Supply responses to targeted government aid: Evidence from free college in Chile

Esperanza Johnson *†

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Abstract

Access to free public higher education is a popular demand and an active political debate. There are multiple implementations of this policy, from free college for all to targeted subsidies. In this paper I focus on a national policy implemented in Chile in 2016, that is a targeted full-tuition subsidy for students from the bottom fifty percent of the income distribution. Most of the policies that aim at reducing education costs for students also constrain the revenue of higher education institutions. In response, institutions may optimize other factors such as their programs' capacity and prices. Free college generates a combination of demand and supply responses that affect the current equilibrium. In this paper, I characterize and measure the demand and supply reactions to this policy using a combination of descriptive results and a structural model. Specifically, I explore the impact of the policy on students' applications and enrollment as well as programs' pricing and capacity decisions and whether these decisions amplify or moderate the effects of the policy on students' welfare. My model incorporates price and capacity responses from programs in the context of a centralized assignment mechanism. My results show that the policy implemented in Chile is welfare-enhancing for almost 40 percent of eligible students. Nonetheless, the welfare of almost 45 percent of the student body decreases due to supply responses. I use the model to evaluate a counterfactual policy that expands free college to all the student body. This policy would increase access to education for all types of students, and proportionally more for higher income students. However, supply responses dampen this potential increased access to education. Hence, supply responses are crucial to determine welfare and need to be considered when designing and expanding financial aid policies.

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†The University of Chicago Kenneth C. Griffin Department of Economics. Email: esperanza@uchicago.edu

1 Introduction

Access to free public higher education is a popular demand and an active policy debate. There are multiple implementations of this policy, from free college for all to targeted subsidies. These implementations differ in terms of their targeting and scope, [1] but all of them include some version of funding public education. Free college aims at reducing education and wealth inequality and decreasing student debt. Even without these effects, by changing relative tuition prices, free college affects which programs students apply to, and may increase enrollment and graduation of low-income students.

Most of the policies that aim at reducing education costs also affect the revenue of educational institutions. In response, institutions may re-optimize other choices such as their programs' capacity and prices (in the case of targeted subsidies). [2] Thus, free college does not simply impact access to a given set of programs but also affects their characteristics. To fully understand whether free college achieves the goals of policymakers, we must consider equilibrium supply responses, such as programs' pricing and capacity decisions.

In this paper, I investigate the equilibrium effects of a regulatory change that makes higher education free considering both demand and supply responses. I study this question in the Chilean context, where the admissions system to universities uses a centralized assignment mechanism, specifically the student-proposing deferred acceptance algorithm (DAA). In 2016, the Chilean government implemented a national and targeted policy that benefited the poorest 50% of families. The policy defines a voucher that is paid to programs that enroll beneficiaries. Under the Chilean implementation of free college, eligible students face an effective price of zero, and programs receive a payment from the government that is often lower than the "sticker price," i.e., the given tuition without financial aid. In contrast, non-eligible students must pay the sticker price either by themselves or using a combination of self pay and other financial aid. Importantly, the policy introduces price differentiation between eligible and non-eligible students that shifts programs' revenue and can elicit responses from them. I characterize and measure the demand and supply reactions to the policy using a combination of descriptive results and a structural model. My model explicitly incorporates strategic responses from programs within a centralized assignment mechanism extending the literature on the effect of large-scale subsidies on college admission. From a methodological perspective, the model highlights the challenges in dealing with supply-side responses in centralized admission systems and proposes a novel path forward.

Specifically, I explore the impact of free college on students' applications and enrollment as well as programs' pricing and capacity decisions and — most importantly — whether these decisions amplify or moderate the effects of free college on students' welfare measured as the money equivalent of their utility change. Furthermore, I use my model to evaluate a counterfactual policy that expands free college to currently

[1] For example, various countries in Western Europe, such as France and Germany have a national and not targeted policy where the government pays most of the cost of degrees in a public institution. In the US, there are examples of local and targeted subsidies to a subset of students that fund higher education . For example, the SUNY and CUNY system pays tuition for eligible students from families who earned less than $125,000 (2022-23 academic year). A final example of an implementation this type of policy is Gratuidad in Chile. This is a national and targeted policy implemented in 2016. Chile pays tuition for students from families in the bottom 50 percent of the income distribution who enroll in universities in the centralized admission system and certain vocational institutions.

[2] In Chile's higher education system each institution offers several programs with their own price and capacity.

non-eligible students.

The effect of the policy on eligible students combines the mechanical increase in welfare due to the reduction in price with the impact of equilibrium responses on eligible students' enrollment. The effect of the policy on non-eligible students only depends on equilibrium responses because they do not benefit from the reduction in prices. Through demand responses, the change in relative tuition prices produced by free college affects which programs eligible students apply to, and may impact enrollment of all students in the new equilibrium allocation of the DAA. Finally, programs could change their pricing and capacity decisions relative to those in the absence of the policy. These supply responses also affect enrollment in the new equilibrium allocation of the DAA because capacity is a direct input of the assignment mechanism and programs' prices affect which programs non-eligible students apply to. A particular student could change her enrollment, and welfare, in three ways relative to her enrollment in the absence of the policy. She could gain access to education and increase her welfare, be displaced to the outside option and reduce her welfare, or enroll at a program with different characteristics, in which case the effect on welfare is ambiguous. My results show that free college is a welfare-enhancing policy for almost 40 percent of eligible students and 30 percent of non-eligible students. However, the policy reduces welfare for 10 percent of eligible students, and almost 30 percent of non-eligible students. Furthermore, the supply responses to the policy made almost 45 percent of the student body worse off relative to a case without supply responses. Overall, the policy does not have a relevant effect in access to education as it increases displacement to the outside option for certain students and access for others in similar amounts. However, access to education increases if free college expands to all students. Particularly, access increases by 2 percentage points for eligible students and by 6 percentage points for non-eligible students. Nonetheless, supply responses dampen the positive effect on access for all the student body. Hence, supply responses are crucial in assessing the benefits of free college and need to be considered when designing and expanding such financial aid policies.

I solve a model that allows for programs' strategic responses within a centralized assignment mechanism, which are widely used in many educational markets. To the best of my knowledge, my paper is one of the first to make this connection. In my model, programs choose price and capacity, and enrollment is defined by the DAA considering programs' capacity constraints. This occurs in the context of price differentiation between free college eligible and non-eligible students. My model shows how this price differentiation mediates how programs respond to the implementation of the free college policy.

The paper includes two sets of results. First, I present evidence from a reduced-form analysis of the free college policy to describe its direct impact on students' behavior and programs' decisions. Second, I use a structural model to compute the welfare changes associated with the policy and to identify the role of supply responses in these changes. I also use the model to simulate expansions of free college.

In the first set of results, I use a difference-in-difference strategy with variation in treatment intensity at the program level to analyze students' behavior and programs' decisions. For students, treatment intensity is the relative price of the program prior to the policy implementation. More expensive programs potentially face larger increased demand once the free college policy brings their effective prices down to zero for eligible students. The results show that eligible students increase their applications and enrollment more in programs that were more expensive before free college. This is consistent with an indirect utility model in which price reduces the likelihood of choosing a program. The policy therefore affects programs differently, even within an institution, because the intensity of the treatment mediates its impact.

For programs, treatment intensity is a measure by the revenue change due to free college. Specifically, treatment intensity is the difference between the revenue prior to the implementation of free college and a counterfactual revenue where programs do not change their price and capacity but demand is still responding to the policy. This measure approximates what would have happened to programs' revenue if programs did not make changes in reaction to free college. My results show that programs that experienced a larger increase in capacity and price are those whose revenue would have decreased more, given the change in demand. This implies that programs that adjusted more are those whose revenue would have been most significantly impacted. The effect of free college on revenue is mediated by how demand varies due to the policy. Some programs experienced a more substantial increase in the demand from eligible students. Those programs would have reduced their revenue more if not for their capacity and price changes.

The second set of results of the paper comes from developing and estimating a model of the higher education market. Since the Chilean admissions system uses a version of the student-proposing DA algorithm, I assume that students declare their rankings truthfully considering the restriction imposed by their test scores (Fack, Grenet, and He (2019)). In practice, students may omit programs perceived as beyond reach or irrelevant, but they are still matched with their favorite program among those for which they qualified ex-post. I capture students' preference heterogeneity following Hastings, Hortaçsu, and Syverson (2017) and Abdulkadiroğlu et al. (2020) and using rich and fine-grained observable data at the student level. I divide my sample into geographic-socioeconomic cells, where I allow for differences in student preferences across regions, academic achievement, and income. Preference parameters, including price sensitivity, are the same within each cell. However, each student has its own choice set that considers the preferences of students in her cell restricted by her own test scores and programs' cutoffs. Conditional of her choice set, each student ranks up to ten programs, which motivates a rank-ordered multinomial logit model. I estimate price sensitivity using a two-step approach. First, I estimate programs' mean utility at the cell level by maximum likelihood. Second, I use policy and across-market variation to identify price sensitivity and the valuation of a set of program characteristics at the cell level. My results show that most students appear price inelastic, with eligible students showing a greater dispersion of price elasticity than non-eligible students. This result implies that after the implementation of free college, programs have incentives to increase prices because the demand of students who face prices is less price sensitive than the relevant demand before the policy. Moreover, my results show that students value programs with high achieving peers.

In the model, programs maximize their expected objective function by choosing price and capacity. The standard approach to estimate supply side parameters is to invert the first order conditions for these two variables that arise from the maximization problem. Since programs' enrollment shares are the output of the deferred acceptance algorithm, the specific functional form of the price elasticity is mediated by the algorithm.

Also, price changes that are small enough will lead to no changes in enrollment for oversubscribed programs. These issues render the standard approach intractable. I solve this technical challenge using a discrete choice model, turning the game into one of choice over discrete pricing and capacity changes. I discretize the action space using program baseline characteristics available in the data. In this modified game, programs choose actions by taking into account the expected revenue and capacity costs of each action. Programs are also allowed to have idiosyncratic preferences for actions, which may be correlated within institution-quality tiers. Programs do not observe the actions of their competitors, so the supply model assumes that programs make their price and capacity decisions in a Bayesian game, where they form expectations about the choices of other programs, whose payoffs are observed with logit noise. Following Sweeting (2009), in a first stage of the model, I estimate the probabilities of observing competitors' actions as a flexible function of programs characteristics. Furthermore, while the revenue function is known, it is computationally costly to compute for all the possible price and capacity combinations considering all the programs because the market clears by the DAA. Then, I approximate the revenue function using a random forest model. To do so, I first solve the DAA for a limited set of combinations of programs' prices and capacities and compute their revenue under the corresponding assignments. This constitutes the data set with which I train the random forest model. The model also allows me to select the variables capturing programs' competition that should enter into the revenue function. The result of the discrete choice model predicts programs' actions closely to the observed data.

I use the model to answer how supply responses to free college affect welfare measured as the money equivalent of their utility change, and to evaluate expansion of the policy to students who are eligible in the original design. I analyze a decomposition counterfactual comparing the welfare of students before and after the implementation of free college along with a counterfactual scenario where supply responses are restricted. This analysis allows me to understand the extent of supply responses and whether they amplify or mitigate the effect of free college. As mentioned before, supply responses dampen the welfare gains produced by the policy on average. Also, supply responses increase the dispersion of welfare changes, specially for non-eligible students. Furthermore, if free college expands to all students, supply responses will dampen eligible students' increased access to education more than for non-eligible students.

Finally, my results show that if the policy expands to all students, the impact on welfare would be mixed, as some students will benefit from access and lower prices but others will be displaced. On average, expanding free college benefits high-income students because of the price reduction and also because of increased applications and enrollment. In principle, this increased enrollment may imply a crowd-out of low income students because, in this context, they tend to have worse test scores than previously non-eligible students. However, if the shift in demand of high-income students is such that it increases vacancies in programs that previously eligible students include in their rank order lists and are achievable, then crowd-out could be mitigated or non existent. Furthermore, the impact on access to education also depends on programs' capacity decisions. Eligible students' access to education may increase if programs for which they are competitive candidates increase their capacity after the expansion of free college. My results show that low-income students also benefit from an expansion of the policy to free college for all on average. Part of this is capacity expansion: there are more seats available to students after the policy. Another part is the change in high-income students' applications. Some high-income students switch to programs that were previously under-subscribed, vacating slots from over-subscribed programs. Since these vacated slots are valued by low-income students above the outside option, we end up in a situation where all types of students benefit on average. Overall, access to education increases for all the student body, but proportionally more for high-income students who are not the target of the actual free college policy.

Several papers have studied policies that affect student costs in higher education . Murphy, Scott-Clayton, and Wyness (2019) describe the effects of the abolition of free college in England on university enrollments, equity, and proxies for institutional quality. After the abolition of free college, the British system experienced an increase in funding per student and enrollment, with no apparent widening in the access gap between advantaged and disadvantaged students.

Dynarski et al. (2018) analyze a targeted subsidy aimed at high-achieving, low-income students that reduced uncertainty by guaranteeing free tuition at a flagship university before application. The policy did not increase aid relative to what students would have qualified for after admission, but it reduces uncertainty. This policy is focus on a particular institution and the results raise an interesting point. The results show that the offer substantially increased both application and enrollment even though aid did not change. The authors suggest that this result highlights the importance of behavioral factors, such as uncertainty, in understanding students' college decisions. The Chilean implementation of free college also reduces uncertainty for eligible students, even more than the program in Dynarski et al. (2018) because it does not have an academic requirement and applies to all low-income students. I do not incorporate behavioral factors in my model, but they do not seem to be the main driver of my results as shown by a simple test, described in section 3.1, that compares the application behavior of similar students with and without uncertainty. Nonetheless, these behavioral factors could be relevant in understanding the long-term effects of Chile's free college policy or other implementation of this type of policy.

Evaluations of targeted subsidies in developing countries also show an impact on student enrollment that is consistent with my results. Using and RD design and a DID approach, Londoño-Vélez, Rodríguez, and Sánchez (2020) find that a large-scale scholarship targeting low-income high-achieving students positively affects their enrollment in high-quality colleges in Colombia. This expansion of financial aid also generates a response from private colleges which increased their capacity as a response to the increased demand. Note, however, that the policy studied by Londoño-Vélez, Rodríguez, and Sánchez (2020) is more targeted than the Chilean implementation of free college and does not generate a change in programs' revenue, where the Chilean implementation of free college does. These differences strengthen the incentives for supply responses. Furthermore, my structural model allows me to study these responses in depth and their impact on students' welfare.

Bennett (2020) studies the reduced form effects of the Chilean implementation of free college on student enrollment and applications using a generalized regression discontinuity design that expands the standard regression discontinuity analysis to a broader population further away from the cutoff. She finds that enrollment of eligible students around the eligibility cutoff increases after implementing the policy and that this result is mainly driven by an increase in applications. This result is consistent with my analysis which not only shows the policy's effect on enrollment but also on programs' decisions. Also, my structural model builds on these reduced-form results to understand the mechanism driving the effects of the policy.

Bucarey (2018) uses the expansion of a scholarship program in Chile to approximate the effects of the implementation of free college on the enrollment of eligible students. This scholarship does not change programs' revenue directly. However, the Chilean implementation of free college has an impact on programs' revenue that elicits supply responses that might not happen in absence of the revenue changes induced by the policy. His results show that the funding expansion increased demand for selective programs, making these programs more competitive and crowding-out many low-income students who would have qualified otherwise. This result assumes that the capacity of the institutions is fixed. In contrast, I relax this assumption and show that even in the presence of the crowd-out effect, an expansion to free college for all increases access to education for low-income students.

There is evidence in the literature that the effects of regulation in higher education are likely to be mediated by institutions' responses. For example, Arcidiacono et al. (2014) studies the ban on using racial preferences in admissions at public colleges in California. These institutions responded to this change in the regulation by investing more in their students or easing requirements, which can explain the gains in the graduation rates of students affected by the ban of the policy. This case shows how institutions adapt to changes in regulation. More importantly, it suggests that even if a change in regulation implies a gain or a loss for a particular group of students, it is necessary to consider the responses of students and institutions to evaluate the overall effect of the policy on the targeted group. This implies that educational institutions are relevant agents whose responses to changes in regulations may have welfare implications as also suggested by my results.

Finally, my paper is also related to other empirical work that considers products with more characteristics than price , for example, Fan (2013), Wollmann (2018), and Allende (2019). The results of these papers suggest that ignoring adjustments to non-price product characteristics causes significant differences in estimated welfare effects. My model allows programs to adjust price and capacity within an admissions system that uses the DAA. This happens in the context of price differentiation between eligible and non-eligible students. I argue that price and capacity are key strategic forces that can affect eligible and non-eligible students' enrollment differently and impact the welfare gains of the policy. Programs' pricing decisions do not shift the demand of eligible students, but capacity decisions do. Therefore, capacity decisions have a direct effect on eligible students' access to education. As mentioned before, my results show that access to education of eligible students is reduced by programs' responses to the policy.

The rest of the paper is organized as follows. Section 2 provides institutional background and describes the Chilean free college policy and the data. Section 3 presents reduced-form evidence on the impact of the policy on students' behavior and programs' decisions. Section 4 develops an empirical model of the higher education market. Sections 5 and 6 present the results of the model estimation. Section 7 analyses the impact of the policy and the role of supply responses, and section 8 simulates policies with different targeting. Finally, section 9 concludes.

2 Background and data

2.1 Brief description of the Chilean higher education market

In the past decades, Chile has experienced a dramatic increase in higher education enrollment. Thirty years ago, total enrollment was slightly above 230,000; today, it is more than 1,200,000.[3] While total first-year enrollment in higher education has stabilized recently, Chile has high participation in tertiary education, especially given its income level. In 2017, 33 percent of 19-20 years old were enrolled, higher than the OECD average of 30 percent.[4]

The higher education system is composed of universities and vocational institutions, and quality varies within each group.[5] The main focus of this paper is on universities of medium to high quality that participate in a centralized admissions system which uses an algorithm built on Gale and Shapley (1962)'s student-proposing deferred acceptance algorithm (DAA). In 2018, 39 universities participated in the centralized admission system out of 58 total universities. Universities that do not participate in the centralized admission system do not meet the requirements of the that system and have their own admission process that is neither centralized nor has the same rules across institutions.

Among institutions that participate in the centralized admission system are public and private universities, although the field is not strictly divided along those lines. "Traditional" private universities were founded before 1980, and they form a conglomerate alongside public universities (CRUCH) that, since 1954, has a goal of coordinating the higher education system, and its members tend to act as a block. Non-traditional private universities have become a relevant group recently as they represent a growing number of students.[6]

Finally, the universities that participate in the centralized admissions system differ in quality, as mentioned previously, and, on average, private-traditional institutions tend to have higher quality, measured by their certification in 2018 (See table 23 on the appendix for a description of the differences between types of institutions).

[3] This significant expansion has been fueled by various reasons. On one side are government policies: increased state-funded grants and loans and lax regulations in the creation and function of higher education institutions. On the other, is a strong demand for higher education due to increasing income and a vast higher education wage premium. See Bordon et al. (2016) for more details on their discussion on entry and quality cannibalization among universities.

[4] OECD, Education at a Glance

[5] The Ministry of Education certifies institutions and programs based on different measures of inputs and outputs, such as faculty-student ratio and student graduation. All the different measures are used to construct an indicator of quality. This indicator goes from 1 to 7 and indicates the years left for the following certification process. Universities with a higher timespan between certification processes are of higher quality. Universities must be certified to access public funds.

[6] Around 30% of total tertiary education enrollment in 2015

2.1.1 Centralized admission system

The system has the following timing. First, twelfth graders must sign up to take the standardized college admission test (PSU) in December, which is the end of the academic calendar year. The PSU includes mandatory math and language exams and optional science and history tests. Scores for these tests are scaled to a normal distribution with a range of 150 to 850 and a mean and median of 500. The test results are given to students a few weeks later. If students want to receive state financial aid (grants or loans), they also complete a socioeconomic verification form at the same time as applying for the PSU. [7] Students' access to state financial aid depends on the information from that form, their PSU scores, and their GPA. At this point, students know whether they are eligible for financial aid and also which type. Students know the requirements to obtain financial aid before they start the application process.

The standardized university admission process considers PSU scores, high school GPA, and the student's ranking within her school.[8] All these elements are combined using known weights to create a composite score that varies at the institution-program level. After receiving their PSU scores, high school graduates know their composite application scores, and they choose to apply to up to ten institution-program combinations. The centralized admission system then accepts the students to at most one program using the DAA given students' applications, GPA, rankings within the school, PSU scores, and programs' capacities. Note that students at this point do not have any additional choice within the centralized admission system, they are assigned a single option and they can accept or reject it.

This process creates an admission cutoff for each program, corresponding to the composite score of the least qualified admitted student. Rejected students are entered into a waitlist for that program. After students decide whether to accept the admission offer, waitlisted students might be offered admission to a second program. The algorithm guarantees that students are assigned to their most preferred program among those that would accept them.[9] The student-proposing DAA is strategy-proof, so applicants should report a rank-order list corresponding to their actual preferences. In practice, students may omit programs perceived as beyond reach or irrelevant, but they are still matched with their favorite program among those for which they qualified (Fack, Grenet, and He (2019)).

2.1.2 Implementation of free college

In 2014, Chileans elected Michelle Bachelet for president, who promised in her campaign to make college free for all by 2020. The details of President Bachelet's proposal were described in her presidential plan

[7] Note that since 2014 the state-guaranteed loan has not had a binding economic requirement due to the availability of resources.

[8] See González and Johnson (2018) for a discussion on the introduction of ranking to the system.

[9] Three aspects of the system can affect this result as described by Bucarey (2018) First, the system allows students to rank up to ten options. If binding, students would need to act strategically given the possibility that they are not assigned their most preferred option from the pool for which they qualify. However, just 1.5 percent of students rank ten alternatives, and only 0.02 percent are admitted to their tenth option. Second, some institutions restrict acceptance to student ranking levels, e.g. two of the 39 institutions will only admit students that rank them fourth or higher. However, 88 percent of students were admitted to one of their top three choices, so these restrictions are not generally binding. Finally, the weighted score used by programs might include ties in the last admitted student, which the system solves by adjusting capacities to fit all students with identical scores. However, this does not impose violations on stability (Ríos et al. (2014))

presented at the end of 2013 (Bachelet (2013)) and were a response to students led protests demanding higher education to become more affordable. In 2015, more than a year into President Bachelet's tenure, free college was enacted and came into effect for the 2016 admission process. Free college was implemented as a national and targeted policy that pays tuition for students from families in the bottom 50 percent of the income distribution who enroll in universities in the centralized admission system. As of today, the promise of free college for all has not been achieved.[10]

Free college coexists with an array of financial aid instruments, including scholarships for students up to the third income quintile (Bucarey (2018)) and income-contingent government-backed loans with low-interest rates (Aguirre (2019), Espinoza (2017), and Solis (2017)).[11]

Specifically, *before* the implementation of free college, students pay for higher education with their resources, scholarships or loans from by the government, and internal scholarships from institutions. The government's financial aid was assigned based on socioeconomic and academic requirements; the particular amount that was given was set at the institution-program level according to the program's *reference tuition*[12]. The aid amount covers on average 80 to 90 percent of the sticker price.[13] Students and their families paid the difference between the sticker price and reference tuition with their own resources or used institution-specific internal scholarships.

After the introduction of free college, government aid expands as the poorest 50 percent of families have access to free college if they enroll at a university in the centralized admissions system that chose to join the policy. Along with having to be part of the centralized admission system, institutions must have four or more years of certification to join.[14] Given these restrictions, all traditional private institutions in the system are eligible, and approximately 40 percent of private institutions qualify.[15] In 2015, all public and private traditional institutions joined free college. It was expected that CRUCH universities would join and provide access to free college for low-income students. However, this was not necessarily the case for non-traditional private universities, and 8 of 13 non-traditional private eligible institutions did not join the program.[16]

The Chilean implementation of free college is a demand voucher set at the institution-program level according to the program's baseline characteristics. It is essential to reinforce that eligible students face a price of zero under this policy. Hence, institutions lose the amount between their sticker price and the voucher. This introduces price differentiation between eligible and non-eligible students that only existed after the introduction of free college.

[10]In 2017, the free college policy expanded to eligible vocational institutions, but today, the promise of free college for all has not been achieved. It only covers the families in the poorest 60 percent, which implies that it effectively works as a voucher for disadvantaged students that coexists with other types of pre-existing financial aid.

[11]The financial aid alternatives are described in appendix A.1 in more detail.

[12]Reference tuition is defined by the Ministry of Education of Chile using a formula that considers past levels of tuition and corrections for quality and inflation. For more detail on how reference tuition is defined, see appendix A.1

[13]In 2015, the average across universities was 84 percent. Appendix A.2 summarizes the main statistics of this difference and its distribution for different types of universities.

[14]Private institutions that do not participate in the centralized admission system and meet the quality requirement can join if they have a transparent and non-discriminatory admissions system

[15]The specific number depends on the year in which these requirements are measured

[16]Private institutions that abstained have the highest price gap, twice as much as those of those that joined the program. On top of this, they are strongly reliant on tuition as a source of revenue. They also enroll fewer eligible students on average. However, the variance within this group is high. Note that these private institutions have a similar quality to public institutions, and in terms of prices, some of them are similar to traditional private institutions

2.1.3 Details about the voucher

The voucher v_{ij} varies at the institution-program level based on the 2015 program characteristics, including its quality. Specifically, it depends on the program's reference tuition and the institution's quality. First, a regulated price r_{ij} is computed as the mean of the reference tuition of all institutions in the same quality group. Then, the actual voucher is calculated using a known formula:

$$v_{ij} = p_{ij}^{15}\mathbf{1}\{r_{ij} \geq p_{ij}^{15}\} + min\{1.2r_{ij}; p_{ij}^{15}\}\mathbf{1}\{r_{ij} < p_{ij}^{15}\} \tag{1}$$

Where r_{ij} is the regulated price, and p_{ij}^{15} is the 2015 sticker price adjusted by inflation. If the sticker price is lower than the regulated price, the voucher equals the sticker price. Otherwise, the voucher equals the minimum between the sticker price and the regulated price compensated by 20%. This formula is adjusted yearly for inflation. As mentioned before, institutions that join free college lose revenue based on this, as the policy introduces price differentiation between student payment types. Among all programs in 2016, the mean ratio between the voucher and the sticker price is 88 percent, which represents a mean difference of 500 dollars.

2.2 Data

The Ministry of Education of Chile (MINEDUC) provides access to several data sets that follow high school graduates into higher education. Student-level data includes their college application, enrollment and graduation; financial aid; and demographics. Application and enrollment data are PSU scores and the rank-order list of students participating in the centralized admission system. Enrollment information at the program level is available for all students, even if they do not participate in the centralized admission system. The data also includes retention and graduation information at the cohort level. Financial aid data specifies application and assignment and contains family income decile and quintile depending on the year. MINEDUC also provides data at the program level. This includes sticker price, program capacity, location, duration, accreditation, and study area. Moreover, since the implementation of free college, the data includes voucher information. Finally, since 2012 MINEDUC has been publishing institutional financial statements, including revenue sources and internal scholarships at the institutional level. This high-quality and finely-grained data supports my methodological approach to estimating demand and supply. My analysis includes data from 2013 to 2018. I focus the analysis on recent high school graduates and first-time participants in the centralized admission system. Every year around 100,000 to 115,000 recent graduates participate in this system. Of these students, 27 percent graduated from public schools, 56 percent from voucher schools, and 17 percent from private schools.

It is important to mention that student performance and their socioeconomic background are correlated. Students who graduate from private high schools have significantly higher performance compared to their peers. Particularly, their performance on the PSU is 1.25 standard deviations higher than that of students who graduated from public schools. Also, student performance increases with family income; the difference between students from the lowest income group and the highest is more than 1.5 standard deviations in the PSU.[17] Also, students' rank-order lists mostly include programs inside of their region; 70 to 80 percent of those programs ranked are in their region. Finally, approximately 40 percent of the students reside in the capital region, 35 percent in the south, and the rest in the north. Most students apply and enroll in programs in the same region they reside. This is relevant for my methodology because I divide the sample into three markets according to regions, and all the analysis is done at the market level. In terms of first-year enrollment, 25 percent of students enroll in an institution in the northern region, 45 percent in the capital region, and the rest 30 percent in the southern region.

The sample includes all the institutions that participate in the centralized admission system and all the undergraduate programs that they offer. There are 39 institutions in the system during my time frame, with an average of 48 programs each and more than 76,000 entry-level slots yearly. Of these institutions, 12 are in the northern region, 17 in the capital, and 18 in the southern region.

3 Descriptive evidence from the implementation of free college

This section presents descriptive evidence of the impact of implementing free college on the higher education market. The analysis encompasses student outcomes, such as application behavior and enrollment, and program outcomes including their price and capacity decisions. To analyze the data, I use a difference-in-difference strategy with variation in treatment intensity at the program level.

In the case of students, eligible students are more likely to apply and enroll in programs that were relatively more expensive before free college. In the case of programs, those that would experience higher revenue drops if they did not respond to the policy are more likely to expand their capacity, and their tuition levels although the latter not by very much.

This evidence depicts equilibrium effects, and it only suggests potential mechanisms in which the implementation of free college could elicit responses from students and institutions. The next section develops and estimates a model of higher education in order to address the potential underlying mechanisms.

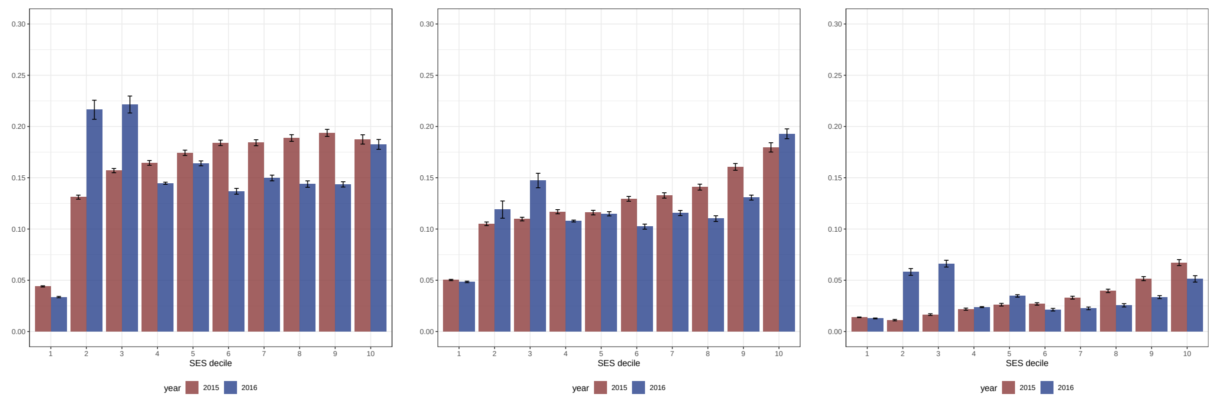
3.1 Impact on student behavior

The implementation of free college is associated with an increase in eligible students' participation in higher education. Specifically, conditional on taking the college entry exam (PSU), the fraction of students who enrolled in any type of university grew. Low-income students in this group, especially those in the second and third deciles of the income distribution, are more likely to enroll generally and in private universities after the implementation of free college, as seen in figure 1.

Figure 1 shows the composition of students in the different types of free college institutions. The increase of student participation overall and especially in private universities could be due to increased applications from eligible students or because they had a higher performance on the PSU after the policy. The latter

[17] Family income is self-reported and divided into 10 to 12 income brackets depending on the year.

Figure 1: Enrollment in universities that joined free college, before and after implementation



(a) Public (b) Private traditional (c) Private non-traditional

Notes: 95% confidence intervals
Sixth decile and above are not eligible for free college

is not verified by the data. As described by Bennett (2020), the increase in enrollment of eligible students into these institutions is mostly driven by growth in applications. The impact on applications seems to be due to a change in student preferences because the academic performance of eligible students did not change around the implementation of the policy (See figure 16 in the appendix).[18] However, this does not suggest that free college would not lead to an increase in the performance of eligible students in the long run, as free college tends to increase the return to higher education by reducing the cost of higher education, all else equal.

Given the increased applications, enrollment in participating institutions should also increase but less than applications, as the admissions process is mediated by the DAA which considers more elements than students' rank-order lists. I use a difference-in-difference framework with variation in treatment intensity at the program level, similar to Finkelstein (2007) and Bucarey (2018), to explore this possibility and further describe the changes in student behavior.

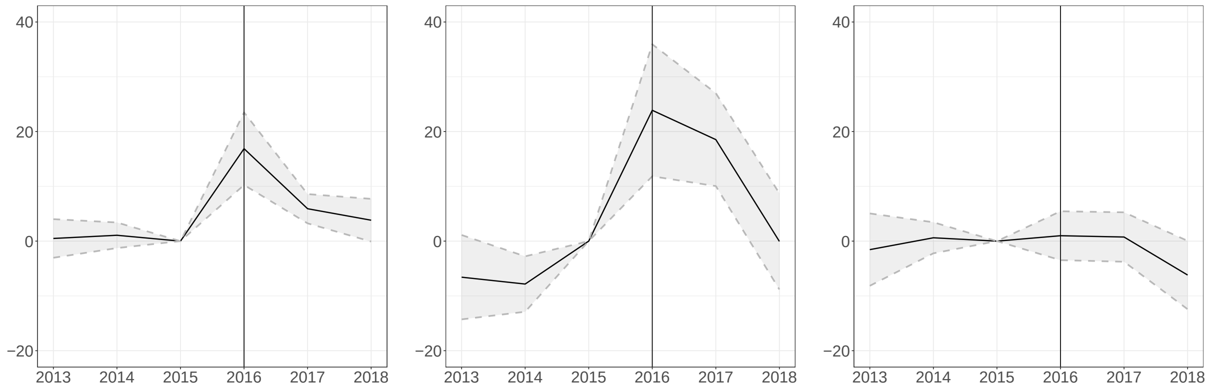
$$y_{jt} = \delta_t + \delta_j + \sum_t \rho_t * e_j + \epsilon_{jt} \tag{2}$$

This approach compares programs with different pre-policy exposure e_j to free college before and after its implementation, as presented in (2). The outcomes of interest y_{jt} are applications and enrollment at the program level. Finally, exposure e_j is measured as program j's relative price in the baseline year of 2015.

Eligible students tend to increase their applications to and enrollment in programs that were relatively more expensive before free college, which is consistent with a change in preferences due to the price reduction induced by the policy.

[18]Figures 16 in the appendix presents the distribution of the PSU scores around the policy implementation for different groups of students and years. The performance of low-income students is stable in the years around the discussion and implementation of free college. Specifically, when looking at the mean of the Math and Language section of the PSU —which are mandatory and considered for program admission by all relevant institutions — eligible (poorer) students tend to have worse performance than non-eligible (richer) students.

Figure 2: DID: Change in applications of eligible students —
Exposure is the relative price in the baseline year 2015

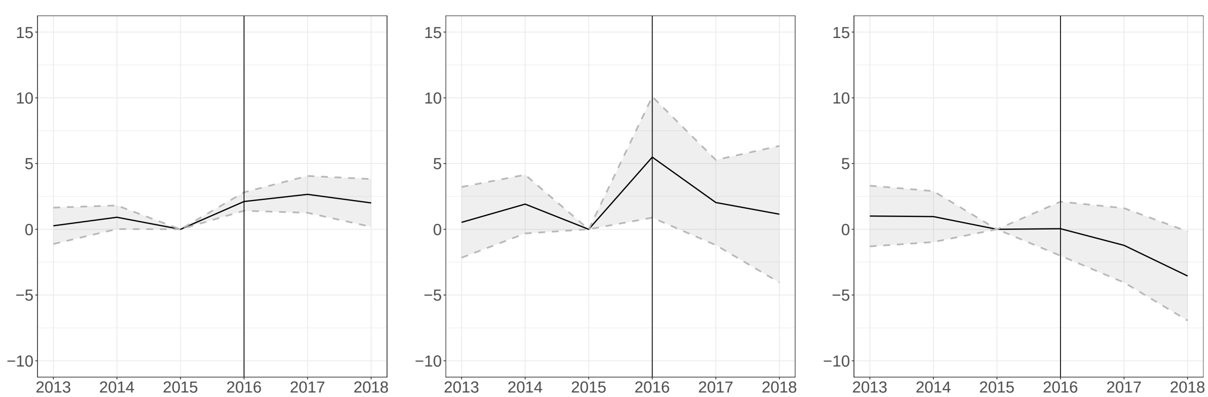


(a) CRUCH universities (b) Private free college (c) Private outside free college

Note: 95% confidence intervals. Scaled coefficients. Regression results in the appendix (table 24).

Figure 2 presents the estimation results of (2) using applications as an outcome. Applications in 2016 increased more for relatively more expensive programs compared to 2015; programs that are one standard deviation above the mean of the relative price had an increase of around 20 applications for CRUCH universities and almost 40 for non-traditional private universities. Programs from institutions that did not join free college did not have any significant increase. However, the increase in the application is mitigated or even reduced from 2017 onwards. This is most likely because of the 2017 expansion of free college to a group of high-quality vocational institutions, which makes the outside option of eligible students more attractive.

Figure 3: DID: Change in enrollment of eligible students —
Exposure is the relative price in the baseline year 2015



(a) CRUCH universities (b) Private in free college (c) Private outside free college

Note: 95% confidence intervals. Scaled coefficients. Regression results are in the appendix (table 25).

Prices are a relevant element in the application process because they negatively impact utility, all else being equal. Free college affects students' preferences because it reduces the price to zero, which not only reduces the cost but also the uncertainty around affordability as suggested by Dynarski et al. (2018). These effects are confounded. I perform a simple exercise that allows me to conclude that the price reduction might have affected preferences beyond the decreased uncertainty. To separate both effects, I compare the price distribution of first-ranked programs for the 2015 eligible cohort who would have been eligible for free college and were assigned a scholarship in 2015 to eligible students in the 2016 one. Both groups secured financial aid after knowing their PSU scores, so they did not face uncertainty. However, eligible students in 2016 knew they would not have to pay anything, whereas their 2015 counterparts faced the potential of their financial aid not quite meeting their needs as scholarships tended to cover 80 to 90 percent of sticker tuition. The remainder could be covered by institution funding but also might not be, leading students to have some sort of payment. Figure 17 in the appendix shows that the price distribution moved to the right after the implementation of free college, suggesting that the reduction in prices might have affected preferences beyond the decrease in uncertainty.

I perform the same difference-in-difference analysis to explore enrollment changes in the context of (2). Figure 3 shows the results of the estimation. As mentioned, free college positively impacts eligible students' enrollment, but the effect is smaller than the application impact. This is because enrollment is an equilibrium outcome that depends on more than their preferences. Enrollment of eligible students in 2016 in programs that were one standard deviation above the mean of the relative price increased by almost two students in CRUCH universities and nearly five in non-traditional private universities. Their enrollment decreases in non-free-college institutions.

Non-eligible students' enrollment could be affected through equilibrium effects. I use the same difference-in-difference approach to describe the change in enrollment of non-eligible student around the implementation of the policy. The enrollment of students who are not income eligible does not significantly changed after the policy is implemented. This happens in programs from institutions that ascribed to free college and also from institutions that do not. Table 26 in the appendix show the regression results for non-eligible students' enrollment.

It is essential to mention that enrollment changes could impact the student composition within programs. Bucarey (2018) anticipates free college could crowd out the lowest-income students. This is through negative spillovers to students receiving financial aid before implementing free college. These spillovers capture the correlation between family income and academic performance. As funding expands toward relatively higher-income groups, it includes more high-performance students who apply and replace beneficiaries with lower performance.[19] This spillover effect does not directly account for responses of the institutions that could have either enhanced or counteracted the crowd-out effect, which is relevant as enrollment is an outcome that confounds multiple factors, including institutions' decisions. I describe the responses of institutions in the next section.

[19] Remember that performance is correlated with family income in Chile.

3.2 Impact on programs' choices

Free college is a market shock that could have impacted programs' capacity and pricing decisions depending on their exposure to the policy. The voucher defined by the policy functions as a cap on the revenue that programs receive from enrolling an eligible student because it is often lower, and cannot be larger, than the tuition price, as seen in the definition of the voucher (1). The restriction in revenue can create incentives to expand or contract programs, as a function of the value of the voucher and the relative mass of paying and non-paying students. The policy also introduces price differentiation between eligible and non-eligible students, who still pay tuition. This changes the price elasticity that programs face, as paying students are now richer, creating incentives to raise prices. These policy's implications can differ across programs , according to their characteristics, then exposure mediates the policy's impact and varies across programs.

For the case of programs, exposure is defined as the counterfactual impact on revenue in a case where programs do not respond to the policy but students' applications do. I construct an exposure variable by comparing programs' revenue under two different assignments of the student-proposing deferred acceptance algorithm. First, the 2015 DAA assignment considers the rank-order lists of students from 2015 with the actual prices and capacities from 2015. Second, a counterfactual assignment that considers the rank-order lists of students from 2016 but keeps capacity and price fixed at 2015 levels.

$$Exposure_j = Rev_{j,\text{DAA 2015}} - Rev_{j,\text{DAA without responses}} \tag{3}$$

This exposure measure is an approximation to the projected revenue change that is associated with the shift in students' preferences induced by the policy and summarizes the implications of the policy at the program level. Programs' pricing and capacity decisions can be related to the revenue change measured by the exposure variable. Figures 18 and 19 in the appendix explore this possibility in the raw data considering capacity and price changes between 2015 and 2016.

Figure 18 shows the capacity change and its relationship with the revenue shift measured by the exposure variable. The data has both large and small changes in capacity, but it seems like a relationship with revenue change emerges; programs that would have a larger revenue drop given the shift in students' preferences also experienced increased capacity. However, note the concentration around zero capacity changes. This suggests that changing capacity is costly. As expected, the relationship becomes more robust if the zero capacity changes are removed.

Figure 19 depicts the percentage change in real prices from 2015 to 2016 and its relationship to percentage revenue changes. Price changes are primarily positive and no larger than 2 percent, equivalent to almost 60 US dollars in the sample. This change might seem small, but institutions have multiple programs and enroll thousands of students.[20]

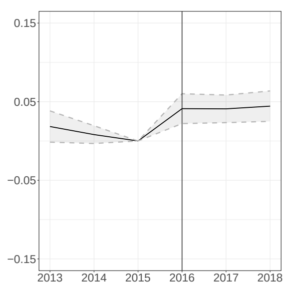
I introduce more structure to the data analysis using a difference-in-difference framework with variation in treatment exposure at the program level.

[20] In 2016, the average number of programs per institution was 42, and the average first-year enrollment per program was 59.

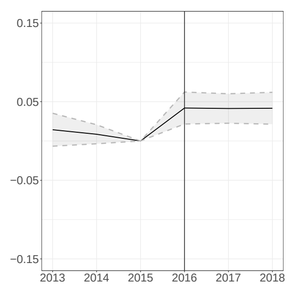
$$log(y_{jt}) = \delta_t + \delta_j + \sum_t \rho_t * e_j + \epsilon_{jt} \tag{4}$$

The outcomes of interest $log(y_{jt})$ are capacity and price changes at the program level, and exposure e_j is the revenue change defined in (3) standardized at the program level. Figures 4 and 5 show the results of the estimation of (4) for all institutions and specific groups of institutions. These exercises show if and how program decisions are mediated by exposure to the policy, measured as the impact on revenue produced by the demand shift induced by the policy. The change in revenue captured in the exposure variable encompasses many of the elements in which the policy operates and impacts programs.

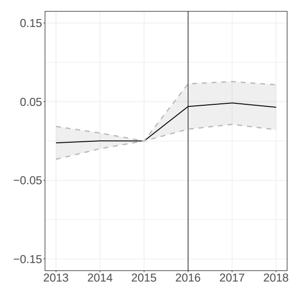
Figure 4: DID: Percentage change in program's capacity —
Exposure is standardized revenue change



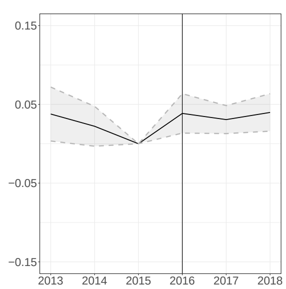
(a) All joined free college



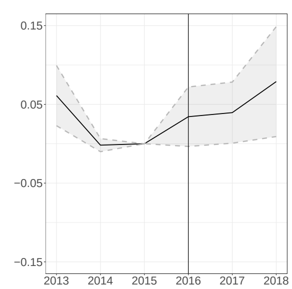
(b) CRUCH



(c) Public



(d) Private traditional



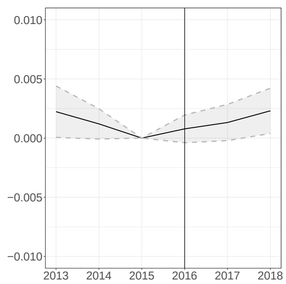
(e) Private non-traditional

Note: 95% confidence intervals. Regression results are in the appendix (table 27).

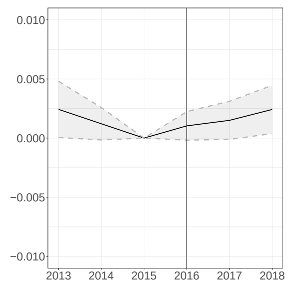
In general, programs that projected a reduction in revenue increase their capacity more after implementing the policy. The difference-in-difference analysis suggests that the relationship between revenue change and capacity change remains after controlling for year and program fixed effects. This implies the impact of free college on programs' revenue might have driven changes in programs' capacity related to how the policy operates. Programs that are one standard deviation above the mean of exposure increase their capacity in almost four percent more after the implementation of the policy. This change is not large because capacity changes are not common. In 2016, 30 percent of programs changed their capacity, and across the full sample this goes up to 45 percent of observations. However, across the full sample, programs that increase their capacity do it on average in 20 percent. An increase of four percent of this rate implies on average almost 3 more slots.

This result holds across types of institutions, and the effect level is similar and stable over time, except for private non-traditional institutions. These institutions represent a small part of the sample so their results are noisier.

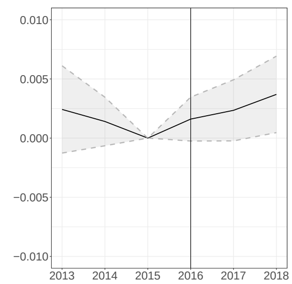
Figure 5: DID: Percentage change in programs' price —
Exposure is standardized revenue change



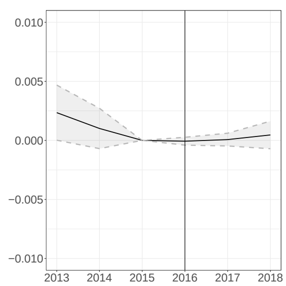
(a) All joined free college



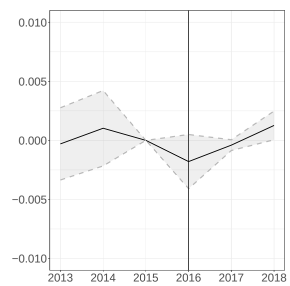
(b) CRUCH



(c) Public



(d) Private traditional



(e) Private non-traditional

Note: 95% confidence intervals. Regression results are in the appendix (Table 28).

Figure 5 shows the results for the same difference-in-difference strategy but using real price changes as an outcome. Similar to the effects on capacity, the mechanism of revenue change seems to affect price changes after the policy's implementation, but this association is less strong. Programs that are more exposed to free college increase their prices more after implementing free college. This impact on the price change is small and is significant a few years into the policy, but it seems consistent across all types of institutions. Two years into the policy, programs that are one standard deviation above the mean of exposure increase their real price in almost two percent more than before the implementation of the policy. As mentioned before, such small changes over an entire university can have larger impacts. This result in price changes is noisier for private non-traditional institutions because they represent a smaller fraction of the sample.

4 An empirical model of higher education

This section develops and estimates a model of the higher education market. Preference heterogeneity is captured thanks to the rich observable data at the student level as in Hastings, Hortaçsu, and Syverson (2017) and Abdulkadiroğlu et al. (2020). I use policy and across-market variation to estimate price sensitivity and the valuation of program characteristics. The results are consistent with the evidence in section 3.

Programs maximize expected profits by choosing over a discrete set of price and capacity strategies. Price and capacity play a different role in rationalizing demand because of the price differentiation introduced by the free college policy. Eligible students' rank-order lists do not depend on prices but their enrollment depends on program capacity. The results suggest that the expansion or contraction of capacity — rather than price changes — might be impacting access to education at the margin of enrollment.

I use the model to address the potential underlying mechanisms behind the impact of free college on student welfare in section 7.

4.1 Equilibrium

The centralized admissions system is based on Gale and Shapley (1962), therefore I assume that students report their rank order lists truthfully. In practice, students may omit programs that are perceived as out of reach or irrelevant. As argued by Fack, Grenet, and He (2019), when students are ranked by their test scores, stability is a plausible assumption, as every student is matched with her favorite program among those she qualifies for ex post.

The algorithm generates a stable match μ that allocates students to programs, given the reported preferences of students and the capacity of each program k_j. The allocation also defines a cutoff score $\underline{c}_j$ for each program that corresponds to the PSU score of the last enrolled student.

$$\underline{c}_j = \underset{n \in \mu_j^{-1}}{Min}\ e_j \tag{5}$$

Where n_j corresponds to students who apply to program j, and e_j is the vector of these students' test scores. The implementation of free college does not affect the definition of equilibrium. However, it does affect the allocation produced by the matching function μ because both the preferences of students and the price and capacity of the programs can be affected by the policy.

4.2 Preferences

I follow the approach of Hastings, Hortaçsu, and Syverson (2017) and Abdulkadiroğlu et al. (2020) to model students' preferences. Let U_{ij} denote student i's utility of enrolling in program j, and $\mathcal{J} = \{1, ..., J\}$ is the set of all available programs. The first program ranked by a student i is defined by:

$$R_{i1} = \underset{j \in \mathcal{J}}{\arg\max}\ U_{ij}$$

And subsequent ranks satisfy:

$$R_{ij} = \underset{j \in \mathcal{J}\ \{R_{im:m<k}\}}{\arg\max}\ U_{ij}, k < 1$$

Student i's rank-order list is then $R_i = \{R_{i1}, ..., R_{il(i)}\}$, where $l(i)$ is the length of the list submitted by student i. Student i's utility from enrolling in program j is:

$$U_{ij} = p_{jc(X_i)}\alpha_{c(X_i)} + X_j\beta_{c(X_i)} + \xi_{jc(X_i)} + \epsilon_{c(X_i)j} = \delta_{c(X_i)j} + \epsilon_{c(X_i)j} \tag{6}$$

$c(X_i)$ is the function that assigns students to a covariate cell based on the variables in the vector X_i. p_j is the price of program j, X_j and ξ_j are observed and unobserved characteristics of program j, and $\epsilon_{c(X_i)j}$ is the unobserved match utility. The parameter $\delta_{c(X_i)j}$ is the mean utility of program j for a covariate cell $c(X_i)$. I assume that $\epsilon_{c(X_i)j}$ follows an iid extreme value type I distribution conditional on $\delta_{c(X_i)j}$.

This utility captures flexible preference heterogeneity using observed student characteristics. Students have exact match utility and preference parameters within each cell, and no structure is imposed on preferences within cells. This strategy allows for the estimation of the mean utility of multiple programs leveraging rich observable data.

Students rank-order lists mostly include programs inside of their region; 70 to 80 percent of the ranked programs are in their region.[21] PSU scores and subjects also restrict which programs are available for students. The restriction of students' choice set also reduces the large dimensionality of the problem. In my setting, there are more than 1300 programs in the centralized admission system. The restriction of the choice set is the product of the interaction of students' characteristics, test scores, and program cutoff scores. The choice set is defined at the cell level as it considers the actual preferences of students within each cell. However, the choice set is also restricted for each student within the cell because it considers her test scores and cutoff scores. The choice sets are determined across and within each cell. The restrictions across cells are based on cell definition and how this definition is related to students' actual preferences. For a given cell, the choice set is defined considering the existing rank-order list of all of the students in that cell. This reduces all available programs to those considered by students in a particular cell. Then, the specific choice set of student i in cell c is restricted considering the student's test scores and the programs' cutoff scores. All programs with a cutoff score of 50 or more points above the student's score for that program are filtered out of her choice set.[22]

Conditional on these elements, the choice set of student i depends on the cutoff scores of the programs.

$$CS_i(e_i, X_i, \mathbf{c}) = \left\{ j \in J_i | \underline{c}_j \leq e^i_j \right\}$$

Where the characteristics of students restrict the programs under consideration to J_i and PSU scores to available programs to $CS_i(e_i, X_i, \mathbf{c})$ as mentioned before.

Therefore, equation (6) implies a rank-ordered multinomial logit model (Hausman and Ruud (1987)) where

[21] Just like Bucarey (2018), I consider three macro regional zones.

[22] Bucarey (2018) and Hastings, Neilson, and Zimmerman (2015) also create personalized choice sets based on students' test scores for the case of the Chilean higher education market.

each student has her own choice set. I restrict the choice set of students from all available programs to CS_i as described before. Hence, the conditional likelihood of rank-list R_i is:

$$L\left(R_{ij}, X_j\right) = \prod_{r=1}^{l(i)} \frac{exp\left(\delta_{c(X_i)_{R_{ir}}}\right)}{\sum\limits_{j \in \mathcal{J} \setminus \{R_{im}: m<r\}} exp\left(\delta_{c(X_i)_j}\right)}$$

This specification allows for flexible preferences and heterogeneity in tastes by estimating models separately for more than 430 covariate cells defined by the intersection of the region, PSU score terciles, elective PSU topics (i.e., Science and History), free college eligibility, non-free-college financial aid eligibility, and year.

I assume that once free college is implemented, the utility of eligible students is not affected by price. This assumption restricts the model because, once controlling for other resources and characteristics of the program, as seen in equation (6), a price change does not affect eligible students' preferences.

Programs' mean utility is estimated by maximum likelihood and these mean utilities are used to estimate price sensitivity and the valuation of other program characteristics as discussed in section 5.

4.3 Market shares

Students are allocated into programs using the DAA mechanism and conditional on their rank-order lists and the programs' inputs. This allocation is assumed to be pair-wise stable. Stability implies that students are assigned to a program that is their preferred option on their choice set conditional on acceptance. The allocations induced by the assignment algorithm are translated into market shares for each program j.

$$s_j = s(\mathcal{R}, p_j, \mathbf{p_{-j}}, k_j, \mathbf{k_{-j}})$$

Total enrollment in program j depends on the vector of rank-order lists $\mathcal{R}$ of all students participating in the centralized admission system and program inputs such as prices $\mathbf{p}$ and capacity $\mathbf{k}$. Enrollment can be defined for particular groups of students, conditioning on their characteristics. Income is a characteristic of particular interest because the free college policy is based on it. Suppose eligible students are those with income m_i less than $\bar{m}$.

$$s_j^l = s(\mathcal{R}, p_j, \mathbf{p_{-j}}, k_j, \mathbf{k_{-j}}; m_i \leq \bar{m})$$
$$s_j^h = s(\mathcal{R}, p_j, \mathbf{p_{-j}}, k_j, \mathbf{k_{-j}}; m_i > \bar{m})$$

These definitions are used later in the programs' objective function. It is essential to highlight that these shares are affected differently by price changes because, even though eligible students are not affected directly by prices, their share of enrollment is. Price changes affect the rank-order list of non-eligible students, which impacts the allocation from the deferred acceptance algorithm and the vector of cutoff scores. Thus the price sensitivity of s_j^l depends on the latter. If p_j increases, the utility of non-eligible students decreases, and program j is less likely to be included in their rank-order list. Then, the cutoff score of program j, $\underline{c}_j$, decreases because some non-eligible students who would have applied and enrolled in program j do not do so once p_j increases. Therefore, the share of eligible students who enroll in program j is likely to increase, and $\partial s_j^l/\partial p_j \geq 0$ due to the decrease in $\underline{c}_j$.

4.4 Programs' decisions

Programs report their price and capacity before students apply using the centralized admission system. Both choices are inputs for the final assignment produced by the DAA. Where capacity is a direct input of the algorithm, price, on the other hand, is an indirect input that operates through preferences and students' rank-order lists. Given the price level and capacity chosen by programs, some programs can have excess demand and be oversubscribed. This implies that for price changes that are small enough, the number of students accepted to a program does not vary.

Programs are not perfect substitutes for each other as they have different qualities. In this context, they compete with each other to attract students. The DAA allocation determines enrollment, and programs cannot accept or reject students based on any student observable characteristics not included in the assignment mechanism.

In my setting, programs have to deal with price differentiation between students who are and are not eligible for free college. This price differentiation affects the program's revenue but only affects the rank-order lists of non-eligible students. This leaves capacity as the only factor that could affect the enrollment of eligible students directly.

A simple pricing model illustrates how price differentiation shapes the equilibrium. In such a model, the markup is defined by the following expression,

$$\frac{p_j^* - C'(s_j^*)}{p_j^*} = -\underbrace{\frac{1}{\eta_{jj}^{*h}}}_{1} - \underbrace{\frac{v_j}{p_j^*}}_{2} \underbrace{\frac{\frac{\partial s_j^l}{\partial p_j}}{\frac{\partial s_j^h}{\partial p_j}}}_{3} \tag{7}$$

Equation (7) groups the determinants of the markup under price differentiation into three. The first determinant is the price elasticity of non-eligible students. With price differentiation, program j only considers the elasticity of non-eligible students to determine its price. If non-eligible students, who have a higher income than eligible students, are less sensitive to price, then the markup would be larger.

The second determinant is the ratio between the voucher as defined by the policy and the sticker price of program j. The voucher reduces program revenue because it cannot be larger than the sticker price, as seen in equation (1). This reduction in revenue pressures the markup up. This pressure is mediated by the third determinant, which captures the fraction of eligible to non-eligible students at the margin of enrollment. Note that $\partial s_j^l/\partial p_j \geq 0$ because as the price of the program goes up, the enrollment of eligible students cannot decrease because their preferences remain the same and the enrollment of non-eligible students cannot increase. Thus, if there are no eligible students at the margin of enrollment, the gap between the sticker price and the voucher does not affect the markup. However, when this fraction is large, the effect of the voucher on the markup increases.

Equation (7) highlights that price and capacity are tools that affect the enrollment of eligible and non-eligible students differently. Mainly, capacity is a tool that could affect revenue beyond prices given the presence of students who do not respond to prices. In the appendix A.3, I describe two more simple models (i.e., vertical differentiation and perfect substitutes) that show this role of capacity and how pricing and capacity decisions might be affected when the policy introduces differential prices.

4.4.1 An empirical model of programs' decisions

I assume that programs maximize their objective function by deciding prices and capacity over a discrete set of choices. The reason for the simplification of the action space is two-fold. First, the standard approach supposes computing and inverting first-order conditions in order to recover the marginal cost. This inversion needs the price elasticity of all programs. But in this empirical setting, some programs are oversubscribed, and thus the elasticity would be zero for price changes that are small enough. Moreover, the DAA mediates the elasticity, and since it does not have a closed form, it could be discontinuous. All these make inverting first-order conditions for price and capacity overly computationally intensive. Therefore the discretization of the action space reduces this complexity and makes the model tractable.

Secondly, the discrete action model better captures how programs choose prices and capacity. Programs negotiate with their institution to determine real prices and capacity. In practice, these variables do not experience changes every single year. The data suggest that price and capacity changes are restricted and could be modeled as a discrete variable. Figure 6 depicts the sample's real price and capacity changes. Eighty percent of real price changes are nonnegative, and the mean of these changes is almost two percent. Regarding capacity changes, almost 60 percent of the programs in the sample do not change their capacity. The remainder of the changes are divided almost evenly between positive and negative, where the median of the former is 25 percent and of the latter is -25 percent.

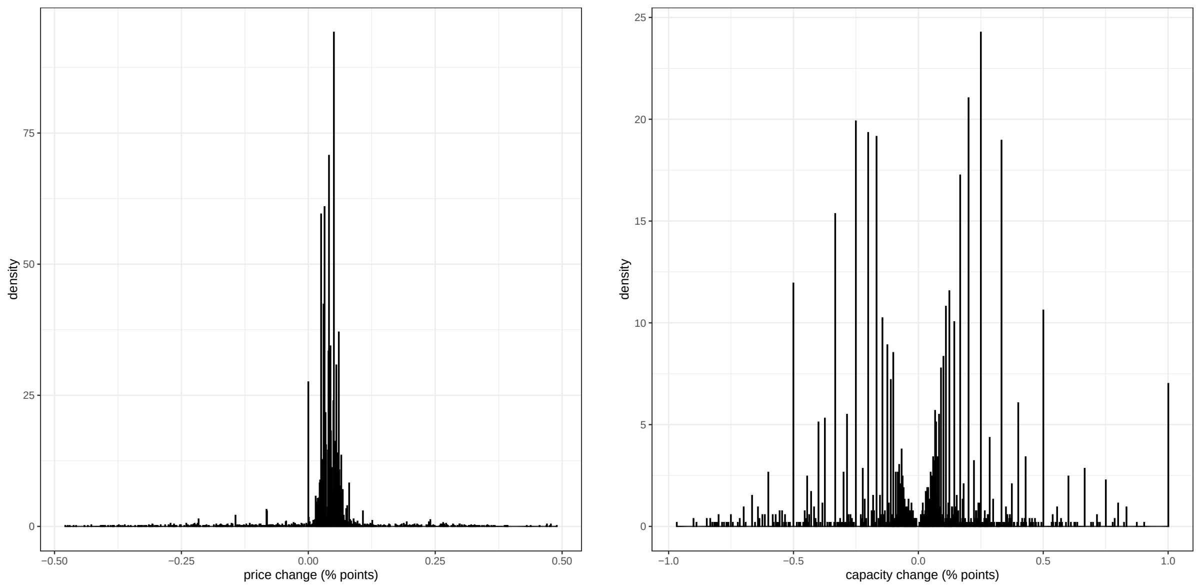
In the discrete choice model, program j chooses strategies defined as pairs of price and capacity. Price and capacity could decrease, not change, and increase, i.e. $p_j \in \{p_{j1}, p_{j2}, p_{j3}\}$ and $k_{ja} \in \{k_{j1}, k_{j2}, k_{j3}\}$. The specific level of price and capacity change comes from the data. The levels represent the terciles of the distribution of changes of each variable.[23] Therefore, programs have different choice sets. The choice set variation at the program level is linked to their characteristics, specifically their initial price and capacity. Moreover, this model presents a local objective function in that it is specified for the set of choices within the program's discrete choice set.

Program j chooses strategy s with price and capacity elements p_j and k_j to maximize their expected objective function by comparing the nine potential combinations.

$$E\left[\pi_j\left(p_j, k_j\right)\right] = NE\left[p_j s_j\left(p_j, k_j; p_{-j}, k_{-j}\right)\right] + (c_0 + c_1 k_j)k_j + d_{Institution-Action} + \sigma\eta_s \qquad (8)$$

[23] These are -0.25,0, 0.25 percent for capacity, and -19, 0, and 2 percent for prices.

Figure 6: Changes in price and capacity
All observations from 2014 to 2017



(a) Price changes

(b) Capacity changes

Note: These figures include price changes between -50 to 50 percent and capacity changes between -100 to 100 percent. Panel (a) depicts changes in real prices. Panel (b) only includes non-zero changes of capacity; these represent 45 percent of cases.

Where $s_j\left(p_j, k_j; p_{-j}, k_{-j}\right)$ is the market share resulting from the DAA for a particular vector of price and capacities for all programs; $\{c_0, c_1\}$ are the capacity cost parameters; $d_{Institution-Action}$ are a set of fixed effects grouping programs from the same institution that chose the same strategy or action; and η_s is a logit error defined at the choice level. This implies that the action chosen by the program has a dollar impact, which could be driven by the interaction with the centralized institution, as mentioned before. I assume programs have incomplete information about the actions of other programs. Even though prices and capacities are reported before the DAA assigns students, programs do not know the exact realization of the logit error term of other programs. Then, programs choose a strategy to maximize their objective function using their beliefs on other programs' actions. I discuss the estimation of these beliefs in section 6.

It is essential to highlight that prices and capacity impact revenue through the DAA, and they might do it differently. For example, if programs are oversubscribed, a price change might not change the market share, but if capacity changes, this would have a one-to-one effect on the market share.

As mentioned, the logit error is defined at the action level, typical for a consumer problem where utility is ordinal. In this context, revenue is cardinal, and the error is measured in dollars, implying that the strategy chosen has a dollar impact. Introducing this logit error smooths out the profit function and allows for estimation while approximating the random error at the cost level. A strategy to deal with part of the interpretation of the specification is to add a fixed effects at the institution-strategy level. This captures a structure in the error term and introduces dependencies between programs in the same institution. These dependencies allow me to measure how aligned programs are within the same institution, i.e. a summary of coordination.

The objective function allows for profit maximization but also incorporates other factors in the objective. The fixed effect at the institution-strategy level that captures dependencies between programs in the same institution encompasses factors that are measured in dollars but that are not directly profits.

5 Estimation and identification of preferences

I estimate program mean utilities $\hat{\delta}_{jct}$ by maximum likelihood based on student preferences as described in section 4.2. Then, I use $\hat{\delta}_{jct}$ to estimate price sensitivity and the valuation of other program characteristics.

$$\hat{\delta}_{jct} = p_{jtc}\alpha_c + \sum_r X_{rjt}\beta_{cr} + \gamma_j + \gamma_c + \gamma_t + \gamma_{\text{Inst-Area}} + \gamma_{\text{j is new}} + \epsilon_{jct} \tag{9}$$

Where p_{jtc} is the price of program j for cell c at year t;, X_{rjt} includes: program j's mean PSU score, its size, the fraction of students from private HS, and the fraction of low SES students. This specification also includes a set of fixed effects: program, cell, time, institution area, and a dummy for new programs. The cell fixed effect is the cell-specific estimate of mean value and depends on the particular choice set defined at the cell level. This specification groups all estimates $\hat{\delta}_{jc}$ across years and controls for time fixed effect to compute α_c at the cell level. This assumes that the underlying preference parameters are the same for each cell regardless of year. However, years matter because they affect which programs are available and their prices.

In principle, the challenge to estimating equation (9) is that a program's price can be correlated with its unobserved quality. Thus, to identify these parameters, I follow a strategy based on a policy instrument constructed using the implementation of the free college policy.

The free college policy uses an arbitrary income cutoff to separate students into eligible and non-eligible for free college. Eligible students face exogenous price variation introduced by the policy. For non-eligible students, price variation after free college is the institutions' choice, which could be correlated with unobservable program quality. Thus, I construct a price instrument for these students that uses price variation of a similar program, at the cell level, for different regions (markets). The other regions are used to construct the instrument because, from the student perspective, they are different markets. For a particular program in region 1, there are other similar programs [24] in regions 2 and 3, and the instrument is constructed using the prices of those programs. I argue that the instrument is exogenous because the unobserved preferences for a particular program are uncorrelated with the prices of similar programs in other parts of the country after controlling for a fine array of fixed effects. Moreover, I argue that the instrument is relevant because it captures price variation from other markets related to program characteristics and their cost but not student choice.

[24] The definition of a similar program is based on MINEDUC's classification of the program's topic of study.

This strategy is complemented by incorporating fixed effects that can capture the relationship between price variation and program quality. For example, program fixed effects address across-program price variation, and cell fixed effects with across-cell variation in the quality of the outside options faced by students in different cells. Time fixed effects account for time variation that affects all programs. The fixed effect that combines institution and area of knowledge accounts for variation across different types of programs provided by institutions of varying quality. The estimation of (9) is done by two-stage least-squares separately for the two types of students.

5.1 Results

This section presents results of the estimation of equation (9) separately for cells with students who are eligible and non-eligible for free college. Tables 1 and 2 depict these results, and are organized as follows. The upper panel shows the estimation of the coefficients of (9) in levels, and the bottom panel contains the coefficients in dollars, in absolute value, for ease of interpretation.

Table 1 presents the results of the second stage estimation by OLS for the cells with free college. As explained before, these are the cells for which the policy instrument has a perfect first stage. Note that price sensitivity is negative and more significant for students who are not eligible for financial aid before free college. This result is consistent with the fact that students who were not eligible for financial aid before free college faced higher prices compared to students who were eligible for other aid before free college.

Secondly, consider the bottom panel of table 1. This shows the dollar value of other program characteristics. The most important is the mean PSU of the program, which measures the program's quality. The coefficient on the fraction of students who graduated from private schools is negative and the coefficient on the fraction of students from low SES is positive after controlling for the program's quality. This could be capturing the fact that students prefer to have similar peers. Students eligible for free college have lower SES than those who do not, and enrollment in private schools represents less than 10 percent of total enrollment.

Table 2 presents the second set of results. This is for students in those cells that are not eligible for free college, and the estimation uses an instrument at the cell level, as described before. The first column is the OLS estimation, and the subsequent columns are the IV estimation for different groups of students.

Consider the upper panel of table 2; the OLS price coefficient is not statistically different from zero. At the same time, the IV estimate is negative, which implies a higher price sensitivity than the OLS estimate. This suggests that price is positively correlated with unobservable program characteristics, and if this relationship is not taken into account, the price sensitivity is biased towards zero.

Moreover, just like table 1, students who are not eligible for financial aid other than free college are more sensitive to price. Furthermore, among this group, comparing students who qualify for free college with those who do not reaffirms the fact that price sensitivity depends on the menu of prices faced by students. Those who access free college face a price of zero in participating institutions even if they are not eligible for other aid. Also, similar to the previous case, the mean PSU is the most important program characteristic. The critical difference between the cells eligible for free college and those that are not is that the fraction of low

Table 1: Second stage — Cells eligible for free college
Estimation by OLS

	Dependent variable: $\hat{\delta}_{jct}$		
	All	Eligible for other aid	Ineligible for other aid
Price (dollars)	-0.0001^{***}	-0.00003^{***}	-0.0001^{***}
	(0.000004)	(0.00001)	(0.00001)
Mean PSU (std)	1.01^{***}	0.82^{***}	1.29^{***}
	(0.03)	(0.04)	(0.05)
Number of students	0.003^{***}	0.003^{***}	0.002^{***}
	(0.0004)	(0.0005)	(0.001)
Fraction private HS	-0.46^{***}	-0.66^{***}	-0.34^{**}
	(0.11)	(0.13)	(0.17)
Fraction low SES	0.29^{***}	0.37^{***}	0.16
	(0.07)	(0.08)	(0.11)
		Fraction $\left\lvert \frac{\alpha}{\beta_r} \right\rvert$ in dollars	
Mean PSU (1 sd)	13719.64	22568.72	15566.98
Number of students	35.07	88.04	27.16
Fraction private (1%)	-63.93	-192.25	-41.30
Fraction low SES (1%)	40.78	107.06	18.83
Year FE	Yes	Yes	Yes
Program FE	Yes	Yes	Yes
Institution-Area FE	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes
Observations	60,017	36,058	23,959
Mean PSU	591.11	590.74	591.68
SD mean PSU	55.38	54.09	57.25
Note:			*p<0.1; **p<0.05; ***p<0.01

SES students in a given program reduces its value for those who are not eligible. This result, again, could be explained because students prefer peers who are similar to them, and there are SES differences between the two groups.

Appendix A.4 shows the results for cells where free college eligibility is broken down into income deciles: first to fourth, fifth, sixth, and seventh to tenth, and unknown.[25] This alternative estimation captures income heterogeneity in price sensitivity more precisely. The results are consistent in the sense that conditional on income, students who are not eligible for financial aid other than free college are more price sensitive. Also, conditional on not being eligible for aid other than free college, price sensitivity increases with income.

My estimates of price sensitivity α are broadly consistent with other demand estimations done in the same context as my paper (Bucarey (2018).

Figure 7 depicts the distribution of price elasticity of eligible and non-eligible students derived from the demand estimation. The figure includes observations at the student-program level and is restricted to 2013 to

[25]Students have to apply to be eligible for free college and other financial aid. After they apply, their income is verified and classified into income deciles. Students who do not apply are not assigned to an income decile group.

Table 2: Second stage — Cells ineligible for free college
Estimation by IV

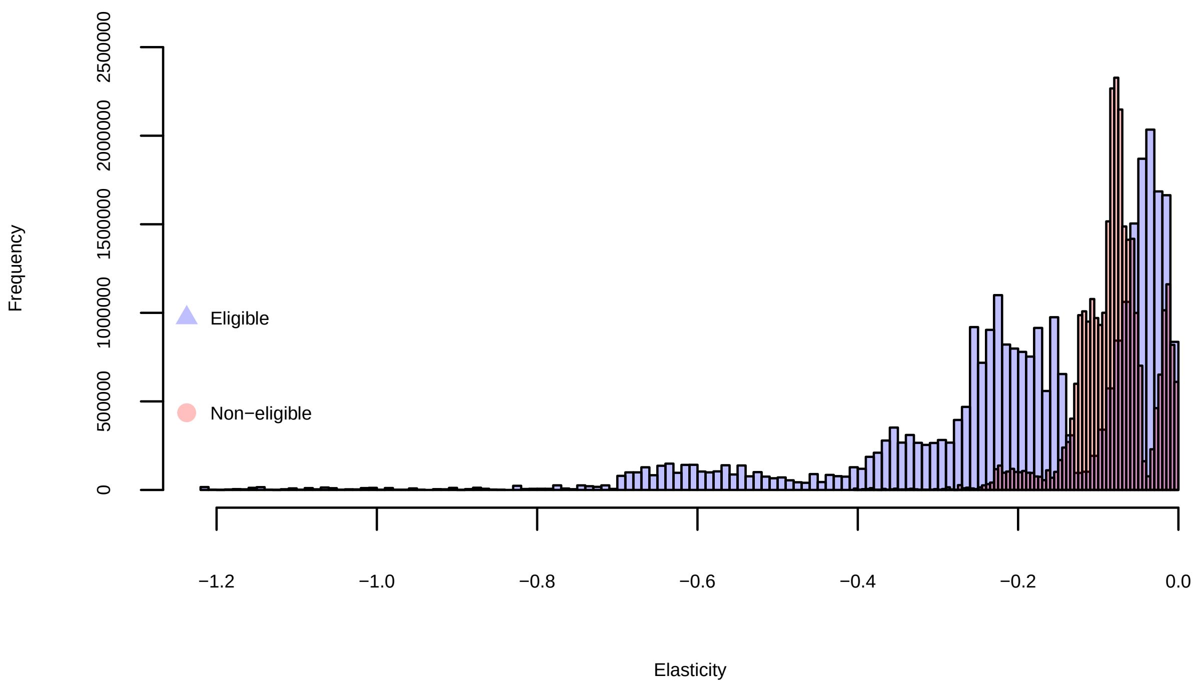
	Dependent variable: δ_{jct}			
	OLS	IV: All	Eligible for other aid	Ineligible for other aid
Price (dollars)	-0.000004	-0.00002^{***}	-0.00003^{***}	-0.002^{***}
	(0.00001)	(0.00001)	(0.00001)	(0.0003)
Mean PSU (std)	0.90^{***}	0.90^{***}	0.61^{***}	0.94^{***}
	(0.03)	(0.03)	(0.05)	(0.04)
Number of students	0.002^{***}	0.002^{***}	0.001	0.001^{**}
	(0.0004)	(0.0004)	(0.001)	(0.0005)
Fraction private HS	-0.17^{*}	-0.19^{*}	-1.00^{***}	-0.14
	(0.09)	(0.10)	(0.17)	(0.11)
Fraction low SES	-0.22^{***}	-0.23^{***}	-0.32^{***}	-0.43^{***}
	(0.07)	(0.07)	(0.12)	(0.09)
	Fraction $\left\lvert \frac{\alpha}{\beta_r} \right\rvert$ in dollars			
Mean PSU (1 sd)	222710.09	41075.28	21411.09	462.72
Number of students	479.92	87.94	19.37	0.60
Fraction private (1%)	-424.16	-84.47	-345.80	-0.70
Fraction low SES (1%)	-533.41	-102.83	-112.30	-2.11
Year FE	Yes	Yes	Yes	Yes
Program FE	Yes	Yes	Yes	Yes
Institution-Area FE	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes
FS F statistics	-	321017	79249	572
Observations	59,105	58,719	12,278	46,441
Mean PSU	602.41	602.41	602.90	602.28
SD mean PSU	57.68	57.68	57.42	57.74

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

2015 because eligible students do not face prices after 2015. The elasticity considers different price sensitivity parameters and program menus because each student has their own choice set of programs. Overall, the results show that students are price inelastic. Note that non-eligible students with higher incomes tend to have lower elasticity. Nonetheless, there is a fraction of eligible students that have smaller price elasticity for certain programs. In my empirical setting, where PSU scores and SES are correlated, non-eligible students have more high-quality programs in their choice set as well as programs with higher price. These could explain why most of them have lower price elasticity than eligible students.

Finally, the results of Bucarey (2018) also show that students are price inelastic. However, he finds that students with lower income have lower elasticity. This is not necessarily inconsistent with my results for two reasons. First, Bucarey (2018) reaches his results using the full price of all programs. Whereas, I consider the programs in the specific choice set of each student. Furthermore, students with lower income are more likely to face a menu of price that are lower due to access to financial aid. Second, my results show that the price elasticity of certain eligible students is lower than the one of most of non-eligible students, as seen in figure 7.

Figure 7: Price elasticity by student eligibility —
Student-program observations from 2013 to 2015



Note: Observations before free college because, after its implementation, eligible students do not face prices.

6 Estimation and identification of programs' problem

I assume programs use static Bayesian Nash equilibrium strategies because they have incomplete information. Programs do not observe the realization of the error term of other programs and thus they choose a strategy to maximize their objective function using their beliefs on other programs' strategies. Beliefs are estimated separately using the data's panel structure, similar to Sweeting (2009). Then, these beliefs are used to compute expected revenue and maximize the objective function by comparing a program's nine possible strategies that combine price and capacity. Appendix A.5 contains details on the estimation of beliefs.

The model described in section 4.4.1 and captured in equation (8) is estimated by multinomial logit using the following specification,

$$E\left[\pi_j\left(p_j,k_j\right)\right]=\underbrace{NE\left[p_j s_j\left(p_j,k_j;p_{-j},k_{-j}\right)\right]}_{\text{expected revenue}}+\underbrace{(c_0+c_1k_j)k_j}_{\text{direct capacity cost}}+\underbrace{d_{InstQuality-Strategy}}_{\text{FE}}+\underbrace{\sigma\eta_s}_{\text{error in dollars}} \tag{10}$$

The coefficients of this specification are normalized by σ, and the level of the fixed effect is allowed to change considering the quality of the institution that the programs belong to, $InstQuality-Strategy$. In principle, I could include a fixed effect at the institution-action level. This fixed effect would capture the negotiation process between programs and the institution they belong to, particularly the dollar value of making a decision conditional on a particular program's choice set of a program. However, the institution-action fixed effect is too granular to be identified. Thus, I use an institution characteristic that aggregates the fixed effects but still models relevant features of the relationship between programs and institutions and their costs from changing prices and capacity.

Assuming that η_s follows an extreme value type-1 distribution, the choice of a program is rationalized using a logistic probability model where the probability of program j choosing the action $\{p_j,k_j\}$ is,

$$Pr(p_j,k_j;p_{-j},k_{-j})=\int\frac{exp\left(\tilde{\pi}_j(p_j,k_j;p_{-j},k_{-j})\right)}{\sum_{s=1}^{9}exp\left(\tilde{\pi}_j(p_s,k_s;p_{-j},k_{-j})\right)}d(p_{-j},k_{-j}) \tag{11}$$

Where $\tilde{\pi}(\cdot)$ is the normalized objective function,

$$E\left[\tilde{\pi_j}\left(p_j,k_j\right)\right]=\gamma E\left[rev_j\right]+(w_0+w_1k_j)k_j+\tilde{d}_{X_{InstQualirt}-Strategy}+\eta_s \tag{12}$$

The estimation of the parameters is done by maximum likelihood. These parameters are the best fit that rationalizes the observed equilibrium assuming the equilibrium maximizes the expected revenue of each program.

Since the market clears by the deferred acceptance algorithm, it is not possible to write a closed-form expression for the revenue function of a program as a function of its capacity and price choice, along with the capacity and price choices of its competitors. In principle, it is possible to solve the deferred acceptance algorithm thousands of times to compute each program's revenues for every action across the distribution of rival programs' actions. The algorithm's rules are known, and computing the algorithm a handful of times is simple. However, solving the algorithm for all 500^9 possible combinations of strategies in one market is computationally costly. My solution is to run a limited set of simulations of the DAA to generate a data set that links each program's revenue to its price and capacity and the pricing and capacity decisions of its rivals, as well as with the voucher defined by the government. Then, I approximate the revenue function using a random forest model trained on this data set. The random forest algorithm also helps me select the variables regarding competitors that should enter into the revenue function. This approach allows me to compute revenues for each action while integrating over rivals' strategies efficiently and accurately. Appendix A.6 describes the random forest model used to approximate the revenue function. The approximation approach follows a rationale similar to Bodéré (2023).

The comparison between actions allows me to recover $\{\gamma, w_0, w_1, \tilde{d}\}$. It is essential to highlight that capacity actions identify the cost parameters when programs are oversubscribed because price changes do not affect enrollment. Capacity changes, however, produce different revenue across actions, even for oversubscribed programs. In this case, increasing or reducing capacity has a one-to-one relationship with enrollment.
The identification of the parameters of the profit function also relies on the following assumptions,

Assumption 1: Distribution of $\eta \sim EVT1$

Assumption 2: Independence of η

Assumption 1 imposes restrictions on the data-generating process, obtaining a parametric model. More importantly, assumption two states that the error term is independent of rev and k. Unlike linear models, where identification typically relies on an assumption of no correlation, nonlinear models often need to assume complete independence. The main implication of this assumption is that the cost function estimates are the same for both observed capacity and capacity changes within the choice set of programs. A threat to this assumption occurs if capacity changes are such that the cost function also changes. However, the capacity actions are restricted to relatively small changes, which mitigate this threat but impose the local interpretation of the profit function and the results of the model.
The following section presents the results of the estimation equation (12).

6.1 Results

This section presents the results of the estimation of the supply model. I estimate equation (12) using different levels of fixed effects, $\tilde{d}_{Quality_{Inst}-Action}$. The results are presented in table 3 in two ways. Panel A gives the estimates from the logit estimation of equation (10), and panel B presents the coefficients in thousands of dollars as in equation (10), which eases its interpretation because of the magnitude of the raw coefficients.
The first column presents the results of the specification without fixed effects; this specification serves as a baseline for analyzing the relevance of including a fixed effect that captures the cost of choosing a particular action for each program. The ideal level of the fixed effect would be institution-action as discussed in section 4.4.1. However, the data does not have enough variation to do so. Hence, the specification in column (2) increases the granularity of the fixed effect, which is defined as interacting the program's chosen strategy with the quality of its institution. This fixed effect encompasses all the costs or benefits of choosing a particular strategy for a program of a certain quality, which are not included in the common capacity cost.
Including a fixed effect rationalizes the variability of choices across programs, particularly programs that belong to an institution of similar quality. Table 4 depicts the fit of the model.
Moreover, including a fixed effect captures variation in the objective function within an institution, which suggests a degree of dependency between programs in the same institution. The estimates of fixed effects presented in table 21 in the appendix, show this variation across institutions of different quality. For example, conditional on a strategy that increases price, high quality institutions prefer to increase capacity rather than

Table 3: Estimation of supply model

Panel A: Variables	(1)	(2)
Revenue (US$)	-0.00340***	0.000433
	(0.000611)	(0.000624)
Capacity (slots)	0.00346**	-0.00670*
	(0.00137)	(0.00356)
$Capacity^2$ (slots)	-5.67e-06**	4.39e-06
	(2.51e-06)	(4.19e-06)
Panel B: Thousand $US		
$\hat{\sigma}$	-294	2310
$\hat{c}_0$	1.02	-15.5
$\hat{c}_1$	-0.002	0.01
Observations	50,616	50,616
Fixed effect	No	Quality-Type

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The estimation is done by multinomial logit, with strategy nine as the baseline. The difference between columns is the fixed effect. The first column does not include a fixed effect. The second column includes a fixed effect at the action institution-quality level with 45 levels. Quality is defined by the regulator and has 5 categories. Note that the marginal cost of capacity is positive for all the capacity actions included in the strategies of the programs.

Table 4: Model fit — Observed and predicted probailities

Strategy	1	2	3	4	5	6	7	8	9
Observed	6.5	4.5	5	11.7	28.7	22.5	3.4	8.5	9.2
Predicted (N=1,000)	5.6	4.9	5.2	12	29.8	24	2.7	7.5	8.1

decrease, and prefer to not change their capacity rather than increase. On the contrary, faced with the same alternatives, low quality institutions prefer to decrease and not change capacity respectively. The difference captures the impact of strategies beyond the direct capacity cost for institutions of different quality. Which suggests that the objective function of programs could be interpreted as a combination of profit maximization and something else. My model does not directly define the elements of the objective function that are not profits, but still accommodates an objective function that includes them.

I use the specification in column (2) to analyze counterfactual scenarios. This specification includes a fixed effect at the institution-quality action level and encompasses how institutions of the same quality negotiate with their programs. Institutions of higher quality could be more resilient to increasing capacity relative to institutions of less quality. A reduction in profits beyond the marginal cost captures this.

The specification in column (2) can be expanded to include heterogeneous coefficients for different types of programs. The results for this specification are presented in appendix A.8.

7 The impact of the policy and the role of supply responses

In this section, I describe the impact of the policy and analyze a decomposition counterfactual to answer whether supply responses amplify or moderate the effects of free college on student welfare.[26] To answer this question, I compare the welfare of students derived from three different DAA allocations. First is the actual allocation of 2016, the year when free college was implemented. Second is a counterfactual allocation where only demand responds to free college. And finally, third is a counterfactual allocation without free college.

For each allocation, I solve the maximization problem of every program using the estimation of the marginal cost function. I approximate the expected revenue of each strategy using the random forest estimated in section A.6. The solution to the maximization problem is a probability distribution over strategies. Then, I use this distribution to simulate a sample of $N = 100$ vectors of programs' strategies. For each vector, I draw a realization of the utility error and compute the equilibrium allocation using the DAA. I compare the 2016 counterfactual allocation to the actual 2016 allocation and the scenario where only demand responds to free college. I then compute mean welfare, measured as the money equivalent of their utility change, across all realizations of the utility error and all the vectors of strategies in the sample.

Finally, I pay special attention to specific subsets of students. Specifically, I distinguish between eligible and non-eligible students because this distinction is essential to the policy. I also consider students more likely to enroll at baseline in a program with high exposure to the policy, i.e. whose revenue is more affected. Section 4.4 describes exposure as the interaction between the gap induced by the policy and the fraction of eligible marginal students (see equation (7)). Programs with higher exposure at baseline are more likely to respond to the policy by increasing their prices. Finally, I also consider students who are more likely to enroll in programs of low and high quality at baseline. This distinction may be relevant for the policymaker because it is related to the quality of education students are receiving.

This section also describes how the programs' price and capacity choices change with free college.

7.1 Students

The implementation of free college has a positive aggregate effect on eligible students as seen in table 5. The effect on the welfare of non-eligible students is small but in aggregate it is also positive. Table 5 also presents statistics of the distribution of the impact of the policy, and they show that its impact on eligible and non-eligible students is heterogeneous. The results presented on this table are complemented by figure 8 that shows the distribution of changes in students' mean utility.

On average, eligible students are better off as they benefit from the reduction in price and some increased access to education. This effect is heterogeneous, as seen in the first and third quarter of the welfare change distribution. Eligible students who do not gain access to education do not benefit from the policy. Those eligible students who would be enrolled with and without free college benefit from the price reduction induced by the policy. And students who access higher education because of the policy perceive a large benefit

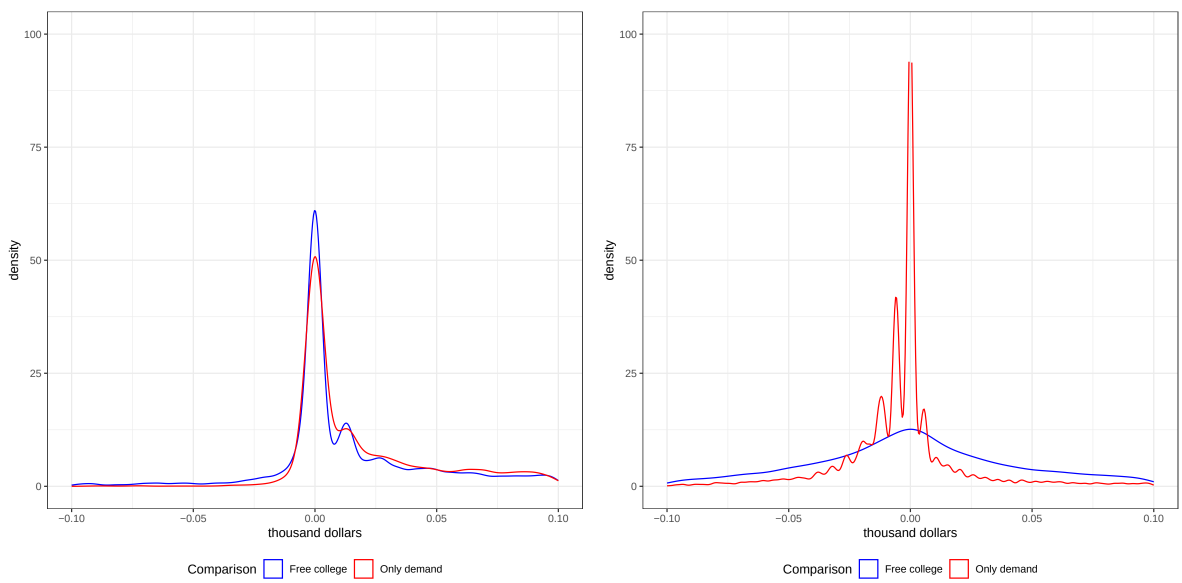
[26] The current analysis only includes students in the northern region. This is due to computing time. The results will be updated as simulations from other regions become available.

Table 5: Summary of the impact of the policy

	Eligible	Non-eligible
Mean welfare change (US$)	561	21
1st quarter welfare change (US$)	0.32	-30
3rd quarter welfare change (US$)	995	53
Welfare increased: baseline → free college	37.6%	30.2%
baseline → demand only	39.2%	28.6%
Welfare decreased: baseline → free college	10.6%	37.4%
baseline → demand only	3.2%	36.9%

because they gain access to free higher education. Considering all these case, almost 40 percent of eligible students experienced increased utility due to the implementation of free college, and around 90 percent are at least weakly better off. Then, free college is weakly welfare-enhancing for most eligible students. Supply responses slightly mitigate welfare gains of eligible students who are better off due to the policy. However, supply responses amplify loses for those eligible students who are made worse off due to free college, as shown in table 5. This is in part driven by the increase in displacement to the outside option produced by supply responses as seen in table 6.

Figure 8: Distribution of changes in mean utility by eligibility, in dollars



(a) Eligible (b) Non-eligible

The impact of the policy on non-eligible students is small on average. The fraction of non-eligible students who benefit from the policy is similar to the one that is worse off due to its implementation. The level of the impact is small because increased their welfare after the implementation of free college, and 71 percent are at least weakly better off. In this case, supply responses also amplify welfare gains from the policy but also welfare loses as seen in table 5. Remember that non-eligible students are not directly impacted by free college; its impact is through the assignment mechanism and supply responses induced by implementing free college.

Figure 8 presents the distribution of mean welfare change from a comparison of the baseline scenario without free college to two possible cases, i.e., in blue the case of free college and in red the case of only demand. Welfare changes are computed as the average across all simulations. Panel (a) depicts the distribution for eligible students and panel (b) for non-eligible. First, in panel (a), the mass at zero corresponds to students who are in the outside option in both scenarios. Negative changes in utility could be driven by displacement to the outside option or enrolling in a less preferred program. Second, in panel (b), the mass at zero not only corresponds to students who are in the outside option in both scenarios, but also includes students who are enrolled in the same program in both scenarios and the program did not change its characteristics. In the case of non-eligible students, mean utility decreases for the same reasons as eligible students and also because non-eligible students could pay a higher price than at the baseline scenario.

Table 6: Changes in enrollment outcomes with and without supply responses

	Eligible	Non-eligible
Baseline → Free college		
Same program (if always enrolled) (%)	44.3%	46.3%
Displacement to o.o (unconditional) (%)	6.9%	6.9%
Access college (unconditional) (%)	8.3%	8.2%
Baseline → Only demand		
Same program (if always enrolled) (%)	90.8%	92.3%
Displacement to o.o (unconditional) (%)	1.3%	1.2%
Access college (unconditional) (%)	2.6%	2.3%

To analyze the effect of supply responses, I compare the blue and red distribution for eligible and non-eligible students separately. In the case of eligible students, supply responses reduce access to education as seen in the larger mass at zero in the blue distribution. Also, they tend to dampen welfare gains and amplify loses. For non-eligible students, the impact of supply responses on welfare is mixed, which is reflected in the aggregate effect shown in table 5.

Table 6 describes changes in students' enrollment outcomes that provide insights on the reasons for the changes in utility depicted in figure 8. First, free college induces changes in enrollment for those students who are enrolled before and after its implementation. The corresponding change in utility depends on the characteristics of the program students enroll into.

Also, displacement to the outside option increases by almost seven percent. At the same time, access increases in more than eight percent. Supply responses contribute to the amount of displacement and access. Importantly, supply responses increase the mass of eligible students who stay in the outside option once the policy is implemented, as mentioned before.

I consider other characteristics of students to describe the impact of the policy. Particularly, I consider the type of institution students enroll into and other characteristics of students. Table 7 suggests that there is a difference between the aggregate effect of the policy and the effect for certain subsets of students. This difference is given by the exposure that those groups of students have to the effects of the policy as described

Table 7: Fraction of students who are strictly better off relative to a baseline without free college

	Free college	Only demand
In program with low exposure	43.5%	46.2%
Eligible students	59.9%	63%
Non-eligible students	34.9%	37.3%
Marginal students	23.3%	29.6%
Infra-marginal students	44.4%	48.3%
In program high exposure	31.7%	35.8%
Eligible students	38.3%	43%
Non-eligible students	23.8%	27.1%
Marginal students	13%	20.9%
Infra-marginal students	33.4%	38.9%
In program of low quality	46.2%	23.8%
Eligible students	22.1%	29.9%
Non-eligible students	10.2%	7.3%
Marginal students	8%	16.2%
Infra-marginal students	18%	25%
In program of high quality	41.9%	46.2%
Eligible students	54.2%	58.7%
Non-eligible students	34.2%	38.3%
Marginal students	19.3%	26.3%
Infra-marginal students	43.1%	47.3%

Note: This table shows the fraction of eligible and non-eligible students who are strictly better off in each scenario relative to the baseline without free college. This fraction is the mean probability of being better off considering all the possible vectors of prices and capacities in the sample of actions and all the simulations for each vector.

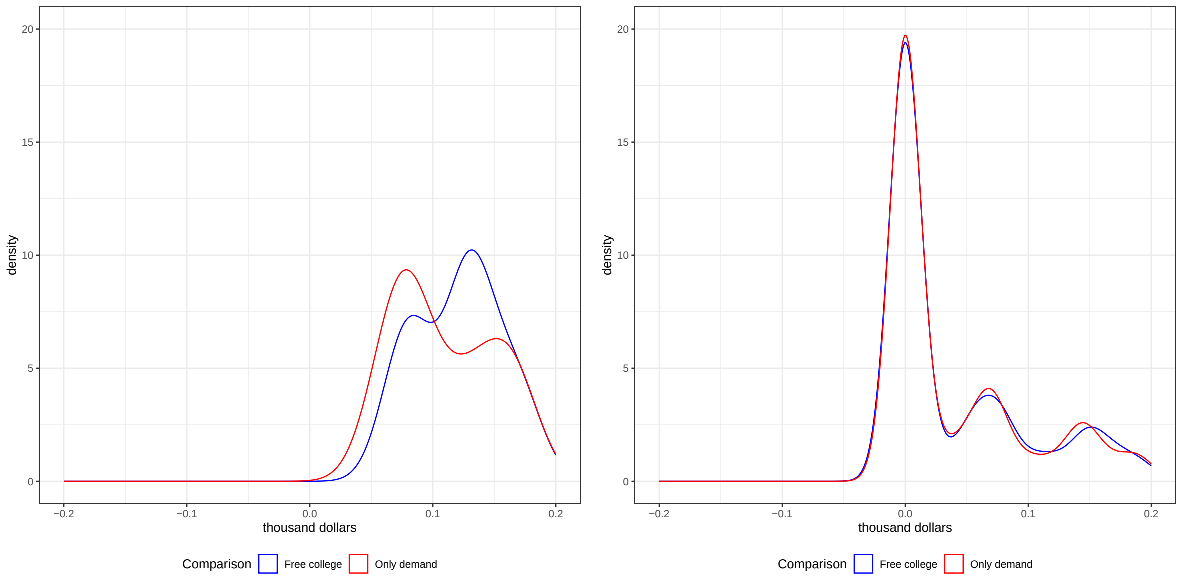
below for each one of them.

Programs with high exposure to the policy in terms of equation (7) tend to have responses that decrease the welfare of all types of students, particularly for non-eligible students. These responses may include actions that reduce enrollment in preferred programs such as price increases and capacity reduction, which is consistent with the predictions of the supply model. The simple pricing model described in 4.4 emphasizes that programs with a high fraction of eligible marginal students have more incentives to increase the price because the reduction in revenue produced by the free college voucher is larger. It, of course, reduces program revenue because there is usually a gap between the sticker price and the voucher, as seen in equation (7). This reduced revenue pressures price increases. However, this pressure is mediated by the fraction of eligible to non-eligible students at the margin of enrollment. If there are no eligible students at the margin of enrollment, the gap between the sticker price and the voucher does not pressure the sticker price.

Another relevant distinction is the quality of the programs where students enroll at baseline. Less than a quarter of eligible students who enroll in low-quality programs are better off after implementing free college. However, this more than doubles for high-quality programs. This is a relevant distinction because policymakers could aim to increase eligible students' enrollment in high-quality programs. Figure 9 depicts the change in mean utility for eligible students depending on the quality of the institution they enroll at baseline. [27]

[27] Students who for a particular vector of programs' strategies enroll more than half of the time in a high quality institution

Figure 9: Distribution of changes in eligible students' mean utility by program quality at baseline



(a) High quality

(b) Low quality

Eligible students who, at baseline, enrolled in a high-quality program experienced a large welfare gain mostly because they face a price of zero after the implementation of the policy. In the case of eligible students who at baseline enrolled at a low quality institutions had a much lower welfare gain. This could be driven by large fraction who enroll in a different program after the implementation of free college as seen in table 8. [28]

Table 8: Changes in eligible students' enrollment outcomes with and without supply responses, for programs of different quality

	High quality	Low quality
Baseline → Free college		
Mean welfare change (US$)	1,642	218.7
Same program (if always enrolled) (%)	79.2%	20.8%
Displacement to o.o (unconditional) (%)	7%	7.1%
Baseline → Only demand		
Mean welfare change (US$)	1,652	228
Same program (if always enrolled) (%)	77.6%	22.4%
Displacement to o.o (unconditional) (%)	9.5%	4.1%

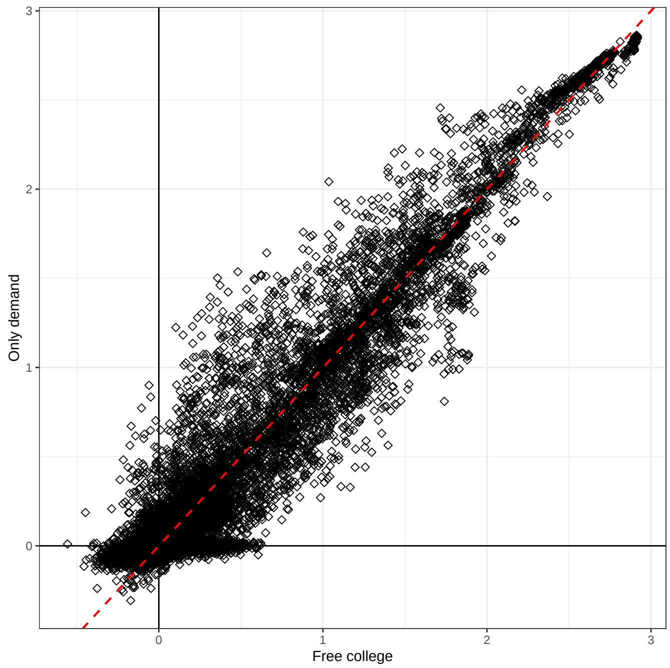
Figure 20 in the appendix presents the distribution of the change in mean utility for other subgroups of students for both comparisons. I define eight subgroups by interacting student characteristics and the programs' level of exposure to free college [29] All these dimensions are related to factors that my model anticipates should affect welfare after the implementation of the policy.

are classified as enrolling in a high quality program at baseline.

[28] I also analyze welfare change on students depending on their enrollment in programs that are more and less exposed to the policy. A detail on aggregate effects and mechanisms is presented in tables 29 and 30 in the appendix.

[29] Measured at the fraction of eligible marginal students. This fraction is defined as more than 75% of eligible students around the cutoff (+/- 2%).

Figure 10: Correlation in mean utility change at the student level for both comparisons



Note that each point depicted in the distribution from figures 8 and 9 does not represent the same student. Some students are worse off because of supply responses. Those students would have had a bigger utility in the 2016 counterfactual scenario than in the allocation with free college. I continue analyzing the role of supply responses in figure 10. This figure plots the mean change in utility of both comparisons at the student level, and shows groups of students are better or worse off due to supply responses. This figure allows me to recognize and characterize which groups of students are better or worse off due to supply responses. In the x-axis, I depict the change in the utility from comparison 1, and the y-axis shows the corresponding change from comparison 2. The 45-degree line is in red.

I use figure 21 to classify students into four groups: win-win, win-lose, lose-lose, and lose-win. For the first group, free college is welfare-enhancing, and supply responses amplify free college's effect on their welfare. For the win-lose group, supply responses dampen the increased utility produced by the policy. The students in the lose-lose group are those for which free college diminishes their welfare, and supply responses amplify this reduction. Finally, the lose-win group is students who experienced a decline in their utility due to free college, but supply responses overturn this reduction. Many students are better off after free college. However, students in the win-lose could have been better off without supply responses. Similarly, supply responses also amplify the reduction in utility for students in the lose-lose group. Considering both cases, I observe that 45 percent of students could have been better off if not for supply responses (groups win-lose and lose-lose). Specifically, 42 percent of eligible students and 47 percent of non-eligible students experienced a reduction in their welfare due to supply responses.

Table 9 shows the descriptive demographics of these four groups of students. Even though most eligible

Table 9: Characteristics of student groups affected differently by the policy

	win-win	win-lose	lose-lose	lose-win
Free college eligible (%)	44	85	12	71
Financial aid eligible (%)	33	43	21	67
Income decile 1 (%)	0.19	0.26	0.05	0.32
Income decile 2 (%)	0.35	0.83	0.15	0.7
Income decile 3 (%)	0.65	1.12	0.2	1.05
Income decile 4 (%)	35	67	10	55
Income decile 5 (%)	8	16	2	14
Income decile 6 (%)	6	2	11	4
Income decile 7 (%)	7	2	13	5
Income decile 8 (%)	7	2	11	3
Income decile 9 (%)	12	3	18	6
Income decile 10 (%)	5	1	6	2
Income decile NA (%)	19	7	30	9
Marginal students (%)	5	4	5	5

Note: This table characterizes the four student groups affected by free college differently. Total students is the only variable in levels; all other characteristics are in percentages. Financial aid eligibility is different from free college eligibility because the former includes academic requirements and not only financial requirements. The regulator defines the student's income decile for all students who apply for financial aid, comparing the verified self-reported income to the national income distribution. So the variable income decile NA corresponds to students who do not apply for financial aid. Finally, I define marginal students as the likelihood of being accepted in the bottom 20 percent of enrollment in the baseline allocation. The table reads as follows: 44 percent of students in group win-win are eligible for free college.

students are not worse off after the implementation of free college, 85 percent of students in the group win-lose are eligible. These are students for whom supply responses dampen the increased welfare. Conversely, non-eligible students represent a large fraction of students in the lose-lose group.

Table 10 complements the previous analysis and presents the students' likelihood of being part of one of the four groups affected by free college, i.e., win-win, win-lose, lose-lose, and lose-win. Table 10 reinforces the idea that eligible students are better off because of free college. However, almost 40 percent are worse off because of supply responses (groups win-lose and lose-lose). The opposite happens with non-eligible students. Even if nearly a third of them are better off because of free college, they have fifty percent chances of being losers (groups lose-lose and lose-win).

7.2 Programs

Free college induces changes in program decisions that impact students' welfare. This impact was summarized in the previous section. In this section, I describe the price and capacity changes induced by free college by comparing the optimal choices between the scenario with free college, including demand and supply responses, and the baseline without free college. The results from the previous section imply that we should not expect to see large changes in programs' decisions. This is the case because overall access to education is not drastically affected and also because the aggregate impact of price changes leaves non-eligible students almost indifferent. The reduced form results are consistent with this as they suggest that the effects of the

Table 10: Composition of student groups by students' characteristics

	win-win (%)	win-lose (%)	lose-lose (%)	lose-win (%)
Free college eligible	39	36	6	19
Financial aid eligible	39	24	14	23
Income decile 1	43	28	7	22
Income decile 2	34	38	8	20
Income decile 3	40	33	7	19
Income decile 4	40	36	6	18
Income decile 5	37	37	5	21
Income decile 6	41	5	44	9
Income decile 7	43	5	43	9
Income decile 8	48	5	40	6
Income decile 9	49	5	39	7
Income decile 10	55	3	37	5
Income decile NA	46	8	40	6
Marginal students	45	17	26	12

Note: This table describes the composition of each group of students considering a set of characteristics. Total students is the only variable in levels; all other characteristics are in percentages. Financial aid eligibility is different from free college eligibility because the former includes academic requirements and not only financial requirements. The regulator defines the student's income decile for all students who apply for financial aid, comparing the verified self-reported income to the national income distribution. So the variable income decile NA corresponds to students who do not apply for financial aid. Finally, I define marginal students as the likelihood of being accepted in the bottom 20 percent of enrollment in the baseline allocation. The table reads as follows: from all eligible students, 39 are in groups win-win, 36 in win-lose, 6 in lose-lose, and 19 in lose-win.

policy on programs' decisions are not large. However, small changes over an entire higher education system can have a much larger impact on total student welfare.

Particularly, in this section I compare the equilibrium distribution of actions in both scenarios and how the probability of each strategy changes across them. Table 11 compares the probability distribution over actions between the baseline and free college using different outcomes. In specific, it shows the average change, between the two situations in the probability of choosing each strategy.

For example, considering all programs, the probability of not changing the same price in the scenario with free college increases by 0.004 percentage points from the baseline case. The changes in the probabilities over strategies are small. But considering all programs and realizations of the vector of strategies they account for 49 percent of program increasing their price from baseline to the case with free college. The average price increase is 35 US dollars, consistent with the reduced form results.

In the case of capacity, the changes in the probabilities over strategies are also small. Considering all programs and realizations of the vector of strategies they account for of 49 percent of program increasing their capacity from baseline to the case with free college. The mean capacity increase is 1 slot, which is also consistent with the reduced form results. Programs that decrease their capacity also do it on average in 1 slot, which is consistent with the policy's small effect on access to education.

Finally, in terms of program revenue, programs from private institutions are relatively more prevalent among those programs that increased their revenue, whereas programs from public institutions are relatively more

Table 11: Average change in programs' probability of choosing each strategy after free college (percentage points)

	All programs
Same price	0.004
Increase price	-0.0006
Decrease price	-0.009
Same capacity	-0.001
Increase capacity	0.0005
Decrease capacity	-0.004

Note: This table shows how the actions of programs change, on average, when comparing the scenario with free college to the one without. The model predicts probabilities over actions, and in this table, I compare those distributions using different outcomes. The table shows the difference in the probability of each action in percentage points.

prevalent among those that decreased their revenue. More details on the characteristics of programs that increase or decrease their revenue with free college are in table 31.

8 Expanding the target of free college

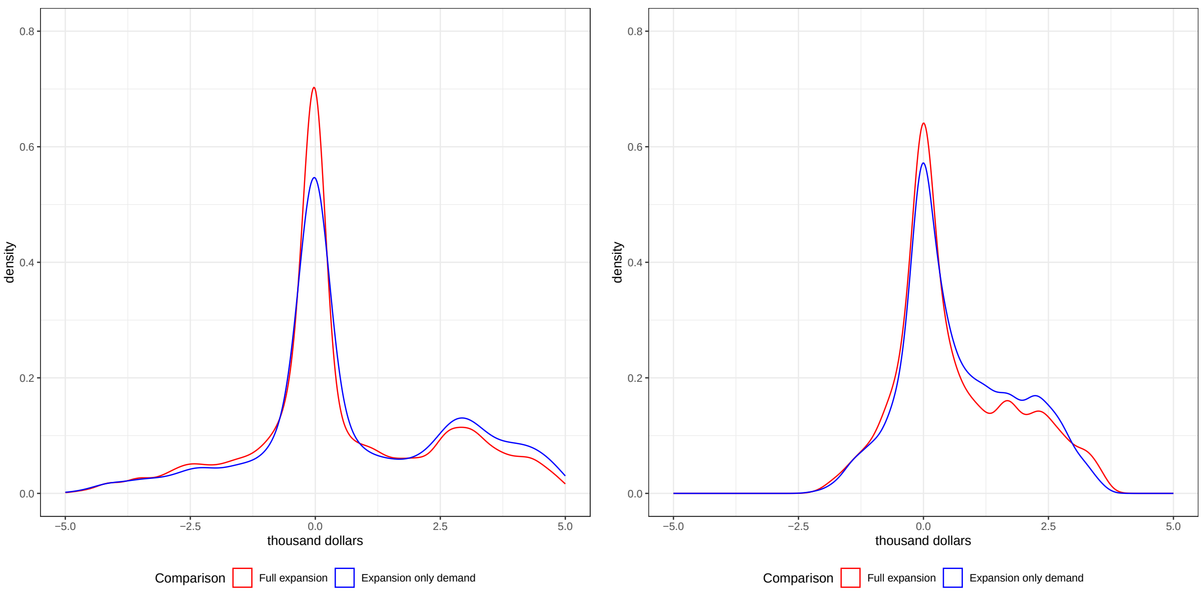
In this section, I use the model of higher education to analyze a counterfactual policy that expands free college to students from income decile 6 and above. Analyzing this counterfactual allows me to explore the policy question of expanding free college to all and its impact on welfare. If a policy of free college for all has no targeting, then we should expect that its impact on access to education is large. However, access to education of students from different income levels could be affected differently because, in the context of my application, income and academic performance are correlated. This is relevant because if increased access to education is limited by capacity constraints, students in the bottom 50 percent of the income distribution could be crowded out by richer students who are more likely to apply to the centralized admissions system once they receive free higher education.

8.1 Students

I compare the counterfactual expansion policy to the actual Chilean implementation of free college using the framework of section 7. I also compare a counterfactual expansion without supply responses (i.e., expansion demand only) to the actual policy to disentangle the impact of supply responses from the total equilibrium effects.

When the policy expands to all students, the rank-order lists of all previously non-eligible students change and through equilibrium effects, this shift impacts students' enrollment into programs, displacement to the outside option and access to education. The overall effect on access may imply a crowd-out of eligible students because they tend to have a worse PSU performance than non-eligible students. However, if the shift in demand of non-eligible students is such that it increases vacancies in program that eligible students include in their rank-order lists and are achievable, then crowd-out could be mitigated or non existent. Furthermore, the impact on access to education also depends on programs' capacity decisions. Eligible students' access to education may increase if programs for which they are competitive candidates increase their capacity after the expansion of free college. All in all, the effect of the policy is mixed, as some students will benefit from access and lower prices but others will be displaced.

Figure 11: Distribution of students' change in mean utility for different policies by eligibility in the actual policy



(a) Students from decile 1 to 5

(b) Students from decile 6 and above

Note: These figures show the distribution of the change in the mean utility at the student level using all the simulations to compare both scenarios. The axes are measured in thousand dollars. The case of expanding free college to all is depicted in red, and the case of expansion without supply responses is depicted in blue.

Overall, my results show that, on average, expanding free college is welfare enhancing because it increases access to education, even for previously eligible students. The increased access is the product of changes in capacity and the shift in demand of non-eligible students, as explained before. The aggregate impact on welfare is summarized in table 12, and figure 11 depicts the distribution of students' change in mean utility from the actual policy to an expansion of free college to all students, with and without supply responses. The impact for students from income decile 1 to 5, who are eligible under the actual policy, is mixed as depicted in the descriptive statistics of the distribution of welfare changes. The median impact is not large, mostly because a large mass of eligible students do not gain access to education once the policy expands, as seen in the mass at zero on figure 11's panel (a). Nonetheless, access to education increases welfare for a subset of previously eligible students, which are depicted by the mass at the right end of the distribution of welfare change. These students experienced a large increase in welfare as they enter the system.

Previously non-eligible students will also experience changes in enrollment, access to education and displacement to the outside option when the policy expands to all students. Moreover, when enrolled, they will also benefit from the reduction of prices. Considering all these channels, free college for all makes more than

Table 12: Welfare change after the expansion of free college to all students

	Decile 1 to 5	Decile 6 and above
Welfare change in dollars: Actual policy → Expansion		
1st quantile	-161	-149
Median	125	150
Mean	794	756
3rd quarter	1838	1697
Welfare change in dollars: Actual policy → Expansion demand only		
1st quantile	-113	-102
Median	263	307
Mean	926	882
3rd quarter	2,114	1,920

a quarter of non-eligible students worse off and implies a positive median and mean effect on non-eligible students' welfare. The effect of the policy is mixed, however the reduction of prices has a positive effect on many non-eligible students as seen in panel (b) of figure 11. This is depicted by a fat right end of the distribution.

Table 13 summarizes the impact on access to education of expanding free college, for students of different income levels. Overall, expanding free college increases access to higher education. This is true for all types of students, but it is more pronounced for students with higher income. As mentioned before, in the Chilean context income and PSU performance are correlated. Then students with higher income are more likely to enroll, conditional on certain capacity constraints. Nonetheless, the combination of demand and supply responses increase access of previously eligible students in 2 percentage points.

Table 13: Enrollment outcomes under different policies for different groups of students

Enrolled in scenario	Decile 1 to 5	Decile 6 and above
Actual policy	29%	26%
Expansion	31%	32%
Expansion demand only	34%	34%

Table 13 also shows that supply responses dampened the increase in access to education produced by the expansion of free college, and more for previously eligible students. The table compares access to education for the actual policy, the counterfactual expansion of free college, and an expansion without supply responses (expansion demand only). Even though access to education would increase for all types of students if the policy expands, programs would respond in a way that diminishes the increased access more for student with lower income relative to a case where supply responses are restricted. In the next section I describe the changes in supply responses that produced this result.

8.2 Programs

Programs that subscribe to free college choose their capacity to maximize their objective function. Programs that do not subscribe to the policy choose price and capacity. These choices are discrete and defined just

Table 14: Probability distribution over capacity choices of actual policy and free college for all

Predicted probability (N=1000)	Actual policy	Free college for all
Reduce capacity (%)	16	12.1
Keep capacity (%)	65.8	70.4
Increase capacity (%)	18.2	17.5

like in section 4.4.1. The maximization problem follows the same steps as in the supply model. First, I define beliefs over the choices of the competition. Second, I estimate a random forest model to approximate revenue. Finally, I solve the maximization problem of the program using the estimates for the parameters in the objective function.

For this analysis, I assume that the beliefs over the actions of the competitors are fixed and given by the ones estimated in A.5. This is a simplification as new beliefs could be estimated as part of the new equilibrium. However, as capacity is harder to change than price, the beliefs predicted in the supply model are a good approximation. Along these lines, keeping beliefs constant implies that the choices of the programs can be interpreted as short-term responses because they have the same alternatives as before free college for all.

Expanding free college to free college for all eliminates the possibility of price discrimination. The strategies available to programs are unidimensional; with capacity being the only possible action. Price is no longer a tool that affects demand and the composition of the enrollment of a program does not have an impact on its revenue. Once free college expands to all students, the marginal revenue of programs decreases mechanically because they lose the gap between the sticker price and the voucher for each student who enrolls. However, this does not imply that total program revenue decreases. First, enrollment is expected to increase because applications increased due to the expansion of free college, as suggested by my previous results. Furthermore, programs could also increase their capacity as a result of the expansion of free college. This capacity increase is likely to translate into increased enrollment because of the increase in applications induced by the policy. Note however, that increasing capacity also has a direct cost that impacts programs' profits.

If free college is expanded to all students, the probability distribution over actions puts less weight on capacity reductions. Particularly, as seen in table 14 programs are, on average, 4 percentage points less likely to reduce capacity. Therefore, if free college is expanded to all students, on average, 54 percent of programs would increase their capacity which would add 420 seat into the system. Note that this is not the only way in which expanding free college increases access. Programs that do not change their capacity might fill all their seats due to the increase in demand induced by the expansion of free college. Also, changes in the demand of previously non-eligible students could be such that more achievable seats are available for low income students. After the expansion of free college access to education would increase due to a combination of all these factors because the average increase in capacity is not enough to accommodate the increase in enrollment shown in table 13.

This analysis considers the strategies that are in the choice set of programs. It could be argued that other strategies might be pertinent when free college expands to free college for all. Also, my analysis does not take into account the long-term effects of free college for all, like potential decreases in program quality. Or increases in the number of students who take the PSU and their performance in this test.

9 Conclusion

The affordability of public higher education is a social and political debate that has gained traction in many countries. This is usually called "free college" despite that it includes various options from targeted subsidies to universal free college. Each option has its pluses and minuses. A less targeted subsidy is likely to benefit more students, but also will have a larger impact on the higher education system overall including universities' financial situations and the revenue from specific programs. This impact can lead to reactions such as adjusted prices or capacity per program, which will then impact students, even those who do not receive such aid. It could affect access to college overall or specific programs for certain students, while also changing the nature of programs. Thus, free college policy produces demand and supply responses that impact the equilibrium. This paper studies the extent of these responses in the context of the Chilean implementation of targeted free college and, particularly, analyses whether supply responses amplify or moderate the effects of free college.

Evidence from a difference-in-difference strategy with variation in treatment intensity at the program level suggests that students eligible for free college are more likely to apply and enroll in relatively more expensive programs compared to before the policy. This evidence points towards a change in students' behavior due to it. A similar difference-in-difference strategy concludes that programs whose revenue would have decreased more, given the shift in demand, increase their capacity and price more. This reduced-form evidence shows that free college does impact demand and supply decisions. Even though the impact on supply decisions is small at the program level, small changes over an entire higher education system can have a much larger impact on total student welfare.

I develop and estimate a model of the higher education market, while using rich observable data on student characteristics to capture flexible preference heterogeneity. I identify price elasticity using the arbitrary income cutoff of the free college policy and across market price variation. The parameter of price sensitivity is critical to analyzing counterfactual scenarios. Then, I present and estimate a supply model of discrete choice in which programs maximize their objective function by choosing price and capacity. The rationale behind this model is two-fold. First, it solves the computational complexity of the standard approach of inverting first-order conditions. The discrete actions also better capture how programs choose capacity and price.

I solve a model that allows for programs' strategic responses within a centralized assignment mechanism, which are widely used in many educational markets including Chile's higher education market. To the best of my knowledge, my paper is one of the first to connect these two literatures. In my model, programs choose price and capacity, and enrollment is defined by the DAA considering programs' capacity constraints. This occurs in the context of price differentiation between free college eligible and non-eligible students. My model shows that price and capacity are key strategic forces that can affect eligible and non-eligible students' enrollment differently.

I compute the impact of the policy and the role of supply responses by analyzing a decomposition counterfactual in which I compare the welfare of students before and after free college and in a case where supply responses are restricted. My results show that supply responses have a relatively small effect in aggregate compared to demand responses, however, their effect is large for certain subsets of students, and, more importantly, these responses affect the success of the policy because they increase the mass of eligible students who stay in the outside option both before and after the implementation of the policy. The impact on supply responses is mediated by student characteristics. Free college is a welfare-enhancing policy for 40 percent eligible students since they no longer must pay for or figure out how to pay for tuition. However, the welfare of almost 45 percent of the student body could have been higher if it were not for supply responses. Non-eligible students experienced a significant reduction in welfare primarily driven by both displacements to the outside option and price increases. Moreover, the policy does not have a relevant effect in access to education as it increases displacement to the outside option for certain students and access for others in similar amounts.

Finally, my results show that expanding free college to all students will necessarily create winners and losers among previously eligible students. On average, eligible students would be better off if the policy expands as their access to education increases in 2 percentage points. Also, access of non-eligible students would increase in 6 percentage points. Nonetheless, supply responses dampen the positive effect on access to education for all the student body. Hence, supply responses are crucial in assessing the benefits of free college and need to be considered when designing and expanding such financial aid policies.

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A Appendix

A.1 Other financial aid programs

Free college coexists with other types of financial aid created before 2016. The financing mechanisms include loans and scholarships. Notably, a substantial state-guaranteed loan (CAE) that expanded in 2012 by reducing its interest rate from 5.8 to 2 percent. Free college also coexists with scholarships considering academic and socioeconomic requirements. The eligibility for these scholarships expanded between 2011 and 2015, increasing and diversifying the potential student body.

CAE is a massive state-guaranteed loan program created in 2006, under which private banks provide college tuition loans to eligible students who enroll in accredited institutions.[30] Students decide the amount to request to meet their financial needs up to the reference tuition[31] and pay a rate of 5.8%. The interest rate was cut down to 2% in 2012. Access to the loan depends on socioeconomic need and a test score cutoff[32] if the student wants to apply to a university, or a GPA or PSU cutoff if the application is for vocational education. By 2015, the program could be used by students of all income levels who meet the academic requirement.

The CAE loan has been widely studied in the literature. Based on a regression discontinuity design on CAE's requirements, Solis (2017) presents evidence of credit constraint in Chile's higher education. Notably, the author finds that the gap between high-income and low-income students closes after creating CAE. Aguirre (2019) also analyzes the effects of CAE using an RD design. However, she considers its long-term outcomes by comparing students who qualified to use the loan in universities and vocational education. The results show that loans for universities induce low-performing students away from technical schools and towards higher-quality university alternatives, where they have little chance of succeeding.

Scholarships were available for students before the creation of CAE. The scholarships[33] are assigned to students who enroll in accredited institutions using cutoff rules for family income quintile and admission test scores. Scholarship eligibility expanded between 2011 and 2015, increasing and diversifying the potential student body.

Bucarey (2018) analyze this expansion and concludes that it might have crowded-out students at the bottom of the income distribution that is less competitive for the scholarships once it expands to students who are relatively less poor and that might have better academic credentials.

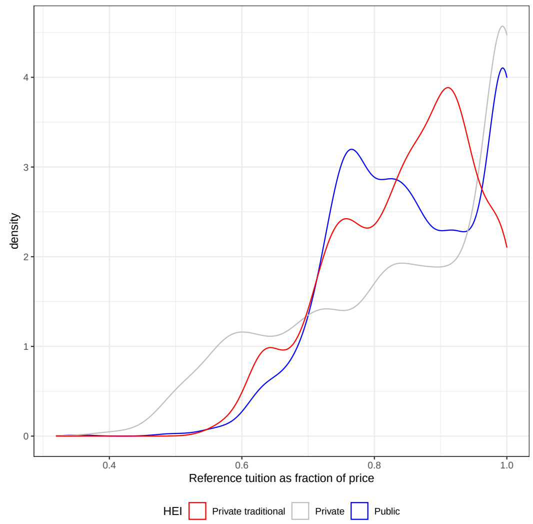
[30]Institutions are certified by the *Comision Nacional de Acreditacion* (CNA) that aims to secure and promote quality of HEIs. Accredited institutions can receive public funds through different mechanisms, such as CAE.

[31]Reference tuition is also defined by the Ministry of Education using a formula.

[32]The cutoff is defined using the college admission exam PSU.

[33]These scholarships are for accredited institutions and have requirements, as mentioned before. Mainly, Beca Bicenteraio is for CRUCH universities, Beca Juan Gomez Millas for all those universities founded after 1980, and Beca Nuevo Milenio for vocational education.

Figure 12: Distribution of reference tuition as a fraction of full tuition in 2015 by type of university



A.2 Reference tuition 2015

Reference tuition defines a student's maximum from CAE or a scholarship. In 2015, reference tuition covered, on average, 84 percent of the real price. This number varies year by year and across institution-program pairs. One year before the implementation, reference tuition covered 30 to 100 percent of full tuition. On average, reference tuition covers a higher fraction of full tuition in public universities and less in private universities.

Table 15: Reference tuition as a fraction of full tuition in 2015

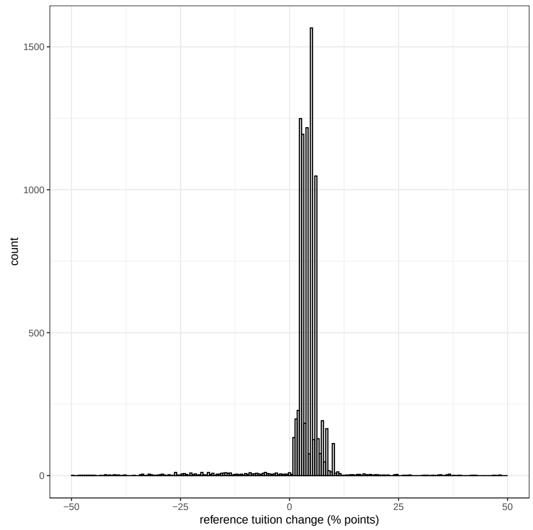
HEI	Mean	P10	P25	P75	P90
Public universities	0.86	0.72	0.77	1.00	0.11
Private universities	0.83	0.59	0.72	1.00	0.16
Private traditional universities	0.85	0.70	0.76	0.99	0.11

Figure 13 depicts the change in reference tuition in the sample. This distribution mimics the distribution of price changes. Ninety-six percent of changes are non-negative, and the mean of the change is 3.8 percent.

A.3 Illustration of the effect on price differentiation in the choices of programs

This section briefly illustrates how pricing and capacity decisions might be affected when the policy introduces differential prices. I consider two simple cases to describe how capacity choices can increase revenue in the presence of differential prices. The conclusions drawn from this section provide insights into how capacity choices are a tool for institutions beyond prices that could increase revenue in the presence of students who do not respond to price.

Figure 13: Change in reference tuition from 2013 to 2018



Note: This figure only includes price changes between -50 to 50 percent.

A.3.1 Perfect substitutes

Consider the case of two firms that are perfect substitutes and, in the first stage, commit to a level of capacity and then, in the second stage, compete in prices. Kreps and Scheinkman (1983) shows that the Cournot outcome holds as a unique equilibrium of this two-stage game under some circumstances. Then, using the Cournot outcome, I will argue that the price differentiation introduced by free college could induce prices to increase and capacity to decrease due to using capacity as a commitment device.

The traditional Cournot analysis, as presented in Tirole (1988), concludes that the Lerner index is proportional to the firm's market share and inversely proportional to the elasticity of demand.

$$L_j = \frac{P\left(Q\right) - C_j^{'}\left(q_j\right)}{P\left(Q\right)} = \frac{q_j}{Q} \times -\frac{P^{'}\left(Q\right)}{P\left(Q\right)} Q$$

Now consider that demand is differentiated between those consumers who pay full price Q^p and those who do not pay but for which firm j receives a transfer equal to v_j, Q^v. Notice that if firm j changes capacity, the effect on q_j^p and q_j^v depends on how these types of consumers are ordered in terms of willingness to pay. The allocation of the goods is done considering willingness to pay. Then, it is not hard to derive the Lerner index for firm j:

$$L_j = \frac{P\left(Q^p + Q^v\right) \times \frac{\partial q_j^p}{\partial q_j} + v_j \times \frac{\partial q_j^v}{\partial q_j} - C_j^{'}\left(q_j^p + q_j^v\right)}{P\left(Q^p + Q^v\right)} = \frac{q_j^p}{Q^p + Q^v} \times -\frac{P^{'}\left(Q^p + Q^v\right)}{P\left(Q^p + Q^v\right)}\left(Q^p + Q^v\right)$$

Relative to the standard case, the revenue produced by increasing q_j depends on the type of consumer assigned the extra units and the value of those units for the institution. Also, the Lerner index is proportional to the firm's market share of consumers type p and inversely proportional to the elasticity of demand of these consumers. Regarding differential prices, capacity q_j could decrease if the elasticity of consumer type p is higher than the standard case. If these consumers are more willing to pay because these conditions imply a higher price, a smaller capacity is needed for market clearing.

A.3.2 Vertical differentiation

Consider the case of two firms of a different quality that commit to a capacity level in the first stage and then in the second stage compete in prices. All consumers agree on which level of quality is best, but they all have a different willingness to pay for quality. Now consider that demand is differentiated between those consumers who pay full price Q^p and those who do not pay but for which firm j receives a transfer equal to v_j, Q^v. Notice that if firm j changes capacity, the effect on q_j^p and q_j^v depends on how these types of consumers are ordered in terms of willingness to pay. If capacity is costly, the level chosen in the first stage should bind in equilibrium. Then, there is an equilibrium in which capacities are binding; prices maximize revenue given capacity such that the marginal consumer is indifferent between both firms.

Now consider that demand is differentiated between consumers type p who pay full price and consumers of type v who do not pay but for which firm j receives a transfer equal to v_j. Notice that if the firm of high-quality changes capacity, the effect on profits depends on how many consumers of type p and v are around the margin of the marginal consumer, which depends on their willingness to pay for quality.

In this case of vertical differentiation, the new equilibrium might feature a larger capacity of the high-quality firm to increase profits. This could happen if there are more type p consumers relative to type v at the margin of the original capacity, which implies that an increase in capacity captures more consumers of type p if the price is low enough.

In my application, programs are not perfect substitutes, and they display different levels of quality, particularly when comparing the same program across institutions. Also, students are sorted into programs according to their preferences and PSU scores. Then, an institution cannot reject a particular student based on any observable characteristics, including their eligibility for free college, besides their PSU scores. In this context, the insights from the previous analyses suggest that program capacity could decrease or increase in the new equilibrium with differential prices depending, in part, on the ratio of eligible (or type l) and non-eligible students (or type h) at the score cutoff, the elasticity of non-eligible students and the relationship between the voucher and the price.

A.4 Results of demand estimation using income deciles to define cells

A.4.1 Cells defined using groups of deciles: 1 to 4, 5, 6, 7 to 10, and unknown.

I extend the previous results of the demand estimation by introducing an alternative definition of cells that uses the income to define income decile groups instead of grouping them into a binary category, like free college eligibility. This alternative definition aims to introduce income heterogeneity in the analysis. This type of heterogeneity is relevant if the counterfactual of interest is expanding free college to a specific income group, as mentioned before. Tables 16 and 17 present the results of estimating (9) defining c using income decile groups and the same identification strategy described before.

To compare the different income decile groups, I consider students with similar price menus considering two dimensions. Then, tables 16 and 17 separate students according to their eligibility for aid other than free college and their income decile group. Both dimensions are relevant to define the menu of prices. First, consider students eligible for free college; all of them face a zero price after implementing the policy. However, before the policy, those students eligible for other aid observed a price menu with lower prices than those who were not. The other dimension is the income decile; in principle, students from higher income deciles could be less sensitive to price. Moreover, both dimensions interact. Students from a higher income decile are less likely to be classified for financial aid because of how this aid is assigned. Then, students from a higher income decile tend to face larger prices. It is also important to mention that institutions could provide financial aid directly to students and are more likely to give this aid to low SES students. This data is not observable, implying that the price menus observed by low-income decile students could have lower prices than in the observed data.

Table 16 shows that students from income deciles 1 to 4 are more sensitive to price if they are not eligible for aid other than free college when comparing columns 1 and 2. This is consistent with those students facing a price menu with higher prices. It isn't easy to make the same comparison for income decile group 2 because the specification in column 4 produces a statistically zero coefficient. However, I can compare students from columns 1 and 3. This comparison keeps aid eligibility constant and presumably price menus, but income varies across these columns. Students with lower income (column 1) are less sensitive to price than students with higher income (column 3). This result is not as expected but could be related to the fact that these two groups do not face the same price.

Furthermore, table 17 presents the results for students who are not eligible for free college. Students not eligible for free college are less likely to qualify for other aid because these two subsidies are assigned based on income. From the group of students who are not eligible for free college, group 3, which corresponds to those students from income decile 6, is of utmost interest because this group is the natural group to which the policy could expand (and expanded a few years after its implementation).

Table 17 shows that students from income decile 6 (group 3) eligible for aid other than free college are more sensitive to price than students from higher income groups. This is also the case when comparing within group 3 and across aid eligibility (columns 1 and 2). However, as seen in column 2, the price coefficient is not statistically significant from zero for students from income decile 6 who are not eligible for aid other than free college. This could be because of the sample size.

Now consider group 4 in columns 3 and 4. In this case, the comparison is complicated as the price coefficient in column 3 is not statistically different from zero. This implies that aid-eligible students, hence observing a menu of lower prices, are less sensitive to price than those who do not qualify for other aid. However, this conclusion reverses if I consider the level of the price coefficients.

Finally, students from group 5 are more sensitive to price than other groups from lower income deciles. This

Table 16: Second stage: Cells eligible for free college by decile group - Estimation by OLS

	Dependent variable: δ_{jct}			
	Group 1 Aid Eligible	Group 1 Aid Ineligible	Group 2 Aid Eligible	Group 2 Aid Ineligible
Price (dollars)	-0.00002^{**}	-0.00004^{***}	-0.00003^{***}	0.00003
	(0.00001)	(0.00001)	(0.00001)	(0.00002)
Mean PSU	1.43^{***}	1.76^{***}	1.17^{***}	1.93^{***}
	(0.05)	(0.06)	(0.05)	(0.14)
Number of students	0.003^{***}	0.003^{***}	0.002^{***}	0.002
	(0.001)	(0.001)	(0.001)	(0.002)
Fraction private HS	-0.91^{***}	-0.69^{***}	-0.97^{***}	-0.01
	(0.20)	(0.21)	(0.19)	(0.50)
Fraction low SES	0.63^{***}	0.36^{***}	-0.03	0.08
	(0.12)	(0.13)	(0.12)	(0.32)
Year FE	Yes	Yes	Yes	Yes
Program FE	Yes	Yes	Yes	Yes
Inst-Area FE	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes
Observations	33,782	20,812	11,735	8,255

Note: Group 1 contains income deciles 1 to 4, and group 2 only decile 5.
*p<0.1; **p<0.05; ***p<0.01

result is similar to what was described in table 16; it is possible that students from lower-income groups receive direct aid from institutions, affecting the interpretation of price sensitivity.

A.5 Estimation of beliefs about the actions of competitors

I estimate the beliefs about the actions of competitors using an alternative-specific multinomial logit model that includes alternative and case variables.

$$choice_{ij} = \beta_{jk} \sum x_{ik} + \delta_r \sum x_{jr} + \nu_{ij}$$

Each program i chooses among $j = 9$ alternatives or strategies combining price and capacity actions. Alternative specific variables x_r include the level of capacity and price change, also an indicator for increasing capacity and an indicator for increasing price. These variables capture the adjustment in capacity and price at the program level. Also, the model includes case variables characterizing the choice situation, including the program's standardized capacity and price before the choice and fixed effects for program type, type of institution the program belongs to, year, and zone. Case variables x_k have alternative-specific coefficients β_{jk}.

The estimation of beliefs is done prior to the solution of the supply model, as in Sweeting (2009). This model is estimated using observed data on price and capacity changes for all markets from 2014 to 2018. Table 18 presents the results of the logit model estimation. First, strategies that reduce capacity or price are

Table 17: Second stage: Cells ineligible for free college by decile group -
Estimation by IV

	Dependent variable: δ_{jct}				
	Group 3 Aid Eligible	Group 3 Aid Ineligible	Group 4 Aid Eligible	Group 4 Aid Ineligible	Group 5 Aid Ineligible
Price (dollars)	-0.00003^{***}	-0.001	-0.00002	-0.003^{***}	-0.003^{***}
	(0.00001)	(0.001)	(0.00003)	(0.001)	(0.001)
Mean PSU	1.11^{***}	1.69^{***}	1.08^{***}	1.44^{***}	1.56^{***}
	(0.05)	(0.11)	(0.19)	(0.05)	(0.08)
Number of students	0.002^{**}	0.004^{***}	-0.001	-0.001	0.0005
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Fraction private HS	-1.13^{***}	-1.24^{***}	-1.11^{*}	-0.16	-0.04
	(0.19)	(0.40)	(0.59)	(0.18)	(0.23)
Fraction low SES	0.08	-0.31	-0.76^{*}	-0.86^{***}	-0.16
	(0.13)	(0.27)	(0.40)	(0.14)	(0.24)
Year FE	Yes	Yes	Yes	Yes	Yes
Program FE	Yes	Yes	Yes	Yes	Yes
Inst-Area FE	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes
FS F statistics	62409	106	54846	467	222
Observations	10,407	7,852	8,269	36,907	23,791

Note: Group 3 contains income decile 6, group 2 deciles 7 to 10, and group 5 is for unknown decile.
*p<0.1; **p<0.05; ***p<0.01

less likely to be chosen relative to the baseline. This is consistent with the fact that all else equal, reducing capacity or price decreases revenue. Second, state variables capture specific characteristics of the program, and the coefficients from strategies 1 to 8 show the impact of choosing that action over the baseline. For example, programs that are relatively more expensive (Std price) are more likely to choose strategies that increase price relative to the baseline. Third, all specifications include fixed effects with strategy-specific coefficients.

Table 18: Alternative-specific logit model of beliefs about the actions of competitors

Variables	(1) Strategy	(2) 1	(3) 2	(4) 3	(5) 4	(6) 5	(7) 6	(8) 7	(9) 8
Alternative specific									
Level capacity change	-0.0183***								
	(0.00242)								
Level price change	-3.10e-06***								
	(3.18e-07)								
Binary capacity increase	-1.821***								
	(0.246)								
Binary price increase	-0.313								
	(0.236								
State variables									
Std capacity		-0.000117	0.000132	-0.000721***	-0.000357*	-0.000172	-0.000243	-0.000655**	-4.50e-05
		(0.000234)	(0.000256)	(0.000244)	(0.000200)	(0.000173)	(0.000169)	(0.000263)	(0.000197)
Excess capacity FE		-1.421***	-1.547***	-1.664***	-0.777***	-0.380***	-0.630***	-0.224	0.341***
		(0.142)	(0.150)	(0.144)	(0.124)	(0.108)	(0.102)	(0.160)	(0.121)
Std price		-9.48e-05	-0.000129*	5.59e-05	4.00e-05	-6.60e-06	0.000203***	-2.30e-05	2.37e-05
		(7.19e-05)	(7.45e-05)	(7.40e-05)	(6.43e-05)	(5.30e-05)	(5.22e-05)	(8.19e-05)	(6.06e-05)
Observations	65,979	65,979	65,979	65,979	65,979	65,979	65,979	65,979	65,979
Program type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Institution type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: Strategies 1 to 3 have a capacity that decreases, and the price is decreased, constant, and increased respectively. Strategies 4 to 6 have a constant capacity, and the price is decreased, constant, and increased respectively. Strategies 7 to 9 have a capacity that increases, and the price is decreased, constant, and increased respectively. All specifications include fixed effects for program type, institution type, year, and region that have strategy-specific coefficients.

The predicted probabilities fit the observed data very well. Over two random samples of $N = 100$ and $N = 2000$ vectors of strategies drawn using the predicted probabilities, the predicted frequency of each strategy is very similar to the frequency of observed strategies. The comparison is presented in the following table.

Table 19: Frequency of strategies for different samples

Strategy	Observed	Predicted (N=100)	Predicted (N=2000)
1	0.0650	0.0639	0.0640
2	0.0454	0.0447	0.0450
3	0.0502	0.0487	0.0491
4	0.1170	0.1195	0.1191
5	0.2873	0.2892	0.2890
6	0.2252	0.2290	0.2285
7	0.0338	0.0321	0.0324
8	0.0845	0.0851	0.0851
9	0.0915	0.0880	0.0878

Note: The frequency is measured in percentage points.

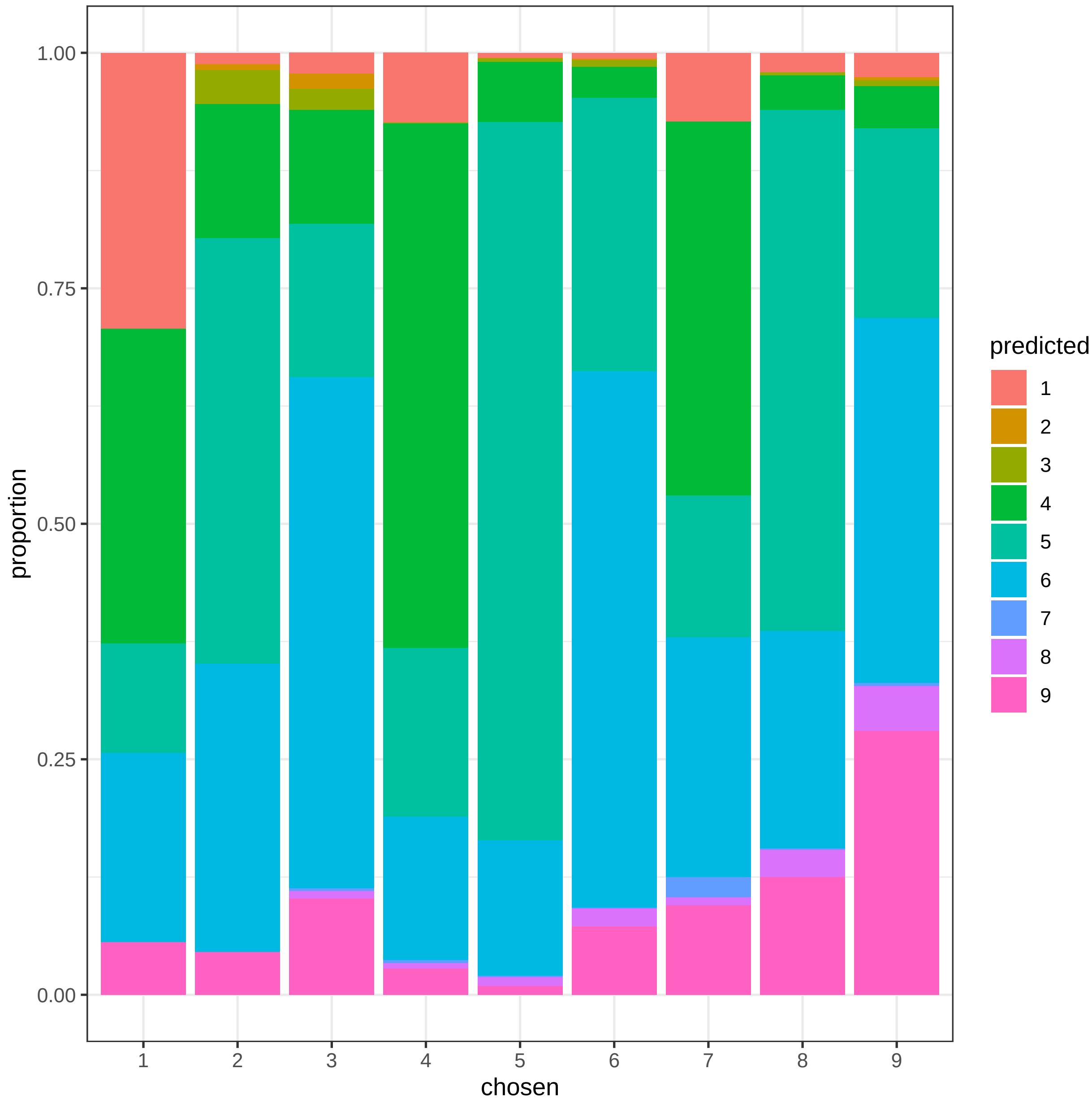
Figure 14 depicts the model's performance by presenting the coincidences between the chosen and predicted strategy. The model performs better for those strategies that are more likely to be selected, such as 4, 5, and 6.

A.6 Random forest model

To estimate the cost function, I need profits under different combinations of prices and capacity strategies. The revenue function is known for a given vector of prices and capacities; it is price times quantity. Price can have two components: sticker price and voucher. Quantity is defined by the DAA. The algorithm takes capacity and preference as inputs to produce an allocation. The algorithm's rules are known, and computing the algorithm a handful of times is simple. However, solving the algorithm for all 500^9 possible combinations of strategies in one market is computationally costly. So even though the revenue function and its inputs are known, an approximation is needed. This approximation captures how the DAA operates.

Because I have tabular data and do not need the reduction of dimensionality provided by the hidden layers of a deep neural network (DNN), a random forest model is better than a DNN model because they are faster to estimate (Grinsztajn, Oyallon, and Varoquaux (2022)). Random forests are effective methods for flexible estimating functions where out-of-sample performance is important (Athey and Imbens (2019). The main idea of the method is to split the sample into subsamples and estimate the regression function within the subsamples and then average the outcome. As suggested by Athey and Imbens (2019), one way to interpret a tree is that it is an alternative to kernel regression and a random forest as a way of generating weighting functions analogous to kernel weighting functions. Or that the estimator from a single regression tree is a matching estimator with nonstandard ways of selecting the nearest neighbors. And since each tree is a form of matching estimator, the forest is an average of matching estimators.

Figure 14: Performance of beliefs model

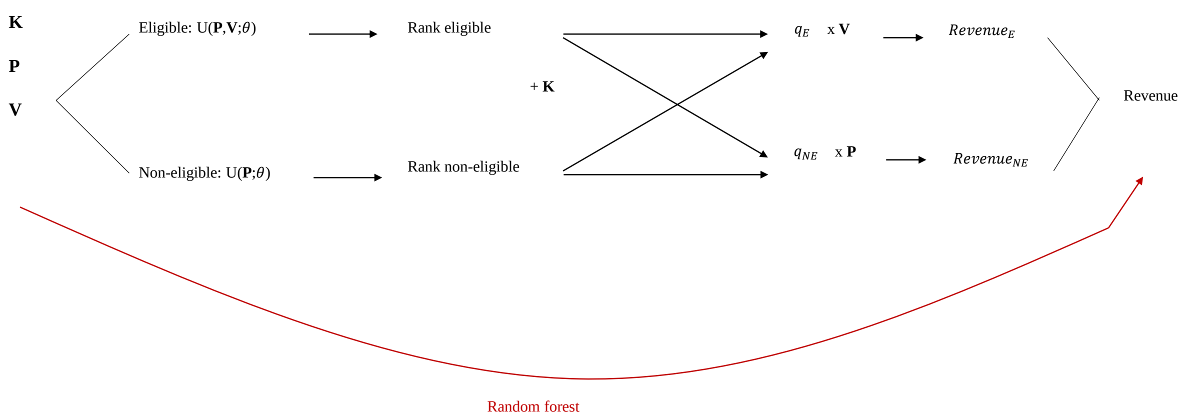


Note: The frequency of each strategy is presented in table 19.

In a random forest model, the training data provides all the information used to estimate the model. Preference parameters and the structure and characteristics of the market are embedded in the data-generating process as depicted in figure 15.

The random forest model is estimated at the program level using a training sample of size 801. The training sample includes four different years, two before and two after the implementation of free college. The training sample is formed according to the data-generating process and selected without replacement using

Figure 15: Data-generating process for random forest estimation



Note: This diagram depicts the data-generating process used to estimate a random forest model for each program. Programs choose price and capacity, P and K, and the regulator defines a voucher V. Conditional on the price and voucher level of each program, eligible and non-eligible students for a rank order list according to the preference parameters θ estimates by the demand model. These rank lists and the capacity of programs are inputs of the DAA, and the algorithm outputs the quantity of eligible and non-eligible students enrolled in each program, q_E and q_{NE}. Given these quantities, the revenue of each program is computed.

Table 20: Variable importance for different markets

(1) North		(2) Capital		(3) South	
First importance					
$price$	91%	$price$	82%	$price$	76%
Second importance					
pc_{d2}	9.8%	pnc_{d5}	13.7%	pnc_{d4}	14%
pc_{d9}	9.8%	pnc_{d2}	10.5%	pnc_{d7}	9.8%
pc_{d1}	9.2%	pc_{d9}	8.4%	pnc_{d6}	8.5%
vc_{d1}	9%	pc_{d1}	7%	pnc_{d5}	8.3%
pc_{d5}	6.2%	pc_{d2}	5.9%	pnc_{d2}	7.2%
Third importance					
pnc_{d2}	10.2%	pnc_{d5}	13.9%	pnc_{d4}	11.9%
pc_{d5}	9.6%	pnc_{d6}	10.6%	pnc_{d6}	10.6%
pc_{d2}	7.6%	pnc_{d8}	8.6%	pnc_{d5}	10%
vc_{d1}	6.3%	pc_{d8}	5.1%	pnc_{d2}	9.8%
pnc_{d6}	5.9%	pc_{d2}	4.8%	pnc_{d7}	9.5%

Note: This table presents a summary of the variable importance for all random forest models for markets in the north, capital, and south regions. Each region includes data on programs from four years, from 2014 to 2017. The number of programs in each region is 511, 526, and 529 respectively. The table shows the top 5 variables that are of first, second, and third importance considering all the random forest models in each region. Price and capacity are the own price and capacity, pnc_d variables are the decile d of the price of non-competitors, i.e. programs from a different type, and pc_d are the decile d of the price of competitors.

the estimated belief described in A.5. The training sample maps the price and capacity of a program into its revenue. The particular allocation of students into programs is computed using the DAA. The model is implemented in R using the package 'ranger' (Wright et al. (2019)). The parameters of the random forest model, number of trees, and minimum node size were chosen, among 40 possible models, as the result of the minimization of the MSE of the testing sample.

Table 20 shows the variable importance of the random forest models of programs in different markets. The price of the program is the most important variable for programs in all markets. This is expected because the price has a direct effect on revenue and also an indirect effect through its impact on the rank order lists of students. Capacity is also a variable that is either of first or second importance for many programs. Remember that capacity is a direct input of the DAA. Finally, the price of competitors and non-competitors appear in the top 5 of the first, second, and third importance. Prices of other programs seem to have higher predictive power than the capacity or voucher of other programs. This could be because the price of other programs impacts the rank order list directly.

I use the predicted random forest models to predict the revenue of each program conditional on a particular price and capacity. The output of the approximation is the revenue of the program and the inputs are the capacity, price, voucher of the program, and decile of capacity, price, and voucher of close competitors (same type of program), and decile of capacity, price, and voucher of other competitors (different program type).

A.7 Estimates of FE from supply model

The following table presents the estimates of the fixed effects from model (12).

Table 21: Estimates of FE from supply estimation

Strategy	A	B	C	D
1	-0.140	-1.018***	-1.003***	1.275
2	-0.131	-1.039***	-0.810***	1.907**
3	-0.582***	-0.808***	-0.157	0.588
4	0.765***	0.0765	-0.931***	3.119***
5	2.010***	0.632***	0.861***	3.633***
6	1.675***	0.627***	0.926***	-0.0517
7	-0.495***	-1.479***	-1.521***	-0.00759
8	0.457***	-0.862***	0.539***	1.942**
9	-	-	-	-

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: The estimation is done by multinomial logit, with strategy nine as the baseline.

A.8 Supply model with heterogeneous coefficients

The following table presents a version of model (10) where the supply is heterogeneous and depends on the type of program.

Table 22: Estimation of supply model with heterogeneous coefficients

Variables	(1)	(2)
Revenue (US$)	0.00634***	0.00987***
	(0.000922)	(0.000975)
Capacity (slots) x		
Administration	0.0102	0.0136**
	(0.00705)	(0.00625)
Agriculture	0.0319*	0.0247
	(0.0192)	(0.0176)
Art	0.0169	0.00647
	(0.0142)	(0.0128)
Science	0.0376***	0.0327***
	(0.0107)	(0.00991)
Social science	0.00508	-0.00218
	(0.00859)	(0.00718)
Law	-1.97e-05	0.00581
	(0.00983)	(0.00950)
Education	0.0480***	0.0333***
	(0.0114)	(0.00966)
Humanities	0.0748**	0.0580*
	(0.0328)	(0.0305)
Health	-0.00626	0.00265
	(0.00921)	(0.00794)
Technology	0.0176***	0.0132***
	(0.00476)	(0.00359)
Observations	50,472	50,472
Fixed effects	Action-Type	Action-Quality

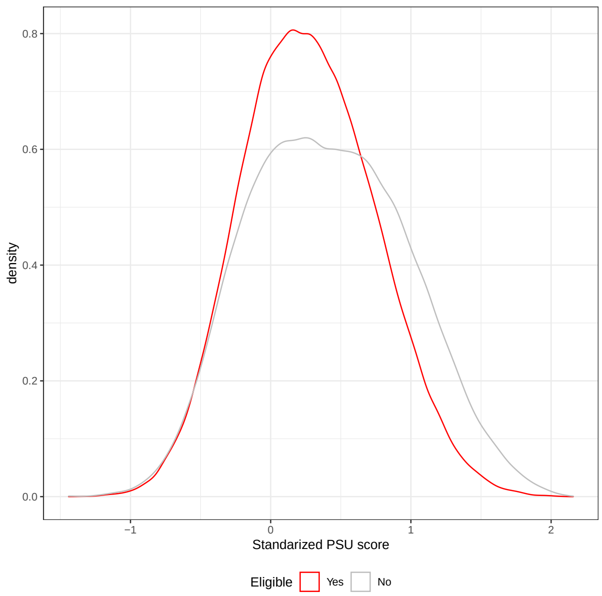
Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

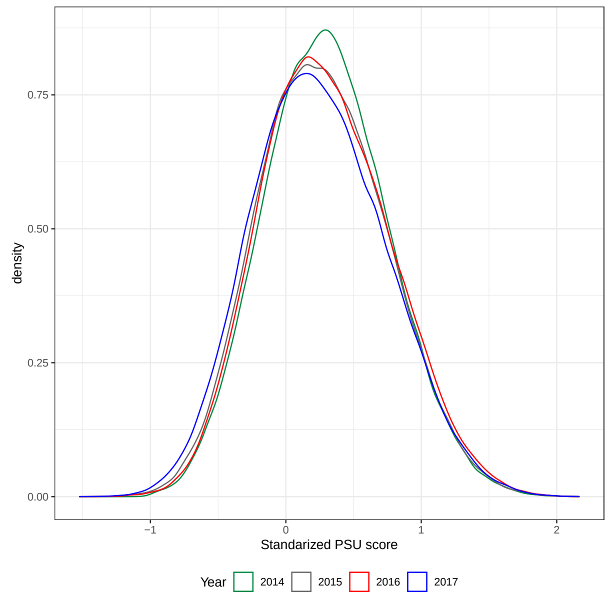
Note: This table only depicts the linear coefficient of capacity on equation (10) for ease of presentation. The type of program is defined by MINEDUC.

B Figures

Figure 16: PSU results are stable around policy change -
Math and Language PSU mean score

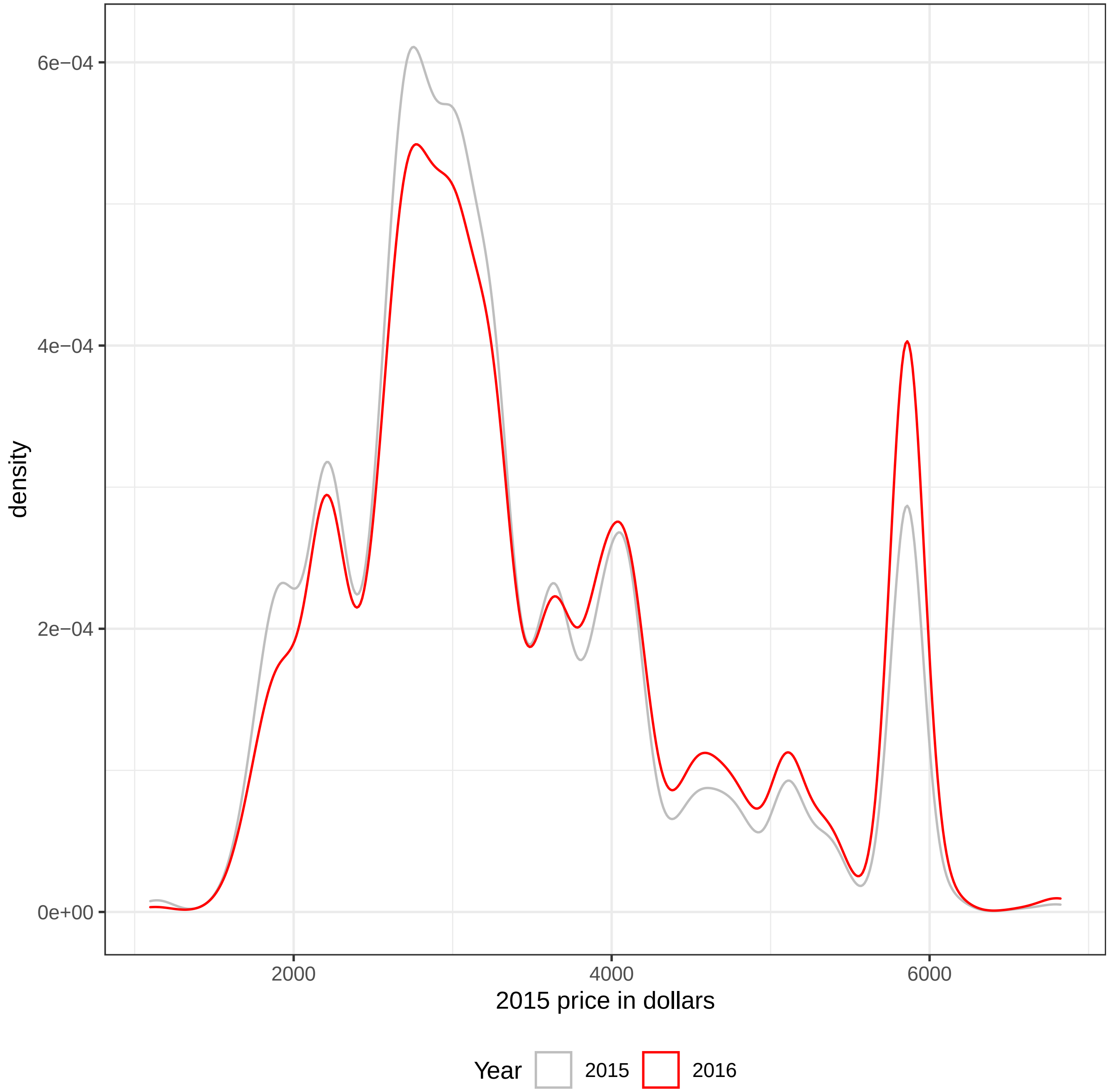


(a) By eligibility on 2015



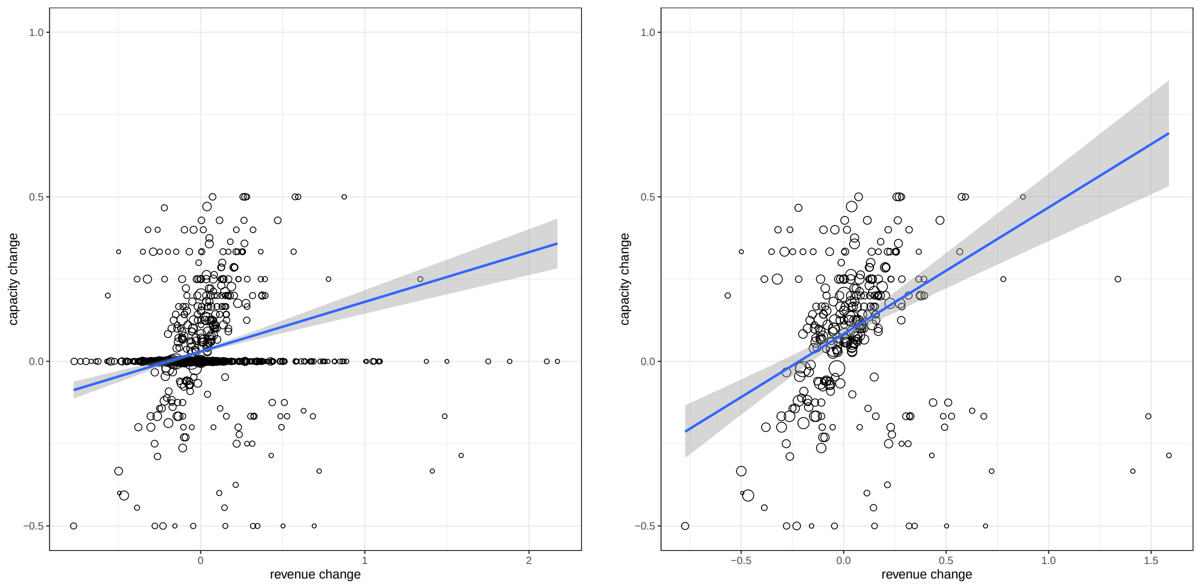
(b) Eligible students by year

Figure 17: Distribution of prices of eligible students' first ranked program before and after free college



Notes: Considers institutions that joined and students with the minimum score to participate in the centralized admissions system. The 2015 cohort considers students who would have been eligible for free college and received a scholarship. Real prices in 2015. Each observation is a student.

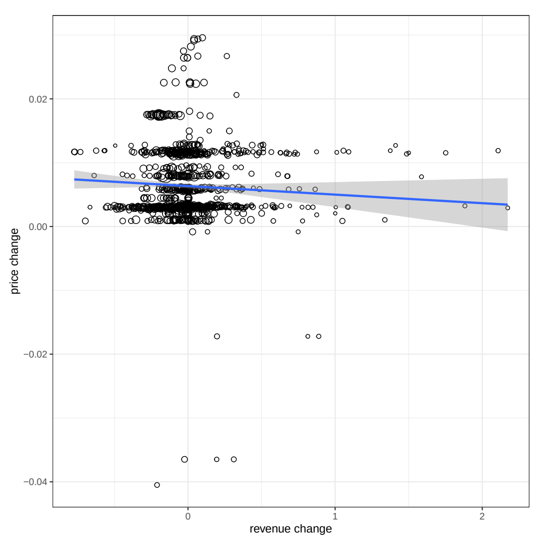
Figure 18: Changes in capacity are related to exposure to the policy —
2016 change in capacity at the program level



(a) All changes (b) Non-zero changes

Note: These figures only include capacity changes between -50 to 50 percent. Each dot and the fitted line are weighted by 2015 enrollment. 95% confidence intervals. The axes are in percentages. Panel (b) only includes non-zero changes of capacity; these represent 30 percent of cases.

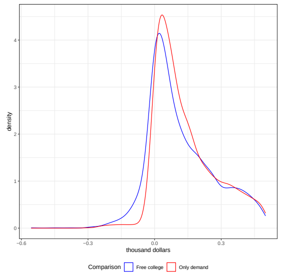
Figure 19: Changes in price are related to exposure to the policy —
2016 change in prices at the program level



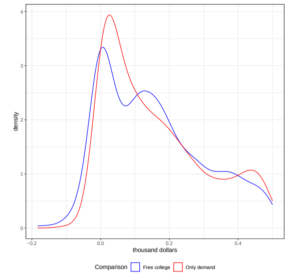
Note: Each dot and the fitted line are weighted by 2015 enrollment. 95% confidence intervals. The axes are in percentages.

Panels (a) and (b) in figure 20 depict the distribution of the change in utility for eligible students who enroll in programs with different marginal exposure to the policy. Most eligible students perceived an increase in

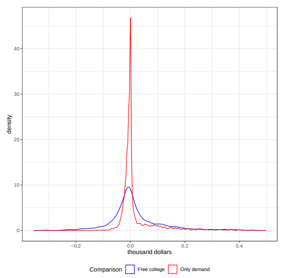
Figure 20: Distribution of changes in students' mean utility by program exposure



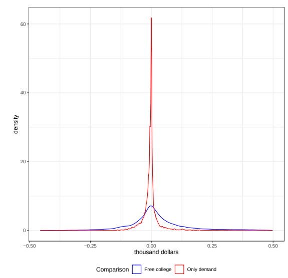
(a) Eligible; High exposure



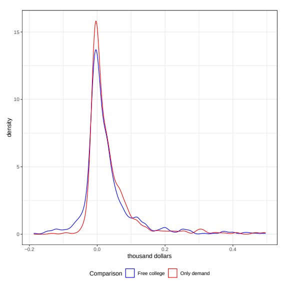
(b) Eligible; Low exposure



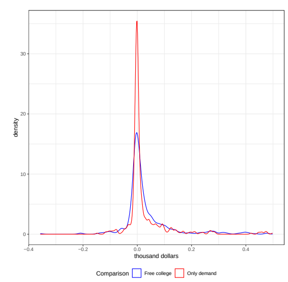
(c) Non-eligible; High exposure



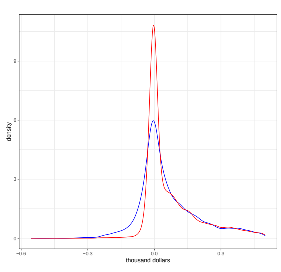
(d) Non-eligible; Low exposure



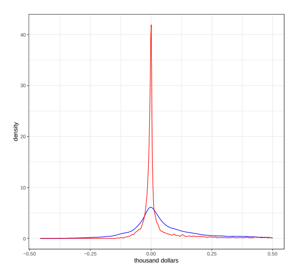
(e) Marginal; High exposure



(f) Marginal; Low exposure



(g) Infra-marginal; High exposure



(h) Infra-marginal; Low exposure

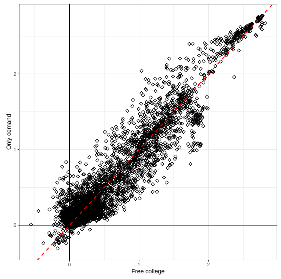
Note: The x-axis depicts the change in mean utility measured in dollars using all the simulations to compare the baseline scenario of no free college to both comparisons. This axis is truncated at $500 for ease of presentation. The program's exposure to the policy is the share of eligible students at the margin of enrollment.

welfare due to free college. However, those eligible students who at baseline are more likely to enroll in a program with high exposure to the policy are more likely to be displaced to the outside option. This pattern is amplified by supply responses, which is consistent with what was predicted by the supply model.

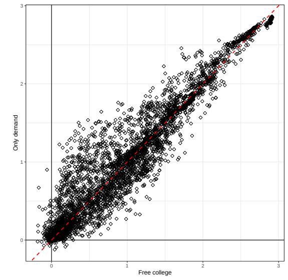
Panels (c) and (d) present a similar comparison for non-eligible students. In this case, the main difference between them is given by choosing the outside option, which as expected is larger in panel (c). The mass on zero in panel (c) is larger than the one on panel (d), and this indicates the increase in the share of the outside option.

Another relevant comparison is between marginal and infra-marginal students. The former should be more exposed to changes in welfare as predicted by the model, and my results verified this. Comparing panels (e) and (g), and (f) and (h), we observe that, conditional on the type of program students enroll in, marginal students are worse off because of the implementation of free college in the case of only demand responses. This is amplified by supply responses.

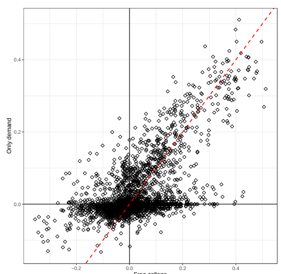
Figure 21: Correlation in mean utility change at the student level for subsets of students for both comparisons



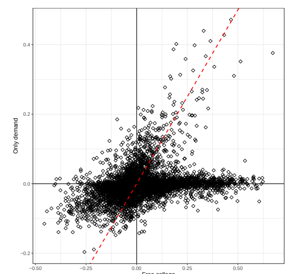
(a) Eligible; High exposure



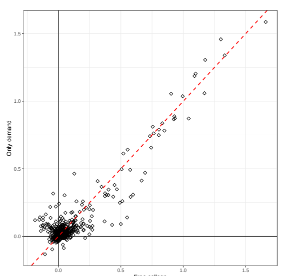
(b) Eligible; Low exposure



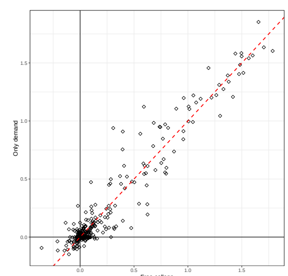
(c) Non-eligible; High exposure



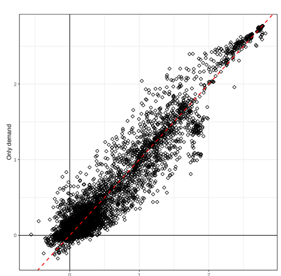
(d) Non-eligible; Low exposure



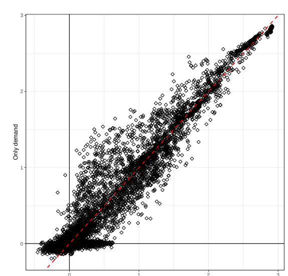
(e) Marginal; High exposure



(f) Marginal; Low exposure



(g) Infra-marginal; High exposure



(h) Infra-marginal; Low exposure

Note: These figures show the change in the mean utility at the student level using all the simulations to compare both scenarios. The axes are measured in thousand dollars. The 45-degree line is depicted in red. The program's exposure to the policy is the share of eligible students at the margin of enrollment.

C Tables

Table 23: Description of universities in 2018

	Public	Private-traditional	Private
Observations	18	9	33
Total enrollment	178,482	142,618	328,792
Certified status	0.89	1	0.67
Years certified	4.62	5.67	3.77
SD years certified	1.02	1.12	1.11
Max years certified	7	7	5
Min years certified	3	4	2
Gratuidad eligibility status	1	1	0.42
First-year enroll 50 percentile	0.53	0.5	0.29

Notes: Made by the author with Mineduc 2018 data. Total enrollment corresponds to all students enrolled by type of institution.

Table 24: DID: Change in applications of eligible students -
Exposure is the relative price in the baseline year

	Dependent variable: applications (1st ranked)		
	Cruch	Private joined	Private not joined
Relative price 2015 x			
Pre 2013	1.600	-14.547^{*}	-3.069
	(5.071)	(8.690)	(6.669)
Pre 2014	2.680	-17.161^{***}	1.191
	(3.321)	(5.661)	(2.830)
Pre 2015	-	-	-
	-	-	-
Post 2016	45.579^{***}	51.597^{***}	1.919
	(9.117)	(13.293)	(4.429)
Post 2017	16.087^{***}	40.038^{***}	1.455
	(3.684)	(9.359)	(4.478)
Post 2018	9.895^{*}	-0.100	-12.161^{*}
	(5.402)	(9.695)	(6.262)
Year FE	Yes	Yes	Yes
Program FE	Yes	Yes	Yes
Institution FE	Yes	Yes	Yes
Observations	6,033	488	1,352
R^2	0.954	0.878	0.908
Mean eligible applicants	62	62	57
Scaled coefficient 2016	16.41	23.88	1

Note: Clustered at program level *p<0.1; **p<0.05; ***p<0.01

Table 25: DID: Change in enrollment of eligible students -
Exposure is the relative price in the baseline year 2015

	Dependent variable: eligible enrollment		
	Cruch	Private-Grat	Private-NonGrat
Relative price 2015			
Pre 2013	0.929	1.170	1.990
	(1.946)	(3.036)	(2.328)
Pre 2014	2.413*	4.196*	1.888
	(1.259)	(2.497)	(1.932)
Pre 2015	-	-	-
	-	-	-
Post 2016	5.546***	11.855**	0.087
	(0.949)	(5.077)	(2.037)
Post 2017	7.015***	4.400	−2.372
	(1.967)	(3.573)	(2.806)
Post 2018	5.244**	2.487	−6.991**
	(2.515)	(5.739)	(3.405)
Year FE	Yes	Yes	Yes
Program FE	Yes	Yes	Yes
Institution FE	Yes	Yes	Yes
Observations	6,008	488	1,346
R^2	0.957	0.936	0.947
Mean eligible applicants	35	43	41
Scaled coefficient 2016	2	5.5	0.04

Note: Clustered at program level *p<0.1; **p<0.05; ***p<0.01

Table 26: DID: Change in enrollment of non-eligible students -
Exposure is the relative price in the baseline year 2015

	Dependent variable: non-eligible enrollment	
	All joined	Did not join
Relative price 2015 x		
Pre 2013	0.424	0.121
	(0.787)	(1.704)
Pre 2014	0.823	−0.622
	(0.693)	(1.454)
Pre 2015	-	-
	-	-
Post 2016	0.790	−0.146
	(0.767)	(1.564)
Post 2017	0.791	1.521
	(0.813)	(1.515)
Post 2018	1.405***	3.520***
3.313		
	(1.241)	(2.691)
Year FE	Yes	Yes
Program FE	Yes	Yes
Institution FE	Yes	Yes
Observations	7,494	1,346
R^2	0.941	0.921
Mean eligible enrollment	21	26

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

Table 27: DID: Change in capacity -
Exposure: $Rev_{\text{DAA 2015}} - Rev_{\text{DAA without responses}}$

	Dependent variable: log capacity				
	All joined	Cruch	Public	Private Traditional	Private
Revenue change (std institution level) x					
Pre 2013	0.018*	0.014	−0.002	0.038*	0.061*
	(0.010)	(0.011)	(0.011)	(0.017)	(0.020)
Pre 2014	0.008	0.009	0.0001	0.022	−0.002
	(0.006)	(0.006)	(0.005)	(0.013)	(0.004)
Post 2016	0.041***	0.042***	0.044***	0.039**	0.034
	(0.010)	(0.010)	(0.015)	(0.013)	(0.019)
Post 2017	0.041***	0.041***	0.048***	0.031***	0.040
	(0.009)	(0.010)	(0.014)	(0.009)	(0.020)
Post 2018	0.044***	0.042***	0.043**	0.040**	0.079
	(0.010)	(0.010)	(0.015)	(0.012)	(0.036)
Year FE	Yes	Yes	Yes	Yes	Yes
Program FE	Yes	Yes	Yes	Yes	Yes
Mean capacity	69	67	63	74	89
Observations	6,124	5,673	3,369	2,304	451
R^2	0.945	0.945	0.954	0.930	0.950

Note: Clustered at institution level. *p<0.1; **p<0.05; ***p<0.01

Table 28: DID: Change in prices -
Exposure: $Rev_{\text{DAA 2015}} - Rev_{\text{DAA without responses}}$

	Dependent variable: log(price)				
	All joined	Cruch	Public	Private Traditional	Private
Revenue change (std institution level) x					
Pre 2013	0.002*	0.002*	0.002	0.002*	−0.0003
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Pre 2014	0.001*	0.001*	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Post 2016	0.001	0.001	0.002	−0.0001	−0.002
	(0.001)	(0.001)	(0.001)	(0.0002)	(0.001)
Post 2017	0.001	0.002*	0.002*	0.0001	−0.0004
	(0.001)	(0.001)	(0.001)	(0.0003)	(0.0002)
Post 2018	0.002**	0.002**	0.004**	0.0005	0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Year FE	Yes	Yes	Yes	Yes	Yes
Program FE	Yes	Yes	Yes	Yes	Yes
Mean price	2918	2852	2753	2995	3749
Observations	6,077	5,628	3,330	2,298	449
R^2	0.991	0.990	0.980	0.998	0.994

Note: Clustered at institution level. *p<0.1; **p<0.05; ***p<0.01

Table 29: Mechanisms explaining the welfare change between the baseline and only demand counterfactual

	Eligible-Low	Eligible-High	Non-eligible-Low	Non-eligible-High
Welfare change (US$)	956	561	-2	20
Same program (%)	91.9	91.8	93.2	93.3
Displaced to outside option (%)	1.37	1.42	1.22	1.2
Free college transfer (US$)	2910	2866	-	-
Average price ((US$)	-	-	2912	2881
Program with lower price (%)	-	-	3.67	3.74
Program with higher price (%)	-	-	3.84	3.76

Note: This table presents the channels that explain the average change in welfare for different types of students. The program's exposure to the policy is the share of eligible students at the margin of enrollment. Welfare change is the average dollar equivalent change in utility. The variable same program is the percentage of students in the same program in the baseline scenario and the case with only demand responses. Displacement to the outside option measures the percentage of students ending up in the outside option after implementing free college. Policy transfer is the average value of the voucher paid by the government to the institution. Finally, programs with lower or higher prices are the percentages of students who enroll in programs with lower or higher prices relative to their baseline enrollment.

Table 30: Mechanisms explaining the welfare change between the baseline and free college counterfactual

	Eligible-Low	Eligible-High	Non-eligible-Low	Non-eligible-High
Welfare change (US$)	916	556	24	15
Same program (%)	68.9	70.2	70.4	72.1
Displaced to outside option (%)	6.96	7.13	7.03	6.7
Free college transfer (US$)	2891	2860	-	-
Average price (US$)	-	-	2889	2872
Program with lower price (%)	-	-	41.66	41.13
Program with higher price (%)	-	-	40.06	40.36
Program with lower capacity (%)	37.64	36.75	37.31	37.31
Program with higher capacity (%)	39.08	39.64	38.18	38.42

Note: This table presents the channels that explain the average change in welfare for different types of students. The program's exposure to the policy is the share of eligible students at the margin of enrollment. Welfare change is the average dollar equivalent change in utility. The variable same program is the percentage of students in the same program in the baseline scenario and the case with only demand responses. Displacement to the outside option measures the percentage of students ending up in the outside option after implementing free college. Policy transfer is the average value of the voucher paid by the government to the institution. Finally, programs with lower or higher prices are the percentages of students who enroll in programs with lower or higher prices relative to their baseline enrollment.

Table 31: Composition of programs that increase and decrease its revenue due to supply responses

	Increase revenue	Decrease revenue
Total	894	514
Traditional university (%)	32	32
Public university (%)	40	53
Private university (%)	28	15
Northern region (%)	28	38
Capital region (%)	38	25
Southern region (%)	33	37
Quality A (%)	39	41
Quality B (%)	41	38
Quality C (%)	14	13
Quality D (%)	3	5

Note: This table describes programs that increase and decrease their revenue due to supply responses induced by free college. The description includes a series of characteristics of the programs, including the type of institution, its location, and quality.