upon learning their eligibility score, each student i submits a strictly ordered, unrestricted length, rank ordered list (ROL) of program preferences $R_i = \{R_{i1} \succ R_{i2} \succ \cdots \succ R_{iK_i}\}$ of student-specific length K_i. Each item in the list R_i corresponds to a program (j, m). For instance, program R_{i1} is the most preferred and R_{iK_i} is the least preferred program for student i. We assume that the lowest-ranked program is strictly preferred to all unranked programs.

Each program (j, m) has a fixed, government sanctioned capacity where affirmative action rules targeting SC/ST and BC students apply to 50% of seats[3] and all caste categories compete for the remaining 50% of seats. The centralized admission mechanism uses a student-proposing deferred acceptance algorithm to generate student-program matches. When reserved category seats are processed, they are assigned to the targeted students with the highest eligibility scores and when open category seats are processed, they are simply assigned to student with the highest eligibility scores. Therefore, the deferred acceptance mechanism assigns students to their most preferred eligible program, respecting caste quotas and score cutoffs. Under these conditions, we reasonably

[3] A detailed breakdown of affirmative action rules in this engineering college market is provided in Table 1.

assume that students are incentivized to truthfully report preferences and that final assignments are stable. These properties allow us to use the submitted ROLs and observed matches to estimate student preferences over programs (Gale and Shapley, 1962; Abdulkadiroğlu and Sönmez, 2003; Azevedo and Leshno, 2016; Fack et al., 2019; Agarwal and Somaini, 2020; Otero et al., 2021).

We parametrize utility for student i ranking program (j, m) in academic year t using the specification in Equation 4.

$$\begin{aligned} u_{ijmt} &= V_{ijmt} + \epsilon_{ijmt} \\ &= \alpha \cdot \mathbf{oop}_{ijt} + \mu_q \cdot \mathbf{q}_{jt} + \delta_{jm} + \epsilon_{ijmt} \end{aligned} \tag{4}$$

Where a student's utility comes from out-of-pocket expense $\mathbf{oop}_{ijt}$, observed college quality (salary per teacher) $\mathbf{q}_{jt}$, and a time-invariant program fixed effect δ_{jm} that captures all unobserved preferences for programs. Students' price sensitivity is given by $\alpha = \sum_K \mathbb{1}[k(i) = k]\alpha_k \; \forall k \in K = \{GEN, BC, SC/ST\}$ which enables the estimation of a single caste-specific price preference parameter. Students' sensitivity to college quality is denoted by μ_q. One arbitrarily chosen program is designated as the *outside option* with utility 0 and therefore all δ_{jm}'s are interpreted relative to this. ϵ_{ijmt} is assumed to follow an extreme-value type I distribution with location parameter 0 and scale parameter 1. The probability that student i submits ROL R_i is given by

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

where $y_{ik'} = 1$ if $k' \geq k$ and 0 otherwise. L_i 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. This formulation therefore lends itself to a closed-form solution that enables estimation of $\Theta = \{\alpha, \mu, \delta\}$ using a maximum likelihood (MLE) approach.[4]

5.2. Supply: Profit Maximization and Optimal Quality

In this section I explain the objective function of a profit-maximizing college in this market. Since colleges cannot choose their price in this setting, they choose their optimal quality to maximize profits. A typical college j faces the profit maximization problem given by

$$\arg\max_{q_j} \Pi_j = \left[\overline{p_j} - MC(\mathbf{q}_j)\right] \sum_{k \in K} n_{j,k}(\mathbf{q}_j, \mathbf{oop}_{j,k}) - F_j \tag{5}$$

Where $j \in \mathcal{J} = \{1, \ldots, J\}$ 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. $MC(q_j) = c_q \cdot q_j$ is the marginal cost at college j as a linear function of quality q_j. F_j are fixed costs at college j. Enrollment is denoted by $n_j(\mathbf{q}, \mathbf{oop}) = \sum_{k \in K} n_{jk}(\mathbf{q}_j, \mathbf{oop}_{j,k})$, where n_{jk} is the number of students

[4]Additional details about the estimation procedure, minorization techniques for the estimation of high-dimensional fixed effects, gradient of the log-likelihood, and computation of standard errors can be found in Appendix B.

from caste k who enroll at college j. $n_{jk}(.)$ is a function of college quality $\mathbf{q}_j$ and price p_j operating through the out of pocket expense $\mathbf{oop}_{j,k}$ a student from community $k \in K$ has to pay at college j.

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

$$q_j^* = \underbrace{\frac{\overline{p_j}}{c_q}}_{q_j^{comp}\textbf{: competitive quality}} - \underbrace{n_j(\mathbf{q}_j, \mathbf{oop}_j) \cdot \left[\frac{\partial n_j(\mathbf{q}_j, \mathbf{oop}_j)}{\partial q_j}\right]^{-1}}_{q_j^{mkdown}\textbf{: quality markdown}} \tag{6}$$

Equation 6 shows the two factors affecting a college's optimal quality decision. Each term in this equation highlights a mechanism through which the government mandated price increase can affect optimal quality, and therefore students' utility as they incorporate college quality into their ROL preparation. The first term q_j^{comp}, measuring competitive quality, represents the *direct effect* of a price change. An increase in tuition prices $\bar{p}_j$, with an unchanged cost parameter c_q, should lead to an increase in competitive education quality that college j provides. The second term q_j^{mkdown}, measuring quality markdown is a proxy for a college's market power. It represents the *indirect effect* on quality resulting from a price change. This term is a product of two positive terms if enrollment responds positively to quality changes. Therefore colleges with higher enrollment, n_j, and an inelastic enrollment response to quality will have greater markdowns in their quality, relative to the competitive benchmark, q_j^{comp}.

5.3. Preference Parameters and WTP for Quality

In this section I present the estimates of preference parameters $\Theta = \{\alpha, \mu, \delta\}$. Figure 12 shows the estimates of program mean utility parameters, δ_{jm}. There are three primary takeaways from this plot. First, δ_{jm} captures information about how often a program is mentioned as well as how high students are ranking it within their ROLs. Therefore we see that public programs are mentioned frequently and represent the largest utility to students. Second, we observe that colleges which received an above-median price change (represented by the green dots) are also historically the most popular programs in terms of how often they are mentioned and offer higher utility to students in general. Third, in contrast, colleges with a below-median price change (represented by red dots) are typically mentioned less by students and offer lower utility to students. Table 4 combines the information from the heterogeneous, caste-specific, price sensitivity parameters α and the quality sensitivity to present *willingness to pay* (WTP) estimates for quality improvements. All caste groups have a negative utility associated with increases in out-of-pocket expenditure ($\alpha_k < 0$). We see that GEN category students are the most price sensitive while BC students are the least price sensitive. This is reflected in their WTP for quality as BC students have the highest WTP for quality, willing to pay ₹526 per ₹10,000 increase in teacher salary.

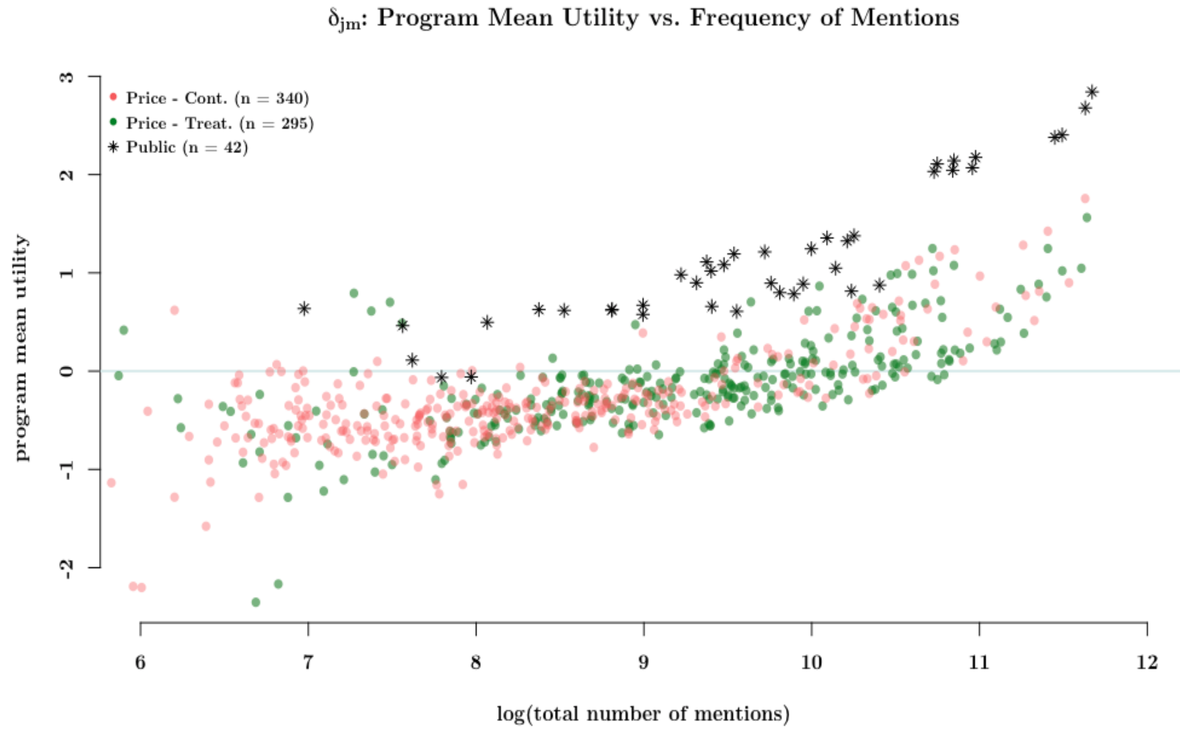

Figure 12: ***Program mean utility parameters*** δ_{jm}. *The horizontal axis represents the number of times a program is mentioned in students' preferences, on the log scale. The vertical axis represents the estimated value of* δ_{jm} *for a program. Black stars, green dots, and red dots correspond to the mean utility of public, treated or high-change colleges, and control or low-change colleges respectively.*

6. EQUILIBRIUM AND WELFARE

In this section, I use the estimated estimated structural parameters from the demand and supply models to characterize equilibrium outcomes in the engineering college market following the government price-setting policy. Students select programs based on preferences over price, quality, and perceived utility from a program while colleges set quality to maximize profits given fixed prices and estimated demand elasticities. We examine implications of the price policy in three ways. First, I compute the equilibrium college quality under price regulation conditional on estimated demand and enrollment. I measure quality markdowns by comparing observed college quality to the competitive benchmark implied by the supply model and provide evidence of a market-power driven quality markdown. Second, I decompose enrollment changes into components driven by price increases and quality responses. Third, I compute compensating variation (CV in ₹) to quantify the welfare impact of the policy across different student groups. Jointly, these analyses provide a complete picture of how price regulation reshaped market behavior and welfare outcomes.

Table 4: Caste-Specific Price Sensitivity and Willingness to Pay

Caste	**Estimate ($\hat{\alpha}_k$)**	**WTP (Rs) = $\frac{\mu_q}{\lvert\hat{\alpha}_k\rvert}$**
GEN	−0.1471	₹424
	(0.0015)	(10.0)
BC	−0.1185	₹526
	(0.0012)	(15.0)
SC/ST	−0.1308	₹477
	(0.0043)	(51.0)

6.1. College Quality Markdowns

Figure 13 presents the changes in the college quality measure, namely, salary per teacher, where the difference is expressed on the log scale. Δq^{comp} denotes the implied change in competitive quality in the absence of any quality markdowns. This represents the anticipated improvement of competitive quality in a world with complete passthrough of price changes to quality. Δq^{obv} denotes the observed change in college quality in the post-policy period, relative to pre-policy values, within an enrollment quartile. Three patterns emerge from this figure. First, quality improvements are positive across all quartiles, reflecting that the policy provided colleges with greater revenue to invest in quality. Second, bottom-quartile colleges experienced quality improvements close to the predicted competitive benchmark, suggesting relatively limited market power and greater responsiveness to the price signal. For example, the model implies $\approx 20\%$ improvement of competitive quality in the bottom quartiles and colleges in the bottom quartiles demonstrate an observed quality improvement of $\approx 12\%$. In contrast, colleges in Q4 have an observed quality improvement of under 2% relative to a model implied 24% increase in competitive quality. Third, the gap between observed and predicted quality changes widens in the upper quartiles, highlighting the asymmetric price and quality supply-side response across the market. Taken together, these patterns show that colleges with stronger pre-policy market positions — higher baseline enrollment — exerted greater market power post-policy by passing through price increases into revenues with only modest quality upgrades. Lower-ranked colleges, by contrast, behaved more competitively by improving quality in response to the price shock.

6.2. Enrollment Decomposition

Beyond supply-side quality choices, a key component of post-policy equilibrium adjustment is how student enrollment responds to changes in program quality and out-of-pocket prices. Using the estimated demand parameters, I structurally decompose the change in expected enrollment at each program into two components: one driven by price changes and one driven by quality changes.

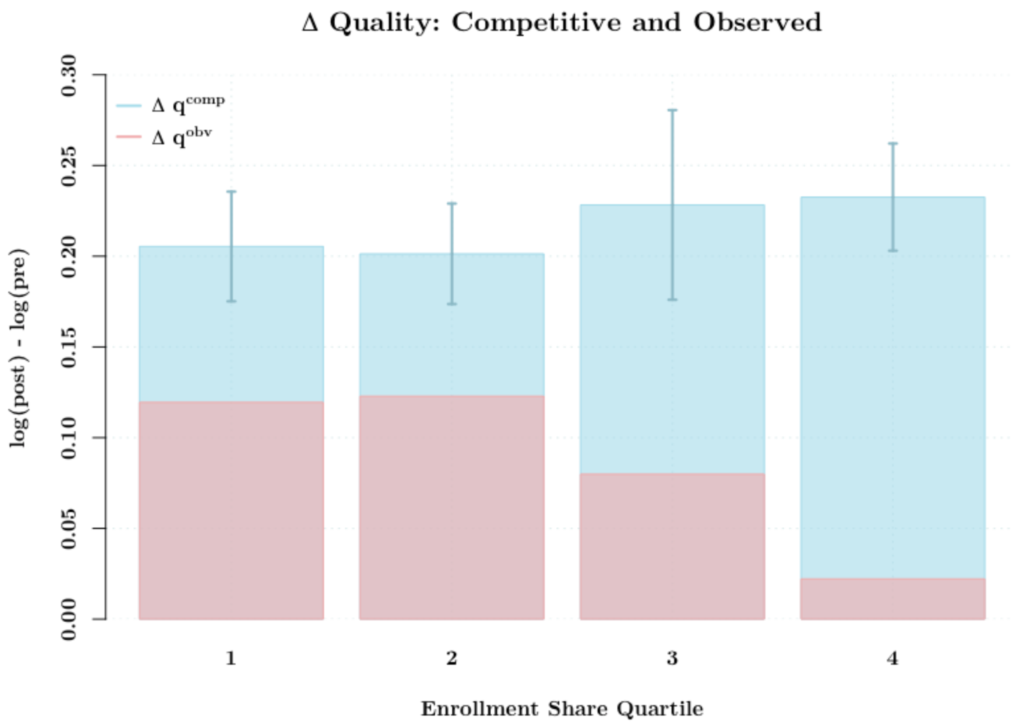

Figure 13: ***Quality Markdown by Market Share Quartile.*** *The horizontal axis represents the pre-period enrollment share quartile. The vertical axis represents the log difference in pre and post period salary per teacher. Pink bars represent the estimated change in salary per teacher within a quartile in the post-policy period relative to the pre-policy salary per teacher. Blue bars represent the model implied change in competitive quality within a quartile in the post-policy period relative to the pre-policy period. Error bars correspond to the 95% interval.*

Formally, the total change in expected enrollment at college j[5] can be approximated by:

$$\Delta n_j \approx \underbrace{\mu_q \cdot \sum_i P_{ij}(1 - P_{ij}) \cdot \Delta q_j}_{\Delta n_j^{\text{quality}}} + \underbrace{\sum_i \alpha_k \cdot P_{ij}(1 - P_{ij}) \cdot \Delta \text{oop}_{ij}}_{\Delta n_j^{\text{price}}}$$

where the first and second terms capture the enrollment effect due to changes in quality ($\Delta n_j^{\text{quality}}$) and price ($\Delta n_j^{\text{price}}$) respectively. P_{ij} denotes the choice probability of student i for program j. Following standard discrete choice models with extreme value shocks (Agarwal and Somaini, 2020), I define the probability that student i chooses program j as

$$P_{ij} = \frac{\exp\left(V_{ij}\right)}{\sum_{j' \in R_i} \exp\left(V_{ij'}\right)}$$

where V_{ij} is the deterministic component of student i's utility as defined in Equation 4. The denominator sums over the exponential utilities of all programs in a student's ROL R_i, ensuring

[5] Note that while estimated enrollment is initially computed at the program level, it is then aggregated to the college level because price and quality changes are realized at the college level.

that choice probabilities lie between 0 and 1 and sum to 1 across all programs for each student. P_{ij} represents the discrete probability that student i selects program j from the set of ranked options, conditional on prices, qualities, and program-specific utilities. These choice probabilities directly inform expected enrollment at the program level and are fundamental to computing demand elasticities , and welfare measures in equilibrium. Further, to summarize the relative relative contribution of each channel, I compute

$$\text{Share}_{\text{price}} = \frac{|\Delta n_j^{\text{price}}|}{|\Delta n_j^{\text{price}}| + |\Delta n_j^{\text{quality}}|}, \quad \text{Share}_{\text{quality}} = \frac{|\Delta n_j^{\text{quality}}|}{|\Delta n_j^{\text{price}}| + |\Delta n_j^{\text{quality}}|}$$

Table 5: Decomposition of Enrollment Change

Group	$\text{Share}_{\text{price}}$ %	$\text{Share}_{\text{quality}}$ %
Bottom-Control	-88%	+12%
Bottom-Treated	-76%	+24%
Top-Control	-96%	-4%
Top-Treated	-91%	+9%

Table 5 reports the decomposition across the four mutually exclusive college groups. Three patterns emerge in this table that provide insight into which factors are responsible for enrollment changes. First, across all groups, price effects account for the majority of enrollment changes, indicating that students are highly responsive to increases in out-of-pocket costs. Second, the signs of the decomposition components provide additional insight: a negative price component reflects that higher prices led to reductions in enrollment, while a positive quality component reflects that improvements in program quality partially mitigated these declines. Third, the contribution of quality improvements is largest for Bottom-Treated colleges, where 24% of the enrollment change is attributable to quality responses. This is consistent with these colleges investing more aggressively in faculty quality following the policy shock, thereby retaining or attracting students who would otherwise have exited the market. In contrast, Top-Control colleges exhibit a negative quality contribution suggesting that marginal quality improvements, or an absence of these altogether, reinforced enrollment losses caused by price increases. Jointly we infer that while price regulation triggered large direct enrollment responses through tuition hikes, supply-side quality adjustments played an important, asymmetric role across college tiers in shaping post-policy student sorting.

6.3. Compensating Variation and Welfare

To quantify the welfare effects of the price-setting policy on students, I compute individual-level compensating variation (CV). CV measures how much monetary compensation would be required to make a student indifferent between the pre- and post-policy environments, given changes in program qualities and out-of-pocket expenses. Formally, CV is calculated using the log-sum of deterministic utilities across each student's choice set, scaled by the student's caste-specific price sensitivity parameter α_k. Letting V_i denote the inclusive value for student i, the compensating variation is constructed from the difference between post-policy and pre-policy inclusive values. Equation 7 shows the exact formulation used to compute compensating variation for a student CV_i.

$$CV_i = \frac{1}{\alpha_k}\left[\psi_i^{post} - \psi_i^{pre}\right] \tag{7}$$

where $\psi_i = \log\Big(\sum_j \exp(V_{ijm})\Big)$. Formally, ψ_i denotes the log-sum of utilities or the expected maximum utility for a student from their entire choice set. V_{ijm} is the deterministic component of student i's utility as defined in Equation 4.

Table 6: Welfare Summary by Caste Group: CV in ₹

Caste	**25%** (₹)	**Median** (₹)	**75 %** (₹)	**Gain** (₹M)	**Loss** (₹M)	**Net Loss** (₹M)
SC/ST	–5,500	–4,210	–2,462	–25	+13	–12
BC	13,812	16,958	18,580	–95	+315	+220
GEN	15,674	17,936	19,194	–7	+203	+196

Table 6 summarizes the distribution of CV across caste groups. There are two main takeaways from this table. First, the median compensating variation for BC and GEN students is positive, implying that these students need to be paid money to face post-policy prices and quality. This suggests that the majority of students in these groups are worse off under the post-policy equilibrium. In contrast, SC/ST students experience a negative median CV implying they would be willing to pay money to participate in the post-policy world. Second, decomposing total welfare changes into gains and losses shows that losses dominate for BC and GEN students, leading to net welfare losses of ₹220 million and ₹196 million, respectively. SC/ST students experience smaller positive redistribution in welfare with a net welfare gain of ₹12 million. These results highlight that the price-setting policy imposed substantial welfare losses on 80% of the student body who were directly affected by the increase in out-of-pocket expenditure with modest welfare gains that do not offset the losses.

7. CONCLUSION

This paper studies how government price regulation affects student choices, college quality, and welfare in a centralized college admissions market. I examine a policy change in a large Indian state that raised engineering college tuition prices by an average of 20%, leaving tuition subsidies for the majority of marginalized students unchanged. Using administrative data on students' rank-ordered lists of program preferences, student demographics, and college characteristics, I construct a panel dataset to analyze how government price fixation jointly affects the demand and supply side of this market. I define *salary per teacher* as the primary measure of college quality.

Using a combination of empirical, reduced-form approaches, I highlight three primary findings. First, the price-setting policy increased prices more for colleges with greater market share. Accompanied by unchanged subsidies, this led to increased out-of-pocket expenditure for 80% of students. Second, I find that the policy led to substantial declines in enrollment at colleges that experienced larger price increases, with losses concentrated among wealthier, high-ability students. In contrast, some poorer students sort into colleges with lower market share and lower quality in level terms. Third, I find that there is significant heterogeneity in passthrough from price increases to quality improvements based on pre-period enrollment share quartile. Faced with a price increase, bottom-quartile colleges improved quality substantially whereas top-quartile colleges passed through larger relative price increases with minimal investment in quality upgrades.

To quantify these dynamics, I structurally estimate a student demand model and a college profit maximization model. On the demand side, students exhibit strong sensitivity to out-of-pocket expenses, with heterogeneous price sensitivity by caste. On the supply side, colleges choose program quality to maximize profits given fixed prices and estimated enrollment elasticities. Structural estimates reveal large quality markdowns relative to competitive benchmarks, especially among historically popular, high-enrollment colleges. Analyzing post-policy equilibrium outcomes, I find that the combination of increased tuition prices and uneven quality responses reshaped enrollment patterns and welfare. Enrollment decomposition shows that price increases accounted for the majority of the enrollment decline, but supply-side quality improvements mitigated some of these effects, particularly at lower-ranked colleges. Compensating variation estimates indicate that most BC and GEN students experienced substantial welfare losses, while SC/ST students gained modestly. Overall, the policy redistributed surplus away from wealthier students but imposed large aggregate welfare losses on the market as a whole.

This study highlights how price regulation in higher education markets interacts with existing market power to change both institutional behavior and student welfare. In markets where admissions are centralized and colleges cannot freely set prices, institutional responses along the quality margin become critical to understanding the welfare consequences of regulation.

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APPENDIX A: SUPPLEMENTAL RESULTS

A.1. Event Study Difference-in-Differences Regression Results

Table A.1: ESDiD Results - OOP Expense by Caste

Out-of-pocket Expense:	SC/ST (1)	BC (2)	GEN (3)
$\mathbb{1}[D_j^{price} = 1] \times \mathbb{1}[T = 2015]$	-0.756	-4.64***	-3.14***
	(1.08)	(0.819)	(1.03)
$\mathbb{1}[D_j^{price} = 1] \times \mathbb{1}[T = 2016]$	-0.033	0.046	0.411
	(0.950)	(0.396)	(0.699)
$\mathbb{1}[D_j^{price} = 1] \times \mathbb{1}[T = 2017]$	0.334	0.408	0.403
	(0.960)	(0.433)	(0.752)
$\mathbb{1}[D_j^{price} = 1] \times \mathbb{1}[T = 2019]$	0.523	11.2***	9.47***
	(1.10)	(0.594)	(1.04)
$\mathbb{1}[D_j^{price} = 1] \times \mathbb{1}[T = 2020]$	-0.707	7.23***	7.44***
	(1.07)	(0.835)	(1.34)
N	3,379	3,553	3,237
R^2	0.563	0.912	0.790

Note: This table reports the change in out-of-pocket expenses (OOP) for each caste group of students. Estimates are based on the specification in Equation 1. All columns include major, college, and year fixed effects. Standard errors are clustered at the college level and are reported in parentheses below the corresponding estimate. *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

Table A.2: ESDiD Results - Enrollment by Caste

Enrollment:	SC/ST	BC	GEN
	(1)	(2)	(3)
$\mathbb{1}[D_j^{price} = 1] \times \mathbb{1}[T = 2015]$	-0.852	0.927	0.275
	(0.645)	(1.15)	(0.861)
$\mathbb{1}[D_j^{price} = 1] \times \mathbb{1}[T = 2016]$	0.579	-1.88	-0.659
	(0.507)	(1.17)	(0.808)
$\mathbb{1}[D_j^{price} = 1] \times \mathbb{1}[T = 2017]$	0.471	-0.739	0.418
	(0.422)	(0.789)	(0.644)
$\mathbb{1}[D_j^{price} = 1] \times \mathbb{1}[T = 2019]$	0.667	-1.18	-3.05***
	(0.462)	(0.795)	(0.646)
$\mathbb{1}[D_j^{price} = 1] \times \mathbb{1}[T = 2020]$	1.58	-2.52**	-3.74***
	(0.612)	(1.07)	(0.863)
N	3,379	3,553	3,237
R^2	0.563	0.912	0.790

Note: This table reports the change in enrollment for each caste group of students. Estimates are based on the specification in Equation 1. All columns include major, college, and year fixed effects. Standard errors are clustered at the college level and are reported in parentheses below the corresponding estimate. *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

Table A.3: ESDiD Results - High-School Marks by Caste

High-School Marks:	SC/ST (1)	BC (2)	GEN (3)
$\mathbb{1}[D_j^{price} = 1] \times \mathbb{1}[T = 2015]$	-0.355	0.578	-0.825
	(0.786)	(0.565)	(0.724)
$\mathbb{1}[D_j^{price} = 1] \times \mathbb{1}[T = 2016]$	-0.146	1.26**	1.04
	(0.703)	(0.539)	(0.754)
$\mathbb{1}[D_j^{price} = 1] \times \mathbb{1}[T = 2017]$	1.15	1.50***	0.714
	(0.707)	(0.519)	(0.708)
$\mathbb{1}[D_j^{price} = 1] \times \mathbb{1}[T = 2019]$	0.537	-0.262	-1.57**
	(0.747)	(0.580)	(0.777)
$\mathbb{1}[D_j^{price} = 1] \times \mathbb{1}[T = 2020]$	1.47*	0.472	-0.724
	(0.866)	(0.703)	(0.909)
Observations	3,379	3,553	3,237
R^2	0.60619	0.68472	0.60794

Note: This table reports the change in high-school marks for each caste group of students. Estimates are based on the specification in Equation 1. All columns include major, college, and year fixed effects. Standard errors are clustered at the college level and are reported in parentheses below the corresponding estimate. *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

A.2. Quartile Split Pre-Post Regression Results

Table A.4: Quartile Split Pre-Post Regression Results: Δ Enrollment

	Enrollment	SC/ST	BC	GEN
	(1)	(2)	(3)	(4)
$\mathbb{1}[D_t^{post} = 1] \times \mathbb{1}[Q_j = 1]$	6.24	2.24**	2.64	1.37
	(3.98)	(0.986)	(2.06)	(1.32)
$\mathbb{1}[D_t^{post} = 1] \times \mathbb{1}[Q_j = 2]$	-0.824	1.29**	-0.339	-1.78**
	(1.28)	(0.544)	(0.869)	(0.694)
$\mathbb{1}[D_t^{post} = 1] \times \mathbb{1}[Q_j = 3]$	-8.51***	-0.042	-4.06***	-4.41***
	(1.53)	(0.596)	(1.03)	(0.576)
$\mathbb{1}[D_t^{post} = 1] \times \mathbb{1}[Q_j = 4]$	-11.6***	-0.391	-5.15***	-6.09***
	(1.47)	(0.484)	(0.867)	(0.608)
N	3,030	3,030	3,030	3,030
R^2	0.87238	0.71773	0.81673	0.73239

Note: This table reports the enrollment changes within an enrollment share quartile after the policy. Estimates are based on the specification in Equation 2. All columns include quartile and college fixed effects. Standard errors are clustered at the college level and are reported in parentheses below the corresponding estimate. *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

Table A.5: Quartile Split Pre-Post Regression Results: Δ HS Marks

	Overall (1)	SC/ST (2)	BC (3)	GEN (4)
$\mathbb{1}[D_t^{post} = 1] \times \mathbb{1}[Q_j = 1]$	0.032	1.78	0.459	1.59
	(0.748)	(1.30)	(0.935)	(2.25)
$\mathbb{1}[D_t^{post} = 1] \times \mathbb{1}[Q_j = 2]$	0.287	1.58	1.26*	1.75*
	(0.623)	(1.13)	(0.670)	(0.946)
$\mathbb{1}[D_t^{post} = 1] \times \mathbb{1}[Q_j = 3]$	-1.34***	1.50***	-0.484	-1.60**
	(0.440)	(0.512)	(0.566)	(0.636)
$\mathbb{1}[D_t^{post} = 1] \times \mathbb{1}[Q_j = 4]$	-2.44***	0.620*	-2.30***	-3.30***
	(0.231)	(0.369)	(0.272)	(0.360)
N	3,030	2,822	2,971	2,692
R^2	0.71763	0.58526	0.66305	0.59688

Note: This table reports the change in high school marks of incoming students, within an enrollment share quartile after the policy. Estimates are based on the specification in Equation 2. All columns include quartile and college fixed effects. Standard errors are clustered at the college level and are reported in parentheses below the corresponding estimate. *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

Table A.6: Quartile Split Pre-Post Regression Results: Δ College Quality

	Salary/Teach (1)	Academic Infra. (2)	Capital Exp. (3)	Operational Exp. (4)	Total Exp. (5)
$\mathbb{1}[D_t^{post} = 1] \times \mathbb{1}[Q_j = 1]$	0.119*	0.220***	0.599	0.469*	0.131**
	(0.060)	(0.082)	(0.714)	(0.261)	(0.064)
$\mathbb{1}[D_t^{post} = 1] \times \mathbb{1}[Q_j = 2]$	0.123**	-0.472*	0.129	-0.232	0.085
	(0.049)	(0.240)	(0.338)	(0.153)	(0.053)
$\mathbb{1}[D_t^{post} = 1] \times \mathbb{1}[Q_j = 3]$	0.080	-0.216	-0.467*	0.079	0.029
	(0.058)	(0.349)	(0.236)	(0.071)	(0.053)
$\mathbb{1}[D_t^{post} = 1] \times \mathbb{1}[Q_j = 4]$	0.022	0.236*	-0.112	0.018	0.020
	(0.021)	(0.134)	(0.126)	(0.029)	(0.029)
N	375	257	257	261	375
R^2	0.358	0.282	0.293	0.712	0.743

Note: This table reports the change in college quality and expenditures, within an enrollment share quartile after the policy. Estimates are based on the specification in Equation 2. All columns include quartile and college fixed effects. Standard errors are clustered at the college level and are reported in parentheses below the corresponding estimate. *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

A.3. Triple Difference Regression Results

Table A.7: Triple Difference - Policy Impact on Enrollment and Quality

	Enrollment (1)	SC/ST (2)	BC (3)	GEN (4)	log(sal/teach) (5)
Price Treat × Top Quartiles × Post	-6.29*	-1.86*	-2.84	-1.59	-0.074
	(3.60)	(1.05)	(1.95)	(1.82)	(0.105)
Price Treat × Post	5.74*	3.26***	2.90*	-0.419	0.165*
	(3.27)	(0.877)	(1.65)	(1.68)	(0.097)
Top Quartiles × Post	-9.59***	-2.04***	-4.33***	-3.23***	-0.031
	(1.66)	(0.605)	(1.07)	(0.658)	(0.046)
N	3,036	3,036	3,036	3,036	375
R^2	0.874	0.726	0.821	0.735	0.913

Note: This table reports the regression results for the triple difference design, described in Equation 3, applied to key enrollment and college quality variables. All columns include college and year fixed effects. Standard errors are clustered at the college level and are reported in parentheses below the corresponding estimate. *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

APPENDIX B: STRUCTURAL ESTIMATION DETAILS

Utility specification and Likelihood:
Consider the utility for student i ranking program (j, m) in year t, given by:

$$\begin{aligned} u_{ijmt} &= V_{ijmt} + \epsilon_{ijmt} \\ &= \alpha \cdot \mathbf{oop}_{ijt} + \mu_q \cdot \mathbf{q}_{jt} + \delta_{jm} + \epsilon_{ijmt} \end{aligned}$$

Here, $\mathbf{oop}_{ijt}$ denotes the student's out-of-pocket cost, $\mathbf{q}_{jt}$ is college quality, proxied by *salary per teacher*. δ_{jm} is a time-invariant program fixed effect. Price sensitivity α varies by caste group k as:

$$\alpha = \sum_{k \in K} \mathbb{1}[k(i) = k]\alpha_k,$$

where $K = \{\text{GEN}, \text{BC}, \text{SC/ST}\}$. The idiosyncratic shock ϵ_{ijmt} follows an Extreme Value Type I distribution, leading to standard logit choice probabilities.

Each student i submits a strict rank-ordered list (ROL) $R_i = \{R_{i1} \succ R_{i2} \succ \cdots \succ R_{iK_i}\}$ over programs. The probability that student i submits ROL R_i is:

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

where $y_{ik'} = 1$ if $k' \geq k$ and 0 otherwise. That is, the denominator in the k-th term sums over all programs ranked worse than or equal to k.
Taking logs yields the student-specific log-likelihood:

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

The full sample log-likelihood is:

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

Minorization technique to solve for program fixed effects δ_{jm}:
To estimate the high-dimensional vector $\vec{\delta} = \{\delta_{jm}\}$ of program fixed effects, I use a minorization strategy based on a fixed-point mapping.
Fixing (α, μ_q), I differentiate LL with respect to δ_{jm}:

$$\frac{\partial LL}{\partial \delta_{jm}} = \sum_{i=1}^{N} \sum_{k=1}^{K_i} \left(\mathbb{1}[j_k = (j, m)] - \frac{y_{ik} \exp\{V_{ik}\}}{\sum_{k'=1}^{K_i} y_{ik'} \exp\{V_{ik'}\}} \right),$$

where j_k denotes the program assigned to position k.

Setting the derivative equal to zero yields the first-order condition (FOC):

$$\sum_{i=1}^{N} \mathbb{1}[(j,m) \in R_i] = \sum_{i=1}^{N}\sum_{k=1}^{K_i} \frac{y_{ik}\exp\{V_{ik}\}}{\sum_{k'=1}^{K_i} y_{ik'}\exp\{V_{ik'}\}} \cdot \mathbb{1}[j_k = (j,m)].$$

Let N_{jm} denote the number of students who list program (j,m) in their ROL. Then:

$$N_{jm} = \exp\{\delta_{jm}\} \times \left(\sum_{i=1}^{N}\sum_{k=1}^{K_i} \frac{y_{ik}\exp\{\alpha \cdot \mathbf{oop}_{ik} + \mu_q \mathbf{q}_j\}}{\sum_{k'=1}^{K_i} y_{ik'}\exp\{V_{ik'}\}} \cdot \mathbb{1}[j_k = (j,m)]\right).$$

Taking logs and rearranging yields the fixed point mapping:

$$\delta_{jm}^{(n+1)} = \log\left(N_{jm}\right) - \log\left(\sum_{i=1}^{N}\sum_{k=1}^{K_i} \frac{y_{ik}\exp\{\alpha \cdot \mathbf{oop}_{ik} + \mu_q \mathbf{q}_j\}}{\sum_{k'=1}^{K_i} y_{ik'}\exp\{V_{ik'}\}} \mathbb{1}[j_k = (j,m)]\right).$$

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 $\Omega(\delta^{(n)})$.

Gradients and standard errors for structural parameters:
The gradients of the log-likelihood with respect to the structural parameters (α_k, μ_q) are:
<u>Gradient with respect to α_k:</u>

$$\frac{\partial LL}{\partial \alpha_k} = \sum_{i=1}^{N}\sum_{k=1}^{K_i}\left(\mathbb{1}[i \in k] \cdot \mathbf{oop}_{ik} - \frac{\sum_{k'=1}^{K_i} y_{ik'}\mathbb{1}[i \in k']\mathbf{oop}_{ik'}\exp(V_{ik'})}{\sum_{k'=1}^{K_i} y_{ik'}\exp(V_{ik'})}\right)$$

<u>Gradient with respect to μ_q:</u>

$$\frac{\partial LL}{\partial \mu_q} = \sum_{i=1}^{N}\sum_{k=1}^{K_i}\left(\mathbf{q}_j - \frac{\sum_{k'=1}^{K_i} y_{ik'}\mathbf{q}_{j_{k'}}\exp(V_{ik'})}{\sum_{k'=1}^{K_i} y_{ik'}\exp(V_{ik'})}\right)$$

<u>Standard errors for (α_k, μ_q):</u>

Standard errors for the estimated structural parameters (α_k, μ_q) are computed using the inverse of the negative Hessian matrix of the log-likelihood evaluated at the MLE:

$$\text{Var}(\hat{\theta}) = \left(-\nabla^2 LL(\hat{\theta})\right)^{-1}$$

The Hessian can be calculated either analytically using second derivatives or numerically via finite differences.

Steps of the estimation algorithm:

The estimation proceeds through the following steps:

1. Initialize guesses for (α_k, μ_q) and δ_{jm}.
2. Compute utilities V_{ijmt}.
3. Compute choice probabilities L_i and log-likelihood LL.
4. Minorize to update $\vec{\delta}$ via the fixed-point mapping.
5. Compute gradients with respect to (α_k, μ_q).
6. Update (α_k, μ_q) using a gradient-based optimizer.
7. After each update, re-solve for $\vec{\delta}$.
8. Check convergence (changes in parameters and log-likelihood).
9. Compute standard errors using the Hessian.