Aftermarket Frictions and the Cost of Off-Platform Options in Centralized Assignment Mechanisms

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Abstract

In many settings, market designers must contend with the presence of firms who participate in the broader game surrounding a market but do not participate in the portion under the designer's control. In this paper, we study the empirical relevance of the configuration of on- and off-platform options in the context of a centralized college-major choice system. We quantify significant negative externalities generated by off-platform options and measure the aftermarket frictions that contribute to generating them in practice. Our empirical application uses administrative data from the centralized assignment system for higher education in Chile and leverages a recent policy change that increased the number of on-platform slots by approximately 40%. We first present a policy analysis which shows that expanding the centralized platform leads students to start college sooner and raises the share of students who graduate within six years. We develop an empirical model of college applications, aftermarket waitlists, and matriculation choices. We estimate the model using students' ranked-ordered applications, on- and off-platform enrollment, and on-time graduation outcomes. We use the estimated model to quantify welfare impacts, decompose different mechanisms and to conduct counterfactual exercises. We find that when more programs are available on the centralized platform, welfare increases substantially. These externalities are driven by students who receive and decline on-platform offers, and are amplified by substantial frictions in waitlists. Our results indicate that expanding the scope of a higher education platform can have real impacts on welfare and human capital. Importantly, the effects are larger for students from lower SES backgrounds, suggesting the design of platforms can have effects on both efficiency and equity.

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1 Introduction

Centralized assignment systems are increasingly used in education settings all over the world. As of 2018, at least 46 countries use centralized choice and assignment mechanisms for at least part of their higher education system.[1] Centralized systems are theoretically appealing and have been empirically successful in many settings (Abdulkadiroğlu et al., 2017). In practice, however, designing an assignment system requires additional considerations, as the setting may depart from the theoretical ideal (Roth, 2002, 2007). One such consideration is that in virtually every practical implementation there exist many off-platform options that are available to participants of the match. In primary and secondary education, these include private schools or charter schools that do not participate in the centralized system. In other cases, such as higher education, some providers may be excluded from the platform by regulation, while others may choose not to participate. In practice, applicants may renege on their assigned matches in favor of programs that did not participate in the centralized process. In turn, these decisions lead to the use of waitlists and aftermarkets, which may be impractical and inefficient due to the presence of congestion and matching frictions, negating some of the benefits of the match.

In this paper, we study the empirical relevance of the configuration of on- and off-platform options for students' welfare and for persistence and graduation in higher-education programs. We document the importance of negative externalities generated by off-platform options and quantify a measure of aftermarket frictions that contribute to generating them in practice. Our empirical application uses data from the centralized assignment system for higher education in Chile, which has one of the world's longest running college assignment mechanisms based on the deferred-acceptance algorithm.[2] We take advantage of a recent policy change that increased the number of on-platform institutions from 25 to 33, raising the number of available slots by approximately 40%. We first present an analysis of the policy which shows that when these options are included on the centralized platform, students start college sooner, are less likely to drop out, and are more likely to graduate within six years. Importantly, these effects are larger for students from lower SES backgrounds, suggesting that the design of platforms can have effects on both efficiency and equity.

Next, we develop an empirical model to obtain an estimate of aftermarket frictions and to quantify the negative impacts caused by off-platform options as a function of these frictions and the configuration of on- and off-platform options. We estimate a model of college applications, aftermarket waitlists, off-platform offers, matriculation choices, and on-time graduation outcomes

[1] See Neilson (2019) for a review of countries that have implemented centralized choice and assignment mechanisms. See worldwide coverage map in Figure A-1.

[2] A common national entrance exam was first implemented in 1967, and centralized assignment based on a Deferred Acceptance algorithm has been used for at least the last 45 years.

using individual-level administrative data on almost half a million on-platform applications, test scores, enrollment decisions, and student records at all on- and off-platform higher education options, spanning the years 2010-2012. We show that when students are allowed to express their preferences for a larger variety of options on the platform, welfare increases substantially, as does the share of students graduating on time. According to our estimates, the welfare gains from platform expansion are greater than half of the gains from expanding the platform *and* removing all frictions in waitlists. These impacts, in turn, are 7.5% as large as the welfare impacts of making on-platform programs free for all students from public schools, a much more expensive policy change. Enrollment gains from platform expansion are more than 90% of those of platform expansion and removing all frictions in waitlists. These quantitative results suggest that off-platform options generate negative impacts on the efficiency of the assignment system and that these costs can be economically meaningful.

We use the estimated model to further explore which students are affected by the off-platform options. We find that in the case of Chile, women and more disadvantaged students are the most adversely affected by the inefficiency created by off-platform options. This pattern may be partly due to their higher sensitivity to price and lower utility for private off-platform options. We then use the model to evaluate how our results would change in counterfactual exercises when different combinations of higher education options are on or off the platform. We find that more desirable options create larger welfare losses when they are not on the platform.

Intuitively, when a desirable program is not on the platform, it can cause some students who would have placed in that program to instead receive a placement in a different program which is available on the platform. These students may then decline that placement in favor of the off-platform program, creating vacancies, which in turn lead to increased reliance on waitlists which may be subject to frictions. Moreover, the absence of a particular program may distort the placements of other students, even if the students whose placements are affected would never enroll in that program. These students may also be less satisfied and more likely to decline their placement.

Taken together, our results show empirically that the existence of off-platform options affects the equity and efficiency of centralized assignment systems. The type of options and the expected aftermarket difficulties can be evaluated by policymakers to consider actions to mitigate these problems or to incentivize the more desirable options to join the platform. Our empirical framework and counterfactual analysis allow us to quantify the welfare effects of adding universities to the platform. The model and the empirical strategy can be used to quantify the costs of off-platform options in other settings in order to inform policy regarding the costs of off-platform options.

This paper builds on and contributes to the empirical literature on the design of assignment and matching procedures for education markets. Abdulkadiroğlu et al. (2017) estimate the welfare impacts of the introduction of a centralized match in New York City schools. Several papers estimate welfare impacts of changes in school assignment mechanisms (Agarwal and Somaini, 2018; Calsamiglia et al., 2018; Kapor et al., 2020). Aue et al. (2020) empirically investigate a merger of school districts. We contribute by quantifying the impacts of a novel aspect of the design of the market—which options are on-platform—and by linking it to real outcomes, such as dropout/graduation rates, in addition to revealed-preference welfare measures. Methodologically, we build on the Gibbs-sampler estimation procedure introduced by McCulloch and Rossi (1994) and extended to the case of choice over lotteries by Agarwal and Somaini (2018). We extend this procedure to accommodate an aftermarket in which individuals' choice sets are unobserved. Our procedure assumes that students truthfully report preferences over the subset of programs at which their placement chances are nontrivial; it is related to the stability-based approach of Fack et al. (2019).

Our question is particularly related to issues surrounding "common enrollment" –i.e. school choice policies in which all available schools participate in a single centralized assignment process. Ekmekci and Yenmez (2019) prove that, in the absence of frictions, full participation by all schools or programs is best for students, but programs have incentives to deviate from the match and "poach" students in the aftermarket. Andersson et al. (2018) consider a setting in which private-school and public-school matches take place sequentially. The theoretical literature abstracts from frictions and communication failures in the aftermarket. Our goal is to quantify the impacts of platform expansion in the presence of the frictions that exist in the market, motivating the use of empirics.

More broadly, we contribute to a literature on problems that may arise in decentralized or imperfectly centralized matching markets. These include (lack of) market thickness, "congestion" in decentralized markets, and the inefficient timing or sequencing of transactions (Agarwal et al., 2019; Roth and Xing, 1994; Niederle and Roth, 2009). Our notion of aftermarket frictions captures the idea of congestion: a program has a limited time to process its waitlist, and may fail to contact some students to whom it wishes to extend offers, such as when a student fails to answer his/her phone. However, our model of aftermarket frictions does not accommodate frictions related to exploding offers, which were not present during our sample period.[3]

Our paper adds to a literature that relates choice behavior to outcomes in assignment mechanisms. In contemporaneous work, Agarwal et al. (2020) provide nonparametric identification results for preferences and outcomes in assignment markets. They observe that, in addition to an "assignment shifter" such as discontinuities in admissions offers, an additional source of varia-

[3]Programs may have incentives to make offers with short deadlines, either prior to the match or prior to waitlist movement, in order to capture some students who face uncertainty. Anecdotally, in the years prior to our sample period, off-platform programs made offers which required a large non-refundable deposit which was due after the initial match but before on-platform waitlists cleared. This practice was prohibited by the consumer protection law of Bill 19.955 in 2004, which required that such deposits be refundable as long as the academic program had not yet begun.

tion in choices is needed which is excluded from outcomes. In our setting, year-to-year variation in programs' cutoffs plays this role.[4] Our approach to estimation is closest to Geweke et al. (2003) and Agarwal et al. (2020), who jointly estimate preferences and outcomes (mortality, life-years) using a Gibbs sampler, in hospitals and deceased-donor kidney assignment procedures, respectively. In contemporaneous work using data from the Chilean higher education system, Larroucau and Rios (2020) estimates a dynamic model of preferences, learning about ability, and outcomes such as switching and dropout after enrolling in college. Other papers that combine preference estimation with "outcomes" such as health, human-capital, or labor-market impacts include Hull (2018), Walters (2018), and van Dijk (2019). Finally, we contribute to a body of research that exploits data from centralized higher-education assignment procedures to evaluate the impacts of higher-education policies. For example Bucarey (2017) estimates a model of college choice to study equilibrium effects of a reform in Chile which made college free in 2016.

2 Context and Data

2.1 Administrative Data Sources

Our administrative data come from three sources. The Ministry of Education of Chile (MINEDUC) provides data for each combination of campus, institution, and major, which we refer to as a *program*. The data provided by MINEDUC assigns each program to a standardized category of broad area and field or major of specialization. MINEDUC also provides panel data on individual-level enrollment and financial aid allocated to each student.

The second source is the *Consejo Nacional de Educación* (CNED) which is the regulatory agency that provides accreditation to higher education programs. This agency publicly reports program information such as accredidation status, posted tuition and student body characteristics.

The third source of data is the agency that runs the centralized application and assignment mechanism (DEMRE) for participating universities. This agency also administers the national college entrance exam, the *Prueba de Selección Universitaria* (herein, PSU). The college entrance exam is a set of multiple-choice tests that comprise a verbal and math component, as well as optional history and science tests. All test scores are standardized so that the sample distribution of each test in each year resembles a normal distribution with a mean of 500 points and a standard deviation of 110 points. The minimum score of the test is assigned a score of 150 points, and the maximum corresponds to 850 points. High school GPA is also transformed to be on the same scale.

[4] Alternative approaches include distance as an excluded preference shifter in school choice (Walters, 2018), variation in the set of other units available in a housing allocation mechanism (van Dijk, 2019), and variation in the distribution of future offers in a dynamic decision problem (Agarwal et al., 2020).

DEMRE provides masked individual level data on students who took the PSU test including their gender, high school, approximate geographic location, GPA, and test score results.

The agency also provides student-level data on rank-ordered applications, the assignment associated with the initial application, and reported matriculation from the institutions. Importantly, unique identifiers allow us to cleanly link individuals across datasets. The study focuses on the years 2010, 2011 and 2012. Descriptive statistics of the data are described in Table A-1.

2.2 Chilean Higher Education in Context

2.2.1 Growth and Consolidation of Higher Education

Over the last three decades, the Chilean higher education system expanded dramatically. This rapid growth in tertiary enrollment in Chile is broadly believed to have been spurred by a combination of a growing middle class and policies such as government backed student loans and scholarships. The enrollment growth has led to an expansion in the number of programs at newer private institutions (Marta Ferreyra et al. (2017)). In 1989 there were 25 (16 public and 9 private non-profit) universities in Chile, which we will call the G25. These universities enrolled a total of 112,000, 215,000 and 310,000 students in the years 1990, 2000 and 2010, respectively. The decade after 2010 saw a period of consolidation with smaller growth in enrollment, with total matriculation at G25 universities reaching 366 thousand in 2019. Since the 1970s the G25 universities have participated in a centralized clearinghouse for processing college applications and admissions. The emergence of newer universities established after 1990 led to an increasing share of enrollment off the centralized platform and represented 68% of total enrollment in 2010. There are other universities outside the G8 that are smaller and less selective. In addition, there are also many professional institutes and technical formative centers. See Table A-2 for a description of selectivity by type of institution.

2.2.2 Rise of G8 private universities

Although G25 enrollment increased during the 1990s and 2000s, most of the growth in enrollment occurred at newer private universities outside of the G25. Private universities outside of the G25 enrolled 20,000, 100,000 and 320,000 students in 1990, 2000 and 2010, respectively. By 2019, matriculation had reached 350 thousand, representing 27% of all college enrollment. A group of eight of the largest and more selective private universities not only saw their enrollment grow but also their share of higher scoring students, especially from private schools. We refer to this group the G8 throughout the paper. This group is heterogeneous in the location of their campuses and the strengths and specialties of their institutions but had become a close substitute for many traditional programs in the G25. By 2010, the G8 universities had 32% of total G8 + G25 enrollment.

Figure A-11 shows the growth in G8 enrollment as a share of G8+G25 enrollment over the period leading up to 2012 when G8 was added to the centralized platform. Table A-2 lists each institution in the G25 and G8 and presents statics regarding the distribution of student test scores at each institution. While the most selective institutions are in the G25, some G8 institutions are much more selective than most G25 institutions with considerable overlap of selectivity among them.

2.2.3 Financial Aid

One distinctive feature of the structure of financial aid in Chile is that the eligibility rules are a clear function of student and program characteristics known before applying. The average of students' math and verbal test scores determine one dimension of eligibility. The second dimension is a publicly known SES index. Students above a test score cutoff and with sufficiently low SES become eligible for low interest government-backed-student loans and scholarships to use at accredited university-level programs. Throughout our study period of 2010-2012, scholarship programs provided varying amounts of aid, and government-backed loans would cover the remainder up to a program-specific reference tuition. Students could use this financial aid at any eligible program. Importantly, this funding was not tied to whether the program participated in the centralized assignment platform. Moreover, eligibility for financial aid is determined before students apply to programs, and follows students to programs. While few general-use scholarships were being provided in 2010, government-backed student loans were used widely and have been shown to significantly alleviate credit constraints and facilitate college attendance (Solis, 2017) when comparing students at the margin of loan eligibility. The vast majority of students that are eligible to apply to programs on the centralized platform are eligible for student loans, and all options in the G25 and G8 were eligible to receive both loans and scholarships.

In 2011 a significant new scholarship policy called the *Beca Vocación de Profesor* (BVP) was introduced. This scholarship covered the full tuition bill for high-achieving students (one σ above the mean) who enrolled at eligible teaching colleges. It also limited the ability for participating teaching colleges to accept low-scoring (below average) students. Gallegos et al. (2019) describe the policy and find large impacts on enrollment decisions via regression discontinuity and difference-in-difference designs. In 2010, teaching was the most popular major in Chile, so this policy shifted choices for a significant portion of students by effectively eliminating tuition at a subset of options for some students and drastically limiting access to programs for other students. While this program is not the focus of this paper, we use it as a source of match-level price variation in order to estimate willingness to pay for programs. More detail about the policy and the price variation it generates is provided in the Appendix and Figure A-8 shows a timeline indicating the major policies in higher education before and after our studied period of 2010-2012.

2.3 Institutions Surrounding College Applications and Enrollment

2.3.1 Students Take Tests

Each year, students interested in potentially applying to universities must register to take the national college entrance exam in mid December. This test is free for over 90% of high school graduates and the vast majority of them take test each year. In 2011, 67% of all 2011 high school graduates took the test, representing 79% of all test takers that year (graduates from previous years may take the test as well). Test results are made available to students in early January. Students are eligible to apply through the centralized admissions system if they obtain a simple average of at least 450 points between their math and verbal tests (note 450 is $\sim 0.5\sigma$ below the mean of each test). Students with an average math and verbal score below 450 cannot apply, but may retake the tests in the following year if they want to do so. Approximately 250,000 students took the college entrance exam in 2010, 2011 and 2012. In each of these years approximately 72% of test takers were students who were graduating from high school that same year, and 10% of test takers were graduates from private high schools which are not subsidized.

2.3.2 Programs Report Capacities and Admissions Rules

Each program on the centralized platform reports to the mechanism a set of weights on subject test scores and high school GPA. Programs choose their weights, subject to constraints, to express preferences for their applicants, who will be ranked according to the weighted average of their scores induced by these weights.[5] Programs also report the desired number of slots to be provided to the mechanism. In 2011, There were approximately 1000 programs among the G25 universities, which together accounted for 67,000 slots. The G8 universities offered 350 additional programs that accounted for an additional 25,000 slots.

2.3.3 Students Report Ranked Ordered Lists

Eligible students who decide to apply to universities on the centralized platform must do so within a short window of time (approximately a week) after receiving their scores. Applications consist of a rank ordered list of *programs*, where a program is a narrow field of study (or major) at a specific campus and university. Of the 130,526 students who were eligible to apply in 2011, 63% submitted a rank-ordered list. Table A-1 shows more details regarding the number of test takers, eligible applicants, submitted applications and final assignments.

[5]These weights typically vary depending on the type of coursework the program offers, with more weight on math and science when programs have more STEM coursework, and less weight on math and science when the program provides more qualitative coursework. See Figure A-9 for the distribution of these weights and Figure A-10 for the relationship between test score weights and coursework focus.

At the time that ordered lists are submitted, students have access to the following public information: the number of slots that each program offers, how the program *weighs* the test scores of applicants, their personal weighted score if they were to apply to a given program, and the weighted score of the last admitted student in previous years for every program on the platform. Additional eligibility requirements can include minimum scores and minimum average weighted scores depending on each program.[6] Figure A-12 shows changes in the score of the lowest-scoring admitted student at each G25 program. Cutoffs have considerable persistencem with a correlation of 0.96 in 2010 to 2011. Nonetheless, this figure shows that there is non-negligible movement in the cutoffs from year to year, especially at programs with fewer seats and at those with lower selectivity.

2.3.4 Students Are Assigned Seats and Waitlists Are Formed

After submitting their ordered lists, students are assigned to higher education programs following the college-proposing deferred acceptance (DA) algorithm of Gale and Shapley (1962) and is discussed in detail in Rios et al. (n.d.). Programs' preferences for applicants are given by their corresponding weighted scores after filtering out students that do not meet the stated requirements. Students are assigned to their best feasible option, conditional on all the information in the platform, and receive an admission offer from the corresponding university if they are accepted into a program.

Applicants may be waitlisted in zero, one, or multiple programs. A student will be accepted by a program with capacity k if she is one of the top k applicants in terms of weighted score in that given program. If this student ranks below the kth position of applicants in that program, she will be automatically waitlisted at the program. In other words, students are never completely rejected, but are instead placed on waitlists if they are not accepted. Once a student is assigned into an option, all the stated preferences ranked below the option of acceptance are discarded. Thus, after discarding post-acceptance options, students observe the same list they submitted to the system filled with a waitlist indicator in options ranked ahead of their placement, and with an acceptance indicator in the last option.

2.3.5 Enrollment Decisions On and Off Platform Are Made

Students that receive an acceptance offer have the chance to enroll in that program. If they decide to do so, they pay the corresponding matriculation fees to secure a spot in the program. There is no punishment or cost for not enrolling in a program. After the initial enrollment process ends, waitlists are processed independently by each institution in a decentralized manner.

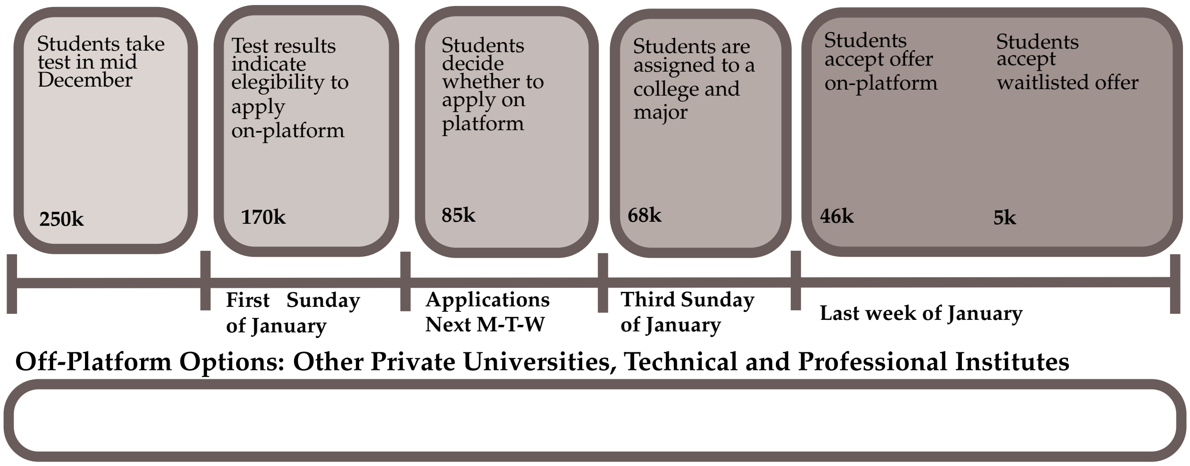
[6] The two most selective universities have an addition requirement that makes programs ranked below the fourth place be ineligibile. See Lafortune et al. (2018) for a description of how this feature affects student applications.

In addition to the options offered on the centralized platform, students can also apply directly to any number of off-platform university programs as well as a variety of less-selective technical and professional institutes. The decentralized admissions process has varied deadlines and potentially different application requirements, but the vast majority require the college entrance exam. While not coordinated, admissions processes at universities tend to track the timeline of G25 universities with a lag, so that most off-platform offers are finalized after students and programs learn on-platform match assignments. Most of the broader higher education system has rolling admissions until the beginning of classes.

2.3.6 Summary of Application, Enrollment and Aftermarket

To summarize, Figure 1 describes the timing of the admissions process, the aftermarket and enrollment. Students take the PSU in December and receive their test results in early January. Given information on test scores, students can calculate the financial aid and loan packages that are available to them at each program. Equipped with this information, applicants have approximately one week to submit a rank-ordered list. Programs provide weights that describe their priorities, their desired number of slots, and, if they choose to do so, a number of extra slots to deal with offers being declined. Applications are processed using a DA algorithm, and assignments are communicated to students. At this point, the aftermarket begins: students decide to accept or reject offers, and programs begin calling waitlisted applicants. Off-platform enrollment decisions occur simultaneously. Once all enrollment and waitlist-enrollment decisions have been made and the incoming cohort for each program has been determined, each program begins its regular academic year in a decentralized fashion.

Figure 1: Diagram of the on-platform application process

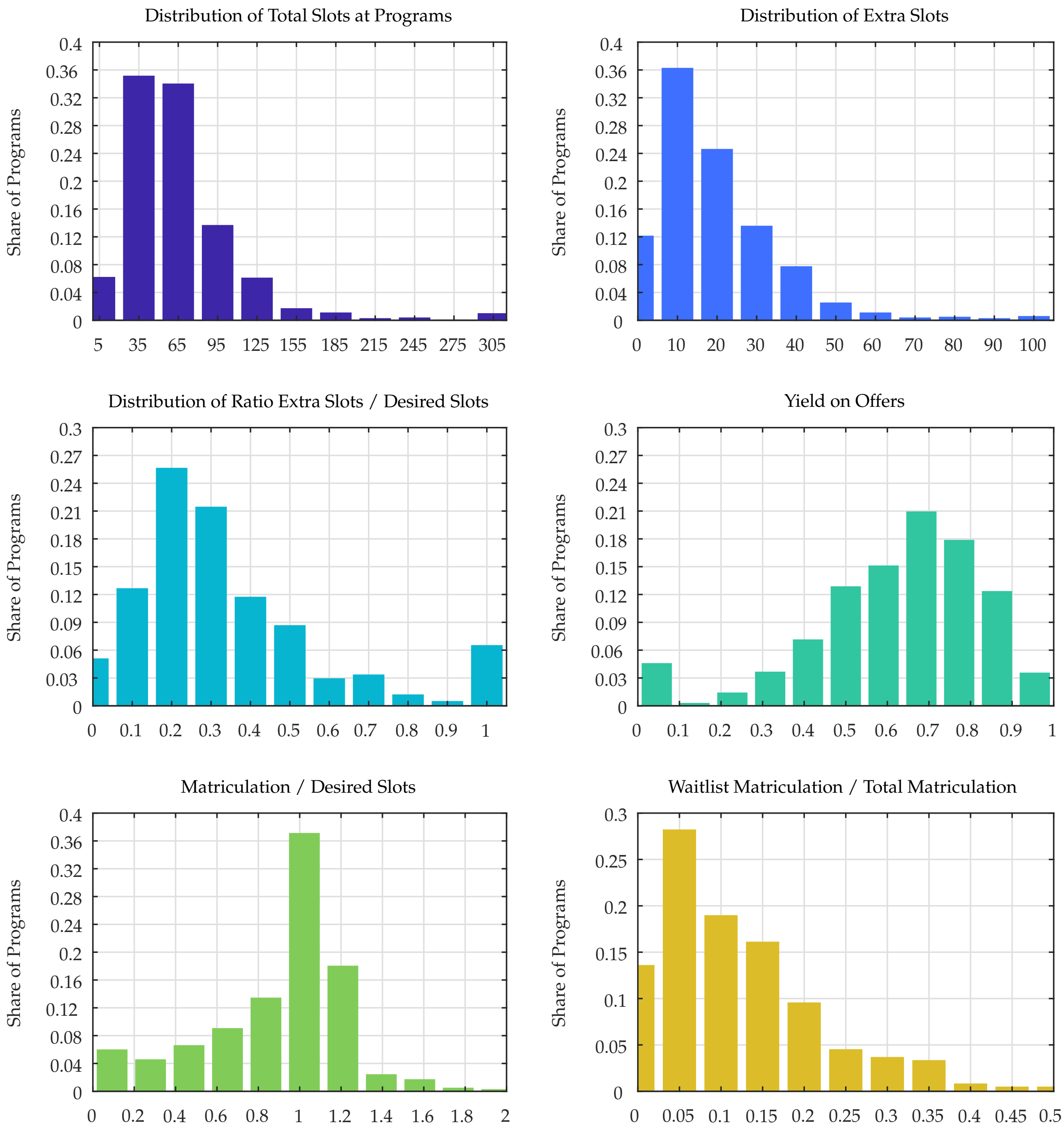


Note: Diagram shows the progression of steps for applicants on and off the centralized assignment platform. The numbers of students in each step is for 2011, before the platform was expanded. The baseline is the cohort of students that take the national college entrance exam in 2011.

2.4 Waitlists and Evidence of Aftermarket Frictions

In this subsection we document the overall prevalence of waitlists and show evidence of aftermarket frictions. We see that the system takes steps to reduce the scope of waitlists. In particular, to partially accommodate the possibility of declined offers, the mechanism elicits from each program two capacity measures: a "true" slot count and a number of "extra" seats. The program's capacity in the DA algorithm is the sum of these numbers. Thus, programs may supply excess slots in anticipation of some students declining their offers. An on-platform program may contact students on its waitlist only in the event that enrollment would otherwise fall below its "true" capacity. Therefore, programs which use "extra" seats reduce their reliance on waitlists but face the risk of more acceptances than their "true" capacity.

Figure 2: Total Slots, Excess Slots, Program Yield



Note: This figure describes the distribution of posted slots, extra slots, yield, matriculation and waitlist matriculation in 2011. The top left panel shows the distribution of total slots , with the highest 2% of programs not show. The top right panel shows the distribution of extra slots posted in expectation of declined offers . The left middle panel presents the distribution of the ratio between extra slots and desired matriculation . The right middle panel presents the distribution of the yield that initial offers have . The bottom left panel shows the ratio between ex-post matriculation and ex-ante desired slots . The bottom right panel shows the number of waitlist matriculated students as a share of total matriculation . 34% of the programs do not have any waitlist matriculation either because it was not needed or not possible because they had no excess demand.

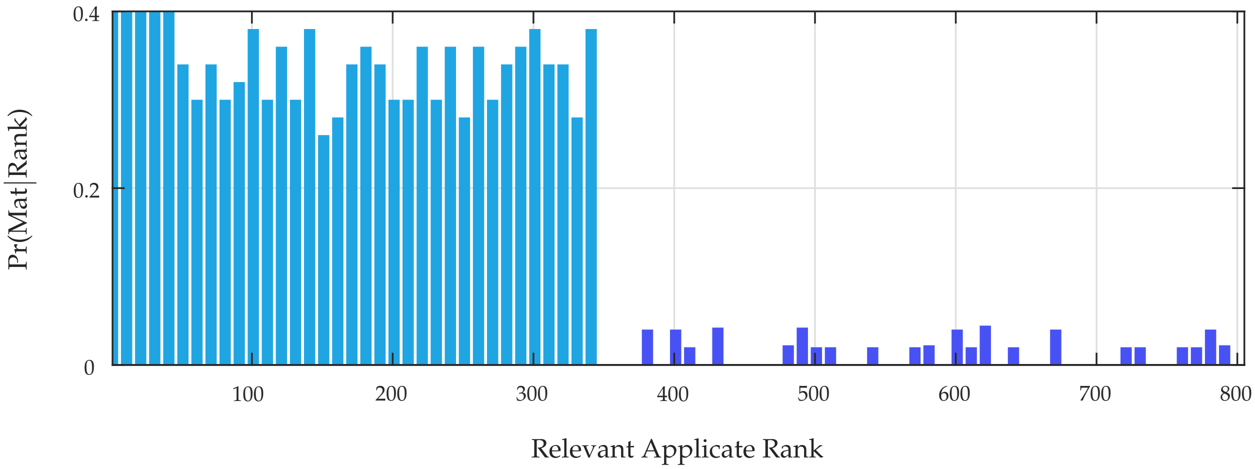
In practice, programs choose fewer excess slots than needed to achieve full enrollment via initial offers. Figure 2 shows that despite the presence of excess slots, students have a positive probability of receiving waitlisted offers in the aftermarket. Empirically, we see that ex-post some schools overshoot and other schools undershoot. This fact may be due to financial constraints that put an upper bound on "worst-case" enrollment and therefore place bounds on the number of excess slots. The resulting effect is that on average, enrollment is 12% lower than the desired seats originally posted, despite the use of excess slots. Of the programs that had excess demand beyond the desired and extra slots (88%), 70% of these ended up matriculating students from their waitlists. Overall in both 2010 and 2011, approximately 4000 students matriculated through waitlists, which represents 8% of all the matriculation on the centralized platfrom in those years.[7] Figure 2 describes the distribution of "true" and "excess" seats as well as programs' yield. We observe heterogeneity in the use of excess seats, with some programs offering none and some offering double their true capacity. Importantly, unlike in the U.S. context in which people apply to universities, the typical program is small and hence faces nontrivial "sampling" uncertainty in the number of accepted offers.

If a program contacts students on its waitlist, the commonly adopted approach is to go through the waitlist in order and inform (through a phone call) each waitlisted applicant that they now have an available slot. Students may accept or decline any waitlist offers that they receive. If a student declines to enroll (or does not answer the phone, for example), the corresponding institution moves ahead with the next waitlisted applicant. This process is full of nuisances and frictions: students may be called by multiple waitlisted programs; there may be communication issues (e.g. wrong numbers may be dialed); students may renege on a waitlisted offer after verbally accepting it but before formally enrolling; the waitlist process operates in real time and terminates at a fixed date, potentially before the market "clears".

Because the use of excess seats means that some programs do not contact their waitlists, one might expect a discontinuity in enrollment chances on average at programs' cutoffs. However, in the absence of frictions one would expect no discontinuity in enrollment probabilities at the initial cutoff among those programs that do contact their waitlists. In Figure 3 we present two case studies that show that discontinuities exist for these programs, and that waitlists exhibit "gaps".

[7] These numbers do not include students who are admitted off the waitlist through the BEA policy. These waitlist matriculations account for an additional 400 students who get in off the waitlist.

Figure 3: Case Study: Enrollment Probability at Economics - University of Chile - 2010/2011



Note: This figure shows the probability of enrolling students who are admitted or waitlisted as a function of their rank. The figure shows Economics at the University of Chile which is a highly selective program with a large class of over 300 slots offered. Two of the authors did their undergraduate training at this program. The x-axis shows the student rank (from 1 being the highest to the last admit). The y-axis shows the probability that students will enroll, shown in bins of 10 students.

The waitlist process is not explicitly regulated by the platform beyond the limit on total slots, so it is difficult to get direct data on the way that waitlists are processed. To understand how this process works, we conducted interviews with a handful of officials who administer the recruiting process and, in particular, that supervise the processing of waitlists. Transcripts of these interviews are given in Appendix A-1. One such administrator who works at a highly-selective program indicated that at their program they don't always go to the waitlist, but when they do, they provide callers three times more numbers than they need to recruit, expecting many to not answer and some to decline. In addition, administrators indicated that they typically expect to conduct multiple rounds of calls, as some students that accept verbally over the phone might not appear to matriculate the next day. The entire process is done quickly as programs scramble to sign up students before they commit to other options.

> *Each university clears their waitlist with call-centers... we informed them that they got off the waitlist and asked them if they would like to enroll. If they said yes, we would ask them to come early next morning. If they did not arrive, we would try to contact them again. If someone did not want to enroll or did not pick up the phone, we would call the next one... If two students were called and both decided to enroll we would let both of them in... for a single slot in the waitlist, we would call 3 students and then potentially discard some... it is not a rule, it is discretionary.*
> *-Admissions Officer*

While this anecdotal evidence is not necessarily representative of the experiences at all programs, the evidence from data on applications, assignments and enrollment seem to suggest that this description may be typical, and that the significant aftermarket frictions described here exist more broadly.

3 The Expansion of the Platform

When the G8 universities joined the centralized platform, the number of options available to students increased by over 30% and the number of slots increased by almost 50%. This was an unparalleled change in the supply side of the platform.[8] Figure A-2 depicts the evolution of platform slots over this time.

Increasing the number of slots in the system naturally implies that the number of applicants that eventually enroll in an on-platform option also increases. This is mechanical, as incorporating the G8 options means that G8 placements and enrollment in G8 programs are now counted as on-platform placements and matriculations. A less immediate consequence is that students that were admitted into G25 options increased their enrollment *rate* in G25 institutions after the policy. As depicted in Figure A-3 and summarized in Table A-1, when compared to 2011, students placed in G25 programs were around 7 percentage points ($\sim$ 10%) more likely to enroll in their assigned programs in 2012. This effect is driven by students' ability to express preferences for G8 programs and their inability to enroll in G8 programs if assigned to a G25 option, unless they move off a waitlist ($\sim$ 1% of G25 admits). Prior to 2012, students who had been admitted to G25 programs could decline their on-platform offers in favor of an off-platform offer from a G8 program.

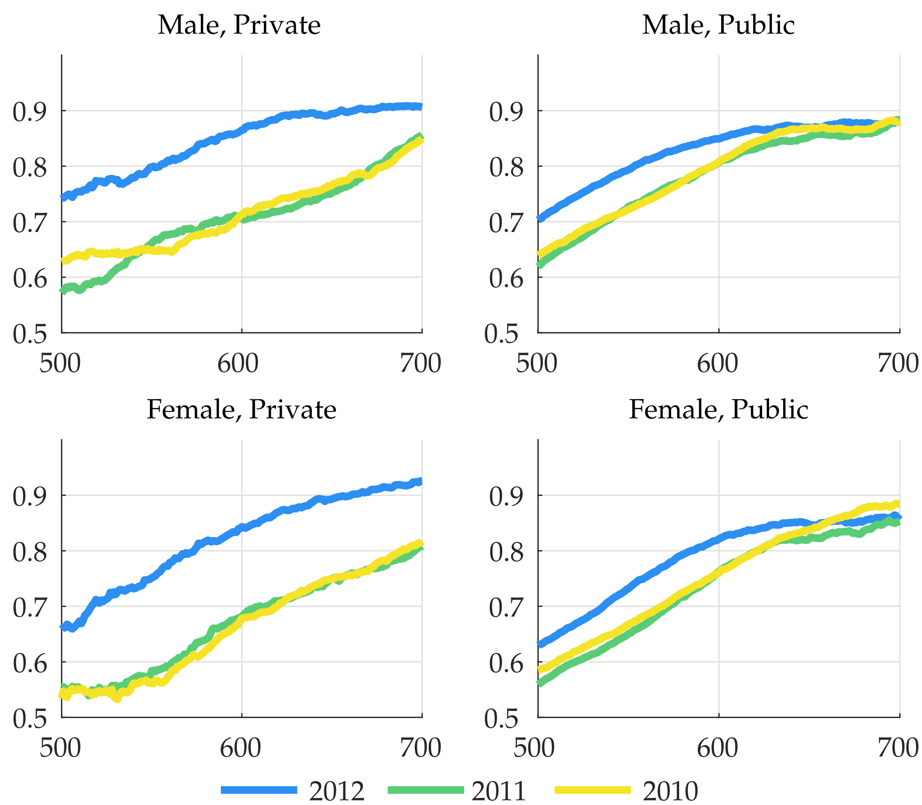
We find that students who are initially placed in G25 programs are more likely to enroll in their initial placement over a wide range of PSU scores and program selectivities. This fact is shown in Figure A-4, where sample probabilities are plotted in 70-point bins for all the years in our data. Overall, we observe a significant average increase in enrollment rates for G25 admits with scores below 750 points. It is worth noting that, as test scores are adjusted to resemble a normal distribution with a mean of 500 and a standard deviation of 110 points (see Table A-1), 750 points is approximately the 99th percentile of the score distribution. Thus, the policy increased the enrollment yield for the vast majority of G25 admits.

Figure 4 shows the results of this last exercise conditional on gender and high school type. In all cases, there are significant differences between enrollment rates in 2012 and previous years, but the impacts are larger for low-scoring and private school applicants. Intuitively, the enrollment rate of private-school students should be more affected by the policy if they were more likely to renege on their platform offers and enroll in private, off-platform institutions. We show evidence of this

[8] Other preceding policy changes, such as making the PSU tests free for applicants, had important impacts on the number of students applying through the platform, but no other policy had a similar impact on the number of options from which students could choose. Other policies that expanded access to higher education in Chile are summarized in Figure A-8.

behavior and estimate higher average valuations for G8 options from private school students in section 5.

Figure 4: Enrollment probability, conditional on scores, gender, and type of school.

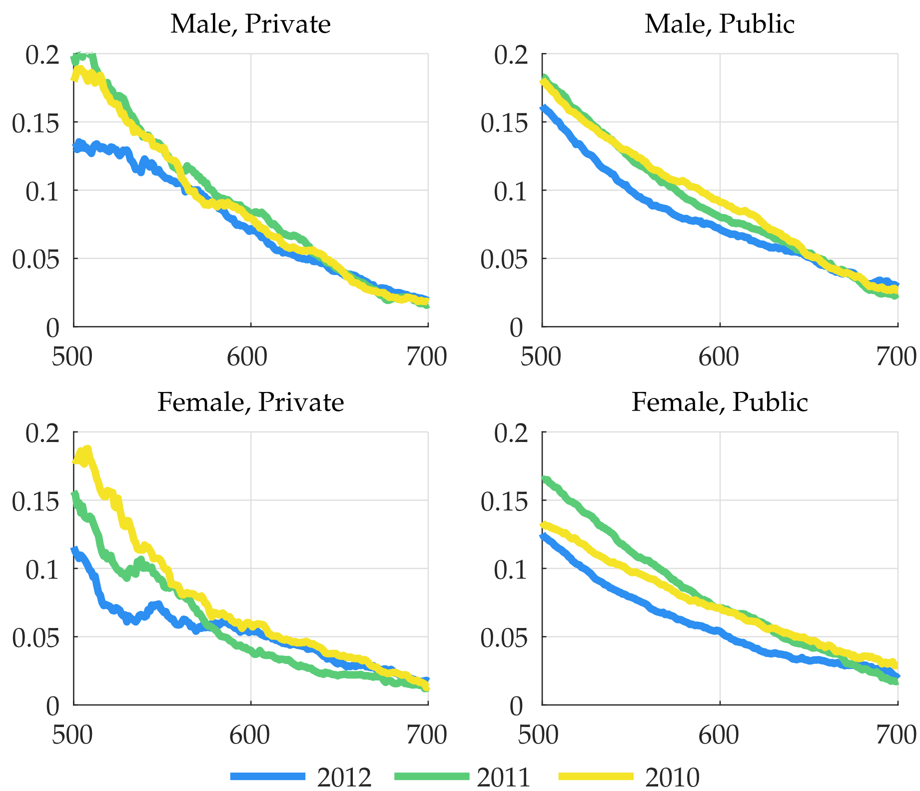


Note: This figure shows the probability that a student assigned to an option on the platform, accepts and enrolls in that option. The lines show conditional means within 70 points, and the "floor" of the range is shown in the x-axis (e.g. 600 corresponds to the range [600, 670]). The probability of enrollment increases substantially for assignments that occur in 2012, especially for private school students.

To quantify the externalities on other applicants induced by students' decisions to decline on-platform placements, one might ask the following (infeasible) counterfactual question: if applicants that were to ex-post renege on their assignments were ex-ante excluded from the platform, what would happen to the matches of other applicants? Figure A-6 depicts this counterfactual exercise in which students who receive and ex-post decline on-platform placements are removed from the match ex-ante, for each year. Prior to 2011, removing such students would cause at least 27% of students to receive a placement that they ranked ahead of what they received in the data. This fraction of match-improvements falls to 20% in 2012 following the expansion of the platform, indicating that people who decline offers impose substantial externalities on others' placements. This rematch fraction can be interpreted as another measure of inefficiency that is enhanced after the policy.

Increasing enrollment rates fosters efficiency in the system. If students are more likely to leave programs that they consider less desirable, then a second measure of inefficiency is the rate at which students drop out of the system once enrolled. If match quality increases, we should expect to see fewer students dropping out over time. When exploring the evolution of freshmen dropout rates in the system, we find a significant reduction of about 1.1 percentage points, which accounts for over a 10% fall in overall dropout by the end of the first year of college (Figure A-5). Figure 5 shows how the probability of dropout varies over time and by gender, scores, and type of school. Public-school students and low-scoring private school students, especially women, mostly drive the reduction in dropout rates. Retention rates are stable for high-scoring students.

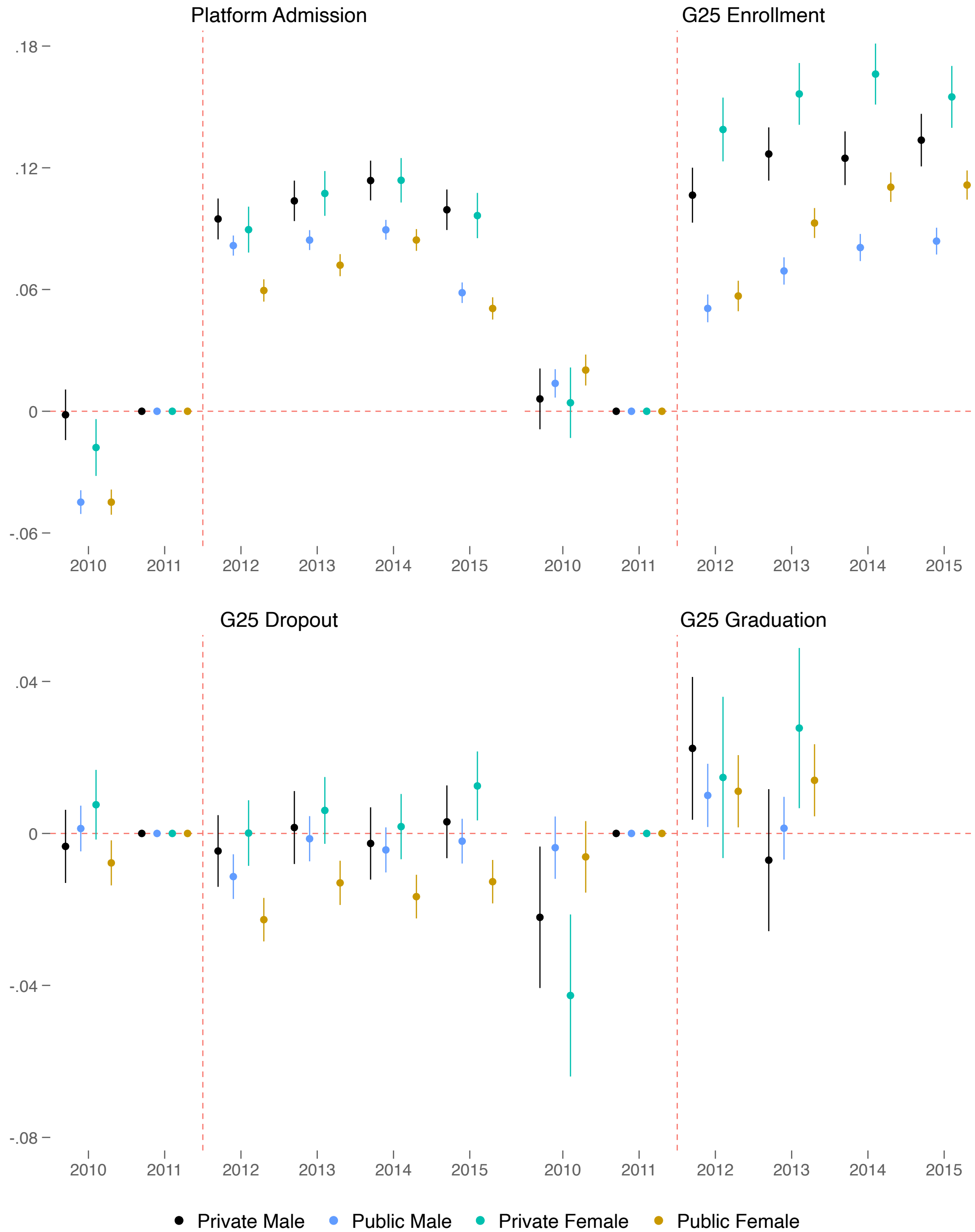
Figure 5: Freshmen dropout rate for G25 enrollees, conditional on scores and gender



Note: This figure shows the probability that a student enrolled in a G25 option drops out of college within one year after enrolling. The lines show conditional means within 70 points, and the "floor" of the range is shown in the x-axis (e.g. 600 corresponds to the range [600, 670]). The probability of dropout decreases substantially for assignments that occur in 2012 relative to the previous two years, especially for low-scoring students.

Finally, Figure 6 shows changes from 2010 to 2015 in key academic outcomes of interest for different types of students: platform admission rates, enrollment rates, 1-year dropout rates, and 6-year graduation rates. The plotted coefficients $\{\hat{\beta}_t\}_{t=2010}^{2015}$ are OLS estimates from the following specification:

Figure 6: Admission, Enrollment, Dropout and Graduation rates by year



Note: This figure shows the admission, enrollment, dropout and graduation rates by year and student type, relative to 2011. Admission refers to the probability of being assigned a seat in the platform; Enrollment refers to the probability of enrolling in a platform program conditional on being admitted in a G25 option; Dropout refers to the probability of not being enrolled in any option the year after enrolling in a G25 program; and Graduation refers to the probability of graduating within 6 years of enrolling in a G25 program. The results on graduation rates are limited to years before 2014 because we do not have data after 2019. Analogous results, controlling for test scores and student-type fixed effects, are reported in Table A-3.

$$Y_{ist} = \alpha + \sum_{t=2010}^{2015} \beta_t 1[cohort_{is} = t], \qquad s = \{1, 2, 3, 4\},$$

where Y_{ist} denotes the outcome (admission, enrollment, dropout, graduation) of student i, of sex-school type s (1 $\rightarrow$Private-Male, 2 $\rightarrow$Public-Male, 3 $\rightarrow$Private-Female, 4 $\rightarrow$Public-Female), in application-cohort t. The year 2011 is excluded, so that all outcomes are relative to this year. The coefficients β_t correspond to the conditional average differences explained by the indicators $1[year = t]$, which equal 1 for application year/cohort t and 0 otherwise. The estimates are reported separately for each outcome, year and student type, and 95% confidence intervals are based on heteroskedasticity-robust standard errors.

We find that platform admission rates jump by about 9 percentage points. Enrollment rates increase by about 7 percentage points, dropout rates fell by roughly 1.1 percentage point, and graduation rates increase by almost 4 percentage points. These averages mask substantial heterogeneity: private school students increase their admission and (G25) enrollment probabilities more than public school students, but the latter, especially public school women, exhibit larger decreases in their (G25) dropout rates.

4 Model

4.1 Theoretical Model

In order to estimate the welfare impacts of the policy change and assess which programs' participation decisions had the largest impacts, we estimate a model of students' on-platform applications, aftermarket frictions, enrollment decisions, and human capital outcomes. Our goal is to provide a tractable framework that uses variation in students' choices around the policy change to identify key frictions, and their impacts, in the partially decentralized market.

Our model has four stages, which we discuss below.

1. Students submit on-platform applications.
2. The DA procedure runs, and students receive initial placements and waitlist positions.
3. The aftermarket takes place. Students receive off-platform and waitlist offers and make final enrollment decisions.
4. Production of human capital takes place. Students drop out or graduate from programs.

We now describe the game in detail. A market $t \in T = \{2010, 2011, 2012\}$ is an application cohort. Within market t, N_t students apply to a set of available programs $j \in J_t$. Each option $j \in J_t$

is characterized by observable exogenous characteristics $x_j \in \mathbb{R}^M$. Each student $i \in \{1, ..., N_t\}$ is characterized by a tuple $(x_i, \eta_i, \varepsilon_i)$, which comprises observable covariates $x_i \in \mathbb{R}^K$, tastes for observable covariates based on observable student characteristics $\eta_i^o \in \mathbb{R}^{M\times K}$, tastes based on L unobservable student characteristics $\eta_i^u \in \mathbb{R}^L$ and a random idiosyncratic preference-shock $\varepsilon_i \in \mathbb{R}^{J_t}$.

If student i attends program j, he receives utility

$$u_{ij} = \delta_j + \lambda_{distance} D_{ij} + \lambda_p(discount_{ij}, \text{potential discount}_{ij}) + \eta_{ij} + \epsilon_{ij}, \tag{1}$$

where D_{ij} is distance, δ_j is a program-level mean utility term, and

$$\eta_{ij} = \sum_{m=1}^{M}\sum_{k=1}^{K} x_i^k x_j^m \eta_{m,k}^o + \sum_{\ell=1}^{L} x_{j,\ell}^l \eta_{i,\ell}^u \tag{2}$$

is a measure of match quality that depends on observed interactions of student and program characteristics as well as unobserved tastes.

There is also an outside option, $J = 0$, whose value is given by

$$u_{i0} = \max\{u_{i0}^0, u_{i0}^1\}.$$

u_{i0}^0 is known at the time of applications, and represents the value of the best nonselective or noncollege alternative that is known before applications are due. In contrast, u_{i0}^1 is learned after the DA procedure takes place, but prior to the aftermarket. This shock rationalizes the decision to apply to programs but then decline all offers.

These outside options are lognormally distributed with means that depend on student-level covariates.[9] We have

$$\log u_{i0}^0 \sim N(x_i^{oo}\lambda^{oo,0}, \sigma_{0,0}^2)$$

and

$$\log u_{i0}^1 \sim N(x_i^{oo}\lambda^{oo,1}, \sigma_{0,1}^2).$$

Outside-option shifters (equivalently, shifters of all inside options) consist of a constant, i's math and verbal test scores, year indicators, scholarship amount $scholarship_i$,[10] and indicators for urban location and current high-school enrollment (as opposed to older applicants applying

[9]We have also estimated models in which outside options are normally distributed. The lognormal functional form improves model fit, especially of the probability of accepting an offer and the number of applications.

[10]Each student received a subsidy from a government scholarship program as a function of an index of socioeconomic status. Importantly, this amount does not vary across programs within a person. Hence it may be treated as a shifter of all inside options, and included in outside-option indices.

for a second time). Program characteristics x_j which enter η consist of measures of STEM and humanities course content. (Mean effects of program characteristics are subsumed by program fixed effects). Observed match terms consist of a full set of interactions between individuals' math and humanities test scores and the STEM and humanities course content of each program. Distance is an indicator for program and student in the same region of Chile. We place random coefficients η_i^u on programs' STEM and humanities course content.

In the absence of additional grants such as the BVP, a student would pay $listprice_j - scholarship_i$ to attend program j. Variation in $listprice_j$ is absorbed by program fixed effects. Willingness to pay is given by the coefficient on $discount_{ij}$, which represents the value of the scholarship provided by the BVP program. It is equal to $listprice_j - scholarship_i$, the amount saved by obtaining a full scholarship, in the event that student i is eligible for the BVP scholarship and program j participates in it in the year in which i applies. If i is not eligible or j does not participate, it is equal to zero. $(\text{potential discount})_{ij}$ is equal to the value of the scholarship at program j if i qualifies for BVP and program j ever participates in the program, even if j does not participate in the year in which i applies. In the following section we discuss the design that motivates this specification.

We assume $\epsilon_{ij} \sim N(0,1) iid$, fixing the scale of utility. Because each term with a random coefficient also enters mean utility, η^u terms are mean zero. We assume that $\eta_i^u \sim N(0, \Sigma^{rc})$.

Importantly, preference parameters, including δ and Σ^{rc}, differ arbitrarily for each of four types $s \in S \equiv \{male, female\} \times \{\text{public/voucher school}, \text{private school}\}$. Thus low- and high-SES applicants—as proxied by type of high school attended—need not agree on a vertical ranking of quality.

As an outcome, we consider graduation within six years from the program in which a student enrolls. In the event i enrolls in j, he graduates iff his potential human capital h_{ij} satisfies $h_{ij} > 0$. h_{ij} is distributed according to

$$h_{ij} = \overline{\beta}_j + \beta_{distance} D_{ij} + \beta_p p_{ij} + \beta_x x_i^{oo} + \sum_{m=1}^{M} \sum_{k=1}^{K} x_i^k x_j^m \beta_{m,k}^o + \beta_u u_{ij} + \nu_{ij}$$

where $\overline{\beta}_j$ are school effects and ω_{ij} is a standard normal shock which normalizes the scale and location of parameters. Importantly, our specification allows everything that enters utility to enter the outcome production function. In addition, we include utilities of the chosen option and of the first outside option directly, allowing for match effects on observed and unobserved determinants of preferences.[11]

Programs are partitioned into on- and off-platform programs. Let $J_t^{\text{on}} \subseteq J_t$ denote the set of on-platform programs in market t, and $J_t^{\text{off}} = J_t \setminus J_t^{\text{on}}$ the set of off-platform programs.

[11] Because the linear indices in utilities are of the same functional form as the indices in the production function, it would be equivalent to allow the unobserved utility shocks, rather than utilities, to enter the outcome equation.

In the first stage of the game, students learn their preferences for all programs except u_{i0}^1, then submit rank-ordered application lists over on-platform programs to a centralized mechanism. Programs rank students according to an index of four test scores and high school GPA, with program-specific weights, which we denote $index_{ij}$.[12] Each program has a fixed number of slots. A college-proposing deferred acceptance procedure runs, producing initial placements.[13]

In addition to its assigned students, each program maintains a waitlist of length R. The R highest-ranked students who applied to program j but were not placed in j or in a program they prefer to j are waitlisted at j. Students may be on multiple waitlists. At the end of the procedure, students learn their initial placements and waitlist status.

We now consider the aftermarket, which we model as as a college-proposing DA procedure with a friction. At the beginning of this stage, students learn their second outside option, u_{i0}^1.[14] Students receive offers from off-platform programs and from on-platform programs at which they are waitlisted, and may decline or provisionally accept them.[15] At the end of the process, students enroll in the program they most prefer among programs that have made them an aftermarket offer, their original match, and their outside options.

Off-platform programs $j \in J_t^{\text{off}}$ rank students according to $index_{ij}$—the formula they ultimately adopt when the join the platform—and have fixed capacities. On-platform programs j give maximum priority to students who received an initial placement at j, guaranteeing that a student who receives an initial placement at j can keep that placement if he desires to do so. They rank the remaining students according to their position on the relevant waitlists. If a student is not waitlisted at on-platform program j, he/she is not acceptable to j in the aftermarket.

Let

$$a_{ij} \in \{0, 1\}$$

indicate the event that j is able to successfully contact i. We assume

$$Pr(a_{ij} = 0) \equiv \alpha_{s,o},$$

[12]In addition to the index formula, some programs have eligibility rules, such as a minimum score on a subset of the exams. In the DA algorithm, applicants who are not eligible are dropped from the program's preference list.

[13]Programs' $index_{ij}$ formulas admit the possibility of ties. In the Chilean process, in practice as well as in our simulations, if in round t of the DA algorithm a program's final proposal would be to some student i with score $index_{ij}$, it proposes to all students i' such that $index_{i'j} = index_{ij}$.

[14]Formally, in the first stage of the aftermarket DA, the second outside option makes a proposal to each student. This offer provides utility u_{i0}^1.

[15]In the aftermarket DA, we assume that off-platform programs k drop students from their preference lists who prefer the first outside option, i.e. for whom $u_{i0}^0 > u_{ik}$. That is, students must have been willing to apply to k ex-ante in order for k to propose. This does not affect the final allocation, but greatly reduces the number of iterations required. We have also estimated a model in which off-platform programs do not propose to students who prefer their initial placement. An interpretation of this alternate model is that students must apply to off-platform programs after learning their initial assignments. The results are unchanged.

independently across i and j, where s denotes student type and $o \in 0,1$ indicates on-platform status. When $a_{ij} = 0$, program j is unable to reach i, in which case i is dropped from j's aftermarket preference ordering.

The parameters α summarize the extent of aftermarket frictions. When α is large, programs need to make many calls to fill a given vacancy, and thus are likely to leave gaps when they move down their waitlists.

Person i's initial on-platform program $placement_i$ is a special case. For this program, we have $a_{i,placement_i} = 1$. Similarly, we have $a_{i,0} = 1$ as well.

4.2 Identification

4.2.1 Reports and preferences

To infer preferences from reports, we assume that students truthfully report their preferences over programs at which they have nontrivial admissions chances. In particular, for each program, we define score bounds,

$$\overline{\pi}_j > \pi_j > \underline{\pi}_j.$$

Say that a program j is

- **ex-ante infeasible** for student i if $index_{ij} < \underline{\pi}_j$.
- **ex-ante marginal** for student i if $\underline{\pi}_j \leq index_{ij} < \overline{\pi}_j$.
- **ex-ante clearly feasible** for student i if $\overline{\pi}_j \leq index_{ij}$.

A program has nontrivial admissions chances if it is not ex-ante clearly infeasible and is not listed below an ex-ante clearly feasible (i.e. "safety") program.

Formally, suppose student i's' true preference ordering over J_t satisfies

$$u_{i1} > \ldots > u_{ik} > u_{i0}^0 > u_{ik+1} > \ldots > u_{i|J_t|}.$$

Let $\overline{u}_i^{\text{feas}}$ denote i's highest payoff among clearly feasible options:

$$\overline{u}_i^{\text{feas}} = \max \left\{ u_{i0}^0, \max_{\{j \in J_t^{on} : \overline{\pi}_j \leq index_{ij}\}} u_{ij} \right\}.$$

Let

$$J_i^{\text{relevant}} = \{ j \in J_t^{on} : index_{ij} \geq \underline{\pi}_j \text{ and } u_{ij} \geq \overline{u}_i^{\text{feas}} \}$$

be the subset of on-platform programs that are not ex-ante infeasible for i and not worse than the best clearly-feasible option. We assume that the restriction of i's report to schools that are not ex-ante infeasible consists of all elements of J_i^{relevant} in the true preference order.

Because reports are truthful within the applicant's relevant choice set, we may infer preferences using standard discrete-choice arguments.

Our strategy is related to the stability-based approach of Fack et al. (2019), and reduces to it as the score bounds $\overline{\pi}$ and $\underline{\pi}$ approach π.[16] The use of additional rank-ordered preference data allows us to learn substitution patterns in a way that is consistent with theory and evidence on deferred acceptance mechanisms, without making the potentially strong assumption that applications are truthful.

Stable matching mechanisms, such as the college-proposing deferred acceptance algorithm, have optimal reports which are "dropping strategies" that may omit some programs but rank the listed programs truthfully (Kojima and Pathak, 2009). Constraints on list length may lead applicants to drop some programs (Haeringer and Klijn, 2009). In principle, truthful reporting of preferences in college-proposing DA is approximately optimal in a large market (Azevedo and Budish, 2019). In practice, however, applicants to centralized mechanisms may omit schools that are out-of-reach or irrelevant (Fack et al., 2019; Artemov et al., 2020; Shorrer and Sóvágó, 2018; Hassidim et al., 2016). Larroucau and Rios (n.d.) provide evidence from the Chilean match that some students omit programs at which they have very low admissions chances. Our procedure allows applicants to omit such schools from their lists.

4.2.2 *Willingness to pay*

To learn individuals' willingness to pay, we exploit match-level price variation induced by the introduction of the nationwide BVP scholarship program, which made scholarships available to students with scores above 600 at certain programs in the years in which those programs participated. Our design is a triple-differences design exploiting this policy change, embedded in our structural model, which allows us to estimate a price coefficient jointly with other demand parameters.

In particular, we observe programs' list prices, $listprice_j$ as well as a government-provided subsidy, $scholarship_i$, which is based on household SES and does not vary across programs within a person. In the absence of the BVP scholarship, a student enrolling in program j would need to pay $listprice_j - scholarship_i$ with some combination of loans and out-of-pocket payments.[17]

[16] It is also related to Che et al. (2020), which uses an alternate approach to rule out payoff-relevant departures from truthful play.

[17] For expositional simplicity, in this paragraph we are assuming $scholarship_i < listprice_j$. In the event the scholarship is larger than the list price, the student would pay zero, and the net savings from BVP eligibility would be zero.

Hence, if j is a program that ever participates in the BVP program, and i's mean math and verbal score is at least 600, then i's $p$otential BVP discount in application-cohort t is equal to $listprice_j - scholarship_i$; otherwise, it is zero. Person i in year t receives a BVP discount equal to (potential BVP discount)$_i * 1(j$ participates in BVP in year $t)$.

In estimation, we include program fixed effects, which subsume list prices, and include $scholarship_i$ and (potential BVP discount)$_i$ as demand shifters. Interpretation of the effect of $scholarship_i$ is complicated: presumably more funding makes college more attractive, but the scholarship is assigned on the basis of an SES index which is associated with demand through other channels. Including potential BVP discount allows high-scoring students to have potentially different tastes for programs which ultimately participate in BVP. The coefficient on the BVP discount reveals willingness to pay.

4.2.3 Aftermarket frictions

We say that program j is **ex-post feasible** for student i if $index_{ij}$ is at least as high as the lowest value of $index_{ij}$ among students enrolling in j and, in the event j is on-platform, then i applied to j. Program j is **available** to i if it is ex-post feasible for i and we have $\alpha_{ij} = 1$. Our assumptions imply that i enrolls at his most preferred program that is available to him.

If j is not i's original placement, we have $a_{ij} = 1$ with probability α_{o_j,s_i}. Our strategy relies on the fact that ex-post feasibility is observed. For on-platform programs, we observe the index of the lowest enrolled student. Because a program in college-proposing DA process does not make additional offers when its capacity is filled, this student represents the lowest score to whom it ever extends an offer. Hence, for an on-platform program j, if $\alpha \rightarrow 0$ then no student who is waitlisted at this program would remain in their original match, $placement_i$. The share of students who have ex-post feasible programs that they prefer to their original placement according to their application, but who enroll at their original placement, reveals the extent of frictions.

Our approach to off-platform programs is similar. A complication is that applicants' ranking of off-platform programs is unobserved. We exploit the panel structure of the data to identify the distribution of preferences for these programs. G8 programs' unobserved demand-relevant characteristics are identified from rank-order application data in 2012, when they participate in the platform.[18] Pre-reform data then allows us to estimate frictions for off-platform programs.[19] We allow these frictions to differ by type. Discrimination in favor of high-SES applicants, for example,

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We allow for this case in estimation.

[18]We allow on-platform status to enter applicants' utility. Unobserved program characteristics are held fixed.

[19]In this draft, we model off-platform programs as conducting admissions as they would if on platform, but with frictions that may differ from those of the on-platform waitlists. Doing so is not essential. The model could be extended to allow other characteristics, including student unobservables to enter off-platform programs' admissions decisions.

would enter our estimates as larger frictions for low-SES applicants at off-platform programs.

4.2.4 Human-capital production function

In the Chilean college match, otherwise-similar students are assigned to programs discontinuously as a function of exam scores. Many papers conduct regression discontinuity designs in Chile and other matching settings to recover local average treatment effects (LATEs) of program assignment on student-level outcomes of interest such as graduation among the populations local to each discontinuity. Our model implicitly uses this source of variation. In order to identify the distribution of graduation rates under counterfactuals that shift program assignments, however, an additional "choice shifter" is needed that is otherwise excluded from outcomes (Agarwal et al., 2020). In our paper, year-to-year variation in programs' cutoffs plays this role; an observably identical student faces a different choice set in 2010 than in 2012.

4.3 Estimation

We estimate the model using a Gibbs sampler, using the universe of data from 2010-2012. Our estimates may be interpreted as approximate maximum-likelihood estimates. The Gibbs sampler is convenient for our setting, which involves an unobserved choice set—a high-dimensional discrete unobservable—determined by realizations of a_{ij}.

In each market $t \in \{2010, 2011, 2012\}$, we augment the data with auxiliary variables $u_i \in \mathbb{R}^{|J_t|}$, $h_{i,enroll_i} \in \mathbb{R}$, and $a_i \in \{0,1\}^{J_t}$, representing utility, human capital, and availability, respectively, for all students i and programs j, as well as random coefficients $\eta_i^u \in \mathbb{R}^L$ and outside-option utilities $(u_{i0}^0, u_{i0}^1) \in \mathbb{R}^2$ for each i. If person i does not enroll in any inside option, we adopt the convention $h_{i,0} = 0$.

For each applicant, we observe the submitted rank-order list ℓ_i, the enrollment outcome $enroll_i \in \{0\} \cup J_t$, observed graduation outcome $graduate_{i,enroll_i}$ for the program in which i enrolls. and exogenous characteristics $\omega_i \equiv (D_{ij}, p_{ij}, x_i, x_j)$. Our sampler iterates the following steps. We omit s subscripts on parameters for brevity, as well as the exogenous observables ω.

1. For each market t, for each type s, for each $i \in \{1, \ldots, N_t\}$ of type s:
   (a) Draw $u_{i0}^0 | u_i, u_{i0}^1, \ell_i, enroll_i, \lambda^{oo,0}, \sigma_{0,0}^2$.
   (b) Draw $u_{i0}^1 | u_i, u_{i0}^0, \ell_i, enroll_i, \lambda^{oo,1}, \sigma_{0,1}^2$.
   (c) for each $j \in \{1, \ldots, J_t\}$
      - If $j \neq enroll_i$:
         i. Draw $u_{ij} | a_i, u_{i0}^0, u_{i0}^1, u_{i,-j}, \ell_i, enroll_i, \eta_i^u, \eta^o, \delta_j$.

ii. Draw $a_{ij}|u_i, u^0_{i0}, u^1_{i0}, \ell_i, enroll_i, \eta^u_i, \eta^o, \delta_j$.

- Else:

  i. Draw $u_{ij}|a_i, u^0_{i0}, u^1_{i0}, u_{i,-j}, \ell_i, enroll_i, \eta^u_i, \eta^o, \delta_j, h_{ij}, \overline{\beta}, \beta$.

  ii. Draw $h_{ij}|graduate_{ij}, u_{ij}, \overline{\beta}, \beta$.

  iii. Draw $a_{ij}|u_i, u^0_{i0}, u^1_{i0}, \ell_i, enroll_i, \eta^u_i, \eta^o, \delta_j$.

(d) Draw $\eta^u_i|u_i, \Sigma^{rc}$

2. for each observable type $s \in S$

   (a) Draw $\sigma^2_{0,0}|u^0_0$.

   (b) Draw $\sigma^2_{0,1}|u^1_0, \mu^1_0$.

   (c) Draw $\mu_{0,1}|u^1_0, \sigma^2_{0,1}$.

   (d) Draw program random effects $\xi|u, \{\eta^u_i\}_{\forall i}, \eta^o, \overline{\beta}$.

   (e) Draw $\overline{\beta}|u, \{\eta^u_i\}_{\forall i}, \eta^o, \xi$.

   (f) Draw $\eta^o|u, \{\eta^u_i\}_{\forall i}, \overline{\beta}, \xi$.

   (g) Draw $\Sigma^{rc}|\{\eta^u_i\}_{\forall i}$.

   (h) Draw $\alpha|a$.

   (i) Draw $(\overline{\beta}, \beta)|h, u,$ graduate.

We use standard conjugate priors. We choose the prior parameters to be relatively uninformative. Regression coefficients and program fixed effects have independent $Normal(0, 100 * I)$ priors, where I is the identity matrix. Each a_{ij} is Bernoulli, so we use a $Beta(1, 1)$ prior for each of the eight elements of α. Scalar variances have $InverseGamma(1, 1)$ priors. Variance-covariance matrices of size (k, k) have $InverseWishart(k + 1, 10 * I)$ priors.

The only nonstandard steps are those drawing individuals' u_i and a_i. Building on insights from McCulloch and Rossi (1994) and Agarwal and Somaini (2018), we observe that updating each u_{ij} consists of drawing from a truncated Normal distribution. The mean of this distribution depends on $(\overline{\beta}, \eta^u_i, \eta^o)$, and conditional on these parameters and the data, the variance of u_{ij} is given by $var(\epsilon_{ij}) = 1$. In the case that i enrolls in j, we account for the fact that u_{ij} enters the human-capital index.[20]

[20] Let β_u denote the coefficient on u_{ij} in h_{ij}. Let $\mu_u \equiv u_{ij} - \epsilon_{ij}$, and let $\mu_h \equiv h_{ij} - \beta_u u_{ij} = \overline{\beta}_j + \beta_{distance} D_{ij} + \beta_p p_{ij} + \beta_x x^{oo}_i + \sum_{m=1}^{M} \sum_{k=1}^{K} x^k_i x^m_j \beta^o_{m,k}$ denote the deterministic portion of h_{ij}. The likelihood of $u_{ij}|h_{ij}$ is proportional to $\phi(u_{ij} - \mu_u)\phi(h_{ij} - \beta_u u_{ij} - \mu_h)$. With some algebra one can show:

$$u_{ij}|h_{ij} \sim N\left((\mu_u + \beta_u \mu_h)\tilde{\sigma}^2, \tilde{\sigma}^2\right),$$

where $\tilde{\sigma}^2 = \frac{1}{\beta^2_u + 1}$.

Truncation bounds come from two sources: the submitted application and the enrollment decision. The submitted application reveals a partial ranking of programs. We first drop programs outside of $J_i^{relevant}$ from i's application. If $j \in J_i^{relevant}$ was ranked mth on i's application, then its utility is bounded below by the utility of the $m+1$th option if there is any, and above by the $m-1$th when $m > 1$.[21] If j is the final option on the list, u_{ij} is bounded below by u_{i0} if the application list was not of full length once restricted to relevant programs, and otherwise by the max of u_{i0}^0 and highest-utility program in $J_i^{relevant}$ that was not listed. If j was not listed, its utility is bounded above by u_{i0}^0 if the list was not full, and by the final listed program if the list was full. When updating u_{i0}^0, the construction of bounds is analogous.

Bounds from the enrollment decision are simpler: a_i determines the choice set, and $enroll_i$ indicates the best option within the choice set. If $j = enroll_i$ then

$$u_{ij} > \max\{u_{ik} : k \geq 0,\ k \neq j,\ k \text{ ex-post feasible for } i,\ a_{ik} = 1\}.$$

If $j \neq enroll_i$ then whenever $a_{ij} = 1$ we must have $u_{ij} < u_{i,enroll_i}$.

The lower bound on u_{ij} is the maximum of the lower bound from the enrollment decision (if any) and the lower bound from applications (if any). The upper bound is analogous.

Some elements of a_i are observed. If i enrolls in his original match or in a waitlist offer, then $a_{ik} = 0$ for all waitlisted programs k that i ranks above where he enrolls. If i enrolls in program j or was placed in j then $a_{ij} = 1$. When a_{ij} is not observed, we have $a_{ij} = 0$ whenever $u_{ij} > u_{i,enroll_i}$, and $a_{ij} \sim Bernoulli(1-\alpha)$ otherwise.

[21] The first-ranked program is unbounded above.

5 Results and Counterfactual Simulations

5.1 Results

In this section we report selected model estimates. All parameters are estimated separately by student type (male - private school, male - public school, female - private school and female - public school). We focus on estimates of frictions and of selected human-capital parameters. A full set of estimates is available in appendix A-4 tables A-4 through A-6.

Table 1: Selected Estimates

Parameters	Male Private	Male Public	Female Private	Female Public
Aftermarket frictions (α)				
On-Platform	0.8711	0.8146	0.8542	0.8049
	(0.0037)	(0.0042)	(0.0036)	(0.0036)
Off-Platform	0.378	0.6073	0.4032	0.6598
	(0.0142)	(0.0074)	(0.0068)	(0.016)

Note: Preference parameters were estimated via Gibbs sampling and include program fixed effects. The number of observations used for the estimation are 484549 and the number of options are 1334 over three years.

Table 1 shows aftermarket friction parameters. We find that on-platform frictions are high and similar across types, with α ranging from roughly .80 to .87, indicating that roughly a fifth to an eighth of attempts to contacted waitlisted students are successful. Off-platform frictions are lower, but in contrast to on-platform frictions they differ markedly across types, with the failure rate $\alpha \approx .38$ and .40 for private-school men and women, respectively, compared to $\alpha \approx .61$ and .66 for public-school men and women.

In appendix figure A-19 we show the distribution of program mean utility terms (δ) by type. The results indicate that private-school students systematically exhibit stronger preferences for G8 programs, relative to G25 programs, than do students from public schools. Thus private-school students' greater probability of enrolling in G8 programs arises from stronger preferences as well as lower frictions.

Appendix table A-6 shows production-function parameters. Students with higher math scores are more likely to graduate, but we find small impacts of verbal scores. In addition, we find positive "match" effects on the interaction of STEM coursework and math test scores. For public-school types, the symmetric 95% posterior probability intervals do not cover zero. In addition, our specification allows for the possibility of match effects on unobservables—for instance, students who prefer their enrolled program to all other feasible and nearly-feasible programs may be more likely to graduate on time than students who just miss out on programs that they prefer. We find that match utility positively and significantly predicts on-time graduation, with the correlation between the utility shock and the human-capital shock in the range .19 to .63, depending on type.

5.2 Impacts of Platform Expansion

Table 2 displays the impact of platform expansion on welfare, probability of enrolling in an inside-option program, and probability of on-time (six-year) graduation conditional on enrollment.[22] All counterfactuals are conducted in 2012. We focus on the comparison of model-predicted impacts in 2012, with all inside-option programs on the platform, to an "as-if 2011" counterfactual, in which the population is as in 2012 but the G8 institutions are excluded from the platform. To provide context, we also evaluate the impacts of a "No Frictions" counterfactual in which all inside options are on platform and $\alpha = 0$ for all types. In this counterfactual, each program's capacity is the maximum of its realized enrollment in the 2012 counterfactual and the sum of its true and excess seats. Thus we do not reduce the supply of excess seats. We treat the "No Frictions" counterfactual as a benchmark, and report *differences* in outcomes, relative to this benchmark, under the other counterfactuals.[23]

Panel A of table 2 shows welfare in units of 1 million Chilean Pesos. We find that removing all frictions would lead to mean welfare equivalent to 1.29 million pesos. Estimated welfare is larger, in these units, for private-school households because we estimate a price (BVP scholarship) coefficient that is closer to zero for these households; this need not reflect social weights. Relative to this benchmark, the 2012 baseline gives households an average loss equivalent to 0.026 million pesos. The loss from excluding the G8, 0.057 million pesos, is over twice as large. Importantly, excluding the G8 may result in welfare gains for male private-school students, at the expense of students from public schools.

The next row, labeled "Exclude G8, Equal α," refers to a counterfactual in which on- and off-platform frictions α are each equalized across types at a level that sets the same total amount of missed calls from on- and off-platform programs. Because private-school students have lower frictions, especially at off-platform programs, this counterfactual would redistribute seats toward public-school students relative to the "Exclude G8" counterfactual. Because private school students' preferences for college are larger in dollar terms, this would lead to losses on average, but would provide gains for public-schools students.

[22] We should note that some medical degrees in Chile have a duration longer than six years but represent a small fraction of students. A longer horizon is not possible with the data available at this time.

[23] We have also evaluated an (even more infeasible) counterfactual in which all options, including the second outside option, are included on the platform, so that there is no need for an aftermarket. In principle this counterfactual might differ from the "No Frictions" counterfactual because some students who renege due to an outside-option shock in the "No Frictions" counterfactual may have formed part of a blocking pair. In practice we find that these two counterfactuals produce identical allocations for all except a single-digit number of students.

Panel B shows impacts on the probability of enrolling in any inside-option program. Private-school students are much more likely to enroll, with roughly 69% attending an inside option, relative to 41% of public-school students. We find that excluding the G8 would lead to large drops in enrollment, but that the baseline comes within half a percentage point of the frictionless upper bound.

Finally, panel C shows impacts on six-year graduation rates. These are larger for women and, conditional on gender, for private-school students. Excluding the G8 would lead to a half-percentage-point reduction in graduation rates of enrolled students, relative to the case of no aftermarket frictions. In contrast, at baseline graduation rates are similar to those of the frictionless case.

5.3 Impacts of Aftermarket Frictions

The results of table 2 suggest that the interaction of frictions and programs' nonparticipation produces welfare losses. We now explore the role of frictions in detail. In figure 7, we plot welfare, enrollment rates, graduation rates conditional on enrollment, and welfare by type as all friction parameters are multiplied by a factor $(1 - p)$ for $p \in [0, 1]$. We conduct this exercise with all programs on platform, as well as when the G8 is excluded.

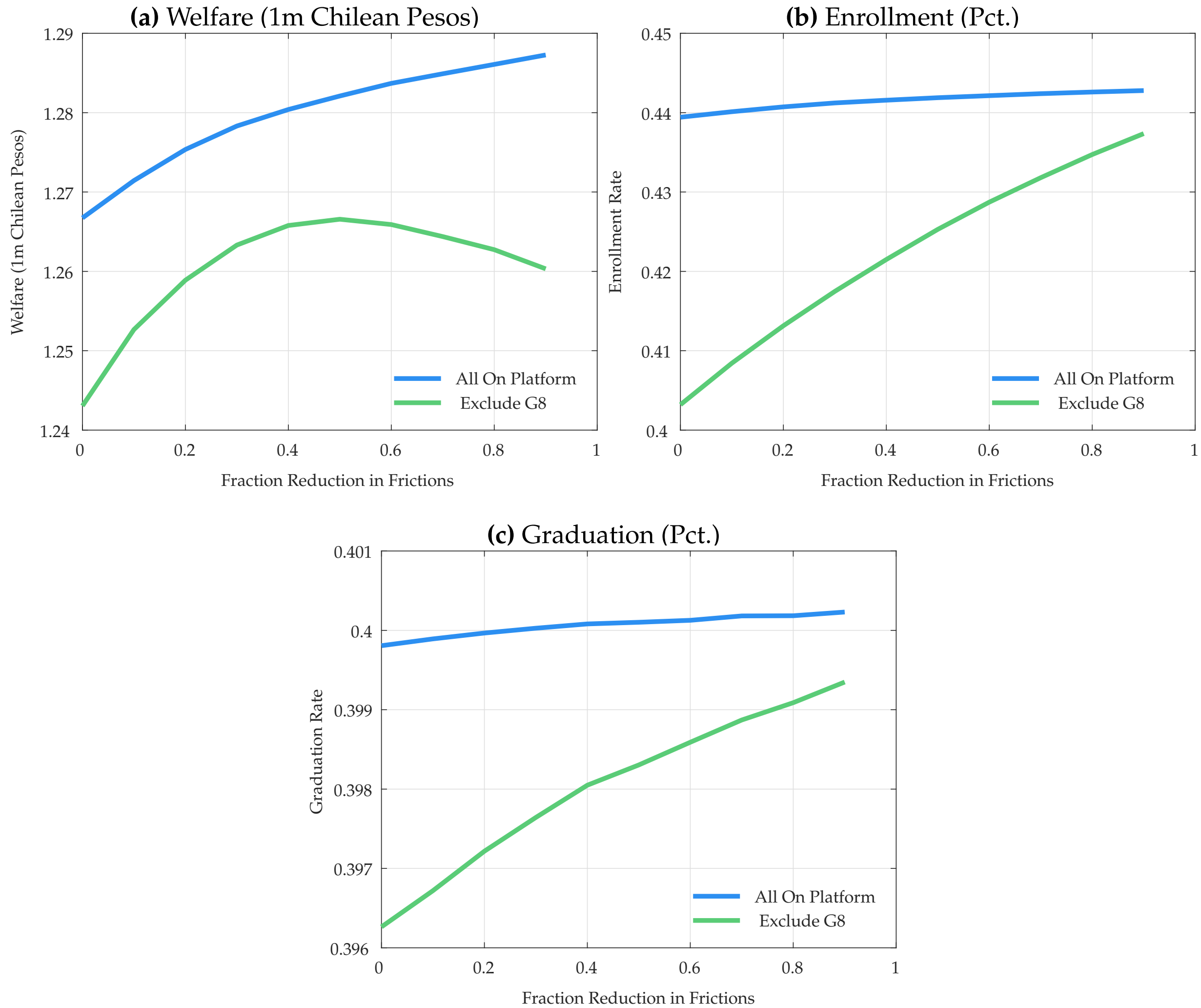
Figure 8 shows the results of the same exercise differentiating by type of student. The results indicate that, for students from public high schools, welfare increases monotonically as frictions are reduced, both with all programs on-platform and when the G8 is excluded. For these students, frictions and platform status interact so that the marginal gains from friction reduction are larger when the G8 is excluded. For students from private schools, in contrast, when the G8 is excluded, the optimal amount of frictions is interior. Intuitively, these students benefit from the lower standards at off-platform programs when public-school students are subject to larger frictions, and this benefit outweighs the direct cost of frictions. A second observation is that, in the absence of waitlist frictions, welfare is higher when the G8 participates in the platform. The presence of the G8 induces additional chains of proposals by colleges, which in turn lead to an allocation that is more favorable for students.

Table 2: Main Counterfactual Results

Counterfactual	All (Avg.)	Male Private	Male Public	Female Private	Female Public
A. Welfare					
No Frictions (*)	1.2873	3.9592	0.8959	2.2383	1.0028
	(0.059)	(0.762)	(0.0256)	(0.1853)	(0.0715)
Baseline - *	-0.026	-0.0806	-0.0229	-0.0349	-0.0175
	(0.0021)	(0.0175)	(0.002)	(0.0073)	(0.0021)
Exclude G8 - *	-0.0571	0.105	-0.0691	-0.0256	-0.0807
	(0.0045)	(0.0606)	(0.0045)	(0.023)	(0.0042)
Exclude G8, Equal α - *	-0.0895	-0.3118	-0.0592	-0.2783	-0.0457
	(0.0093)	(0.079)	(0.0046)	(0.0325)	(0.0045)
B. Enrollment (pct)					
No Frictions (*)	44.2784	69.3081	41.5431	69.1557	38.1491
	(0.0448)	(0.0801)	(0.0557)	(0.0786)	(0.069)
Baseline - *	-0.4176	-0.4253	-0.4949	-0.4296	-0.3445
	(0.0374)	(0.0637)	(0.0609)	(0.0723)	(0.0415)
Exclude G8 - *	-4.5335	-6.4697	-3.7625	-8.5353	-4.2232
	(0.0777)	(0.5037)	(0.0719)	(0.3564)	(0.1845)
Exclude G8, Equal α - *	-4.973	-12.6229	-3.5139	-14.9696	-3.2691
	(0.1109)	(0.4488)	(0.0981)	(0.4285)	(0.0768)
C. Six-Year Graduation (pct)					
No Frictions (*)	40.0231	38.2235	30.1209	53.5756	46.3127
	(0.2265)	(0.6485)	(0.388)	(0.6102)	(0.3422)
Baseline - *	-0.0501	-0.0868	-0.0754	0.0691	-0.087
	(0.0568)	(0.136)	(0.1148)	(0.0949)	(0.0516)
Exclude G8 - *	-0.4521	0.0897	-0.4326	-0.5414	-0.3366
	(0.0829)	(0.1951)	(0.1485)	(0.2222)	(0.0867)
Exclude G8, Equal α - *	-0.6244	-0.3509	-0.3687	-1.0405	-0.323
	(0.0821)	(0.2433)	(0.1356)	(0.2605)	(0.0956)

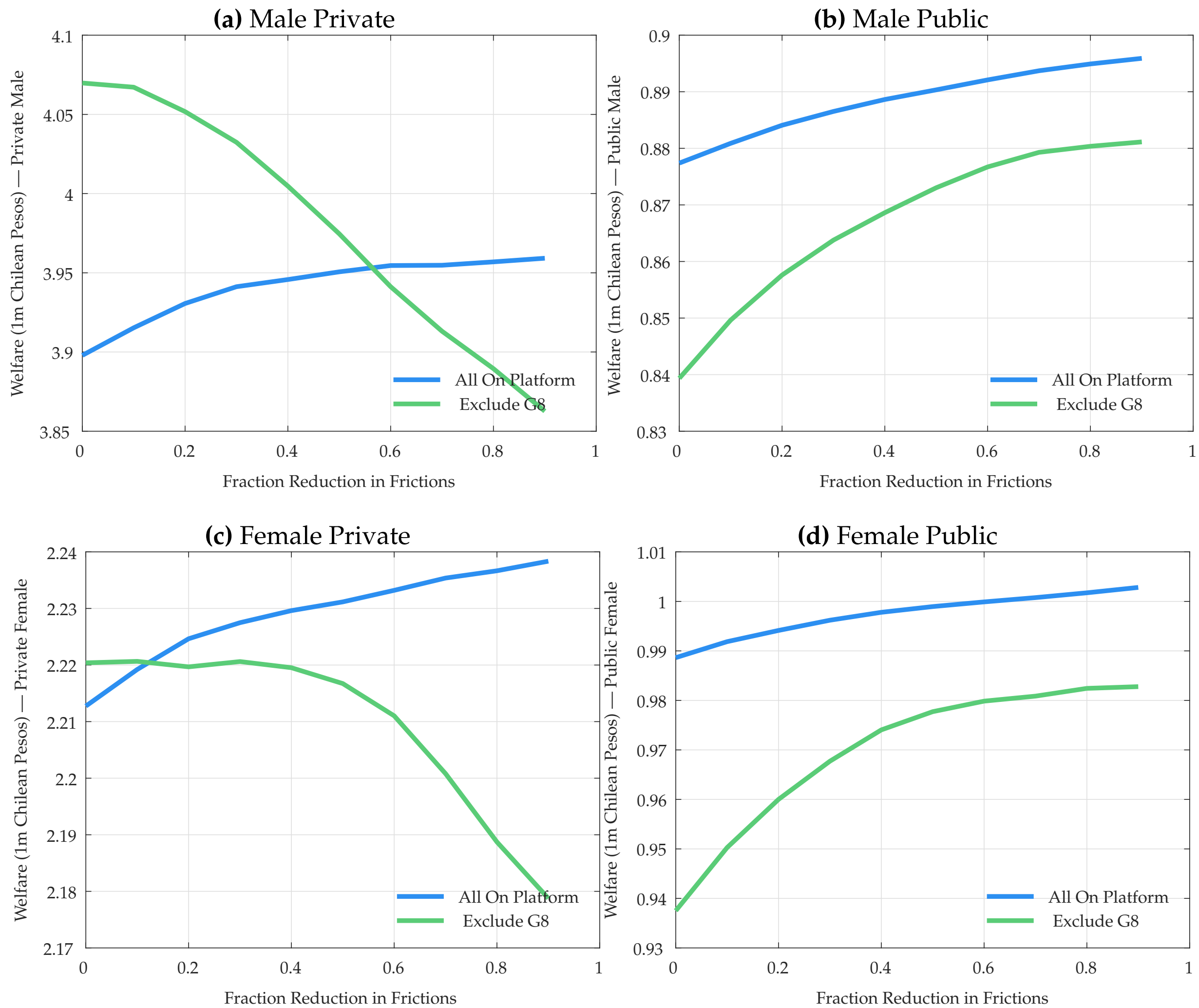
Note: All counterfactuals conducted using 2012 data. We draw from the posterior joint distribution of parameters and latent utilities (u, u_0). Waitlist processes and realizations of frictions a are simulated according to parameters α. We conduct 26 draws for each counterfactual. "No Frictions": all programs on platform, $\alpha^{on} = \alpha^{off} = 0$ for all types. "Baseline": all programs on platform, parameters as estimated. "Exclude G8": G8 programs off platform. "Equal α": for each platform status, α equal across types.

Figure 7: Impacts of Reducing Frictions (α)



Note: All friction terms α multiplied by $(1-p)$, where p is "fraction reduction in frictions" on X-axis.

Figure 8: Welfare Impacts of Reducing Frictions (α): Heterogeneity by Type



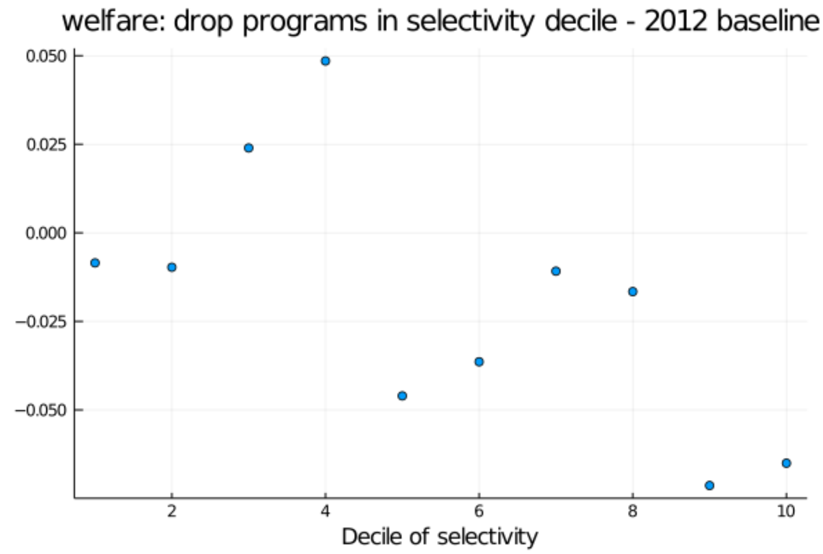
Note: All friction terms α multiplied by $(1 - p)$, where p is "fraction reduction in frictions" on X-axis.

5.4 Which Programs are Most Important to Include?

Given the estimated parameters, we computed the average welfare loss of removing programs from the platform. We sort programs by selectivity, as measured by mean math+verbal test scores, and divide them into ten equal-sized bins by realized enrollment. We then evaluate the impacts of dropping these programs, one decile at a time, relative to the baseline setting in which all programs are on-platform. We present the results from least to highest selectivity.

Results are shown in Figure 9. We show that the utility loss is higher if the programs in the top two deciles of selectivity are removed. Intuitively, when the most elite programs on the platform are absent, students who would have placed in them instead occupy places in lower-ranked programs, leading to the longest chains of displacement of other students.

Figure 9: Utility loss of removing options ordered by selectivity

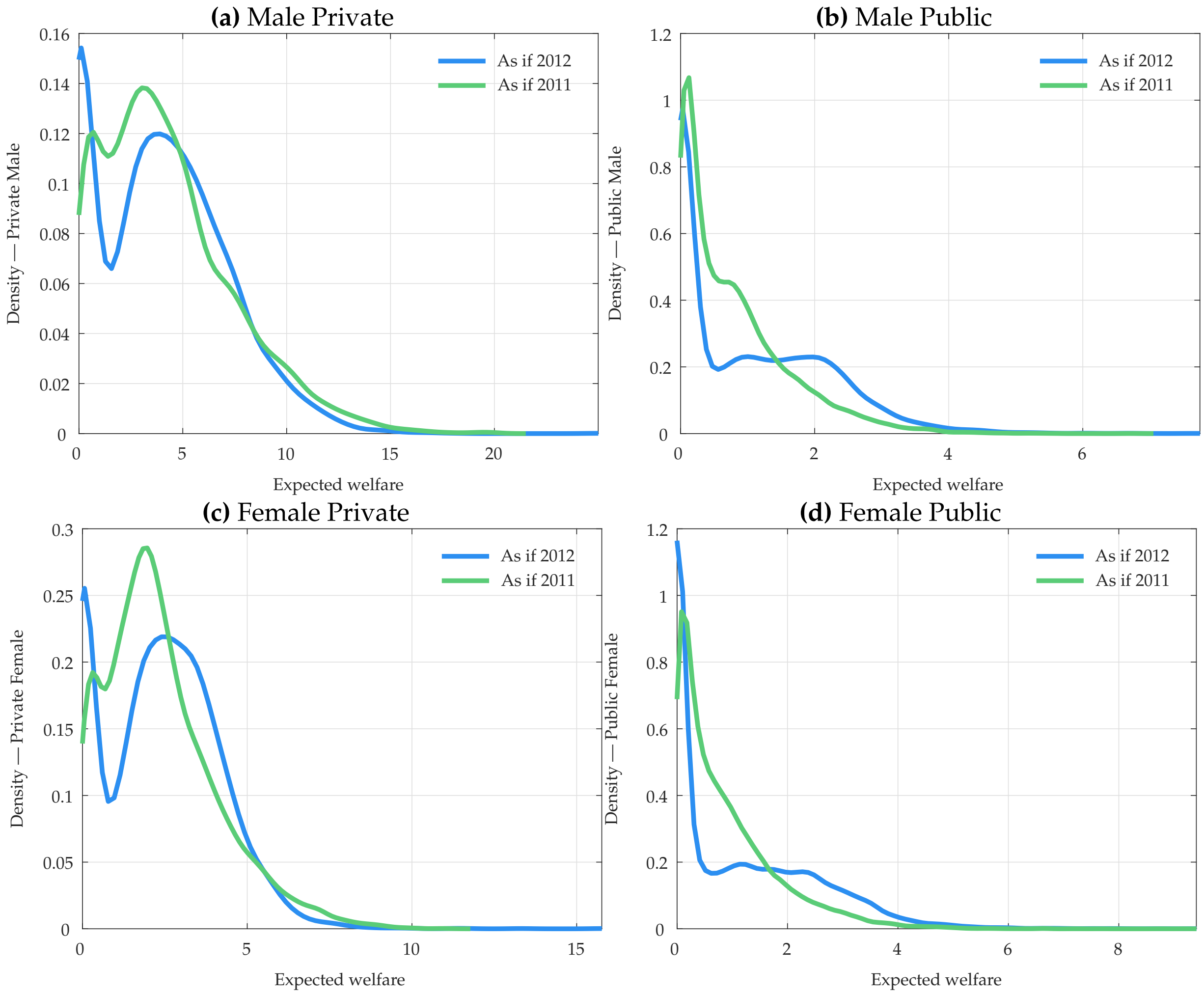


Note: Loss is calculated as the difference in mean utility, in units of 1m Chilean Pesos, between the model-simulated 2012 baseline and the counterfactual in which all program seats in the d'th decile of selectivity—as measured by programs' 2012 mean math+verbal scores—are withheld from the platform. Negative (positive) values indicate losses (gains) relative to baseline.

5.4.1 Heterogeneous Impacts

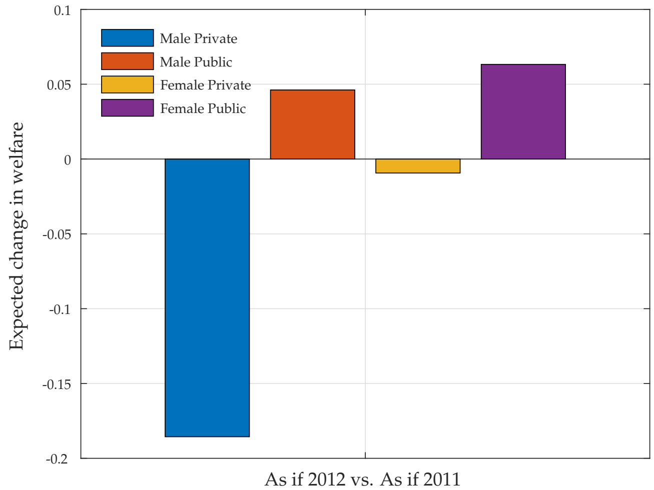
We now turn to heterogeneity across and within types. We focus on the main counterfactual of removing the G8 from the platform. Figure 10 depicts the estimated utility distributions while Figure 11 highlights welfare gains in different dimensions. The first set of bars shows that excluding G8 programs from the platform results in a 30% decrease in welfare, which is relatively invariant across groups. However, our second set of bars suggest that public school students substantially increase their probability of being matched and enrolling in a higher education degree after the policy: in absence of G8 programs an additional 15% of public school applicants would not enroll in any program. In contrast, excluding G8 programs would make 7% of private school applicants choose their outside option. Finally, the last set of results in Figure 11 shows that unmatched private-school applicants that end up enrolling in a program after the policy benefit the most. These students increase their utility by 49% for males and 54% for females. The impact on the analogous group of public school applicants is smaller, with an estimated average change of 39%. Taken together, these estimates suggest that public school students benefit more in terms of the extensive margin of now being able to attend college, while private school students benefit from the intensive margin of being matched to better degrees.

Figure 10: Distributional change in welfare after policy change in 2012

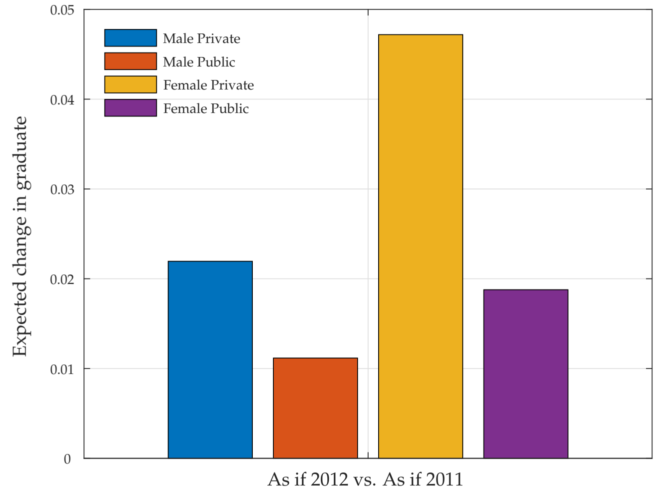


Note: The densities plotted in the figure are the estimated enrollment utilities for students in years 2011 and 2012. For each plot, the x-axis corresponds to the average utility levels across draws for each individual and the y-axis indicates the conditional kernel density estimates.

Figure 11: Change in Welfare and Graduation Rates by Type



(a) Δ welfare for students by type



(b) Δ graduation for students by type

Note: The left panel shows, for each type of student, the estimated change in welfare (in millions of Chilean pesos) after the policy took place. The right panel shows, for each type of student, the estimated change in graduation rates after the policy took place.

5.5 Impacts in Context

Table 3 shows impacts of additional counterfactuals relative to the no-frictions benchmark. We consider two policies which make on-platform programs cost-free for all students from public high schools: in "Free G33" all programs are on the platform; in contrast, in "Free G25" only the G25 participates. We find that welfare gains are roughly 50% larger when all programs participate. When all programs participate, the average student welfare gain is roughly .76 million Chilean Pesos. The welfare impact of platform expansion is roughly 7.5% as large as the additional welfare impact of free college—a much more expensive policy change—would be.

Finally, we compute an assignment that maximizes the sum of students' utilities, as measured in Chilean Pesos, subject to programs' eligibility rules (such as requiring a simple average of 450 points on math and verbal scores) but otherwise ignoring programs' rankings of students. The gains from this counterfactual are roughly 25% larger than those of providing full scholarships to the 90% of students who come from public high schools. The gains from allowing the G8 to join are roughly $0.058/1.09 \approx$ five percent of the size of the difference between student welfare under the frictionless and utilitarian student-welfare-maximizing allocations. However, this welfare-maximizing counterfactual would lead to decreases in total enrollment.

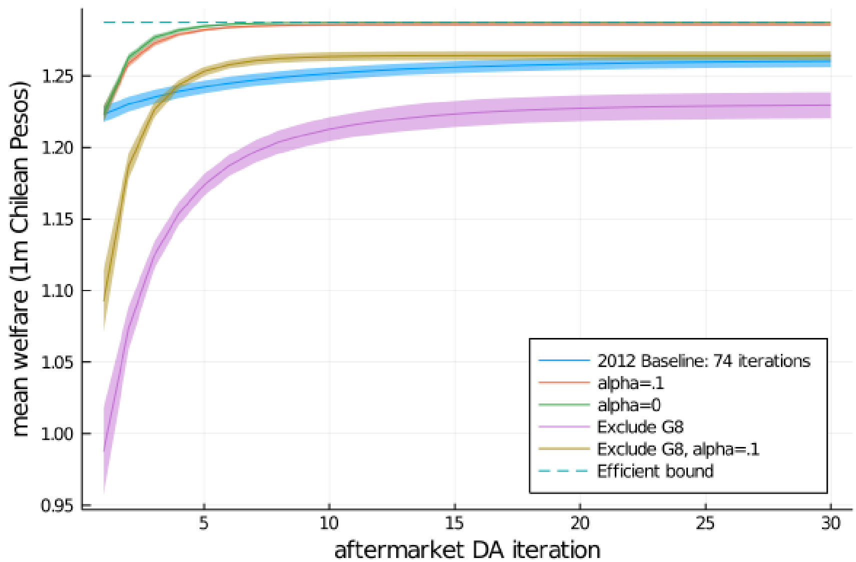
Table 3: Additional Results: Platform Expansion in Context

Counterfactual	All (Avg.)	Male Private	Male Public	Female Private	Female Public
A. Welfare (1m CLP)					
No Frictions (*)	1.2873	3.9592	0.8959	2.2383	1.0028
	(0.059)	(0.762)	(0.0256)	(0.1853)	(0.0715)
Free G33 - *	0.7595	-0.4176	1.0517	-0.232	0.8708
	(0.0069)	(0.0917)	(0.0077)	(0.0291)	(0.0166)
Free G25, G8 off - *	0.4812	-0.0119	0.6791	-0.0774	0.4832
	(0.0046)	(0.0392)	(0.0075)	(0.0274)	(0.0095)
Max Welfare - *	1.0871	2.9252	0.5854	1.6904	1.1097
	(0.0451)	(0.5815)	(0.023)	(0.1362)	(0.0579)
B. Enrollment (pct)					
No Frictions (*)	44.2784	69.3081	41.5431	69.1557	38.1491
	(0.0448)	(0.0801)	(0.0557)	(0.0786)	(0.069)
Free G33 - *	6.5293	-4.9212	9.0908	-4.9206	8.1617
	(0.9848)	(0.1922)	(1.0645)	(0.2852)	(1.3936)
Free G25, G8 off - *	-0.8058	-8.6425	1.5189	-10.2264	0.0555
	(0.5129)	(0.4664)	(0.5979)	(0.4063)	(0.6571)
Max Welfare - *	-2.5787	-13.1457	-2.8264	-11.8771	1.0776
	(0.1768)	(0.6469)	(0.2797)	(0.4703)	(0.3002)
C. Six-year Graduation (pct)					
No Frictions (*)	40.0231	38.2235	30.1209	53.5756	46.3127
	(0.2265)	(0.6485)	(0.388)	(0.6102)	(0.3422)
Free G33 - *	0.9958	0.2058	2.7767	0.4464	0.4113
	(0.2154)	(0.1442)	(0.3594)	(0.1182)	(0.3515)
Free G25, G8 off - *	0.5644	0.4868	1.9195	-0.1948	0.2699
	(0.2161)	(0.1983)	(0.3749)	(0.2397)	(0.2957)
Max Welfare - *	1.2627	6.7549	1.0559	2.4439	-0.5035
	(0.3239)	(1.1308)	(0.3405)	(1.2825)	(0.6212)

Note: All counterfactuals conducted using 2012 data. We draw from the posterior joint distribution of parameters and latent utilities (u, u_0). Waitlist processes and realizations of frictions a are simulated according to parameters α. We conduct 26 draws for each counterfactual. "No Frictions": all programs on platform, $\alpha^{on} = \alpha^{off} = 0$ for all types. "Baseline": all programs on platform, parameters as estimated. "Free College (1)": All programs on platform, all programs free for students from public schools. "Free College (2)": G8 off platform, all G25 programs free for students from public schools. "Max Welfare": maximize sum of student utilities subject to eligibility constraints but otherwise ignoring programs' preferences.

Finally, figure 12 illustrates the length of the aftermarket process. In our counterfactuals, we simulate the DA process until convergence, which occurs after roughly 70 rounds when all programs are on platform, longer when some programs are excluded. This process occurs within a few weeks after the match is announced before classes begin. Figure 12 illustrates that, if this process were to stop early, welfare losses relative to a frictionless benchmark would be larger, especially when frictions are large and some programs do not join the platform.

Figure 12: Welfare by Round of Aftermarket DA Process



Note: Mean welfare at baseline and under counterfactuals if aftermarket DA process were to terminate at round t. At baseline, DA takes 70 iterations on average to terminate.

6 Concluding Remarks

This paper studies the empirical relevance of the negative impacts on students that arise in a centralized assignment mechanism when there are off-plaform options. When a desirable program is not on the centralized platform, applicants have no ability to communicate to the mechanism how they rank that option relative to other options. Some students may value off-platform options more than the placement that the platform gives them, leading them to decline their placement and creating vacancies in turn. Moreover, the absence of a particular program on the platform may distort the placements of other students, even if the students whose placements are affected would never enroll in that program. These displaced students be less satisfied with their assignment, and may be more likely to decline their placement, creating further vacancies. These vacancies can lead to an increased reliance on drawing students from waitlists in the aftermarket period.

Aftermarket frictions that generate even small difficulties in processing these waitlists—such as problems contacting or confirming enrollment with applicants —contribute to an assignment that unfairly "skips" some applicants whose scores qualify them for an offer of admission. Depending on the magnitude of the aftermarket frictions and the extent of the use of waitlists, off-platform options may have large impacts on the resulting assignment. To the extent that the quality of the match assigned is associated with real outcomes like retention and on-time graduation rates, off-platform options and aftermarket frictions can have important effects on these outcomes as well.

To study the empirical importance of off-platform options and aftermarket frictions, we use rich administrative data from the higher education system in Chile, one of the longest running centralized assignment systems in the world. We focus on a policy change in 2012 that expanded the supply of slots of the centralized platform by 40%. We document the impacts on assignments and outcomes. When a significant amount of off-platform options were added in Chile, matriculation in placed slots rose by 8%. Dropout rates at the end of the first year of college decreased by 2 points (a 16% drop) and on-time graduation rates for students of that cohort improved by 1 point (a 3% increase). Importantly, these results were largest among students from more disadvantaged backgrounds, suggesting effects on equity in addition to those on efficiency.

We propose an empirical model to estimate preferences and to quantify aftermarket frictions using information from students' ranked-ordered lists of on-platform options and their enrollment decisions at both on- and off-platform options. Our empirical results show that the configuration of on- and off-platform options can have meaningful impacts on students' welfare, dropout and graduation in higher education.

A post-estimation decomposition shows that the lower-scoring students, women and underprivileged populations benefited the most from having more options on the centralized platform. Programs' absence from the platform redistributes welfare away from public-school students and women toward high-SES private-school men, while reducing total welfare. Counterfactual analysis reveals that more desirable options cause larger negative impacts, as the 10% most selective programs leaving the platform generates 7% more welfare loss than the average college.

We find that aftermarket frictions and off-platform programs interact so that the marginal cost of frictions on student welfare is smaller when all programs are on platform. Moreover, when programs are off platform, match quality decreases, and some students with high scores at waitlisted programs lose their positions to students with lower scores. Because our estimates indicate that scores and idiosyncratic "fit" both contribute to on-time graduation, these two channels lead to lower on-time graduation rates when some programs do not join the platform.

These results show that off-platform options can generate important costs which are relevant to policymakers seeking to implement a centralized assignment system. While we study higher education, the considerations highlighted in this paper are common in many practical settings. One example is urban education markets in developing countries, which typically have a large share of private providers. As more developing countries follow their richer counterparts in implementing centralized systems, policymakers should incorporate the consequences of off-platform options into market design, in the spirit of the broader agenda described in Pathak (2017).

We show that empirical analysis can be helpful to guide policy discussions and quantify key parameters that are needed to evaluate the potential costs of non-participation by different institutions. Our estimates provide a specific metric to evaluate the cost of losing each university on the platform, but our model and empirical strategy also highlight ways to quantify the costs of off-platform options in other settings and provide a route to informing policy regarding the costs of off-platform options.

In this paper we have abstracted from several important aspects of the higher education market when evaluating the benefits of platform expansion. These include the potential benefits of transparency about the process of assignment. One such benefit is that, in a centralized process in which programs rank applicants according to known functions of public information, it may be easier to communicate the rules to applicants. Recent controversies surrounding the admissions process at elite universities in the United States suggest that this margin could be important. We have also ignored the fixed costs of running an admissions office. These costs presumably would be lower when participating in a centralized platform. Finally we have abstracted from supply side considerations related to the incentives that individual providers have to join the platform, and from any effects that platform expansion has on competitive incentives. We leave these topics for future research on how best to design markets in practice.

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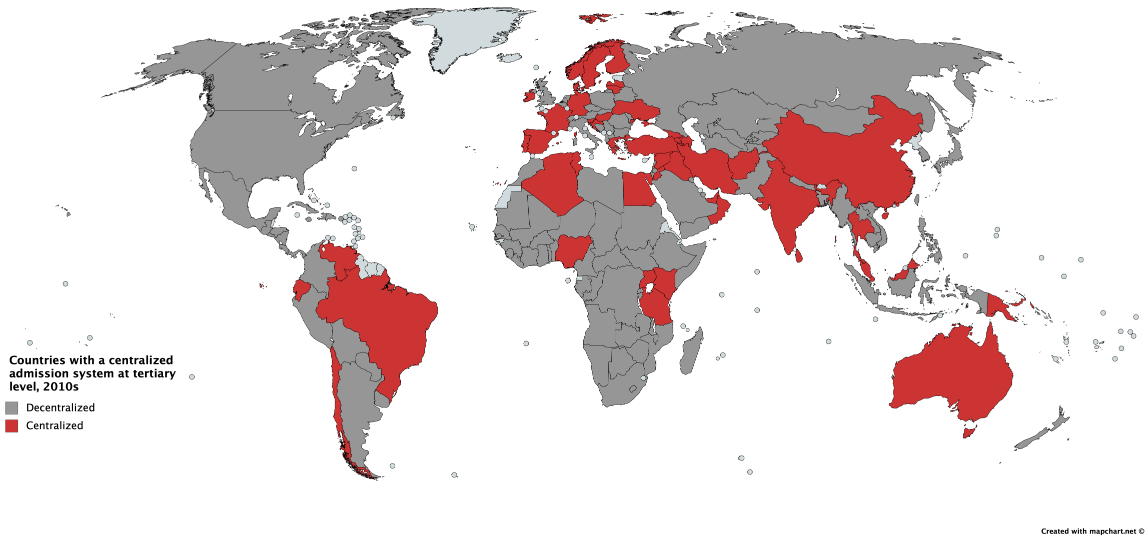
Appendix

Figure A-1: Use of Centralized Assignment Systems in Higher Education Across the World



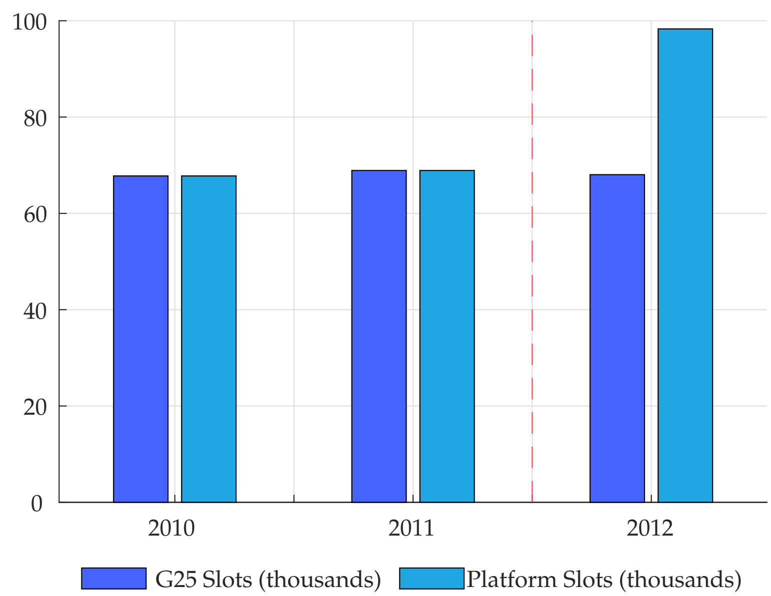
Note: This figure is replicated from (Neilson, 2019). The map shows a large number of countries currently utilize centralized assignment mechanisms in higher education. Red countries indicate that the country has at least a subset of higher education options that are assigned by a centralized assignment mechanisms. Virtually none of these platforms include all of the higher education options.

Table A-1: Sample Descriptive Statistics 2010-2012

	Year 2010		*Year 2011*		*Year 2012*	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
Test Takers						
Male	0.47	0.50	0.48	0.50	0.47	0.50
Private HS	0.10	0.30	0.10	0.30	0.11	0.31
Metro Area	0.65	0.48	0.64	0.48	0.64	0.48
GPA	529.53	115.51	531.64	110.07	535.76	113.45
Math Score	500.79	110.77	501.07	111.27	503.94	110.63
Verbal Score	500.64	108.92	501.04	108.34	504.28	109.74
Platform App.	0.35	0.48	0.34	0.47	0.45	0.50
Observations	251634		250758		239368	
G25 Admits						
G25 Enrollee	0.75	0.43	0.74	0.44	0.80	0.40
G8 Enrollee	0.06	0.23	0.06	0.25	0.01	0.08
Other/Unenrolled	0.20	0.40	0.20	0.40	0.20	0.40
Observations	67013		67803		64662	

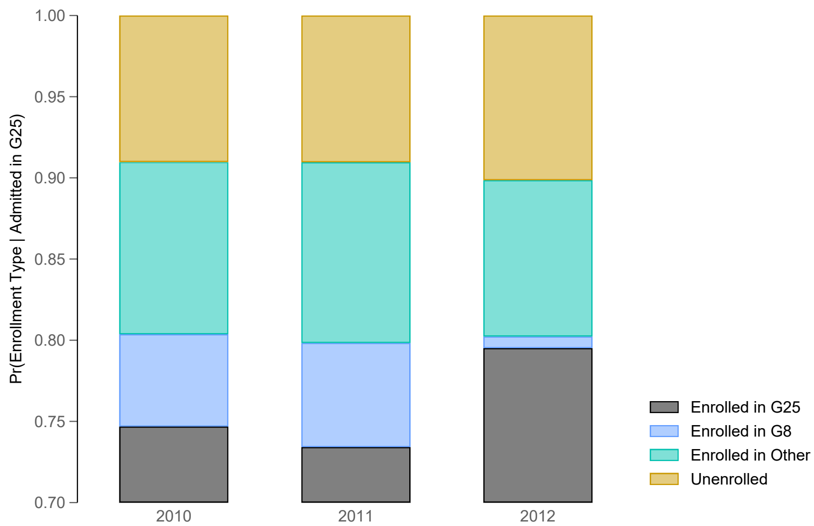
Note: This table shows descriptive statistics of the administrative data from DEMRE, the agency that runs the centralized assignment mechanism in Chile.

Figure A-2: Platform slots and applicants (in thousands)



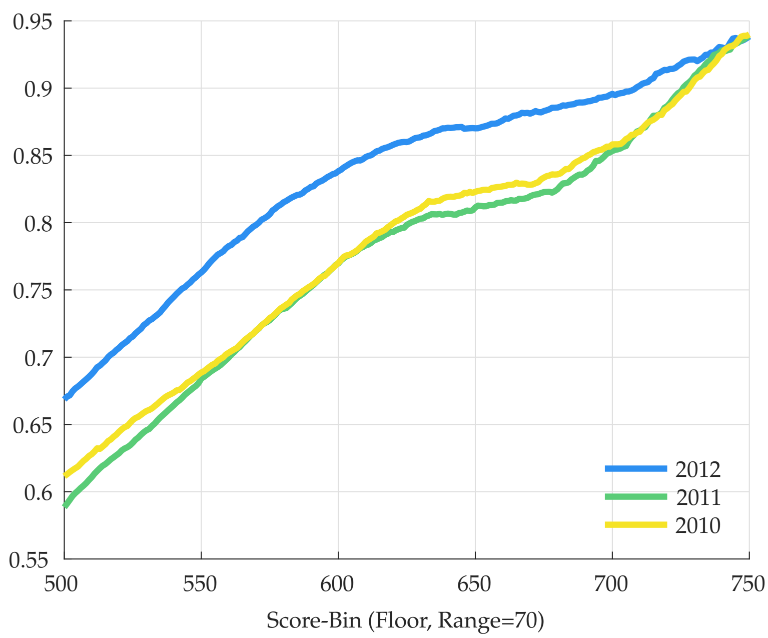
Note: This figure shows the number of G25 slots as well as the total slots available on the platform from 2010-2012. The increase in 2012 is due to adding the G8 programs.

Figure A-3: Enrollment probabilities for G25 admits



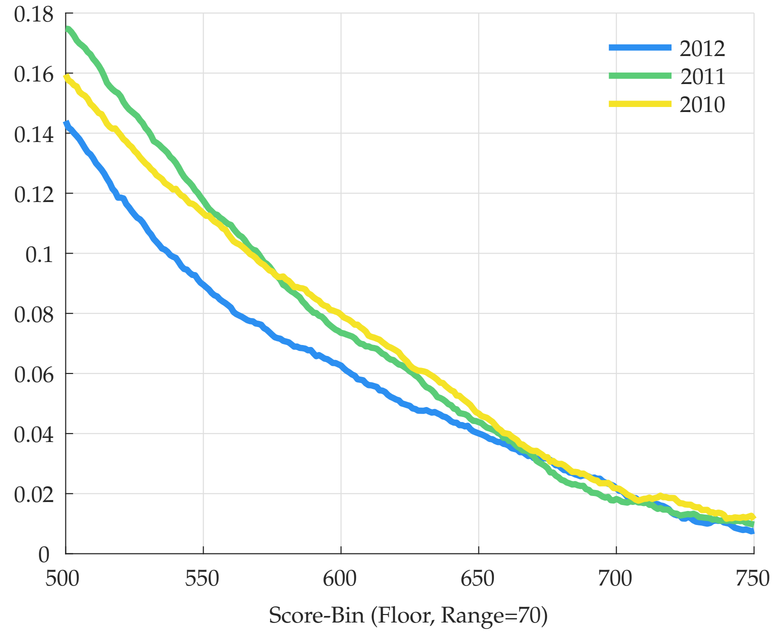
Note: This figure shows enrollment probabilities for students admitted to traditional ("G25") options, by year. The share of such students who enrolled in G25 programs increased, and the share enrolling in G8 programs decreased, in 2012. In 2012, the only way for such students to be admitted to G8 programs was off of waitlists.

Figure A-4: Enrollment probability for G25 assignments, conditional on score



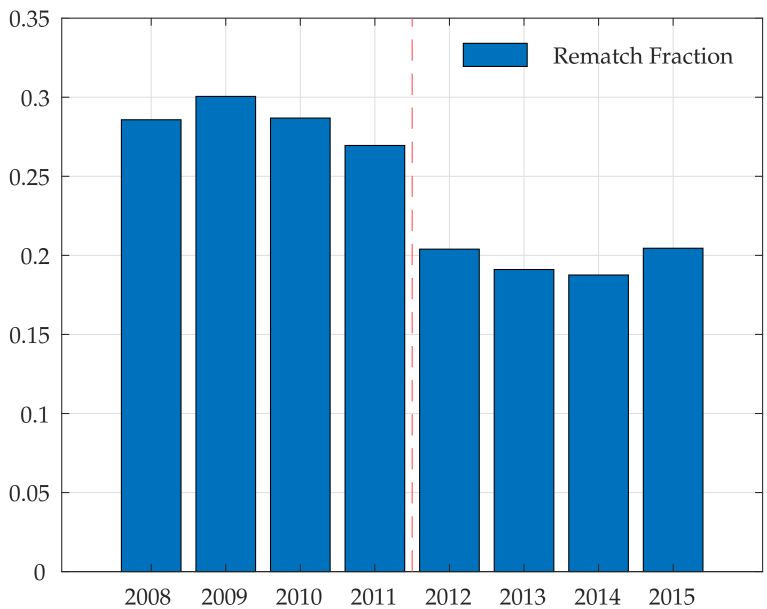
Note: This figure shows the probability that a student assigned to an option on the platform, accepts and enrolls in that option. The lines show conditional means within 70 points, and the "floor" of the range is shown in the x-axis (e.g. 600 corresponds to the range [600, 670]). The probability of enrollment increases substantially for assignments that occur in 2012 relative to the previous two years.

Figure A-5: Freshmen dropout rate for G25 enrollees



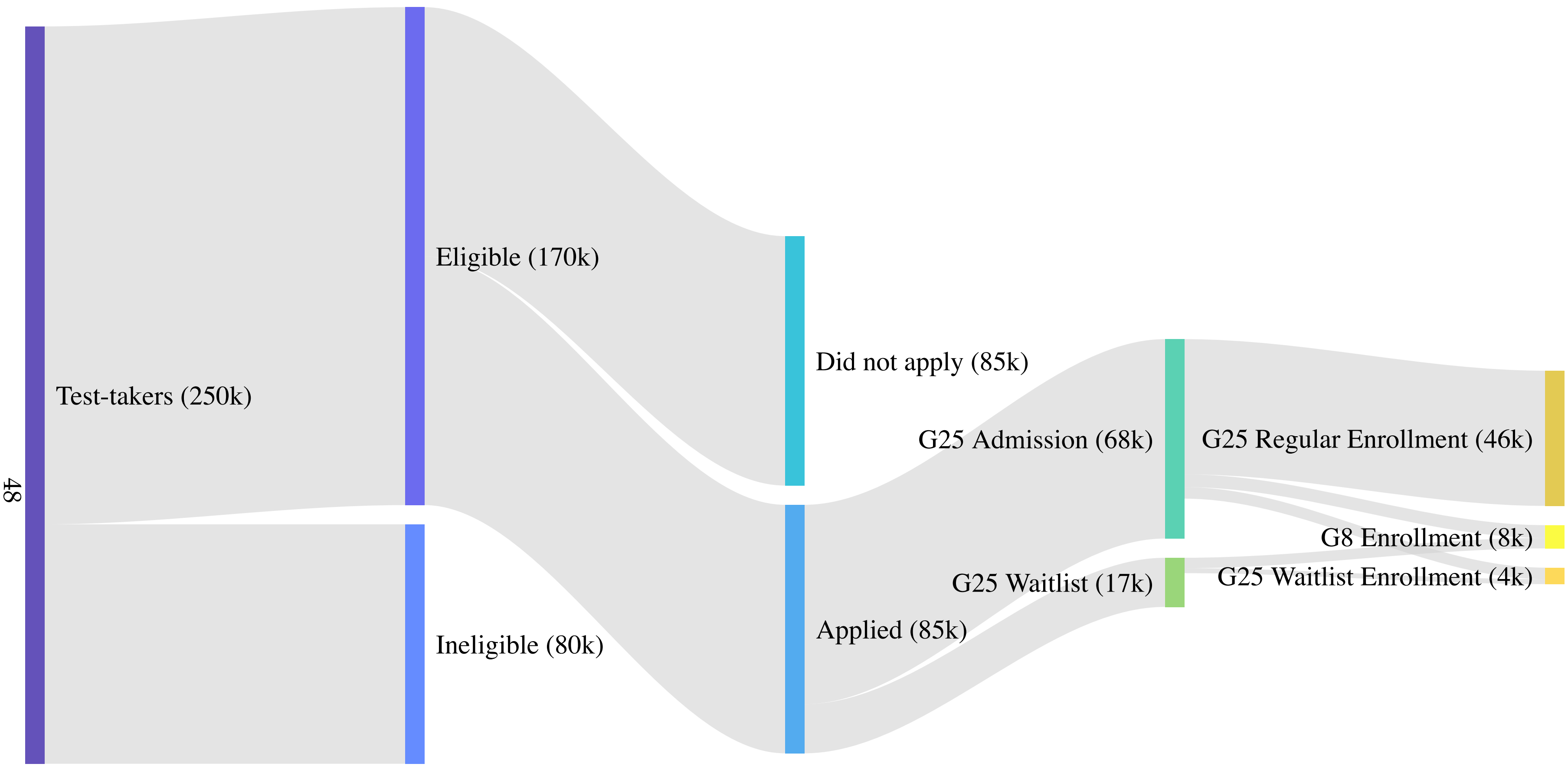
Note: This figure shows the probability that a student enrolled in a G25 option drops out of college a year after enrolling. The lines show conditional means within 70 points, and the "floor" of the range is shown in the x-axis (e.g. 600 corresponds to the range [600, 670]). The probability of dropout decreases substantially for assignments that occur in 2012.

Figure A-6: Rematch fraction when (ex-ante) dropping students who decline placements



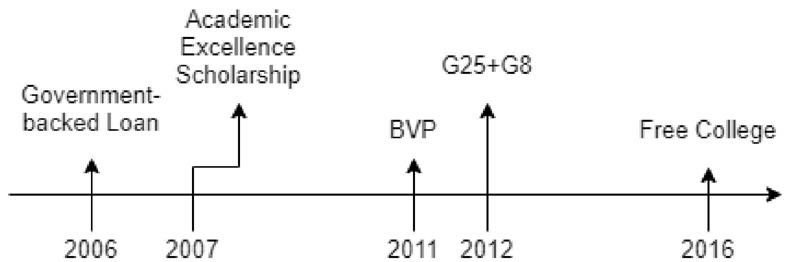
Note: This figure shows the fraction of match participants by year, other than those who renege on offers, whose initial assignment would change if students who decline their offers are removed from the match ex ante.

Figure A-7: Eligibility, application, admision and enrollment flow of 2011 test takers



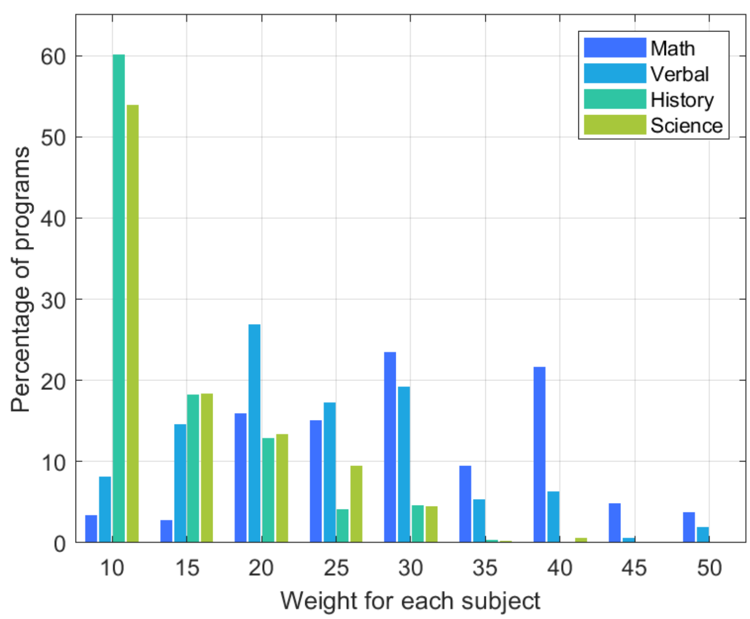
Note: This figure shows a Sankey diagram with the population of test takers in 2011 and their subsequent eligibility, application, admision and enrollment behavior.

Figure A-8: Policies Expanding Access to Higher Education in Chile - Timeline



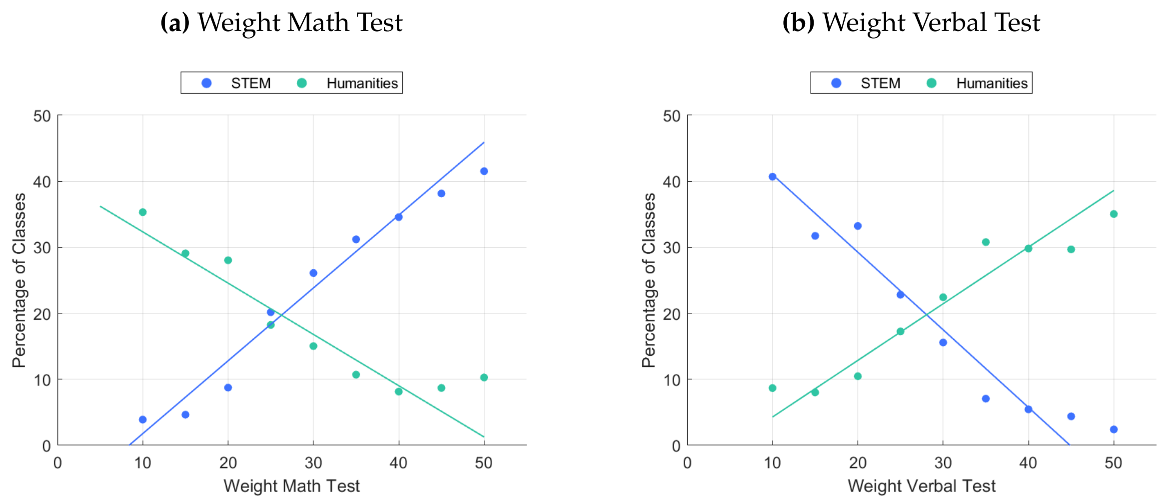
Note: This figure shows a timeline indicating the major policies in higher education that were implemented in Chile before and after the time period under study in this paper. The first one is the *Government-backed Loan (CAE)*, aid open to students applying to CRUCh or accredited non-CRUCH higher education institutions. Importantly eligibility was not tied to participation on the centralized platform. The second one is the *Academic Excellence Scholarship*, aimed to cover part of the annual fee of students belonging to the 10% of higher achievement. They have to apply to CRUCh or accredited non-CRUCH higher education institutions, come from public or private voucher schools, belong to the 80% most vulnerable population, and enter the year right after they graduated secondary school. Again this policy is unrelated to participation on the centralized platform. The *Teacher Scholarship* (BVP) which began in 2011 provided full scholarships for high-scoring students at eligibile teacher training programs. This was unrelated to participation on the platform. Finally, the Free College policy established that 50% of most vulnerable students do not have to pay tuition or annual fee in CRUCh or accredited non-CRUCH higher education institutions attached to the agreement.

Figure A-9: Weights on each subject



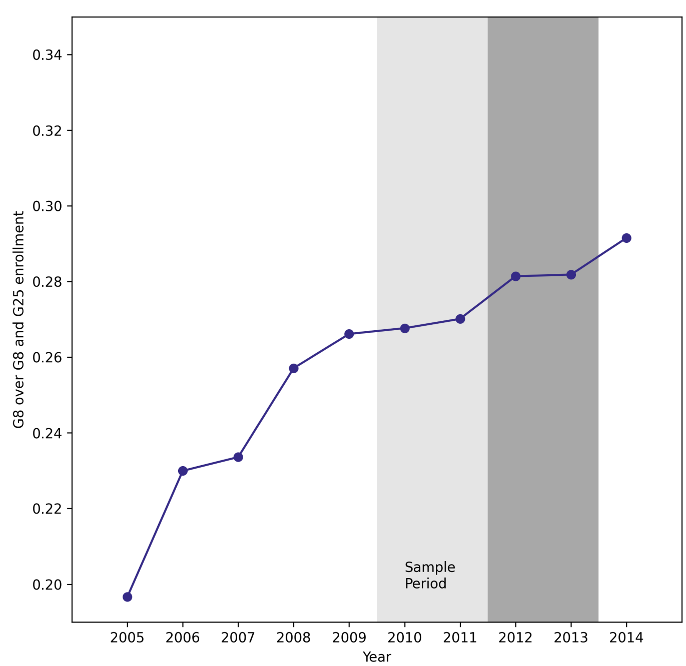
Note: This figure shows the distribution of weights that each program in 2011 considers for PSU's different subjects.

Figure A-10: Weights on Math and Verbal tests by type of classes



Note: This figure shows the conditional means of course contents by test weight in 2011.

Figure A-11: G8 enrollment as a share of G33 enrollment



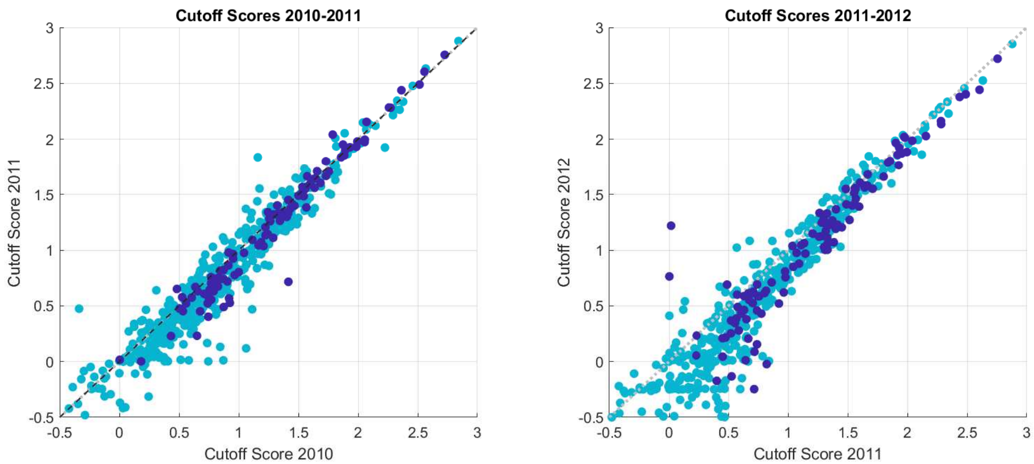
Note: This figure shows the fraction of students that enroll in G8 options relative to the total enrollment in G33 options over time. The light-gray area corresponds to our pre-policy sample, whereas the dark-gray area is our post-policy sample.

Table A-2: Selectivity by Institution

Univ.	Mean Score	Std. Dev.	P10	P25	P50	P75	P90	Total Adm.	Tier
11	691.56	46.09	630.9	658.25	688.9	723.55	751.9	5424	1
12	694.75	52.53	630.6	652.8	690.4	734.2	769.9	4754	1
16	633.9	36.64	591.8	610.7	631.75	654.9	676.6	4725	2
42	656.25	37.1	610.3	633.7	655.55	678.3	702.3	1868	2
43	657.23	53.55	586	613.6	657.6	694.9	723.9	1221	2
13	602.88	62.86	521.3	554.3	601.85	645.05	687.45	6377	3
15	615.26	78.9	506.9	547.7	629.2	680.5	708.2	4346	3
19	596.58	54.47	532.7	558.7	589.875	625.3	671.5	3984	3
14	610.95	43.06	557.4	581.4	608.3	637.7	667.3	3448	3
17	582.65	58.14	514.55	541.6	577.15	617.025	660.4	3076	3
44	605.96	55.06	537.85	566.2	603	636.1	673.9	2903	3
38	617.22	40.02	571.2	590	613.325	638.85	668.6	2726	3
30	592.74	56.16	525.1	549.9	586.3	627.1	669.2	2354	3
18	589.36	55.32	520.4	546.35	583.6	625.1	664.8	2322	3
34	616.17	52.12	551.4	582.925	615.025	646.9	685.9	1904	3
35	581.56	48.03	527.8	546.1	573.25	606.75	644.3	1639	3
45	595.67	38.86	547.4	567.5	593.9	619.6	646.8	1539	3
40	580.95	59.61	509.7	540.85	575.7	613.7	660.05	1145	3
20	605.76	33.62	570	580.775	603.325	624.95	649.05	1092	3
41	550.38	53.7	484.5	511.9	546.8	583.7	618.6	12615	4
39	571.86	56.56	501.4	529	568	604.4	645.8	4895	4
36	563.23	51.92	502.75	525.6	557.6	593.4	625.45	2451	4
29	577.58	43.7	523.4	544.5	572.45	604.35	639.7	2449	4
21	548.76	36.01	503.2	524.55	548.35	574.25	595.05	2392	4
37	543.96	43.09	492.05	509.6	540.05	571.35	598.8	2206	4
25	575.44	45.06	521.4	542.5	569.4	605.7	635.4	1791	4
26	556.07	37.49	512.05	530.025	553.025	578.55	604	1748	4
22	557.07	51.94	493.7	517.175	549.025	594.4	627.8	1720	4
24	566.13	65.25	487.2	515.7	558.3	606.7	662.15	1433	4
23	550.89	47.1	493.8	514.075	541.3	583.875	616.45	928	4
27	550.61	50.05	486.85	511.9	549.5	585.7	616.6	815	4
32	541.04	44.78	484.4	508.2	535.8	571	603.75	785	4
33	554.09	50.7	492.1	516.15	547.45	586	626.05	499	4

Note: This table summarizes the admission scores for each on-platform institution in 2012. Universities are grouped by "tiers", where tier 1 is defined as universities with average scores in $[660, 700)$, tier 2 in $[620, 660)$, tier 3 in $[580, 620)$, and tier 4 in $[540, 680)$. Within each tier, universities are sorted by the number of applicants they admitted.

Figure A-12: Changes in Cutoffs Over Time



Note: The figure shows the correlation between program cutoffs from 2010-2011 (left panel) and 2011-2012 (right panel). Darker colored markers show cutoffs for programs with at least 100 seats in 2012. Ligher colored markers show cutoffs for all programs with excess demand.

A-1 Interviews with Admission Process and Waitlist Coordinators

We interview admissions officers at universities in Chile to obtain a richer description of the process through which the waitlist is processed. We report the interviews here.

> When it comes to waitlists, DEMRE does nothing: each university clears their waitlist with call-centers... we used to call students and ask them if they had enrolled in some other place. Regardless of the answer, we informed them that they got off the waitlist and asked them if they would like to enroll. If they said yes, we would ask them to come early next morning. If they did not arrive, we would try to contact them again. If someone did not want to enroll or did not pick up the phone, we would call the next one... If two students were called and both decided to enroll we would let both of them in... for a single slot in the waitlist, we would call 3 students and then potentially discard some... it is not a rule, it is discretionary... If we were to fill 10 slots and the first 10 people we called said "yes", we would still call 15, but if some said "no" we would go even further down and keep calling. In terms of logistics, we usually had like 3 rounds where we called waitlisted applicants until we filled the list... sometimes, people did not have money to enroll again, so they lost their seats... If 15 people showed up for 10 waitlist slots that we had to fill, we enrolled all 15, otherwise they could file a complaint with the Ministry of Education and we could get sued. That's why, when we had to call waitlisted applicants, there is someone with a high rank that gives you the list of whom to call. She told me to call the first 5, and if they did not pick

> up by noon I had to inform her... In extreme cases, when we did not fill the slots, we would grant enrollment to some low-rank students that begged for admission, as most of the other students that ranked above them did not show any interest in enrolling. I even know of some universities that eventually give up and allow waitlist enrollments on a first-come-first-serve basis.

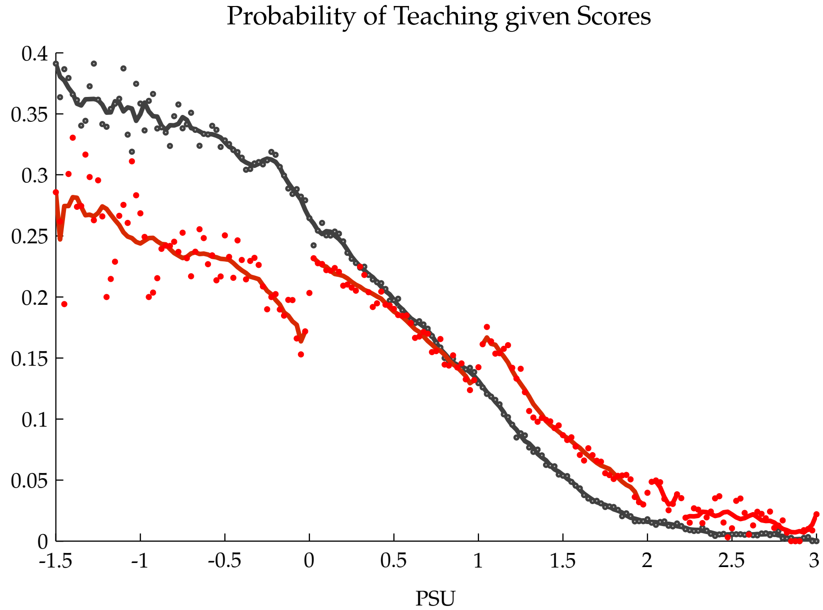
– Subject A

A-2 Further Details about *Beca Vocacion Profesor*

The BVP policy was intended to induce higher-scoring students to enter the teaching profession in two ways: if a program chose to participate, then students with a simple average of at least 600 on their math and verbal scores received full scholarships. However, the policy placed a cap on the number of students with scores below 500 (the mean test score) that the program was allowed to admit. Approximately 50% of programs joined in 2011, and a handful more chose to participate in 2012. Overall almost all students who could apply to the programs on the platform saw their choice sets vary due to the policy.

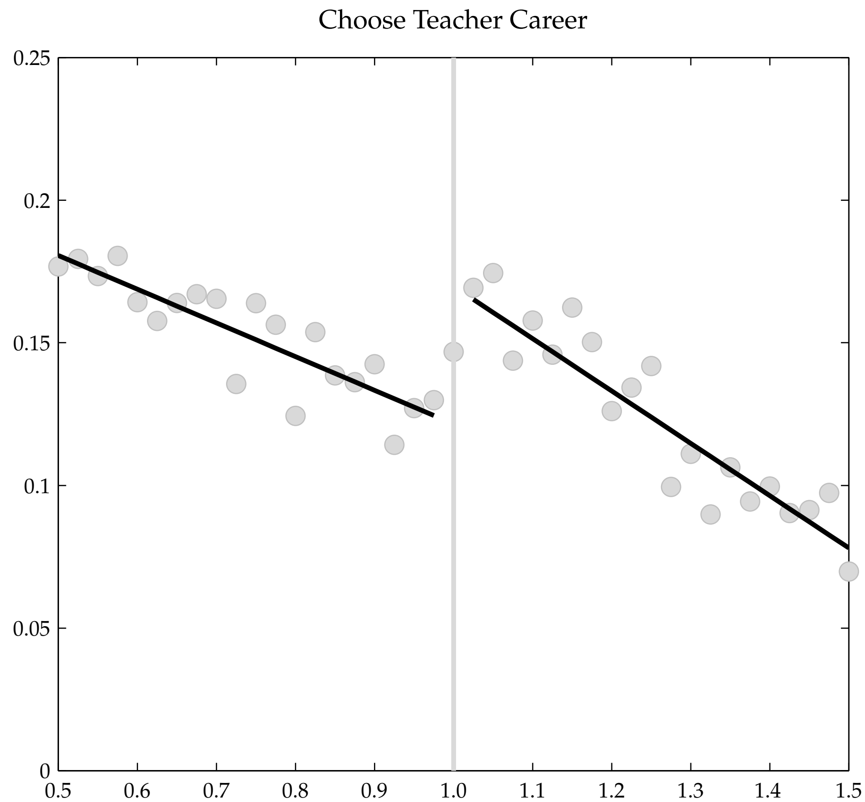
Figures A-13 from Gallegos et al. (2019) (reproduced below) shows the probability of enrollment in teacher training programs, conditional on enrolling in some higher-education program, as a function of year and average test score. At baseline, roughly 30% of students with test scores near the population mean were enrolled in teaching programs. One can observe the discontinuities at 500 (the average) and 600 ($\mu + \sigma$) points, as well as a level shift for high-scoring students. We use this variation later to relate the impacts of platform expansion to those of changes in prices. Figure A-14 shows a zoom in of the cutoff for eligibility at 600 points to show the discrete jump in choice probabilities that is induced by the policy. See more details about the policy in Gallegos et al. (2019).

Figure A-13: Enrollment Probability and Targeted Tuition Subsidies



Note: This figure is a reproduction from (Gallegos et al., 2019). It shows the probability of enrollment in a teaching major as a function of average college entrance exam scores and time.

Figure A-14: Enrollment Probability Around The Eligbility Cutoff



Note: This figure is a reproduction from (Gallegos et al., 2019). It shows the probability of enrollment in a teaching major as a function of average college entrance exam scores in 2011 at the cutoff.

Figure A-15: Diagram of preference ordering for applications and matriculation choices

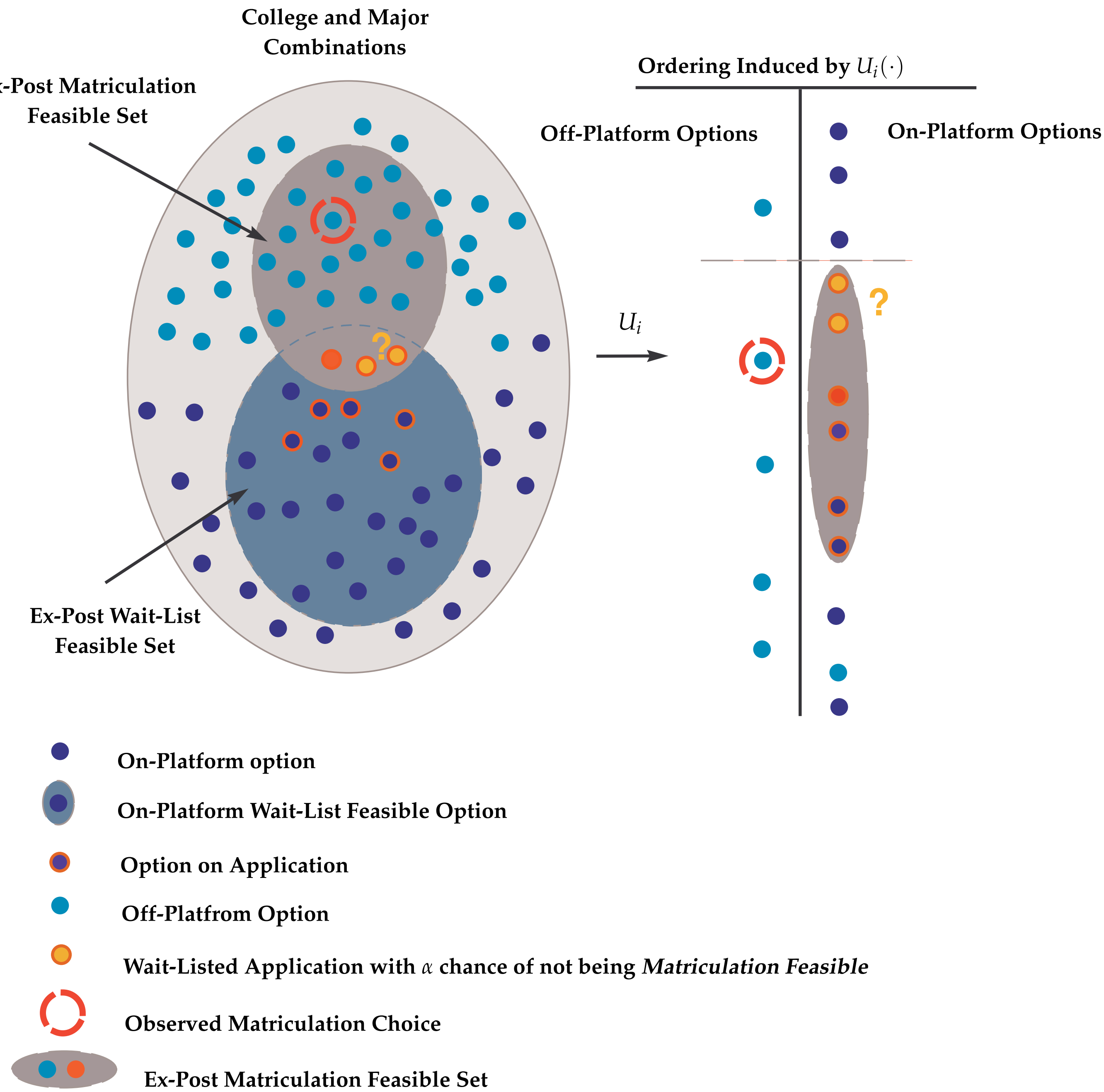
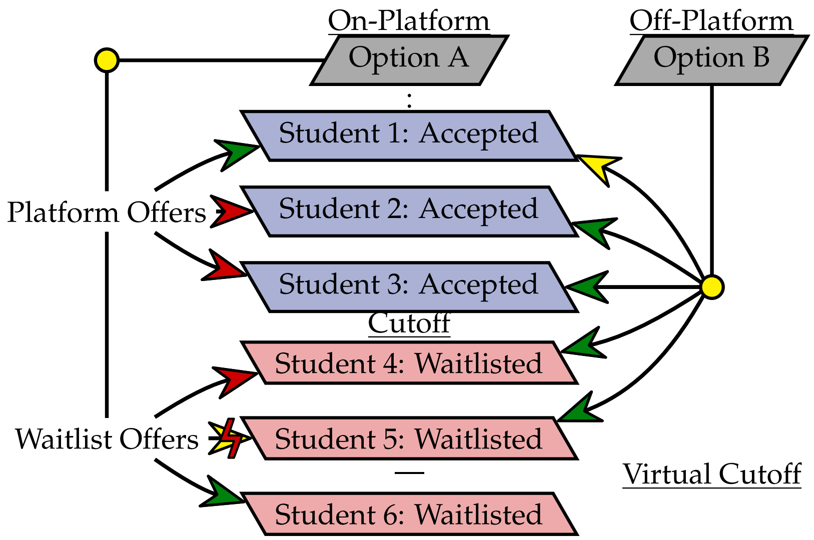
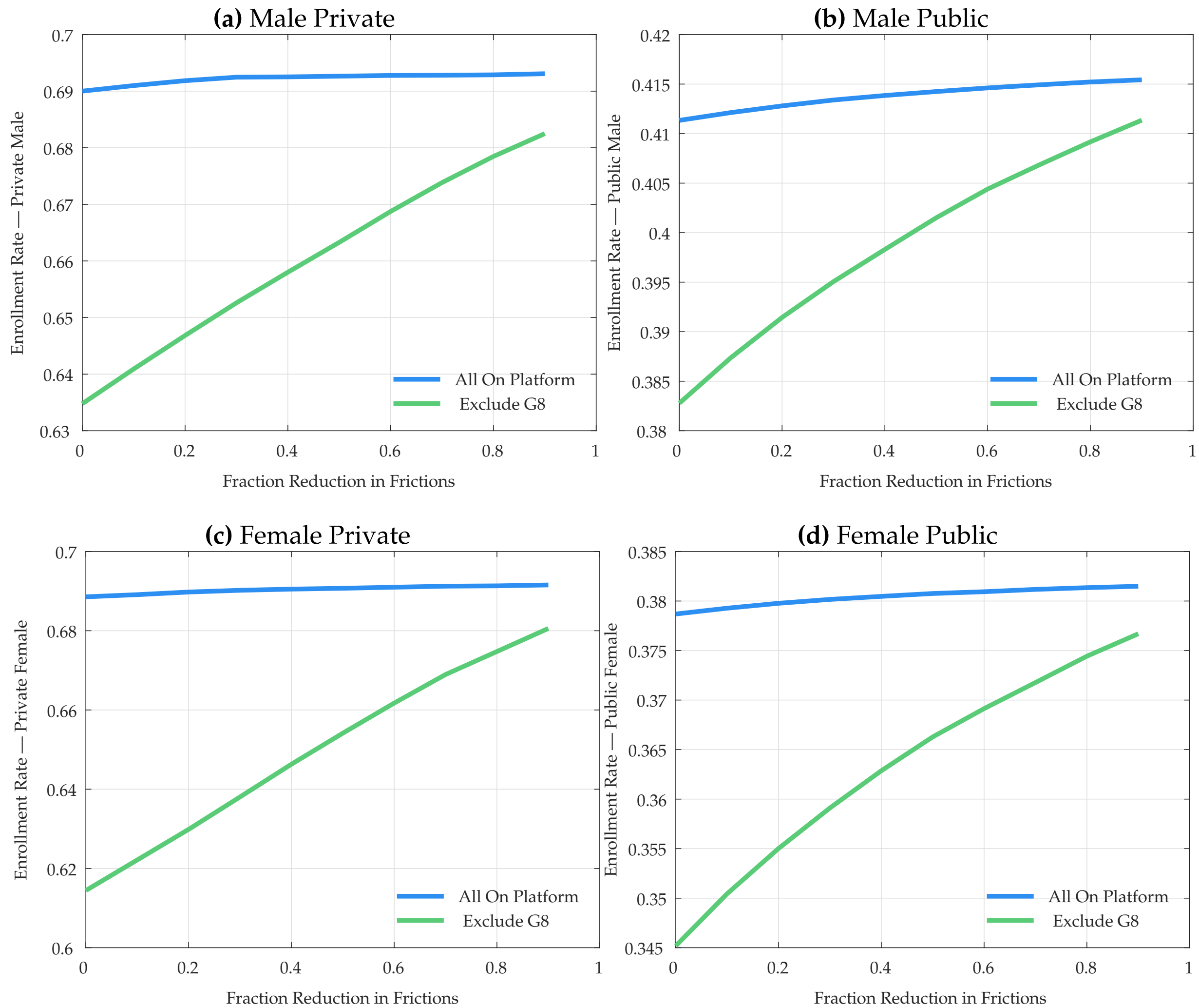


Figure A-16: Diagram of Waitlist Frictions



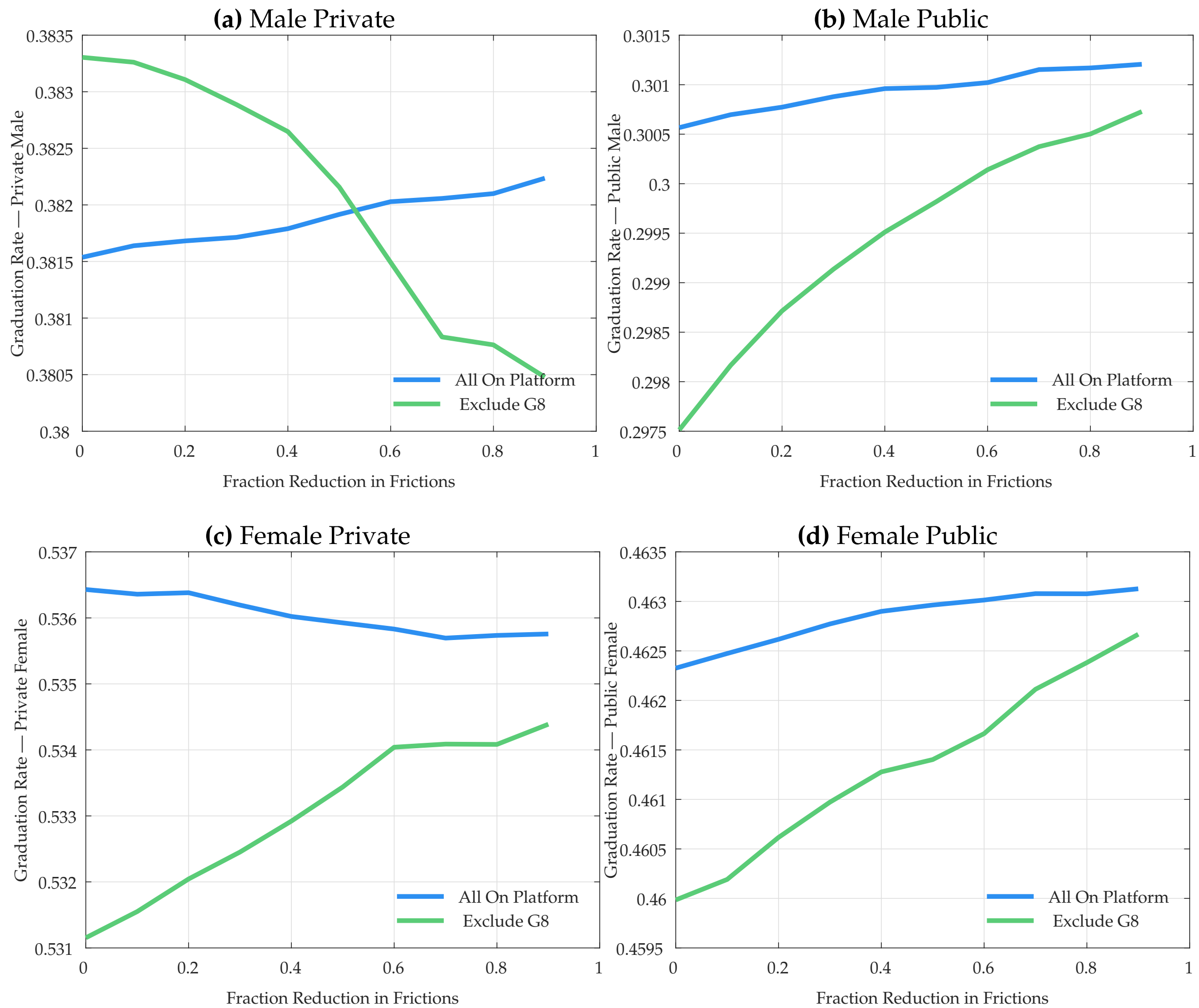
A-3 Heterogeneous Impacts of the Policy on Enrollment and Graduation rates

Figure A-17: Enrollment Impacts of Reducing Frictions (α): Heterogeneity by Type



Note: All friction terms α multiplied by $(1-p)$, where p is "fraction reduction in frictions" on X-axis.

Figure A-18: Graduation Impacts of Reducing Frictions (α): Heterogeneity by Type



Note: All friction terms α multiplied by $(1 - p)$, where p is "fraction reduction in frictions" on X-axis.

A-4 Additional Model Estimates and Results

This section reports parameters from the estimated model. We divide the results into three tables, displaying inside-option preference and friction parameters, outside-option parameters, and parameters of the graduation production function, respectively. Means and standard errors are reported.

Table A-4: Preference estimates: inside-option parameters

Parameters	Male Private	Male Public	Female Private	Female Public
Preferences (ψ^o)				
BVP Discount	0.0595	0.1417	0.099	0.1151
	(0.0102)	(0.0039)	(0.0073)	(0.0078)
Potential BVP Discount	-0.0279	-0.1062	-0.0718	-0.1109
	(0.0145)	(0.0037)	(0.0064)	(0.0035)
Same City	1.1436	1.2162	1.1454	1.2662
	(0.0076)	(0.0041)	(0.0109)	(0.0026)
STEM x Math	0.1373	0.1597	0.1216	0.2189
	(0.009)	(0.0051)	(0.0104)	(0.0014)
Humanities x Math	-0.0505	-0.0541	-0.0393	-0.001
	(0.0063)	(0.002)	(0.0089)	(0.0028)
STEM x Verbal	-0.0374	-0.0142	-0.0075	-0.0088
	(0.0043)	(0.0017)	(0.0038)	(0.0043)
Humanities x Verbal	0.0956	0.1246	0.0935	0.1099
	(0.0035)	(0.0031)	(0.0038)	(0.0027)
Aftermarket frictions (α)				
On-Platform	0.8711	0.8146	0.8542	0.8049
	(0.0037)	(0.0042)	(0.0036)	(0.0036)
Off-Platform	0.378	0.6073	0.4032	0.6598
	(0.0142)	(0.0074)	(0.0068)	(0.016)
SD of program FE				
σ_{FE}	0.7531	0.5844	0.8163	0.6607
	(0.0131)	(0.0025)	(0.0186)	(0.0044)
RC covariance matrix (ψ^u)				
STEM	0.1272	0.1225	0.2154	0.2075
	(0.0045)	(0.004)	(0.0077)	(0.0015)
Humanities	0.1424	0.1212	0.1796	0.1602
	(0.0045)	(0.0035)	(0.0058)	(0.0022)
Humanities vs STEM (ρ)	0.078	0.0682	0.1359	0.1196
	(0.004)	(0.0015)	(0.0062)	(0.0046)

Note: Preference parameters were estimated via Gibbs sampling and include program fixed effects. The number of observations used for the estimation are 484549 and the number of options are 1334 over three years.

Table A-5: Preference estimates: outside-option and individual-level parameters

Parameters	Male Private	Male Public	Female Private	Female Public
First Outside Option ($\beta_{0,0}$)				
Constant	0.9294	1.0311	0.9724	1.0597
	(0.0161)	(0.0042)	(0.0167)	(0.0017)
Math	0.0926	0.0595	0.0667	0.0402
	(0.0054)	(0.0016)	(0.0066)	(0.0011)
Verbal	0.0482	0.0307	0.0588	0.0478
	(0.0054)	(0.0016)	(0.0068)	(0.0008)
Big City	0.1963	0.1379	0.2007	0.1375
	(0.0114)	(0.0031)	(0.0106)	(0.0016)
Current Cohort	0.0002	0.0282	-0.0027	0.0238
	(0.008)	(0.0028)	(0.0095)	(0.0013)
1(2011)	0.0145	0.024	0.0173	0.023
	(0.0133)	(0.0038)	(0.0104)	(0.0016)
1(2012)	0.0739	0.0705	0.0876	0.0719
	(0.0109)	(0.0031)	(0.0114)	(0.0016)
Scholarship Amount	-0.0254	0.0082	-0.0202	0.0052
	(0.0373)	(0.0044)	(0.0351)	(0.0016)
$\sigma_{0,0}$	0.0528	0.0501	0.053	0.0515
	(0.0014)	(0.001)	(0.001)	(0.0009)
Second Outside Option ($\beta_{0,1}$)				
Constant	0.5512	0.8372	0.5371	0.9899
	(0.0588)	(0.1162)	(0.0324)	(0.0446)
Math	-0.0602	-0.0765	-0.1011	-0.0242
	(0.017)	(0.0565)	(0.0141)	(0.02)
Verbal	-0.025	-0.0372	0.0079	0.0139
	(0.0104)	(0.0282)	(0.0076)	(0.0103)
Big City	0.1771	0.2121	0.1407	0.1423
	(0.0132)	(0.0375)	(0.0153)	(0.0064)
Current Cohort	-0.2432	-0.0066	-0.1896	0.0093
	(0.0294)	(0.0129)	(0.0154)	(0.0039)
1(2011)	-0.0161	0.0219	0.0074	0.0321
	(0.0133)	(0.0038)	(0.0147)	(0.0026)
1(2012)	0.2255	0.1238	0.2381	0.1153
	(0.025)	(0.0248)	(0.0133)	(0.0135)
Scholarship Amount	0.1332	0.0945	-0.0244	0.0332
	(0.0469)	(0.0333)	(0.0382)	(0.0077)
$\sigma_{0,1}$	0.5989	0.3298	0.5904	0.1547
	(0.0704)	(0.1472)	(0.0371)	(0.0557)

Note: Preference parameters were estimated via Gibbs sampling and include program fixed effects. The number of observations used for the estimation are 484549 and the number of options are 1334 over three years.

Table A-6: Preference estimates: outcomes

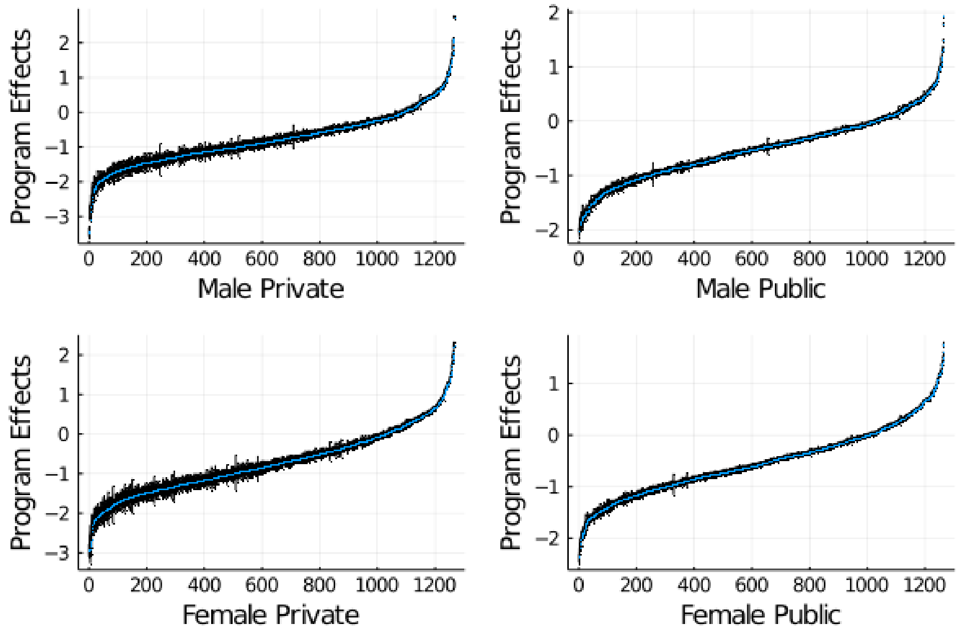
Parameters	Male Private	Male Public	Female Private	Female Public
Production Function				
utility shock	0.6296	0.352	0.2855	0.1878
	(0.0871)	(0.0402)	(0.1084)	(0.0491)
Constant	-3.1276	-2.1087	-1.6527	-1.2795
	(0.2673)	(0.1543)	(0.346)	(0.1689)
Math	0.108	0.231	0.152	0.2911
	(0.0291)	(0.011)	(0.0293)	(0.0125)
Verbal	-0.0588	-0.0174	-0.0152	0.0051
	(0.0244)	(0.0096)	(0.0234)	(0.0105)
Big City	-0.1941	-0.1156	-0.1201	-0.1291
	(0.0764)	(0.0231)	(0.085)	(0.0297)
Current Cohort	0.1011	0.0768	0.1591	0.1036
	(0.0239)	(0.0121)	(0.0211)	(0.0103)
1(2011)	0.0754	0.0139	0.0872	0.0544
	(0.0268)	(0.0152)	(0.0214)	(0.015)
1(2012)	0.0233	0.0393	0.1307	0.0956
	(0.0308)	(0.0155)	(0.0294)	(0.018)
Scholarship Amount	0.1357	0.1666	0.1899	0.1295
	(0.1365)	(0.0198)	(0.0958)	(0.0159)
BVP Discount	0.1469	0.0862	-0.001	0.0009
	(0.0967)	(0.0314)	(0.0474)	(0.026)
Potential BVP Discount	-0.1056	-0.0876	-0.0456	-0.0209
	(0.1034)	(0.0299)	(0.0446)	(0.0259)
Same City	0.6413	0.4287	0.3372	0.2574
	(0.0997)	(0.0448)	(0.1162)	(0.0581)
STEM x Math	0.0275	0.0315	0.0528	0.0587
	(0.0262)	(0.0163)	(0.0264)	(0.0179)
Humanities x Math	-0.1015	-0.1005	-0.0017	-0.0613
	(0.0286)	(0.0167)	(0.023)	(0.0161)
STEM x Verbal	0.0043	0.0245	-0.0239	0.021
	(0.0214)	(0.0137)	(0.0209)	(0.0161)
Humanities x Verbal	0.0586	0.0551	0.0037	0.0387
	(0.0244)	(0.0148)	(0.022)	(0.0151)

Note: Preference parameters were estimated via Gibbs sampling and include program fixed effects. The number of observations used for the estimation are 484549 and the number of options are 1334 over three years.

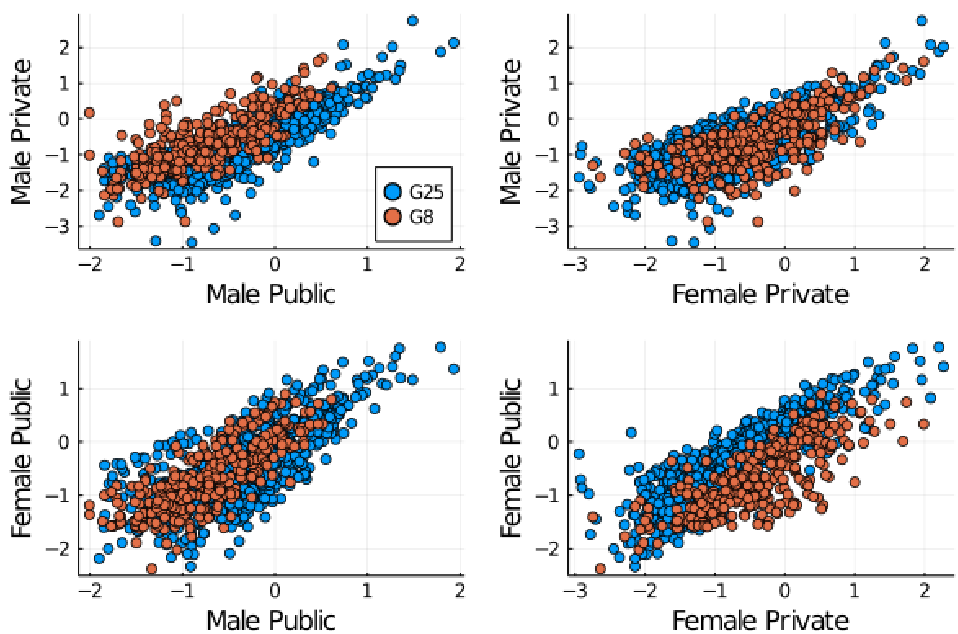
Figure A-19 shows the distribution of program mean utility terms δ, which are estimated separately by type. These vary from roughly -3 to 2, relative to the idiosyncratic utility shock which is normalized to have variance 1. The left panel of this figure indicates that the types disagree about the relative ranking of G8 vs G25 programs, with students from private schools (a proxy for SES) systematically exhibiting stronger preferences for G8 programs, relative to G25 programs, than students who attended public schools. In addition, while students of all types tend to rank top programs similarly, the scatter plots indicate disagreement about middle- and lower-ranked programs.

Figure A-19: Distribution of Program Fixed Effects (δ)

(a) Distribution of Program Fixed Effects δ



(b) Comparisons across types



Note: Figures display estimates of program fixed effects δ. Parameters are estimated separately by type. Left panel: sorted within each type, black lines represent 95% posterior probability intervals. Right panel: scatter plots comparing means of each program across types. Blue indicates G25, red indicates G8.

Table A-3: Event study outcomes by type: Admission, Enrollment, Dropout, Graduation

	Admission	Enrollment	Dropout	Graduation
Year 2010×Male×Private	-0.002	0.005	-0.004	-0.022**
	(0.006)	(0.007)	(0.005)	(0.009)
Year 2012×Male×Private	0.125***	0.113***	-0.014***	0.024**
	(0.005)	(0.007)	(0.005)	(0.009)
Year 2013×Male×Private	0.134***	0.134***	-0.007	-0.008
	(0.005)	(0.007)	(0.005)	(0.009)
Year 2014×Male×Private	0.145***	0.134***	-0.012**	
	(0.005)	(0.007)	(0.005)	
Year 2015×Male×Private	0.130***	0.140***	-0.003	
	(0.005)	(0.006)	(0.005)	
Year 2010×Male×Public	-0.042***	0.012***	0.001	-0.004
	(0.003)	(0.003)	(0.003)	(0.004)
Year 2012×Male×Public	0.089***	0.056***	-0.017***	0.012***
	(0.002)	(0.003)	(0.003)	(0.004)
Year 2013×Male×Public	0.093***	0.076***	-0.008***	0.004
	(0.002)	(0.003)	(0.003)	(0.004)
Year 2014×Male×Public	0.097***	0.087***	-0.010***	
	(0.002)	(0.003)	(0.003)	
Year 2015×Male×Public	0.066***	0.087***	-0.006**	
	(0.002)	(0.003)	(0.003)	
Year 2010×Female×Private	-0.017**	0.004	0.008*	-0.042***
	(0.007)	(0.009)	(0.005)	(0.011)
Year 2012×Female×Private	0.121***	0.143***	-0.005	0.017
	(0.006)	(0.008)	(0.004)	(0.011)
Year 2013×Female×Private	0.145***	0.168***	-0.003	0.030***
	(0.005)	(0.008)	(0.004)	(0.011)
Year 2014×Female×Private	0.148***	0.176***	-0.005	
	(0.005)	(0.008)	(0.004)	
Year 2015×Female×Private	0.135***	0.168***	0.004	
	(0.005)	(0.008)	(0.005)	
Year 2010×Female×Public	-0.043***	0.020***	-0.008***	-0.008
	(0.003)	(0.004)	(0.003)	(0.005)
Year 2012×Female×Public	0.071***	0.061***	-0.027***	0.016***
	(0.003)	(0.004)	(0.003)	(0.005)
Year 2013×Female×Public	0.086***	0.100***	-0.019***	0.019***
	(0.003)	(0.004)	(0.003)	(0.005)
Year 2014×Female×Public	0.098***	0.119***	-0.024***	
	(0.003)	(0.004)	(0.003)	
Year 2015×Female×Public	0.063***	0.116***	-0.018***	
	(0.003)	(0.004)	(0.003)	
Constant	0.047***	0.020***	0.566***	-0.069***
	(0.005)	(0.007)	(0.006)	(0.010)
Observations	606280	393193	318809	218271

Note: This table shows estimates of the average difference in each outcome, for each type of student, and for each year after 2009. The base year is 2011 and the base type is Female-Public. Admission refers to the probability of being assigned a seat in the platform; Enrollment refers to the probability of enrolling in a platform program conditional on being admitted in a G25 option; Dropout refers to the probability of not being enrolled in any option the year after enrolling in a G25 program; and Graduation refers to the probability of graduating within 6 years of enrolling in a G25 program. The estimating equation includes student covariates (GPA and test scores) and student-type fixed effects. These estimated coefficients are not reported in the table. The results on graduation rates are constrained to years before 2014 because we do not have data after 2019. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$