

# Negative Externalities of Off Platform Options and the Efficiency of Centralized Assignment Mechanisms

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## Abstract

We study the efficiency of a centralized college admissions platform that operates jointly with a decentralized “off-platform” aftermarket. We exploit a policy change in 2012 in which a significant number of off-platform higher education options joined a centralized assignment system for higher-education programs in Chile. We show evidence that this policy change had impacts on real outcomes finding that the share of students declining their placed spot decreased by 8% and dropout rates at the end of the first year of college dropped by 2 percentage points (a 16% drop) following this event. To quantify the welfare impacts of the aftermarket on the efficiency of the match, we develop and estimate an empirical model of college applications, aftermarket waitlists and matriculation choices, using individual-level administrative data from Chile on almost half a million applications, including test scores and enrollment decisions at all on- and off-platform higher education options. According to model estimates, welfare increases substantially, students begin their studies sooner, and fewer students drop out by the end of the first year of study when top off-platform programs join the platform. These benefits are greater for less advantaged students and for women. Counterfactual analysis suggests that more desirable options generate larger negative externalities when not on the platform. These externalities are mostly driven by students admitted on on-platform options that decline their spots to pursue off-platform programs; and are amplified by frictions in waitlists that yield socially inefficient allocations. Our results indicate that platform design can have real impact on outcomes of interest. Specifically, our findings suggest policymakers need to consider the implications of off platform options and their characteristics when designing regulation surrounding centralized assignment systems.

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# 1 Introduction

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

In this paper we study the empirical relevance of the configuration of on and off platform options. We document the importance of negative externalities generated by off-platform options and we 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 is one of the world’s longest running college assignment mechanisms based on Deferred Acceptance.<sup>2</sup> We take advantage of a recent policy change that significantly increased the number of on platform institutions from 25 to 33, raising the number of available slots by approximately 25%. We first present evidence using an event study analysis to show that when more relevant options are included on the centralized platform, students start college sooner and drop out less later on. Importantly these effects were larger for students from lower SES backgrounds suggesting the design of platforms can have effects on both efficiency and equity.

We develop an empirical model to quantify the negative externalities caused by off-platform options as a function of the configuration of on- and off-platform options as well as an empirical estimate of aftermarket frictions. We estimate a model of college applications, aftermarket waitlists and matriculation choices using individual-level administrative data on almost half a million applications, test scores, and enrollment decisions at all on- and off-platform higher education options. We show that when students are allowed to express their preferences for a larger variety of options on the platform and have fewer options that do not participate in the platform,

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<sup>1</sup> See worldwide coverage map in Figure A-1) and Neilson (2019) for a review of countries that use policies that implement centralized choice and assignment mechanisms.

<sup>2</sup>A unique national entrance exam was first implemented in 1967 and central assignment based on a Deferred Acceptance algorithm has been used for the last 50 years.

welfare increases substantially, students begin their studies sooner, and fewer students drop out by the end of the first year of study. 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 on-platform program. 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 fail to clear the market. Moreover, the program’s absence may distort the placements of other students, even if these students would never enroll in the off-platform program. These students may also be less satisfied and more likely to decline their placement. Our estimated model quantifies the impacts of these forces.

Taken together, our results show empirically that considering off-platform options can be very important when planning a policy to implement a centralized assignment system. The type of options and the expected after market difficulties can be evaluated to consider actions to mitigate this problem or to incentivize the most important options to join the platform. Our empirical framework and counterfactual analysis provide a specific metric to evaluate the benefit of adding each university to the platform. The model and the empirical strategy can be used to quantify the costs of off-platform options in other settings in order to inform policy regarding the costs of off-platform options.

## **2 The Centralized College Admissions System and Its Expansion**

### **2.1 Context and Setting**

There are currently 18 public universities in Chile. Two of these were created in 2016 and will be excluded in this paper, leaving us with 16 public universities in our data. Among the private universities in the country, nine are considered traditional and are pooled together with public universities in a consortium called the *Chilean Council of Universities* (CRUCh). These 25 (16 public and 9 private) CRUCh universities, which we will interchangeably call G25, participate in the

Unique Admission System (SUA), which is a centralized college admission clearinghouse.

This centralized admission system has a long history. The first admission process was held over half a century ago, in 1967, when over 30 thousand applicants were tested on a standardized battery of questions, and then were eligible to apply for a slot in one of the eight founding universities in the system. Except for a policy in the 70's that split the largest university of the country into regional branches, the number of institutions in the platform remained relatively invariant until 2012.

The basic structure of the Chilean centralized admission is as follows. High school graduates register to take the *Prueba de Selección Universitaria* (herein, PSU), which is a set of multiple-choice tests that comprise a verbal and a math multiple choice test, and optional history and science tests. Students who do not attend the math test or the verbal test are immediately disqualified from the process. All test scores are standardized so that the sample distribution resembles a normal distribution each year, for each test. The target means of these (truncated, discretized) normal distributions are set to be 500 points, and their standard deviations are set to 110 points. The minimum score of the test is assigned a score of 150 points, and the maximum corresponds to 850 points.

After receiving their test scores, students who obtained a simple average of at least 450 points between their math and verbal tests are allowed to apply through the centralized admission system. 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.

Students who score at least 450 and decide to apply must do so by submitting a ranked list of *program-university* pairs<sup>3</sup>, in which they express their preferences for programs in the system. Each program in each university ranks students according to a weighted average of subject test scores. Programs choose their weights, subject to some constraints, so weighted scores capture the preferences of programs for their applicants.

When students submit this ordered list, they have access to the following relevant, public information: the number of slots that each program offers, how the program *weights* the test scores of applicants, their personal weighted score if they were to apply to a given program, and the weighted score of the last admitted student in all previous years for every program in the platform.

After submitting their ranked program-list, which defined their strictly ordered preferences in the platform, students are assigned to higher education programs following the Deferred Acceptance (DA) algorithm proposed by (Gale and Shapley, 1962), where programs' preferences for applicants are given by their corresponding weighted scores. Students are assigned to their best feasible option, conditional on all the information in the platform, and receive an admission offer

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<sup>3</sup>Applicants immediately enter a major field of study when they are admitted in a university. See (Bordon and Fu, 2015) for more details.

from the corresponding university if they are accepted in a program.

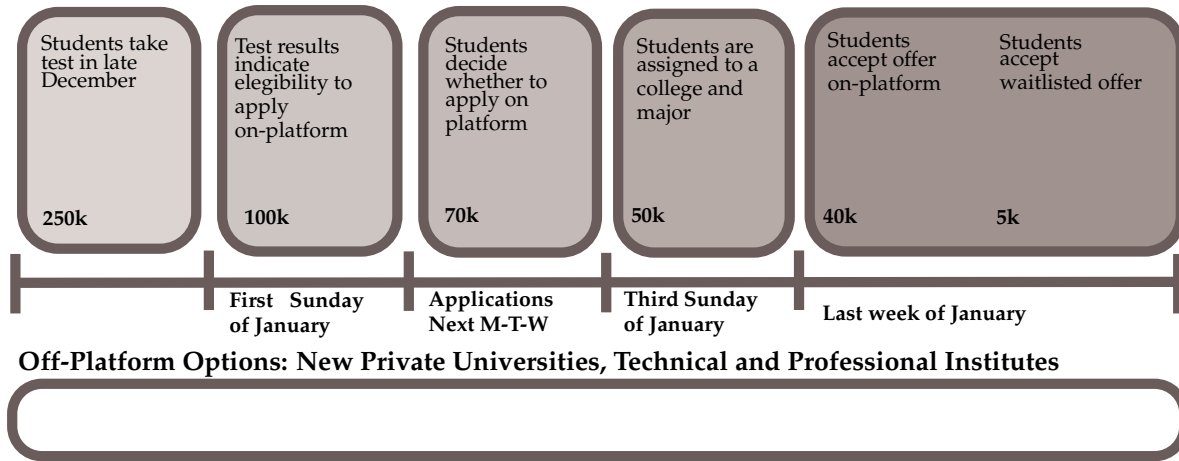
Applicants may be waitlisted in zero, one, or multiple programs. A student will be accepted by a program with capacity  $k$  if she is one of the top  $k$  applicants in terms of weighted score in that given program. If this student ranks below the  $k$ th position of applicants in that program, she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

Students that received an acceptance offer then 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 a program. There is no punishment or cost for not enrolling in a program. If a student decides to enroll, however, but later wishes to renege, the matriculation fee is sunk.

After the initial enrollment process ends, waitlists are processed independently by each institution in a decentralized manner. The commonly adopted approach is to go through the waitlist and inform (through a phone call, for example) each waitlisted applicant that they now have an available slot. Students may accept or decline waitlist offers that they receive. If a student accepts an offer, he must go through the enrollment process again for their new programs, paying a matriculation fee for this program. If a student declines to enroll (or does not answer the phone, for example), the corresponding institution moves ahead with the next waitlisted applicant. This process is full of nuisances and frictions: students may be called by multiple waitlisted programs; there may be communication issues (e.g. wrong numbers may be dialed); students may renege on a waitlisted offer after verbally accepting it but before formally enrolling; the waitlist process operates in real time and terminates at a fixed date, potentially before the market “clears”.

Once all enrollment and waitlist-enrollment decisions have been made and the entry cohort for each program has been finally determined, each program begins their regular academic year in a decentralized fashion. The whole process is repeated in the following year.

**Figure 1: Diagram of Application Process On-Platform**



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

There have been some mild adjustment in the contents and structure of the tests<sup>4</sup>, but the most relevant alteration in the structure of the system was due to a centralization policy in which eight large, off-platform universities were merged into the centralized system, increasing the number of institutions from 25 to 33.

## 2.2 The Expansion of the Platform

The centralized match (i.e. the Unique Admission System (SUA)) is operated by the Chilean Council of Universities (CRUCH). Non-CRUCH universities were excluded from the SUA prior to 2012. In 2012, the CRUCH allowed eight non-CRUCH institutions to join the platform.

Prior to joining the platform, these universities had operated under their own decentralized rules. Typically, enrollment in these universities' programs took place just after the initial match results were revealed, allowing applicants who were unsatisfied with their on-platform match to choose an off-platform option.

<sup>4</sup>In 2004 the name of the admission test changed from *Prueba de Aptitud Académica* (PAA) to *Prueba de Selección Universitaria* (PSU), and so did the evaluated contents. Nevertheless, the same 25 universities remained in the system and the assignment mechanism was practically the same. See (Lafortune et al., 2016) for another policy that restricted the choices that applicants could make.

### 3 The Data and Stylized Facts

We use administrative records from the Chilean Ministry of Education (MINEDUC), which comprise population-level data on high school records, demographic characteristics of students and higher education enrollment, both in and out of the platform. We matched MINEDUC’s data with DEMRE’s application records, which includes all platform applicants, their PSU test scores, ordered preferences for programs, application status and rank in each program. Finally, we also engineered some additional features of each program, such as the number of “quantitative” and “qualitative” courses they include, and categorized them in standardized program groups to make them comparable.

Our data spans all academic years from 2010 to 2012, and we report descriptive statistics for all our most relevant student-level variables for each year in Table 1. With this dataset we are able to observe some meaningful changes in the system after the addition of the G8 universities. Firstly, as commented before, the number of slots in the system increased by almost a half, while the number of applicants incremented just by around a quarter of the pre-policy state. In absence of significant changes in the number of slots offered by each institution, and considering that there is excess demand for them, this suggests that about a half of the students that usually enroll in G8 universities also made use of the platform. This is supported by Figure 2, which depicts the evolution of platform slots and applicants over time. Indeed, in the year of implementation of the policy, excess demand fell from over 50% of vacancies to around 30%.

Increasing the number of slots in the system naturally implies that the number of applicants that eventually enroll in an on-platform option also increases. This is mechanical, as incorporating new G8 options increases the number of admitted students in the platform and thus increases on-platform enrollment in absolute terms. A less obvious observation is that students that were admitted into a G25 option increased their enrollment *rate* in G25 institutions after the policy, just as shown in Figure 3. This effect is fully driven by the inability to deviate to another G8 option after being admitted in a G25 program. Thus, students that prefer G8 programs, who must now rank them above other G25 options, allow a better sorting of students who prefer G25 options, which are around 7.5 percentage points ( $\sim 10\%$ ) more likely to enroll into their assigned programs.

Moreover, we find that this G25 enrollment-likelihood effect is observed across the whole distribution of PSU scores, i.e. G25 admits are more prone to enroll into their admission programs over a very wide range of the test score’s support. This is shown in the left panel of Figure 4, where sample probabilities are plotted in 20-point bins for all the years in our data. Its right panel depicts local polynomial smoothed probabilities with 99% confidence intervals. Overall, we observe

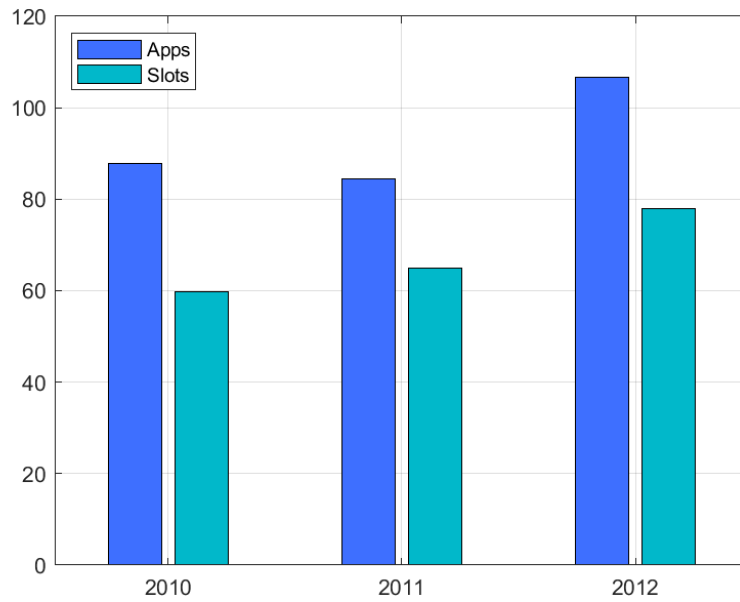
**Table 1:** Descriptive Statistics by Year

|                                | Mean   | Std. Dev. | Obs    |
|--------------------------------|--------|-----------|--------|
| <b>Year 2010</b>               |        |           |        |
| <i><b>Pre-Application</b></i>  |        |           |        |
| Male                           | 0.47   | 0.50      | 251634 |
| Private High School            | 0.10   | 0.30      | 251634 |
| Metro Area                     | 0.65   | 0.48      | 251634 |
| GPA                            | 529.53 | 115.51    | 251634 |
| Math Score                     | 500.79 | 110.77    | 251634 |
| Verbal Score                   | 500.64 | 108.92    | 251634 |
| <i><b>Post-Application</b></i> |        |           |        |
| Applied Through Platform       | 0.35   | 0.48      | 251634 |
| Admitted in Platform           | 0.76   | 0.43      | 87875  |
| Admitted in First Preference   | 0.36   | 0.48      | 87875  |
| Enrolled in Platform           | 0.64   | 0.48      | 67013  |
| Platform Program Dropout       | 0.09   | 0.29      | 42657  |
| <b>Year 2011</b>               |        |           |        |
| <i><b>Pre-Application</b></i>  |        |           |        |
| Male                           | 0.48   | 0.50      | 250758 |
| Private High School            | 0.10   | 0.30      | 250758 |
| Metro Area                     | 0.64   | 0.48      | 250758 |
| GPA                            | 531.64 | 110.07    | 250758 |
| Math Score                     | 501.08 | 111.27    | 250758 |
| Verbal Score                   | 501.04 | 108.34    | 250758 |
| <i><b>Post-Application</b></i> |        |           |        |
| Applied Through Platform       | 0.34   | 0.47      | 250758 |
| Admitted in Platform           | 0.80   | 0.40      | 84512  |
| Admitted in First Preference   | 0.42   | 0.49      | 84512  |
| Enrolled in Platform           | 0.59   | 0.49      | 67803  |
| Platform Program Dropout       | 0.10   | 0.30      | 40011  |
| <b>Year 2012</b>               |        |           |        |
| <i><b>Pre-Application</b></i>  |        |           |        |
| Male                           | 0.47   | 0.50      | 239368 |
| Private High School            | 0.11   | 0.31      | 239368 |
| Metro Area                     | 0.64   | 0.48      | 239368 |
| GPA                            | 535.76 | 113.45    | 239368 |
| Math Score                     | 503.94 | 110.63    | 239368 |
| Verbal Score                   | 504.28 | 109.74    | 239368 |
| <i><b>Post-Application</b></i> |        |           |        |
| Applied Through Platform       | 0.45   | 0.50      | 239368 |
| Admitted in Platform           | 0.88   | 0.33      | 106706 |
| Admitted in First Preference   | 0.45   | 0.50      | 106706 |
| Enrolled in Platform           | 0.62   | 0.48      | 93562  |
| Platform Program Dropout       | 0.08   | 0.28      | 58360  |

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

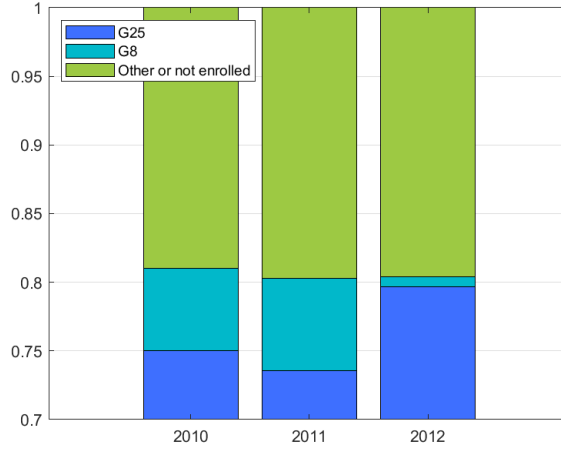


**Figure 2:** Platform slots and applicants (in thousands)

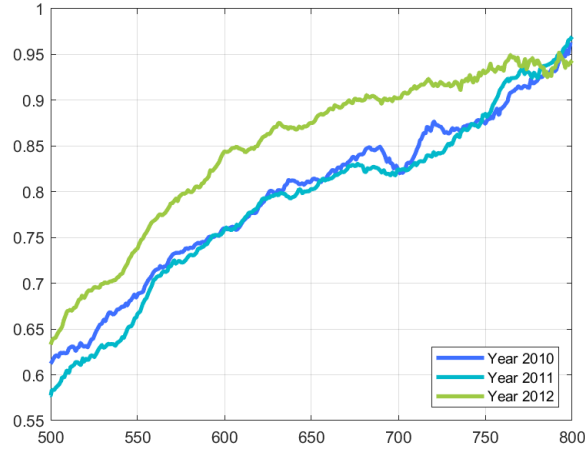


a significant average increase in enrollment rates for G25 admits with scores below 760 points. It is worth noting that, as test scores are adjusted to resemble a normal distribution with a mean of 500 and a standard deviation of 110 points, 760 points is above the 99th percentile of the score distribution. Thus, the policy increased the enrollment yield for the vast majority G25 admits.

**Figure 3: Enrollment probabilities for G25 admits**



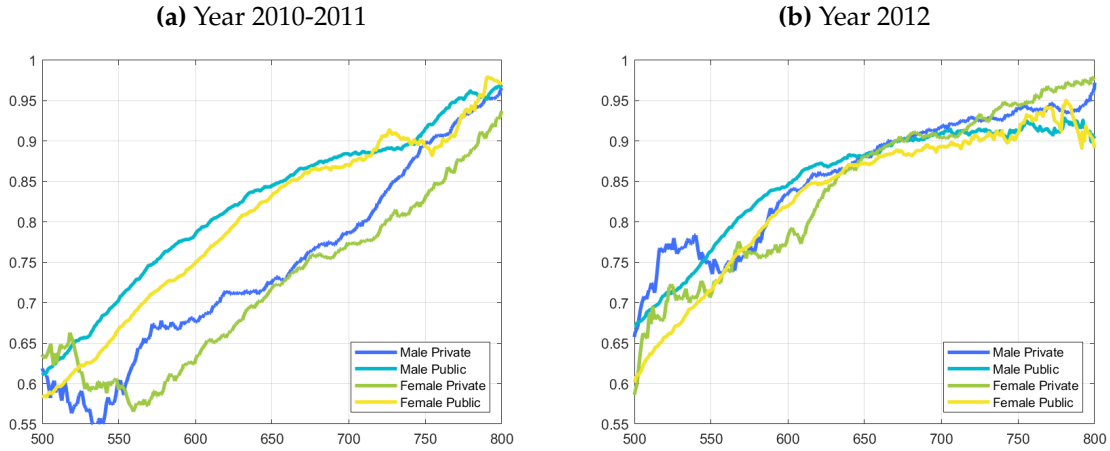
**Figure 4: Enrollment Probability for On-Platform Assignments**



Note: This figure shows the probability that a student assigned to an option on the platform, accepts and enrolls in that option. The lines show conditional means within  $0.2\sigma$  standardized test score bins (plus and minus  $0.1\sigma$  points). The probability of enrollment increases substantially for assignments that occur in 2012 relative to the previous two years.

We also repeat this exercise conditioning on gender and high school type in Figure 5 and Figure 5a, respectively. In all cases, there are significant differences between enrollment rates in 2012 and previous years, with larger impacts on mid-range-score and private school applicants.

**Figure 5:** Enrollment probability, conditional on scores, gender, and type of school.

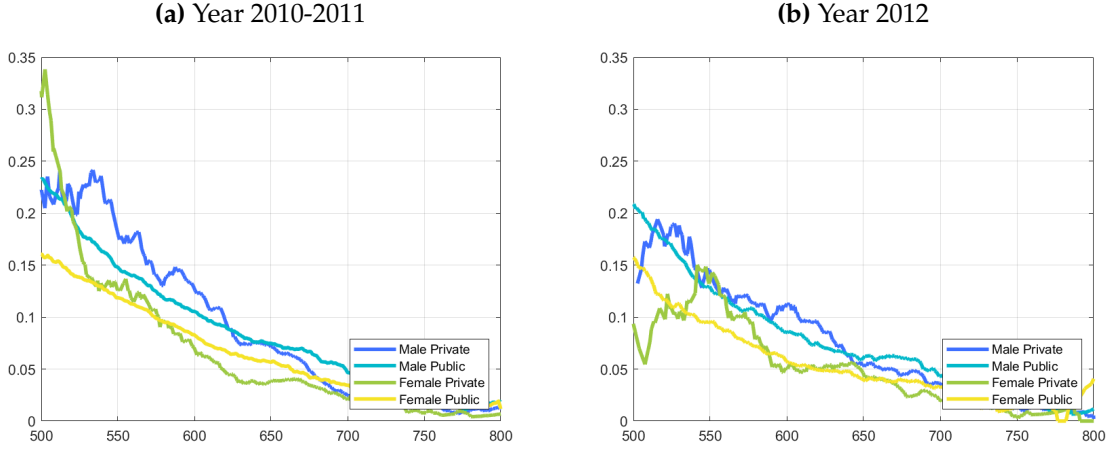


Note: This figure shows the probability that a student assigned to an option on the platform, accepts and enrolls in that option. The lines show conditional means within  $0.2\sigma$  standardized test score bins (plus and minus  $0.1\sigma$  points). The left panel shows the probability for four distinct types of students prior the policy change that increased on-platform options. The right panel shows the same probability for each type of student in 2012 when the platform was expanded. The probability of enrollment increases substantially for assignments that occur in 2012, especially for public school students.

Increasing enrollment rates fosters efficiency in the system, as waitlists are avoided, along with their potential inefficiencies. Another measure of inefficiency is the rate at which students dropout of the system once enrolled. If the quality of the matches generated goes up, we might expect to see less students dropping out over time. When exploring the evolution of freshmen dropout rates in the system, we find a significant reduction of about 1.5 percentage points, which account for almost a 15% reduction in overall dropout by the end of the first year of college.

Figure 6 shows how the probability of dropout varies over time and by gender, scores and type of school. It can be seen that the majority in the increases student retainment appear to be driven by female and public-high-school G25 enrollees. The reduction in dropout rates for males is slightly lower, and there is no significant change in dropout rates for private-high-school freshmen.

**Figure 6:** Freshmen dropout rate for G25 enrollees, conditional on scores and gender



Note: This figure shows the probability that a student that enrolled in an assigned option dropped out of school by the beginning of their second year of studies. Low scoring public school students seem to benefit more and drop out less after the platform in enlarged.

We build upon the previous descriptive findings by estimating descriptive probability models. These estimations do not aim to pinpoint the causal impact of the policy on any outcome, but rather provide more descriptive correlations. All of our statistical models are either linear probability models or nonlinear Probit models of the form:

$$Y_i = \alpha + \beta \times \mathbf{1}[AppYear_i = 2012] + \mathbf{B}\mathbf{X}_i + \varepsilon_i, \quad (1)$$

where  $Y_i$  is some outcome variable for student  $i$ ,  $\mathbf{X}_i$  is a vector of control variables including gender, high school type, GPA, test scores and student's region. In the case of our linear models, which we estimate by OLS,  $\hat{\beta}$  recovers the difference in the conditional means  $Y_i$  when comparing year 2012 with other years.

Our first outcome of interest is the probability of being admitted in an on-platform option. The first two columns of Table 2 report the coefficients for the OLS and Probit-MLE estimates. These suggest that admission probabilities rose in around 12-13 percentage points, which would translate to a jump of over 15% in the probability of being admitted in a platform option.

An additional exercise is to attempt to account for the fact that admission is conditional on having applied through the platform. This introduces a potential participation bias which we attempt to partially correct by computing a simple two-step Heckman estimator for both of our previous specifications. Our exclusion variable in this case is an indicator for receiving *BEA*, which is a financial aid status that increases the value of participating on the platform as it may yield financial assistance and increases admission probabilities for some programs with special wait-

**Table 2:** OLS and Probit (marginal effects) estimates of on-platform admission probabilities

|              | (1)                      | (2)                      | (3)                      | (4)                      | (5)                      | (6)                      |
|--------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|
| Year 2012    | 0.12339***<br>(0.00136)  | 0.13103***<br>(0.00149)  | 0.12462***<br>(0.00141)  | 0.15234***<br>(0.00198)  | 0.09438***<br>(0.00184)  | 0.09358***<br>(0.00181)  |
| Male         | 0.04022***<br>(0.00145)  | 0.04063***<br>(0.00143)  | 0.04152***<br>(0.00145)  | 0.04945***<br>(0.00166)  | 0.06894***<br>(0.00189)  | 0.06871***<br>(0.00188)  |
| Private HS   | -0.05787***<br>(0.00192) | -0.06467***<br>(0.00214) | -0.03804***<br>(0.00216) | -0.03033***<br>(0.00287) | -0.05945***<br>(0.00267) | -0.05906***<br>(0.00265) |
| GPA          | 0.00064***<br>(0.00001)  | 0.00063***<br>(0.00001)  | 0.00058***<br>(0.00001)  | 0.00061***<br>(0.00001)  | 0.00082***<br>(0.00001)  | 0.00081***<br>(0.00001)  |
| Verbal Score | 0.00036***<br>(0.00001)  | 0.00041***<br>(0.00001)  | 0.00021***<br>(0.00001)  | 0.00020***<br>(0.00002)  | 0.00042***<br>(0.00002)  | 0.00040***<br>(0.00002)  |
| Math Score   | 0.00093***<br>(0.00001)  | 0.00105***<br>(0.00001)  | 0.00075***<br>(0.00001)  | 0.00079***<br>(0.00002)  | 0.00095***<br>(0.00002)  | 0.00095***<br>(0.00002)  |
| Observations | 279093                   | 279093                   | 741760                   | 741760                   | 279093                   | 279093                   |

lists. The results of our sample-selection-bias corrected are in columns (3) and (4) of Table 2. Our estimates now imply a similar increase of 12-15 percentage points.

In columns (5) and (6) we replicate the estimation procedure, but with  $Y_i$  being an indicator that equals one when student  $i$  is admitted in her first preference, i.e. the program she ranked at the top of the program list she submitted to the platform. Our results suggest that the conditional probability of being accepted in a first pick increased by 9 percentage points, which corresponds to an increase of at least 22% in the likelihood of this event.

We then turn to estimate models that only consider students admitted through the platform. In the first two columns of Table 3 we take as outcome variable the probability of enrolling in the program assigned by the platform. The next four columns repeat the exercise, but conditioning on being admitted in a G25 program. The difference between columns (3)-(4) and (5)-(6) is that the former ones preserve the same outcome variable (enrollment on platform assignment) on this new subsample (G25 admits), while the latter ones study the probability of enrolling in *any* G25 program, conditional on being admitted on a G25 option. The difference is only due to waitlists or special admission processes, which are very limited in the Chilean system.

Platform enrollment rates rose by about 5 percentage points, i.e. by over 7.5% when considering the full sample. When focusing on those students that were admitted in G25 options, we observe an increase of about 7.5 percentage points in the odds of enrolling in their assigned option, and an increase of a bit over 6 percentage points in the probability of enrolling in any G25 university.

Table 4 shows analogous estimates, but now focusing on freshmen dropout rates of platform admits as outcomes of interest. In the first pair of columns, our outcome variable is simply the

**Table 3:** OLS and Probit (marginal effects) estimates of on-platform enrollment probabilities

|              | (1)                      | (2)                      | (3)                      | (4)                      | (5)                      | (6)                      |
|--------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|
| Year 2012    | 0.04788***<br>(0.00201)  | 0.05061***<br>(0.00202)  | 0.07508***<br>(0.00218)  | 0.07744***<br>(0.00222)  | 0.06346***<br>(0.00192)  | 0.06494***<br>(0.00200)  |
| Male         | 0.02523***<br>(0.00210)  | 0.02554***<br>(0.00210)  | 0.02892***<br>(0.00224)  | 0.02923***<br>(0.00223)  | 0.03451***<br>(0.00199)  | 0.03500***<br>(0.00197)  |
| Private HS   | -0.03104***<br>(0.00285) | -0.03091***<br>(0.00296) | -0.05727***<br>(0.00317) | -0.05755***<br>(0.00330) | -0.07568***<br>(0.00274) | -0.08004***<br>(0.00296) |
| GPA          | 0.00038***<br>(0.00001)  | 0.00038***<br>(0.00001)  | 0.00039***<br>(0.00001)  | 0.00039***<br>(0.00001)  | 0.00040***<br>(0.00001)  | 0.00040***<br>(0.00001)  |
| Verbal Score | 0.00047***<br>(0.00002)  | 0.00047***<br>(0.00002)  | 0.00043***<br>(0.00002)  | 0.00043***<br>(0.00002)  | 0.00035***<br>(0.00002)  | 0.00036***<br>(0.00002)  |
| Math Score   | 0.00108***<br>(0.00002)  | 0.00110***<br>(0.00002)  | 0.00103***<br>(0.00002)  | 0.00105***<br>(0.00002)  | 0.00112***<br>(0.00002)  | 0.00120***<br>(0.00002)  |
| Observations | 228378                   | 228378                   | 199469                   | 199469                   | 199469                   | 199469                   |

first-year dropout probability of any student admitted in the platform. In the last pair of columns, we condition the sample to consider only students that enrolled in a G25 option. These estimates suggest that freshmen dropout rates fell by about 2 percentage points after the policy was implemented. This accounts for at least a 16% drop in the odds of dropping out of a program after the first year of enrollment.

Finally, in our last descriptive exercise we study how the probability of enrolling in a waitlisted program changed with the implementation of the policy. That is, our dependent variable is 1 when a student enrolls in a program in which she was waitlisted in the platform. We do not find any important change in the odds of getting off a waitlist and enrolling in more-desired platform option. Thus, our estimates suggest that this ex-post probability of enrollment stayed constant over time and was not affected by the policy.

**Table 4:** OLS and Probit (marginal effects) estimates of on-platform dropout probabilities

|                     | (1)                      | (2)                      | (3)                      | (4)                      |
|---------------------|--------------------------|--------------------------|--------------------------|--------------------------|
| Year 2012           | -0.01912***<br>(0.00154) | -0.02016***<br>(0.00158) | -0.01675***<br>(0.00165) | -0.01818***<br>(0.00171) |
| Male                | 0.02467***<br>(0.00165)  | 0.02477***<br>(0.00163)  | 0.02458***<br>(0.00175)  | 0.02485***<br>(0.00173)  |
| Private High School | -0.00134<br>(0.00186)    | -0.01065***<br>(0.00242) | 0.00387*<br>(0.00205)    | -0.00602**<br>(0.00275)  |
| GPA                 | -0.00022***<br>(0.00001) | -0.00022***<br>(0.00001) | -0.00023***<br>(0.00001) | -0.00023***<br>(0.00001) |
| Verbal Score        | -0.00007***<br>(0.00001) | -0.00009***<br>(0.00001) | -0.00008***<br>(0.00001) | -0.00009***<br>(0.00001) |
| Math Score          | -0.00052***<br>(0.00001) | -0.00059***<br>(0.00002) | -0.00051***<br>(0.00002) | -0.00058***<br>(0.00002) |
| Observations        | 141028                   | 141028                   | 126621                   | 126621                   |

## 4 Discrete Choice Model

### 4.1 Theoretical Model

In order to estimate the welfare impacts of the policy change, and to assess which programs' participation decisions had the largest impacts, we estimate a model of students' demand for on- and off-platform colleges. Our goal is to provide a tractable framework that uses variation in students' choices and enrollments around the policy change to identify key frictions in the partially-decentralized market. Accordingly, we model students' initial on-platform applications, their resulting placements and waitlist statuses, their decisions to accept positions in off-platform programs, the realization of waitlist offers, and students' ultimate matriculation decisions.

Our model has four stages, which we discuss below.

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

We now describe the game in detail. A market  $t \in T = \{2011, 2012\}$  is an application cohort. Within a market,  $N$  students apply to  $J$  different educational options. Each student  $i \in \{1, \dots, N\}$  is characterized by a tuple  $(x_i, \eta_i, \varepsilon_i)$ , which comprises observable covariates  $x_i \in \mathbb{R}^K$ , tastes  $\eta_i \in \mathbb{R}^L$ , and a random idiosyncratic preference-shock  $\varepsilon_i \in \mathbb{R}^M$ .

Each option  $j \in \{1, \dots, J_t\}$  is characterized by observable characteristics  $x_j \in \mathbb{R}^m$ . If student  $i$  attends an on-platform program  $j$ , he receives utility

$$u_{ij} = \delta_j + \lambda D_{ij} + \eta_{ij} + \varepsilon_{ij}, \quad (2)$$

where  $D_{ij}$  is distance,  $\delta_j = x_j \bar{\beta} + \zeta_j$  is a mean utility term, and

$$\eta_{ij} = \sum_{\ell=1}^M \sum_{k=1}^K x_i^k x_j^m \eta_{\ell,k}^o + \sum_{\ell=1}^L x_j^l \eta_{i,\ell}^u \quad (3)$$

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



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

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

where

$$u_{i0}^0 = \epsilon_{i0}^0, \quad u_{i0}^1 = x_i \beta^{00} + \epsilon_{i0}^1.$$

$u_{i0}^0$  is to be interpreted as the value of the best noncollege alternative, denoted  $j_0^0$  which is known at the time of applications.  $u_{i0}^1$  is the value of the best nonselective or noncollege alternative, denoted  $j_{i0}^1$ , that is not known until the beginning of the aftermarket.

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

In the first stage of the game, students learn their preferences for all programs except  $u_{i0}^1$ , then submit rank-ordered application lists to a centralized mechanism. On-platform programs use eight test scores and high school GPA to generate an index,  $sIndex_{ij}$ . The programs rank students according to this index. We let  $r_{ij}$  denote applicant  $i$ 's rank on college  $j$ 's list. A deferred acceptance procedure is used to conduct the initial on-platform match. Each program has a fixed number of slots in this mechanism. Given a realization of preferences, capacities, and students' applications, we let  $\pi_j$  denote the lowest index that was extended an offer by program  $j$ . Each student is assigned to his highest-ranked program at which his score is above the cutoff. Moreover, each program maintains a waitlist of length  $R$ . The  $R$  highest-ranked students who apply to program  $j$  and are not admitted to  $j$  or programs that they prefer to  $j$  are placed on  $j$ 's waitlist.

We now consider the aftermarket. Off-platform programs  $j \in J_t^{\text{off}}$  rank students according to  $sIndex_{ij}$ . We allow the formula to differ from what they would use if they were on platform. Off-platform programs have cutoffs  $\pi_j$  at which they are indifferent between accepting and declining a student's application given the number of seats that they have and the expected demand and quality of applicants.

Students with  $sIndex_{ij} \geq \pi_j$  therefore have the option to enroll in program  $j \in J_t^{\text{off}}$ . In addition, at this stage each student learns the taste shock  $\epsilon_{i0}^1$  for the outside option component  $u_{i0}^1$ . Students who prefer an off-platform program or the outside option to their on-platform placement will decline their on-platform placement, potentially leading to vacancies in on-platform programs. In turn, this causes on-platform programs to make offers to waitlisted applicants.

We model this aftermarket as a college-proposing DA procedure with a friction. Off-platform programs and on-platform programs make offers to students, who may decline or provisionally accept them. On-platform programs  $j$  give maximum priority to students who received an initial placement at  $j$ .<sup>5</sup> They rank the remaining students according to their position on the relevant wait-

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<sup>5</sup>This guarantees that a student who receives an initial placement at  $j$  can keep that placement if he desires to do so.

lists. If a student is not waitlisted at on-platform  $j$ , he/she is not acceptable to  $j$  in the aftermarket. For each on-platform program  $j \in J_t^{on}$  and student  $i$  on  $j$ 's waitlist, let

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

be in indicator for the event that  $j$  is able to successfully contact  $i$ . We assume

$$Pr(a_{ij} = 0) \equiv \alpha,$$

independently across  $i$  and  $j$ . When  $a_{ij} = 0$ , program  $j$  is unable to reach  $i$ , in which case  $i$  is dropped from  $j$ 's aftermarket preference ordering.

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

We now describe optimal play. The student-proposing DA algorithm used for the initial on-platform match is strategyproof, and in principle applicants should report rank-order lists corresponding to their true preference rankings. In practice, applicants to centralized mechanisms may omit schools that they perceive as unlikely or irrelevant. [CITE stuff here]

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

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

Say that a program  $j$  is

- **ex-ante clearly infeasible** for student  $i$  if  $sIndex_{ij} < \underline{\pi}_j$ .
- **ex-ante marginal** for student  $i$  if  $\underline{\pi}_j \leq sIndex_{ij} < \bar{\pi}_j$ .
- **ex-ante clearly feasible** for student  $i$  if  $\bar{\pi}_j \leq sIndex_{ij}$ .
- **ex-post feasible** for student  $i$  if  $sIndex_{ij} \geq \pi_j$ .
- **ex-post waitlist-feasible** for student  $i$  if  $sIndex_{ij}$  is higher than the lowest score on  $j$ 's waitlist.

Suppose student  $i$ 's true preference ordering over  $J_t$  satisfies

$$u_{ij_1} > \dots > u_{ij_K} > u_{i0}^0 > u_{ij_{K+1}} > \dots > u_{ij_L}.$$

Let  $\bar{u}_i^{\text{feas}}$  denote  $i$ 's highest payoff among clearly feasible options, including the outside option

component known at the time of applications:

$$\bar{u}_i^{\text{feas}} = \max \left\{ u_{i0}^0, \max_{\{j \in J_i^{\text{on}} : \pi_j \leq s\text{Index}_{ij}\}} u_{ij} \right\}.$$

Let

$$J_i^{\text{relevant}} = \{j \in J_t^{\text{on}} : s\text{Index}_{ij} \geq \pi_j \text{ and } u_{ij} \geq \bar{u}_i^{\text{feas}}\}$$

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

We assume that  $i$ 's report consists of all elements of  $J_i^{\text{relevant}}$  in the true preference order. At the end of the aftermarket, our assumptions imply that  $i$  enrolls at his most preferred program (including outside options) that makes him an offer.

## 4.2 Estimation

Let  $v_{ij} \equiv \delta_j + \lambda D_{ij} + \eta_{ij}$  denote the sum of all utility components except for the idiosyncratic shock  $\epsilon_{ij}$ . Let  $\text{lik}_i(v_i, L, D)$  be the exploded-logit likelihood formula for preference list  $L$  and choice set  $D$  under deterministic utilities  $v$ : that is,

$$\text{lik}_i(v, L, D) = \left( \frac{\exp(v_{ij_1})}{1 + \sum_{j \in D} \exp(v_{ij})} \right) \left( \frac{\exp(v_{ij_2})}{1 + \sum_{j \in D \setminus \{j_1\}} \exp(v_{ij})} \right) \cdots \left( \frac{\exp(v_{ij_k})}{1 + \sum_{j \in D \setminus \{j_1, \dots, j_{k-1}\}} \exp(v_{ij})} \right).$$

Suppose that student  $i$  submits list  $L_i$  to the initial match. Dropping programs which are ex-ante clearly infeasible for  $i$ , we obtain a sublist  $L_i^{**} : (j_1, j_2, \dots, j_K)$ , for some  $K \in \mathbb{N}$ . If some program in  $L_i^{**}$  is ex-ante clearly feasible for  $i$ , let  $k$  denote the index of the first such program. Otherwise let  $k = K$ . Let

$$L_i^* = (j_1, \dots, j_k).$$

The likelihood of  $i$ 's application list is given by

$$\text{lik}_i^{\text{app}}(L_i^*, D_i^{\text{on}}) = \int \text{lik}_i(v_i, L_i^*, D_i^{\text{on}}) dF(v_i | x_i, \theta) \quad (4)$$

where

$$D_i^{\text{on}} = \{j \in J_t^{\text{on}} : s\text{Index}_{ij} \geq \pi_j\}$$

is the set of all on-platform programs that are not clearly infeasible for  $i$ .

Let  $\mathcal{L}_i$  be the set of ordinal lists over

$$D_i \equiv D_i^{on} \cup \{j \in J_i^{off} : j \text{ ex-post feasible for } i\}$$

Let  $F_i$  be the set of waitlist outcomes and ordinal preference lists  $(a \in 0, 1^K, L \in \mathcal{L})$  that are consistent with  $i$ 's behavior. In particular, say that  $(a, L) \in F_i$  if  $L$  is an ordered list of some subset of  $J_i^{on} \cup J_i^{off} \cup j_0^0, j_{i0}^1$ , the restriction of  $L$  to  $D_i^{on}$  is  $L_i^*$ , we have  $a_j=0$  whenever  $j$  is not ex-post waitlist-feasible for  $i$ , and  $i$  matriculates at the most-preferred program according to  $L$  which is ex-post feasible or is ex-post waitlist feasible and satisfies  $a_{ij} = 1$ .<sup>6</sup>

Let  $W_i$  denote the set of programs that are ex-post waitlist feasible for  $i$  at which  $i$  is waitlisted. Assume that bandwidths are sufficiently wide that every ex-post waitlist-feasible schools is ex-ante marginal or clearly feasible. In this case  $W_i \subseteq D_i$ .

The full likelihood of  $i$ 's on-platform application and matriculation outcome is given by

$$\ell_i = \sum_{(a_i, L) \in F_i} Pr(a_i | \alpha) \int \text{lik}_i(v_i, L, D_i \cup \{j \in W_i : a_{ij} = 1\} \cup \{j_{i0}^1\}) dF(v_i | x_i, \theta)$$

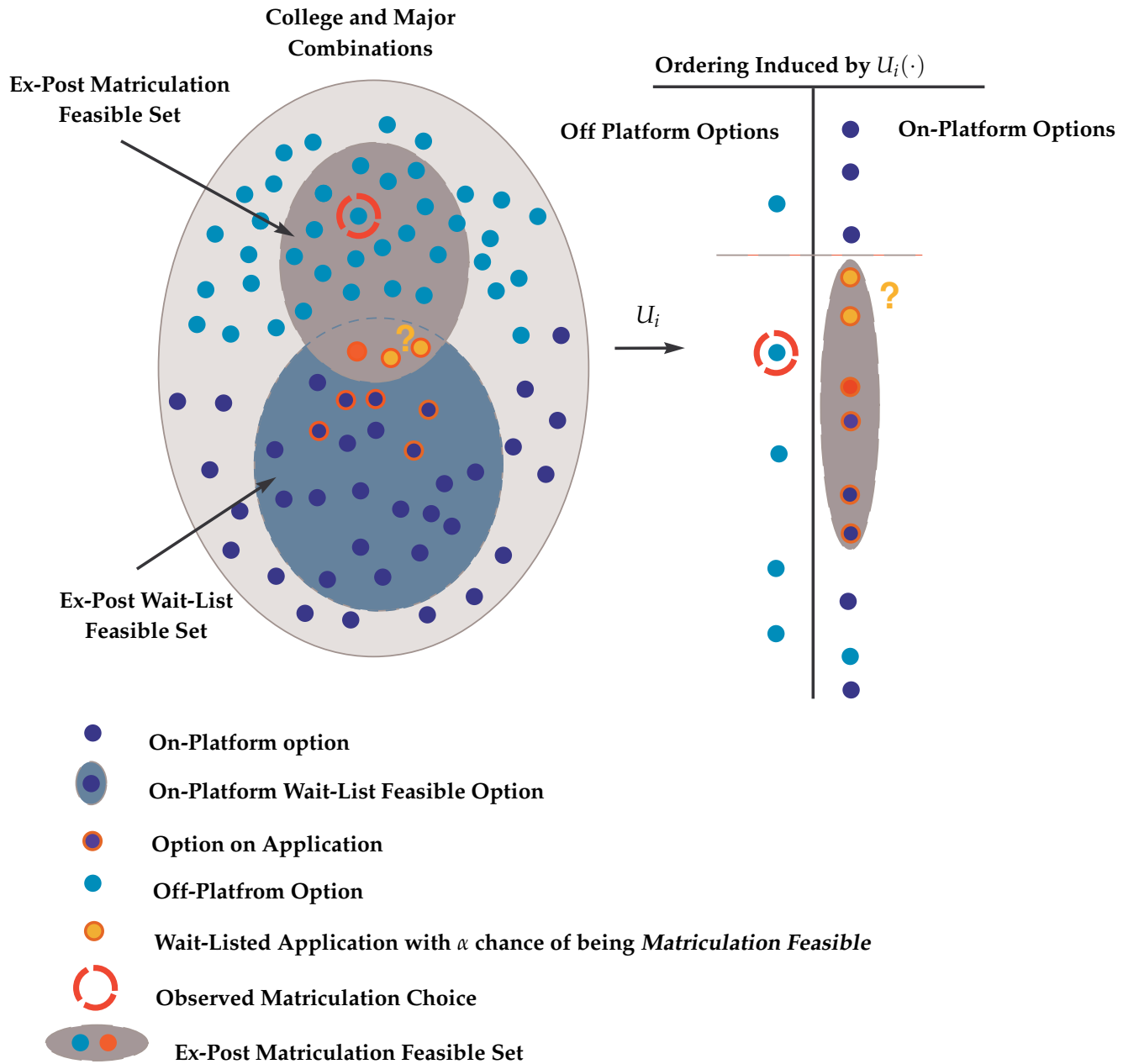
where

$$Pr(a_i | \alpha) = \prod_{\{j \in W_i : a_{ij}=1\}} (1 - \alpha) \prod_{\{j \in W_i : a_{ij}=0\}} \alpha.$$

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<sup>6</sup>If  $i$  enrolls in no program, then either  $j_{i0}^1$  is preferred to the best feasible program, or  $j_0^0$  is. If  $i$  received an initial placement in the match, this program must be preferred to  $j_0^0$ .

**Figure 7:** Diagram of Preference Ordering for Applications and Matriculation Choices



#### 4.2.1 Results

In Table 5 we report select estimates for our more parameterized model for the likelihood  $lik_i$  which considers fixed effects by institution, by major and match effects between student's scores and course composition for each program, and random coefficients. All coefficients are divided by student type (male - private school, male - public school, female - private school and female -

public school). The result of the optimization for the after market friction reports an  $\alpha$  of 0.638.

**Table 5:** Select Preference Estimates for Model with Observable and Unobservable match Effects

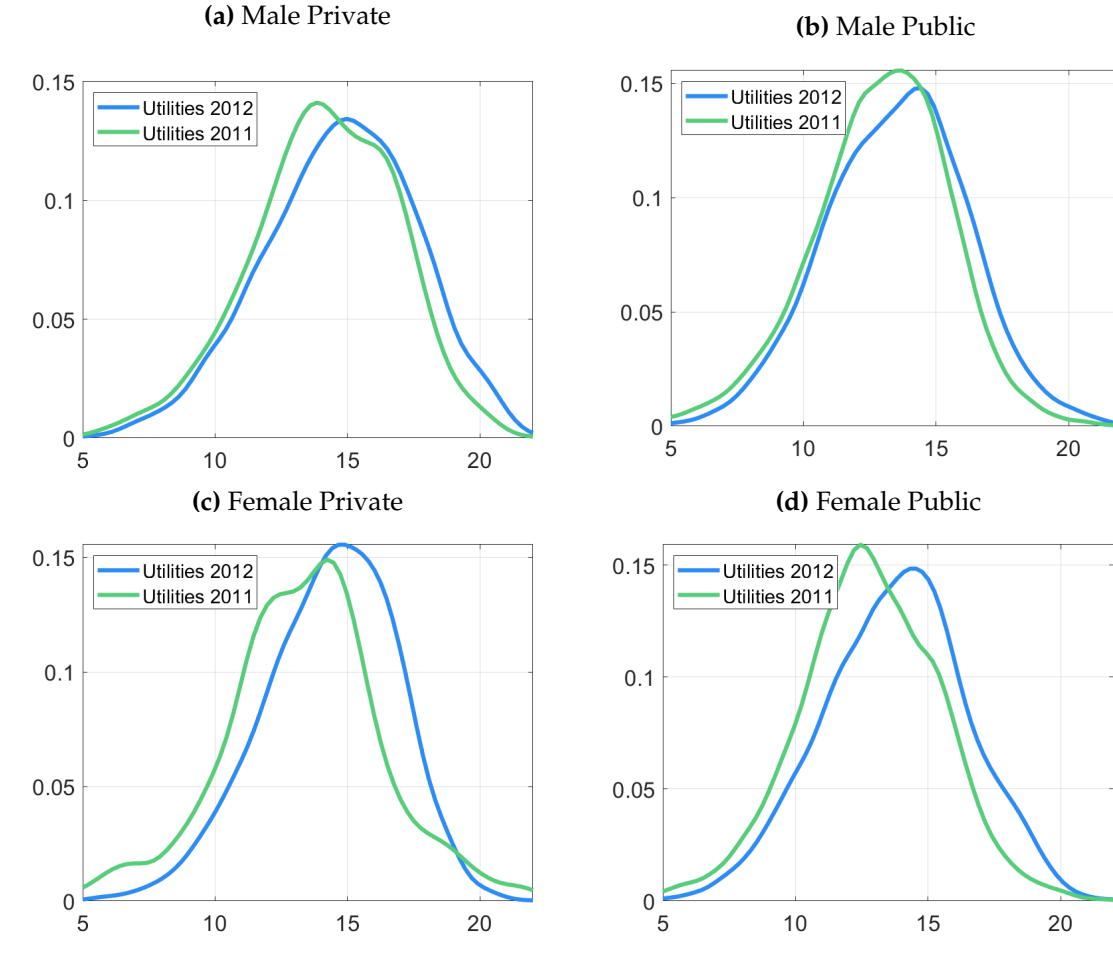
| Prefereces ( $\psi^o$ )            | Male Private | Male Public | Female Private | Female Public |
|------------------------------------|--------------|-------------|----------------|---------------|
| Selectivity                        | 1.475        | 1.525       | 1.330          | 1.444         |
| Selectivity <sup>2</sup>           | 1.395        | 1.222       | 1.596          | 1.464         |
| Math x STEM                        | 0.239        | -0.218      | 0.057          | -0.073        |
| Math x Humanities                  | 0.491        | -0.220      | 0.129          | 0.159         |
| Math x STEM <sup>2</sup>           | 0.218        | -0.129      | 0.040          | -0.074        |
| Math x Humanities <sup>2</sup>     | 0.530        | -0.106      | 0.039          | 0.110         |
| Verbal x STEM                      | -0.347       | -0.295      | 0.107          | 0.263         |
| Verbal x Humanities                | -0.064       | -0.050      | -0.010         | 0.265         |
| Verbal x STEM <sup>2</sup>         | -0.058       | -0.183      | -0.008         | 0.212         |
| Verbal x Humanities <sup>2</sup>   | -0.083       | -0.336      | 0.061          | 0.480         |
| Same City                          | 2.653        | 3.330       | 2.465          | 3.251         |
| Large City                         | 0.490        | -0.966      | -1.196         | -1.689        |
| After-Market friction ( $\alpha$ ) | 0.638        |             |                |               |
| Outside Option ( $u^0$ )           |              |             |                |               |
| Math                               | 1.230        |             |                |               |
| Verbal                             | 1.061        |             |                |               |
| Sex                                | 5.727        |             |                |               |
| School Type                        | 5.038        |             |                |               |
| Big City                           | 1.086        |             |                |               |
| Variance Covariance ( $\psi^u$ )   |              |             |                |               |
| STEM ( $\sigma$ )                  | 0.916        |             |                |               |
| Humanities ( $\sigma$ )            | 0.441        |             |                |               |
| Humanities vs STEM ( $\rho$ )      | 0.0013       |             |                |               |

Note: Preference parameters were estimated via maximum likelihood and consider institution and major fixed effects using 2012 sample. The number of observations used for the regression are 162493 and the number of options are 1334.

#### 4.2.2 Welfare Gains of the Policy

To identify welfare gains of the policy we computed the utility value for the option in which each student ended up enrolling given our estimates of preference parameters in both samples. The utility distribution for 2012 sample is our counterfactual scenario after the policy change, while the distribution for 2011 is our benchmark. We derive those calculations by sub samples of student type. Welfare gains are easy to see from Figure 8.

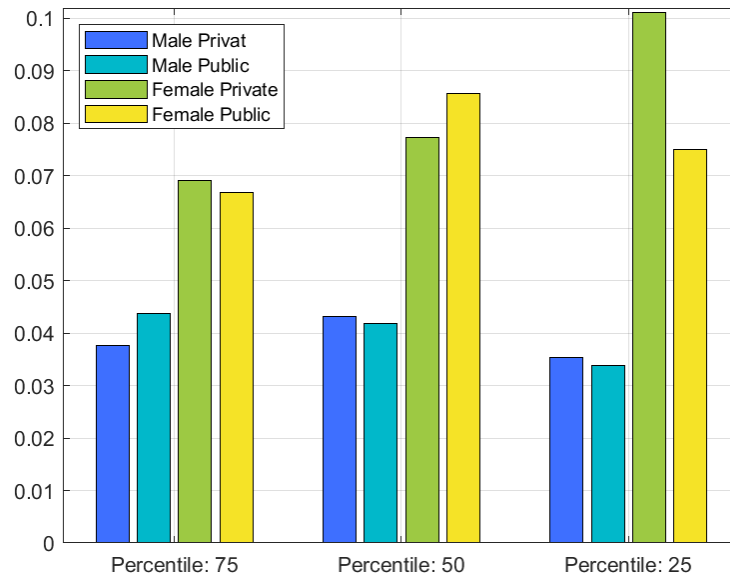
**Figure 8:** Distributional change in welfare after policy change in 2012



Note: The densities plotted in the figure are the enrollment utilities for students in years 2011 and 2012. All students that went to outside option were removed from this calculation. The x-axis correspond to the utility levels in the distribution and the y-axis are the kernel density estimation.

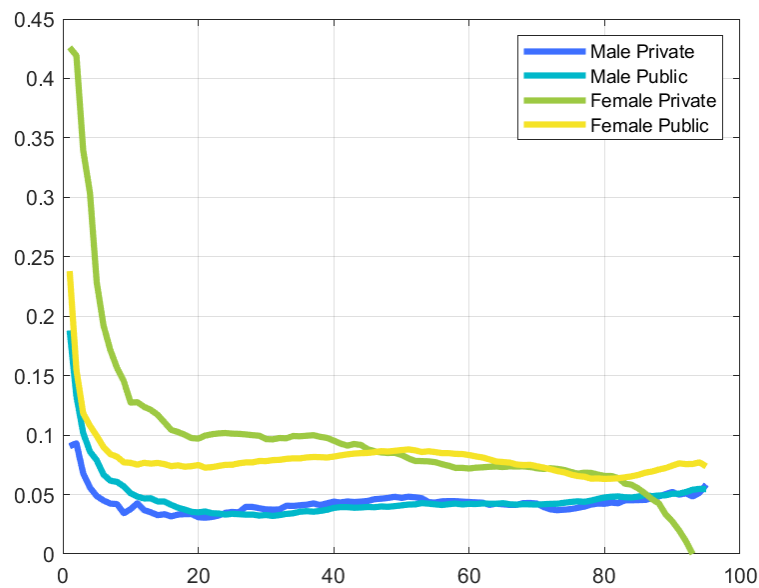
Figures 9 and 10 also evidence the welfare gain. As can be seen, the percentage increase occurs at all percentiles of the utility distribution and for all student types. However, the biggest winners of the policy change appear to be female students, in particular, those that came from private schools and reported low utility levels to begin with. Their utility increase after the policy change in around 12% if they are in the lowest 25 percentile of the distribution. After them, all other student types seem to be increasing their utility levels around 5%.

**Figure 9:** Percentage increase in welfare by percentiles (75, 50 and 25)



Note: We divided utilities for both years 2011 and 2012 in percentiles 25, 50 and 75 and computed the percentage increase.

**Figure 10:** Percentage increase in welfare by percentiles across all utility distribution



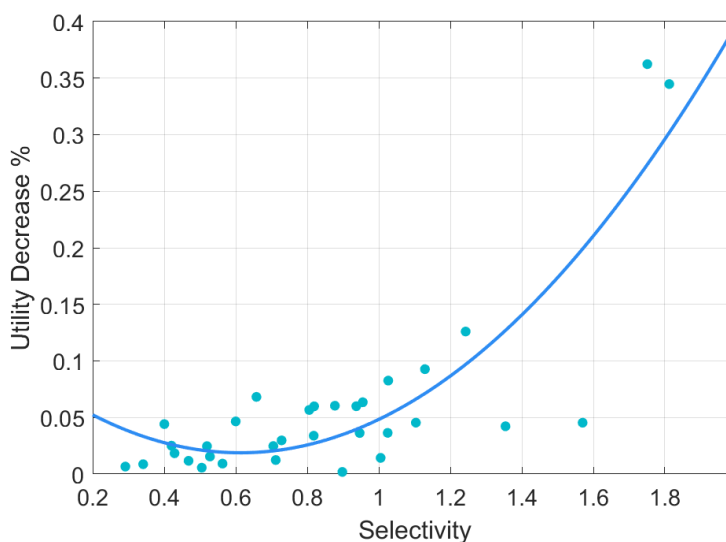
Note: Here we computed the percentage growth for the different levels of utility across all the percentile distribution. The x axis is the utility percentile where we make the comparison, and the y-axis correspond to the percentage increase in the utility in 2012.



## 5 Counterfactual Simulations

Given estimated parameters, we computed the average welfare loss of removing from the platform one program at a time. We present the results from least to highest selectivity as measured by student test scores. Results are shown in Figure 11 and they suggest that the utility loss is higher if the most selective institutes are removed. The relationship seems to be convex such that most of the losses come from losing the most elite schools from the platform.

**Figure 11:** Utility loss of removing options ordered by selectivity



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Note: Utility loss is calculated as the absolute value of the percentage change of the overall utility before removing the institution versus the overall utility after removing it.

## 6 Concluding Remarks

This paper studies the negative externalities off platform options can generate for the efficiency of an assignment mechanism and overall welfare. The empirical results show that when off platform options were added in Chile, matriculation in placed slots rose by 8% and welfare increased by 6%. Dropout rates at the end of the first year of college dropped by 2 points (a 16% drop) showing that these estimated effects had real effects on outcomes policymakers care about. A postestimation decomposition shows that the lower scoring students, women and underprivileged populations were the ones that most benefited from having more options on the centralized platform. Counterfactual analysis reveals that more desirable options cause bigger negative externalities with the most selective college leaving the platform generates 50% more welfare loss than the average college. These results show that off platform options can generate important costs and that considering these negative externalities can be a critical factor when planning a policy to implement a centralized assignment system. We show that empirical analysis can be helpful to guide policy discussions by quantifying key parameters that are needed to evaluate the potential costs of non participation from different actors. The type of options and the expected after market frictions can be evaluated to consider actions to mitigate this problem or to incentivize participation of the most important options. Our estimates provide a specific metric to evaluate the cost of losing each university on the platform. The model and the empirical strategy also highlights ways to quantify the costs of off platform options in other settings and hopefully a route to informing policy regarding the costs of off platform options.

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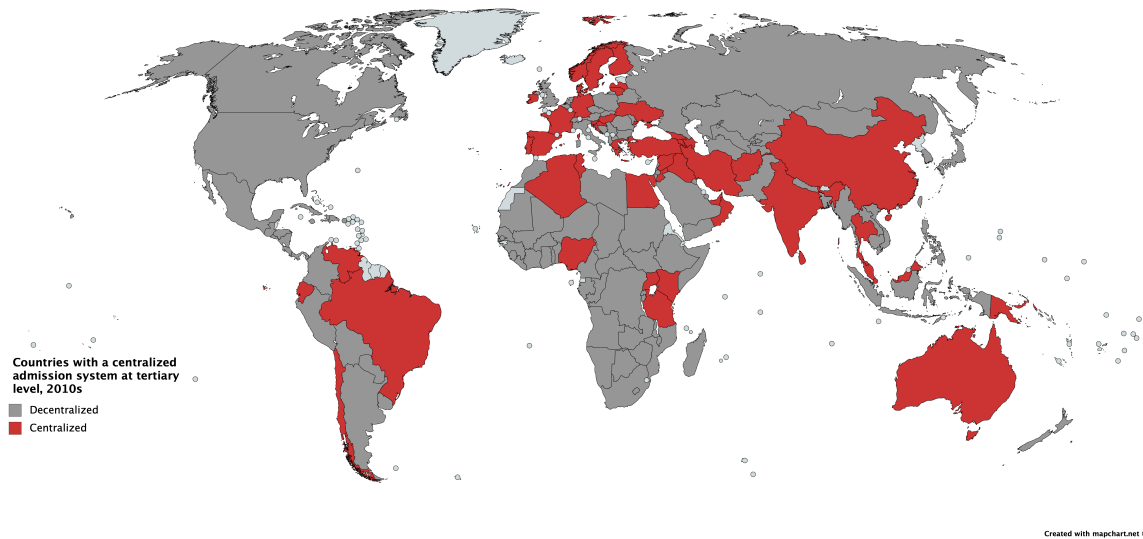
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## Appendix

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

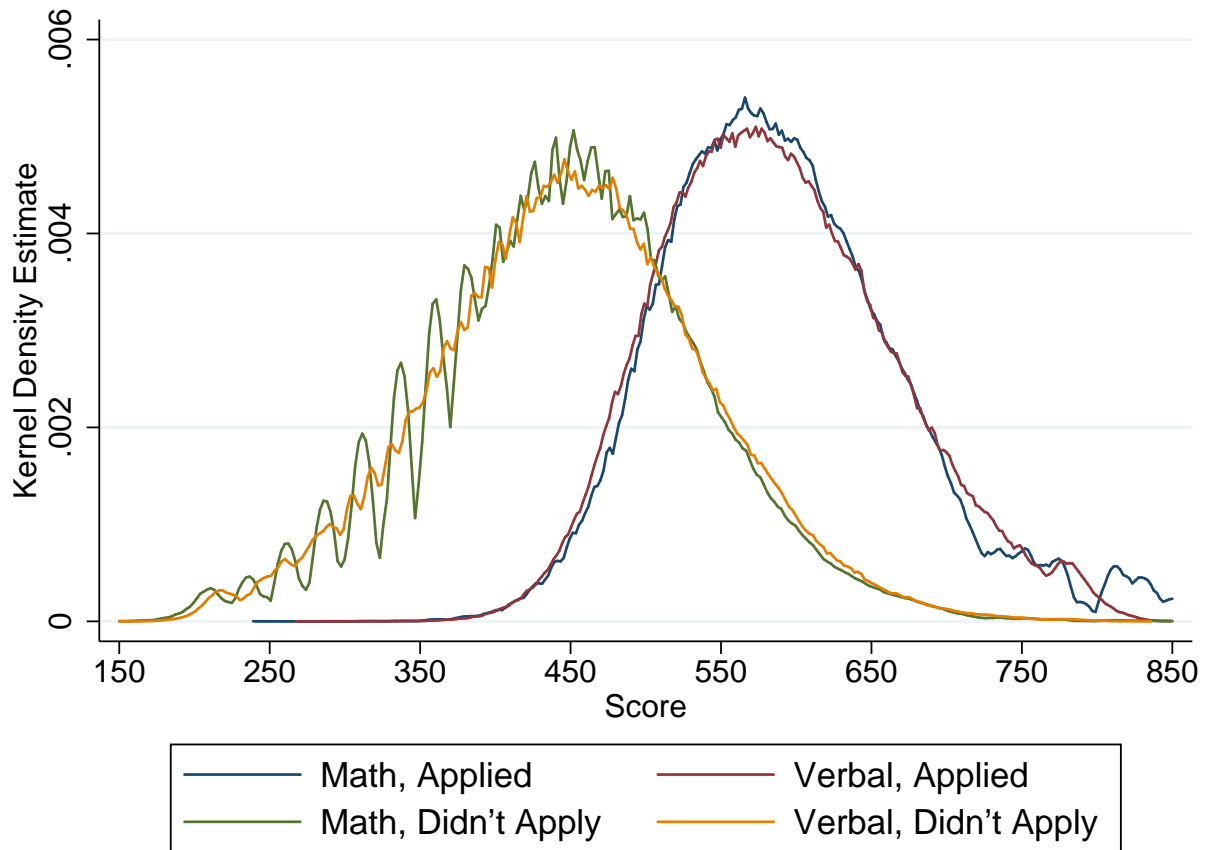


Note: A large number of countries currently utilize centralized assignment mechanisms in higher education. Red countries indicate that the country has at least a subset of higher education options that are assigned by a centralized assignment mechanism. Virtually none of these platforms include all the higher education options.

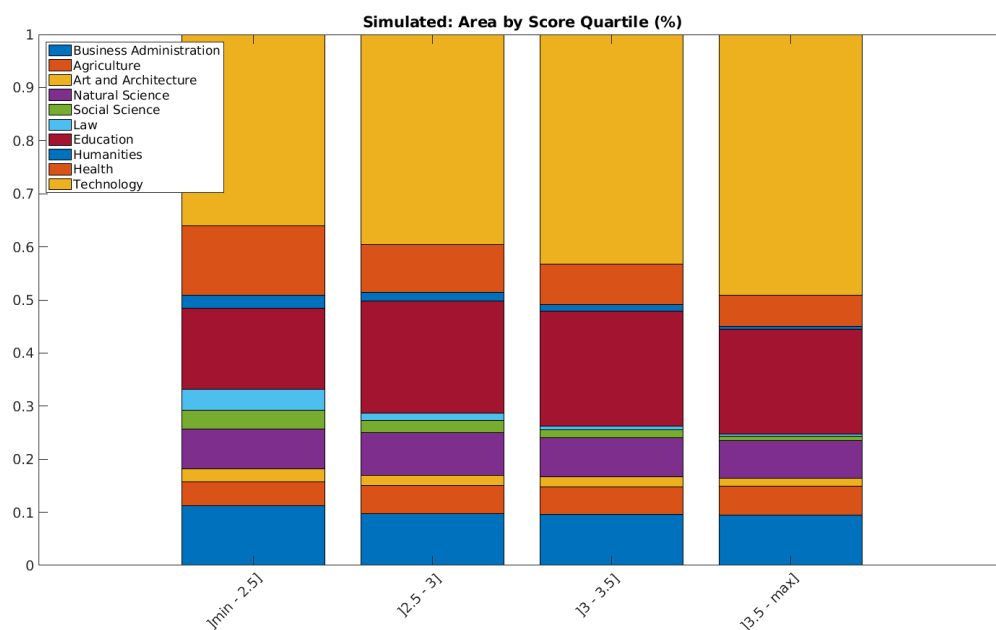
| Type of Institution      | Number of Students | Average Score |
|--------------------------|--------------------|---------------|
| Traditional Universities | 53.00              | 601.2         |
| Private Universities     | 39.71              | 550.7         |
| Professional Institutes  | 21.96              | 505.2         |
| Technical Institutes     | 12.85              | 496.2         |



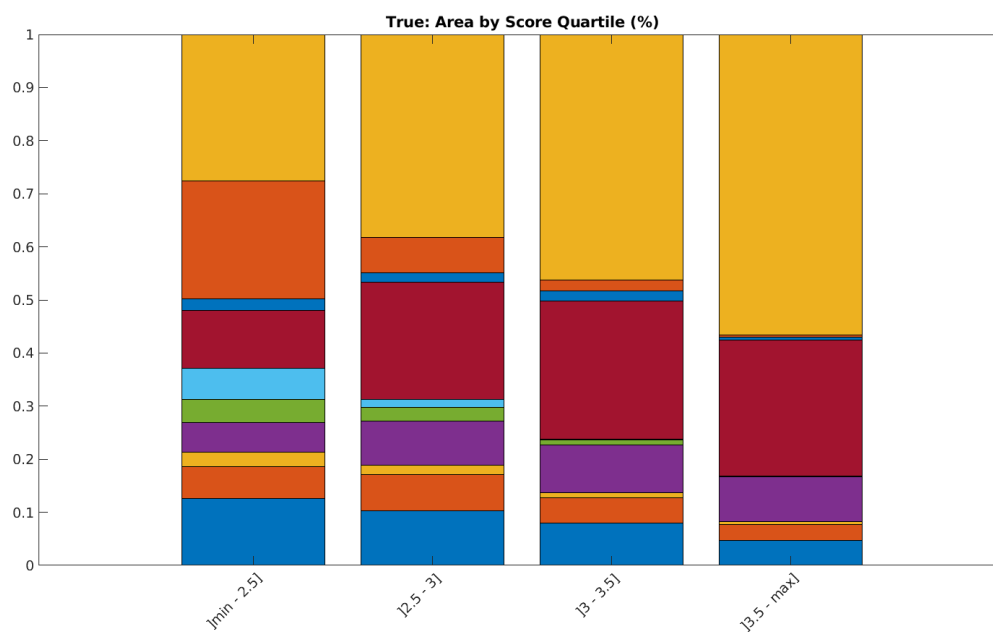
**Figure A-2:** Test score distributions for applicants and non-applicants



**Figure A-3:** Area share by score quartile with simulated data



**Figure A-4:** Area share by score quartile with true data



**Figure A-5:** Outside option shares by type with simulated data

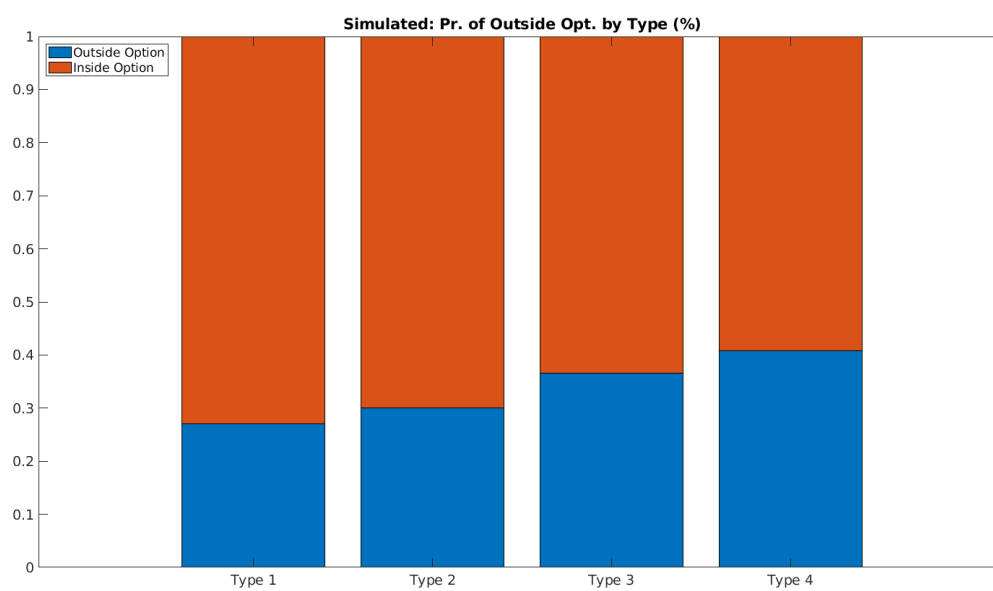


Figure A-6: Outside option shares by type with true data

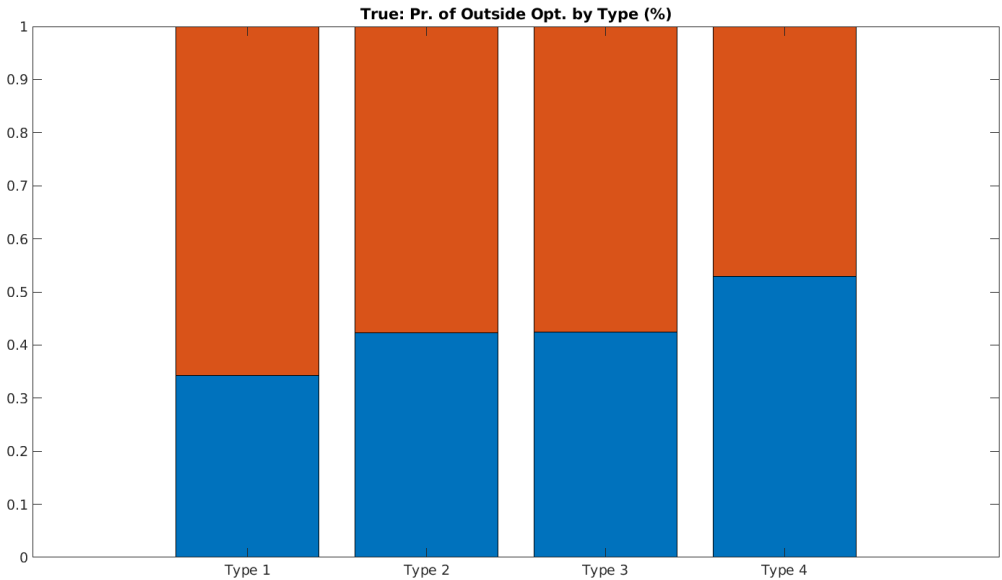
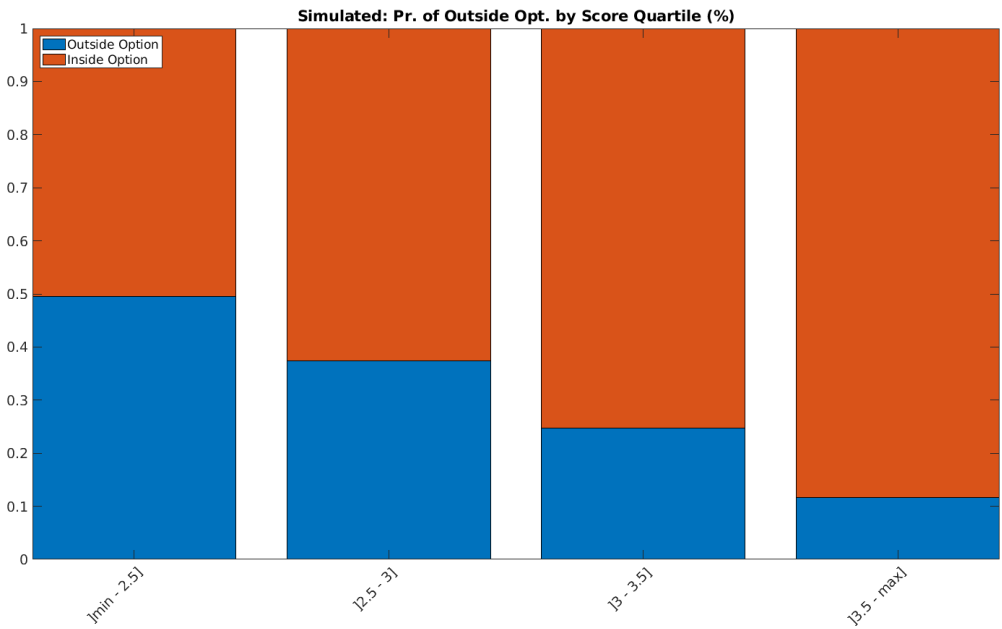
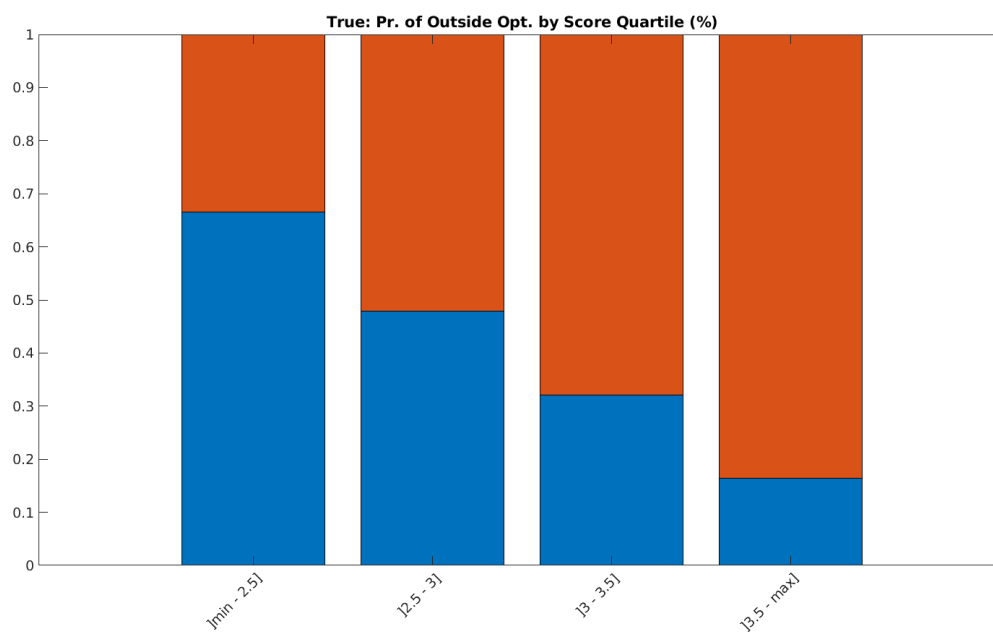


Figure A-7: Outside option shares by score quartile with simulated data



**Figure A-8:** Outside option shares by score quartile with true data



**Figure A-9:** Correlations between true and simulated FL shares

