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Do you like me enough? The impact of restricting preferences ranking in a university matching process*

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Abstract

This paper studies, theoretically and empirically, the impact of imposing preferences-on-preferences (POP) within the context of a deferred-acceptance matching process with uncertainty. Theoretically, this type of rules make students misrepresent their preferences to secure a spot in a POP program, particularly when uncertainty is large. Applicants to Chilean universities responded as predicted by our model to a 2003 policy where one of the main university, UChile, imposed POP and then to a change in the entrance exam, increasing uncertainty. We show that not only were applications altered but eventual outcomes and welfare as well, particularly with higher uncertainty.

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1 Introduction

The benefits of Gale-Shapley-like matching processes have been demonstrated in a number of settings (school choice, the "Match" for medical residencies and even organ donations). However, the reality of many of these processes is not quite the ideal setting of the original model. Very often, only a certain number of choices can be ranked by applicants which may limit the capacity of individuals to provide their full preferences. More importantly, some sides of the matching process may implement "preferences-on-preferences" (POP) such that an application is valued differentially depending on the ranking the applicant provides. While less common than limited ranking, these policies are relatively widespread and have the potential to be much more costly to the properties of the matching algorithm. This may be particularly true when there is more aggregate uncertainty about where applicants are likely to be admitted. In this paper, we theoretically and then empirically study the impact of a new policy implemented by one university in Chile (the Universidad de Chile) in 2003 which started imposing that it would only consider applicants who ranked it amongst the four most preferred options (out of a list of 8 at that time). We then further explore the impact that POP may have when uncertainty is greatly increased by looking at a change in the entrance exam which appeared to have greatly increased aggregate uncertainty. We explore this with the use of a rich administrative data set which allows us to identify the individual application behavior as well as the selection process.

The Gale-Shapley algorithm provides a solution to two-sided matching processes which guarantees a few key properties. In particular, the matching is said to be "stable" in the sense that nobody would like to change their allocation and be able to find a match who would also prefer them to their actual match. It is also "strategy-proof" in the sense that individuals have no incentives not to provide their real preferences. Nevertheless, this is only true in the case where both sides of the market can fully rank any potential match and where POP are not allowed. While the consequences of the first one have been discussed previously (see for example Calsamiglia et al., 2010; Romero-Medina, 1998), we are not aware of any work on the latter. We will look at this in the context of a Gale-Shapley algorithm implemented in the university match for undergraduate applicants in Chile. That system displays both a limited set of slots for applications and POP by the two main universities of the system, one of which implemented the policy in 2003.

We thus start by elaborating a simple matching model where there is some uncertainty in the preferences that other students who are participating in the system have. In Chile, the number of slots available in each program is known since universities have to declare their number of slots before applicants provide their preferences. Our model is meant to capture the uncertainty an applicant face about their likelihood of being accepted in a given program. In this model, we compare a setting where there are no POP to one where at least one university implements this policy. We show that the introduction of these measures may lead individuals "on the margin" to distort the real ranking of their preferences in response to this decision by universities. We show that the model provides clear predictions about who should be altering their stated preferences in response to this policy, both in terms of students and in terms of programs.

We then explore what will be the impact in this setting of increased uncertainty. The rationale for this is that in a case of no uncertainty, students will be able to perfectly predict where they will be admitted. Thus, while they would alter their declared preferences, this would have no impact on the program where they will be admitted. However, as uncertainty increases, students are less able to predict in which program they may or may not be admitted which could raise the cost of having to alter the rank of one's preferences. We show that the model has clear predictions on the impact of increased uncertainty, by type of student and type of program as well.

Having obtained clear theoretical predictions from our model about the impact of POP, we next turn to examining empirically whether there is any support for our model. We use the context of the Chilean university undergraduate application process. Like in most European countries and unlike in the United States, most students apply to a particular program within a university. The system is highly centralized with a unique entrance exam being shared by most universities within the country. Once students learn their scores, they apply to programs. They are restricted in listing no more than 8 programs overall. With these applications and the ranking provided by the university (based on the entrance exam and high school grades), a deferred-acceptance algorithm is conducted and matches are generated. We look at a period preceding the change explored by Espinoza et al. (2017): only "traditional" universities are included in the matching process.

We first examine the patterns of applications to each university and program, comparing 2002 to 2003, the year in which the policy was implemented. We find evidence that the university was able to change the pool of applicants to its program by imposing the "only top 4" rule. More interesting, the type of students who started applying more to that university were exactly student close, but in general above the previous cut-offs, as suggested by our model. Furthermore, we show evidence that is consistent with the model in terms of which programs received more applications in response to the policy change. This is robust to the controls we use to capture predetermined characteristics of students. We also document that this has real consequences in terms of who is being admitted to which program. We finally measure the welfare losses that this policy appears to have generated, finding that they were concentrated in those well above the cut-off of the program where they were selected (ie, those who played it safe) and in students from Santiago.

We then explore the impact of another policy change, this time from 2003 to 2004, where the entrance exam was fundamentally altered. The previous exam (PAA, *prueba de aptitud academica*), which had been in place since 1966, was intended to measure intellectual abilities, had two main exams and 6 additional field exams. The new exam (PSU, *prueba de selección universitaria*) was instead a knowledge exam, meant to measure whether students had acquired the concepts taught in high school. While both exams are normalized, a number of differences were noted in the distributions of scores between the two sets. This implied that students had a limited capacity to translate their score into an admission probability to a given program as they had been able to do previously. By contrasting what happens to the applications in 2003 and 2004, we are able to test whether the predictions regarding our model holds.

We find, as predicted by our model, that better students started altering the ranking of their preferences to make sure they would rank one of the restricted programs within their "top 4". We also show that this affected more the type of programs that our model suggested would be particularly impacted. We again show that this had consequences in terms of where students got admitted. We argue that there is strong evidence that welfare losses were substantial.

This paper is related to a large literature regarding allocation mechanisms in education. In the classical school choice problem, it is well known that agents have incentives to truthfully report their preferences. In two-sided markets, this is still true when the DA algorithm is used, but only for the agents that are on the side that makes the proposals. Moreover, there is no mechanism that induces truth-telling for all agents (for this classical analysis, see e.g. Roth and Sotomayor, 1990). Truth-telling properties do not extend to other mechanisms, and the possibility for families of manipulating the so-called Boston mechanism was one of the main criticisms levelled against it (Abdulkadiroğlu and Sönmez, 2003). But in practice, even if a version of the DA algorithm is used, students are restricted to list only a limited set of schools (for the case of NYC and Costa Rica see Abdulkadiroğlu et al., 2009; Hernández-Chanto, 2017, respectively), and truthfulness is no longer optimal. There has been discussion about the empirical relevance of this fact, with some works reporting that families do not even list all the schools they are allowed to (Abdulkadiroğlu et al., 2009) and others showing that at least, in the laboratory, agents take significant advantage of the possibility of manipulation (Calsamiglia et al., 2010). We contribute to this literature by showing that other constraints, like the impossibility of ranking some schools below a certain level might induce, at an empirically significant level, manipulation by students.

Even more significantly, we show that the non-proposing side of the market can manipulate the system in order to induce a better outcome. As we mentioned, as early as in Roth (1982) it was established that by truncating their preferences (in our context, deciding ex-ante not to accept students below an inefficiently high cutoff) schools can improve their prospects in the matching. However, in real-life situations, this was usually a negligible concern, as reported, among others, by Peranson and Roth (1999), and justified theoretically by Kojima and Pathak (2009). Our contribution is to show that schools can manipulate the outcome significantly if they are allowed to truncate their preferences in a more sophisticated way: by establishing inefficiently high cutoffs *that depend on the rankings submitted by students*.

The restrictions imposed by universities in the Chilean system impose strategic concerns on students similar to the ones imposed by the Boston mechanism (BM), where a student who is not assigned to his top ranked school, is only assigned to his second choice *after the students who have top ranked this option*. Ergin and Sönmez (2006) show that the set of Nash equilibria of the BM coincides with the set of stable matchings under the true preferences. Therefore, the outcome of the BM is Pareto-dominated by the outcome of the Deferred Acceptance algorithm, which picks the student-best stable allocation (in a Pareto sense).

Abdulkadiroğlu et al. (2011), in a dissent, show that BM can perform better than DA when priorities are weak. The argument relates to the fact that there will be many ties, which will be randomly decided, independently of the strength of the families preferences for the school. In that case, BM allows to (imperfectly) communicate the strength of one's preferences, by ranking a school at the top of the list. In many cases, the authors argue, this possibility is more important than the intrinsic defects of manipulable mechanisms. Empirical results supporting this view are presented by Agarwal and Somaini (2018) and Calsamiglia et al. (2018). He (2017) suggests that the answer depends on whether parents play naively or in a sophisticated way. Moreover, strategization is not easy in BM, requiring families to form beliefs about the level of congestion of schools and to use this information to select the portfolio of schools they apply to. Abdulkadiroğlu et al. (2006) show that different patterns of sophistication among players exist, some of them strategizing and others declaring preferences truthfully. Ergin and Sönmez (2008) show that in a world where naive players (which reveal their true preferences) coexist with sophisticated players, the latter are better off. Finally Kapor et al. (2017) show that parents often strategize incorrectly, since they form wrong beliefs about the demand for each school, making DA superior to BM.

The setting that appears to be closest to the assignment mechanism we present is that of Taiwan senior high school placement (see Dur et al., 2018). In that setting, students were given "bonus points" depending on their ranking. It led to large protests for how it encouraged strategic behavior. We can think of the assignment we present as one where the point assignment is completely discontinuous in rank 4.

In our setting, lotteries do not play a relevant role, since students are ranked by programs based on test scores, and ties happen with an extremely small probability (in that case, moreover, all students tied are accepted). However, uncertainty still plays a significant role, since cutoffs vary significantly from year to year. We explicitly model this uncertainty as a shock to aggregate demand, and obtain that strategization has negative consequences in equilibrium.

With this analysis, it is possible to estimate the degree of inefficiency generated by the particular rules of the Chilean admission system. First, students can be inefficiently assigned simply because they could not report their true preferences. Moreover, since agents must act strategically in the presence of significant uncertainty (about other students' preferences, and therefore on admissions cutoffs), they can be inefficiently assigned because they decided to manipulate their report. In this respect, we contribute to the growing literature on the analysis of the inefficiencies introduced by artificial rules on a matching market. For example, when schools have coarse preferences over students (for example, by a law mandate) and ties are broken randomly, Che and Kojima (2010), Manea (2009) and Bogomolnaia and Moulin (2001) look at theoretical properties of different algorithms, while Pathak (2007) looks at the empirical implications for the case of NYC. Agarwal and Somaini (2018) evaluates how to still estimate preferences even when there are incentives to misrepresent them. We see our contribution to this literature as using a "natural experiment" approach to alleviate some of the concerns about identification in this setting and emphasizing the role of uncertainty.

We also contribute to the literature measuring welfare impacts of altering matching mechanisms. Abdulkadiroğlu et al. (2017) show that there were substantial gains when NYC school district adopted a deferred-acceptance algorithm. We show that these gains may be in part diminished when some restrictions are combined with this process and that those may depend on the level of uncertainty present in the market.

Finally, by analyzing the behavior of students in the presence of constraints that make truthful reporting suboptimal, we contribute to the growing literature that tries to estimate agent sophistication (e.g. Chen and Sönmez, 2006, in the lab and Pathak and Sönmez, 2008, at the theoretical and field levels.) We show that the number of agents that act sophisticatedly is significant and, more importantly, they have important consequences on the final allocation.

The rest of the paper is as followed. The next section presents the setting we employ as a source of natural experiments and the institutional context of university admissions in Chile. Section 3 then presents a model that predicts what is the likely impact of introducing POP in a Gale-Shapley algorithm to solve the assignment problem in a many-to-many matching. Section 4 presents the data and empirical methodology we will use while Section 5 show our results. The last section concludes.

2 Matching Process

In Chile, the main selection requirement for almost every higher education program is a national standardized university entrance exam. This exam was the PAA untill 2003 and the PSU afterwards. Moreover, universities members of the CRUCH (Spanish acronym for National Universities Association), which includes the universities existing before 1982, select their students using a centralized matching algorithm. In this algorithm, only test scores and high-school grades and relative performance are considered by universities to establish their preferences about students. The PAA/PSU is also a requirement for almost every university outside the CRUCH, but they perform their own unilateral selection processes.

The matching process operates as follows. First, students take the national exam and obtain their grades from their high schools. Then, before the grades on the national exam are announced, universities declare the number of spots they will have available for each program.[1] They also announce the weights they will assign to each part of the test and to high school grades. This implies that the ranking of applicants in each program, while related to one another, is specific to each one.

Then PAA/PSU grades are made public. Within a very short period, students who want to apply to a program from a CRUCH university must list their preference order over programs in the web page authorized by the CRUCH. This is the part of the process where two important restrictions come in place: 1) applicants can apply to a maximum of 8 programs and 2) two universities, Pontificia Universidad Católica (PUC) and Universidad de Chile (UCH), do not consider applications

[1] Universities in Chile function like in most of Europe in that admission is granted to a program (Electrical Engineering, History, Biology), not a general faculty or school (Arts, Science, etc) within a university.

listed under the 4th preference. This last restriction began in 2003 for UCH and previously to the availability of the data for PUC. Since our data on application starts in 2001, we will focus on the change in applications and selected applications from 2002 to 2003, that is, before and after the UCH implemented this restriction. We call this second type of restrictions "preferences-on-preferences" (POP), since universities act as if they like more a student that in turn likes them enough.

After applications are received, a university-preferred Gale-Shapley algorithm is run on the pool of all applicants to the CRUCH and a set of offers is made.[2] Wait lists are also generated for each program since the existence of private universities outside the CRUCH makes non-registration a possible outcome. The only modification to the algorithm compared to a typical one is how ties are handled. In this matching process, if the last applicant is tied with others, the university program must accept all tied applicants. Selected students can accept the university's offer and enter its program, or can reject it and go outside the system. Students have the chance of being selected into a program where they are wait-listed if enough first-round selected students reject the offer.

Over the period we study, the number of applicants is about 75,000 from an age cohort of about 280,000 where a bit less than 90 percent graduate from high school. About twice as many individuals take the national exam compared to those who apply. This is because to apply, a minimum score of 450 points is required.[3] Furthermore, a student needs 475 points to obtain state-backed student loans, and 500 to obtain state-funding. In 2003, there were 42,569 slots in 773 different programs. Of those, around 7,000 were available in some 80 different programs of the two major universities (UCH and PUC), where POP restrictions are imposed. There were around 350,000 program applications made in the system, implying a rate of about 4.6 applications per applicant. Already, this suggests that restricting applications to 4 alternatives may limit some individuals in ranking their true preferences.

From 1966 until 2002 (the entrance exam is taken in December for the application process of the subsequent year), the set of national exams required to apply to any university in Chile was know as the PAA or *Prueba de Aptitud Académica*. The PAA included 2 required sections. A language section (*Prueba de Aptitud Verbal*) took 2 hours and had 75 questions. The mathematical part was shorter at one hour 45 minutes and included only 60 questions. These tests were meant to measure intellectual capacity and not knowledge of class materials, akin to the SAT. Theoretically, a student only needed to have completed eight grade to be able to answer the questions. However, to be allowed to take the test, high-school graduation was mandatory. These 2 required exams were also supplmented by 6 additional exams (Mathematics, Biology, Chemistry, Physics, Social Science, and History and Geography of Chile) which programs could include as admission requirements.

In 2003, the test was completely changed and the PAA was replaced by the PSU (*Prueba de Selección Universitaria*), which remains in place until today. This exam targeted more the knowledge of high school material than overall intellectual abilities. It retained the two obligatory sections on Language

[2]As it is well-known, for real-world applications, student-preferred or university-preferred Gale-Shapley are almost equivalent. In this particular process, simulations have shown that the assignment differs in approximately 1-5 students out of 75,000.

[3]The test is normalized to have a mean of 500 and a variance of 100 points.

and Communication and Mathematics. The optional sections became only two namely : History and Social Sciences, and Science (where within the exam, there is a common part and then one must elect one specialized module of Biology, Physics or Chemistry). It is also normalized in the same way as the PAA was, however, a number of differences were noted in the distributions of scores between the two sets of exams.

Given that the first PSU exam was given in December 2003, it impacted the 2004 entrance process. This change substantially increased the uncertainty faced by a student. It was much harder to predict the cut-off score to be admitted in each program. We will use this shock to explore the role of uncertainty in this setting.

3 Model

Having described the admission system and the two policy changes we will analyze, we now develop a model to predict the impact that these may have. Our model is meant to capture the key features of the distortion we wish to study in this context: namely that students will only be assigned to some program if they listed it amongst their first preferences.

3.1 Setting

There is a continuum of applicants with quality s distributed according to a probability density function $g(s)$ over $[0,1]$. One can think of s as standardized test scores, and we will assume that all programs prefer applicants with higher s. Students differ not only in their "quality" but also in their preferences. A proportion α of students prefers p_1 to p_2. There is aggregate uncertainty about α, which is distributed according to a distribution Λ over the interval $[\alpha_1, \alpha_2]$, with $\alpha_1 > \frac{1}{2}$. Not enrolling in any program gives a utility of 0, enrolling in the least preferred one L and the preferred one H, where H distributes according to a distribution F over $[L, \bar{H}]$. We assume H to be independent of s. A student knows his own characteristics and the distribution of characteristics on the population, therefore facing only aggregate uncertainty about α.

There are two programs: p_1 and p_2, where p_1 has room for half of the students.[4] Both programs prefer better quality students, so $s' > s''$, implies that student s' is preferred by both programs to student s''.[5]

[4]For simplicity, we assume that p_2 has no capacity constraints. The alternative model where both programs have capacity of 1/2 is, for most students, identical to this model, but it renders additional complications and no additional insights.

[5]In our empirical analysis, programs may rank candidates differently, by weighting differently their results on tests, but preferences are strongly correlated across programs, and adding this dimension would not add much to the conclusions of the model.

3.2 Gale-Shapley benchmark

As a benchmark, let us consider the case where students submit applications to a centralized system and a student-proposal Gale-Shapley algorithm assigns students. As is well known, such a mechanism is strategy-proof for students, therefore a proportion α of applicants will list p_1 as their first option, leading to excess demand for that university. The outcome will be that

- For $s \in [\hat{s}, 1]$ a proportion α of applicants will be matched to p_1 and $1-\alpha$ to p_2 (their preferred option).
- For $s \in [0, \hat{s}]$ every applicant will be matched to p_2.

Where $\hat{s}$ is the cutoff score for p_1, which is given by $\alpha \int_{\hat{s}}^{1} g(i)di \equiv \alpha(1-G(\hat{s})) = \frac{1}{2}$. Note that $\hat{s}$ is a random variable (since α is one). From now on, denote p_1's cutoff when the realization of α is equal to its expectation by $\hat{s}$. Denote also p_1's cutoff when $\alpha = \alpha_1$ by $\hat{s}_1$ and p_1's cutoff when $\alpha = \alpha_2$ by $\hat{s}_2$.

3.3 Modified assignment problem

We now introduce restrictions over declared preferences. Since there are only two programs, we assume that a program might choose to consider eligible only students that applied there as their first choice.

The first observation is that if p_1 imposes a restriction, truth telling is still a dominant strategy. In fact, the worst case scenario for someone who prefers p_1 to p_2 and applies to p_1 first is to be rejected in p_1 and be accepted in p_2, so there is no upside in applying to p_2 first. On the other hand, someone who prefers p_2 will get accepted into it with certainty, so there is no incentive to lie.

Proposition 1. *If p_1 is the only program imposing the restriction, truth telling is a dominant strategy.*

The two remaining cases, namely when only p_2 or both programs impose a restriction, are equivalent since in both cases a student is accepted (with certainty) to p_2 only if she ranks it first. To make the exposition easy, we continue our analysis as if p_2 was the only program imposing a restriction.

Intuitively, agents that prefer p_2 will always reveal their preferences truthfully, since there are unlimited slots. Moreover, among the students that prefer p_1, the best ones have nothing to fear, because they will be accepted in the program of their choice regardless of other people's choices. Therefore we can formulate the following proposition.

Proposition 2. *All applicants that prefer program p_2 report truthfully. Moreover, all applicants with quality $s \in [\hat{s}_2, 1]$ (regardless of their preferred option) report truthfully.*

Remember that $\hat{s}_2$ is the highest possible cutoff for p_1 that occurs when the maximum number of students prefer p_1 to p_2. This is the "most pessimistic" scenario for students that prefer p_1, and it is defined by $\alpha_2(1 - G(\hat{s}_2)) = \frac{1}{2}$.

Agents that prefer p_1, and are below this cutoff, are uncertain about their prospects of getting admitted to p_1. They face a tradeoff: they could apply to p_2 and get accepted (therefore getting utility L) or apply to p_1, foregoing any chance of getting into p_2 because of the restriction on preferences, and risk the chance of not getting in any program (so they get H or 0). For students of quality s close to $\hat{s}_2$, this risk is small (there are few realizations of α for which they are not accepted), and only students who do not care much about the program ($H \sim L$) will apply to p_2. But for smaller s the risk is greater and therefore there will be more agents that "strategize", that is, apply to p_2 while they truly prefer p_1.

Proposition 3. *Applicants $s \in [0, \hat{s}_2)$ who prefer p_1 to p_2 will misrepresent their preferences (i.e. strategize) with some positive probability that decreases in s.*

The logic behind the proposition is simple and we sketch it here since it is illustrative of the mechanism behind the distortions introduced by the restriction. Define as $x(i)$ the probability that a student of quality i that prefers program p_1 applies to program p_2 (i.e. he strategizes). A student of quality s chooses to strategize if

$$\mathbb{P}\left(\alpha \int_{\hat{s}_2}^{1} g(i)di + \alpha \int_{s}^{\hat{s}_2} (1 - x(i))g(i)di < \frac{1}{2}\right) \cdot H < L$$

The random variable in the above equation is α, aggregate uncertainty. Note that there is a fixed point structure to the problem, since in order to compute her probability of getting accepted, a student must take into account the decisions of students that are better-ranked than herself. In other words, a student of type s computes the probability with which p_1 is not going to be filled with students that are of better quality and applied to it. Above $\hat{s}_2$ all students that like p_1 are going to apply to it (amout denoted by $\alpha \int_{\hat{s}_2}^{1} g(i)di$). Below that threshold, the students that apply to p_1 are only the ones that decided not to strategize (denoted by $\alpha \int_{s}^{\bar{s}_2} (1 - x(i))g(i)di$).

Defining $\lambda(s) := \mathbb{P}\left(\alpha \int_{\hat{s}_2}^{1} g(i)di + \alpha \int_{s}^{\hat{s}_2} (1 - x(i))g(i)di < \frac{1}{2}\right)$ as the probability that p_1 is not full, we get the fixed point equation that defines the equilibrium:

$$x(s) = P\left[H < \frac{L}{\lambda(s)}\right] = F\left[\frac{L}{\lambda(s)}\right] \tag{1}$$

This is an integral equation, that coupled with the boundary condition $x(\hat{s}_2) = 0$ gives us the level of strategization among students. The fact that $x'(\cdot) < 0$ comes simply from the fact that $\lambda(s)$ (the probability of getting accepted at p_1 for a student of quality s) is increasing in s for a fixed decision rule of other agents.

Will these changes in the order of application lead to changes in outcomes? On the one hand, the best students from the ones that prefer p_1 and strategize would have entered p_1 in the absence of the restriction. At the opposite end of the spectrum, for the students that still apply to p_1 and that, without POP, would have been forced to enter p_2 (i) the best ones will enter p_1 (in the slots that where released by better students that played safe) and (ii) the worst ones will end up without any program. Thus, end-outcomes are also altered.

3.4 The role of uncertainty

Aggregate uncertainty about preferences is crucial for restrictions on preferences to have a distortionary effect on outcomes. Without uncertainty about α, students would be able to predict with certainty whether they would be admitted in a program or not. Therefore, agents that prefer p_1 would apply to p_2 if they are below the (well-known) cutoff, but this report would have no effect on the equilibrium allocation, which would be the same as in the benchmark.[6] We now study how a change in uncertainty affects the equilibrium level of strategization in the model.

In our framework, an increase in uncertainty corresponds to a change from distribution Λ_l to Λ_h, where Λ_h is a mean preserving spread of Λ_l ($\Lambda_h \geqslant_2 \Lambda_l$). For simplicity, we will assume that Λ_i is symmetric around $\bar{\alpha}$ and, for exposition purposes, that the support does not change.

An increase in uncertainty makes high quality students that are not sure that they will make it into p_1 (that is s below, but not that far from $\hat{s}_2$) strategize more, since it is more likely for α to take high values and for them to be left out. For lower quality students, however, two forces go into the opposite direction to this first effect. First, as better students strategize more, more slots are left unoccupied in p_1, increasing the probability of being admitted and, therefore, lowering the incentives to lie. Second, eventually it is also more likely for α to take very low values, an event which allows low-quality students to be accepted.

Proposition 4. *A change from Λ_l to Λ_h, where $\Lambda_h \geqslant_2 \Lambda_l$, leads to the existence of s^* such that*

- $x_h(s) > x_l(s)$ *for applicants above* s^*
- $x_h(s) = x_l(s)$ *for* $s = s^*$
- $x_h(s) < x_l(s)$ *for some* $s < s^*$

Moreover, $s^* > \hat{s}$.

Proof: See Appendix.

[6] See Romero-Medina (1998).

In other words, near $\hat{s}_2$ strategization is stronger with higher uncertainty. As we move to worst students, the incentives to lie grow faster with lower uncertainty, until the probability to strategize becomes higher with lower uncertainty. Finally, this crossing happens before $\hat{s}$ –the cut-off score of p_1 without POP, when the realization of α is equal to its expectancy (which is $\bar{\alpha}$, in this case).

This change in application strategy will lead to different selection processes. Those who increase their probability of strategizing with the increased uncertainty and place p_2 as their first option will now be guaranteed to enter in that program when, with less uncertainty, they would have entered with some positive probability in p_1. At the opposite end of the spectrum, the increase in uncertainty also makes lower-ranked students to be less likely to strategize. Thus, this will increase the likelihood that students who, without POP, would have been forced to enter p_2, now enter p_1 with a positive probability. Increased uncertainty will also increase the probability that an applicant remains unmatched.

3.5 Empirical Counterparts

The empirical setting is more complicated than the model in some relevant dimensions. First, students compare many pairs of programs, not only one. Second, for the same reason a program can be preferred in the aggregate to some programs and less preferred to others, and, thus, it is not possible to cleanly characterize it as p_1 or p_2. Finally, each of these programs weights tests that are part of PAA/PSU in different ways. Therefore the same student can be an excellent candidate to a program, with a weighted score well above the previous year cutoff, and a very bad candidate at another, with an application being a Hail Mary pass [7].

To address these issues we consider each student-program application separately and construct a quality index relative to that program. A student quality is then program-specific, and recentered at the previous year cutoff. If that cutoff was 700, and the student, *with the weights defined by that program*, scores 720, we say that, in his application to that program he is a $\tilde{s} = 20$ applicant. This simple re-centering then offers us clear empirical predictions that we detail, embedded in our simple model. We first show that the effects of the new restriction is asymmetric in $\tilde{s}$.

Proposition 5. *The introduction of POP restrictions leads to:*

- *No change in the probability of applying if* $\tilde{s} >> 0$
- *An increase in the probability of applying if* $\tilde{s} > 0$
- *A decrease in the probability of applying if* $\tilde{s} < 0$

In our model we only have 2 programs. Moreover, we know that a program p_1 should have a cut-off above that of a program p_2. For a given program j, students that consider it a p_1 program

[7] Note however, that the correlation of rankings between programs is relatively high.

decrease their applications after restrictions are imposed, and the opposite happens with students that consider it a p_2 program, or a "safe option". Students that consider it a p_2 program have higher recentered scores $\tilde{s}$. Moreover their strategization, which increases applications, is present for students well above $\tilde{s_j} = 0$, which perceive this program as a safe option and apply only to guarantee themselves a seat. Students that consider it a p_1 program have lower recentered scores $\tilde{s_j}$. For some, their recentered score $\tilde{s_j}$ can be negative. Their strategization, that decreases applications to program j, is therefore concentrated on lower recentered scores $\tilde{s}$.

This leads to a very clear cut prediction. For scores $\tilde{s} < 0$, we only observe the strategization of students that consider j a p_1 program, and therefore a significant decrease in its applications. For scores $\tilde{s} > 0$, the positive effect kicks in and will dominate the negative effect of those who consider it a p_1 program since the strategization is decreasing in s. Finally, for students with high enough relative ranking, nobody will respond.

Perhaps an easier way to show this proposition is graphically. To do this, we chose specific distributions and values for all parameters to be able to write $x(s)$ as an integral equation that depends on the strategization of students with higher test scores. We then solve numerically for the strategization level $x(s)$. In particular, and for simplicity, we chose uniform distributions for α (between 0.51 and 0.95) and H (between 1 and 5).

To map the numerical solution of the model to the empirical results, we plot the difference in applications to a given program between the benchmark and the case where p_2 imposes the restriction (Y-axis) against test scores (X-axis) in Panel (a) of Figure 1. Note that as the only thing that changes between the benchmark and the restricted scenario is the strategization, plotting the difference in the number of applications is the same as plotting the amount of people that strategize (i.e. $x(s)$) for p_2 and its negative value (i.e. $-x(s)$) for p_1. We show that, starting at a certain value of s, individuals apply more to program p_2 than if the policy had not been in place. Mirroring this is the fact that fewer individuals apply to the p_1 program. The next panel of Figure 1 shows the same curves but this time re-centering them around the cut-off of each program without the policy. As p_1 has a higher cut-off then p_2, we observe that the increase in applications to program p_2 is larger than the decrease in applications to program p_1 at the right of the cut-off. This is a direct consequence of the fact that strategization is decreasing in s. Finally, we show, in Panel (c) of Figure 1 what happens if one observes the aggregate pattern of application around the cut-off, summing the two curves of Panel (b). We observe a fall in applications at the left of the cut-off, a discontinuous jump at the right of that cut-off followed by a fall in the change in the number of applications. This will be exactly the empirical pattern we will look for in the data, which matches that of our proposition above.

While this pattern holds in our simple model, it is even more likely to appear in a more complex setting such as the one we will empirically examine in the next section. First, some programs will be p_1 types for some students (in which case, their score will be more probably below the cut-off of that program) and will be p_2 types for other students (in which case, it is more likely that the student will have a score above the threshold). Re-centering thus allows us to combine both types of behavior for a given program from UCH. If a program is more a p_1-type, we should observe mostly a decrease in applications while the opposite will be true if the program is mostly a p_2-type. Note that for programs that are not from UCH, we should observe only the pattern of p_1 programs since there should be no increased incentive to play it safe with these programs.

Furthermore, this re-centering allows us to focus on the relevant share of students who may be altering their preference ordering since we are able to look more closely at those "close" to the cut-off. In addition, we do not need to determine whether a student would be interested in the given program or not since we can use all students who have a score around a program cut-off to evaluate their behavior.

We can also obtain predictions regarding the programs in which applicants will be admitted using this re-centering. We will observe an increase in the number of students admitted at relative scores $\tilde{s}$ above the threshold since those previously would have entered p_1 with some positive probability but now are admitted to p_2 which has a lower cut-off score. We will also observe an increase in the number of students admitted at relative scores that are slightly below the cut-off since those will be individuals who will be able to enter into p_1 when before, they were admitted to p_2. In both these cases, these increases in being admitted will be countered by decrease in admissions from people slightly above the cut-off ($\tilde{s} > 0$) and by decreases in admissions overall.

By the same type of analysis, we are able to also obtain predictions regarding the behavior of applications in response to an increase in uncertainty. Specifically, we can show that

Proposition 6. *Increasing uncertainty in the presence of POP restrictions leads to:*

- *An increase in the probability of applying for* $\tilde{s} < 0$
- *A discontinuous downward jump in the probability of applying for* $\tilde{s} = 0$*.*
- *A decrease in the probability of applying for some* $\tilde{s} > 0$*.*
- *An increase in the probability of applying for some* $\tilde{s} >> 0$

In other words, if we are agnostic about the program type and we re-center student types around each program's cut-off scores, the probability of applying once we increase uncertainty will have a V-shape.

The proof comes from Proposition 4 and the following observations. The change in the probability of applying will be positive for program p_1 and negative for p_2 for low values of s. As s increases, the change in probability of applying will switch sign, at a point above the no-POP cut-off of program p_1 (from Proposition 4). Thus, if we look at students who have s below the cut-off, we are only looking at applicants to p_1 and their response right below the cut-off must be one where they apply more to p_1 than previously. These are weaker students who are now willing to attempt to get into p_1 since they anticipate a fall in the cut-off driven by more strategization of better students. Right at the point of the cut-off, we start including not only applicants to p_1 but also to p_2 who decrease their probability of applying. This will thus generate a discontinuous fall in the change of the probability of applying. While we cannot say if the overall sum will be positive or negative, we are sure that it will be smaller than the change observed at the left of the cut-off. We also know that at $s*$, the probability of applying to p_1 will be unchanged but that this will correspond to a relative value of s compared to the cut-off where the probability of applying to p_2 is still negative. Thus, at the right of the cut-off, there will be at least one observation where the increased uncertainty will translate into a fall in the probability of applying. Finally, we know that for high values of s relative to the cut-off, there will be no change in the probability of applying to p_1 but that the probability of applying to p_2 will be increasing, thus leading to a positive impact of increased uncertainty on the probability of applying for high enough relative score values. Note again that for a program that is not-POP, we should observe a different pattern, namely a decreasing probability of applying to a program as s increases.

In a similar way as before, we graphically show these propositions by solving the model assuming uniform distributions for the parameters. In this case, nonetheless, as we want to show the effect of an increase in uncertainty, we will numerically solve the model for two levels of uncertainty, high and low. As α distributes uniformly, to increase uncertainty in the same fashion as in Proposition 4, we will expand the support of the distribution of α maintaining its mean. In this way, in the scenario with high uncertainty α distributes between 0.51 and 0.95, whereas in the scenario with low uncertainty it distributes between 0.6 and 0.86 (note that the mean is 0.73 in both scenarios). The values for the distribution of H are as in the first set of figures.

As in the previous figure, Panel (a) plots the difference in applications between both scenarios and the benchmark against test scores; Panel (b) re-centers the test score values around the cut-off of the respective program while Panel (c) combines both responses into an aggregate pattern. In accordance with Proposition 4, in Panel (a) the amount of applications to p_2 is higher in the uncertain scenario for the first students that strategize and it is surpassed by the amount of applications in the more certain scenario just before the cut-off score of p_1; after that crossing, the level of strategization is always higher in the more certain scenario. A mirror pattern is observed for p_1. When we re-center, we move the change in applications to p_2 to the right, making most of the decrease in applications correspond to the same region to the right of the cut-off. Finally, when we combine them, the change in probability of applying to a program in response to more uncertainty is reflected visually in a V-shape, as stated in Proposition 6 and shown in Panel (c). In this specific example, the amount of applications increases as we move to the left of the cut-off.[8] It is higher in the more certain scenario for students just to the right of it and it reverses to be higher in the uncertain scenario as we move more to the right. This will be the pattern we will empirically test.

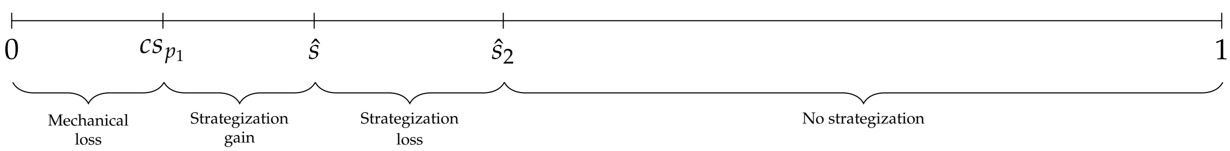
Our prediction regarding admission will be clear at the extremes but not determined in the "middle" of the distribution of scores. We should face an increase in admissions for individuals well above the threshold and an increase in admissions below the threshold of the admitted program when un-

[8] The upward slope in the far left is produced because, as we move to lower types, the probability of strategization in the more certain scenario eventually reaches 1 in this example.

certainty increases. This is because for high enough values of $\tilde{s}$, individuals will strategize more when faced with more uncertainty, which will translate into them being more likely to be admitted to p_2, which will be well above the threshold of admission it would face without POP. But we also know that the probability of applying to p_1 when below the cut-off will also rise with increased uncertainty, leading to more admissions for those with a $\tilde{s} < 0$. It is likely that for those close to the threshold, we will observe a decrease in the number of admissions but this is more difficult to predict.

3.6 Welfare consequences

Strategization by students generates welfare changes on both sides of the market: programs and students, since it distorts the allocation. We will focus on the consequences for students. It is easy to see that the realization of aggregate uncertainty α determines the winners and losers due to the restrictions. Let's denote by cs_{p_1} the actual cutoff for p_1, with the constraint. Note that $cs_{p_1} < \hat{s}$, since less students apply to p_1 in this case, due to strategization.



For students with quality $s \in [\hat{s}, \hat{s}_2]$ we have students that prefer p_1, but apply to p_2, and that in the Gale-Shapley benchmark would have applied to (and been accepted in) p_1. These students bear a welfare loss that we denote as "strategization loss". Defining H_i as the expected value of H conditional on a student being of quality i and strategizing (applying to p_2)[9] we can write

$$S.\ loss = -\alpha \int_{\hat{s}}^{\hat{s}_2} (H_i - L)x(i)g(i)di \tag{2}$$

For every student with $s \in [cs_{p_1}, \hat{s}]$ that prefers p_1 and applies to it will experience a welfare gain product of the strategization of students of higher quality. A student with this score would have never been accepted into p_1 in the Gale-Shapley benchmark. We call this "strategization gain" and can be written as

$$S.\ gain = \alpha \int_{cs_{p_1}}^{\hat{s}} (H_i - L) \cdot (1 - x(i))g(i)di \tag{3}$$

[9]Therefore $H_i = \frac{\int_{L}^{\frac{L}{\lambda(i)}} Hf(H)dH}{F(\frac{L}{\lambda_i})}$

Finally, for students with $s \in [0, cs_{p_1}]$ every student that gambles and applies to p_1 will not enter a program because of p_2's restriction. He would have entered p_2 (his least preferred option) in the benchmark. This is a direct consequence of the restriction and not being able to anticipate correctly the cut-off score of p_1; thus, we call it "mechanical loss" and is given by

$$M.\ loss = -L \cdot \alpha \int_{0}^{cs_{p_1}} (1 - x(i))g(i)di \tag{4}$$

In the extreme case with a restriction but no uncertainty, students are going to anticipate perfectly the cut-off score of p_1 so (i) before cs_{p_1} there will be no strategization and, thus, no strategization loss or gain, and (ii) after cs_{p_1}, everyone who prefers p_1 will strategize with probability 1 and there will not be a mechanical loss.

Translating this into our "relative score" measure, students who suffer "strategization loss" would have been admitted very close to the p_1 cut-off who are now selected by p_2 at a point well above its cut-off. Students who experience "strategization gain", on the other hand, would have been admitted above the cut-off of p_2 without the policy but would now be admitted below the p_1 cut-off. Finally, mechanical loss will be experienced by those who were close to the cut-off of p_2 and now will not be admitted in any program. Thus, overall, welfare changes will have the following pattern: those who are admitted in a program above the cut-off should be showing welfare loss while those admitted below the cut-off should experience welfare gain.

4 Empirical strategy and data

4.1 Empirical strategy

To study the impact of the policy allowing UCH to include POP in its ranking of students, we basically wish to conduct the following thought experiment. Take 2 twins who are identical in all characteristics but one is applying in 2002, when UCH does not restrict the ranking of applications, and the other in 2003, when the applicant must rank any UCH programs within the first 4 options to be admitted. We would thus like to ask whether the twins changed their application behavior in some way. To approximate this thought experiment, we will control for all potential characteristics of applicants we have. We will also include controls for every single sub-component of their score so as to make sure that these applicants are equally valued by all programs (since programs can weight components differently).

However, the "average" behavior of applicants here is not very informative. In our model, introducing POP will lead to a fall in the number of applicants to the program that implements the policy. That is mechanical since all students who were previously ranking the program second will no longer apply to that program. It is unlikely that the strategization will be so large as to undo this effect. Nevertheless, what the model predicts is that the average effect will hide important information by relative score of the applicant.

Our main empirical strategy will thus imply looking at the impact of the policy depending on the relative position of the applicant compared to the cut-off score of 2002. Namely, we will compute probability that an individual i of relative score $\tilde{s}$ applies to a program j of university u in year t change in 2003 compared to 2002 using the following regression:

$$A_{ijut} = \sum_{k=-60}^{60} \beta_k * (t = 2003) * (\tilde{s} = k) * (u = UCH) + \sum_{k'=-60}^{60} \phi_k * (t = 2003) * (\tilde{s} = k') * (u \neq UCH) + \delta * X_i + \gamma * Z_j + \nu_u + \eta_t + \varepsilon_{ijut} \quad (5)$$

We divide the relative scores $\tilde{s}$ in bins of 10 points and pool all applicants above 60 and below 60 in a single group. Given that the change in behavior at ranks 5-8 will be mostly mechanical, we will focus on the applications at rank 3-4 where most strategization should occur.[10]

The estimated βs thus provide us with an estimate of how the application probability of two students with identical observables and with the same relative position changed between 2002 and 2003 in program that were in UCH. We also estimate, through ϕs, the change in application probability to programs that were not in UCH since our model has prediction for this as well.

The identifying assumption of this regression is that controlling for all X_i and Z_j, the change in applications probability between 2002 and 2003 is entirely due to the change in the POP policy. This will not be satisfied if there were tendencies in the share of applications to each universities or if other universities implemented other changes over the same period. We were unable to find any such changes. We also see the fact that our effects are concentrated in some ranks of applications suggestive of the validity of our empirical strategy.

To study the impact of the increased uncertainty, we transform the above equation to reflect the new setting. However, the main identification strategy is the same. In this case, when controlling for every single sub-component of their score, we face a challenge since part of the change from the PAA to PSU involved a change in the number of exams being given, a change in the percentage of missing tests within a category, and a change in the distribution of the scores. To deal with the first issue, we aggregate the 8 PAA exams into 4 different categories, corresponding to the 4 different PSU exams: Math, Spanish, Natural Sciences, and Social Sciences and History. [11] The second problem arises for two reasons. First, before 2004 one of the Social Science and History tests was mandatory, so we have significantly more missing values after 2004. Second, for the Natural Science category, which

[10] Our results are similar when looking at rank 1-4.

[11] The Math category is the average of the base math and the specific Math exams; the Spanish category is equal to the Spanish base exam; the Natural Science category averages Biology, Physics and Chemistry exams; finally, the Social Science and History category averages the base and specific Social Science and History exams. Each average is calculated conditional on the test being rendered (e.g. is a student did not take the specific Math test, the Math category will be equal to the base Math exam).

is not mandatory for both set of tests, we observe much less missing values after 2004. We think this is because more programs started requiring the Natural Science test after the introduction of the PSU, which increased the incentives to take the Natural Science exam. To deal with this, we tried to match the percentage of missing values in both categories in 2004 to 2002. For the Social Science and History category, we regressed the category test score against all the available student characteristics and predicted the score for the missing values in 2004. For the Natural Science category, we repeated the previous regression, but with a dummy indicating of the test score was missing as the dependent variable, to predict the probability of having a missing value in 2004; we then imputed as missing the observations with the higher probability of being missing until the percentage of missing in 2004 matched the percentage in 2002. To address the last problem, we adjusted the distribution of the test scores in 2003 and 2004 such that the standardized test score in each of those years equals the standardized test score in 2002.

We then ask, conditional on those characteristics, did the probability that an individual i with relative score s applies to a program j of university u in year t change in 2004 compared to 2003 using the following regression:

$$A_{ijut} = \sum_{k=-60}^{60} \beta_k * (t = 2004) * (s = k) * (u = POP) + \sum_{k'=-60}^{60} \phi_k * (t = 2004) * (s = k') * (u \neq POP) + \delta * X_i + \gamma * Z_j + \nu_u + \eta_t + \varepsilon_{ijut} \tag{6}$$

The identifying assumption of this regression is that controlling for all X_i and Z_j, the change from 2003 to 2004 was only due to the fact that the entrance exam was changed. This will not be satisfied if there were tendencies in the share of applications or if other universities implemented changes over the same period. Again, we were unable to find evidence of this.

In both contexts, the predictions of the model vary depending on whether a program is competing against a program that implemented a POP-type of restriction or not. To classify programs, we measured the percentage of times a given program was placed above or below a POP or non-POP program in 2002. For example, to determine if a program competes with an UCH program, first we compute the percentage of times that program is placed just above an UCH program over the total number of applications to that program in 2002; then, we classify as competitors all the programs above the median in that measure. In this same way, a given UCH program will compete with a non-POP program if the % of times a non-POP program is placed just above it is greater than the median of all UCH programs.[12]

However, our model not only predicts that there should be an increase in strategization but also that it should be different if the program is more p_1 or p_2-like, that is, if the program is a "safety option". Given that the empirical setting has a lot more than two programs, it is not obvious how

[12] If a student strategizes she will replace a program (POP or non-POP) for a POP program. Thus, when identifying if a program competes with a POP we will look to the application just below it. On the other hand, if we try to identify whether a POP program competes with another POP or with a non-POP program, we will look to the application just above it.

to classify programs into this categories. For example, a program that is a safety option for good students (p_2), maybe is the preferred option in the aggregate (i.e. p_1) for worst students. For these reason, we attempt to classify programs distinguishing between different students, according to their test score. As being p_1 or p_2-like depends on the aggregate preferences for a program, we look at the average rank of all applications to that program; if the rank is below the median (i.e. the program is ranked higher on average), we will call it a p_1-like program. But we want to distinguish between different type of students. To do this, we separate students by their average test score [13] in 9 groups, divided in segments of 50 average test score points. We start with the best group of students (from 800 to 850 points) and we compute the p_1-like indicator; every program to which no one in this group applied to is considered a p_2-like program. Then, we work our way down repeating the same procedure, but imputing as p_1-like every program that was p_1-like in the previous group. Thus, for example, if a program is p_1-like for the first group, it is also going to be p_1-like for the second; on the other hand, if a program is p_2-like for the first group, it can be p_1-like for the second group, if its average rank is below the median. In this way, we hope to account for the fact that the same program can be p_2-like for some (better) students, but p_1-like for other (worst) students.

4.2 Data

Our main data contains the ordered reported preference list of every student that applied to a program of a CRUCH university and the primary outcome of the matching process between 2001 and 2003. In other words, for every student we know every CRUCH program she applied to, the preference ranking of those applications and whether she was selected into any of those programs. We also have the PAA/PSU scores for every student that took it, independently of whether or not they applied to a program of the CRUCH. Combining the test scores of actual applicants with the weights that each program give to each PAA/PSU test we are able to generate a proxy of the programs' preferences over *all* applicants, that is independently of whether they applied to that specific program. The last part is particularly important in the presence of potential strategic behavior because we are only able to observe effective applications and the programs have preference for every student in the system. It is a proxy because a small amount of programs (mainly artistic tracks) have special tests, in addition to the PAA/PSU, to which we do not have access. Nevertheless, when we compare our proxy measure to the actual score that each applicant has (we have the exact score when the student applies to a given program), we find that the correlation between the two measures is 0.96.

In addition, we have other students and program characteristics that we think can (potentially) influence the listing decisions. Among the available students' characteristics we have gender, marital status, municipality of residence, with whom they currently live, whether his parents are alive, the educational level of both parents, when and how they graduated from high school, and their high

[13] As we want to have an unique order of students by their test scores, this average weights equally every exam, and is calculated conditional on the exam being taken. This does not reflect exactly program preferences -because different programs may weight differently each exam-, but we think it comes close to an average notion of preferences.

school characteristics (municipal, voucher or private). Program characteristics were constructed from the applications database in 2001 and are weighted by the amount of slots of the program each year. They include percentage of women, percent of students from municipal high schools, the cut-off score of admission in 2001 (as a measure of the attractiveness of the program) and some university-level characteristics such as whether the university is Catholic, whether it is publicly-owned and whether it is located outside the metropolitan area of Santiago.

We present, in Table 1, the average characteristics of the pool of applicants and of programs. We find that about half of our sample are female and 99 percent of them are single. More than one third are from the metropolitan region of Santiago, about 13 percent from the neighboring region of Valparaiso and Viña del Mar and another 14 percent is from the region of Concepción. This highlights the very concentrated nature of the population of Chile. Applicants come, on average, from household of 4.6 members of which more than 2 are current students. About 25-30 percent of the applicants have college-educated parents. Most students come from schools that are preparatory schools for university ("Humanista y Cientificos"), only 40 percent of them come from municipal schools, another 20 percent are from voucher schools and the remaining 40 percent are from private (not subsidized) institutions. It is important to note that only 88 percent of students are applying within 3 years of completing high school. Our table also allows us, by comparing the two columns, to show that the pool of applicants is relatively stable over the three years we look at since this is relevant for our empirical strategy. The increase in the fraction of applicants coming from voucher school reflects the growing presence this type of school has had in the Chilean school market. While not presented here, other summary statistics of the distribution are also relatively constant over the period.

Programs also greatly differ. The concentration of applicants in Santiago is similar with around 35 percent of slots are available in Santiago-based universities. Almost a quarter of slots are offered in Catholic universities, while 59 of them are in publicly-owned entities (the rest of the spots are offered in non-Catholic privately owned universities). Only 13 percent of all slots gave weight to the science exam and 4 percent to the history exam only. Finally, the average program had 47 percent of their selected students in 2001 being male and 34 percent from municipal schools, but with a very high variance between programs. Once more, we do not see a lot of difference between years in terms of program characteristics, suggesting that the differences we will identify will not stem from a change in program offering by universities.

Finally, Table 2 shows the overall application behavior of students over the 2002-2004 period. Here we can appreciate an increase in the number of applications (and applicants) over this period, part of a slow secular trend. The second panel, however, also shows that the number of slots did not increase in the same fraction, even shrinking between 2003 and 2004.

We can also see from that table that the change in policy of UCH appears to have substantially altered the pattern of applications across different universities between 2002 and 2003. While in 2002, one sixth of all applications to UCH were ranked below the top 4, this number fell to less than 10 percent in 2003. This was only partially compensated by an increase in the number of applications in ranks 4 or higher. This is a relevant margin since in 2002, a bit less than 5 percent of the admitted students had applied in rank 5-8. This fell to 0 in 2003. It can also be seen that PUC, which already had a POP rule in 2002, has a very small fraction of its applications in ranks 4 or below, suggesting that this rule had already been interiorized. We also see little change between 2002 to 2003. Finally, the rest of the universities see an increase in the number of applications because they are in expansion at that point but this is particularly marked at ranks below 4, suggesting that they may have been substituted for UCH in higher positions.

Figure 3 presents the first suggestive evidence of the impact of UCH's policy on their own programs and those competing with them. Panel (a) represents the density distribution of ordinal preferences of programs over applications to programs of UCH ranked fifth in 2002 by quintile of their cut-off scores for 2002 and 2003. The fifth quintile represents the most exclusive programs and the first, the ones with the worse cut-off score in 2001. Panel (b) of that same figure plots this same distributions but for competitors. As expected, the distribution in Panel (a), if something, appears to move to the left, which would mean that programs from UCH started receiving applications from applicants they ranked more highly. This is particularly true for programs in the third and fourth quartile. Little change is observed in programs that are highly selective where we see even a slight decrease in the number of applicants in response to that change of policy. This is consistent with our model since applicants in that range are probably not as likely to be constrained by the policy since these programs are targeting a pool of candidates with better scores. Panel (b) then shows that the programs that were likely to compete with UCH started losing a substantial number of applicants and get worse applicants overall in position 3 or 4. While not shown here, this also translates into an overall less preferred pool of students in all ranks.

Despite this shock, we argue that students could with some relative accuracy predict whether they would be admitted into a given program. Figure 4, in the left-hand panel, shows the distribution of ranking of students applying to each program in 2002 and 2003, depending on the quintile of quality of the program, as defined previously. This figure suggests little difference in how programs ranked the candidates from which they received applications in 2002 and 2003. The two distributions are almost always superimposed. The right-hand panel contrasts the difference between 2003 and 2004. In that case, we see enormous differences between the two distributions, which increase as we go down in program quality. This suggests that the change in the exam format seriously undermined the capacity of students to predict where they would likely be admitted, unlike in previous years.

We also use Table 2 to explore what happened between 2003 and 2004 with the change in the entrance exam. We first notice a significant increase in the average number of applications per applicant as seen from the fall in the number of applications in rank 1-3 in column (3) but the large increase in the number of applications at higher ranks. At the same time as the list of applications increase their length, the probability of being selected in a higher rank increased. This suggests, in itself, that not only did applicants increase the number of lower ranked alternatives they would put out of fear of not finding a program but they also altered the ranking of their preferred options. What we can observe from columns (6) and (9) is that the two universities who impose POP are the ones who saw the largest proportional increase in the number of applicants in 2004. The number of applications to other universities in ranks 1-3 fell suggesting crowd out from the ones that imposed the top 4 rule. However, all programs were able to recruit more students who had ranked them in position 1-3.

5 Results

5.1 Impact on applications

We then move to estimating the impact on the applications to each program, using regression equation (5). Given the large size of the database, we present results with 75 percent of the full sample but similar results were obtained when using 50 percent, which leads us to believe that outliers are unlikely to alter this pattern.

We present our main results graphically given the large number of parameters we estimate. Figure 5 reports the parameters βs of equation (5). These results are consistent with the model predictions. We find that for those with a score below the cut-off, we observe a significant fall in applications. These are students whose applications are likely to be to a type p_1 program where the main impact of the policy is a reduction in the number of applications. We then observe, as predicted by our model, a strong increase in the probability of applying to a program from UCH in 2003 for applicants right at or above the cut-off. This is because these are exactly the students who face the highest pay-offs to strategizing by misreporting their preferences. This appears to play a role until we look at students who are 40 points above the cut-offs where the change in application probability returns to 0. For those above 60 points, we also see a large increase in the probability of applying but with much larger standard errors. This matches the pattern shown in Figure 1. While not reported, the ϕs are much smaller and in general following a different pattern. We will return to these below.

Next, our model suggests that the impact of the policy would differ depending on whether the program is p_2 or p_1. Using the definition we previously presented, we divide the UCH programs in two categories. We present the two sets of βs in Figure 6. We find that the pattern we showed above is mostly driven by p_2-type of programs with a strong jump around the cut-off of the program in 2002. The increase in probability for programs that were more likely to be safety options appear to fall around those who were ranked 30 points above the cut-off. While our model predicts we should see no students on the left-side of the cut-off for programs that are p_2, reality is a bit more flexible since no program is p_2 for all students, but we still observe a very muted fall in applications in that case. On the other hand, programs that were more likely to be favorite appear to suffer mostly a decrease in the probability of application for almost the full range of values. We do not observe a discontinuity at the cut-off for those programs although there seems to be some noisy pattern of increased applications amongst students who were well above the cut-off. Overall, we find that this gives credential to our claim that the pattern we document is likely to be driven by students ranking their safety option above their preferred one when faced with the POP policy.

Finally, we come to our last prediction, namely that the change in applications should come out of programs that were, in the past, competing with UCH. Figure 7, we show that not only is the fall in applications much more marked for programs that competed with UCH in the past but that this fall is concentrated in the range of test scores exactly predicted by the model, namely individuals who were just below the cut-off. There also seems to be a small increase in the probability of applying above the cut-off but much smaller in magnitude than for UCH.

5.2 Impact of increasing risk

We then turn to estimating our equation (6) for the increased uncertainty faced by students in 2004. We present the coefficients of βs in Figure 8. As predicted by our model, we find a $V-$like pattern around the cut-off value. Individuals with 40 points below the cut-off appear to increase their probability of applying to a POP program compared to 2003. This is because they correspond to students who are likely to consider these programs p_1 and who reduce their probability of applying to the program less when faced with more uncertainty than with less. We then find that our coefficients shrink and get very close to 0 around the 2002 cut-off. Finally, we then observe a subsequent increase in the probability of applying in 2004 compared to 2003 starting around those ranked 20 points above the cut-off, as predicted by our model. These represent the response of students who, faced with more uncertainty, apply more strongly to their safety option than before. We do not find a range of scores for which there is a statistically significant fall in the probability of applying, as would have been predicted by our model. This may be because of the noise introduced by rounding our scores in bins.

We then contrast the response of individuals who applied to a program p_2 and p_1 in Figure 9. We find, once more, that the aggregate results appear to be driven mostly by POP programs that are more p_2 than p_1. When we restrict our attention only to p_2 programs, we do observe a significant fall in the probability of applying, and just above the cut-off as predicted by our model. However, we do see an increase for those ranked below the cut-off for programs p_2, which did not exist in our model since no applicant were ever ranked below the cut-off of p_2. This suggests that in reality, our classification of p_2 versus p_1 types may be noisy, which is why for students who are below the cut-off of p_2, we observe a behavior more consistent with a p_1 type of program. For those more attractive programs, we observe that students are simply more likely to apply to a POP program in 2004 than in 2003. We are not observing, as the model predicts, the fall in applications for individuals substantially above the cut-off but this may be because of our classification of programs. Overall, we consider this relatively strong evidence in favor of our model since the non-linear pattern we document would be more difficult to explain through alternative mechanisms.

Finally, we look at the response of programs that are competing or not with a POP program. As can be seen in Figure 10, programs who competed with POP program saw much larger fall in the applications than those who were not in 2004 compared to 2003. More interestingly, this effect is concentrated amongst applicants close to the 2002 cut-off. This is consistent with our hypothesis that individuals who were marginal in non-POP programs responded to the added uncertainty by applying more strongly to POP programs in 2004. However, we see a return to an increase in the probability of applying for students well above the cut-off something our model cannot fully explain.

All these results require that our assumptions regarding the change between 2002 and 2004 be entirely driven by the policy we study. While we only have information starting in 2001, which makes testing for pre-trends a bit challenging, we also have a limited number of individuals who enter the selection process in two consecutive years. The assumption that for them, the only thing that changed between the two years is the policy is more likely to hold. As we show in Appendix Figures A1 to A6, our results are almost identical when using this set of "clones".

Another concern may be that our estimates are corrupted by the fact that some individuals make irrelevant ranking decisions in rank 3-4. If individuals are certain to be picked by programs they placed in rank 1-2, they may simply "play" around by adding irrelevant options below. To exclude that as a concern, we drop from our sample individuals that were at least 60 points above the 2002 cut-off of the programs they ranked in rank 1 and 2. We show these results in Appendix Figures A7 to A12. We find our results almost unaffected by this change, suggesting that this is not a very relevant concern.

5.3 Welfare costs

Having shown that this policy altered the application behavior of some individuals, we now turn to evaluating whether there is any evidence that eventual outcomes and the welfare of participants were affected. After all, individuals could alter the ranking of their preferences in ranges that were irrelevant and led to no change in the final outcome of participants.

We first start by evaluating whether there were changes in the probability of being selected into a program between 2002 and 2003. Our model predicts that this should change and differ by the relative position of the student compared to the program in which she is accepted. We thus repeat our estimation equation 5 but this time using as our outcome variable whether the individual was selected into the program. We continue to restrict our analysis to those in rank 3-4 since this is where we would see the change in application behavior. Figure 11 shows exactly the pattern we had predicted theoretically. There is an increase in the probability that an individual is admitted to a program for those significantly above the cut-off and for those right below it. At the same time, we observe a strong decrease in the probability of being selected by UCH when one is very close to the cut-off.

We repeat the same exercise but for the change between 2003 and 2004. We present, in Figure 12, the coefficients β of estimating equation 6 where the outcome variable is now being selected. We find that the general pattern is as we expected but for those well above the cut-off, we do not find a significant positive increase in the probability of being admitted. The point estimates, while clearly larger than those for individuals close to the cut-off, are negative. This may be because the increased uncertainty led to a overall fall in the probability of being selected in rank 3 or 4. On the other hand, we clearly observe a large and significant increase in the probability of being selected when one's test score was below the previous cut-off, as predicted by our model. This also seems to indicate a shift in the distribution of the scores such that a more significant fraction of applicants had scores below previous year's cut-offs.

However, our model not only supposes that who is selected where may be altered but it also argues that there will be an increased degree of mismatch in the system. After all, POP makes individuals misrepresent their preferences, implying that the outcome may no longer be "stable". We first look at this by measuring the likelihood that someone who was selected into a program in a given year re-enters the matching process in the following year. This is a costly decision since the applicant must re-take the entrance exam. We use a difference-in-difference approach, contrasting the change in the fraction of applications who choose to re-enter the matching process conditional on having being selected by a UCH or a POP program, respectively, in the year before and after the reform. We estimate this by test score range and present the results graphically.[14] In Figure 13, we observe that at all ranges of scores, we find that there were less test re-takers in 2004 than 2003. This is likely to be due to the fact that the new entrance exam in 2004 increased the cost of re-entering the process. However, we observe interesting differences by the type of program in which one was admitted and by scores. We find that the probability of re-entering the process increased much more between 2002 and 2003 for those who were admitted to UCH than those admitted to other programs. This is particularly the case for individuals who are in the lower tail of the score distribution. This suggests that students who were admitted to UCH in 2003 were less happy with their outcome than those selected in 2002, particularly if their test score was below average. This is exactly what we would expect since students selected into UCH in 2003 are more likely to have altered their preference ranking, applying to a program where they were more sure to enter but potentially one that was less preferred.

We repeat the same exercise in Figure 14 this time for the change in the entrance exam in 2004. Once more, we find a pattern suggestive of higher mismatches. We see that amongst those who were admitted to a POP program, there was a larger increase in the rate of test retaking from 2005 compared to 2004 for those with scores between 650 and 800. For those at the extreme of the test score distribution, we find no or opposite patterns. This suggests that students who played their safety option in 2004 and were selected in a POP program ended up more likely to be dissatisfied with their selection than when there was less uncertainty in the system and thus fewer students had not revealed their actual preferences.

Finally, we try to formalize our measure of welfare costs. To do so, we must measure preferences without distortions. To accomplish that, we use the declared preferences of applicants in 2002. It is

[14] Since POP programs admit only students who score more than 600 points on the entrance exam, we focus only on these individuals.

untrue that this would correspond to a world without distortions since PUC had already imposed POP on its applications by then but it is the period in our data set where we observe the fewest distortions possible. We thus, for that year, use the application data and run a oprobit model where we assign a rank of 9 to any unselected options. We use all available program and individual characteristics as covariates in our regressions. However, the ones where we obtain the most explanatory power are interactions between characteristics of the applicants and of the program: geographic proximity, gender of the applicant and past gender mix of the program, school financing of the applicant and school mix of the program, difference between applicants' test score and program past cut-off, etc. Since one may be worried that the limited number of slots available to applicants may lead them to distort their preference in their ranking, we exclude all programs where an individual has a score 60 points below the 2002 cut-off. These programs would be unlikely to be part of the choice set of the individual given how unlikely one's admission would be. We find that the exclusion of these programs alter the results of the preference estimation but not very dramatically so. The exact model estimation is included in Appendix Table A1.

With this estimation in hand, we compute, for each applicant, the predicted rank of the program to which he or she is admitted. We then compare the average predicted rank of a group in a given year to that of a different year as a measure of welfare. Now, one must take into account that our predicted rank measure is such that moving from one's favorite option to one's 4th listed program increases the predicted rank in 0.09. Moving from one's favorite option to one's 8th ranked program generates an increase in the predicted rank of 0.15. Finally, moving from one's favorite option to one that was not listed increases the predicted rank in 0.28, showing that not ranking a program generates a substantial difference in the way that programs are valued. We will compare our change in predicted ranking as a result of the policies to these values.

We present the results of UCH policy change in Table 3. We focus on applicants who are selected within the rank 3-6 since those are likely to be impacted by the policy. We show the impact on those selected into a UCH program in the first two columns and then those selected to other programs in the last two. The odd columns include all those who were admitted in ranks 3-6 while the even columns restrict the sample to those who were selected in ranks 3-4. Our first panel shows that overall, the policy from UCH appear to have lowered the welfare of those selected in the Chilean university system, particularly for those selected into UCH. The comparison between the first two columns suggests that those who were previously selected in ranks 5-6 in 2002 were particularly penalized by the change in UCH policy since the fall in welfare is much larger for those who had previously been selected in rank 5-6 who now need to apply in ranks 3-4, which is exactly what is our model predicts. The magnitudes depend on the specification. For UCH in ranks 3-6, they correspond to going from one's favorite option to one's 3rd listed program. For non-UCH programs, this is much smaller.

We then, in Panel B, contrast the impact of the policy for students depending on their relative test score. We must specify that the overall effect is mostly stemming from changes between relative test score bins than within. That is that to explain the overall effect we documented in Panel A, one must particularly understand how the relative score of accepted applicants changed between 2002 and 2003. Nevertheless, there are still changes within bins that are worth exploring. In Panel B, we observe a very interesting pattern, matching our theoretical predictions. We find that for UCH, only those who were admitted well above the cut-off suffered large welfare losses, particularly when we restrict to those admitted in ranks 3-4. We also see some welfare gains for those really close to the cut-off, particularly for those below. For non-UCH, we should see no "strategization loss" since nobody would invert their ranking to go into those programs. So we should only see "strategization gain" and "mechanical loss". We see evidence of gains although in some cases, amongst applicants who are "too good" compared to what our theory would suggest. Nevertheless, on average, the magnitudes are small suggesting that most effects were concentrated in those who were admitted to UCH.

In Panel C and D, we look at other types of characteristics that we are not part of our model but that may be highly relevant in terms of understanding the distributive impacts of the policy. In Panel C, we observe that our welfare loss for those who were admitted to UCH are concentrated amongst students of private high schools which are those who wish to "play it safe" while students from subsidized voucher and municipal schools face much smaller losses, maybe because their scores had previously prevented them from accessing the programs of their choice. A similar story can be observed in Panel D when we divide the sample by whether they are from the same region as the institution as the university. We find that the biggest welfare losses were born by those from the same region, who may have been particularly keen on entering UCH, at the cost of going to a lower-ranked program. Patterns are flipped for those admitted to a non-UCH program.

We then compute the same estimates this time for the 2004 policy experiment. This time, we only include those selected in ranks 3-4 for POP programs since starting in 2003, there are almost no accepted students below rank 4. Our model would suggest that POP policies would generate much more losses to students when there is added uncertainty. We find that the results presented in Table 4 indicate much larger welfare losses than previously, although particularly for non-POP programs. The average losses are equivalent to being assigned to a program that has a predicted ranking 0.04 point higher, which is like passing from a program ranked 1st to a program ranked 3rd.

In panel B, we separate the effects by students' relative score. For POP, we find that the only students who benefited from the added uncertainty are exactly those predicted by our model to be better off, namely students who had scores below the initial cut-offs and were thus likely to get in with the added uncertainty. For non-POP programs, we see much of a less clear pattern than what we had observed in the previous experiment. Applicants all across the relative score range appear to suffer welfare losses. Those who suffer more are closer to the cut-off which is consistent with our model but the results overall appear to suggest that the incapacity of predicting expected cut-offs generated large welfare losses for almost all those selected in programs in ranks 3-6.

In the next panel, we estimate the impact on welfare by school type. We find that the largest aggregate impacts are for students who are from municipal and voucher schools, particularly when looking at those who were selected in a POP program. This may be because these are the students who would have been most risk-averse and most likely to apply to programs that they preferred less but were safer options.

Finally, the last panel separates the welfare loss by geographical location. We once again find that students from the same region as the institution are suffering the most. Students from the Metropolitan Region may again have been less willing to not be admitted into one of the POP university, leading them to play more their safety option, reducing their welfare.

6 Conclusions

This paper has thus been able to show that when participants in a Gale-Shapley matching process imposes "preferences-on-preferences", the other side of the market responds by altering their ordering of preferences, as predicted by our theoretical model. We see that this is particularly the case for students who had more to gain by altering their preferences. We also show that this has real consequences as it alters not only the presentation of preferences but also the matching process. This contrasts with some existing school-choice papers that argue that alternatives to the DA mechanism may increase welfare. This may be because there are many more choices in this setting but also because there are no ties that are broken through lotteries.

Furthermore, this paper also exploits a policy change that increased the amount of uncertainty faced by the applicants and showed that the strategization increased in response to that policy and that it generates stronger welfare losses. This suggests that while POP may have limited impacts in steady-state situations, they may generate more substantial costs when the applicants face a system that is changing. This appears to be the first paper to empirically study the role of uncertainty in the impact that variants of the DA mechanism may have on outcomes.

We see this result as very important when thinking about optimal design of matching policies. This suggests that some of the desirable properties of centralized matching through deferred acceptance mechanism may be lost when some small changes to the canonical model disappear. More work on this may be warranted, given that many school systems in the world are switching to deferred acceptance mechanisms for the application systems.

A key question that is not addressed by our study also concerns the reason why some participants in this matching process would elect to use a POP system. Our results highlight that they are able, through that mechanism, to alter the preference ranking of some applicants and through that, may be able to attract better, albeit fewer, students. We leave the development of that argument to future research.

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7 Figures and Tables

Table 1. Summary statistics

	(1) 2002	(2) 2003	(3) 2004
Student Characteristics			
Single	0.985	0.987	0.991
Females	0.490	0.492	0.513
Finished high school<=3 yrs before PAA	0.870	0.868	0.903
Worked in high school	0.066	0.073	0.061
Family size	4.631	4.627	4.633
N of family mbrs that work	1.340	1.339	1.332
N of family mbrs in elem/high school	1.541	1.561	1.619
N of family mbrs in tertiary education	0.535	0.527	0.535
N of family mbrs in other education	0.078	0.072	0.073
Both parents live	0.917	0.918	0.899
Only mother lives	0.011	0.012	0.013
Only father lives	0.062	0.063	0.080
Father has less than HSD	0.236	0.237	0.234
Father has HSD	0.263	0.270	0.261
Father has non-universitary tertiary	0.081	0.084	0.110
Father has some college or more	0.317	0.312	0.301
Mother has less than HSD	0.296	0.293	0.284
Mother has HSD	0.316	0.321	0.312
Mother has non-universitary tertiary	0.098	0.105	0.135
Mother has some college or more	0.255	0.249	0.244
Living in RM	0.366	0.364	0.350
Living in the 8th Region	0.141	0.139	0.141
Living in the 5th Region	0.133	0.137	0.131
High school characteristics			
Preparatory high schools	0.792	0.794	0.806
Does not have	0.001	0.000	0.000
Private	0.227	0.206	0.189
Voucher	0.369	0.391	0.412
Municipal	0.398	0.397	0.393
Other program characteristics			
Avg. % of females	0.465	0.468	0.473
Avg. % of municipal	0.340	0.340	0.340
Avg. cut score	610.205	610.793	610.858
% of total vacancies in a:			
University in the RM	0.365	0.356	0.327
Catholic university	0.240	0.234	0.229
Public university	0.587	0.593	0.592
Private non-catholic university	0.173	0.173	0.179

Table 2. Number of Applications and Applicants

Rank	All 2002	All 2003	All 2004	UCH 2002	UCH 2003	UCH 2004	PUC 2002	PUC 2003	PUC 2004	Other 2002	Other 2003	Other 2004
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Number of Applications												
1-8	346833	360039	362518	29958	29196	30056	17284	17931	18643	299591	312912	313819
1-3	210739	218724	206582	20213	21302	20911	14317	15056	15557	176209	182366	170114
4	50086	52700	53225	4494	5255	6034	1213	1205	1256	44379	46240	45935
5-8	86008	88615	102711	5251	2639	3111	1754	1670	1830	79003	84306	97770
Panel B: Number of Selected Applications												
1-8	52012	54081	52440	4279	4258	4201	3599	3691	3707	44134	46132	44532
1-3	43935	46624	46305	3781	3926	3926	3597	3687	3707	36557	39011	38672
4	3595	3500	2672	288	332	275	1	2	0	3306	3166	2397
5-8	4482	3957	3463	210	0	0	1	2	0	4271	3955	3463

Table 3. Change in predicted ranking of selected program 2002-2003.

Rank:	(1) UCH 3-6	(2) UCH 3-4	(3) NON-UCH 3-6	(4) NON-UCH 3-4
Panel A: Overall				
	0.043	0.073	0.000	0.003
Panel B: By Distance to Cut-Off Score				
60-50 above	0.086	0.133	0.004	0.001
50-40 above	0.105	0.133	-0.004	-0.013
40-30 above	0.110	0.161	0.008	-0.001
30-20 above	0.008	0.019	-0.004	-0.000
20-10 above	-0.038	-0.015	-0.033	-0.032
10-0 above	-0.092	-0.058	-0.008	0.000
0-10 below	0.092	0.151	0.026	0.015
10-20 below	-0.148	-0.148	0.042	0.050
20-30 below	.	.	-0.018	-0.024
30-40 below	.	.	0.391	0.419
40-50 below	.	.	-0.475	-0.505
Panel C: By School Type				
Private	0.056	0.095	-0.013	-0.023
Voucher	0.001	0.005	-0.001	0.009
Municipal	0.019	0.036	0.008	0.011
Panel C: By Location relative to University				
Same Region	0.053	0.080	-0.013	-0.009
Other Region	0.003	0.020	-0.004	-0.004

Table 4. Change in predicted ranking of selected program 2003-2004.

	(1)	(2)	(3)
	POP	NON-POP	NON-POP
Rank:	3-4	3-6	3-4
	Panel A: Overall		
	0.041	0.043	0.044
	Panel B: By Distance to Cut-Off Score		
>60 above	0.263	0.023	0.036
60-50 above	0.013	0.037	0.037
50-40 above	0.027	0.030	0.022
40-30 above	-0.007	0.032	0.033
30-20 above	0.115	0.057	0.051
20-10 above	0.065	0.075	0.066
10-0 above	0.114	0.038	0.039
0-10 below	-0.084	0.074	0.061
10-20 below	-0.005	0.131	0.134
20-30 below	.	0.212	0.198
30-40 below	.	0.158	0.191
40-50 below	.	0.176	0.189
50-60 below	-0.121	0.069	0.077
	Panel C: By School Type		
Private	0.027	0.031	0.041
Voucher	0.037	0.058	0.055
Municipal	0.063	0.033	0.032
	Panel C: By Location relative to University		
Same Region	0.043	0.062	0.062
Other Region	-0.010	0.018	0.020

Figure 1. Change in x(s) when u2 imposes the restriction

(a) By type of Program **(b)** By type of Program, re-centered **(c)** Aggregated

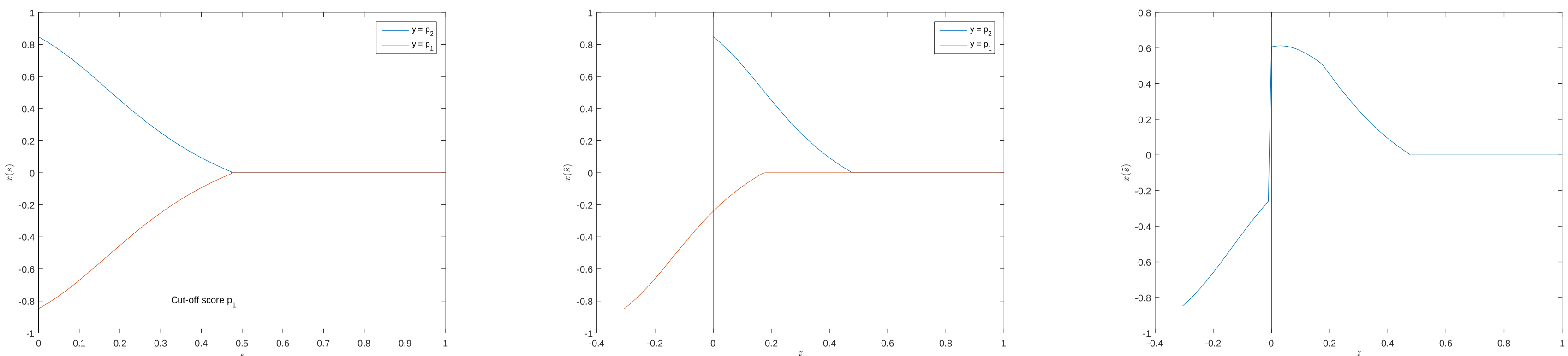
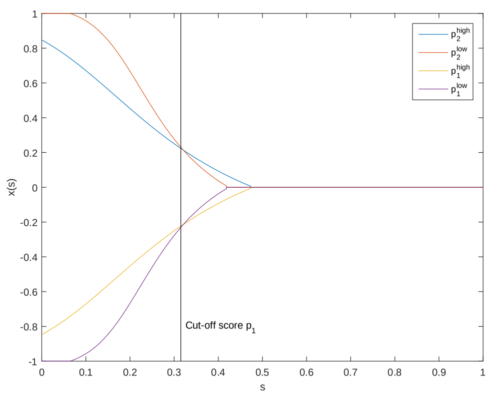
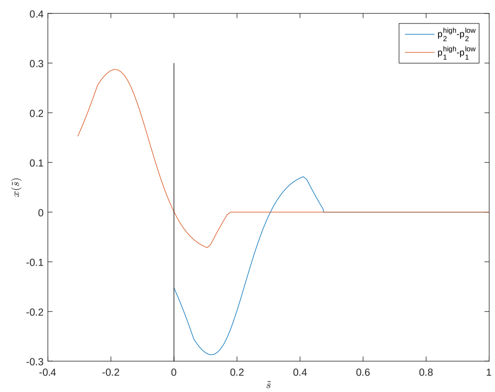


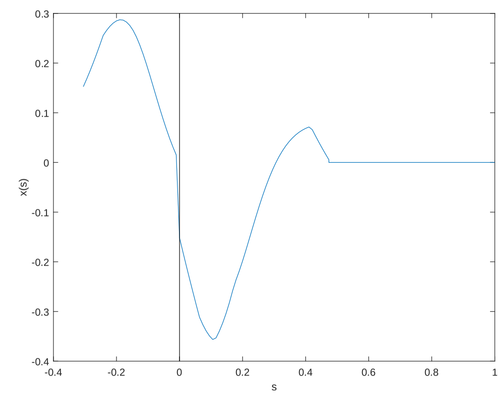
Figure 2. Change in x(s) when uncertainty increases



(a) By type of Program



(b) By type of Program, re-centered



(c) Aggregated

Figure 3. Graphical depiction of impact of UCH policy

(a) UCH programs ranked 5 in 2002 **(b)** Related programs ranked 3 or 4

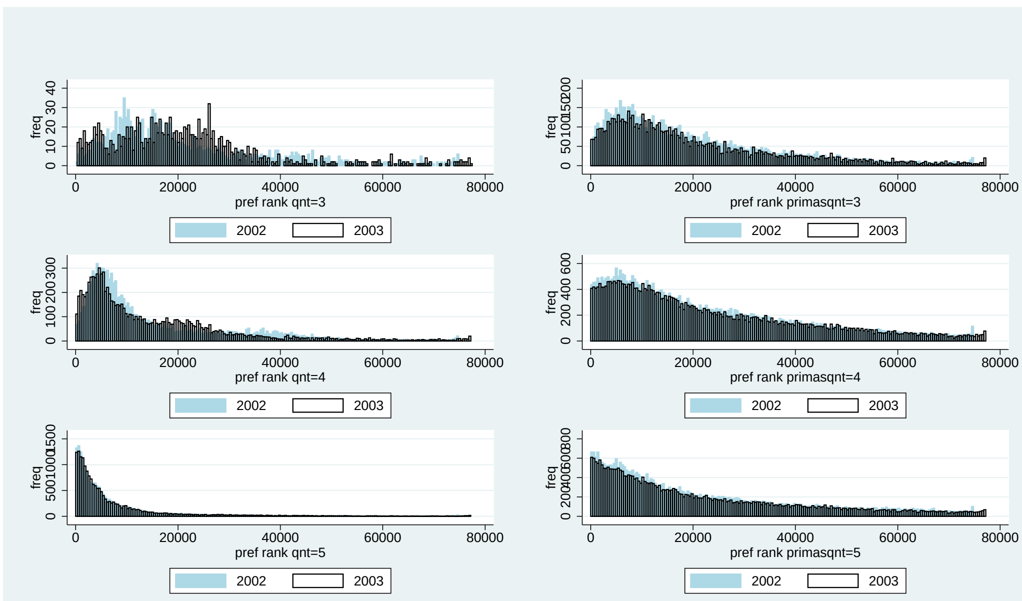


Figure 4. Change in applications' predictability

(a) 2002/2003 **(b)** 2003/2004

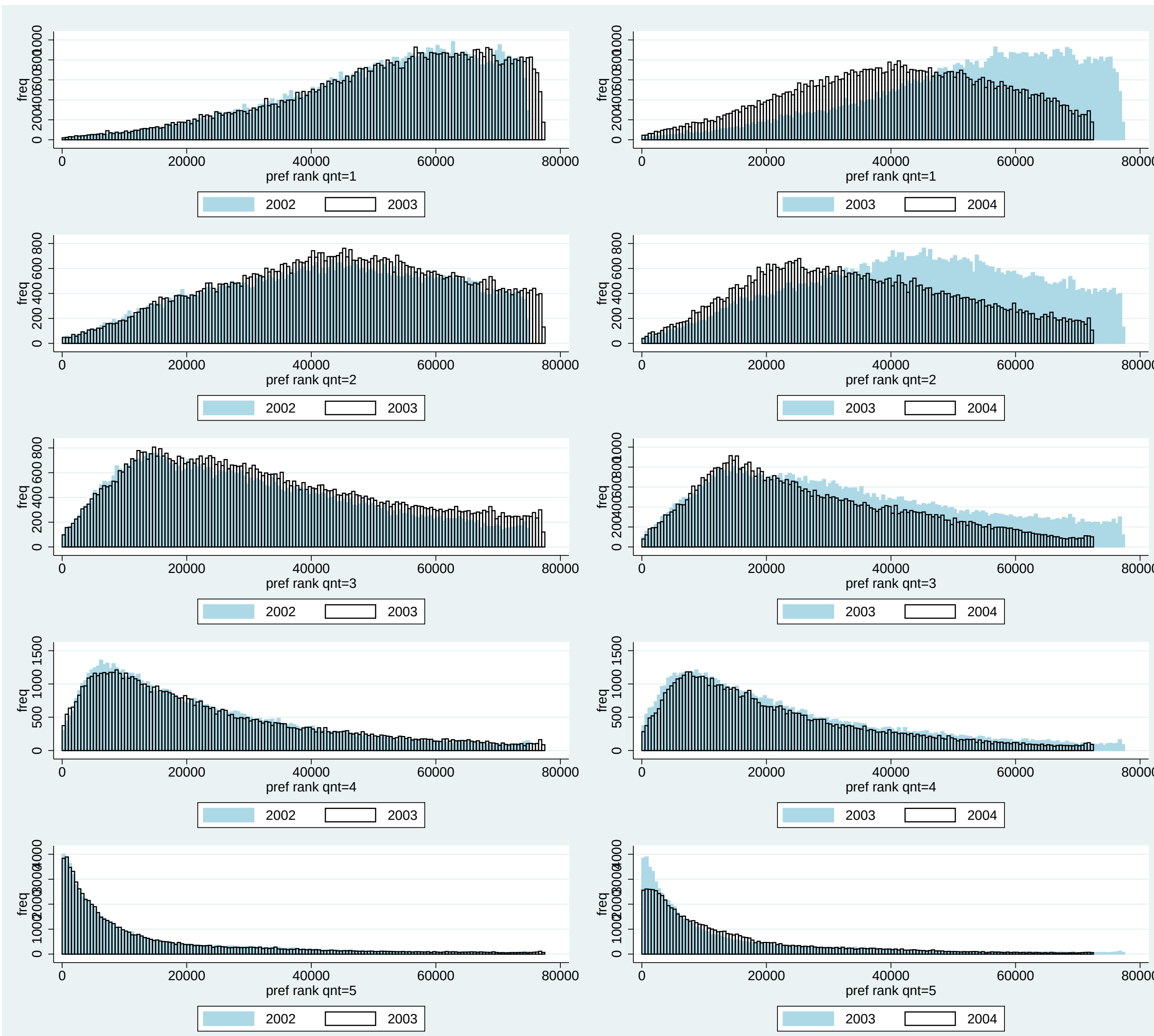


Figure 5. Impact on the probability of applying in rank 3-4, by relative position of student, 2002-2003

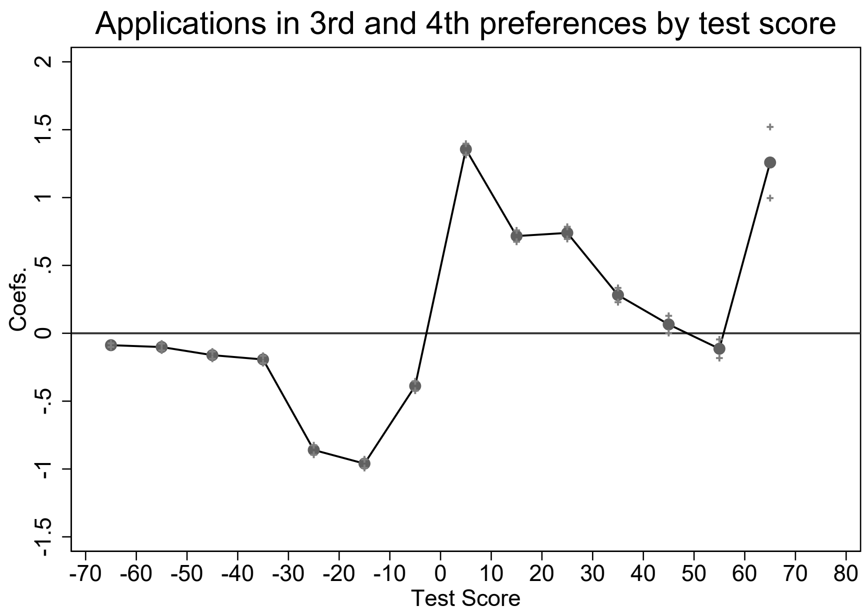


Figure 6. Impact on the probability of applying in rank 3-4, by relative position of student, depending on type of program, 2002-2003

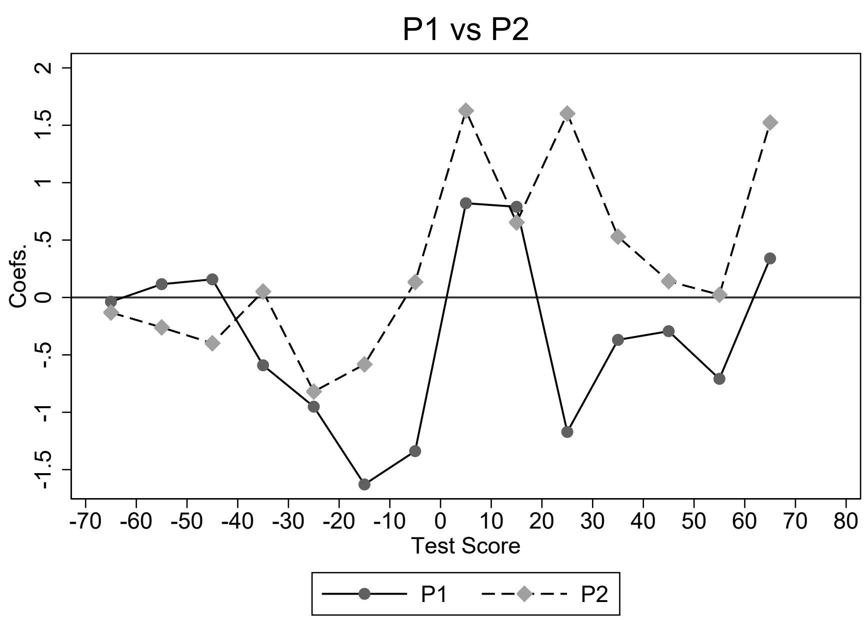


Figure 7. Impact on the probability of applying in rank 3-4, by relative position of student, depending on whether they competed with UCH, 2002-2003

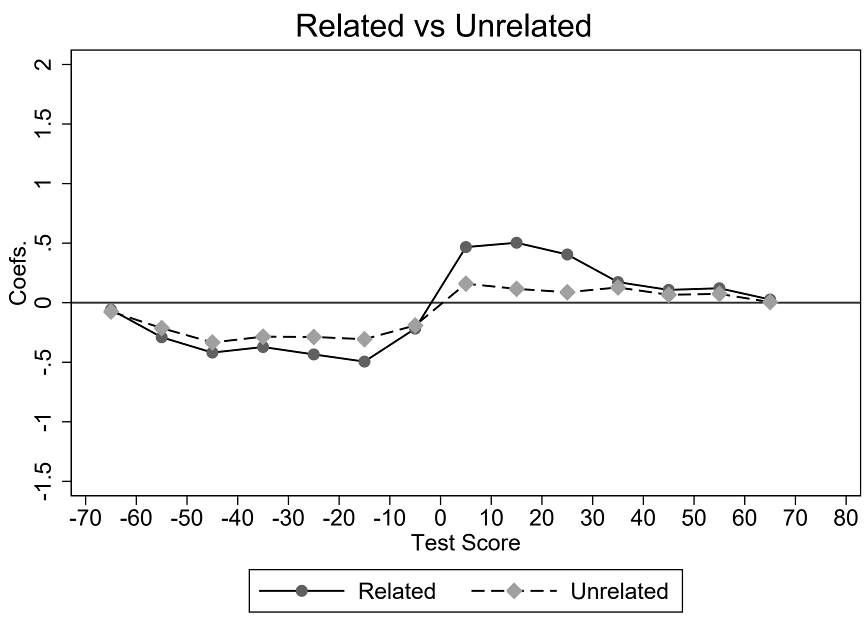


Figure 8. Impact on the probability of applying in rank 3-4, by relative position of student, 2003-2004

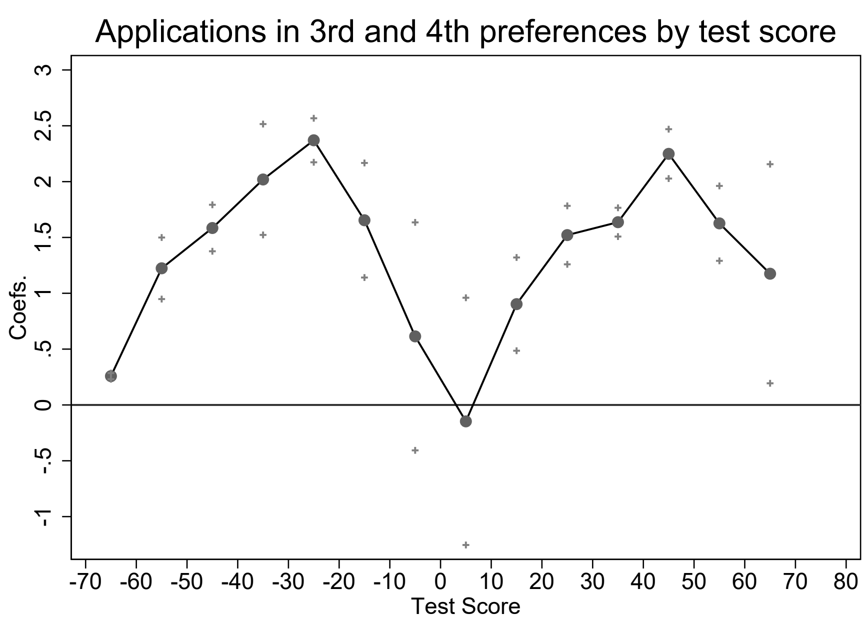


Figure 9. Impact on the probability of applying in rank 3-4, by relative position of student, depending on type of program, 2003-2004

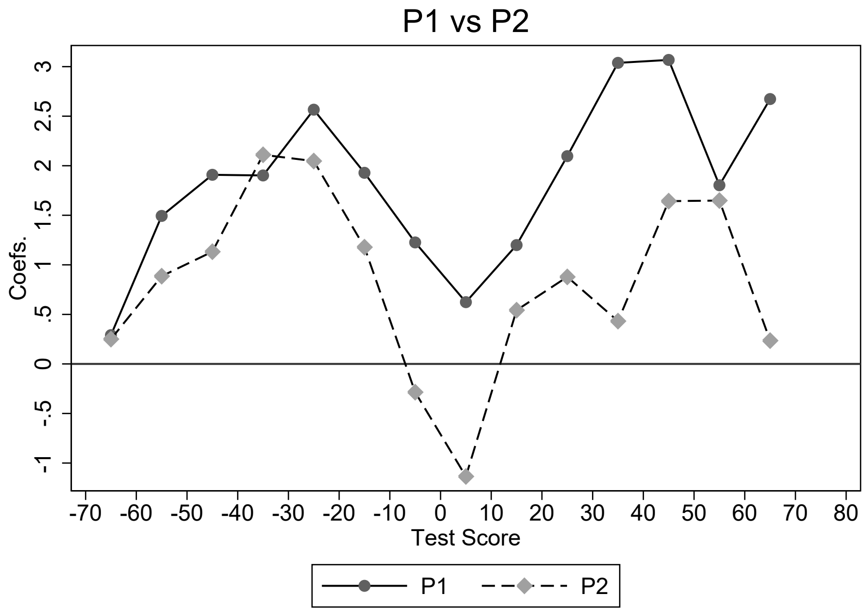


Figure 10. Impact on the probability of applying in rank 3-4, by relative position of student, depending on whether they competed with UCH, 2003-2004

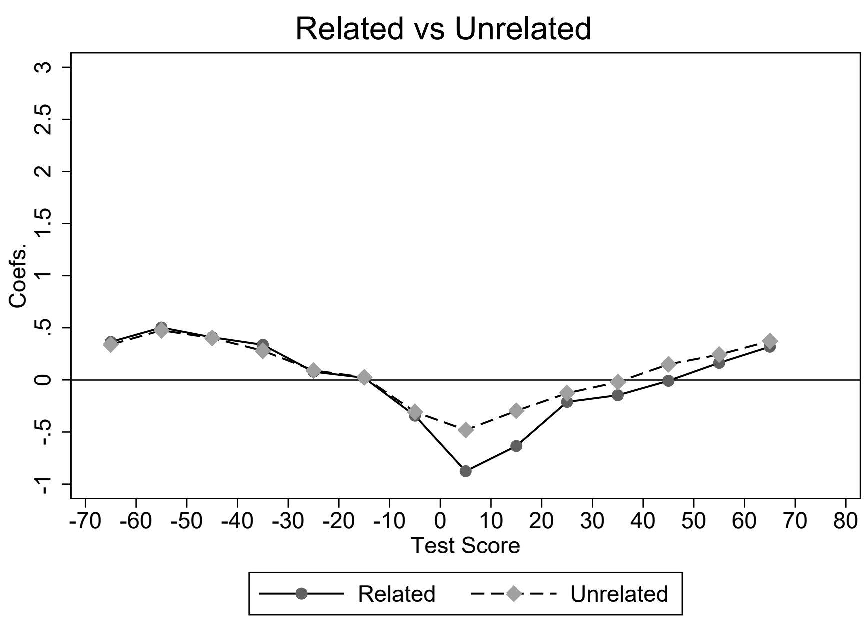


Figure 11. Impact on the probability of being selected in rank 3-4, by relative position of student, 2002-2003

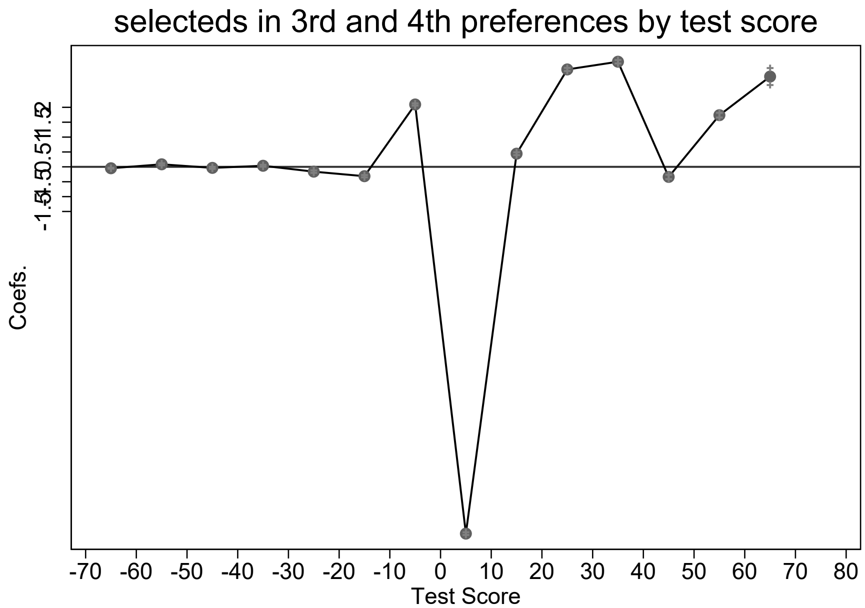


Figure 12. Impact on the probability of being selected in rank 3-4, by relative position of student, 2003-2004

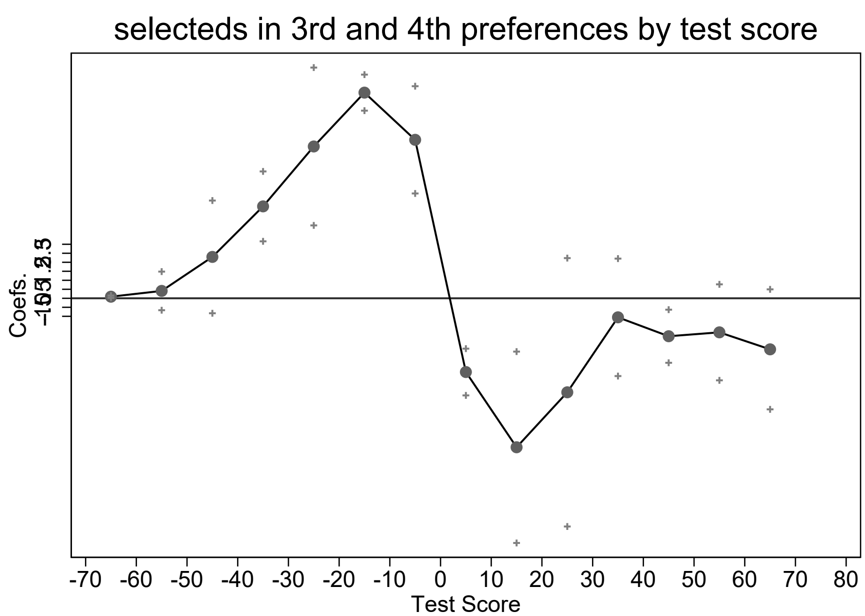


Figure 13. 2002/2003 difference in % of repeated tests by admitted program

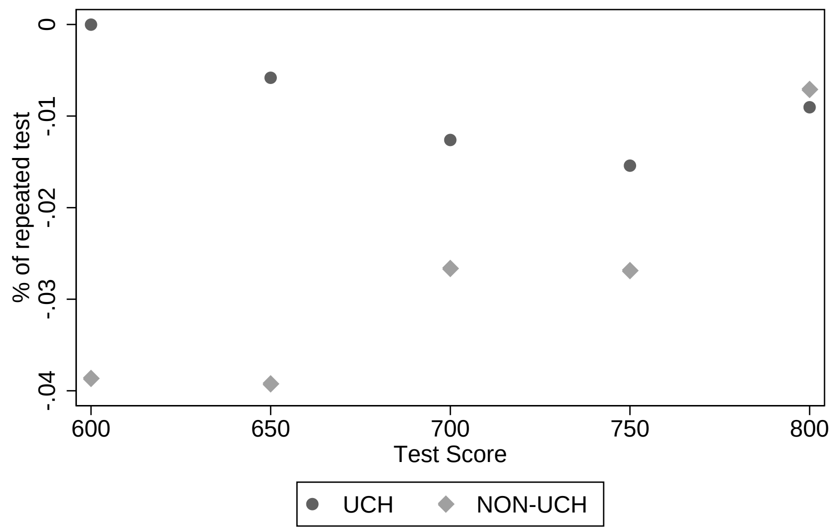
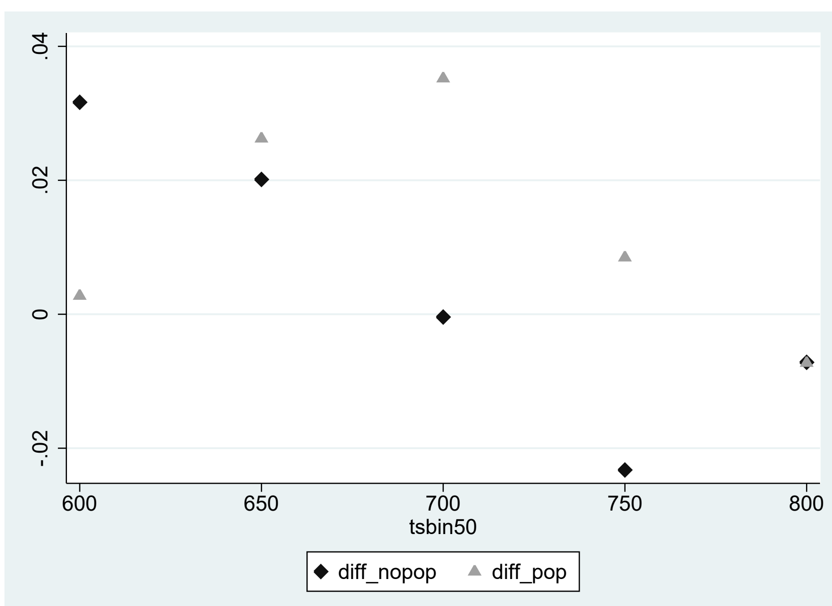


Figure 14. 2003/2004 difference in % of repeated tests by admitted program



A Appendix

A.1 Proposition 4

As we know that near $\hat{s}_2$ strategization is stronger with high uncertainty, but that eventually strategization has to be stronger with low uncertainty, we want to have a sense of where this happens. We will explore this using $\hat{s}$ as a reference point because is a known element in both the model and the empirical setup and, thus, it is going to be helpful in mapping the two. The first thing to remember about $\hat{s}$ is that it is the cut-off score of p_1 in the benchmark without POP when $\alpha = \bar{\alpha}$.

To understand the relationship between $\hat{s}$ and s^*, first note that for every s there is going to be an associated critical α upto which that s is going to be left out of p_1.[15] Now imagine a naive world in which students do not take into account the fact that other students may strategize. In this world, for a given student, (i) $\lambda(s)$ is going to depend only on the distribution of α (and not on whether better students strategized) and, thus, (ii) the critical α for that student is going to be the same with any level of uncertainty. Therefore, $x_h(s^*) = x_l(s^*)$ if and only if the cumulative distribution up to the critical α for s^* is the same in the high and in the low uncertainty scenarios. Since $\Lambda_h \geqslant_2 \Lambda_l$ and both are centred around $\bar{\alpha}$, this will happen in $\bar{\alpha}$. In other words, $\hat{s}$ (i.e. the student for which the critical α is $\bar{\alpha}$) is also the point where $x_h(s) = x_l(s)$ in the naive world.

Now lets move to a more sophisticated world (our current model) in which strategization of other students is taken into account. With any positive level of uncertainty, $x(\hat{s})$ will be lower than in the naive world, precisely because the students take into account that other students are going to strategize and leave more slots unoccupied in p_1. Given that near $\hat{s}_2$ the strategization is stronger with high uncertainty, there are going to be less applications to p_1 in this scenario and, thus, it has to be that $x_h(s) = x_l(s)$ before $\hat{s}$.[16] In other words, $x_l(s)$ is going to catch up faster with $x_h(s)$ in the sophisticated world, because students take into account that more slots are left unoccupied in the high uncertainty scenario.

A.2 Additional Tables and Figures

[15] That is, s is going to be left out of p_1 if the realization of α is bigger than the critical α.

[16] One can also think that, as the decrease in $x(s)$ is higher in the high uncertainty scenario (at least near $\hat{s}_2$), it cannot be that $x_h(\hat{s}) = x_l(\hat{s})$, and that, because of this, the equality has to occur before that point.

Table A1. Coefficients of preference estimation

	(1) Beta	(2) S.D.
Single	-0.0512368	0.0082208
Female	0.7065178	0.0044356
Graduation Year	-0.0430975	0.0028735
Work	-0.006604	0.0038332
Family Size =2	-0.0072879	0.005842
Family Size =3	-0.0031162	0.0047091
Family Size =4	0.0012007	0.0040184
Family Size =5	-0.0007585	0.0037151
Family Size =6	0.001229	0.0039222
Family members that work =0	0.0093032	0.0058131
Family members that work =1	0.0003066	0.0046783
Family members that work =2	0.0067307	0.0047071
Number of family members in school	0.0084594	0.001103
Number of family members in superior education	-0.0063692	0.0014098
Number of family members in other type of education	-0.0013527	0.0028658
Both Parents Live	0.011191	0.0114002
Only Mother Lives	-0.006646	0.0131258
Only Father Lives	0.014229	0.0117018
Both Parents are Dead	0.0094783	0.0206831
Father's education < Complete High School	0.0009215	0.0042382
Father's education = Complete High School	0.0109984	0.0041896
Father's education <= Technical Superior	0.006112	0.0048846
Father's education <= University	0.0095728	0.0042883
Father's education is Other	0.0134783	0.0062785
Mother's education < Complete High School	-0.0135867	0.008731
Mother's education = Complete High School	-0.0102323	0.0087219
Mother's education <= Technical Superior	-0.0115813	0.0090219
Mother's education <= University	-0.0111967	0.0088257
Mother's education is Other	-0.0053994	0.0105426
School type: Does not have	0.0553767	0.0272734
School type: Polytechnic	0.1390053	0.0156187
School type: Free students	0.2395283	0.0145228
School type: Scientific Humanist and Maritime	0.2174816	0.0143983
Private School	0.1704696	0.0070123
Voucher School	-0.0566073	0.0089641
Test Score: High School Grades	0.0017542	0.000017
Test Score: Math	0.0025997	0.0000244
Test Score: Spanish	0.0015663	0.000019
Test Score: Science	0.0003361	0.0000162
Test Score: History	0.0004396	0.0000134
History Test not rendered	0.1379092	0.0087508
% of Females in Program	0.7719395	0.0092112
% of students from voucher schools	-0.6495954	0.1906539
% of students from municipal schools	-0.7809558	0.1908123
% of students from private schools	-0.9623412	0.1908948
% of students from mixed-sex schools	-0.0051433	0.00199
Cut-off score in 2002	-0.0060199	0.0000908
Selection score	-0.0014911	0.0000972
Same Region	-0.9095165	0.0029626
Distance to HE headquarters	9.09E-07	1.06E-08
Distance to HE headquarters ^{2}	-4.19E-13	8.50E-15
Distance to HE headquarters ^{3}	6.98E-20	1.76E-21
Rendered all required Tests	-0.5175964	0.0092851
Female x Female Ratio in Program	-1.499333	0.0080382
Private School x Private School Ratio in Program	-1.094781	0.0118494
Voucher School x Voucher School Ratio in Program	-0.2886058	0.0159514
Municipal School x Municipal School Ratio in Program	-0.4085932	0.0120663
50-60 points below cut-off	0.2098087	0.0130822
40-50 points below cut-off	0.1019957	0.0122495
30-40 points below cut-off	0.0072454	0.0114364
20-30 points below cut-off	-0.0794812	0.0106361
10-20 points below cut-off	-0.1618727	0.0098497
0-10 points below cut-off	-0.2335492	0.0090822
0-10 points above cut-off	-0.2557486	0.0083694
10-20 points above cut-off	-0.228923	0.0077298
20-30 points above cut-off	-0.1913163	0.0071766
30-40 points above cut-off	-0.1503679	0.0067366
40-50 points above cut-off	-0.1128558	0.0064475
50-60 points above cut-off	-0.0699858	0.0063885
N	33847493	

Figure A1. Impact on the probability of applying in rank 3-4 for Clones, by relative position of student, 2002-2003

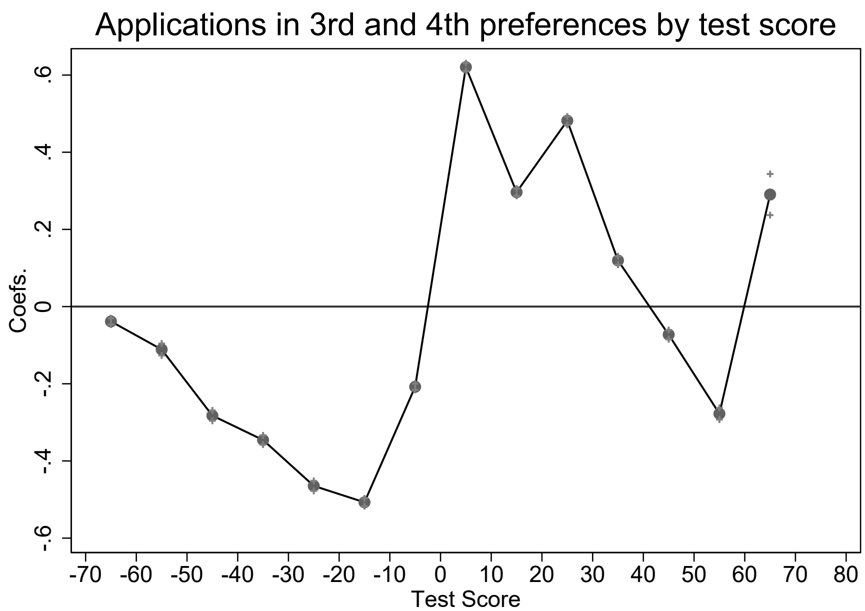


Figure A2. Impact on the probability of applying in rank 3-4 for Clones, by relative position of student, depending on type of program, 2002-2003

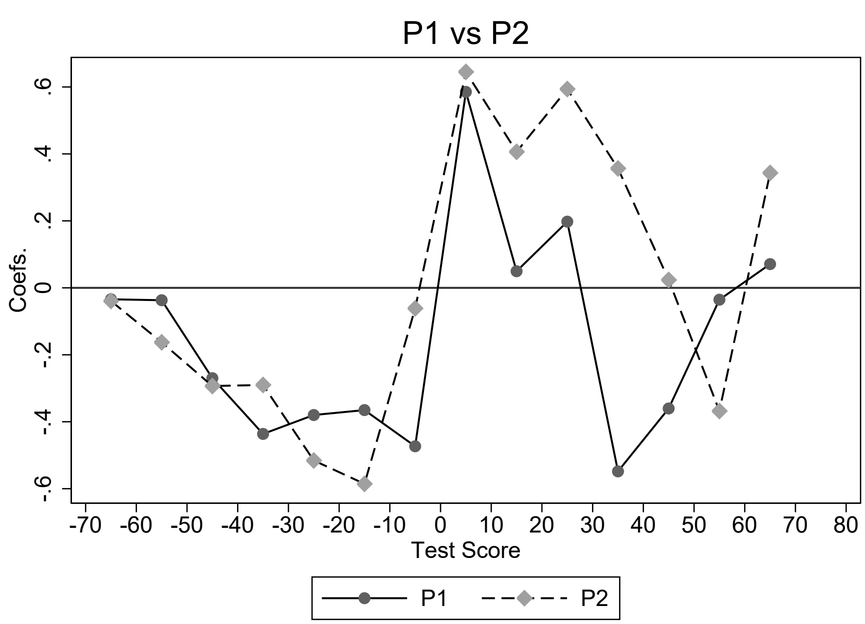


Figure A3. Impact on the probability of applying in rank 3-4 for Clones, by relative position of student, depending on whether they competed with UCH, 2002-2003

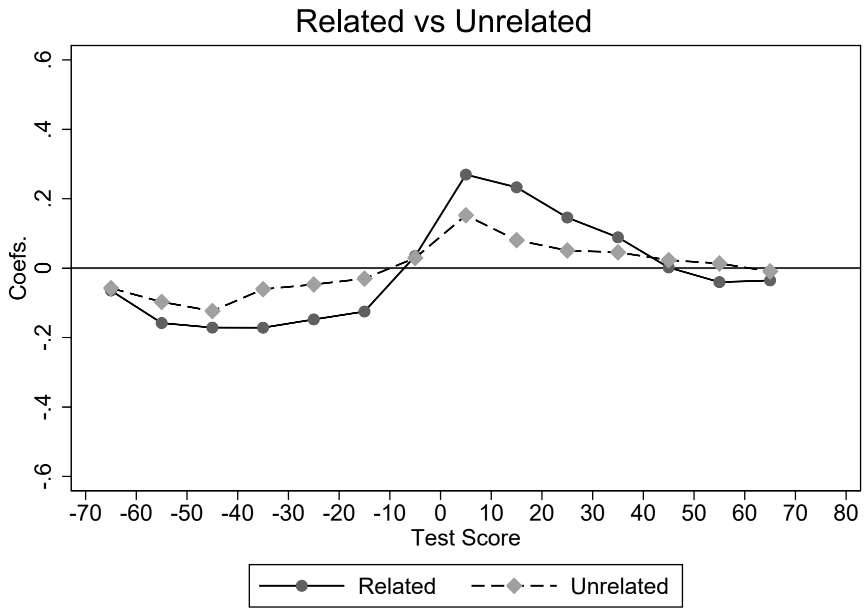


Figure A4. Impact on the probability of applying in rank 3-4 for Clones, by relative position of student, 2003-2004

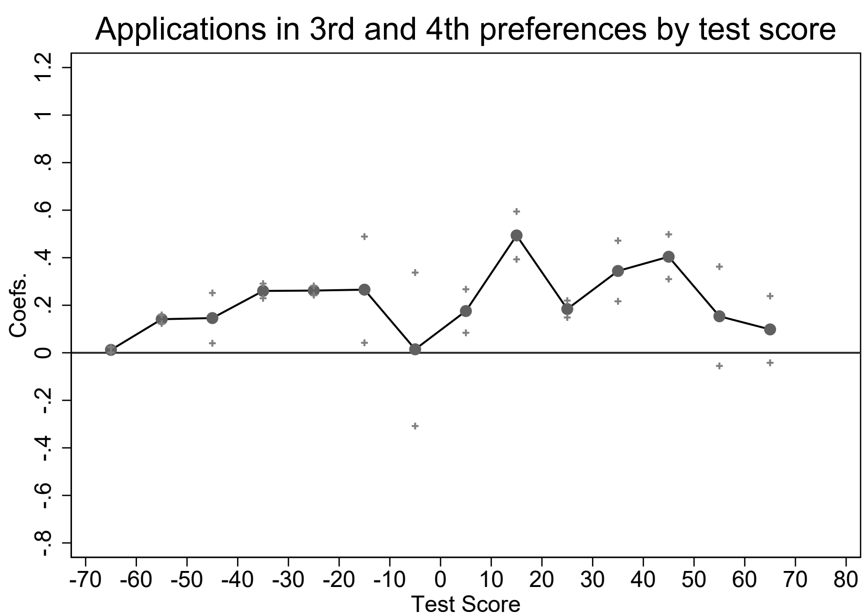


Figure A5. Impact on the probability of applying in rank 3-4 for Clones, by relative position of student, depending on type of program, 2003-2004

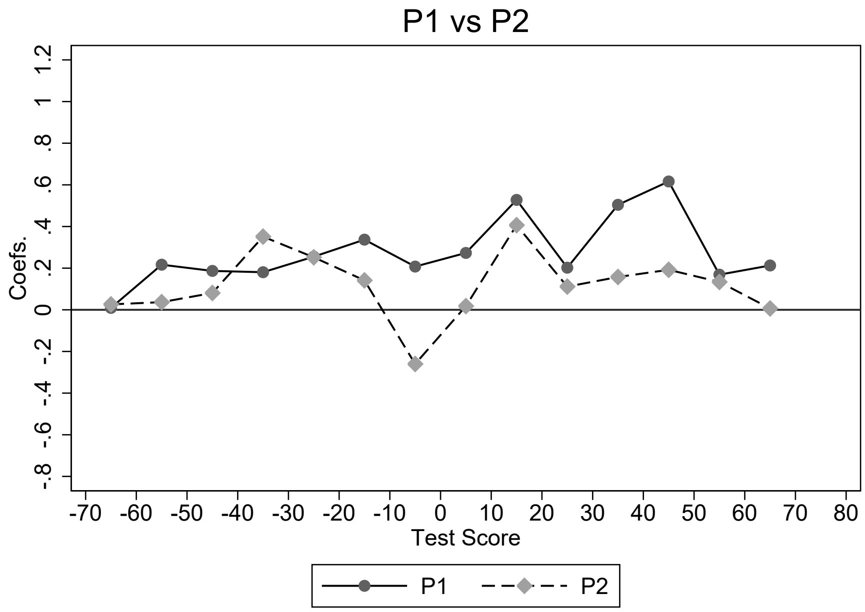


Figure A6. Impact on the probability of applying in rank 3-4 for Clones, by relative position of student, depending on whether they competed with UCH, 2003-2004

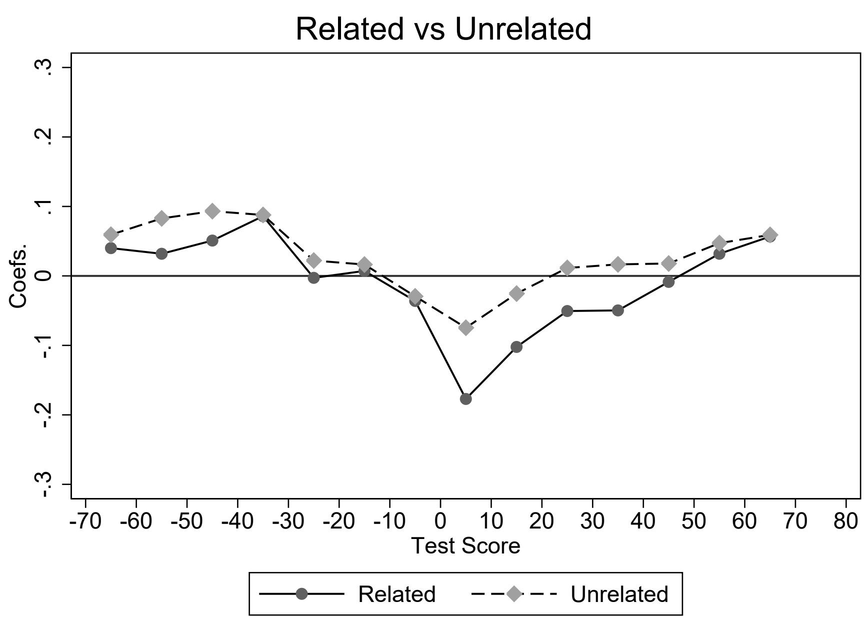


Figure A7. Impact on the probability of applying in rank 3-4, by relative position of student, 2002-2003, excluding safe students

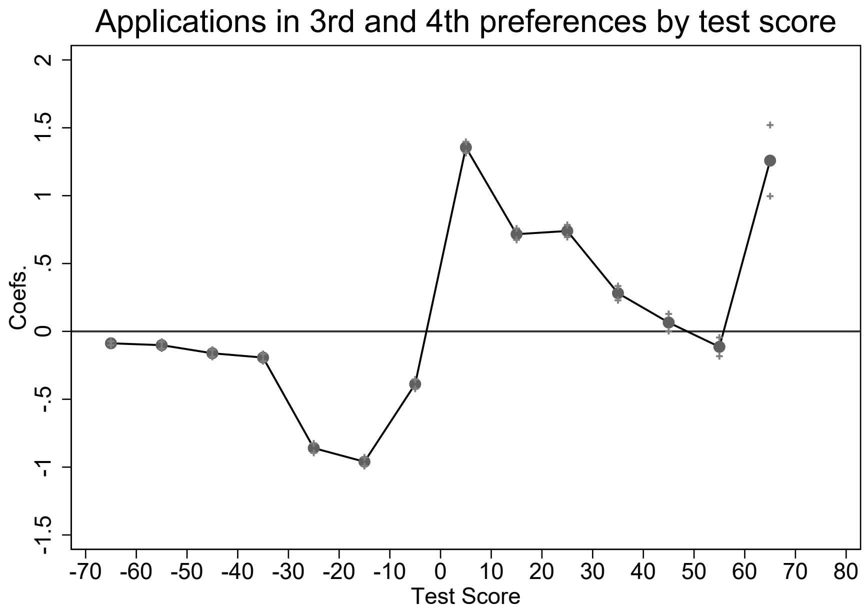


Figure A8. Impact on the probability of applying in rank 3-4, by relative position of student, depending on type of program, 2002-2003, excluding safe students

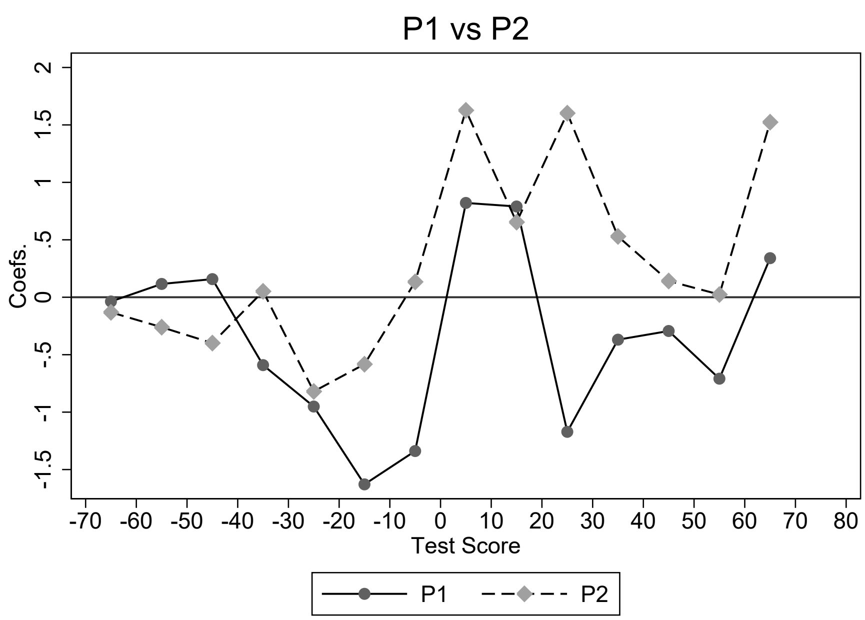


Figure A9. Impact on the probability of applying in rank 3-4, by relative position of student, depending on whether they competed with UCH, 2002-2003, excluding safe students

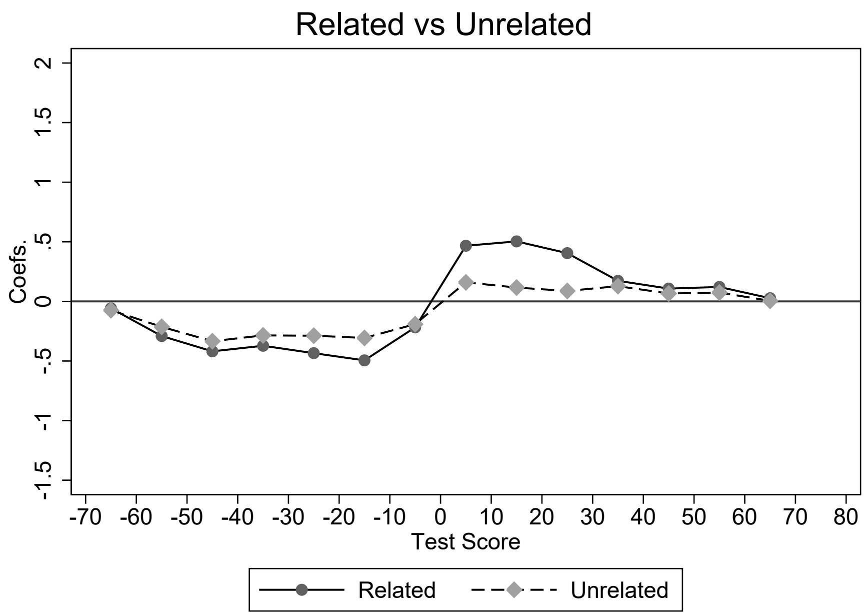


Figure A10. Impact on the probability of applying in rank 3-4, by relative position of student, 2003-2004, excluding safe students

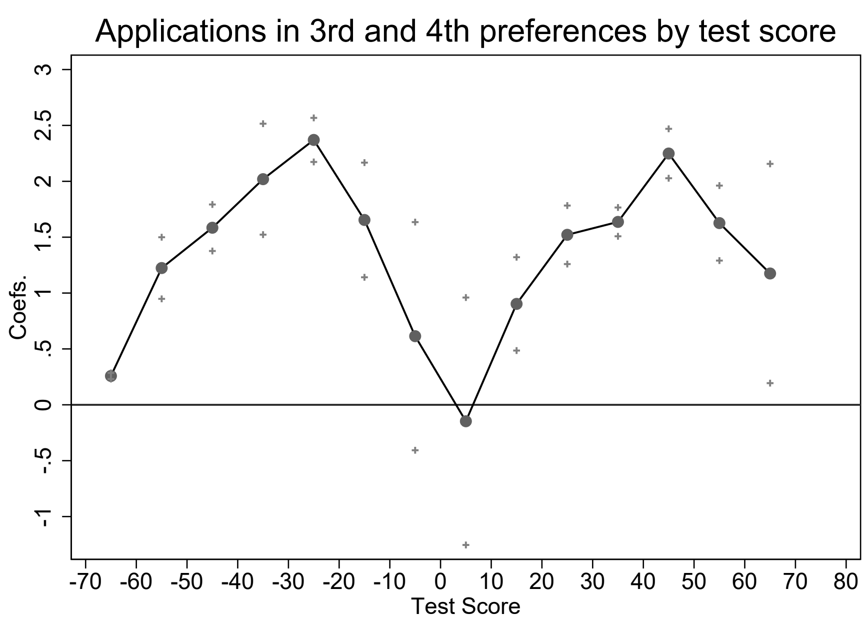


Figure A11. Impact on the probability of applying in rank 3-4, by relative position of student, depending on type of program, 2003-2004, excluding safe students

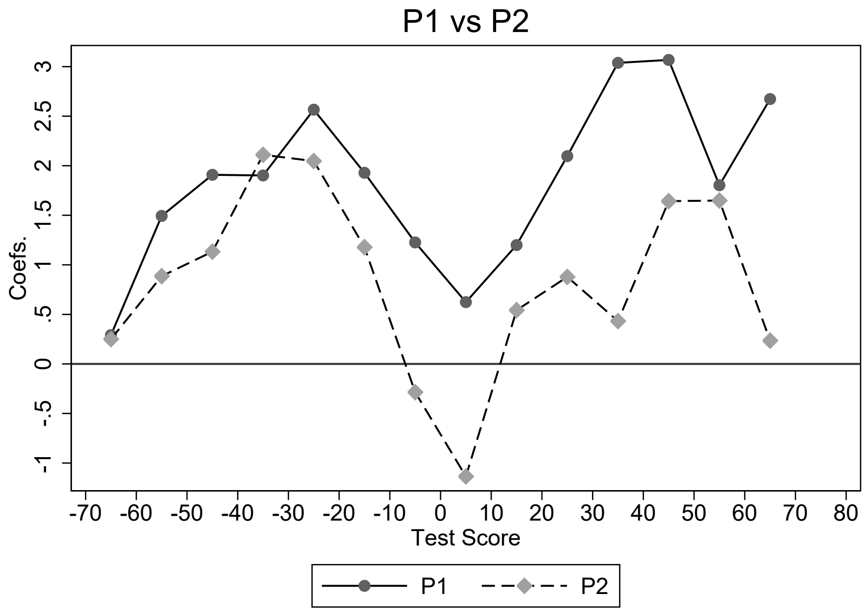


Figure A12. Impact on the probability of applying in rank 3-4, by relative position of student, depending on whether they competed with UCH, 2003-2004, excluding safe students