The Cost of Strategic Play in Centralized School Choice Mechanisms

Sepehr Ekbatani*

May 26, 2022

Abstract

This paper evaluates the welfare consequences of limiting the number of choices in deferred acceptance mechanisms. I show that when the number of choices is capped, some agents must be strategic and that increasing the size of the submittable list can result in better matches, and therefore lead to welfare improvement. I use the Iranian college entrance dataset, in which students are allowed to list up to 100 choices, to estimate a novel discrete choice model for centralized university systems, while relaxing the independence of unobserved preference shocks assumption. I validate the model with out-of-sample data from a quasi-experimental policy change, in which the list cap was increased by 50 percent. In my counterfactual analysis, I calculate that a list cap of 10 choices would incur a 14.2 percent welfare loss. This is equivalent to a 453 km increase in home-university distance, which is 2.6 times the average distance traveled by Iranian students. I also show that a more restrictive list cap would generate heterogeneous effects. While a more restrictive list cap does not affect students at the top or bottom of the ranking, it hurts students with average scores and benefits students in the lower quartile.

Keywords: Matching, School Choice, Deferred Acceptance, Strategy-proof
JEL Classification: D47, D82, I23

---

*Tehran Institute for Advanced Studies, Khatam University; sepehrekbatani@teias.institute.
This paper is a revised version of the first chapter of my 2020 doctoral dissertation at the University of California, Los Angeles (UCLA). I am very grateful for the support, guidance, and encouragement of Adriana Lleras-Muney, Till von Wachter, Natalie Bau and Rodrigo Pinto. I thank Martin Hackmann, Moshe Buchinsky, Mohammad Akbarpour, Amir Kermani, Simon Board, Jay Lu, Christopher Neilson and Margaux Luflade for their feedback. I also thank my colleagues Carolina Arteaga, Alexandre Fon, Manos Hatzikonstantinou, Alex Graupner, Rustin Partow, Saber Ahmadi, Ehsan Azarmsa and seminar participants at UCLA, CCPR, Sharif University of Technology, and the HAND Foundation for insightful discussions. Mohammad Vesal's help was invaluable in providing access to the data.

1 Introduction

Assignment mechanisms that use reported rankings of various options to determine who gets what are widespread around the world. Admissions to public schools and colleges, the assignment of residents to hospitals, and market for clinical psychologists are only a few examples of settings in which such mechanisms are used (Roth [2008]; Roth and Xing [1997]; Abdulkadiroglu and Sönmez [2013]). In the context of school choice, many cities around the world such as New York, Paris, and Madrid and countries like Norway, Chile, Turkey, Tunisia, and Iran, among others, use a centralized mechanism to assign students to secondary and post-secondary educational institutions (Neilson [2019]).

Market designers typically advocate mechanisms that incentivize truthful reporting, for a variety of theoretical and practical reasons (Abdulkadiroglu et al. [2006], Akbarpour et al. [2020]). Leading among those mechanisms is the celebrated deferred acceptance (**DA**) algorithm presented by Gale and Shapley [1962], that guarantees a stable matching, and is strategy-proof for one side (Abdulkadiroğlu and Sönmez [2003]; Dubins and Freedman [1981]; Roth [1985]). However, when agents are constrained and are only allowed to reveal a subset of their preferred choices—like most real-life implementations—the mechanism is no longer strategy-proof and it is unclear whether matching under such a mechanism remains stable (Haeringer and Klijn [2009]; Pathak and Sönmez [2013]; Fack et al. [2019]).

The manipulability and non-stability of the standard restricted-list DA poses two questions. First, what are the welfare consequences of limiting the submittable choices? Second, would a more restrictive list have distributional effects? The goal of this paper is to employ a unique data set with more than 4 million observations from the Iranian university entrance exam to empirically study the welfare costs induced by the constraint on the list size in settings in which DA is implemented and the constraint's distributional effects across students. I have two main findings. First, a more restrictive cap causes considerable welfare loss. Second, I show that there will be winners and losers. In a binding mechanism, students give up desirable choices that might be taken by a student with a lower rank.

To answer the question and to incorporate realistic assumptions on students' choice behavior, I propose a two-dimensional choice model in which each choice bundle consists of a major and a university, while each element is valued separately by the agent. The model allows me to distinguish the demand for majors from the demand for schools, which is crucial for analyzing the choice behavior of students in college choice settings. The main contribution of this model is to relax the independence of the preference shocks assumption imposed by the usual rank-ordered logit models. Relaxing this assumption is important in contexts in which choices are close substitutes, such as college choice settings. As an example, a student's unobservable taste for major A in school X is highly correlated with his taste shock for major B in school X or major A in school Y. The independence of preference shocks fails in other situations as well, such as settings in which students simultaneously choose high school and track or specialty and hospital, etc. I relax this assumption by introducing two taste shock terms that allow students' preference shocks to be correlated in two dimensions: major preferences and university preferences.

I also partially relax the truthfulness assumption. In principle, one can fully relax this assumption using the presented revealed preferences approach to derive countable moment inequalities and estimate the parameters based on the method proposed by Andrews and Shi [2013]. However, this method is computationally infeasible because of the size of my dataset and the number of covariates in the model. So instead, I partially relax the truth-telling assumption by presenting a maximum likelihood estimator and show that the proposed model provides accurate predictions of the choice-making behavior of students both in and out of sample.

I use data on Iranian university applicants who are assigned through a student-proposing DA in which all universities give a fixed priority to an individual based on the student's performance on the nationwide exam.[1] Abdulkadiroğlu et al. [2011] argue that DA scores well in terms of welfare in settings where universities' rankings over all students are strict.[2] I observe ordered choices submitted by more than 71,000 students who applied to enroll in Iranian postsecondary education in 2012. Students were allowed to submit an ordered preference list with up to 100 choices out of around 8,000 available options, in which each choice was a bundle of a major *and* a school (henceforth *a program*). The result is a dataset that includes more than 4 million observations at individual-program level. Additionally, I use data from a quasi-experimental policy change in 2013, in which the list cap was increased by 50 percent, to evaluate the out-of-sample performance of my model.

Using these data, I estimate a novel model of major and university choice and use the counterfactual analyses to evaluate the welfare costs of the imposed constraint in deferred acceptance mechanisms. The counterfactual results are based on exposing agents to different list caps and analyzing their choice of optimal portfolio by implementing the algorithm proposed by Chade and Smith [2006]. The main

[1] Given this feature of the setting, the focus of this study would only be on modeling the strategic behavior of students.

[2] More specifically, the system is categorized as a serial dictatorship in which matching is conducted using only one side's submitted preferences. An unconstrained serial dictatorship is *obviously strategy-proof*, according to Li [2017].

source of the welfare loss in my counterfactual analyses is when the list cap is more restrictive, a student submits a less diversified list which potentially generates a worse outcome for him.

A key advantage of my setting is that in addition to estimating the model, I can use a policy change to obtain experimental reduced-form estimates. Reduced-form results, based on the quasi-experimental policy change in 2013, show that the list cap change from 100 to 150 generated welfare improvement, which can be interpreted as a 56 km decrease in the home-university distance traveled by the students, 31 percent of the average distance traveled by Iranian students. My counterfactual results from the model are consistent with this observation. Additionally, I find that if students faced a list cap of 10 instead of 100, 14.2 percent of total welfare would be lost, equivalent to a 453 km increase in the distance traveled by an average student. A list cap of 15 would decrease welfare by 10 percent, which is equivalent to a 319 km increase in the distance traveled by students.

Another important result of my paper is that a more restrictive cap has a distributional effect across students and produces winners and losers. Students whose score is slightly above average lose the most, but students in the lower quartile of the ranking benefit from a smaller cap. Overall, a smaller cap hurts total welfare as well as the fairness of the mechanism. The fact that students omit a desirable program in the presence of a restrictive cap causes the system to assign that program to students with lower ranks. If the cap was not restrictive, students would apply to all desirable programs and would have no regret (known as justified envy in the literature) after the assignment is done.

The paper is closely related to some recent research on school and college choice mechanisms and restrictions in DA settings. For instance, Abdulkadiroğlu et al. [2017] show that a coordinated single-offer system dominates the uncoordinated offers in NYC's high school assignment system and those students who remained unassigned under the uncoordinated system gain the most from this algorithm modification. Luflade [2018] discusses the welfare improvements caused by the sequential implementation of DA in Tunisia. She finds that updating the information set of students on the remaining vacancies leads to a considerable welfare increase, while disadvantaged students are the ones who benefit the most. In my paper, I find the welfare improvements caused by relaxing the list size constraint in DA settings.

Artemov et al. [2017] show that Australian students submit ordered lists that are different from their true preferences. They assert that in the case of constrained DA, skipping *out of reach* and *not good enough* options can be part of the equilibrium, so truth-telling is not the dominant strategy. Fack et al. [2019] and Agarwal and

Somaini [2018] show that in constrained DA settings, estimates under a truth-telling assumption turn out to be biased.

Abdulkadiroglu et al. [2006] show that moving away from a priority matching mechanism (the Boston mechanism) to a strategy-proof one will remove the strategic burden from parents and give equal chances to both well-informed families and those who are poorly informed. This is an important policy issue, since the amount of information that families have is highly correlated with the amount of resources available to the students. Thus, any policy that removes the strategic incentives and favors unsophisticated players can lead to greater fairness and more equal access. Kapor et al. [2018] also show that moving from a strategic mechanism to a strategy-proof deferred acceptance mechanism benefits students applying to public schools in New Haven, Connecticut. In my paper, I empirically estimate the welfare consequences of strategic play in settings in which DA is constrained.

To the best of my knowledge, the only paper that estimates the list size limitations of centralized mechanisms is Ajayi and Sidibe [2015]. They use applications of high school students in Ghana to estimate a model of high school choice and evaluate the welfare costs by removing the cap on the number of listings from a baseline of 6. In Ghana, however, students submit their preferences before taking the exam and before knowing their rankings, which is a considerable deviation from the regular deferred acceptance mechanism and renders students' belief formation process very complicated. In contrast, the only source of uncertainty in my setting is the lack of information on other students' preferences which more closely represents an assessment of the classic DA. The student knows his score in the centralized exam and his priority index in the rankings, and also has access to previous years' matching outcomes. Also, the novel two-dimensional model developed in my paper provides more accurate predictions of choice-making patterns than models of major choice in the literature and is also able to capture strategic behavior in constrained school choice mechanisms.

The paper is organized as follows. In Section 2, I describe the data used in the study and also the institutional background of the higher education system in Iran. I develop the model and discuss the identification strategy in Section 3. The estimation of the model is presented in Section 4. Finally, Section 5 discusses the welfare analysis, and Section 6 concludes.

2 Data and Institutional Background

This section provides a general description of secondary and postsecondary education in Iran. Figure 1 provides a timeline of high school events. Details on the public and unique administrative data used in this study are also discussed.

At the end of the first year of high school, students in Iran have to choose between three broad tracks– Mathematics and Physics, Experimental Sciences, and Humanities and Literature– which will determine the set of courses they will take in the following 3 years of high school. Mathematics and Physics students will have some exclusive courses, such as Geometry, Calculus, etc. Exclusive courses for Experimental Sciences include Biology and Geology, among others, and for Humanities they include Philosophy, Advanced Literature, and others.

Students participate in nationwide diploma exams at the end of their third year of high school, which are held at the same time across the country for everyone pursuing a diploma from one of the aforementioned broad tracks. The scores on these exams will be a small portion of their final score when applying to universities.

The fourth year of high school is not compulsory for those who don't want to pursue higher levels of education. These students will receive their diplomas by passing the diploma exams and can enter the job market. Those who plan to go to university have to sign up for the last year of high school, called the *pre-university* year. Students have regular school classes for the first 6 months of the school year and have the other three to prepare for the university entrance exam, which is usually held in late June of each year.

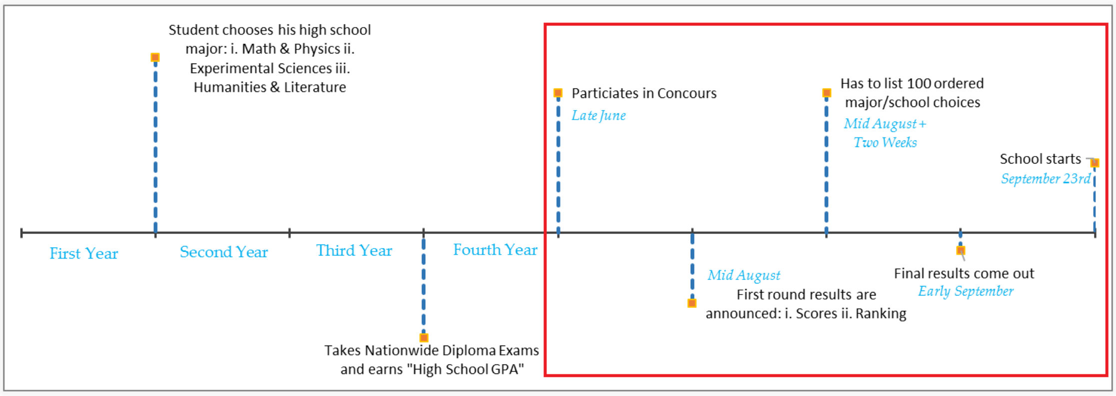


Figure 1: High School and Pre-University Timeline of Events

Concours is a 4-hour multiple choice exam which, for each broad track, consists of the courses students have taken throughout their 4 years of high school. Every year, around 900,000 students who have completed 4 years of high school participate in Concours. To enter a university, students must participate in Mathematics and

Physics, Experimental Sciences, or Humanities Concours based on their major in high school. Participation in the Arts and/or Foreign Languages Concours is open to all tracks.

After taking the Concours, students have to wait for about 45 days for the first round of results to come out, which includes their score on the exam and their ranking among all students. The final score is a weighted average of *relative grades*, meaning that a student will receive a higher score if the average grade of other students is very low, compared to a case in which everybody does well. Students will be ranked based on their final score to determine their priority index at the time of assignment to universities.

Along with the announcement of scores and rankings, the National Organization of Educational Testing (**NOET**) publishes a handbook containing information on programs' codes and also the capacity of for each program. Students have 2 weeks to fill out a form with 100 (before 2012 and 150 after) programs and submit it to the NOET. Students can access information that provides them with previous years' results and the placement of students with rankings similar to theirs. Thus, students have some broad idea of which programs they are likely to be admitted to and which programs they have no chance of getting admitted. Although 100 choices is relatively high compared with most other settings in which DA algorithm is used, it is still small relative to the total number of programs students could choose from. According to Figure 2, this limit seems binding for the 25 percent of students who list all 100 rows in the registration form; most of whom have done poorly on the exam.[3]

In 2012, math and physics students were allowed to choose from 8,602 different programs. Programs are very detailed in the sense that, for example, software engineering and hardware engineering (both known as Computer Engineering) have different codes and a student must apply to each separately. In 2012, the total number of majors students had as their options added up to 241 different majors and sub-majors. The available universities numbered 854, with a minimum of three and maximum of 46 presented majors. Some of these institutions are branches of a head institution and are located in different cities, with each offering a different set of programs with different codes.

After this, it is NOET's turn to assign students to programs. The system starts with the first person in the ranking and assigns her to her desired choice. This process continues until all seats for a program are filled. From then on, students

[3]The size of the list for the case of Chile is eight (Hastings et al. [2015]); Norway 15 (Kirkeboen et al. [2016]); Tunisia 10 (Luflade [2018]); Ireland 10 (Chen [2012]); Turkey 24 (Saygin [2016]), etc.

who have chosen that option as their first choice will be rejected and the system will go to their second choice on the list. The process ends when either all of the seats in all programs are filled or the last student in the ranking is assigned. There is no administrative assignment for unassigned students, and those who are left without an admission must take the exam the next year and go through the whole process again. This high cost of being left out ensures that truth-telling will not be the best strategy for students with low scores. Also, the system bans an assigned student who does not enroll from retaking the exam for 1 year, in order to ensure that students do not randomly include programs they do not like and occupy a spot that potentially could be assigned to another student.

The assignment is a one-sided Gale Shapley algorithm (serial dictatorship), in which universities' preferences for students are only based of the priority index determined by the student's score on the nationwide exam.[4] Students are encouraged to list their choices in order of their preference, and since the mechanism has been in use for many years, its features are well known to the majority of students. Table 1 shows the summary statistics for students who took the Math and Physics Concour on June 28, 2012.

Panel A describes students' characteristics such as age, gender, city of residence, and whether they are retaking the entrance exam. Of all students who took the Concour in 2012, 60 percent were female; The share for the Math and Physics Concour was 41 percent. Students from the five largest cities (Tehran, Isfahan, Mashhad, Tabriz, and Shiraz) make up 35 percent of the sample, while students from mid-size cities are 43 percent of the sample and the rest come from small cities and villages. Of all students, 28 percent had taken the exam more than once prior to 2012.

Panel B summarizes the pattern of choices that are submitted by students. Students have, on average, filled 63.6 choices out of 100. About 26 percent of their choices were in the same city of residence, while 21 percent of their choices were for programs in Tehran. Each student has, on average, listed 17.1 different majors and 20 different universities. Panel C describes three attributes of students' first choices and Panel D shows the description of the assigned choice. Ten percent of students are unassigned, and will have to take the exam the next year in order to enter university. The rest of the students are on average admitted to their 31st choice; 24 percent are admitted to one of their first 10 options, and 3 percent are admitted to one of their last 10 options.

Table 2 presents some statistics for students' behavior on their submitted lists.

[4]Description of DA is presented in Appendix A.

Column (1) shows that 3.71 percent of students submitted lists with fewer than 10 choices, and 31.19 percent of students submitted lists with more than 90 choices. Column (2) shows that more than half of the students are assigned to one of their top 30 choices, and around 10 percent of students are assigned to one of the last 30 choices they submitted. As column (3) shows, choices at the top of students' lists are closer to their city of residence compared with lower-ranked choices, while column (4) shows that top choices were more selective in the previous year. The last column shows the share of majors at Sharif University as the most prestigious engineering school. Note that this school has a capacity for only 885 students, which is equal to 0.34 percent of students.

Students show a strong preference for popular programs and programs close to their city of residence. They also choose their safe options from programs that are not popular but are located close to their hometown. Figure 5 shows students' choice behavior throughout their list. The trend is very consistent for the choice of popular programs, but not for distance. Closer programs are definitely more appealing to students, but only up to a point. Safe options are also chosen from schools that are close to their city of residence.

As I will discuss in more details later on, the data show that students have a preference over universities and a preference over majors. Based on these preferences, they choose a set of programs, rank them, and submit their list. Figure 3 shows the patterns for the first and second choices submitted by students. Figure 3a shows the correlation between first and second submitted majors, and, as stated, 49.74 percent of students submit programs that share a common major, while Figure 3b shows that the first and second choices are at the same university for 49.9 percent of students.

Along the same line, Table 3 documents the fact that in the majority of students' lists, there exists one major (and/or a university) that many programs are chosen because of its desirability. Column (1) shows the share of students who applied to one major in many universities: 70.6 percent applied to one major at more than 10 universities. These students show a strong preference for that specific major, and their list conveys information on their ranking of universities. Column (2) of the same table shows that 71.9 percent of students apply to one university for more than 7 majors. Similarly, the ranking of these majors by these students helps us identify the major specific parameters of the model.

2.1 Policy Change in 2013

Addition to the 2012 data, I obtained access to data on students who took the Concours in 2013. A nice feature of this dataset is that it provides me with out-of-sample variations that can be used to validate my model. Students were allowed to submit lists with up to 150 choices after 2013, which was 50 slots more than 2012. The number of choices students submitted in 2013 are shown in Figure 4. Around 8 percent of students submitted all 150 options, while around 27 percent submitted more than 100 choices. This is an additional information on the list size of 100 being binding for students in 2012. Interestingly, the list cap of 100 is 4 to 12 times the list caps in other countries with similar settings.

Table 4 shows students' behavior facing different caps in 2012 and 2013. Comparing students' behavior in 2012 and 2013 shows how students in 2013 were able to better diversify their submitted lists. Students in 2013, on average, submitted longer lists and listed more popular programs and more programs with lower ex ante probability of admission.

3 The Model

In this section, I present the two-dimensional choice model that I develop to analyze students' choice behavior. The most important property of the model is that it allows the unobservable taste shocks for programs to be correlated in two dimensions: majors and universities. With this feature, the model is able to explain the behavior of those students who apply to many majors at a specific university or one major at many universities.

There are N individuals with priority indexes, $rank_i$ ($i = 1, ..., N$), who are allowed to list K choices in an orderly fashion from the set of J ($J > K$) available programs, and each option is a bundle of a *major* (m) and a *school* (s): $\mathcal{J} \equiv \{(m, s) : m \in \{m_1, ..., m_M\} \ \& \ s \in \{s_1, ..., s_S\}\}$. Each element of this set has a capacity, $q(j)$ ($j \in \mathcal{J}$), of seats specific to itself, while all programs have the same preference over the pool of individuals; This is determined by the priority index.

The problem of choosing a list of programs, given the constraint on the list size, is one kind of simultaneous search problems discussed by Chade and Smith [2006] in which the cost of listing an extra choice goes to infinity after listing the K^{th} option. In these types of problems, an individual optimally chooses a portfolio from available programs that can include up to K choices, taking into account both the ex post utilities and possibility of admission.

A student receives a von Neumann-Morgenstern (**vNM**) utility, u_{ij}, by enrolling in program $j \in \mathcal{J}$, conditional on her admittance. Admission outcomes are determined by DA algorithm and after processing all the applications, but since the student is not fully informed about the preferences of other students, she will have a subjective probability in mind, p_{ij}, that represents her admission chance to program $j \in \mathcal{J}$.

The truncated DA does not allow students to list all of the available programs, so those who have more than K desirable programs for listing face a trade-off between the value they put on some of the competitive programs and their admission chances. Given the fact that a majority of students like to attend popular programs, those who are not at the top of the priority ranking have to play strategically. Otherwise, by only listing their most desirable programs, they face the risk of complete rejection by the system.

The underlying assumption is that individuals are rational agents who maximize an expected utility function when listing their preferences. The expected payoff of the list relies both on the ex post utility and the probability of acceptance of the choices. Consequently, most desirable programs might not be on the list because of their low contribution to the expected payoff, due to the low probability of admission. The following equation shows the expected utility that student i derives from list $L_i = (l_i^1, ..., l_i^k, ..., l_i^{K_i})$, where l_i^k is student i's k^{th} choice:

$$EU_i(L_i) = \sum_{k=1}^{K_i} \left[\left(\prod_{r=1}^{k-1} (1 - p_{ir}) \right) p_{ik} u_{ik} \right] + \prod_{k=1}^{K_i} (1 - p_{ik}) u_{i0} - c|L_i| \tag{1}$$

In this equation, K_i is the total number of listings by student i ($1 \leq K_i \leq K$), p_{ik} is the subjective probability of admission, and u_{ik} is the utility the student receives by studying at his k^{th} listed choice. The nature of the DA algorithm implies that the student will be assigned to his k^{th} choice only if he is rejected by the $k-1$ choices listed before that. This explains the second term on the right-hand side of the equation, which defines the utility the student derives from his outside option (u_{i0}) in case of getting rejected by all of the listed choices. Finally, the cognitive cost of an extra listing is denoted by c.

Each individual has a vector of vNM utilities of being admitted to all programs, $u_i = (u_{i1}, ..., u_{iJ})$, a vector of subjective admission probabilities, $p_i = (p_{i1}, ..., p_{iJ})$, and a reservation utility, (u_{i0}). Using these values, a student will form the portfolio that generates the highest expected utility for her. As Proposition 4.2 in Haeringer and Klijn [2009] suggests, a student cannot do any better than to list her choices in the order of ex post utilities. This intuition follows from the assignment mechanism being deferred acceptance. A student will get assigned to her second choice only if she is rejected by the first one, so rationality would imply that the choice with higher utility should be listed first. An important point is that the chosen programs will be sorted by utility, but information about the options that are left out stems from the revealed preferences assumption of the model. As mentioned before, the left-out options might be superior to the chosen programs, but are not listed because of the low probability of admission.

In my model, the cost of an extra listing is small as long as the number of choices has not reached the list cap. This cost can be interpreted as any nonmonetary cost, such as the cognitive cost students might incur while they are listing their choices. This marginal cost is calibrated to improve the accuracy of the model when predicting the share of students who submit a full list. Overall, a small marginal cost does not affect the counterfactual analysis, since it would be the same regardless of the list cap size.

Solving the model requires finding the utility and subjective probability vectors for each student and then the portfolio that maximizes their expected utility. As I will discuss in the next subsection, utilities can be found independently of the probability values and only by making assumptions about students' choice behavior. Assumptions on how to treat the revealed preferences and the unobservable taste shocks are the key determinants of the estimation outcomes.

3.1 Recovering Students' Preferences

In this subsection, using the evidence from data, I will describe the shortcomings of the usual indirect utility approach in my setting and, more broadly, in the college choice setting. Then I propose an alternative model that is based on a weaker and more plausible assumption on the unobservable taste shocks that can fit the data accurately.

A typical indirect utility function for choice models looks like the following:

$$u_{ij} = V_{ij} + \epsilon_{ij} = V(Z_{ij}, \beta) + \epsilon_{ij}. \tag{2}$$

This equation identifies the deterministic part of the utility student i receives from being assigned to program j, with a parametric assumption on function V and matrix of observables Z_{ij}. Randomness is introduced by adding an idiosyncratic taste shock ϵ_{ij}, which is assumed to be i.i.d with a type-I extreme value distribution.

The i.i.d assumption over i and j is common in estimation of different types of choice models. In the context of college and school choice, the i.i.d assumption over i implies that there are no peer effects and over j implies that a student's unobservable taste for one choice is independent of his taste for the other choices. I assert that this *Independence of Irrelevant Alternatives* (**IIA**) would be problematic in a college choice setting and other settings in which each choice is a choice of more than one object.

In my setting, independence of preference shocks implies that a student's unobservable taste for *UCLA Mathematics* is independent of his taste for *UCLA Statistics* and *UC Berkeley Mathematics*, which does not seem realistic, particularly with typically sparse educational administrative data. A student who has a strong preference for a major can apply to that major at many different universities. Or someone who has a strong unobservable preference for one university (like someone whose sibling is enrolled at that university) can apply to many different majors in that school. This makes the choices of one student highly correlated rather than independent. As discussed in Section 2, looking at Figure 3 and Table 3 further suggests that students' choices are highly correlated.

This leads to introduction of the two-dimensional choice model. The main goal of this model is to relax the i.i.d assumption of unobservable taste shocks in settings in which choices are correlated along several dimensions. In college choice settings, each choice of a student is in fact two choices over the pool of majors and over all universities. A student cares about the university where she will study and the major she will study separately. In my model, student i receives the following utility if she is assigned to major m at school s:

$$u_{ims} = V(Z_{ims}, X_{ms}, \beta) + \nu_{im} + \xi_{is}, \tag{3}$$

where V is assumed to be linear in covariates such as major and university fixed effects, distance, distance squared, program location, and its popularity. The main property of this model is the distinction between the student's unobservable taste shock for major m, ν_{im}, and her unobservable taste shock for school s, ξ_{is}. This will allow the model to account for the correlation between taste for programs that share a common major or a common university. In the case of the aforementioned example, the student's tastes for *UCLA Mathematics* and *UCLA Statistics* are correlated through ξ_{is}, and the term ν_{im} connects her tastes for *UCLA Mathematics* and *UC Berkeley Mathematics*.

The main identification assumption is that there is no individual-major-school specific taste shock. In other words, any unobservable taste shock is either major specific or university specific and, conditional on them, preferences are explained by the observable terms. This assumption seems to be supported by the data, since only 0.75 percent of all submitted choices are singletons—i.e., both program's major and program's university are unique in the student's list. Further, ν_{im} and ξ_{is} are assumed to have independent type-I extreme value distributions.

As previously asserted, given the choice of programs, there will be one ordered list that produces the highest expected utility and that is created by sorting the programs by their ex post utilities. The student will only take his admission probability into account when deciding on which K options to choose out of the possible J programs. Put differently, deciding which programs to list is accomplished using data on utility and probability combined, but ordering the chosen programs is only conducted by the order of utilities.

3.2 Revealed Preferences

In this subsection, I explain the idea behind my identification strategy to partially relax the truth-telling assumption on revealed preferences and describe the best model that can fully relax it. Appendix B provides a general discussion of different approaches to using revealed preferences to estimate model parameters and different implications of each assumption. I will discuss that the best model cannot be estimated because of computational difficulties. Instead of full relaxation, I describe my strategy to partially relax the truth-telling assumption and explain the underlying intuition.

Fack et al. [2019] and Agarwal and Somaini [2018] argue that the truth-telling assumption is unrealistic under a constrained DA, and show that estimates under this assumption turn out to be biased. A less limiting assumption about students' decision-making behavior is *undominated strategy*, which only assumes that students do not play dominated strategies. This assumption implies that the submitted list should be sorted by the order of preference, and no information is obtained from left-out choices. In other words, in equilibrium student will submit a *partial preference order* of the options he finds both desirable and feasible given his priority. This approach by students results in a not unique, but an undominated strategy Nash equilibrium in which the student submits an ordered list of those programs he thinks he has a chance of getting into. Under the undominated strategies assumption, j is revealed preferred to j' if the former is ranked higher on the list. The implication of such an assumption about observing such ordering can be written as

$$\begin{aligned} Pr\,(j \succ_i j') &= Pr(u_{ij} > u_{ij'} \; and \; j, j' \in L_i) \\ &\leq Pr(u_{ij} > u_{ij'}). \end{aligned} \tag{4}$$

My proposed identification strategy is to use revealed preferences on majors and universities separately. Comparing two majors that are listed in the same university allows me to focus only on the unobservable taste shocks for majors. A similar argument about comparing two universities with the same major holds for the unobservable taste shocks for universities. The following definitions shed more light on the identification strategy.

Definition 1 *Major m_1 is revealed preferred to m_2 at school s if program (m_1, s) is listed higher in ranking compared to (m_2, s):*

$$\begin{aligned} Pr(m_1 \succ_{i|s} m_2) &= Pr(u_{im_1 s} > u_{im_2 s} \ \cap \ (m_1, s), (m_2, s) \in L_i) \\ &\leq Pr(u_{im_1 s} > u_{im_2 s}) \end{aligned} \tag{5}$$

Equation 5 yields a lower bound for $Pr(u_{im_1 s} > u_{im_2 s})$, while the following shows a higher bound for the same term:

$$1 - Pr(m_2 \succ_{i|s} m_1) \geq Pr(u_{im_1 s} > u_{im_2 s}). \tag{6}$$

The probability on the right-hand side of both equalities only consists of major-variant terms; the school-specific terms cancel out. Similarly, the next definition compares choices with a common major that will omit the major-specific terms.

Definition 2 *School s_1 is revealed preferred to s_2 for major m if program (m, s_1) is listed higher in ranking compared to (m, s_2):*

$$\begin{aligned} Pr(s_1 \succ_{i|m} s_2) &= Pr(u_{ims_1} > u_{ims_2} \ \cap \ (m, s_1), (m, s_2) \in L_i) \\ &\leq Pr(u_{ims_1} > u_{ims_2}). \end{aligned} \tag{7}$$

And for the higher bound:

$$1 - Pr(s_2 \succ_{i|m} s_1) \geq Pr(u_{ims_1} > u_{ims_2}). \tag{8}$$

Using these two definitions, the model is identified by the distributional assumption on each error term, ν_{im} and ξ_{is}, separately. The right-hand-side probabilities will take a logistic form, assuming that the error terms have a Gumbel distribution. Estimation based on this assumption is more complicated than the alternatives because of the introduction of inequalities. In Appendix B, I will describe how one can use moment inequality methods to estimate the parameters of the choice model, assuming undominated strategies.

The computational intensity of estimating the model based on moment inequalities forces me to make further assumptions and estimate the model based on maximum likelihood. If inequalities in Equation 5 - Equation 8 are replaced by equalities, they imply that students are truthful about the majors they list in a given school, or about the universities that they list for studying a given major.

Although this sounds like general truthfulness, it is a partial relaxation of the regular truth-telling assumption. If a student has listed major A at school X but has not listed major B at school Y, truth-telling implies that program (A, X) is preferred to (B, Y). However, the assumption I am making does not put any restriction on the preference over these two programs that do not share a common major or a common university. Still, assuming equalities is a stronger assumption compared to undominated strategies, because it assumes that all of the majors that are not listed by the student at a given school are less preferred to majors that are listed at that school. Also, all of the schools that are not listed for a given major are inferior to those schools that are listed for that major.

3.3 Recovering Subjective Admission Probabilities

The second component of the expected utility equation in Equation 1 is the subjective admission probabilities. How students form their expectations about their chance of admission matters for the choice of options that will ultimately be listed.

I assume that the student has access to historical public data on admission thresholds and how variant those thresholds have been over the years. For that purpose, I use a representative sample of students who has listed a program over the course of 7 years prior to the year of this study to run a *limited dependent variable* model and to estimate the probability of admission, given the ranking of each student. Student i computes his probability of getting admitted to program j by estimating the share of students who had his ranking on the exam and were accepted to the program. The following equation,

$$P(\text{Accepted to } j|\text{Rank} = r_i) = F_j(r_i), \tag{9}$$

can be estimated using logit. The subjective probability of admission given student i's ranking will follow:

$$p_{ij} = \hat{F}_j(r_i). \tag{10}$$

The data and fitted values are shown for a selected number of programs in Figure 8. This figure shows four different programs, from the most popular program to some not so popular ones that almost all students have some chance of getting admitted to. I used data on all students who showed interest in a specific program, including students who were assigned to it and students who had listed that program but were assigned to another one.

Another approach could be to examine the cutoffs over the years and find the fitted probabilities based on potential acceptances. My approach takes into account the number of students who have shown interest in addition to the assigned students. The logit estimates will be determined both by the pattern of thresholds and also the average number of students applying to that program.

This reduced form estimation of the set of admission probabilities, follows the same logic as the concept of *oblivious equilibrium* presented by Weintraub et al. [2008]. For counterfactual analyses, it is assumed that each student makes decision based only on his own preferences and the long run outcome averages, while he ignores current information about preferences of other students. It is shown that in a large market, like the setting of this paper, players can make near-optimal decisions by using only the average state rather than the current state of the market.

4 Estimation and Results

Based on the assumption on revealed preferences and the unobservable taste shocks which I explained in the previous section, in this section I will describe the identification strategy and provide the results on students' preferences. These results, along with the estimated subjective probabilities, allow me to use the model in the counterfactual analysis that will follow.

I estimate the model based on the probabilities of observing a preference list of majors and a preference list of schools for each student. To be able to estimate the model using maximum likelihood, I assume that students are truthful when it comes to listing their preferred majors and schools; I discussed the implications in Subsection 3.2. In Appendix C, I discuss in length the maximum likelihood estimator as well as the Monte Carlo simulation I run to prove its validity.

The estimation results based on these assumptions are shown in Table 5. For comparison, I have included the estimates obtained by commonly used rank-ordered logit method in Table 7. It is clear that rank-ordered logit estimates are biased, as other papers have shown. When the regression is run without the university fixed effects, the rank-ordered logit coefficient for distance turns out to be positive. This means that if a program is moved 100 km farther from the student, the log odds of it being chosen goes up by 1.2 percent. This is inconsistent with what is documented in Table 2 and Figure 5, that students prefer programs that are closer to their hometown. This positive coefficient flips sign when university fixed effects are added to the regression, but still shows a downward bias compared to the two-dimensional estimator in column (2).

Focusing on the second column of Table 5 shows that students dislike distance and 2-year programs. Closer universities are more important to female students and slightly more to students from large cities. Students strongly prefer universities that are located in their city of residence and less strongly universities that are located in their province of residence. There is a strong preference for programs that are in Tehran, but most of it is captured when the fixed effects for famous universities, that are located in capital (such as Sharif; Tehran etc.), are taken into account. Coefficients on major fixed effects are relative to a village male student's preference for a major in humanities. Engineering, architecture and civil engineering are the most popular majors, followed by computer science.

Using the parameters in Table 5, I find the flow utility that each individual receives from all programs, $u_i = (u_{i1}, ..., u_{iJ})$. Some programs generate positive and some negative utility for students. Based on the vector of all flow utilities and the vector of all subjective probabilities that I found in Subsection 3.3, in the next section I describe how I find the portfolio with the highest expected utility from the pool of all programs, given different list size caps.

4.1 Model Fit

Finding the optimal portfolio is not a computationally easy task, because of the large number of programs an individual can choose from. For instance, for an individual who chooses 100 programs out of almost 8,000 options, the number of potential portfolios is on the order of 10^{232}, which is infeasible to solve. To be able to solve the model, I use the algorithm presented by Chade and Smith [2006], the *marginal improvement algorithm* (**MIA**). The authors prove that to reach the optimal portfolio, one must, at every step, pick the next best choice that contributes the most to the expected utility of the existing list.

MIA runs in the following steps:

1. Start with $L_i = \emptyset$; Discard all alternatives with flow utility less than the outside option (u_{i0}).

2. The program with the highest expected utility ($p_{ij}u_{ij}$) is chosen first: $L_i = \{j_1\}$.

k. Select the best complement to the current list L_i:

$$\max_{j_k} \quad EU(L_i')$$

$$L_i' = \text{arranged elements of } (L_i \cup \{j_k\}) \text{ in decreasing order of utility.}$$

The algorithm starts with an empty portfolio, then finds the program that gives the highest expected utility— i.e., the program with the highest interaction of utility and subjective admission probability. After that, it finds the program that improves the expected utility the most, with the consideration that programs should be ordered by utility. In other words, the student has the option to choose a program to add to the top (Extension), bottom (Insurance), or middle (Diversification) of his list. He might choose a top school that he loves but for which he does not have much of a chance. He might add a safe option to the bottom of his list, which he does not prefer over all other options, but adding it will reduce the risk of getting rejected by the system. Or he might just add to the diversity of his portfolio by adding another option to the middle of his list; still, this option will be added after the ones that dominate it. The improvement will depend on where the program is added because of the interactions of the $(1 - p_{ir})$ terms in the expected utility function described in Equation 1.

Chade and Smith [2006] prove that the marginal improvement algorithm will yield the optimal portfolio for the student. The implication of this method is that programs are not chosen in the order of utility but in the order of the improvement they make to the expected utility of the list. If the list size the student can submit is increased, the student will add a desirable choice with a nonzero chance of admission to his list. This can potentially change the outcome of his assignment in equilibrium, given the lists submitted by other students. This is the main source of the welfare improvement observed, which will be discussed shortly.

I assume that the outside option for students provides them with zero utility, which can easily be relaxed to mimic the inequality in access to outside options (Akbarpour et al. [2020]). I calibrate the marginal cost of an additional listing (c) to fit the fact that 25 percent of students submit a full list. I expose students to a list cap of 100 and compare the predicted behavior with the observed data. Figure 9 suggests that with $c = 10^{-8}$, model prediction fits the number of students who submit a full list. The model predicts that 25 percent of students submit a full list, which is equal to the observed 25 percent.

The model does well when it comes to predicting students' behavior throughout their submitted list. Figure 10 shows that students list programs they have around

10 percent chance of getting into as their first choice. They list less popular programs with higher ex ante probability of admission as they move down their list. This observation is captured pretty well by the model, since the numbers are very close to the real data. The only difference is the last couple of listings, where model students act more conservatively and the probability of acceptance shoots up. This can be explained by the one-time shot that students in the model get versus the option of taking the exam the next year for students in the real world.

The policy change in 2013 provides me with extraordinary information to validate my model out of sample. The parameters of my model are estimated based on data from 2012, when the list cap was 100. If I expose the students in my model to a list cap of 150, they will submit a different composition of programs. Comparing the predicted behavior with the actual data in 2013 can provide information on how good the model can predict students' behavior when they are facing caps other than 100. Similar to Figure 10, the prediction of the model and the 2013 data are shown in Figure 11. The figure shows that the model has a very decent performance, even out of sample, in terms of predicting students' choice behavior.

5 Welfare Analysis

In this section, the welfare gain from changing the list cap in DA is evaluated. Welfare is defined as the following uniformly weighted utilities of the students, where (m^*, s^*) is the program the student is assigned to:

$$W = \sum_{i=1}^{N} u_i(m^*, s^*). \tag{11}$$

Note that the utility here is the ex post utility the student receives after her assignment is completed. This welfare measure can be defined with unequal weights to also include the fairness of the assignment. In what follows, I evaluate the welfare effects of the policy change from 2012 to 2013, and then describe the counterfactuals I run using my model and discuss their welfare implications.

5.1 Quasi-experimental Policy Change

In 2013, students were allowed to submit 50 more choices compared with students who took the exam in 2012. Figure 4 depicts the distribution of the number of choices submitted by students in 2013. It shows that around 8 percent submitted the full 150 choices, and around 27 percent submitted a list with more than 100 choices. This number is close to the number of students who were facing a list cap of 100 in 2012 and submitted a full list.

Using the parameters in Table 5, which are based on the data from 2012, the flow utility of students' assigned choices is calculated for both 2012 and 2013. Figure 12 shows that the flow utility of students has improved as a result of the policy change. This result shows that welfare is increased by an equivalent of 56 km after the policy change. This number is close to the median of distance traveled by students, which is 63 km.

This can be seen as evidence on how changing the list cap can affect total welfare. The cohort in 2013, who were allowed to make 150 choices, were able to submit a more diversified list, which benefited them. This can be seen by comparing Figure 10 and Figure 11. While the patterns through the lists are close to each other, students in 2013, on average, list programs in which they have a lower chance of admission compared with students who submitted their applications in 2012. Interestingly, according to Table 4, the rate of rejection doesn't change from 2012 to 2013, so the change in welfare is only due to better matches for students who were facing a binding list of 100 in 2012.

5.2 Counterfactual Results

Using the utility and probability values, I expose students to different list limitations. When students are playing a quota game they do not list their most preferred choices; instead, their first pick will be the option that gives them the highest expected utility. The student will continue by choosing the option that gives her the most marginal expected utility, given her previous list up to the point that she runs out of choices or the cost of an extra listing dominates the benefit. Another way of putting the same concept is to ask her to remove options from her submitted list to reach a list with a more binding cap. She will not simply omit her last options; instead, she gives up some of the diversification of her list. This removes her chance of getting into a program for which she had a minimal admission chance. This arises because the ex ante probabilities of admission are not taken from a complete information set on the submitted lists of other students. In this situation, removing some options might change the final outcome and ultimately hurt the student.

In response to different list sizes, students will submit different lists; thus, a different equilibrium is expected. Submitted lists in each round will be fed to the DA algorithm to find the final allocation of students and also the students who remain unassigned. Each match generates some utility for assigned students, and unassigned students will receive their reservation utility. I use Equation 11 to calculate the total welfare under each counterfactual and show the results in Figure 13. I show the total welfare calculated for each list size and normalize the result with respect to the list size of 100.

Figure 13 shows that given my model, an increase of 50 choices from 100 to 150 should generate 0.89 percent improvement in total welfare. According to the results in Table 5, this welfare improvement is equivalent to a 27 km decrease in the home-university distance for an average student. Comparing this result with the reduced-form results shows that, as discussed before, the model produces a lower bound for the welfare gain, since all agents in my model are well informed and sophisticated.

The main result of this paper is that total welfare would be 10 percent lower if students were facing a list cap of 15, and 14.2 percent lower if the cap were only 10. Ten percent lower welfare is equivalent to a 319 km increase in distance traveled by an average student, which is double as the average distance an average student travels in Iran.[5] In the case of the list cap being equal to 10, the average student will lose utility equivalent to traveling 453 km more. This considerable welfare mainly comes from the worse matches that students receive when the cap is more binding. Figure 14 depicts the welfare change in terms of change in the distance traveled by an average student.

Another important implication of my results is that a less binding cap will produce winners and losers. Intuitively, Figure 15 shows that top- and low-ranked students are not affected by the increase in the list cap from 10 to 100. This figure shows that students who have a moderate score benefit the most from a less binding list, which provides them with a better match, while students who are in the 20th to 40th percentiles lose some of their utility. The reason behind this is that some programs were not listed by students in the middle of their ranking because of the binding cap they were facing, and initially these programs would go to the lower-ranked students. This phenomenon does not happen when the cap is 100 and the middle-ranked students will fill the programs they are qualified for and receive a higher utility from them.

This sheds light on the fact that in addition to improving welfare, a less binding cap will add to the fairness and meritocracy of the matching—higher fairness in the sense that students who have done better on the exam and come out higher in the ranking receive better matches.

[5] The average distance traveled by students is 176 km and the median is 63 km.

6 Conclusion

In this paper I developed a two-dimensional discrete choice model for college major choice to evaluate the welfare costs of list truncation in deferred acceptance settings. I estimated the model using a rich dataset from Iran, in which students are allowed to make a list with up to 100 choices out of around 8,000 options available. I moved away from the usual assumptions in the literature; specifically, I relaxed the independence assumption on individual taste shocks for programs and partially relaxed the truth-telling assumption. I showed that many students, mostly those with low ranks, play strategically and are not truthful. I also showed that students have either a strong preference for the university or the major of study. In this situation, the independence of unobservable taste shocks is unrealistic, and the model needs to be built on a different set of assumptions.

For demand estimation, I developed the true model based on moment inequalities— but, due to computational complexities, estimated the model using maximum likelihood. I showed that the usual rank-ordered logit model generates biased estimators that cannot be reliable. The estimated model was used in counterfactual analysis to find the welfare cost of strategic play in DA systems. To find the optimal portfolio under different list caps, I used the marginal improvement algorithm proposed by Chade and Smith [2006].

My results show that a more binding implementation of DA reduces welfare considerably. Having a list cap of 10 instead of 100 reduces welfare equivalent to a 453 km increase in the home-university distance traveled by students, which is three times the average distance students travel. I showed that increasing the list size from 100 to 150 has a positive welfare impact that is close to the impact of other modifications proposed in the literature, such as sequential implementation of DA.

I showed that changing the cap does not affect two groups of students, those at the top and those at the bottom of the ranking. However, I showed that a less binding mechanism produces a fairer matching, which can be tied to the stability of the mechanism. In a binding mechanism, students give up desirable choices that might be taken by a student with a lower rank.

Increasing the list cap may be the most efficient and cheapest modification of systems in which truncated DA is implemented. The costs of such modification are mainly the information processing cost and the cognitive cost of listing additional choices. In the current era, the former cost seems negligible compared to the benefits of such improvement. The cognitive cost of listing more choices is also dominated by the cost of strategic play in settings that are not strategy-proof.

References

Atila Abdulkadiroglu and Tayfun Sönmez. Matching markets: Theory and practice. *Advances in Economics and Econometrics*, 1:3–47, 2013.

Atila Abdulkadiroglu, Parag Pathak, Alvin E. Roth, and Tayfun Sonmez. Changing the Boston school choice mechanism. Technical report, National Bureau of Economic Research, 2006.

Atila Abdulkadiroğlu and Tayfun Sönmez. School choice: A mechanism design approach. *American economic review*, 93(3):729–747, 2003.

Atila Abdulkadiroğlu, Yeon-Koo Che, and Yosuke Yasuda. Resolving conflicting preferences in school choice: The" boston mechanism" reconsidered. *American Economic Review*, 101(1):399–410, 2011.

Atila Abdulkadiroğlu, Nikhil Agarwal, and Parag A. Pathak. The welfare effects of coordinated assignment: Evidence from the New York City high school match. *American Economic Review*, 107(12):3635–89, 2017.

Nikhil Agarwal and Paulo Somaini. Demand Analysis using Strategic Reports: An application to a school choice mechanism. *Econometrica*, 86(2):391–444, 2018.

Kehinde Ajayi and Modibo Sidibe. An empirical analysis of school choice under uncertainty. Technical report, Boston University Working paper, http://people. bu. edu/kajayi/research. html, 2015.

Mohammad Akbarpour, Adam Kapor, Christopher Neilson, Winnie L. Van Dijk, and Seth Zimmerman. *Centralized School Choice with Unequal Outside Options*. Princeton University, Industrial Relations Section, 2020.

Donald WK Andrews and Xiaoxia Shi. Inference based on conditional moment inequalities. *Econometrica*, 81(2):609–666, 2013.

Georgy Artemov, Yeon-Koo Che, and Yinghua He. Strategic 'Mistakes': Implications for Market Design Research. Technical report, mimeo, 2017.

Eric Budish and Estelle Cantillon. The multi-unit assignment problem: Theory and evidence from course allocation at Harvard. *American Economic Review*, 102(5):2237–71, 2012.

Hector Chade and Lones Smith. Simultaneous search. *Econometrica*, 74(5):1293–1307, 2006.

Li Chen. University admission practices–Ireland. *MiP Country Profile*, 8, 2012.

Monique De Haan, Pieter A. Gautier, Hessel Oosterbeek, and Bas Van der Klaauw. The performance of school assignment mechanisms in practice. 2015.

Torben Drewes and Christopher Michael. How do students choose a university?: an analysis of applications to universities in Ontario, Canada. *Research in Higher Education*, 47(7):781–800, 2006.

Lester E. Dubins and David A. Freedman. Machiavelli and the Gale-Shapley algorithm. *The American Mathematical Monthly*, 88(7):485–494, 1981.

Gabrielle Fack, Julien Grenet, and Yinghua He. Beyond Truth-Telling: Preference Estimation with Centralized School Choice and College Admissions. *American Economic Review*, 109(4):1486–1529, 2019.

David Gale and Lloyd S. Shapley. College admissions and the stability of marriage. *The American Mathematical Monthly*, 69(1):9–15, 1962.

Guillaume Haeringer and Flip Klijn. Constrained school choice. *Journal of Economic theory*, 144(5):1921–1947, 2009.

Justine Hastings, Thomas J. Kane, and Douglas O. Staiger. Heterogeneous preferences and the efficacy of public school choice. *NBER Working Paper*, 2145:1–46, 2009.

Justine Hastings, Christopher A. Neilson, and Seth D. Zimmerman. The effects of earnings disclosure on college enrollment decisions. Technical report, National Bureau of Economic Research, 2015.

Martin Hällsten. The structure of educational decision making and consequences for inequality: A Swedish test case. *American Journal of Sociology*, 116(3):806–54, 2010.

Adam Kapor, Christopher A. Neilson, and Seth D. Zimmerman. Heterogeneous beliefs and school choice mechanisms. Technical report, National Bureau of Economic Research, 2018.

Lars Johannessen Kirkebøen. Preferences for lifetime earnings, earnings risk and nonpecuniary attributes in choice of higher education. Technical report, Discussion Papers, 2012.

Lars J. Kirkeboen, Edwin Leuven, and Magne Mogstad. Field of study, earnings, and self-selection. *The Quarterly Journal of Economics*, 131(3):1057–1111, 2016.

Shengwu Li. Obviously strategy-proof mechanisms. *American Economic Review*, 107(11): 3257–87, 2017.

Margaux Luflade. The value of information in centralized school choice systems. *Duke University*, 2018.

Christopher Neilson. The rise of centralized choice and assignment mechanisms in education markets around the world. *Unpublished manuscript*, 2019.

Parag A. Pathak and Tayfun Sönmez. School admissions reform in Chicago and England: Comparing mechanisms by their vulnerability to manipulation. *American Economic Review*, 103(1):80–106, 2013.

Alvin E. Roth. The college admissions problem is not equivalent to the marriage problem. *Journal of economic Theory*, 36(2):277–288, 1985.

Alvin E. Roth. Deferred acceptance algorithms: History, theory, practice, and open questions. *international Journal of game Theory*, 36(3):537–569, 2008.

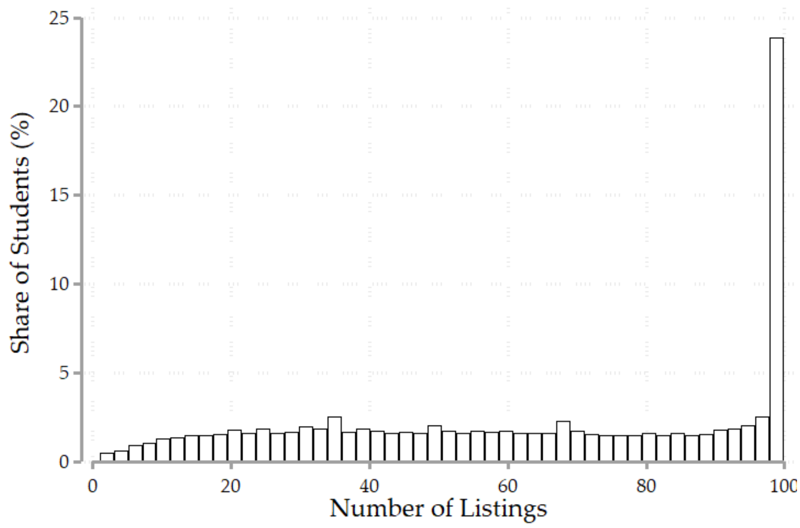
Alvin E. Roth and Xiaolin Xing. Turnaround time and bottlenecks in market clearing: Decentralized matching in the market for clinical psychologists. *Journal of political Economy*, 105(2):284–329, 1997.

Perihan Ozge Saygin. Gender differences in preferences for taking risk in college applications. *Economics of Education Review*, 52:120–133, 2016.

Gabriel Y. Weintraub, C. Lanier Benkard, and Benjamin Van Roy. Markov perfect industry dynamics with many firms. *Econometrica*, 76(6):1375–1411, 2008.

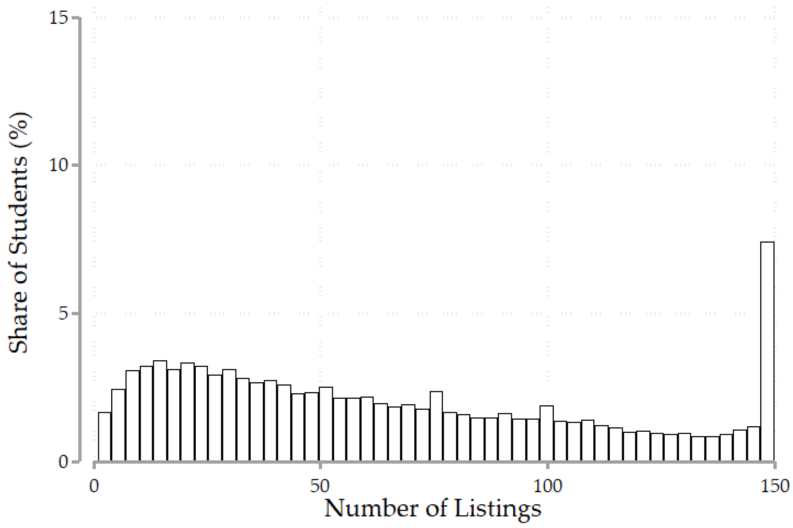
7 Figures

Figure 2: Number of Listings



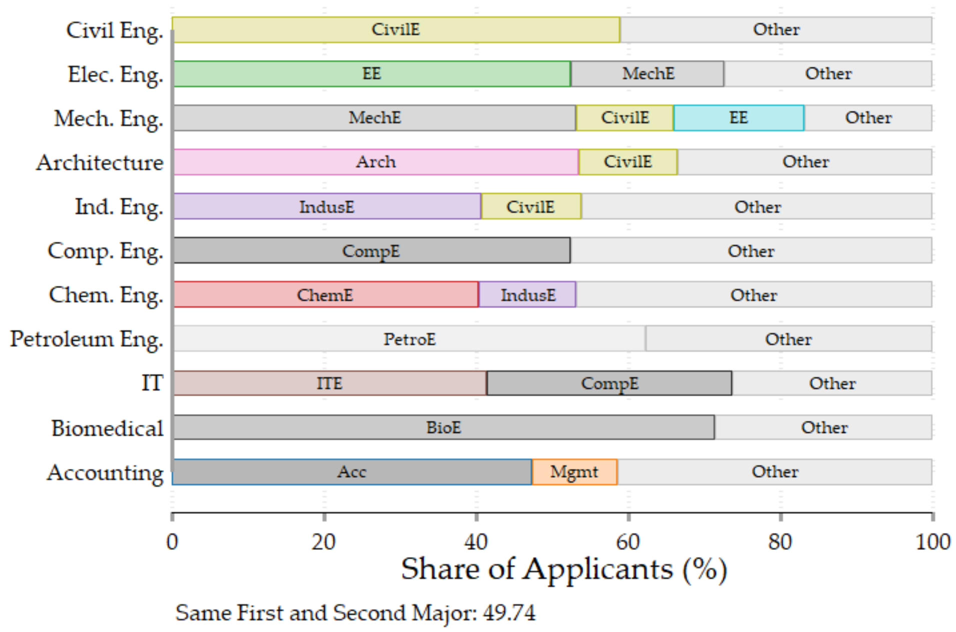
Note: Histogram of the number of submitted choices by students. At 2012, the cap on list size was 100 and students were allowed to submit a list up to size 100. The graph shows that around 25 percent of students submitted a list consisting of 100 options and that the cap had been binding for one in every four students.

Figure 4: Number of Listings Histogram After Policy Change

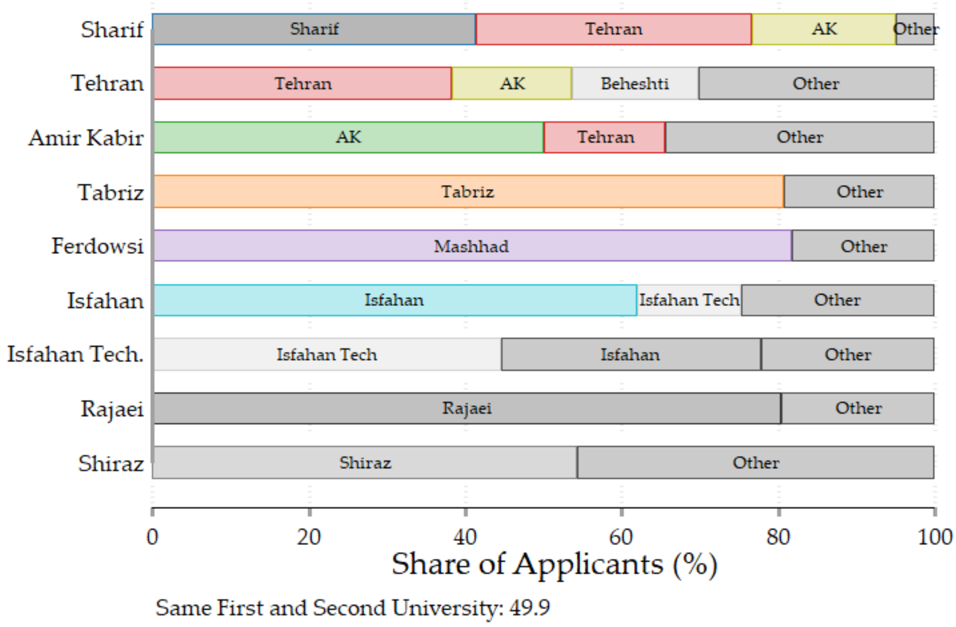


Note: This graph is similar to Figure 2 for 2013 and after the change in the cap from 100 to 150. Note that the scales are different, but it seems that almost the same number of people who were listing 100 in the previous setting are listing 100 or more choices. This could be evidence on the list of 100 being binding for that 25 percent of students in 2012.

Figure 3: Second-choice Program by First-choice Program



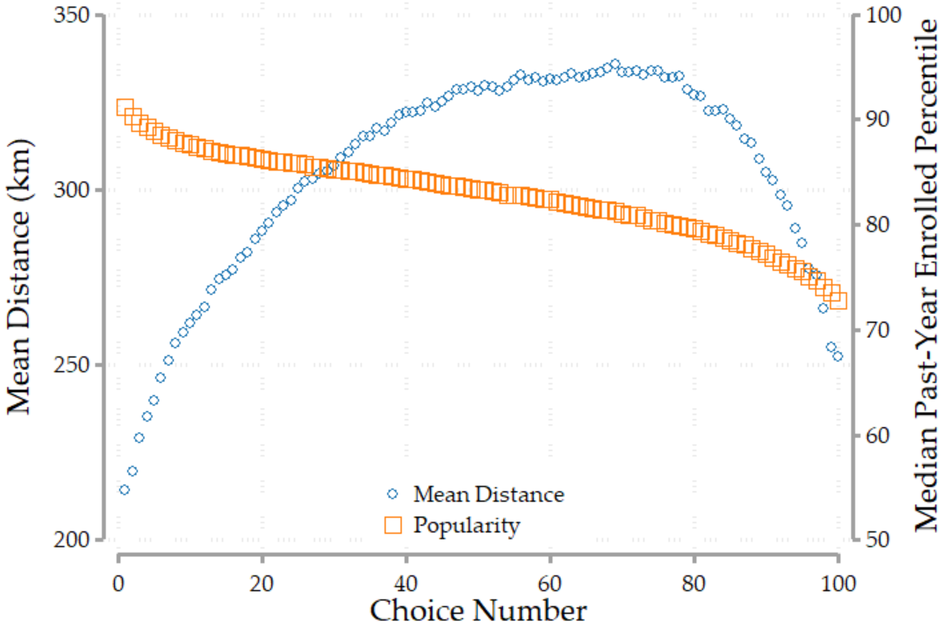
(a) Second-choice Major by First-choice Major



(b) Second-choice University by First-choice University

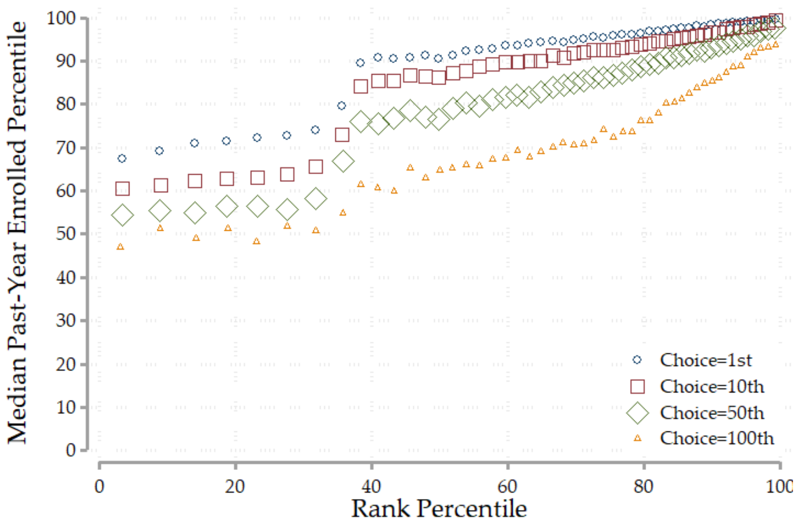
Note: (a) shows the share of choice number 2's major categorized by student's first chosen major. For 49.74 percent of students, choices 1 and 2 share a common major. (b) shows the share of choice number 2's university categorized by the first listed university. 49.9 percent of students listed the same university in their first and second choices. The other 0.36 percent of students chose their first two options, such that they do not share either a common major or a common university. (*Other* includes all major/universities whose share was less than 10 percent.)

Figure 5: Choice Behavior, Distance, and Popularity



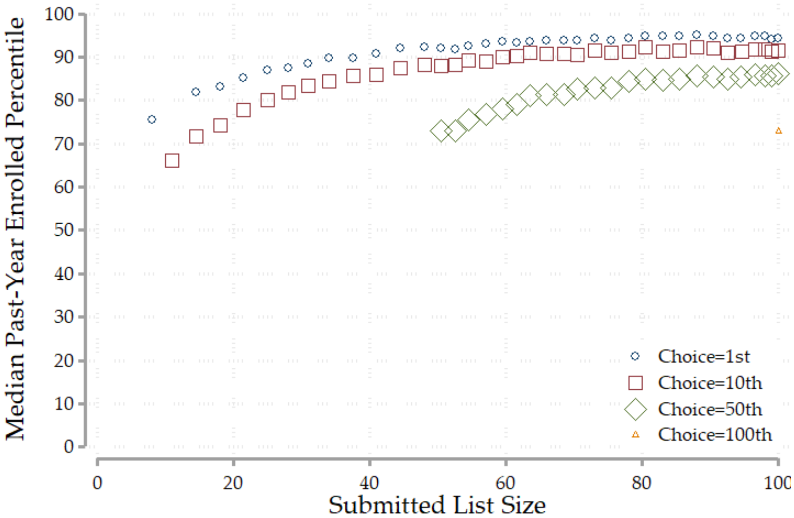
Note: Distance and popularity of choices throughout student's list.

Figure 6: Selectivity of Choices by Student Ranking



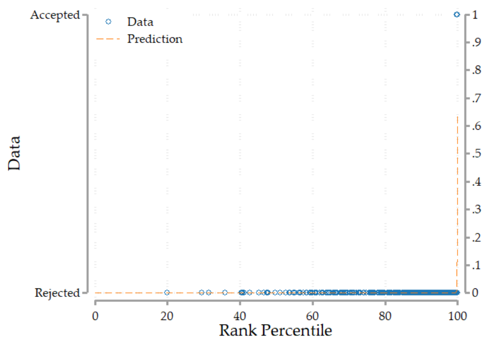
Note: This bin-scatter graph shows the choice behavior of students with different ranks in terms of popularity of the programs. Students are sorted on the x-axis from the one with the lowest score to the top student, who is in the 100^{th}percentile. On the y-axis, programs are sorted by their selectivity, proxied by the median rank of the students who enrolled in that program the year before. Students with higher ranks have listed very selective programs, even as their 100^{th}choice. On the other hand, low-ranked students have not listed very selective programs because of their close-to-zero chance of admission. This figure is provided as evidence that DA is not strategy-proof when agents face a list cap.

Figure 7: Selectivity of Choices by Submitted List Size

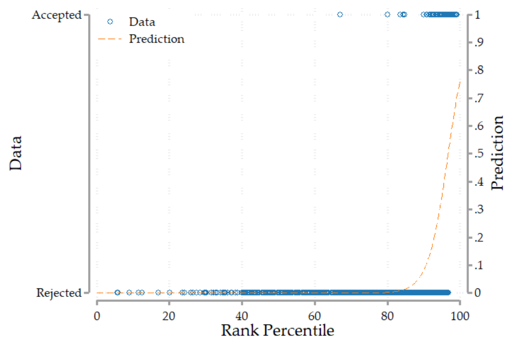


Note: This figure shows that students who submitted a list with fewer than 100 choices (a *short list*) are not necessarily truth-telling. On average, students who submitted a short-list have chosen less selective programs as their 1^{st}choice (blue circles), 10^{th}choice (red squares), etc. This graph provides evidence against the common claim in the literature that short-list students are truth-telling.

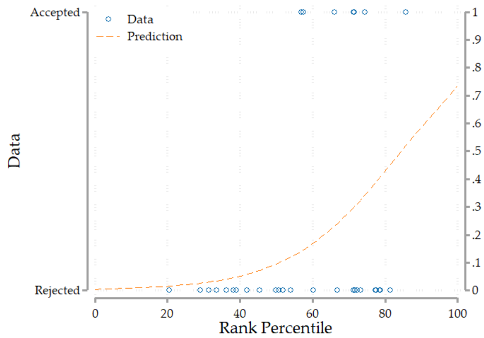
Figure 8: Historical Data on Acceptance by Rank Percentile and Logit Prediction



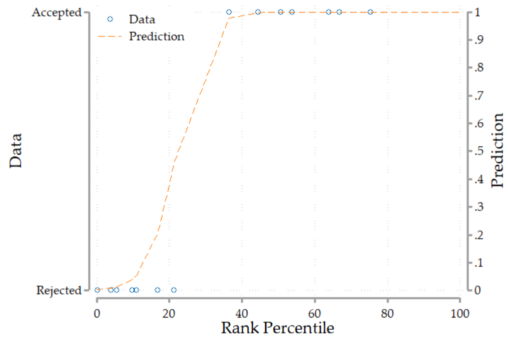
(a) Electrical Engineering, Sharif University of Technology, Tehran



(b) Industrial Engineering, Bu-Ali Sina University, Hamedan



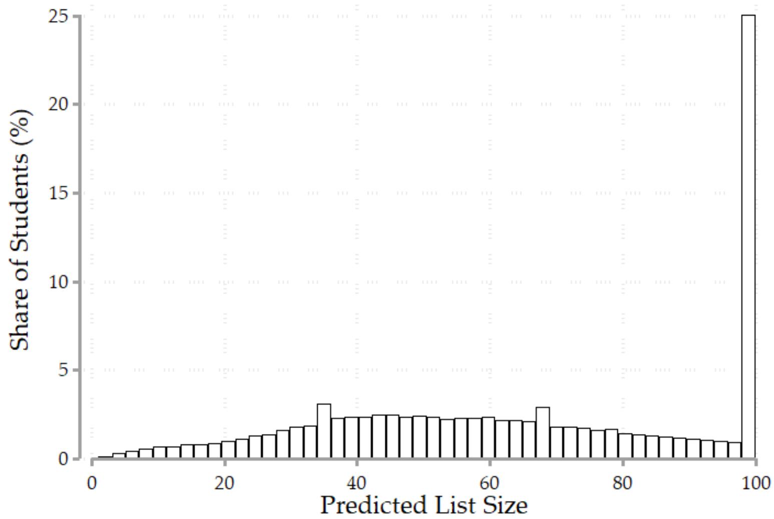
(c) Physics, Lorestan University, Khorram Abad



(d) Accounting, Payam Nour University, Bostan Abad

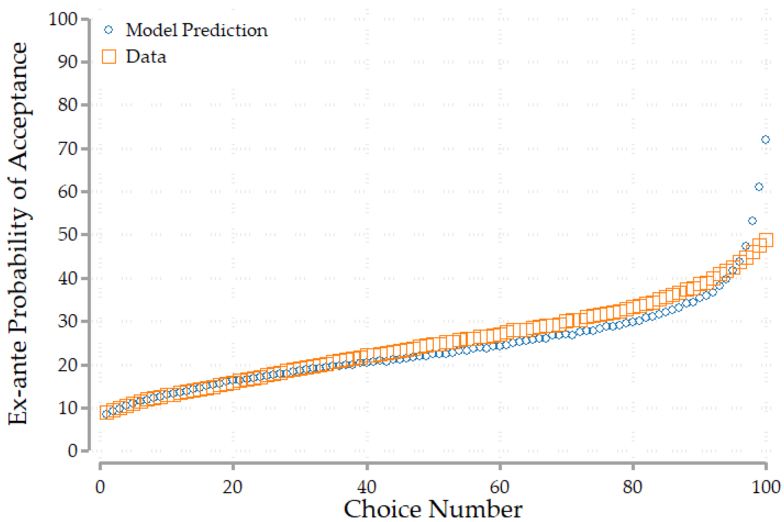
Note: Example of the estimation procedure of the subjective probabilities for four different programs. Students who listed the program over the 7 years prior to the study are sorted on the x-axis based on their ranking, and their result (Accepted or Rejected) is shown as zero or one circles. With logit estimation, the probability of getting accepted given the rank is predicted and used in expected utility Equation 1.

Figure 9: Predicted List-size Histogram



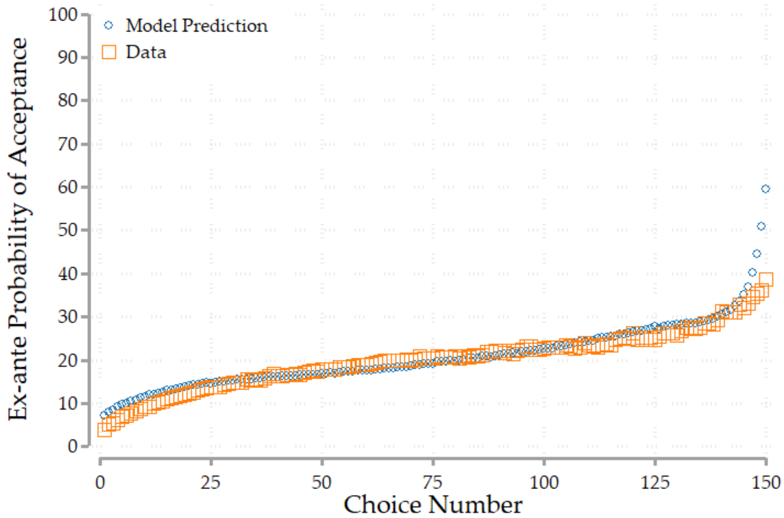
Note: Histogram of number of listings predicted by the model when the list cap is 100. Students stop listing if they have an option with probability 1 in their list, or every available option is less desirable than the outside option or the expected utility improvement of an additional choice is less than the marginal cost. With $c = 10^{-8}$, the share of students who submitted a full list matches the data. For comparison, see Figure 2.

Figure 10: Ex ante Admission Probability of Listings
Data and Prediction



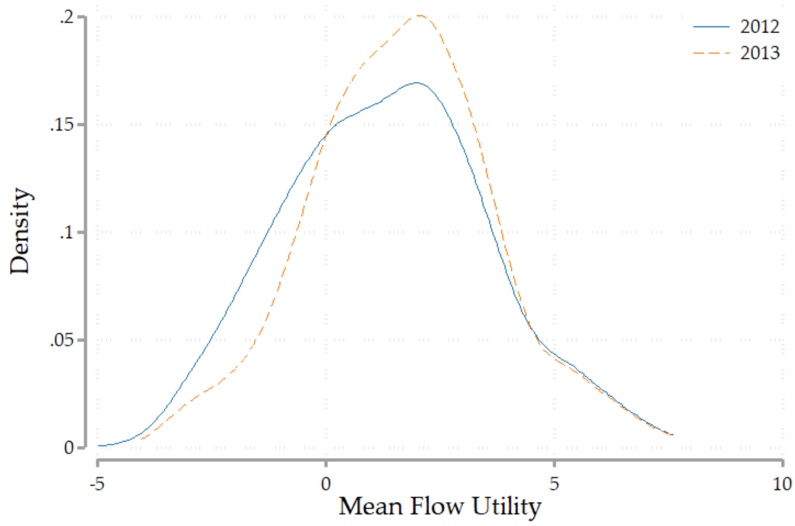
Note: Ex ante probability of admission throughout the list. The first choices on the student's list are on average those for which the student does not have a very high chance of admission. As she moves down the list, she lists programs that are more accessible, although they might be less popular. The model predicts this pattern of students' behavior pretty well. The last four choices by the students in the model are much more conservative than those in the data. The reason is the absence of a retaking option in the model compared with real life.

Figure 11: Out-of-sample Prediction of the Model



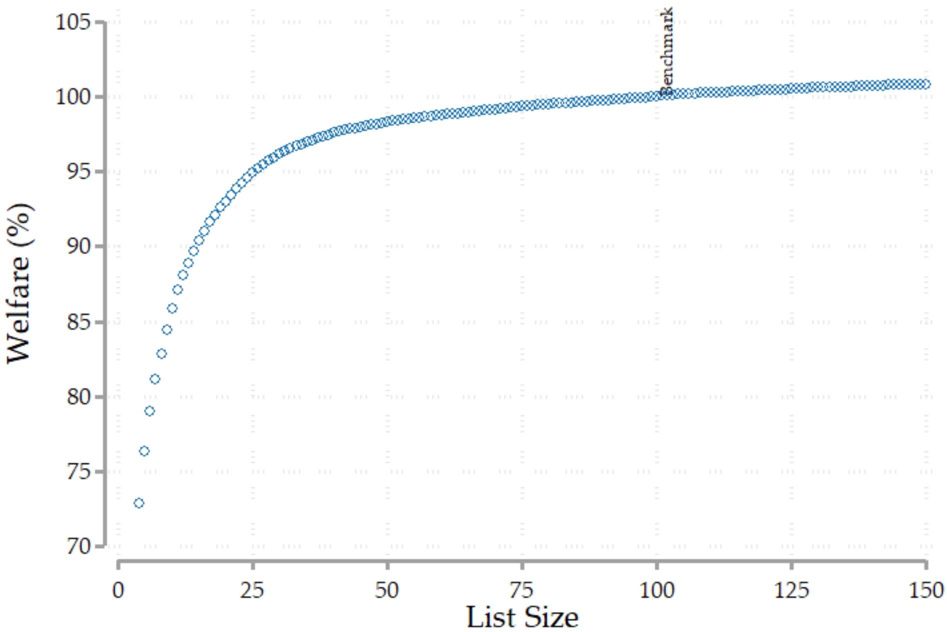
Note: Ex ante probability of admission throughout the list. The model prediction is based on data on applications in 2012 and the data is on applications in 2013. This figure shows the validity of the model out of sample. The first choices on the student's list are on average those for which the student does not have a very high chance of admission. As she moves down the list, she lists programs that are more accessible although they might be less popular. The last choices by the students in the model are much more conservative than in the data.

Figure 12: Demeaned Flow Utility Before and After Policy Change



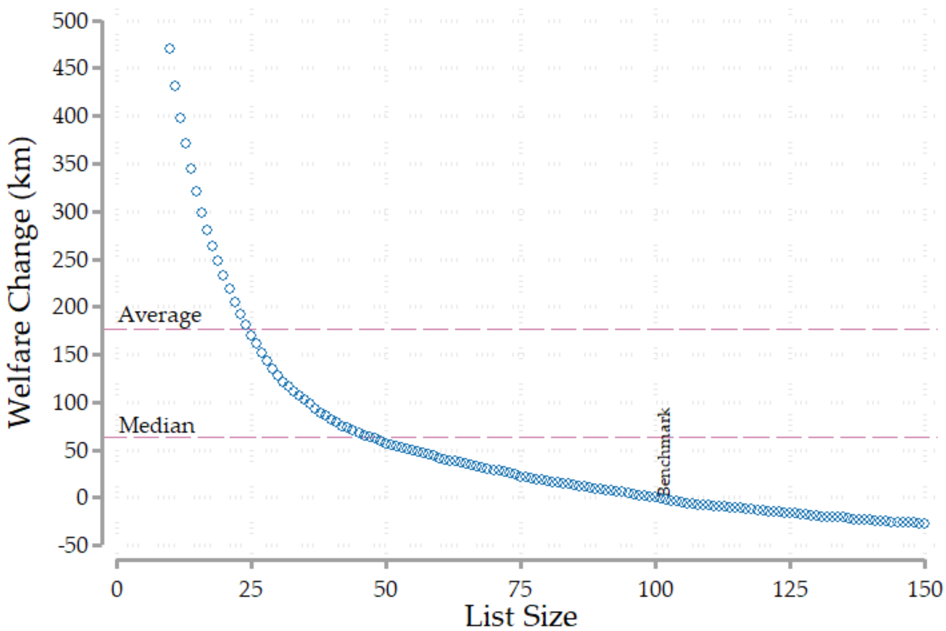
Note: This graph shows a reduced-form result for the welfare improvement of increasing the list size under DA. The solid blue line shows the density of mean flow utilities for the assignments before the policy change (list size equal to 100), and the orange dashed line shows the density after the policy change (list size equal to 150). The distribution has shifted to the right, which suggests welfare improvement.

Figure 13: Counterfactual Welfare Analysis. List Size of 100 is the Benchmark.



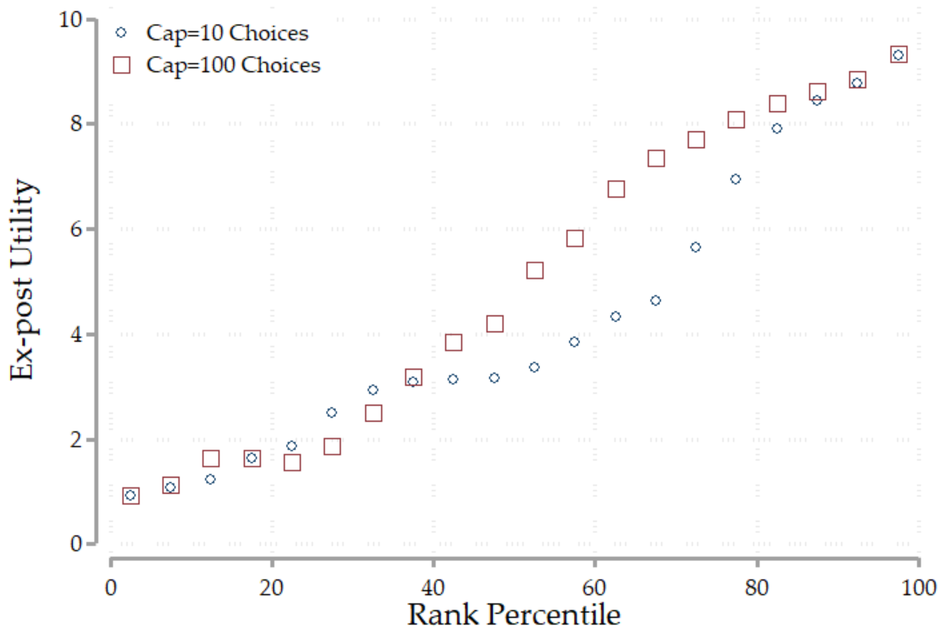
Note: Counterfactual analysis of the model. Total welfare calculated by Equation 11 is shown on the y-axis for different list sizes. Each student submits a different list when facing a different list cap, which will result in a different outcome for him. The sum of the utilities is the measure of welfare under different list sizes.

Figure 14: Counterfactual Welfare Analysis in Distance Terms. List Size of 100 is the Benchmark.



Note: Welfare change is translated to change in distance traveled by an average student. The benchmark is the list cap of 100. Average distance traveled by Iranian students is 176 km, and the median is 63 km. These statistics are shown with dashed lines on the graph.

Figure 15: Winners and Losers



Note: Utility derived from the assigned choice by the student's rank for cap sizes of 10 and 100. Students at the top and bottom are not affected by the change in the cap, while for students in the middle, some benefit and some lose. As the list cap increases, students are able to submit a better diversified portfolio, which will provide them with a more desirable outcome. This takes away the chance of getting into those programs from some students with lower ranks. This can be interpreted as increasing the fairness of the mechanism.

8 Tables

Table 1: Total Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Panel A. Student Characteristics				
Age	19.11	1.86	16	59
Female	0.41	0.49	0	1
Large Cities	0.35	0.47	0	1
Mid-size Cities	0.43	0.49	0	1
Small Cities and Villages	0.22	0.40	0	1
Concour Rank	85,380	61,364	8	229,910
Retaking the exam	0.28	0.45	0	1
Math score (%)	12.76	15.68	-21.2	98.2
Physics score (%)	13.48	16.20	-24.4	97.1
Chemistry score (%)	16.83	17.29	-26.6	97.2
Panel B. Choices				
Number of Listings	63.66	30.84	1	100
Choices within same city of residence	0.26	0.31	0	1
Choices at Tehran	0.21	0.27	0	1
Majors Ranked (Total=241)	17.12	9.48	1	58
Universities Ranked (Total = 854)	20.02	13.19	1	94
Panel C. First Choice				
Distance (km)	214.2	319.8	0	2480
Tehran	0.36	0.48	0	1
Same city as residence	0.35	0.47	0	1
Panel D. Outcomes				
Rejected	0.10	0.30	0	1
Row of accepted choice	30.75	25.94	1	100
Distance (km)	176.2	280.1	0	2480
Same city as residence	0.34	0.47	0	1
Row of accepted choice ∈ [1,10]	0.24	0.43	0	1
Row of accepted choice ∈ [11,20]	0.14	0.35	0	1
Row of accepted choice ∈ [21,30]	0.11	0.31	0	1
Row of accepted choice ∈ [91,100]	0.03	0.15	0	1
Number of Students	71,918			
Total Number of Observations	4,461,572			

Note: This table provides summary statistics for students who took the Iranian nationwide university entrance exam in 2012 and their submitted choices of programs to the National Organization of Educational Testing (NOET). The sample includes 71,918 students out of 260,055 students who took the Concours on June 28, 2012. Values are shares unless stated otherwise.

Table 2: Students' Choice-making Behavior

n	Share of students with a list of size n or shorter (1)	Share of students who are assigned (2)	Mean Distance (km) (3)	Previous Year Percentile (4)	Share of choices at Sharif (5)
1	0.1	5.03	214.26	91.17	11.40
2	0.27	8.04	219.55	90.17	6.13
3	0.49	10.77	229.01	89.52	4.71
4	0.75	13.31	235.02	89.02	4.20
5	1.11	15.64	239.89	88.51	3.35
6	1.54	17.81	246.12	88.21	2.90
7	2.02	19.86	251.09	87.88	2.88
8	2.54	21.79	256.14	87.60	2.57
9	3.06	23.75	259.12	87.28	2.32
10	3.71	25.57	261.81	87.17	2.34
20	11.11	40.63	287.98	85.76	1.54
30	19.72	52.40	306.87	84.86	1.13
40	28.44	61.88	322.21	83.79	0.81
50	36.98	69.45	328.13	82.78	0.73
60	45.45	75.46	331.42	81.54	0.54
70	53.48	80.36	333.64	80.05	0.43
80	61.03	84.03	326.97	78.41	0.36
90	68.81	87.09	304.70	75.39	0.41
100	100	89.65	252.14	69.97	0.73

Note: Numbers are in percentages unless stated otherwise. This table provides statistics for major choice behavior of students in 2012. Column (1) shows the share of students who have submitted a list of n 100 or shorter. Column (2) shows the mean distance between student's residence city and the university for all students who have submitted the row. Column (3) is the share of students who submitted a choice up to a row number. Column (4) is a measure of selectivity of the choice. It shows the precentile rank of the last student who was assigned to the choice in 2011. Column (5) is the share of students who submitted their choices at Sharif University of Technology as the most prestigous school for math and physics students. (Total capacity at Sharif was equal to 885 seats or 0.34% of all students.)

Table 3: Nestedness of Choices

		share of students who applied to *a major* in n or more universities (%)	share of students who applied to *a university* for n or more majors (%)
		(1)	(2)
	1	100	100
	2	99.12	99.26
	3	96.96	96.86
	4	94.01	93.48
	5	90.47	87.48
	6	86.81	80.86
	7	82.95	71.89
	8	79.07	63.5
	9	74.86	54.15
n	10	70.58	46.51
	20	30.18	7.27
	30	10.96	1.14
	40	3.94	0.20
	50	1.61	0
	60	0.68	0
	70	0.31	0
	80	0.18	0
	90	0.09	0
	100	0.01	0
Average		5.07	3.06
Median		3	2

Note: This table shows the correlation between students' choices. Column (1) shows the share of students who revealed their preference to study a major at many universities. For instance, it shows that 66% of students have a major in their list which they have applied for at more than 10 universities. Column (2) shows the same statistic for the choices that share a common university.

Table 4: Choice Behavior Comparison between 2012 and 2013

		n					
	Year	1	10	30	50	100	150
Share of students who submitted the choice number n (%):							
	2012	100	94.4	79.2	62.6	24.8	
	2013	100	92.8	76.6	59.4	27.1	7.1
Share of students who stopped before the choice number n (%):							
	2012	0.10	3.71	19.72	36.98	100	
	2013	0.21	4.23	21.75	39.53	72.95	100
Mean distance from the chosen program (km):							
	2012	187.6	265.5	332.8	364.6	297.9	
	2013	199.1	255.3	306.0	341.6	394.2	347.8
Share of students who are assigned to a program in their list before choice number n (%):							
	2012	4.89	24.91	51.04	67.65	87.33	
	2013	4.96	24.9	49.76	64.38	81.47	86.54
Share of students who submitted Sharif in their list before choice number n (%):							
	2012	11.1	17.0	19.9	20.9	22	
	2013	14.6	22.41	26.3	27.6	28.8	29.2

Note: This table provides statistics on the choice behavior of students in year of 2012, and 2013. In 2012 students were allowed to submit a list with up to 100 options, whereas in 2013 they were allowed to submit up to 150 options. The first two rows show the share of students who submitted the specific choice on the column header. The second two rows show the distribution of maximum number of listings in 2012 and 2013. As shown, more than 27 percent of students submitted a list with 100 or more options in 2013. The third two rows show students' choice behavior in terms of home-university distance. The fourth two rows show the distribution of students' accepted choice for those who are accepted. The fifth two rows show the share of students who ranked Sharif university as the most prestigious school in 2012 and 2013.

Table 5: Utility Parameters Estimation Results

	(1)		(2)	
Distance (100km)	-0.0493***	(0.000)	-0.148***	(0.000)
× Female	-0.0154***	(0.000)	-0.0152***	(0.000)
× Mid Cities	0.00391***	(0.000)	0.00318***	(0.000)
× Large Cities	0.0233***	(0.000)	-0.00546***	(0.000)
Distance (100km) Sq.	0.000545***	(0.000)	0.00560***	(0.000)
Past-Year Median Admit	5.039***	(0.000)	2.044***	(0.000)
2-Year Program	-1.088***	(0.000)	-1.841***	(0.000)
Same City	0.217***	(0.000)	0.346***	(0.000)
Same Province	-0.105***	(0.000)	0.116***	(0.000)
Location: Tehran	0.829***	(0.000)	0.150***	(0.000)
× Female	-0.00887	(0.053)	0.130***	(0.000)
× Mid Cities	0.0544***	(0.000)	0.184***	(0.000)
× Large Cities	-0.296***	(0.000)	0.00768	(0.321)
Major Fixed Effects	X		X	
× Female	X		X	
× Mid Cities	X		X	
× Large Cities	X		X	
University Fixed Effects			X	
Observations	4,067,624		4,067,624	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Estimation of utility parameters by proposed model. Column (1) only includes major fixed effects and the interaction terms with student characteristics. Column (2) adds the university fixed effects to the model. *Distance* is proxied by the distance between student's city of residence and the city the university is located in. Students are divided into three categories: from villages, from mid-size cities, and from large cities (Tehran, Isfahan, Shiraz, Tabriz, Mashhad). *Distance sq.* is square of distance. *Past year median admit.* is the measure of the program's popularity, since more popular programs tend to be filled with students with higher rankings. Broad major fixed effects are included in all columns according to *ISCED97*. Column (2) includes university fixed effects; some institutions that are branches of the same university are grouped together. The variation in these groups allows the estimation of variable *Location: Tehran.*

Appendices

A Description of Deferred Acceptance

Round 1. All students are tentatively assigned to their first submitted choice and sorted based on their score on the exam. The lowest-ranked students who are excess to the capacity of the program are rejected and moved to the pool of unassigned students. Others are temporarily kept for the next round.

Round k. The system will look at the next choice of those students who were rejected in the previous round and update each program's tentative list. The list will be a pool of students who were on the list in Round (k-1) and those who are added in this round. If the program has more students on the list than its capacity, the lowest-ranked students will be rejected and become unassigned students.

Stop. The system will stop when there is no unassigned student or all of the choices of unassigned students are filled.

B Revealed Preferences Assumptions

The difference in the approaches comes from how different papers treat the left-out options and also the assumption they put on idiosyncratic taste shocks. Following Fack et al. [2019]'s notation, I discuss different assumptions that can be put on a student's program selection behavior and then describe the model I develop to recover students' preferences.

Strong truth-telling (**STT**) is a Nash equilibrium under the original deferred acceptance mechanism. When DA is unconstrained, students do not benefit from manipulating their true preference list or dropping any option, so STT suggests that in (a not unique) equilibrium, they will list all the available choices in the order of their true preference. The not-uniqueness of STT is due to *irrelevance at the bottom* and *skipping the impossible* behavior of students.[6] Assuming STT in the setting of this study is not realistic, since it requires students to list all of the available options while they face a constraint on the size of the list they can submit.

Weak truth-telling (**WTT**) is a weaker version of STT and assumes that the student lists the first K options of her true preference list truthfully. This implies that the student's list starts with the most desirable choice, and every option is

[6] For illustration see Example 1 in Fack et al. [2019].

preferred to the next one on the list. Additionally, every choice that is not listed by the student is less preferred than listed options, and not listing them is either because of listing cost or inferiority to the outside option. Most papers that deal with discrete ordered-choice problems tend to assume some version of WTT behavior by decision makers, since it is not as strong as STT and it results in tractable closed-form solutions for the maximum likelihood function. The following describes the probability of observing the student's true list:

$$Pr\left(L = [l_1, ..., l_k, ..., l_K]\right) = \ Pr(u_1 > u_2 > .... > u_K > u_j \ \ : j \notin L) \qquad (12)$$

With a specific distributional assumption on the error term of the utility function, the right-hand side probability would yield a closed-form formula that can be estimated using maximum likelihood, and this is the main reason for the popularity of this assumption in the literature.[7]

Figure 6 shows that truth-telling might be consistent with the choice behavior of top students, but it does not hold for low-ranked students. This figure sorts all of the programs on the Y-axis in terms of the popularity among the previous year's applicants and sorts the current year's students based on their ranking on the X-axis, with 1 being the person with the highest priority index. In that graph, popularity is measured by the median percentile rank of students who enrolled in that program. This figure shows that those who are not at the top of the ranking seem to be omitting the most popular schools because of their close-to-zero chance of admission. This can be an evidence against WTT, since the not-top students do not necessarily prefer their listed choices to the ones they have left out.

Figure 7 shows that assuming WTT for students who have listed fewer than 100 options is also not justified. Students who have listed fewer options seem not to be truthful, in the sense that they do not submit the most popular programs. Thus, using data from these students and generalizing it to other students might also be misleading. Based on the model, listing fewer than the cap size can be a result of (i) having zero subjective probabilities for left-out options and/or (ii) having a safe choice with admission probability equal to 1 that dominates every not-listed option with a positive subjective probability of acceptance and/or (iii) having the outside option, which dominates all the not-listed options with a nonzero subjective probability. At any rate, these students are presumably selected and also may not have representative preferences and/or (iv) dominating cost of adding another choice to the list compared to its benefit.

[7]For instance, Drewes and Michael [2006]; Hastings et al. [2009]; Hällsten [2010]; Kirkebøen [2012]; Budish and Cantillon [2012]; De Haan et al. [2015]; and Luflade [2018].

A less limiting assumption about students' decision-making behavior is *undominated strategy*, which only assumes that students do not play dominated strategies. This assumption implies that the submitted list should be sorted by the order of preference, and no information is obtained from left-out choices. In other words, in equilibrium a student will submit a *partial preference order* of the options he finds both desirable and feasible given his priority. This approach by students results in a not unique but an undominated strategy Nash equilibrium in which the student submits an ordered list of those programs they think they have a chance of getting into. Under the undominated strategies assumption, j is revealed to be preferred to j' if the former is ranked higher on the list. The implication of such assumption about observing such ordering can be written as

$$\begin{aligned} Pr\left(j \succ_i j'\right) &= Pr(u_{ij} > u_{ij'} \text{ } and \text{ } j, j' \in L_i) \\ &\leq Pr(u_{ij} > u_{ij'}). \end{aligned} \tag{13}$$

Undominated strategies, as the weakest assumption on students' choice behavior, seems the most appealing one in this context. Unfortunately, estimation based on undominated strategies is not computationally straightforward because of the introduction of inequalities, and often yields wide and informative bounds on coefficients (Fack et al. [2019]).

The two inequalities provided by Definition 1 can be written in moment terms as follows:

$$\begin{aligned} Pr(u_{im_1s} > u_{im_2s}|Z_{im_1s}, Z_{im_2s}, \beta) - \mathbb{E}\left[\mathbb{1}(m_1 \succ_{i|s} m_2)|Z_{im_1s}, Z_{im_2s}\right] \geq 0 \text{ ;} \\ 1 - \mathbb{E}[\mathbb{1}(m_2 \succ_{i|s} m_1)|Z_{im_1s}, Z_{im_2s}] - Pr(u_{im_1s} > u_{im_2s}|Z_{im_1s}, Z_{im_2s}, \beta) \geq 0 \text{ .} \end{aligned} \tag{14}$$

For every school, there are two moment conditions for each pair of majors that are listed by students. In total, there will be M conditional moment inequalities obtained based on these sets of comparisons. On the other hand, Definition 2 can be used in the same way to find S conditional moment inequalities based on the school comparisons. Writing Equation 7 and Equation 8 in moment terms:

$$\begin{aligned} Pr(u_{ims_1} > u_{ims_2}|Z_{ims_1}, Z_{ims_2}, \beta) - \mathbb{E}\left[\mathbb{1}(s_1 \succ_{i|m} s_2)|Z_{ims_1}, Z_{ims_2}\right] \geq 0 \text{ ;} \\ 1 - \mathbb{E}[\mathbb{1}(s_2 \succ_{i|m} s_1)|Z_{ims_1}, Z_{ims_2}] - Pr(u_{ims_1} > u_{ims_2}|Z_{ims_1}, Z_{ims_2}, \beta) \geq 0 \text{ .} \end{aligned} \tag{15}$$

These inequalities are interacted with Z_{ims} to obtain $M + S$ unconditional moment inequalities. To estimate Equation 3, one can follow the approach proposed by Andrews and Shi [2013] and construct the following objective function $T_{MI}(\beta)$

based on the inequalities in Equation 14 and Equation 15:

$$T_{MI}(\beta) = \sum_{j=1}^{M_1} \left[\frac{\bar{m}_j(\beta)}{\hat{\sigma}_j(\beta)} \right]_-^2 , \tag{16}$$

where $\bar{m}_j(\beta)$ and $\hat{\sigma}_j(\beta)$ are the mean and the standard deviation of the j^{th} moment and $[a]_- = min\{0, a\}$.

C More on Estimation

C.1 Maximum Likelihood Estimator

To identify the model, I would need students' preferences for majors and their preferences for schools. Looking at the ranking of programs by a student, in a given school, informs me on her ranking of majors and how the major-specific parameters of the model shape her list. On the other hand, each student ranks programs which share the same major based on her ranking of schools. Comparing these programs conveys information on the relative importance of each school-specific parameter in the model. In a nutshell, the model is identified by only looking at the ranking of schools and ranking of majors by each student and does not need the full list submitted by the student.

To estimate the parameters, I look for the school with the highest number of listed majors in it and the major that is listed in the greatest number of schools for each student. I then calculate the probability of observing each of these lists given the parameters of the model. One-to-one comparison of majors and using moment inequality techniques would be the best strategy but in the case of my setting and given the size of my dataset it is computationally infeasible to implement. Instead, assuming that students are truthful in listing schools, and independently, in listing the majors they include in their lists allows me to generalize the maximum likelihood estimator used in the literature as follows:

$$\mathcal{L} = \prod_{i=1}^{N} Pr^m(L_i^m | Z_{ims}, \beta).Pr^s(L_i^s | Z_{ims,\beta}) \tag{17}$$

Where $Pr^m(L_i^m | Z_{ims}, \beta)$ stands for the probability of observing L_i^m as the list of majors submitted by student i given the observables Z_{ims} and the model parameters β. Similarly, $Pr^s(L_i^s | Z_{ims}, \beta)$ is the conditional probability of submitting list of schools L_i^s by student i. Note that the interaction is itself the probability of observing L_i^m and L_i^s by student i when the major and school taste shocks are independent.

The parameters $\hat{\beta}$ are estimated such that the likelihood $\mathcal{L}$ is maximized for the observed students' lists.

C.2 Monte Carlo Simulations

To assess the validity of this approach I run Monte Carlo simulations which are heavily based on the code provided by Fack et al. [2019] with modifications made to mimic the setting of my model. In these simulations 500 students are assumed to have preferences over 8 programs (2 majors in 4 schools) and make their choices while taking into the account their chance of admission to each of these programs – which is determined by their priority index and programs expected cutoff. The total capacity of these programs is set to 475 seats which is strictly less than the number of students.

Each program is a bundle of a major m and a school s. Along the same line as Equation 3, the utility that the student derives is determined by the major, school and major-school specific components of each program. Major- and school-specific taste shocks play critical roles and that is how I modify Fack et al. [2019]'s model to mimic my setting. Specifically:

$$U_{ims} = \alpha_m + \theta_s - dist_{is} + 3\ StuScore_i * ProgScore_{ms} + \nu_{im} + \xi_{is}, \tag{18}$$

where, α_m is major m's fixed effects; θ_s is school s's fixed effects; $dist_{is}$ is the traveling distance from student i's city of residence to school s; $StuScore_i * ProgScore_{ms}$ is the interaction between student's score and the mean score of admitted students to a program; ν_{im} and ξ_{is} are individual's major specific and school specific taste shocks, respectively.

Schools are assumed to be located on the corners of a square with diagonal of 1, while students are randomly placed on a disc of radius 1 with the same center as the square. Schools have strict preferences over all students which is determined by the $StuScore \in [0, 1]$ with $StuScore_i = 1$ for the first student in the ranking. Values for $MeanScore_{ms}$ are determined by solving Baysian Nash Equilibrium for 100 initial Monte Carlo samples.[8]

Given this setup, students form their expectations as well as their preferences for all programs and submit a full list for 100 MC samples. For each sample the major and school lists are analyzed and the likelihood in Equation 17 is formed. The coefficients are estimated such that this likelihood is maximized. The results in Table 6 show the validity of the proposed maximum likelihood estimator.

[8] For more information about the setup look at Online Appendix C of Fack et al. [2019].

Table 6: Monte Carlo Results

		2D ML Estimator		Rank-ordered Logit	
	True Value	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)	(5)
Major 2	0.5	0.485	0.093	0.403	0.078
School 2	0.5	0.525	0.308	0.4158	0.092
School 3	1.0	1.011	0.93	0.8144	0.075
School 4	1.5	1.510	0.332	1.223	0.102
Own ability $\times$ school quality	3	3.085	0.107	2.463	0.543
Distance	-1	-1.009	0.899	-0.809	0.0843

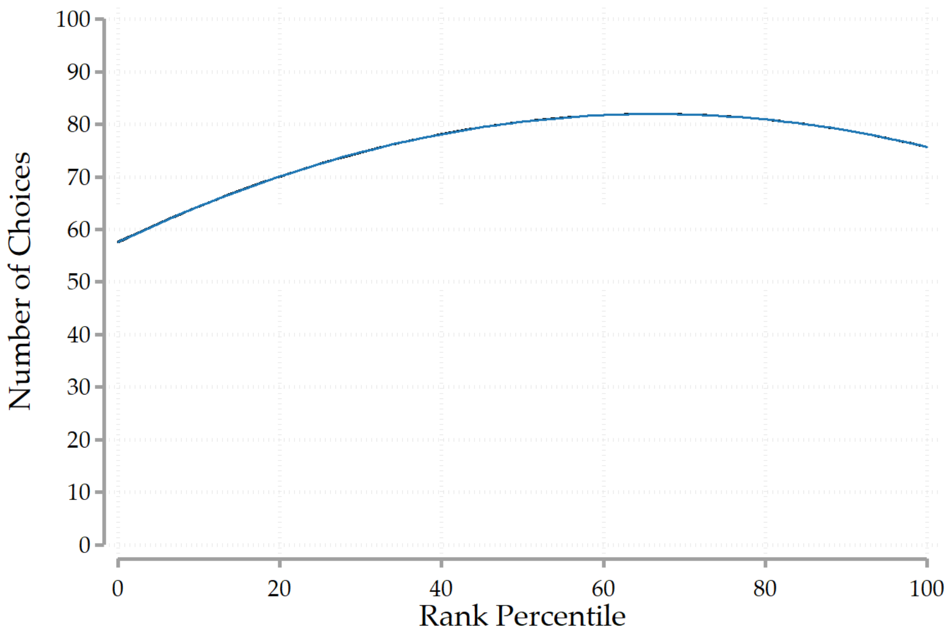
Note: This table shows the results from Monte Carlo simulations with 100 samples. In each sample 500 students form their preferences for 8 programs (2 majors in 4 schools) and submit their list. Column (1) shows the true value of parameters set in the data generating process, Equation 18. After the data simulation, proposed maximum likelihood estimator and the usual rank-ordered logit are used to estimate the parameters. Columns (2) and (3) show the mean and standard deviation of estimated parameters by the maximum likelihood estimator in Equation 17. Columns (4) and (5) show the results from the estimation with the regular rank-ordered logit.

The table shows that the proposed ML estimator does a decent job estimating the unknown parameters by referring to the submitted majors and schools by students. Columns (4) and (5) show that if the preferences are formed with independent tastes for schools and majors, rank-ordered logit estimated coefficients turn out to be biased. It is worth mentioning that the estimation gets more accurate as the economy grows both by the number of students and the number of available programs.

D More on Choices and Data

The number of choices students with different ranks made follows an inverse U shape. Students who are top in the ranking do not need to list many choices to be assigned to a choice. On the other hand, since students who are assigned to a program are banned from taking the exam the next year, students who have done poorly on the exam and want to have the option of retaking the exam avoid submitting a full list with some random programs. The students in the middle of the ranking are the ones for whom submitting a full list matters the most. This is shown in Figure 16.

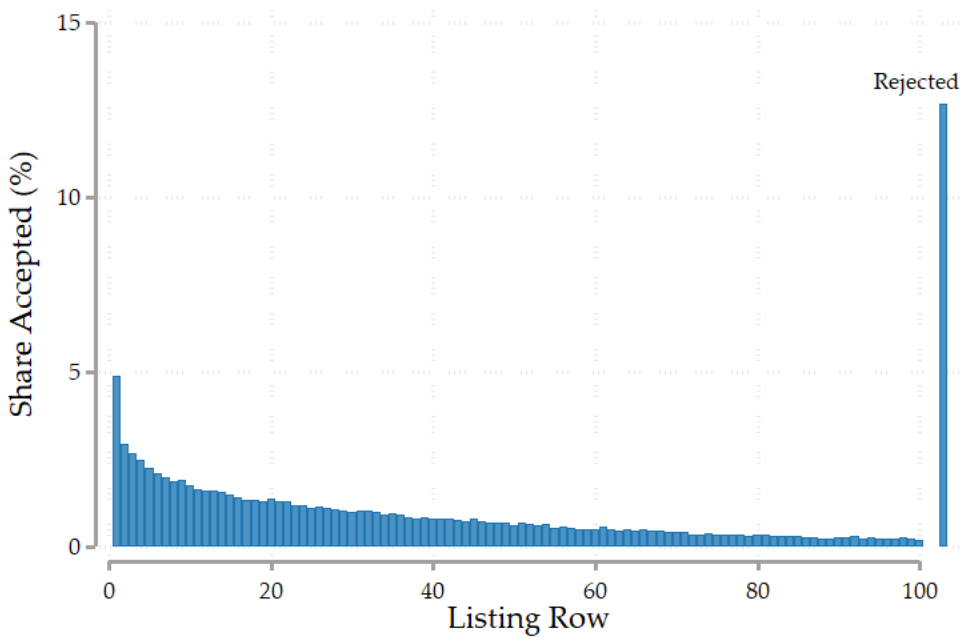
Figure 16: Number of Choices by Rank of Students



Note: Number of listed choices by students with different ranks.

As another descriptive result, I look at the share of students who were assigned by their listing number. In 2012, 10.2 percent of applicants were rejected by all of their choices and were left unassigned. Of those who were accepted to a program, students received their 30th choice on average. Figure 17 shows the share of accepted students for each listing number.

Figure 17: Share of Accepted Students by Listing Number



E Extra Tables

Table 7: Utility Parameters Estimation Results: Proposed Model and Rank-Ordered Logit (1/2)

	Prospsosed Model				Rank-Ordered Logit			
	(1)		(2)		(3)		(4)	
Distance (100km)	-0.0493***	(0.000)	-0.148***	(0.000)	0.0124***	(0.000)	-0.0419***	(0.000)
× Mid Cities	0.00391***	(0.000)	0.00318***	(0.000)	-0.00453***	(0.000)	-0.00500***	(0.000)
× Large Cities	0.0233***	(0.000)	-0.00546***	(0.000)	0.00349***	(0.000)	-0.0173***	(0.000)
× Female	-0.0154***	(0.000)	-0.0152***	(0.000)	-0.00981***	(0.000)	-0.00888***	(0.000)
Distance (100km) Sq.	0.000545***	(0.000)	0.00560***	(0.000)	-0.00131***	(0.000)	0.00173***	(0.000)
Past-Year Median Admit	5.039***	(0.000)	2.044***	(0.000)	3.898***	(0.000)	1.165***	(0.000)
2-Year Program	-1.088***	(0.000)	-1.841***	(0.000)	-0.256***	(0.000)	-1.096***	(0.000)
Same City	0.217***	(0.000)	0.346***	(0.000)	0.0715***	(0.000)	0.133***	(0.000)
Same Province	-0.105***	(0.000)	0.116***	(0.000)	-0.136***	(0.000)	0.00193	(0.420)
Location: Tehran	0.829***	(0.000)	0.150***	(0.000)	0.286***	(0.000)	0.0405***	(0.000)
× Female	-0.00887	(0.053)	0.130***	(0.000)	0.0116***	(0.001)	0.0479***	(0.000)
× Mid Cities	0.0544***	(0.000)	0.184***	(0.000)	0.0791***	(0.000)	0.118***	(0.000)
× Large Cities	-0.296***	(0.000)	0.00768	(0.321)	0.0407***	(0.000)	0.0615***	(0.000)
University Fixed Effects			X				X	
Observations	4,067,624		4,067,624		4,067,624		4,067,624	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Estimation of utility parameters by proposed model (Columns (1) and (2)) and rank-ordered logit(Column (3) and (4)). Column (1) and Column (3) only include major fixed effects and the interaction terms with student characteristics. Column (2) and Column (4) add university fixed effects to the model. *Distance* is proxied by the distance between student's city of residence and the city the university is located in. Students are divided into three categories: from villages, from midsize cities, and from large cities (Tehran, Isfahan, Shiraz, Tabriz, Mashhad). *Distance sq.* is square of distance. *Past year median admit.* is the measure of a program's popularity, since more popular programs tend to be filled by students with higher rankings. Broad major fixed effects are included in all columns according to *ISCED97*. Columns (2) and (4) include university fixed effects; Some institutions that are university of the same brand are grouped together. Variation in these groups allows estimation of the variable *Location: Tehran*.

Utility Parameters Estimation Results: Proposed Model and Rank-Ordered Logit (2/2)

	Prosposed Model				Rank-Ordered Logit			
	(1)		(2)		(3)		(4)	
Social Sciences	-0.0655	(0.306)	0.131*	(0.036)	0.123***	(0.001)	0.393***	(0.000)
× Female	-0.144**	(0.002)	-0.166***	(0.000)	-0.146***	(0.000)	-0.216***	(0.000)
× Mid Cities	-0.117	(0.061)	-0.110	(0.072)	0.140***	(0.000)	0.223***	(0.000)
× Large Cities	0.268***	(0.000)	0.288***	(0.000)	0.156***	(0.000)	0.478***	(0.000)
Business and Administration	0.0628	(0.306)	0.398***	(0.000)	0.0919**	(0.005)	0.555***	(0.000)
× Female	-0.141**	(0.002)	-0.168***	(0.000)	-0.208***	(0.000)	-0.263***	(0.000)
× Mid Cities	-0.0286	(0.630)	-0.0423	(0.466)	0.175***	(0.000)	0.288***	(0.000)
× Large Cities	0.427***	(0.000)	0.367***	(0.000)	0.229***	(0.000)	0.520***	(0.000)
Physical Sciences	0.479***	(0.000)	0.719***	(0.000)	0.316***	(0.000)	0.643***	(0.000)
× Female	-0.223***	(0.000)	-0.245***	(0.000)	-0.204***	(0.000)	-0.263***	(0.000)
× Mid Cities	-0.192**	(0.001)	-0.183**	(0.002)	0.104**	(0.002)	0.174***	(0.000)
× Large Cities	0.272***	(0.000)	0.259***	(0.000)	0.141***	(0.000)	0.328***	(0.000)
Math and Stats	0.494***	(0.000)	0.447***	(0.000)	0.413***	(0.000)	0.399***	(0.000)
× Female	-0.221***	(0.000)	-0.221***	(0.000)	-0.141***	(0.000)	-0.195***	(0.000)
× Mid Cities	-0.267***	(0.000)	-0.249***	(0.000)	0.0472	(0.174)	0.110**	(0.002)
× Large Cities	-0.0340	(0.565)	0.0610	(0.291)	0.0313	(0.351)	0.215***	(0.000)
Computer Science	0.904***	(0.000)	1.281***	(0.000)	0.612***	(0.000)	1.143***	(0.000)
× Female	-0.106*	(0.017)	-0.151***	(0.001)	-0.224***	(0.000)	-0.265***	(0.000)
× Mid Cities	-0.0394	(0.507)	-0.0492	(0.397)	0.148***	(0.000)	0.243***	(0.000)
× Large Cities	0.606***	(0.000)	0.533***	(0.000)	0.200***	(0.000)	0.490***	(0.000)
Engineering	1.485***	(0.000)	1.974***	(0.000)	0.797***	(0.000)	1.517***	(0.000)
× Female	-0.226***	(0.000)	-0.274***	(0.000)	-0.290***	(0.000)	-0.368***	(0.000)
× Mid Cities	-0.0709	(0.232)	-0.0830	(0.153)	0.110***	(0.001)	0.194***	(0.000)
× Large Cities	0.598***	(0.000)	0.489***	(0.000)	0.104**	(0.001)	0.367***	(0.000)
Manufacturing	0.801***	(0.000)	1.136***	(0.000)	0.644***	(0.000)	1.106***	(0.000)
× Female	-0.139**	(0.002)	-0.140**	(0.002)	-0.157***	(0.000)	-0.236***	(0.000)
× Mid Cities	-0.176**	(0.004)	-0.177**	(0.003)	0.0969**	(0.004)	0.158***	(0.000)
× Large Cities	0.512***	(0.000)	0.450***	(0.000)	0.262***	(0.000)	0.449***	(0.000)
Architecture and Building	1.332***	(0.000)	1.830***	(0.000)	0.750***	(0.000)	1.482***	(0.000)
× Female	-0.0941*	(0.035)	-0.131**	(0.003)	-0.264***	(0.000)	-0.297***	(0.000)
× Mid Cities	-0.0133	(0.822)	-0.0267	(0.645)	0.133***	(0.000)	0.227***	(0.000)
× Large Cities	0.794***	(0.000)	0.689***	(0.000)	0.200***	(0.000)	0.511***	(0.000)
Agriculture	0.492***	(0.000)	0.582***	(0.000)	0.512***	(0.000)	0.594***	(0.000)
× Female	-0.233***	(0.000)	-0.248***	(0.000)	-0.203***	(0.000)	-0.283***	(0.000)
× Mid Cities	-0.189**	(0.003)	-0.192**	(0.002)	0.0919*	(0.011)	0.156***	(0.000)
× Large Cities	0.290***	(0.000)	0.266***	(0.000)	0.109**	(0.002)	0.264***	(0.000)
Observations	4,067,624		4,067,624		4,067,624		4,067,624	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$