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

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Abstract

We study the welfare and human-capital impacts of the configuration of on- and off-platform options in the context of Chile's centralized higher education platform, leveraging administrative data and two policy changes: the introduction of a large scholarship program, and an expansion of the number of on-platform slots by approximately 40%. We first show that more programs' joining the platform led students to start college sooner and raised the share of students who graduated on time. We then develop a model of college applications, offers, waitlists, and matriculation choices, which we estimate using students' ranked-ordered applications, on- and off-platform enrollment, and on-time graduation outcomes. When more programs join the platform, welfare increases, and the extent of aftermarket frictions matters less for welfare, enrollment, and graduation rates. High-SES students have greater access to off-platform options, and gains from platform expansion are larger for students from lower-SES backgrounds. Our results indicate that expanding the scope of a higher education platform can have real impacts on welfare and human capital.

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1 Introduction

Providing equitable access to higher education is an important policy objective shared by countries all over the world. One way that education systems support this goal is with centralized application and assignment platforms that minimize application costs and provide transparent rules regarding access[1] Centralized mechanisms are theoretically appealing and have been empirically successful in many settings (Abdulkadiroğlu, Agarwal, and Pathak, 2017). In practice, however, the setting may depart from the theoretical ideal in ways that matter for the efficiency and fairness of students' assignments. One such departure 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. When off-platform options exist, 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 inefficient due to the presence of congestion and matching frictions, and can be inequitable if some students are better able to navigate this partially-decentralized process, 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 seven 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

[1] As of 2020, at least 46 countries use centralized choice and assignment mechanisms for at least part of their higher education system. See Neilson (2019) for a review of countries that have implemented centralized choice and assignment mechanisms.

[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.

the configuration of on- and off-platform options. We estimate a model of college applications, aftermarket waitlists, off-platform offers, matriculation choices, and near-on-time graduation outcomes 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 and exploiting the policy change that expanded the platform. In addition, to recover price sensitivities, our estimation procedure leverages the introduction of a scholarship program with arbitrary eligibility cutoffs, which provides exogenous price variation across options among similar applicants.

We find 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 roughly 0.263m CLP or U.S. $650 per exam taker. The welfare impact of platform expansion, in turn, is over eight times as large as the further gains from removing all remaining matching frictions, and a quarter as large as the welfare impact of expanding the platform and making all on-platform programs free, a much more expensive policy change. Enrollment gains from platform expansion are more than 80% of those of platform expansion and removing all frictions in waitlists.[3] 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.

[3] 0.263m CLP represents welfare differences between a baseline scenario and a counterfactual in which the platform expansion did not occur. The baseline scenario gives 0.031m CLP lower welfare than a frictionless benchmark, while the absence of platform expansion would give 2.94m CLP lower welfare on average than this benchmark. Details are given in Table 5. The exchange rate was approximately 500 CLP per USD in 2012.

Taken together, our results show empirically that the existence of off-platform options affects the equity and efficiency of centralized assignment systems. Our empirical framework and counterfactual analysis allow us to quantify the welfare effects of adding universities to the platform, and provide tools for evaluating the costs of off-platform options in other settings.

This paper builds on and contributes to the empirical literature on the design of assignment and matching procedures for education markets. Abdulkadiroğlu, Agarwal, and Pathak (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, Fu, and Güell, 2018; Kapor, Neilson, and Zimmerman, 2020). Aue, Klein, and Ortega (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) (see also Rossi, McCulloch, and Allenby (1996)) and applied to rank-ordered school choice data by Abdulkadiroğlu, Agarwal, and Pathak (2017). We extend this procedure to accommodate—in addition to rank-ordered application data—ex-post enrollment decisions in an aftermarket in which individuals' choice sets are unobserved. Our procedure constructs person-specific subsets of the set of programs at which placement chances are nontrivial, and assumes that students truthfully report preferences over this subset; it is related to the stability-based approach of Fack, Grenet, and He (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 rare during our sample period.[4]

Our paper adds to a literature that relates choice behavior to outcomes in assignment mechanisms. In contemporaneous work, Agarwal, Hodgson, and Somaini (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 variation in choices is needed which is excluded from outcomes. In our setting, year-to-year variation in programs' cutoffs plays this role.[5] Our approach to estimation is closest to Geweke, Gowrisankaran, and Town (2003) and Agarwal, Hodgson, and Somaini (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.[6] 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).

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 accreditation status, posted tuition and student body characteristics.

[4] 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.

[5] 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, Hodgson, and Somaini, 2020).

[6] Other research estimating preferences for college and major in the context of Chile includes Bucarey (2017), which studies equilibrium effects of a reform in Chile which made college free in 2016. Larroucau and Rios (2020) asks how learning and dynamics can affect the efficiency of the assignment mechanism.

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. 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 presented in Table 1.

Table 1: Sample Descriptive Statistics 2010-2012

	Year 2010		Year 2011		Year 2012	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
Panel A: 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	530	116	532	110	536	113
Math Score	501	111	501	111	504	111
Verbal Score	501	109	501	108	504	110
Platform App.	0.35	0.48	0.34	0.47	0.45	0.50
Observations	251634		250758		239368	
Panel B: G25 Applicants						
Score at top-ranked program	599	68.7	602	69.0	604	69.17
Ranked 1st Technology (G25)	0.27	0.44	0.28	0.45	0.28	0.45
Ranked 1st Medical Sciences (G25)	0.23	0.42	0.22	0.41	0.25	0.43
Ranked at least 3 programs	0.82	0.38	0.80	0.40	0.84	0.37
Ranked at least 7 programs	0.23	0.42	0.20	0.40	0.25	0.43
Assigned to 8th+ program	$\leq$0.01	-	$\leq$0.01	-	$\leq$0.01	-
Maximum List Length	8		8		10	
Enrolled in HS while applying	0.59	0.49	0.62	0.49	0.58	0.49
Observations	84556		81258		75729	
Panel C: G25 Admits						
G25 Enrollee	0.75	0.43	0.74	0.44	0.80	0.40
G8 Enrollee	0.05	0.22	0.06	0.23	0.01	0.08
Other/Unenrolled	0.20	0.40	0.21	0.41	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. Panel A describes the population of test takers each year in our sample. Panel B presents descriptive statistics for applications that had a G25 option listed as a first preference. Panel C presents descriptive statistics for students admitted into G25 options.

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 was spurred by a combination of a growing middle class and policies such as government backed student loans and scholarships. Growth in demand led to an expansion in the number of programs at newer private institutions (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 366,000 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. Non-G25 universities represented 68% of total enrollment in 2010. In addition to universities, there also exist professional institutes and technical formative centers.

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 350,000, 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 as 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.[7] While the two most selective institutions belong to the G25, some G8 institutions are much more selective than most G25 institutions, with considerable overlap of selectivity among them.[8]

2.2.3 *Financial Aid*

A 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 with scores above a test score cutoff and SES below an SES cutoff were eligible for low-interest government-backed student loans and scholarships, which they could use at any eligible program, including all G25 and G8 programs during our study period. These scholarships provided varying amounts of funding as a function of the student's SES. Government-backed loans covered the remainder up to a program-specific reference tuition. 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

[7] See Section 1.1 of the Online Appendix for more descriptive information regarding the evolution of the market shares associated with G8 and G25.

[8] Table 1 in the Online Appendix lists each institution in the G25 and G8 and presents statistics regarding the distribution of student test scores at each institution.

provided in 2010, government-backed student loans were used widely and have been shown to significantly alleviate credit constraints and facilitate college attendance when comparing students at the margin of loan eligibility (Solis, 2017). 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[9].

2.2.4 The BVP Scholarship

In 2011 a significant new scholarship policy called the *Beca Vocación de Profesor* (BVP) was introduced with the goal of recruiting teachers with high exam scores. This scholarship covered the full tuition bill for students scoring at least 600 point average on math and verbal admissions exams, a value one standard deviation above the mean, if they enrolled at eligible teaching programs. In return, it imposed a test-score floor, prohibiting participating programs from admitting students with mean math and verbal test scores below 500 points, a value equal to the mean among test-takers. Gallegos, Neilson, and Calle (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. This policy therefore 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. We use this program as a source of match-level price variation in order to estimate willingness to pay for programs.[10]

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, the majority of whom take the test. In 2011, 67% of all current 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 (450 is half of a standard deviation 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

[9]Figure 2 in the Online Appendix shows a timeline indicating the major policies promoting access to higher education before and after our sample period. Universities also offer some financial aid options. More information on institution-specific aid can be found in Section 1.2 of the Online Appendix

[10]More details about the policy and the price variation it generates is provided in Section 1.3 of the Online Appendix.

the college entrance exam in 2010, 2011 and 2012. In each of these years approximately 10% of test takers were graduates from private high schools which are not subsidized. Panel B of Table 1 shows that, among G25 applicants, the fraction of "current cohort" applicants enrolled in high school at the time of applications did not change significantly within the period studied, going from 59% to 62% between 2010 and 2011, and then to 58% in 2012.[11]

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.[12] 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.[13] Table 1 and Figure 2 present more details regarding the number of test takers, eligible applicants, submitted applications and final assignments.

Throughout the application process, 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 eligibility to apply to a given program, 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

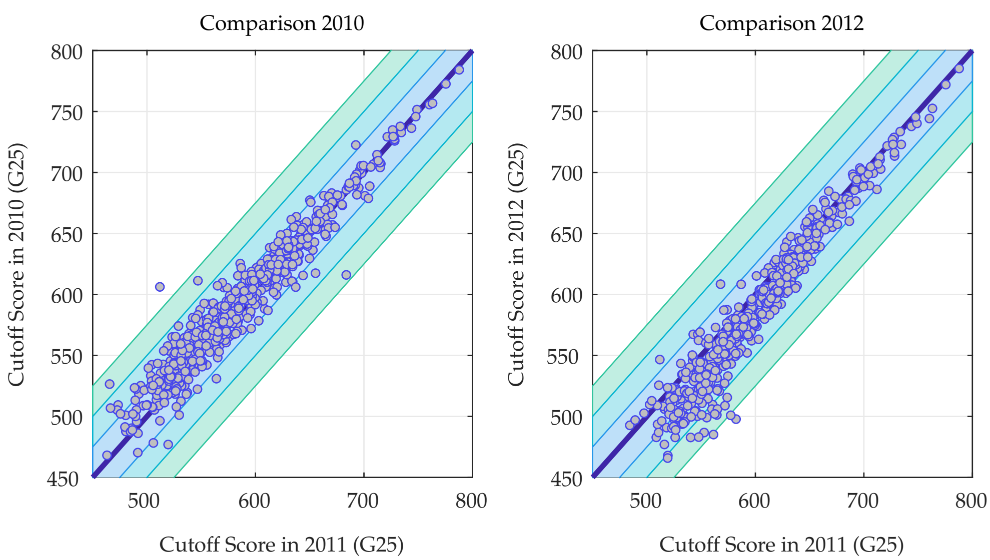
[11] Prior to 2012, PSU scores were valid for a single admissions cycle. In 2012 and following years, PSU scores were valid for two admissions cycles. Therefore, students in 2012 had the option to wait and reuse their test scores in the following year. This policy change increased the attractiveness of dropping out so as to switch programs, as well as the value of the outside option of not enrolling in 2012, for students applying in the 2012 cycle. As we find that the expansion of the platform led to *increased* enrollment and graduation rates, our results are unlikely to be driven by this policy change.

[12] 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 the Online Appendix for a description of the distribution of these weights and the strong correlation between test score weights and the type of coursework conducted at that major.

[13] The maximum number of ranked options increased from 8 to 10 during the period under study. Table 1 shows very few students utilized the 8 or 10 slots, and very rarely were students assigned to these low-ranked options (approximately 1%).

every program on the platform. Program-specific eligibility requirements may include minimum scores and minimum average weighted scores depending on each program.[14] Figure 1 shows changes in the score of the lowest-scoring admitted student at each G25 program. Overall, cutoffs have considerable persistence. This is especially true when we compare 2010 to 2011, where the correlation between cutoffs is 0.96 (see left panel). Nonetheless, the right panel in this figure shows that there is non-negligible movement in the cutoffs from 2011 to 2012, especially for lower selectivity options. More specifically, while the cutoffs rarely fluctuated over 25 points between 2010 and 2011 (2% of the time), in 2012, as new G8 options were added, cutoffs fell for many G25 programs, especially those with low selectivity. Of G25 programs with 2011 cutoffs under 600pts, 30% saw drops of over 25pts, and 9% of these saw drops of over 50pts. Higher selectivity options were much less affected although small negative changes were common.

Figure 1: Changes in Program Cutoffs Over Time



Note: The figure shows program cutoffs in 2011 plotted against those in 2010 (left panel) and again those in 2011 plotted against 2012 cutoffs (right panel). The different colored bands represent ranges of plus and minus 25, 50 and 75 point differences in cutoffs.

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). This process is discussed in detail in Rios et al. (2021).[15] Programs' preferences for applicants are

[14] The two most selective universities have an additional requirement that makes programs ranked below the fourth place ineligible. See Lafortune, Figueroa, and Saenz (2018) for a description of how this feature can potentially affect student applications.

[15] The Chilean process differs from the textbook deferred-acceptance algorithm in its treatment of students with identical scores. If two or more students have identical scores at a program, and the program would otherwise be forced

given by their corresponding weighted scores after filtering out students that do not meet the stated program-specific requirements. We have confirmed that the student-proposing and college-proposing DA algorithms produce identical allocations in this setting under the reported preferences and observed scores in the years 2010-2012, and coincide exactly with the observed allocations in those years. 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. Students are automatically placed on waitlists at all programs that they preferred to their assigned option, according to their submitted list. When a student is assigned to an option, the student's applications to programs that the student ranked lower to the assigned option are discarded.

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.

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 non-university higher education system has rolling admissions until the beginning of classes.

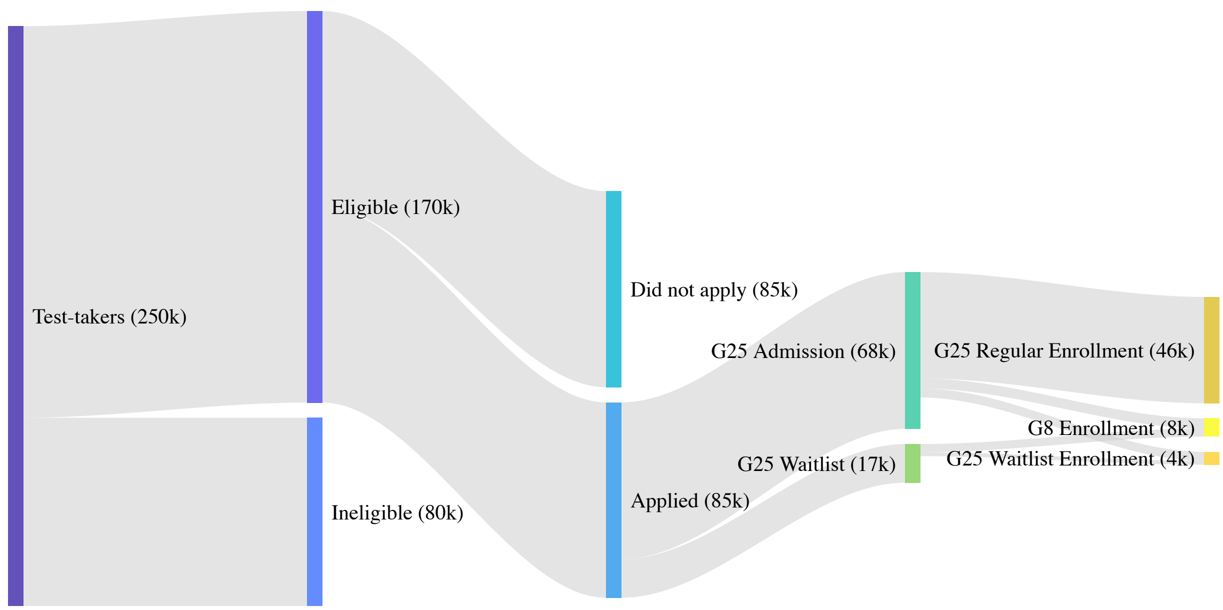
2.3.6 Summary of Application, Enrollment and Aftermarket

Figure 2 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

to strictly rank them in order not to propose to more students than its capacity in some round of the DA algorithm, in the Chilean process it proposes to all such students. Thus, in cases of ties, it is possible for programs to exceed their capacities.

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. Most off-platform enrollment decisions occur at this time as well. 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.

Figure 2: Diagram of the on-platform application process



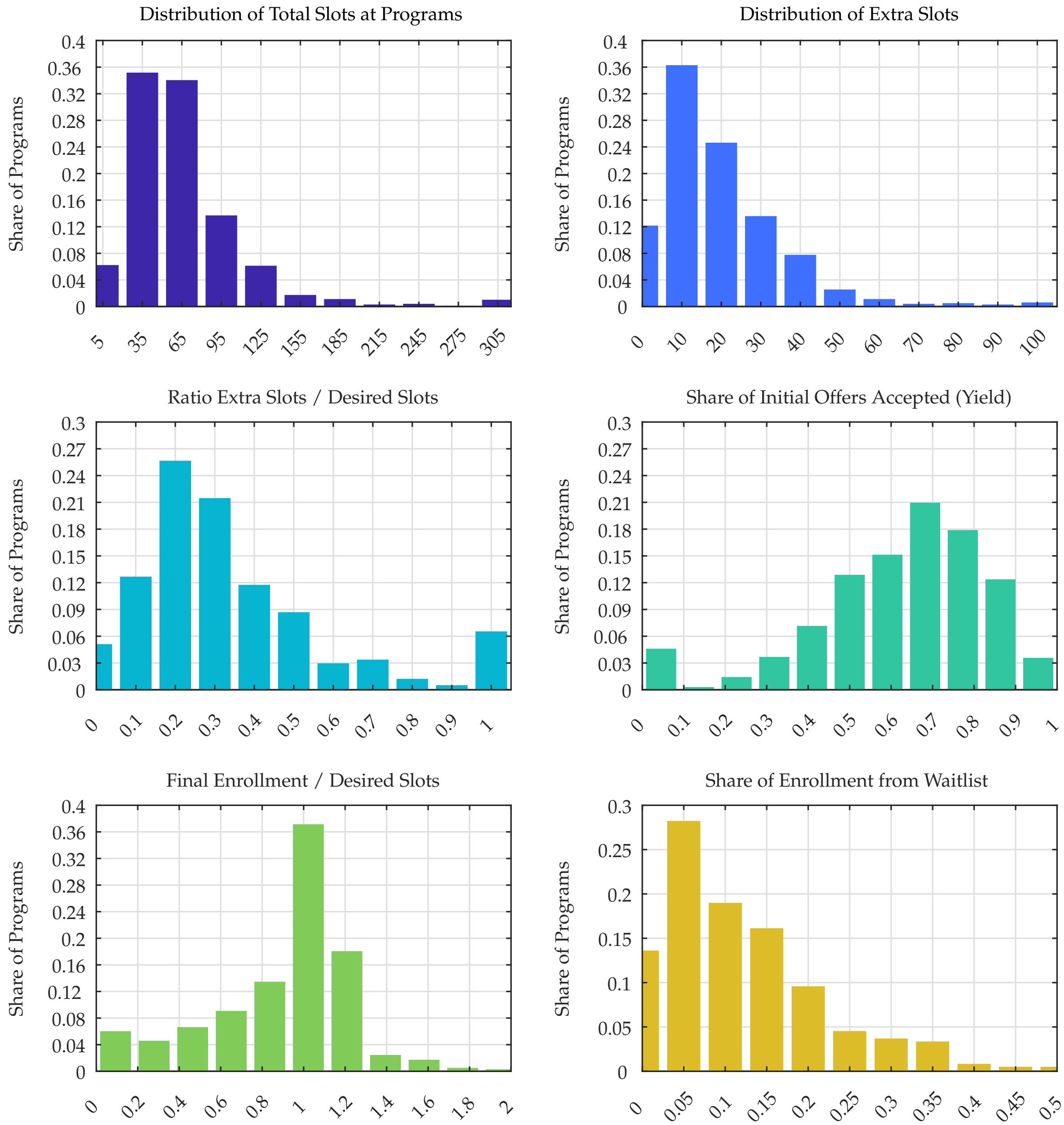
PSU (Dec. 13-14) → Scores (Jan. 3) → Applications (Jan. 3-9) → Offers (Jan. 13) → Enrollment*

Note: Diagram shows the progression of steps for applicants on the centralized assignment platform, and the flow of the mass of applicants throughout the process. 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 late 2010, seeking admission in 2011. *Enrollment dates are not mandated by the platform, but universities usually conduct the enrollment process within a week of the date that offers are released.

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 3: 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 3 shows that despite the presence of excess slots, students have a positive probability of receiving waitlisted offers in the aftermarket. Moreover, ex post some programs exceed their "true" capacities while others undershoot. This pattern may be explained by financial constraints that put an upper bound on "worst-case" enrollment. 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, representing 8% of all the matriculation on the centralized platform in those years.[16] Figure 3 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.

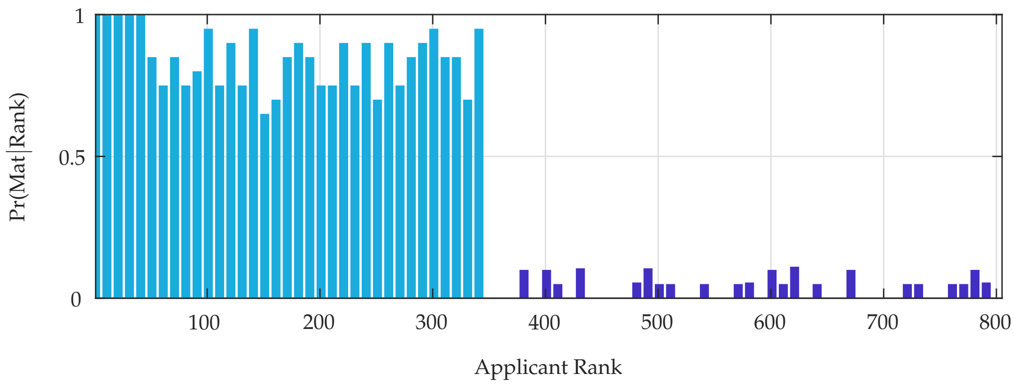
If a program contacts students on its waitlist, the typical approach is to go through the waitlist in order and inform (through a phone call) each waitlisted applicant that they now have an available slot. Students may accept or decline any waitlist offers that they receive. If a student declines to enroll (or does not answer the phone, for example), the corresponding institution moves ahead with the next waitlisted applicant. This process is full of 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.[17] In Figure 4 we present a case study that shows a clear discontinuity in admissions, and then a waitlist which exhibits "gaps".

[16] These numbers do not include students who are admitted off the waitlist through a small government program called *Beca Excellencia Academica* (BEA) that provides additional slots (for more information see the Appendix). These waitlist matriculations account for an additional 400 students who get in off the waitlist.

[17] If a college-proposing deferred acceptance procedure "pauses" at the initial assignment, some students decline offers, and then the procedure resumes with programs that are underenrolled proposing to students at the top of their waitlists, there should be no discontinuity in enrollment probabilities among programs that make waitlist offers.

Figure 4: 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 appendix presents several other case studies for highly demanded majors such as medicine, engineering, and nursing.

The waitlist process is not explicitly regulated by the platform beyond the limit on total slots. Hence 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. Two transcripts are presented below as an example. One 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, with short deadlines for students to respond to offers, 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*

> *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.
- Admissions Officer

While this qualitative interview evidence is not necessarily representative of the experiences at all programs, "gaps" in waitlist enrollment and discontinuities in matriculation probabilities at programs' cutoffs are typical of programs that admit students from waitlists, suggesting that the significant aftermarket frictions described here exist more broadly.

3 The Expansion of the Platform

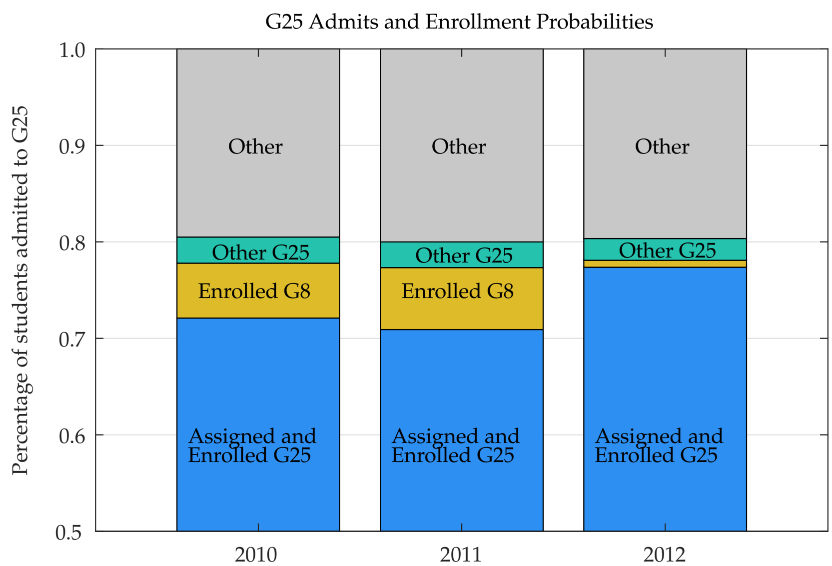
When the G8 universities joined the centralized platform, the number of options available to students increased by over 30% and the number of slots increased by almost 50%.[18] This was an unparalleled change in the supply side of the platform.[19] Increasing the number of slots in the

[18]We did not see any systematic changes in the number of seats within G25 programs in anticipation of platform expansion. Between 2011 and 2012, roughly 40% of programs kept the same number of true seats + extra seats, 20% decreased capacities, and 40% increased capacities. These changes are similar to those that that took place between 2010 and 2011.

[19]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 2 of the Online Appendix.

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 5 and summarized in Table 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.

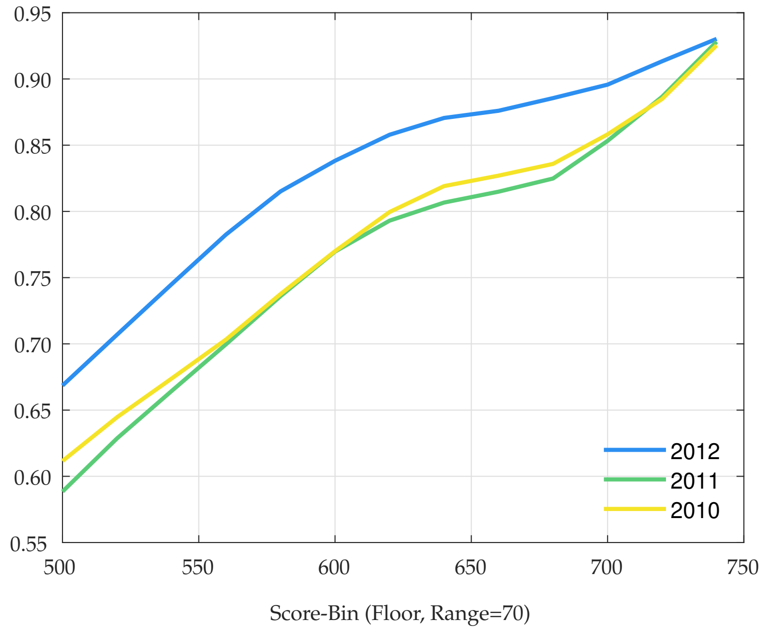
Figure 5: Enrollment probabilities for G25 admits



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.

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 6, 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. As test scores are adjusted to resemble a normal distribution with a mean of 500 and a standard deviation of 110 points (see Table 1), 750 points is approximately the 99th percentile of the score distribution. Thus, the policy increased the enrollment yield for G25 admits across the score distribution.

Figure 6: Enrollment probability, G25



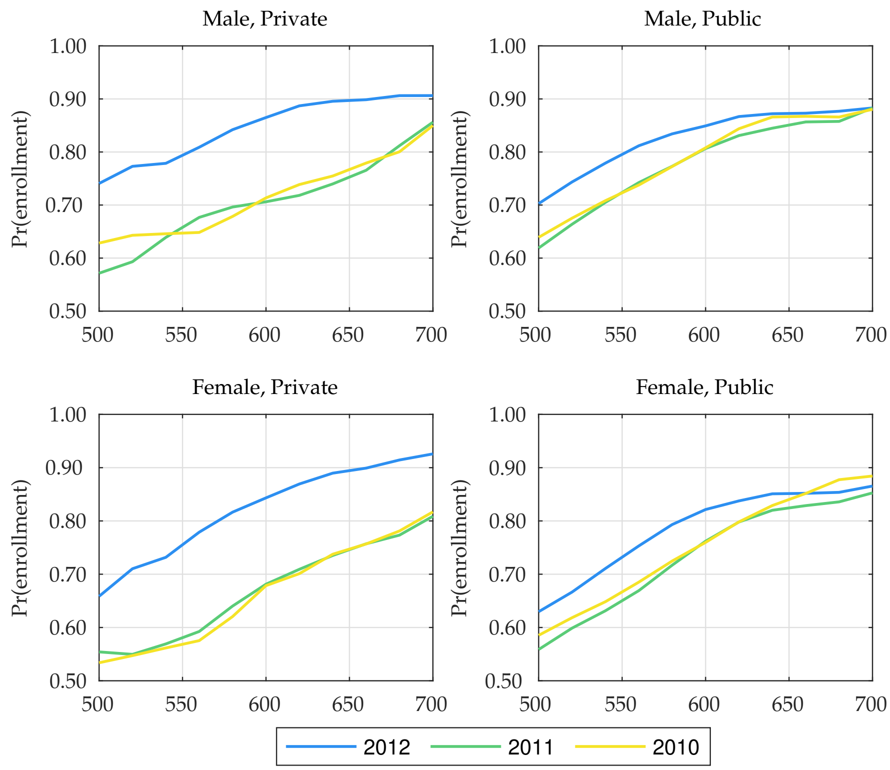
Note: The figure show the probability that a student assigned to an option on the platform, accepts and enrolls in that option. The lines show conditional means within 70 points, and the "floor" of the range is shown in the x-axis (e.g. 600 corresponds to the range [600, 670]).

Figure 7 shows the results of this last exercise broken out by gender and high school type. In all cases, there are significant differences between enrollment rates in 2012 and previous years, but the impacts on enrollment probabilities are larger for low-scoring 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. In in section 5 we show evidence of this behavior, estimating higher average valuations for G8 options from private school students as well as a higher probability that off-platform G8 options extend offers to private school students conditional on test scores.

The observed increase in conditional enrollment rates should foster efficiency in the system. Chains of vacancies left by students who renege on their offers may be filled in the aftermarket. When fewer students renege, there is less work for the aftermarket to do and hence the presence of frictions may matter less for students' outcomes.[20]

[20] 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 7 in the Online Appendix 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.

Figure 7: G25 Enrollment Probability By Gender/SES.



Note: The figures show 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]).

Table 2: Event study outcomes by type: Admission, Enrollment, Dropout, Graduation

	Admission	Enrollment	Dropout	Graduation
Year 2010×Male×Private	-0.002	0.005	-0.004	0.007
	(0.006)	(0.007)	(0.005)	(0.010)
Year 2012×Male×Private	0.125***	0.113***	-0.014***	0.037***
	(0.005)	(0.007)	(0.005)	(0.010)
Year 2013×Male×Private	0.134***	0.134***	-0.007	
	(0.005)	(0.007)	(0.005)	
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	-0.003
	(0.003)	(0.003)	(0.003)	(0.004)
Year 2012×Male×Public	0.089***	0.056***	-0.017***	0.014***
	(0.002)	(0.003)	(0.003)	(0.004)
Year 2013×Male×Public	0.093***	0.076***	-0.008***	
	(0.002)	(0.003)	(0.003)	
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*	-0.023**
	(0.007)	(0.009)	(0.005)	(0.010)
Year 2012×Female×Private	0.121***	0.143***	-0.005	0.027***
	(0.006)	(0.008)	(0.004)	(0.010)
Year 2013×Female×Private	0.145***	0.168***	-0.003	
	(0.005)	(0.008)	(0.004)	
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***	-0.002
	(0.003)	(0.004)	(0.003)	(0.005)
Year 2012×Female×Public	0.071***	0.061***	-0.027***	0.023***
	(0.003)	(0.004)	(0.003)	(0.005)
Year 2013×Female×Public	0.086***	0.100***	-0.019***	
	(0.003)	(0.004)	(0.003)	
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)	
Observations	606280	393193	318809	163531

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 7 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 2013 because we do not have data after 2019. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

If students are more likely to leave programs that they consider less desirable, then an additional 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 and more students graduating. We investigate these outcomes in the following event study. Table 2 shows estimated changes, controlling for test scores and student-type fixed effects, from 2010 to 2015 in platform admission rates, enrollment rates conditional on G25 admission, and 1-year dropout and 7-year graduation rates conditional on G25 enrollment. The coefficients $\{\hat{\beta}_t\}_{t=2010}^{2015}$ are OLS estimates from the following specification:

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

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. and freshman dropout rates fall by roughly 1.1 percentage point in 2012. 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.[21] We find an increase of about 2.5 percentage points, on average, in seven-year graduation conditional on G25 enrollment.

In Appendix Tables 5 and 6 we show that these results are robust under alternative specifications. We focus on the G25 programs here in order to isolate the effects of platform expansion on match quality within a fixed set of programs. Our results indicate that match quality within these programs may have improved as a result of platform expansion. Considering all G33 programs, we find similar patterns in enrollment and graduation (applications and admissions offers are not observed pre-2012 at G8 programs). An event study indicates that overall enrollment among test-takers increased by roughly 1.1 percentage points between 2011 and 2012, with G33 graduation increasing by 2.4 percentage points. We provide these results in Appendix Table 15.

[21] The 1.1 point reduction in freshman dropout rates accounts for over a 10% fall in overall dropout by the end of the first year of college. Public-school students and low-scoring private school students, especially women, mostly drive the reduction in first-year dropout rates. Retention rates are stable for high-scoring students. See figures 9 and 10 in the Online Appendix.

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 describe in detail 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.

A market $t \in T = \{2010, 2011, 2012\}$ is an application cohort consisting of N_t students and a set of available programs $j \in J_t$. Within each cohort t, each student $i = 1, \ldots, N_t$ belongs to one observable group $g \in G$. If student i of group $g(i)$ in cohort $t(i)$ attends program j, he receives utility

$$u_{ij} = \delta_{j,g(i)} + z_i \lambda^z_{g(i)} + w_{ij} \lambda^w_{g(i)} + x_j \eta^x_i + p_{ij} \lambda^p_{g(i)} + \epsilon_{ij}, \tag{1}$$

where δ_{jg} is a program-level mean utility term, z_i is a vector of student-level observables with coefficients λ^z_g which shift the value of all "inside options", w_{ij} are observed match-level terms with group-specific coefficients λ^w_g, and x_j are program characteristics for which students have a vector of unobserved multivariate-normally-distributed random tastes

$$\eta^x_i \sim N(0, \Sigma^{g(i)}).$$

The terms $\epsilon_{ij} \sim N(0, 1)$ are iid match-level preference shocks. p_{ij} is a match-level net price after accounting for government-provided and institution-specific scholarships available to i at program j in i's market $t(i)$, and is multiplied by group-specific coefficients $\lambda^p_{g(i)}$.

The set of inside options J_t consists of all G8 and G25 programs that operated in year t, and is partitioned into on- and off-platform programs. Let $J^{\text{on}}_t \subseteq J_t$ 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. In addition, there is an outside option, $J = 0$, whose value is given by the maximum of two components:

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

These outside option components are independently normally distributed. We have:

$$\begin{aligned} u_{i0}^0 &\sim N(0, \sigma_{0,0,g_i}^2) \\ u_{i0}^1 &\sim N(z_i \gamma_{g(i)}, \sigma_{0,1,g_i}^2). \end{aligned}$$

The first component, 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, such as entering the labor force. In contrast, the second outside option component, u_{i0}^1, is learned during the aftermarket, after the initial match takes place. This shock rationalizes the decision to apply to G33 programs but then decline all offers.

Programs outside the G25+G8 institutions were not on the platform during our sample period, and form part of the outside option. Non-G33 offers that realize after the on-platform match takes place belong to the second outside option component u_{i0}^1. Hence the second outside option consists of selective non-G33 programs, as well as shocks to (e.g.) entering the labor force that may realize after applications are due.

We impose the location normalization $E(u_{i0}^0 = 0)$. However, we allow the mean of the second outside option to vary with all individual characteristics that enter utility, including year-by-group effects, as the quality of the best non-G33 offer may depend on test scores and other observables and may vary over time as the set of non-G33 options evolves. Fixing the variance of $\epsilon_{ij} \sim N(0, 1)$ normalizes the scale of utility. Because our model includes program-by-group effects δ_g which subsume mean effects of program-level unobservables, the random coefficients η_i^x are mean zero without loss. The covariance matrix of random coefficients is unrestricted.

In practice, the groups are $G \equiv \{male, female\} \times \{\text{public/voucher school}, \text{private school}\}$, where the type of high school that the student attended is a proxy for SES in our context. Importantly, all preference parameters, including program effects δ and random-coefficient covariance matrices Σ, differ arbitrarily for each of four types $g \in G$. Thus low- and high-SES students need not agree on a vertical ranking of quality.

Individual-level variables z_i include a constant, i's math and verbal test scores, year indicators, indicators for urban location and current high-school enrollment (as opposed to older applicants applying for a second time), and government-provided scholarship amount. The scholarship amount, scholarship_i, is a known function of a (publicly-known) household SES index, may be used at any G33 institution and hence at any program in $J_{t(i)}$, and can be treated as a shifter of all inside options relative to the outside option because it does not vary across programs within a person.

Program characteristics x_j consist of measures of STEM and humanities course content. 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, as well as an indicator for program and student in the same region of Chile—a coarse proxy for proximity between the student's home and the program—and interactions between an indicator for education major and a third-degree polynomial in student average test scores.[22]

To attend program j, student i in market $t(i)$ would pay

$$p_{ij} = \max\{0, \text{listprice}_{j,t(i)} - (\text{scholarship}_i + \text{discount}_{ij})\},$$

where listprice_{jt} is the program's publicly posted price in year t and discount_{ij} captures additional match-specific discounts and subsidies. While a variety of match-specific discounts existed (see Appendix 1.2), we focus on the match-specific discounts provided to qualifying (high-scoring) students at programs j which participate in the BVP program in year $t(i)$, if $t(i)$ is a year in which BVP is available. We define

$$discount_{ij} = \max\{0, (\text{listprice}_{j,t(i)} - \text{scholarship}_i)1(BVP_{j,t(i)})\},$$

where $BVP_{j,t} = 1$ if program j participated in BVP in year t, or did not formally participate but provided an equivalent scholarship from its own funds.[23]

Program fixed effects absorb variation in listprice_j, and we include scholarship_i in z_i, so that λ_g^p is isolating the effect of price variation caused by the introduction of the BVP scholarship, at certain programs, for those group-g students who qualify.

As an outcome, we consider a policy-relevant near-"on-time" graduation measure, graduation within seven years from the program in which a student enrolls. In the event student i of group $g(i)$ in cohort $t(i)$ enrolls in program j, he graduates if his potential human capital h_{ij} is greater than zero. h_{ij} is distributed according to

$$h_{ij} = \overline{\beta}_{j,g(i)} + z_i\beta^z_{g(i)} + w_{ij}\beta^w_{g(i)} + p_{ij}\beta^p_{g(i)} + \nu_{ij},$$

where $\overline{\beta}_{jg}$ are program effects, not necessarily equal to those that enter utility. The error term

[22]These interaction terms help us isolate "regression-discontinuity" variation in applicants' choices induced by the BVP policy. The next section provides a discussion of the research design.

[23]Every G33 program in the education field provided such a scholarship by 2012. One G8 institution did not participate in BVP but chose to provide an identical scholarship program on its own, presumably to avoid constraints on its ability to admit low-scoring students that would have bound if it had participated.

ν_{ij} is distributed independently across individuals, jointly normally with $(\epsilon_{ij}, x_{j,t(i)}\eta_i^x)$, so that the conditional distribution is given by:

$$\nu_{ij}|\epsilon_{ij}, \eta_i^x \sim N(\rho_{g(i)}(x_{j,t(i)}\eta_i^x + \epsilon_{ij}), 1)$$

for $\rho_g \in \mathbb{R}$. Importantly, our specification allows every term that enters preferences to enter the outcome production function. This specification allows, but does not impose, perfect alignment between preferences and production.[24] We allow match effects on observed determinants of preferences w_{ijt}, p_{ijt} as well as on unobserved determinants of preferences via the correlation terms ρ. These match effects are of interest because the human capital impacts of policies that improve students' welfare will depend on the degree of alignment between preferences and human capital production.

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 $index_{ij}$.[25] Each program has a fixed number of slots. A college-proposing deferred acceptance procedure runs, producing initial placements.[26]

In addition to its assigned students, each program maintains a waitlist. All students who were eligible to apply to program j and applied to j but were not placed in j or in a program they preferred 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 a college-proposing DA procedure with a friction. At the beginning of this stage, students learn their second outside option, u_{i0}^1.[27] Students receive offers from off-platform programs and from on-platform programs at which they are waitlisted, and may decline or provisionally accept them.[28] At the end of the process, students enroll

[24] This would occur when $\beta_j g = \delta_j g$, $\beta_g^z = \rho_g \lambda_g^z$, $\lambda_g^w = \rho_g \beta_g^w$, $\beta_g^p = \rho_g \lambda_g^p$, and $\rho_g > 0$. If these equalities hold, by grouping and rearranging terms we could rewrite our model as: $h_{ij} = u_{ij} + \tilde{\nu}_{ij}$, where $\tilde{\nu}_{ij} \sim N(0,1)$ is a shock that is not predictable at the time of applications and enrollment decisions.

[25] 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 in practice and in our simulations, applicants who are not eligible are dropped from the program's preference list.

[26] 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 $index_{i'j} = index_{ij}$.

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

[28] 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

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

$$a_{ij}^* = v_{ij}\alpha_{g(i)} + \aleph_{ij}$$

measure program j's ability to contact student i in the aftermarket, where g denotes student type, α_g is a vector of type-specific coefficients, the covariates

$$v_{ij} = (1\{j \in G25 \cap \mathcal{J}_{t(i)}^{\text{on}}\}, 1\{j \in G8 \cap \mathcal{J}_{t(i)}^{\text{on}}\}, 1\{j \in G8 \cap \mathcal{J}_{t(i)}^{\text{off}}\}, \text{sameregion}_{ij})$$

consist of indicators for institution type and platform status,[29], as well as an indicator for program and student in the same region of Chile, and the shock term $\aleph_{ij}$ is distributed according to a standard normal distribution, independently across i and j.

Program j is **able to successfully contact student** i if $a_{ij}^* > 0$, if $j = 0$, or if $j > 0$ is i's assigned program in the match. Thus, outside options and the initial assigned program (if any) are always able to successfully contact i, but other programs require a positive draw to do so. If $a_{ij}^* < 0$ and program j is not an outside option or i's assigned program in the initial match, then i is dropped from j's aftermarket priority ordering.

We say that program j is **ex-post aftermarket-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, that i applied to j and was not placed in a program she prefers to j. Thus, if i is placed in j, or is waitlisted at j and has a sufficiently high score, or has a sufficiently high score when j is off-platform, then j is ex-post aftermarket-feasible for i. Outside options and the initial assigned program are always ex-post aftermarket feasible.

Program j is **available** to i if j is able to successfully contact i and, in addition, j is ex-post aftermarket-feasible for i. Let

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

denote the event that j is available to i.

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.

[29] The terms $G25$ and $G8$ denote the set of programs belonging to G25 and G8 institutions, respectively.

Our assumptions imply that i enrolls at his most preferred program j at which $a_{ij} = 1$. The parameters α summarize the extent of aftermarket frictions in availability. These frictions may vary by program type, student type, and student location, as local students may have an advantage. For instance, given that at least some programs ask students to register in person, it may be easier for local students to do so. When the α parameters are small, programs need to make many calls to fill a given vacancy, and thus are likely to leave gaps when they move down their waitlists.

4.2 Research Design

4.2.1 Reports and preferences

To infer preferences from reports, we assume that students truthfully report their preferences over the subset of on-platform programs that is relevant for them: those programs that are within reach and that they like at least as much as their favorite "safety" program, in a sense that we make precise in this section.

For each program, we define score bounds,

$$\overline{\pi}_{jt} > \pi_{jt} > \underline{\pi}_{jt},$$

where the "cutoff" value π_{jt} denotes the minimum value of $index_{ij}$ among students placed in program j in the initial match in year t. Say that a program j is

- **ex-ante clearly infeasible** for student i in market $t(i)$ if $index_{ij} < \underline{\pi}_{j,t(i)}$.
- **ex-ante marginal** for student i if $\underline{\pi}_{j,t(i)} \leq index_{ij} < \overline{\pi}_{j,t(i)}$.
- **ex-ante clearly feasible** for student i if $\overline{\pi}_{j,t(i)} \leq index_{ij}$.

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:

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

Let

$$J_i^{\text{relevant}} = \{j \in J_t^{on} : index_{ij} \geq \underline{\pi}_{j,t(i)} \text{ and } u_{ij} \geq \overline{u}_i^{\text{feas}}\}$$

be the subset of on-platform programs that are not ex-ante clearly infeasible for i and not ranked worse than the best clearly-feasible option.

Let ℓ_i denote i's report after dropping all programs that are ex-ante clearly infeasible and/or are ranked worse than some clearly-feasible program.

We maintain the following assumption, which states that rank-order lists are truthful within the relevant set:

Assumption 1. *For each person i, ℓ_i consists of all elements of $J_i^{relevant}$ in the true preference order.*

Assumption 1 allows students to omit programs that they disprefer to an ex-ante clearly feasible program, and places no restrictions on how or whether students rank ex-ante clearly infeasible options. It implies the following stability properties:

Property 1. *The initial (on-platform) assignment is the program-proposing stable assignment with respect to student preferences for on-platform programs and the first outside option component u_{i0}^0, with capacities equal to the total number of seats for on-platform programs except in cases of ties.*

Property 2. *The final (post-aftermarket) assignment is the program-proposing stable assignment with respect to student preferences, "true" capacities,[30] and the modified program priorities induced by dropping student i from program $j > 0$'s rank-order list in the aftermarket whenever $a_{ij}^* < 0$ and i's initial placement is not j.*

Proof. Say that j is ex-post match-feasible for i if $j \in J_{t(i)}^{\text{on}}$ and $index_{ij} \geq \pi_{j,t(i)}$. Because J_i^{relevant} contains the student's most-preferred match-feasible program whenever this program gives higher utility than u_{i0}^0, each student is necessarily matched to this program if and only if it gives greater utility than u_{i0}^0. The second part then holds by construction. □

Assumption 1 is used in estimation. Because reports are truthful within the applicant's relevant choice set, J_i^{relevant}, we may infer preferences for on-platform programs using standard discrete-choice arguments.

Moreover, although we do not fully specify the mapping from utilities to rank-order lists, Properties 1 and 2 fully specify the mapping from true ordinal preferences, availability realizations, capacities and priorities to enrollment: namely, the mapping induced by running the on-platform and aftermarket program-proposing DA procedures on these inputs. This mapping suffices for counterfactuals.

In practice, we choose a narrow bandwidth, $\overline{\pi}_{jt} - \pi_{jt} = \pi_{jt} - \underline{\pi}_{jt} = 25$ for all j, t. For large bandwidths, list length constraints could prevent students from listing all elements of the feasible set. Given our bandwidth specification, the case that the list length constraint could possibly bind is vanishingly rare in practice. Under our baseline bandwidth specification, the event that

[30] Programs must continue to propose to the students to whom they originally matched who have not declined their offer, even if this would lead them to exceed their "true" capacities.

a student's relevant application is of maximum length but does not contain an ex-post match-feasible program occurs precisely once in our data. In Appendix 3.2 we give details on our choice of bandwidth and provide summary statistics on the relevant set under alternative bandwidths.

Using a subset of rank-ordered preference data in estimation, in addition to the restrictions implied by optimal enrollment decisions, allows us to estimate demand and learn substitution patterns without making the potentially strong assumption that applications are truthful. In particular, our estimation procedure allows students to omit irrelevant programs, consistent with theory and evidence on deferred acceptance procedures. We emphasize that a narrower bandwidth places fewer restrictions on preferences. Our strategy is related to the stability-based approach of Fack, Grenet, and He (2019), and reduces to it as the score bounds $\overline{\pi}$ and $\underline{\pi}$ approach π. It is also related to Che, Hahm, and He (2020), which uses an alternate approach to rule out payoff-relevant departures from truthful play.

Stable matching mechanisms, such as the (unconstrained) college-proposing DA algorithm, have optimal reports which are "dropping strategies" that may omit some programs but rank the listed programs truthfully (Kojima and Pathak, 2009), consistent with our assumptions. Constraints on list length may also 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), and is exactly optimal when there is a unique stable matching, which we have confirmed in our setting in the years 2010-2012. In practice, however, applicants may omit programs that are out-of-reach or irrelevant (Fack, Grenet, and He, 2019; Artemov, Che, and He, 2020; Shorrer and Sóvágó, 2018; Hassidim, Romm, and Shorrer, 2016). Larroucau and Rios (2018) provide evidence from the Chilean match that some students omit programs at which they have very low admissions chances. Our approach is consistent with this literature.

4.2.2 Willingness to pay

In order to obtain welfare estimates in dollars, it is crucial to estimate students' willingness to pay for programs. To do so, we exploit two features of the match-level price variation in our data: discontinuities as a function of students' test scores in the availability and size of program-specific scholarships, subsidies, and discounts, and year-to-year variation in the availability of these sources of program-specific funding.

Our variation comes from the introduction of the nationwide BVP scholarship program in 2011, which made scholarships available to high-scoring students at participating teacher-training programs. Our design is a difference-in-differences design exploiting this policy change, embedded in our structural model, which allows us to estimate a price coefficient jointly with other demand parameters.

BVP provides full scholarships to students with mean math+verbal test scores above 600 at participating programs. The set of participating programs includes all teacher-training programs at public institutions, as well as teaching programs at private institutions which chose to participate. Within the G33, every program that could have adopted BVP did so by 2012, with the exception of the relevant program at Universidad Andres Bello, a private G8 university. However, this university introduced a full institution-funded scholarship for students in the teaching program with scores above 600, exactly as if it had participated in BVP.[31]

Intuitively, high-scoring students are *eligible* for a full scholarship at teaching programs in the *post* years in which these programs are treated. In a two-way fixed effects specification, the coefficient on $\text{eligible}_i * \text{post}_{j,t(i)}$ would reveal the impact on demand of receiving such a scholarship.

In our empirical specification, programs differ in prior attractiveness to students, and students differ in the size of the discount that BVP provides because they receive government scholarships of varying sizes in the event that they do not qualify for BVP. Prior differences in mean utilities between teaching and non-teaching programs are absorbed by program-by-group effects δ_{jg}. We control for the government scholarship amount by including it as an element of z_i.[32] We include math and verbal test scores as an element of z_i as well. In addition, because teaching programs may be differentially (un)attractive to high-scoring students for preexisting reasons (indeed, the introduction of the BVP scholarship was motivated by a public perception that high-scoring students did not want to pursue teaching careers) we include in w_{ij} an interaction between student test scores and an indicator for the teaching major, as well as interactions between squared and cubed student test scores and this indicator.

In summary, our specification includes linear "controls" for test scores, program indicators which subsume an indicator for the teaching major, and a teaching major-specific polynomial in test scores. Modeling the impact of the "running variable" in this way allows us to better isolate the impact on choice probabilities of the variation induced by discontinuities in institutional aid at the test-score cutoff, in addition to the variation due to the policy change.

In addition to the BVP program, there existed other program-specific grants, discounts, and scholarships, which we describe in Appendix 1.2. We have chosen to focus on BVP because of the variation introduced by the policy change, and because all of the match-specific discounts in teaching depend deterministically on test scores, in contrast to other majors in which some discounts and subsidies are discretionary and may depend on unobservables.

[31] BVP provided government funding for these scholarships, but required programs to restrict the number of seats available to students with scores below 500. Universidad Andres Bello did not impose additional constraints on low-scoring students.

[32] Because students receive government scholarships as a function of their socioeconomic status (SES), and SES may enter preferences for programs through multiple channels, we would not wish to use variation in net price that is induced by SES to recover a demand elasticity.

4.2.3 *Aftermarket frictions*

Our strategy relies on the fact that the ex-post aftermarket-feasible set 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. Consider the set of students who are waitlisted in j but have $index_{ij}$ greater than this cutoff value. As $Pr(a^*_{ij} > 0)$ approaches 1, the share of such students remaining in their original match decreases monotonically to zero. Thus the share of students with observables v 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 conditional on v.

In fact, we observe the value of a_{ij} in many cases. For instance, if i enrolls in an on-platform program j at which she was waitlisted, then $a_{ij} = 1$ and $a^*_{ij} > 0$. If there is another on-platform program, k, which i preferred to the on-platform program at which she enrolled, and which was ex-post feasible for i, then $a_{ik} = 0$ and $a^*_{ik} < 0$.

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. Pre-reform data then allows us to estimate frictions for off-platform programs.[33] We allow these frictions to differ by type. Discrimination in favor of high-SES applicants, for example, would enter our estimates as larger frictions for low-SES applicants at off-platform G8 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.[34] 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,

[33] 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, but this is not essential. The model could in principle be extended to allow other characteristics, including student unobservables, to enter off-platform programs' admissions decisions.

[34] For instance, considering students who rank program j just above program k and have scores near the threshold for admission to j, one may obtain the average effect of attending j rather than k by comparing just-admitted to just-rejected students' outcomes.

Hodgson, and Somaini, 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. We choose diffuse priors, so that our estimates may be interpreted as approximate maximum-likelihood estimates. The Gibbs sampler is convenient for our setting, which involves a high-dimensional discrete unobservable–the latent choice set of each agent in the aftermarket—determined by realizations of a_{ij}. Our approach here builds on the procedure of McCulloch and Rossi (1994) to allow for partial rank-order data as well as constraints implied by the enrollment decision when there is a latent "availability set" from which agents must choose.

For each applicant, we observe the submitted relevant rank-order list ℓ_i, initial placement $\text{placement}_i \in \{0\} \cup J^{\text{on}}_{t(i)}$, enrollment outcome $enroll_i \in \{0\} \cup J_{t(i)}$, observed graduation outcome $graduate_{i,enroll_i}$ for the program in which i enrolls, and observed student-, program-, and match-level characteristics $\omega \equiv (v, w, x, z, p)$.

We augment our data with utilities, availability indices, and human capital indices. For each market $t \in \{2010, 2011, 2012\}$, we construct $u_i \in \mathbb{R}^{|J_t|}$, $h_{i,enroll_i} \in \mathbb{R}$, and $a_i^* \in \mathbb{R}^{|J_t|}$, representing utility, human capital, and availability, respectively, for all students i. We choose initial values that are consistent with observed applications, enrollment decisions and graduation outcomes. In addition, we augment the data with 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.

Our sampler iterates through the following sequence of draws from conditional posteriors of the parameters and latent variables:

1. For each market t, for each type $g \in G$, for each $i \in \{1, \dots, N_t\}$ of type g, draw:

$$u_{i0}^0, u_{i0}^1, u_i, a_i^*, h_i, \eta_i^x | \ell_i, \text{enroll}_i, \text{graduate}_i, \alpha_g, \beta_g, \gamma_g, \delta_g, \lambda_g, \overline{\beta}_g, \Sigma_g^{rc}, \rho_g$$

2. For each type $g \in G$, draw:

$$\begin{aligned}
&\alpha_g | \{a_i^*\}_{i \in g} \\
\overline{\beta}_g, \beta_g, \rho_g &| h, \{u_i\}_{i \in g}, \{\eta_i^x\}_{i \in g}, \delta_g, \lambda_g \\
\delta_g, \lambda_g &| h, \{u_i\}_{i \in g}, \{\eta_i^x\}_{i \in g}, \overline{\beta}_g, \beta_g, \rho_g \\
\gamma_g, \sigma_{0,g}^2 &| \{u_{i0}^0, u_{i0}^1\}_{i \in g} \\
\Sigma_g &| \{\eta_i^x\}_{i \in g}
\end{aligned}$$

Conditional draws of linear-index parameters $\alpha, \overline{\beta}, \beta, \eta, \delta, \lambda$ and variance/covariance parameters ρ, Σ^{rc} are standard (e.g. see McCulloch and Rossi (1994) and Agarwal and Somaini (2018)). Building on insights from McCulloch and Rossi (1994) and Agarwal and Somaini (2018), we show that, conditional on the data and on all other latent variables and parameters, each element of u, a^*, u_0^0, u_0^1, and h is distributed according to a truncated Normal distribution.

We provide details in the Estimation Appendix.

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 the Online Appendix, tables 12 through 14.

Table 3: Selected Estimates

Parameters	Male Private	Male Public	Female Private	Female Public
Aftermarket frictions (α)				
G25	-1.551	-0.88	-1.349	-0.84
	(0.03)	(0.014)	(0.035)	(0.014)
G8 On	-0.827	-0.616	-0.739	-0.595
	(0.042)	(0.037)	(0.045)	(0.032)
G8 Off	0.255	-0.435	0.183	-0.739
	(0.024)	(0.016)	(0.021)	(0.01)
Local	0.232	-0.046	0.187	0.041
	(0.027)	(0.014)	(0.029)	(0.01)

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 3 shows aftermarket friction parameters. We find that on-platform frictions are high for all types. For non-local applicants to G25 programs, the probability of successful contact ranges from $\Phi(-1.49) \approx 7\%$ for private-school men to $\Phi(-0.86) \approx 19\%$ for public-school women. Local applicants have somewhat higher chances, ranging from $\Phi(-1.486 + 0.151) \approx 9\%$ for private-school men to to 22% for public-school women. At G8 platforms in 2012, the probability of successful contact is similar acros types, ranging from roughly 22% to 27% for non-local students.

In contrast, off-platform admissions chances exhibit large differences by type. For students whose scores are above the cutoff, successful contact rates are 70% for non-local private school men, as compared to 22% for non-local public school women. Thus, conditional on exam scores, students from private schools are substantially more likely to have the option to attend off-platform G8 programs.

In Figure 14 of the Online Appendix 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 greater admissions chances.

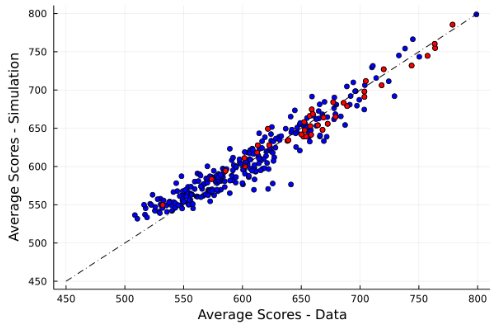
Table 14 in the Online Appendix shows production function parameters. Students with higher math scores are nontrivially more likely to graduate at all programs, but we find much smaller impacts of verbal scores. In addition, we find positive observable "match" effects on the interaction of STEM coursework and math test scores. For public-school students the symmetric 95% posterior probability intervals do not cover zero; effects are more noisily estimated for private-school students. Moreover, we find positive match effects on unobservables. High values of match utility shocks positively predict on-time graduation, significantly so for public-school students.

5.2 Model Fit

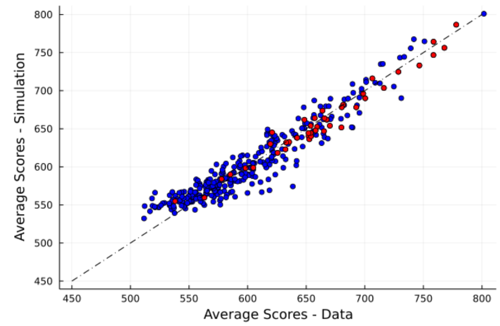
Before presenting the main results, we show that the estimated model fits the distribution of scores within each program well within each year, and closely matches the observed impacts of the BVP scholarship as well as an event study of enrollment and graduation rates. Our estimation procedure did not specifically target these moments, but we believe they are important. Matching the scores of enrolled students is relevant in our context because the test scores of students enrolled in a given program is a key measure of the popularity of the program. Matching the "DiD" and "regression discontinuity" impacts of the BVP policy suggests that our model is exploiting variation that is appropriate for estimating willingness to pay.

To simulate applications, placements, and enrollment, we draw from the posterior distribution of parameters at every 200th iteration, after throwing out initial burn-in draws. Unlike in our counterfactual simulations in the following section, we do not condition on the latent utility values that were drawn during the MCMC procedure. Rather, we discard our data on agents' applications, enrollment, and other endogenous outcomes, draw utilities and availability shocks from their distributions conditional on the parameters that have been drawn, and use these values to simulate the initial match, aftermarket, final enrollment and graduation patterns. We provide details in the Estimation Appendix.

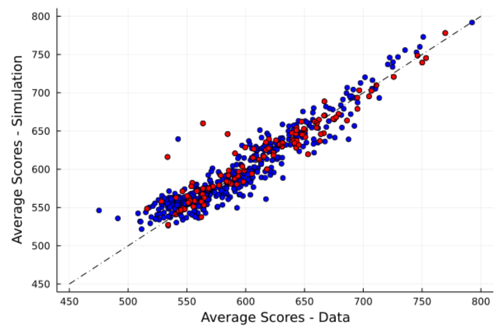
Figure 8: Model Fit - Selectivity



(a) Enrolled students, 2010



(b) enrolled students, 2011

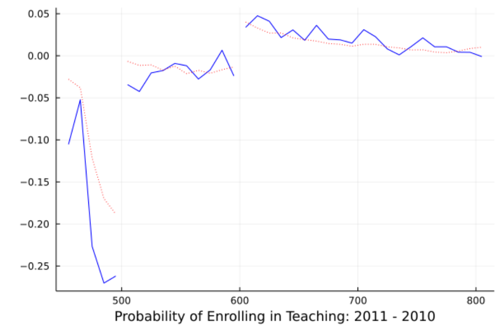


(c) enrolled students, 2012

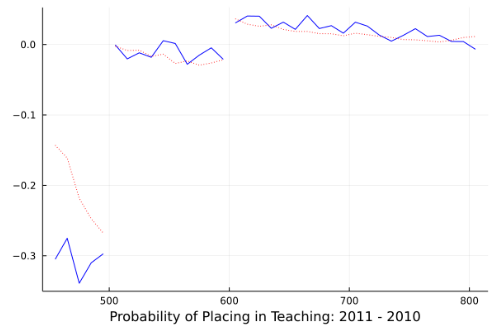
Note: each panel shows, for each program, the mean math and verbal scores of students enrolled in the program in the data (X-axis) and in simulations (Y-axis). We restrict to programs with at least 50 seats. Red dots denote enrollment greater than 100 students.

Figure 8 shows mean math and verbal scores of students enrolled in each program. The X-axis shows observed values, while the Y-axis shows mean model-predicted values. For display purposes we omit programs with fewer than 50 seats. Large (>100 seat) programs are shown in red. Despite the large number of programs in the data, the model fits this measure well. In the Model Fit Appendix we provide an analogous figure that presents results for placements, among on-platform programs, in the initial match.

Figure 9: BVP Impacts



(a) Pr(Enroll in Teaching)



(b) Pr(Place in Teaching)

Note: the left panel shows the difference in the probability of enrollment in teaching majors between 2010 and 2011 as a function of mean math+verbal test scores. The right panel shows differences in the probability of obtaining an initial on-platform placment in a teaching major between 2010 and 2011 as a function of math+verbal test scores. Students above 600 points are eligible for full scholarships, while students with scores below 500 are restricted from entering participating programs.

Figure 8 shows changes in the probability of enrollment in teaching majors between 2010 and 2011 as a function of mean math and verbal test scores. This variation around the introduction of the BVP program is our key source of price variation.

Our model matches the 6-percentage-point increase at the 600-point cutoff, at which students received a full scholarship in the "post" period. Moveover, it fits the change in enrollment well, away from the cutoff, for students with scores above 500. In the Model Fit Appendix we show fit within each year; our model fits the enrollment probabilities well within each year for scores above 500. At very low scores we somewhat underestimate enrollment probabilities.[35]

[35]Certain teaching programs were underenrolled in 2012, even after contacting waitlisted students who were eligible. These programs enrolled some students with scores below 500, which our model, and the rules of the BVP program, disallow.

Table 4: Event study: G33 Enrollment and Graduation

	Data Enroll G33	Model Enroll G33	Data Graduate G33	Model Graduate G33	Data Graduate | Enroll G33	Model Graduate | Enroll G33
			All			
Constant	0.186	0.162	0.067	0.05	0.354	0.359
	(0.0012)	(0.0011)	(0.0011)	(0.0011)	(0.0026)	(0.0035)
Math	0.215	0.201	0.116	0.123	0.015	0.055
	(0.0011)	(0.0013)	(0.001)	(0.0009)	(0.0019)	(0.0021)
Language	0.149	0.132	0.078	0.077	0.024	0.036
	(0.0011)	(0.0017)	(0.001)	(0.0012)	(0.0019)	(0.0023)
GPA	0.055	0.075	0.072	0.056	0.108	0.05
	(0.0008)	(0.0008)	(0.0007)	(0.0009)	(0.0015)	(0.0021)
2010	-0.003	-0.003	-0.007	-0.004	-0.013	-0.01
	(0.0015)	(0.0013)	(0.0013)	(0.0012)	(0.0027)	(0.0028)
2012	0.011	0.022	0.024	0.025	0.026	0.034
	(0.0015)	(0.002)	(0.0013)	(0.0019)	(0.0027)	(0.0034)
Obs.	484549		484549		203596	

Note: this table shows estimates of each outcome for the years 2010-2012. The base year is 2011. We consider the events that a student enrolls in, and graduates within seven years from, some G33 program. "Model" columns: we use the results of 52 simulation draws in which we draw utilities, availability indicators, human-capital indices, and parameters from their estimated posterior joint distribution. In each draw, we simulate the market, then estimate the relevant linear models. We report means and standard deviations of parameter estimates from the relevant models over these draws.

Finally, Table 4 shows regressions of key outcomes—admission to some G33 program, graduation within seven years from some G33 program, and graduation within seven years conditional on having enrolled in a G33 program—on controls and year indicators among all students eligible to apply to on-platform programs. We show results from the data (first column in each pair) and from model simulations (second column in each pair). We find a close fit. For instance, the data show a 2.4 point increase in overall G33 graduation within seven years among the cohort entering in 2012, relative to the 2011 cohort, conditional on our set of controls. In the model, the corresponding value is 2.5 percentage points. We provide additional analyses of model fit, including type-specific event studies of this form, and analyses of outcomes within the G25, in the online appendix.

5.3 Impacts of Platform Expansion

Table 5 displays the impact of platform expansion on welfare, probability of enrolling in an inside-option program, and probability of near-on-time (seven-year) graduation conditional on enrollment.[36] 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

[36] The typical program length is six years. Some medical degrees in Chile have a duration longer than six years but represent a small fraction of students.

inside options are on platform and $a_{ij}^* > 0$ for all students and programs. In this counterfactual, each program's capacity is the maximum of its realized enrollment in 2012 and the number of "true" seats. Thus we do not reduce enrollment in cases in which the program exceeded its "true" capacity. We treat the "No Frictions" counterfactual as a benchmark, and report differences in outcomes, relative to this benchmark, under the other counterfactuals.

Panel A of table 5 shows welfare in units of 1 million Chilean Pesos. We find that a frictionless admissions process would produce mean welfare equivalent to 2.601 million pesos relative to the complete unavailability of all G33 programs. 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 relative to other terms; this need not reflect social weights. Relative to this benchmark, the 2012 baseline gives households an average loss equivalent to 0.031 million pesos. The loss from excluding the G8, 0.294 million pesos, is an order of magnitude larger.

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 67% attending an inside option, relative to 35-39% of public-school students. We find that excluding the G8 would lead to large drops in enrollment, but that the baseline comes within a percentage point of the frictionless upper bound.

Finally, panel C shows impacts on seven-year graduation rates conditional on enrollment in a G33 program. These are larger for women and, conditional on gender, for private-school students. Excluding the G8 would lead to a third of a 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.

5.4 Impacts of Aftermarket Frictions

The results of table 5 suggest that the interaction of frictions and programs' nonparticipation produces welfare losses. We now explore the role of frictions in detail. In figure 10, we plot welfare, enrollment rates, graduation rates conditional on enrollment, and welfare by type as all missed-contact probabilities $pr(a_{ij}^* = 0)$ 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 11 shows the results of the same exercise differentiating by type of student. The results indicate that welfare increases monotonically as frictions are reduced, both with all programs on-platform and when the G8 is excluded. For students other than private-school men, frictions and platform status interact so that the marginal gains from friction reduction are larger when the G8 is excluded. For male students from private schools, in contrast, impacts of friction reductions are more muted. Intuitively, these students benefit from the lower standards at off-platform programs when women and public-school students are subject to larger frictions, and this benefit

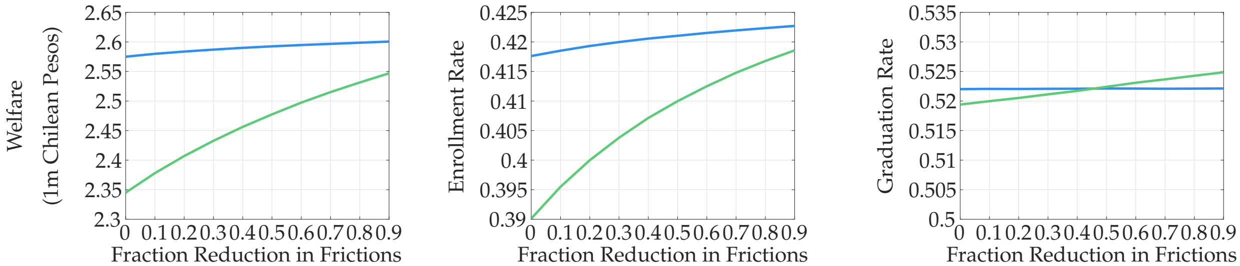
Table 5: Main Counterfactual Results

Counterfactual	All (Avg.)	Male Private	Male Public	Female Private	Female Public
A. Welfare (1m CLP)					
No Frictions (*)	2.601	4.381	2.293	6.211	1.964
	(0.079)	(0.27)	(0.076)	(0.421)	(0.038)
Baseline - *	-0.031	-0.043	-0.034	-0.047	-0.024
	(0.002)	(0.005)	(0.002)	(0.008)	(0.003)
Exclude G8 - *	-0.294	-0.116	-0.303	-0.285	-0.318
	(0.007)	(0.013)	(0.011)	(0.027)	(0.008)
Max Welfare - *	0.639	-0.969	0.321	4.172	0.635
	(0.017)	(0.261)	(0.09)	(0.424)	(0.092)
Free G33 - *	0.73	2.077	0.565	1.736	0.47
	(0.006)	(0.038)	(0.007)	(0.041)	(0.005)
B. Enrollment (pct)					
No Frictions (*)	42.27	67.785	39.674	67.551	35.862
	(0.025)	(0.096)	(0.04)	(0.08)	(0.041)
Baseline - *	-0.621	-0.657	-0.741	-0.548	-0.519
	(0.016)	(0.056)	(0.03)	(0.111)	(0.04)
Exclude G8 - *	-3.891	-1.144	-4.185	-1.315	-4.544
	(0.039)	(0.186)	(0.075)	(0.179)	(0.066)
Max Welfare - *	1.5	-13.916	0.384	12.65	3.455
	(0.067)	(2.427)	(0.71)	(0.734)	(0.742)
Free G33 - *	5.648	9.097	5.518	5.392	5.185
	(0.134)	(0.71)	(0.232)	(0.5)	(0.154)
C. Six-year Graduation (pct)					
No Frictions (*)	52.213	52.895	41.175	69.228	57.74
	(0.202)	(0.762)	(0.341)	(0.521)	(0.281)
Baseline - *	-0.012	-0.017	-0.077	0.031	-0.041
	(0.047)	(0.13)	(0.084)	(0.134)	(0.034)
Exclude G8 - *	-0.338	-0.273	-0.447	-1.043	-0.413
	(0.14)	(0.29)	(0.096)	(0.702)	(0.148)
Max Welfare - *	1.737	0.016	0.909	4.448	0.767
	(0.558)	(0.739)	(0.317)	(3.704)	(0.277)
Free G33 - *	2.605	7.654	1.97	5.471	0.932
	(1.034)	(4.285)	(0.34)	(3.969)	(0.206)

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, $a^*_{ij} > 0$ for all i, j. "Baseline": all programs on platform, parameters as estimated. "Exclude G8": G8 programs off platform. "Max Welfare": maximize sum of student utilities subject to eligibility constraints but otherwise ignoring programs' preferences, holding pricing rules fixed. "Free G33": All programs on platform, all programs free for all students.

counterbalances some of the direct cost of frictions.

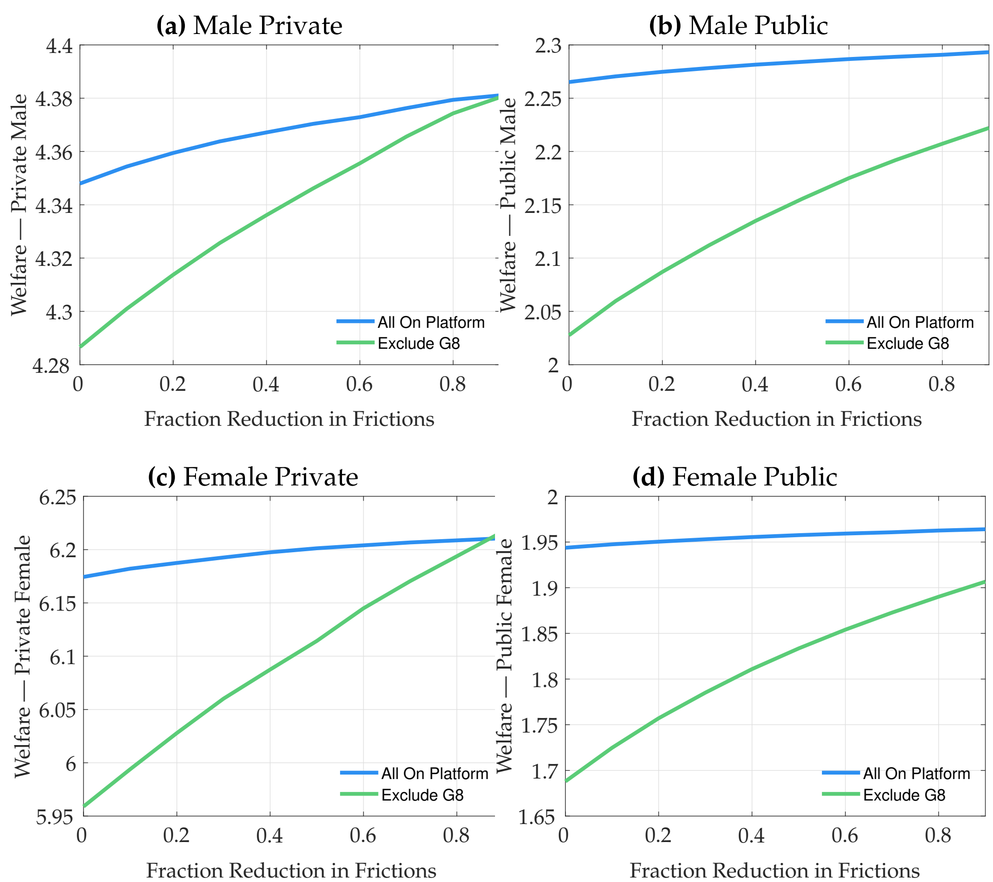
Figure 10: Impacts of Reducing Frictions (α)



(a) Welfare (1m Chilean Pesos) **(b)** Enrollment (Pct.) **(c)** Graduation (Pct.)

Note: Blue lines ( ) indicate when all programs are in the platform, while green lines ( ) indicate when G8 programs are excluded. All model-predicted failed-contact probabilities $Pr(a_{ij} = 0)$ multiplied by $(1 - p)$, where p is "fraction reduction in frictions" on X-axis.

Figure 11: Welfare Impacts of Reducing Frictions (α): Heterogeneity by Type



Note: Model-predicted failed-contact probability $Pr(a_{ij} = 0)$ multiplied by $(1 - p)$, where p is "fraction reduction in frictions" on X-axis.

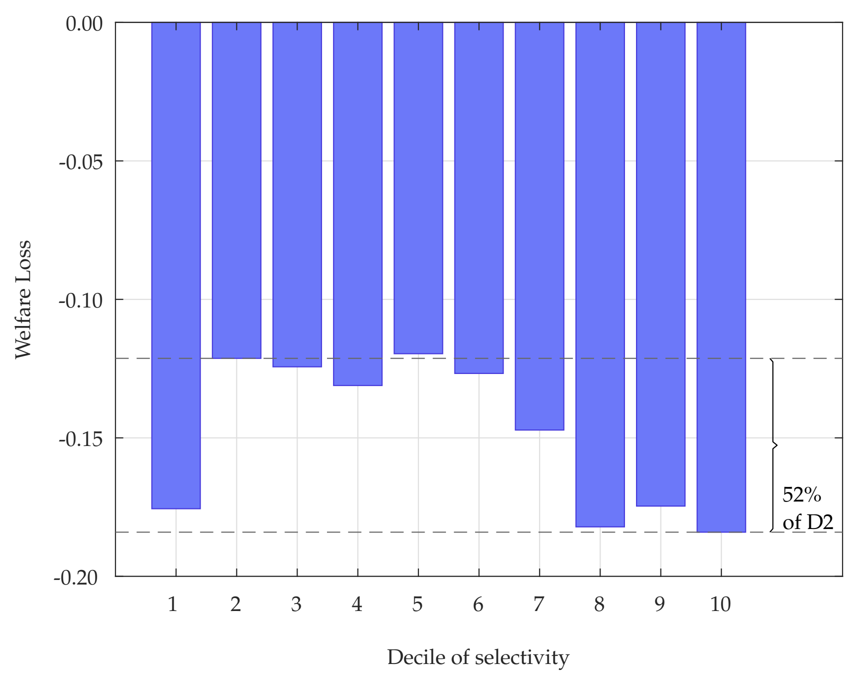
5.5 Which Programs are Most Important to Include?

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 12. We show that the utility loss is highest if the programs in the top decile 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.

Losses are also large, although not as large for the most elite programs, when the least-selective decile is dropped. Including these programs is valuable for a different reason. This decile is the most likely to have vacancies which in turn are less likely to be filled by any student when the programs are off-platform.

Figure 12: 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.

5.5.1 *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 13 highlights welfare gains in different dimensions.[37] The first set of bars shows that utility gains from including the G8 are concentrated among students who are not private-school males.

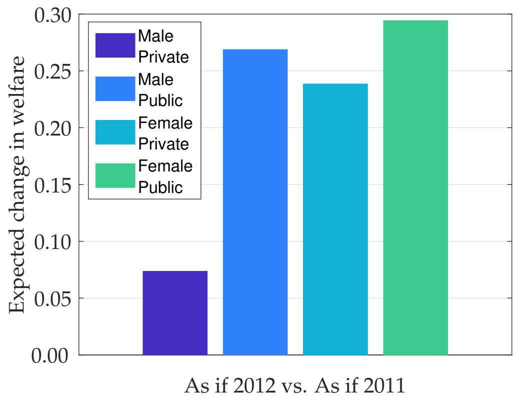
Excluding G8 programs from the platform in 2012 would result in a decrease in welfare of roughly .3m Chilean Pesos for female and public-school male students. For female public-school students, this is roughly 12% of the gap between the 2012 baseline and the complete absence of G33 programs. In contrast, private school male students would experience a smaller loss. 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 4.5% percentage points of public school female and 4.2% of public school male applicants would not enroll in any G33 program. In contrast, excluding G8 programs would make roughly 1.1 to 1.3% of private school students choose their outside option. Impacts on graduation rates conditional on enrollment are smaller. Public school students' graduation rates would fall by 0.4 percentage points, while private school female students' graduation rates would fall by twice that amount.

Results on within-type heterogeneity in Figure A-12 in the Appendix show that the distribution of ex-ante welfare shifts to the right for public school students, with much more mass between the utility equivalent of 1.5m and 3m Chilean Pesos. In contrast, private school welfare impacts are heterogeneous, with some students gaining welfare but also more mass close to zero in 2012. 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 impacts on private school students exhibit greater heterogeneity.

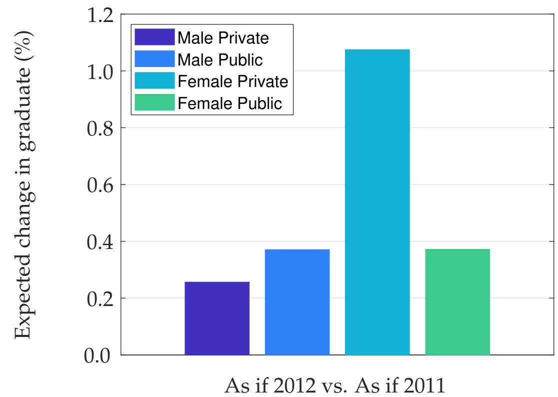
Finally, Figure A-19 in the Appendix evaluates impacts by test score. We find that platform-expansion effects on welfare, enrollment, and graduation rates are positive for all test scores, although the gains are larger for students with scores below the very top. The bottom panel of this figure indicates that welfare gains from platform expansion are small for students with very high (> 700) test score indices, and largest for students with scores roughly one half to one and a half standard deviations above the mean.

[37] Figure 12 in the Online Appendix shows the estimated utility distributions.

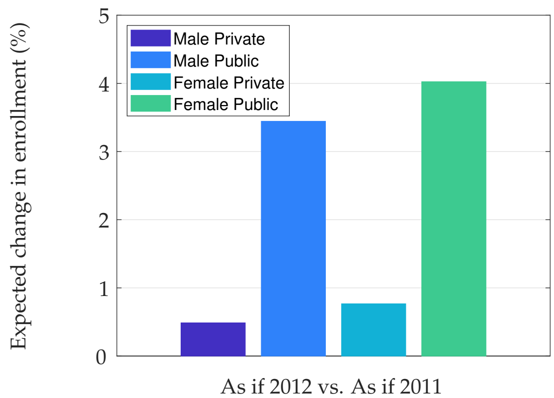
Figure 13: Change in Welfare, Graduation, and Enrollment Rates by Type



(a) Δ welfare for students by type



(b) Δ graduation for students by type



(c) Δ enrollment for students by type

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

5.6 Impacts in Context

Table 5 shows impacts of additional counterfactuals relative to the no-frictions benchmark. In "Free G33", all programs are on the platform, and costs are set to zero for all applicants. The average student welfare gain, relative to the 2012 baseline, is roughly .76 million Chilean Pesos.[38] The welfare impact of platform expansion is roughly a quarter as large as the welfare impact of platform expansion together with free college—a much more expensive policy change—would be.[39]

[38] "Free G33" delivers roughly 0.73 million CLP higher welfare per capita than "No Frictions", and the 2012 Baseline scenario delivers 0.03 million CLP lower welfare than "No Frictions".

[39] ("Baseline" - "Exclude G8")/("Free G33"-"Exclude G8")= 0.26.

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 utility gains from this counterfactual, which holds prices fixed, are slightly smaller than those of providing full scholarships. In addition, this counterfactual, as well as the "free G33" counterfactual, would lead to large gains in enrollment and graduation rates. A "free G33" policy leading to a 5.6 percentage point increase in enrollment relative to the frictionless benchmark, and a 2.6 point increase in the share of students graduating within seven years, while "Max Welfare" would increase enrollment by 1.5 percentage points and graduation by 1.7 points.

6 Conclusion

This paper studies the empirical relevance of the negative impacts on students that arise in a centralized assignment mechanism when there are off-platform 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 the off-platform 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 first document the impacts on assignments and outcomes. Descriptive analyses and interviews with market participants motivate an empirical model of students' preferences, application decisions, matriculation, and graduation rates in the presence of waitlist and aftermarket frictions. We estimate our model using the universe of students' rank-ordered lists of on-platform options and their enrollment decisions at both on- and off-platform options. We find that the configuration of on- and off-platform options can have meaningful impacts on students' welfare, dropout and graduation in higher education. Counterfactual simulations indicate that platform expansion produced additional student welfare worth roughly 0.263 million Chilean Pesos per test-taker, or roughly $650 per person, and increased enrollment in G33 programs by three percentage points, while raising graduation rates conditional on enrollment.

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 welfare is most sensitive to the presence of the most desirable options, as the 10% most selective programs leaving the platform would generate 50% larger losses than removing the median 10% of seats.

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. In our setting, interviews with university administrators suggest that off-platform universities preferred to join the platform, and the binding constraint on their participation was the platform's decision to allow them to enter. However, in other settings, programs may have strong screening motives, or may prefer nonparticipation because of restrictions imposed by the platform on the ranking of applicants and/or the timing of offers. We leave these topics for future research on how best to design markets in practice.

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