Application Mistakes and Information frictions in College Admissions

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Abstract

We analyze the prevalence and relevance of application mistakes in a seemingly strategy-proof centralized college admissions system. We use data from Chile and exploit institutional features to identify a common type of application mistake: applying to programs without meeting all requirements (*admissibility* mistakes). We find that the growth of *admissibility* mistakes over time is driven primarily by growth on active score requirements. However, this effect fades out over time, suggesting that students might adapt to the new set of requirements but not immediately. To analyze application mistakes that are not observed in the data, we design nationwide surveys and collect information about students' true preferences, their subjective beliefs about admission probabilities, and their level of knowledge about admission requirements and *admissibility* mistakes. We find that between 2% - 4% of students do not list their true most preferred program, even though they face a strictly positive admission probability, and only a fraction of this skipping behavior can be rationalized by biases on students' subjective beliefs. In addition, we find a pull-to-center effect on beliefs, i.e., students tend to attenuate the probability of extreme events and under-predict the risk of not being assigned to the system. We use these insights to design and implement a large-scale information policy to reduce application mistakes. We find that showing personalized information about admission probabilities has a causal effect on improving students' outcomes, significantly reducing the risk of not being assigned to the centralized system and the incidence of *admissibility* mistakes. Our results suggest that information frictions play a significant role in affecting the performance of centralized college admissions systems, even when students do not face clear strategic incentives to misreport their preferences.

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1 INTRODUCTION

Centralized admission systems are widely used in the world. Examples include the school choice systems in NYC, Chicago, Boston, New Haven, Paris, Turkey, Ghana, Chile, and the college admissions systems in Turkey, Taiwan, Tunisia, Hungary, and Chile. The most common allocation mechanism in place is the Deferred Acceptance (DA) Algorithm (Gale and Shapley, 1962), which is known to be strategy-proof for students; that is, students face no incentives to misreport their true preferences when submitting their applications. Even though truthful reporting is a dominant strategy for students under DA, recent evidence has shown that students misreport their preferences (Chen and Sönmez, 2006; Rees-Jones, 2018; Hassidim et al., 2017). One possible explanation is that students behave strategically and consider their beliefs on admission probabilities to decide where to apply (Fack et al., 2019; Larroucau and Ríos, 2018; Chen and Sebastián Pereyra, 2019). Another potential reason is that students do not fully understand the mechanism and cannot identify the optimal strategy, which may explain why low cognitive-ability students are more likely to misreport their preferences (Rees-Jones and Skowronek, 2018). In some cases, misreporting may still be weakly optimal (e.g., if students skip programs where they believe that their admission probability is equal to zero or negligible), but in other cases, misreporting may be a dominated strategy. In the latter case, we say that students make an *application mistake*.

The literature on centralized assignment mechanisms has recently focused on understanding the prevalence and relevance of application mistakes. For instance, Rees-Jones (2018) shows that a significant fraction of residents do not report their preferences truthfully in the National Resident Matching, even though they face no incentives to misreport. In a follow-up paper, Rees-Jones and Skowronek (2018) show that this misreporting behavior may be due to several factors, including students' scores, access to advice and information, and optimism. Artemov et al. (2017) study the Australian college admissions system and find that a non-negligible fraction of students makes obvious mistakes. More specifically, some students apply to programs with both full-fee and reduced-fee options but only include the former in their preference list. Nevertheless, the authors show that the vast majority of these mistakes are payoff irrelevant. Shorrer and Sóvágó (2021) study the Hungarian college admissions process and find a similar pattern. Moreover, they estimate the causal effect of selectivity on making dominated choices, and they show that the prevalence of these mistakes is higher in more selective programs. Finally, Hassidim et al. (2020) analyze the Israeli Psychology Master's Match and show that students often report that they prefer to avoid receiving funding. The authors refer to these as *obvious misrepresentations* and argue that there are other kinds of preference misrepresentation. As in previous studies, the authors find that these mistakes are more common among weaker applicants and argue that this may be due to misunderstanding of the instructions (due to lower cognitive ability) and beliefs that assign low admission probabilities.

To analyze the prevalence and relevance of application mistakes, researchers must overcome significant challenges. First, it is not always clear how to identify application mistakes using administrative data. Without access to data on students' true preferences and subjective beliefs on admission probabilities, researchers typically resort to analyzing unambiguous application mistakes that are idiosyncratic to their settings, achieving little external validity. Second, even if we can identify some application mistakes in the data, assessing their relevance to students' welfare is particularly challenging. To do so, we need to understand the effects of mistakes on outcomes and being able to predict counterfactual behavior that would improve students' welfare.

Understanding the drivers of students' application mistakes and addressing them—especially if they are payoff-relevant—is still an open question. For instance, recent evidence in school choice systems shows that application mistakes can be driven by families having incorrect beliefs over their assignment probabilities (Bobba and Frisancho (2019); Kapor et al. (2020)). However, we do not know how much biased beliefs contribute to students' college admissions mistakes. Moreover, there could be other potential drivers for student mistakes that have not being explored, such as lack of understanding about the admission and assignment process, information frictions, or even other behavioral biases.[1]

This paper analyzes the prevalence and relevance of application mistakes in the Chilean centralized college admissions system and investigates the effects of information policies to reduce their incidence. The Chilean system uses a variant of the DA algorithm, which allows us to understand the prevalence of mistakes in similar settings worldwide. We exploit two characteristics of the Chilean system to identify the prevalence and relevance of application mistakes. First, a type of application mistake is observed in the administrative data: students can apply to programs even if they do not meet all the admission requirements. We refer to these as *admissibility* mistakes. Second, there is a substantial variation in admission requirements and *admissibility* mistakes over time: the fraction of students who make an *admissibility* mistake has grown from 17% to more than 33% in the last 12 years.

Our results show that the growth of *admissibility* mistakes over time is mainly driven by growth on active score requirements both in the extensive and intensive margins. Although changes in admission requirements over time seem to increase *admissibility* mistakes, this effect fades out over time, suggesting that students adapt to the new set of requirements but not immediately. Also, we find that students have access to correct information at different stages of the application process. However, a significant fraction of students are not aware of their *admissibility* mistakes and do not understand the consequences of making such mistakes, as they believe there is a positive probability of being admitted to those programs. Finally, we find that *admissibility* mistakes are likely welfare-relevant, as close to 25% of students who only list programs with *admissibility* mistakes could have been assigned in the centralized system if they had included programs in which they were eligible.

In addition, we analyze application mistakes that are not directly observed in the administrative data and assess their relevance. We refer to these mistakes as *strategic* mistakes. To achieve this, we design nationwide surveys and collect novel data on students' true preferences for programs, their subjective beliefs about admission probabilities, and their level of knowledge about admission requirements and *admissibility* mistakes. This

[1]For instance, Dreyfuss et al. (2019) show that some application mistakes can be rationalized if we account for loss aversion.

information also helps us tell apart which information frictions are the most relevant to explain students' mistakes and what we should consider when designing information policies to address application mistakes.

We find that between 2% - 4% of students in our sample do not list their top-true preference, even though they face a strictly positive admission probability and would have unambiguously increased the expected value of their application lists by reporting it as their top preference. Moreover, only a fraction of this skipping behavior can be rationalized by bias on students' subjective beliefs. In addition, we find that students' subjective beliefs are closer to *adaptive* beliefs than *rational expectations* and that students' subjective beliefs are subject to a pull-to-the-center effect, i.e., students' beliefs are biased towards the middle, assigning an attenuated probability to extreme outcomes compared to *Ratex* beliefs. This pattern implies that students tend to underpredict the risk of not being assigned to the centralized system. We conjecture that this bias on students' beliefs can increase the likelihood of students making payoff-relevant application mistakes because they could fail to list enough programs they prefer to being unassigned. In addition, consistent with previous literature, we find substantial differences in the magnitude of the bias depending on students' characteristics, with high score students from private schools having more accurate beliefs than low score students.

Finally, we evaluate the effects of a large-scale outreach intervention designed to decrease information frictions and reduce the incidence of students' application mistakes. In collaboration with MINEDUC and using partial information about students' applications, we created personalized websites. Each website included general information about programs included in the student's application list, personalized information on admission probabilities and applications' risk, and personalized recommendations about other majors of potential interest. We randomized the information shown to students to evaluate the effects of reducing information frictions on different margins. We find that showing personalized information about admission probabilities and risk has a causal effect on improving students' outcomes. Treated students significantly reduced the risk of not being assigned to the centralized system and the incidence of *admissibility* mistakes. Our results suggest that information frictions play a significant role in affecting the performance of centralized college admissions systems, even when students do not face clear strategic incentives to misreport their preferences. Policy interventions that reduce these frictions are then necessary to reduce the incidence of application mistakes.

The paper is organized as follows. In Section 2.1, we describe the Chilean college admissions system and the relevant features to our research questions. In Section 2.2 we describe the administrative data and the design of the surveys. In Section 3, we introduce the environment and define the types of application mistakes that we analyze in the paper: *admissibility* and *strategic* mistakes. In Section 4, we analyze the prevalence, relevance, and drivers of *admissibility mistakes* and explain their growth over time. In Section 5, we analyze the prevalence and relevance of *strategic* mistakes and shed light on their potential drivers. In Section 6, we describe the information policy to reduce application mistakes and report the results. Finally, in Section 7 we conclude.

2 Background and Data

2.1 Background

We focus on the centralized part of the Chilean tertiary education system, which includes the 41 most selective universities.[2] From now on, we refer to this as the admission system.

To participate, students must undergo a series of standardized tests (*Prueba de Selección Universitaria* (PSU) until 2020, and *Prueba de Transición* (PDT) starting from 2021). These tests include Math, Language, and a choice between Science or History, providing a score for each of them. The performance of students during high school gives two additional scores, one obtained from the average grade during high school (*Notas de Enseñanza Media* (NEM)), and a second that depends on the relative position of the student among his/her cohort (*Ranking de Notas* (Rank)).

Before the start of the admissions process, the institutions that participate in the admission system must release the number of seats offered by each of their programs,[3] and the weights they will consider in each admission factor to compute application scores and rank students. In addition, they must report the set of requirements that students must satisfy to be eligible. For instance, some programs require a minimum application score, a minimum average score between the Math and Verbal tests, or require students to take additional specific exams. Some requirements are common to all programs that participate in the admission system (e.g., a minimum average score of Math and Verbal of 450), while others are optional and depend on each program (e.g., some programs require a minimum application score of 450, 500 or 600, while others do not include this requirement). If a student does not satisfy all the requirements imposed by a program, she is not admissible, and thus her chances of admission to that program are equal to zero. In Table 2.1 we show all the admission requirements that programs imposed in the application process of 2019.

Table 2.1: Admission requirements

Requirement	Mistake
Requires High-school GPA (NEM)	Missing NEM, Missing NEM from foreign country
Restricts the number of applications to the Institution of the program	Exceeds the number of applications to the Institution of the program
Restricts province of graduation	Does not satisfy province of graduation
Restricts applicants' gender	Does not satisfy gender restriction
Requires minimum weighted score	Does not satisfy minimum weighted score
Requires special test (exclusion)	Did not take or pass special test (exclusion)
Requires special test (weighting)	Did not take or pass special test (weighting)
Requires a specific year for High-school graduation	Does not satisfy year for High-school graduation
Restricts number of enrollments via Regular Process	Exceeds number of allowed enrollments via Regular Process
Restricts academic qualifications to enroll in the program	Academic qualifications do not allow to enroll in the program
Requires mandatory test of Verbal	Missing score in mandatory test of Verbal
Requires mandatory test of Math	Missing score in mandatory test of Math
Requires History and Social Sciences test	Missing score in History and Social Sciences
Requires Sciences test	Missing score in Sciences
Requires minimum average score Math-Verbal	Does not satisfy minimum average score Math-Verbal
Requires either History and Social Sciences test or Sciences test	Did not take History and Social Sciences test nor Sciences test
Requires minimum average score Math-Verbal ≥ 450	Average score Math-Verbal is below 450
Requires minimum weighted score for special test (weighting)	Does not satisfy minimum weighted score for special test (weighting)
Requires Education prerequisites	Does not meet Education prerequisites

[2]See Larroucau and Rios (2021) for a more general description of tertiary education in Chile and more institutional details.

[3]Students apply directly to programs, i.e., pairs of university-major.

After scores are published, students can access a web portal to submit their applications. In particular, they can list up to ten programs in decreasing order of preference. We refer to these lists as Rank Order Lists (ROLs), and in Section 2.1.1 we discuss more details about the application process. DEMRE collects all these applications, checks students' eligibility in each of their listed programs, and, if eligible, computes their application scores and sorts them in decreasing order. Then, considering the preferences of students and the preferences and vacancies of programs, DEMRE runs an assignment algorithm to perform the allocation. The mechanism is a variant of the DA algorithm, where ties on students' scores are not broken.[4] As a result, the algorithm assigns each student to at most one program, and programs may exceed their capacities only if there are ties for their last seat. We refer to the score of the last admitted student as the *cutoff* of each program.

It is important to highlight that, due to the large nature of the market, students do not face strategic incentives to misreport their preferences when the constraint on the length of the list is not binding (Rios et al., 2020). However, the empirical evidence shows that some students still misreport their preferences, even when this constraint is not binding. As discussed in (Larroucau and Ríos, 2018), it may be weakly optimal for students to misreport their preferences if they face degenerate admission probabilities. Moreover, students for which the constraint on the length of the list is binding might also be strategizing (Haeringer and Klijn (2009)). In both cases, the information provided by previous years' cutoffs could be relevant for students to form correct beliefs about their admission probabilities (Agarwal and Somaini (2018)) and avoid application mistakes due to biases in their beliefs.

2.1.1 Information Access.

Although the information about programs' seats, weights, requirements, and past cutoffs is public, no platform collects and summarizes it for students. Instead, each institution publishes its information and, in many cases, they do not display all the relevant details on the same website. As a result, it is hard for students to collect all the relevant information and compare programs before starting the application process.

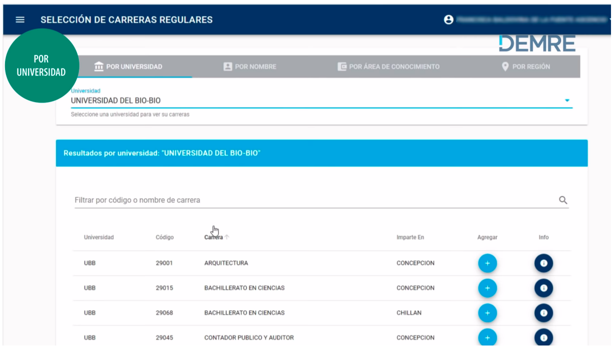
Part of this information—namely, the application scores and whether the student satisfies the requirements imposed by each program—is included in the web portal that students use to submit their application. More specifically, the web portal displays three types of information:

1. **Academic information:** students receive information about their scores, high-school grades, and other academic credentials.[5]
2. **Information about programs:** students can search for the programs they wish to apply to or read more information about using four criteria: (i) search by univer-

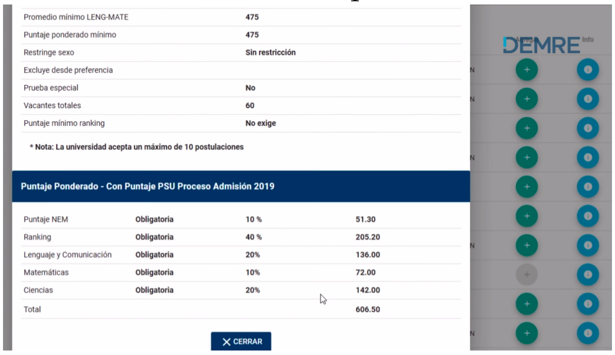
[4]See Rios et al. (2020) for a detailed description of the mechanism used and its properties.

[5]In the simulation period before the application process starts, students, can simulate their applications by entering fictitious scores.

(a) Searching stage



(b) Admission requirements

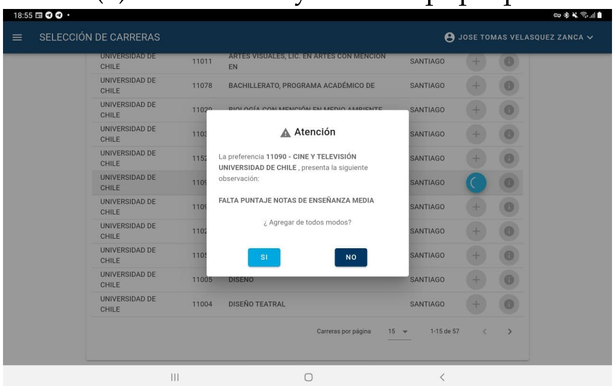


sities, (ii) search by programs' name, (iii) search by major areas, and (iv) search by programs' geographic region. Using this search tool, students can get information about the programs characteristics and requirements, as illustrated in Figures 2.1a and 2.1b.

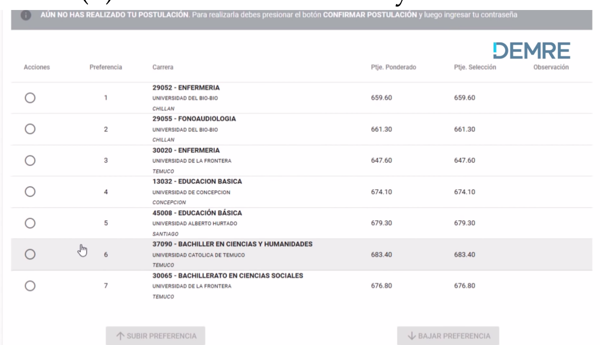
3. **Information about application:** for each of the programs included in the list, students see their application score and whether they satisfy the requirements imposed by the program to be eligible.

   Since 2019, DEMRE includes a pop-up to warn students if they do not meet an admission requirement when adding a program to their application list, as illustrated in Figure 2.2a. Moreover, the portal displays information about the admission requirements not satisfied by the student while students are adding and sorting their options, as shown in Figure 2.2b.

(a) Admissibility mistake pop-up



(b) Potential admissibility mistake



Notice that, even though DEMRE displays precise information about admission requirements, it still allows students to include programs even if they do not meet the admission requirements. As we will show in Section 5, this option, along with the lack of information about the consequences of not satisfying the admission requirements, generates confusion and potentially biases students' beliefs regarding their admission probabilities, especially in those programs where they do not fulfill the admission requirements (which is equal to zero). Moreover, the system does not provide information about cutoffs in previous years or students' admission probabilities. This lack of information could also translate to students' having biased beliefs.

2.2 Data

We combine a panel of administrative data on the admissions process with two novel datasets that we collect to analyze students' mistakes. We now provide details on each of these data sources.

Admissions process. To characterize the historical evolution of the admissions process and how it affects mistakes, we have information on the admissions processes from 2004 to 2020. This dataset includes all the information about students (socio-economic characteristics, scores, and applications), programs (weights, seats available, and admission requirements), and also the results of the admissions process (i.e., for each student and each of their applications, whether the application was valid, and whether the student was assigned to that program or wait-listed). Notice that we have this information for each of the years mentioned above. Having access to such information is relevant because the vacancies and admission requirements of programs change over time. Indeed, in Section 4, we show that the evolution of admission requirements partially explains admissibility mistakes.

Surveys - 2019 and 2020. In 2019 and 2020, we designed and conducted two surveys to gather information on students' preferences for programs and their beliefs on admission probabilities (see Larroucau and Rios (2021)). In both surveys, we ask students about their beliefs on the cutoffs and their admission probabilities for the programs included in their application list and their top-true preference (even if they did not include it in their list of preferences). As shown in Section 5, we use this information to evaluate whether biased beliefs explain the strategic mistakes that we observe in the data.

Intervention 2021. In collaboration with MINEDUC, DEMRE, and ConsiliumBots, we designed and implemented an intervention to evaluate whether information provision can help to reduce admissibility and strategic mistakes. In Section 6.1 we describe this intervention in detail. As previously mentioned, we created a personalized website for each student and randomized the information included in these to measure the effect of different types of information on their chances of making a mistake. Then, by comparing students' application lists before and after the intervention, we can assess the effect of the information displayed on different outcomes, such as their probability of making a mistake and their probability of being admitted in the system, among others.

In addition, we conducted a third survey, similar to that conducted in 2019 and 2020. This survey was sent to students after the application process and before the assignment results were published. Hence, we combine this with data from our intervention to measure how the information provided in the personalized websites changed students' beliefs.

3 Environment

Consider a finite set of students N and a finite set of programs M. Each student $i \in N$ is characterized by a vector of indirect utilities $u_i \sim f_u$, a vector of scores $\vec{s}_i = \left\{s_i^k\right\}_{k \in \mathcal{K}}$, where $\mathcal{K}$ is a set of admission factors considered in the application process, and a submitted list of preferences $R_i \in \mathcal{R}$, where $\mathcal{R}$ is the set of all possible rank-ordered lists. Each program $j \in M$ is characterized by its number of vacancies $q_j \in \mathbb{N}_+$, by a vector of admission weights $\omega_j = \left\{\omega_j^k\right\}_{k \in \mathcal{K}}$, and by a set of eligibility rules that define whether a student is admissible. Let $A_j \subseteq N$ be the set of students that satisfy these additional requirements and thus are admissible in program j.

The application score of a student $i \in A_j$ in program j, s_{ij}, is given by:[6]

$$s_{ij} = \sum_k \omega_j^k s_i^k. \tag{3.1}$$

These application scores are used by programs to rank their applicants in decreasing order. Let $\bar{s}_j$ be the application score of the last admitted student to program j; we refer to it as the cutoff. Let $p_i \in [0,1]^M$ be the vector of rational-expectations admission probabilities of student i, i.e., for each $i \in N$ and $j \in M$, $p_{ij} = \mathbb{P}\left(s_{ij} \geq \bar{s}_j\right)$. Similarly, let $\tilde{p}_i \in [0,1]^M$ be the vector of subjective beliefs on admission probabilities for student i. We now formalize the different types of mistakes.

Definition 1 (Application mistake). $R_i \in \mathcal{R}$ involves an *application mistake* for student $i \in N$ if $\exists R_i' \in \mathcal{R} \setminus R_i$ such that reporting R_i' weakly dominates–in expected utility–reporting R_i given u_i and p_i, i.e,

$$EU\left(R_i'|u_i, p_i\right) \geq EU\left(R_i|u_i, p_i\right)$$

Definition 2 (Obvious mistake). $R_i \in \mathcal{R}$ involves an *obvious mistake* for student $i \in N$ if $\exists R_i' \in \mathcal{R} \setminus R_i$ such that reporting R_i' weakly dominates–in expected utility–reporting R_i for any $u \in \text{supp}(f_u)$ and $p \in [0,1]^M$, i.e,

$$EU\left(R_i'|u, p\right) \geq EU\left(R_i|u, p\right) \forall u \in \text{supp}(f_u), p \in [0,1]^M$$

First, notice that obvious mistakes are a special case of application mistakes, in which there exists an alternative ROL R_i' that dominates R_i for all possible utilities and admission probabilities. Second, the concept of *weakly dominated* implies that mistakes may or may not be welfare relevant. Third, as Definition 1 considers both rational expectations beliefs and expected utility maximization, mistakes might be explained by behavioral reasons (without departing from rational expectations),[7] or by biased beliefs (without departing from rationality).

[6]Without loss of generality, we assume that $s_{ij} = 0$ for $i \notin A_j$.

[7]Several behavioral models could fit this definition, such as bounded rationality, non-expected utility maximization, among others.

Given their empirical relevance, we focus on two types of mistakes: (1) *admissibility* mistakes, which are a special case of *obvious mistakes*; and (2) *strategic* mistakes, which are not obvious mistakes but that play an important role in the Chilean system. Further, we separate *strategic* mistakes in (i) *underconfidence*, (ii) *overconfidence*, and (iii) *ordering* mistakes.

Definition 3 (Admissibility mistake)**.** Program $j \in R_i$ for $R_i \in \mathcal{R}$ involves an *admissibility mistake* for student $i \in N$ if $i \notin A_j$

Notice that an *admissibility* mistake is a particular case of an *obvious mistake* because the student faces zero admission probability to a program where she is not admissible; thus, regardless of students' preferences or beliefs, not including programs with admissibility mistakes weakly dominates including them in the application list. This type of application mistake is observed in the Chilean setting, allowing us to analyze its drivers and relevance (see Section 4.1). To analyze application mistakes that are not *obvious* mistakes, we exploit the data collected in the surveys. We label these mistakes as *strategic* mistakes and analyze them in Section 5.

Definition 4 (Underconfidence mistake)**.** $R_i \in \mathcal{R}$ involves an *underconfidence mistake* for student $i \in N$ if $\exists j' \notin R_i$ such that $p_{ij'} > 0$, $u_{j'} > \min_{j \in R_i} \{u_{ij}\}$ and

$$EU(R_i \cup \{j'\} | u, p) > EU(R_i | u, p).$$

Given a ROL R and admission probabilities p_i, let $\Pi(R_i)$ be the probability that student i results unassigned, i.e.,

$$\Pi(R_i, p_i) = \prod_{j \in R_i} (1 - p_{ij}).$$

We refer to $\Pi(R_i, p_i)$ as the *risk* of submitting a ROL R_i given admission probabilities p_i.[8]

Definition 5 (Overconfidence mistake)**.** $R_i \in \mathcal{R}$ involves an *overconfidence mistake* for student $i \in N$ if $\exists j' \notin R_i$ such that $u_{ij'} > 0$ and

$$\Pi(R_i \cup \{j'\}, p_i) < \Pi(R_i, p_i).$$

Finally, we analyze a type of strategic mistake that impacts in which position the student ranks a given program.

Definition 6 (Ordering mistake)**.** $R_i \in \mathcal{R}$ involves an *ordering mistake* for student $i \in N$ if $\exists R_i' \in \mathcal{R} \setminus R_i$ such that $\{j\}_{j \in R_i} = \{j\}_{j \in R_i'}$ and

$$EU(R_i' | u, p) > EU(R_i | u, p).$$

[8] This definition of risk assumes independence of admisssion probabilities across programs.

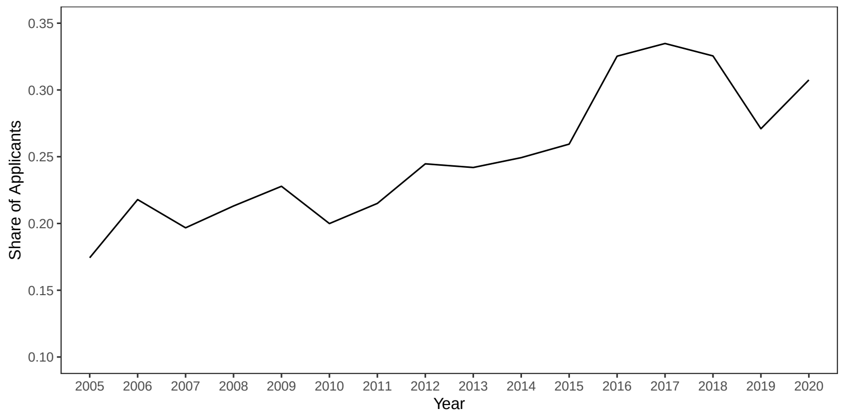
4 Admissibility Mistakes

In this section, we focus on admissibility mistakes. As previously discussed, we say that a student makes an *admissibility mistake* if she includes a program in her preference list for which she does not fulfill all the requirements. Thus, her admission probability to that program is equal to zero. We first explore the prevalence and growth of these mistakes over time, the drivers and causes, and then we analyze their relevance for welfare.

4.1 Prevalence, Growth, and Drivers

In Figure 4.1 we show the evolution of the share of students with at least one *admissibility* mistake between 2004 and 2018. We observe a high increase in the fraction of students with at least one admissibility mistake. Indeed, this fraction has almost doubled in the last 12 years (from close to 17% to more than 33% in 2017).

Figure 4.1: Share of students with *admissibility* mistakes in their ROL



Notes: The share is computed as the total number of students who submitted a ROL with at least one *admissibility* mistake, over the total number of applicants.

Several factors may explain this pattern. We focus on two hypotheses:

Hypothesis 1. The increase in the share of *admissibility* mistakes can be explained by a change in the composition of applicants over time.

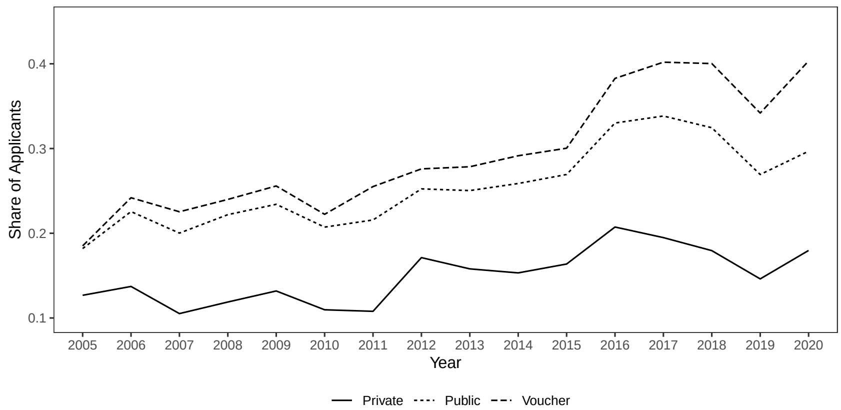
Hypothesis 2. The increase in the share of *admissibility* mistakes can be explained by an increase in the set of admission requirements and additional complexities in the assignment mechanism over time.

Hypothesis 1 states that the increase in the share of *admissibility* mistakes could be attributed to changes in the population of applicants. The intuition is that, if the admission system becomes more inclusive over time, students with lower scores and worse understanding of the assignment mechanism and admission requirements will participate, increasing the fraction of students with admissibility mistakes. The intuition behind Hypothesis 2 is that, if programs increase the number of requirements over the years, a smaller fraction of students will be admissible, increasing the fraction of students that make admissibility mistakes.

4.1.1 Hypothesis 1: Characterizing Mistakers

Growth and school type. Figure 4.2 shows the evolution of the share of students with *admissibility* mistakes over time by school type. We observe that a lower proportion of students from private schools report ROLs with *admissibility* mistakes compared to students coming from public and voucher schools. In addition, the prevalence of *admissibility* mistakes has been rising more in the latter groups of students.

Figure 4.2: Share of students with *admissibility* mistakes by school type

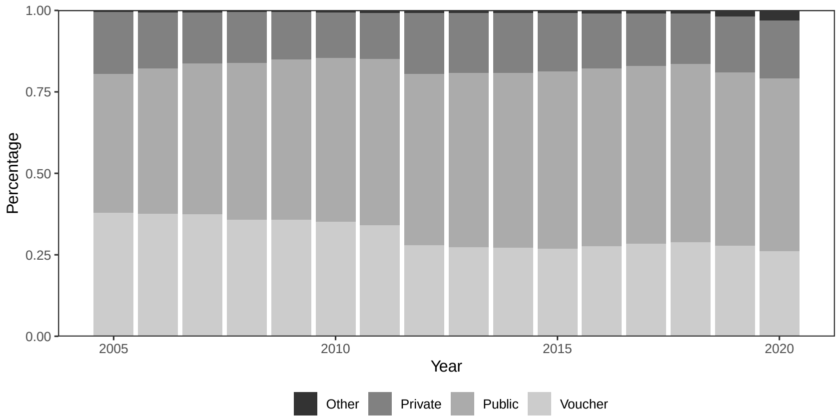


Notes: The share is computed as the total number of students who submitted a ROL with at least one *admissibility* mistake, over the total number of applicants.

Figures 4.1 and 4.2 show that the fraction of applicants with at least one admissibility mistake has increased in the last ten years, and that this pattern is common to students from different socio-economic backgrounds.

Figure 4.3 shows the evolution of the share of applicants by school type. We observe an increase in the share of applicants coming from voucher schools and a decrease in the share of students coming from both public and private schools. The slight decrease in the share of students from private schools and the increase over time in the share of mistakes, mostly coming from public and voucher schools, may explain the increase in the share of mistakes over time.

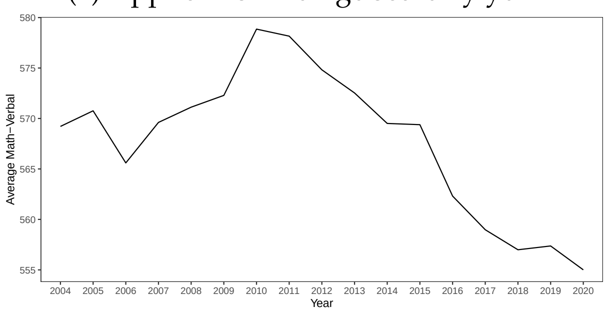
Figure 4.3: Evolution of the share of applicants by school type



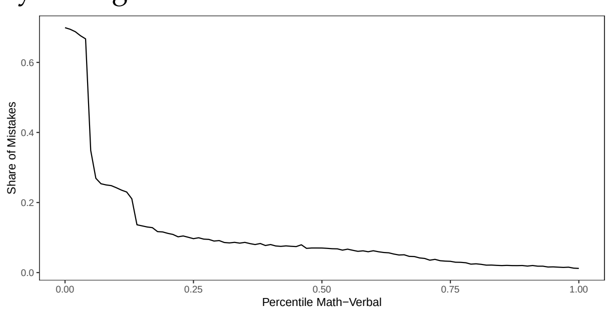
Notes: The share is computed as the total number of students who submitted a ROL by school type, over the total number of applicants.

Average scores and school type. Figure 4.4a shows the evolution of applicants' average scores over time. Although scores are standardized every year regarding the population of students who take the exams, we observe that applicants' average scores have decreased more than 20 points on average (close to 0.2 standard deviations) since 2010. Since many of the requirements rely on students' scores, having lower average scores can increase the fraction of students who face active requirements when they apply, supporting Hypothesis 1. To illustrate this, Figure 4.4b shows the share of students with an *admissibility* mistake as a function of the percentile of average score Math/Verbal among students eligible to apply in the centralized system (i.e., with average Math/Verbal greater than or equal to 450). As expected, the share of students who make *admissibility* mistakes decreases significantly for students with higher scores. As noted before, a large number of requirements in the Chilean college admissions problem is given by minimum application scores and minimum average scores between Math and Verbal. Therefore, students with higher scores face fewer active restrictions when submitting their applications. The minimum score requirements and their effects on the share of mistakes explain the two jumps in the graph (close to percentiles 5 and 15).

(a) Applicants' average score by year



(b) Share of students with *admissibility* mistakes by average score



In Appendix 8.1, we replicate Figure 4.4b separating by school type. Interestingly, for a wide range of average scores, a significantly higher share of students from private schools submit ROLs with *admissibility* mistakes (conditional on scores and within school type), compared to students from voucher and public schools. This pattern is counter-intuitive since students from private schools should presumably be better informed about the admission requirements and, therefore, less likely to make *admissibility* mistakes. A potential explanation for this pattern is preference heterogeneity across students from different school types. For instance, if a significant fraction of students reports truthfully and students from private schools prefer more selective programs (with higher minimum score requirements), these students could have in their choice sets a higher proportion of programs with active minimum score requirements.

Logit model. The previous results suggest that *admissibility* mistakes are correlated with students' scores and their school type. To formally analyze these correlations and better understand what is driving admissibility mistakes, we estimate the following *logit* model:

$$y_{ijt} = \alpha_t + \alpha_j + \gamma_{dep} dep_i + \gamma_{rank} rank_{R_i(j)} + f(\bar{s}_i) + \varepsilon_{ijt}, \tag{4.1}$$

where y_{ijt} is a binary variable that is equal to 1 if student i makes an *admissibility* mistake applying to program j at time t, and $y_{ijt} = 0$ otherwise; α_t is a time fixed effect; α_j is a program fixed effect; dep_i is categorical variable that encodes the school type of student i, i.e., $dep_i \in$ { Private, Voucher, Public }; $rank_{R_i(j)}$ is a vector with a one in the position of program j in student's i ROL, and zero otherwise; and $f(\bar{s}_i)$ is a function of student i's average score in Math and Verbal and is given by

$$f(\bar{s}_i) = \beta_1 p(\bar{s}_i) + \beta_2 p(\bar{s}_i)^2 + \beta_3 \mathbb{1}_{\bar{s}_i<475} + \beta_4 \mathbb{1}_{\bar{s}_i<500}, \tag{4.2}$$

where $p(\bar{s}_i)$ is the percentile of average score $\bar{s}_i$ with respect to the population of students who participate in the admission process and have valid average score. Finally, ε_{ijt} is an i.i.d.Type I Extreme Value shock.

Table 4.1 shows the estimated coefficients of the model given in Equation 4.1. First, we observe that students from public schools are less likely to make a mistake compared to students from voucher and private schools, consistent with the results in Appendix 8.1. Second, we observe no significant differences of the position in the ROL within the top four preferences. However, we observe that, as we move on from the fifth to the tenth preference, the probability of a mistake increases. Finally, we observe that scores are negatively correlated with the probability of making an admissibility mistake. For instance, we observe that students with low Math-Verbal score (below 475 or below 500) are significantly more likely to make an application mistake.

4.1.2 Hypothesis 2: Evolution of requirements

We test if the growth of *admissibility* mistakes is driven by an increase in the number of requirements or the complexities of the application process over time. Figure 4.5 shows the share of students with *admissibility* mistakes by average score for different years. Conditional on students' average scores, the share of mistakers has been increasing over time. In particular, we observe a jump in the share of mistakers for the years 2004 to 2010, close

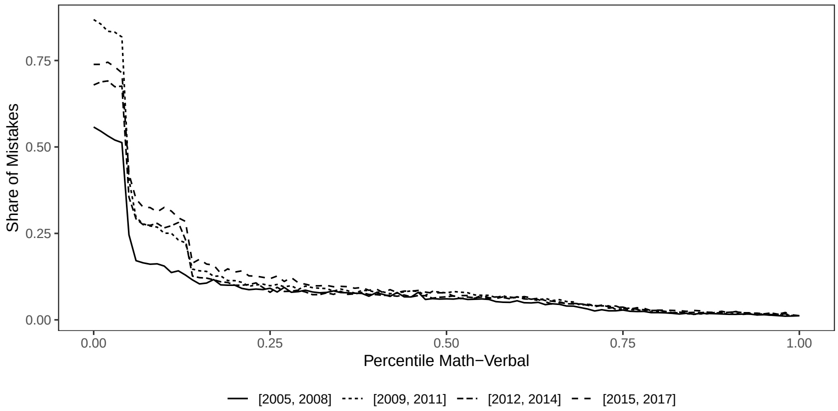
Table 4.1: Determinants of Admissibility Mistakes

	Dependent variable: Mistake		
	(1)	(2)	(3)
Public	-0.088***	-0.085**	-0.128***
	(0.032)	(0.040)	(0.017)
Voucher	-0.050	-0.046	-0.092***
	(0.035)	(0.044)	(0.028)
Preference 2	-0.004	-0.005	-0.011
	(0.007)	(0.008)	(0.010)
Preference 3	-0.0001	-0.001	-0.008
	(0.010)	(0.011)	(0.015)
Preference 4	0.024**	0.021	0.013
	(0.011)	(0.013)	(0.019)
Preference 5	0.167***	0.160***	0.152***
	(0.021)	(0.020)	(0.023)
Preference 6	0.200***	0.183***	0.160***
	(0.030)	(0.032)	(0.040)
Preference 7	0.228***	0.190***	0.164***
	(0.043)	(0.032)	(0.040)
Preference 8	0.289***	0.244***	0.214***
	(0.049)	(0.037)	(0.047)
Preference 9	0.305***	0.247***	0.221***
	(0.053)	(0.035)	(0.044)
Preference 10	0.317***	0.256***	0.228***
	(0.055)	(0.037)	(0.049)
Percentile Math-Verbal	-2.69***	-2.82***	-2.68***
	(0.489)	(0.605)	(0.321)
Percentile Math-Verbal (2)	-0.496	-0.340	-0.721***
	(0.567)	(0.724)	(0.279)
Math-Verbal < 475	0.615***	0.589***	0.628***
	(0.041)	(0.041)	(0.033)
Math-Verbal < 500	0.639***	0.634***	0.537***
	(0.067)	(0.094)	(0.058)
Observations	4,415,327	3,296,828	2,282,209
Pseudo R^2	0.318	0.319	0.331

Note: Column (1) includes data from 2014-2020; column (2) includes data from 2016-2020; column (3) includes data from 2018-2020. Standard errors clustered at the program and year levels. Significance reported: $^{*}p < 0.1$;$^{**} p < 0.05$;$^{***} p < 0.01$

to the percentile 50. This pattern is in line with Hypothesis 2 and suggests that some admission requirements were added around those score percentiles throughout the years of analysis. We now analyze in detail the evolution of admission requirements and changes to the assignment mechanism over time.

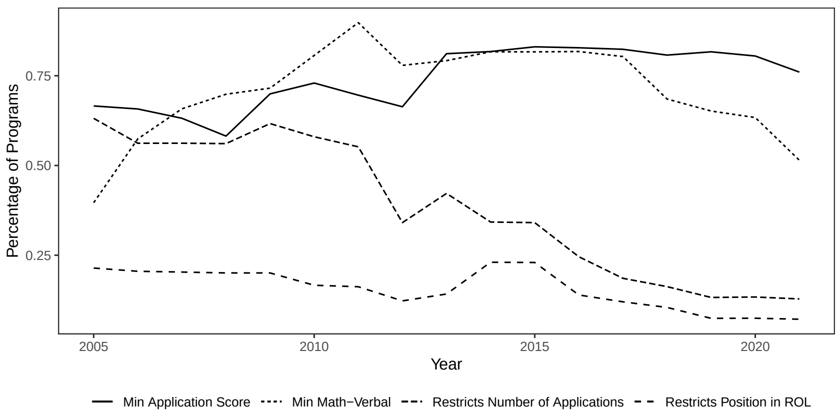
Figure 4.5: Share of students with *admissibility* mistakes by average score and years



Notes: The shares are computed as the total number of students who submitted a ROL with at least one *admissibility* mistake, over the total number of applicants per bin of score percentiles for each group of years. The solid line is a conditional mean computed with a bandwidth of 1 score percentiles and shaded region corresponds to its 95% confidence interval. The score percentiles are computed with respect to the population of students who participated in the admission process and had a valid average Math/Verbal score.

Figure 4.6 shows the evolution of the share of programs with an active admission requirement by type. Overall, we observe that some requirements have increased their prevalence over time (e.g., minimum Math-Verbal), while other requirements have decreased their relevance over time (e.g., restrictions on length of ROL or position of programs in ROLs).

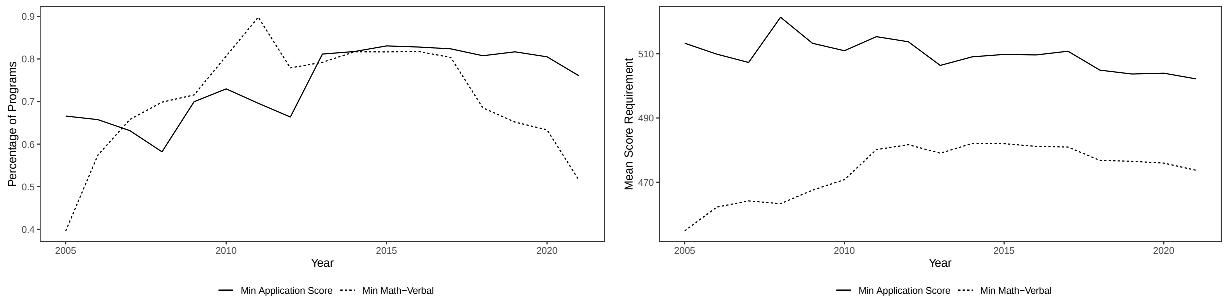
Figure 4.6: Evolution of requirements by year



From Figure 4.6 we observe that the two most crucial requirements—in terms of the number of programs for which they are active and also in terms of the number of students that do not satisfy them—are (1) Min Math-Verbal, which requires that the average score between the Math and Verbal is above some threshold; and (2) the minimum application score, which requires that their weighted score exceeds some threshold. Figure 4.7a shows the share of programs that has such a requirement each year. We observe that until 2013 this share was growing over time and then reaches a plateau (extensive margin). Moreover, Figure 4.7b shows that the required minimum average score increased over time (intensive margin). These statistics suggest that programs increased their admission requirements in both the extensive and intensive margins, adding barriers for entry that made students more likely to make admissibility mistakes.

Figure 4.7: Programs with an active score requirement by year

(a) Share of programs (extensive margin) (b) Mean score (intensive margin)



4.1.3 Admissibility mistakes and the role of information

Although these requirements are announced before the application process starts, some students may not have access to the most updated information and may not be aware of the changes in admission requirements. To assess if such information frictions explain the prevalence of *admissibility* mistakes, we combine the administrative data and the surveys to (i) evaluate the effect of changes in requirements over time on *admissibility* mistakes, to (ii) better understand if students are aware of the admission requirements, and to (iii) shed light on whether students understand the rules of the allocation mechanism and the consequences of making *admissibility* mistakes.

Time series of mistakes. To analyze whether changes in the admission requirements over time can have an effect on *admissibility* mistakes, we run a time series analysis on the share of *admissibility* mistakes by program and year. To accomplish this we consider the following specification:

$$z_{jt} = \alpha_j + \lambda_t + \beta_1 z_{jt-1} + \beta_2 z_{jt-2} + \beta_3 \Delta_{jt} + \varepsilon_{jt} \tag{4.3}$$

where z_{jt} is the share of *admissibility* mistakes by program j in year t; α_t and α_j are time and program fixed-effect, respectively; $\Delta_{jt} = \left\{\Delta^+_{jtl}, \Delta^-_{jkl}\right\}_{l\in\mathcal{L}}$ is a matrix of dummy variables, where $\Delta^+_{jtl} = 1$ if program j increased the admission requirement l in period t, and $\Delta^+_{jtl} = 0$ otherwise; similarly, $\Delta^-_{jtl} = 1$ if program j decreased the admission requirement

l in period t, and $\Delta^{-}_{jtl} = 0$ otherwise. We also include lags for the variables Δ^{+}_{jtl} and Δ^{-}_{jtl} to capture the evolution of the effect of the change in requirements over years. Finally, ε_{jt} is an i.i.d shock.

Table 4.2 shows the estimation results. We observe that increasing an admission requirement increases the share of *admissibility* mistakes. Depending on the requirement, the effect ranges form 3.3% (Min Math-Verbal) to 4.7% (limiting the position of programs in the ROL). On the other hand, reducing the admission requirements decreases significantly the share of admissibility mistakes (from 2.3% to 5.1%). In addition, we observe that the lag variables of the changes in the admission requirements are consistent in sign, and their magnitude is decreasing over time. For instance, increasing the minimum Math-Verbal requirement increases by 4.04% the share of mistakes in the current year, by 0.76% in the following year, and by 0.27% two years later. These results are consistent with students having adaptive beliefs about admission requirements, i.e., a share of students who make *admissibility* mistakes might be unaware of the changes in requirements in the current year, but this share decreases as time goes by. Under this hypothesis, students might adapt to changes in the rules of the admission process, but this adaptation is not immediate. The lack of immediate awareness of students about admission requirements suggests that changes in admission requirements can introduce a negative externality in the centralized system. If *admissibility* mistakes are welfare-relevant, this externality could affect students' outcomes.

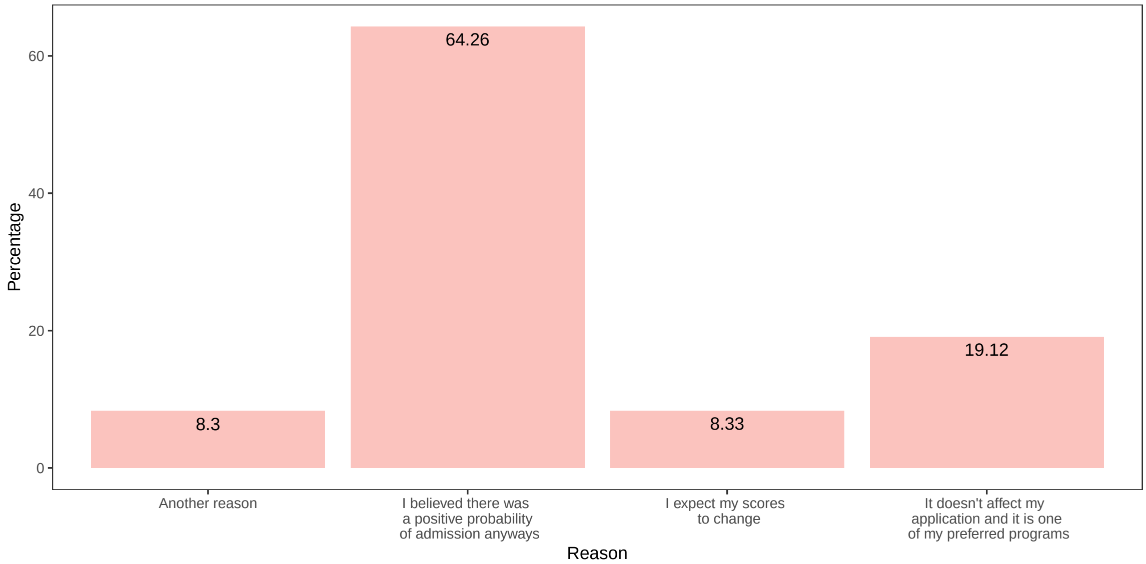
Awareness. To understand the level of awareness of students about their *admissibility* mistakes and how they interpret the information about admission requirements, we leverage the information elicited through the survey implemented by DEMRE in 2020. Overall, 86% of respondents who made an *admissibility* mistake declare to be aware of it at the time of applying. Figure 4.8 shows the reasons why students applied with an *admissibility* mistake conditional on being aware of it. We observe that the majority (close to 64% of students) think that there is a positive probability of admission to a program with an *admissibility* mistake. This lack of understanding about the rules of the admission system could be payoff relevant in some cases. For instance, if a student does not apply to feasible programs besides her application with an *admissibility* mistake, she faces zero probability of admission to the centralized system.

Table 4.2: Effect of Changes in Admission Requirements

	(1)	(2)	(3)	(4)
Min. average score (P0)	0.029***	0.037***	0.034***	0.040***
	(0.006)	(0.008)	(0.005)	(0.006)
Min. average score (N0)	-0.020**	-0.028***	-0.043***	-0.044***
	(0.007)	(0.007)	(0.004)	(0.005)
Min. application score (P0)	0.019***	0.026***	0.036***	0.035***
	(0.005)	(0.007)	(0.005)	(0.006)
Min. application score (N0)	-0.013*	-0.017*	-0.023***	-0.029***
	(0.006)	(0.009)	(0.006)	(0.007)
Special test (N0)	-0.075	-0.130***	-0.304***	-0.425***
	(0.063)	(0.040)	(0.092)	(0.058)
Restricts application rank (P0)	0.056**	0.015	0.047***	0.013
	(0.022)	(0.025)	(0.011)	(0.019)
Restricts application rank (N0)	-0.021	-0.038**	-0.051***	-0.059***
	(0.018)	(0.014)	(0.008)	(0.007)
Min. average score (P1)		0.015***		0.008**
		(0.004)		(0.003)
Min. average score (N1)		-0.027***		-0.024***
		(0.008)		(0.006)
Min. average score (P2)		0.011**		0.003
		(0.004)		(0.002)
Min. average score (N2)		-0.015**		-0.010*
		(0.006)		(0.005)
Min. application score (P1)		0.017**		0.011*
		(0.006)		(0.005)
Min. application score (N1)		-0.007		-0.007*
		(0.006)		(0.004)
Min. application score (P2)		0.008**		0.001
		(0.004)		(0.005)
Min. application score (N2)		-0.008		-0.004
		(0.006)		(0.004)
Special test (N1)		-0.102		-0.139**
		(0.067)		(0.051)
Special test (N2)		-0.092		-0.057
		(0.084)		(0.065)
Restricts application rank (P1)		0.066**		0.051**
		(0.026)		(0.019)
Restricts application rank (N1)		-0.035***		-0.029***
		(0.010)		(0.006)
Restricts application rank (P2)		0.009		-0.011
		(0.013)		(0.011)
Restricts application rank (N2)		-0.028		-0.015
		(0.017)		(0.011)
Share mistakes (1)			0.466***	0.422***
			(0.026)	(0.039)
Share mistakes (2)			0.082***	0.127***
			(0.018)	(0.022)
Program	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Lags - Dependent	No	No	Yes	Yes
Lags - Others	No	Yes	No	Yes
Observations	18,951	14,814	16,799	14,814
R^2	0.839	0.873	0.895	0.904
Within R^2	0.058	0.097	0.312	0.316

Note: P0 (N0) represents the variables Δ^+_{jtl} (Δ^-_{jtl}), while P1 and P2 (N1, N2) capture the first and second lags of these variables. Standard errors clustered at the program and year level reported. Significance: $^*p < 0.1;^{**} p < 0.05;^{***} p < 0.01$

Figure 4.8: Reasons for making admissibility mistakes conditional on being aware



On the other hand, we observe that close to 14% of respondents who made an admissibility mistake declare not to be aware of it when submitting their application.

In Appendix 8.1, we analyze which are the specific requirements that the respondents know and do not know. Overall, we observe heterogeneity in the level of knowledge by requirement type and significant differences between the groups of students who did and did not make an *admissibility* mistake. Indeed, from the students who did not make an *admissibility* mistake, between 60% to 75% declare to know the requirements of minimum scores and specific tests. In contrast, this number is between 59% to 63% among students who made an *admissibility* mistake.

In addition, we observe that students who made an *admissibility* mistake are significantly less correct about programs' vacancies (17% compared to 28%). However, we do not observe substantial differences for other requirements.

In summary, there is poor understanding of the admission requirements and, as expected, students who make *admissibility* mistakes tend to be less aware of these requirements than students who do not make mistakes. This fact suggests that *admissibility* mistakes might be payoff relevant if they are driven by a lack of understanding about admission requirements.

4.1.4 Summary: Hypothesis 1 vs Hypothesis 2

The previous analysis suggests that there is some evidence supporting Hypothesis 1: applicants' average scores have decreased significantly from 2010, which is negatively correlated with the growth of admissibility mistakes over time. On the other hand, there is strong evidence supporting Hypothesis 2: the growth of admissibility mistakes over time is mainly driven by growth on active score requirements in extensive and intensive margins. Moreover, changes in admission requirements over time seem to increase *admissibility* mistakes. However, this effect fades out over time, suggesting that students might adapt to this new information but not immediately.

Finally, regarding the level of awareness of students about admission requirements and their *admissibility* mistakes, we conclude that students do have access to correct information at different stages of the application process. However, a significant fraction of students declares not being aware of their *admissibility* mistakes. For students who declare to be aware of them, a significant fraction does not understand the consequences of making such mistakes, as they believe they still have a positive probability of being admitted. In addition, a small fraction of students—after applying—have correct knowledge about the admission requirements of their listed programs, and students who make an *admissibility* mistake tend to be less aware of these requirements than students who do not make any mistake.

4.2 Relevance

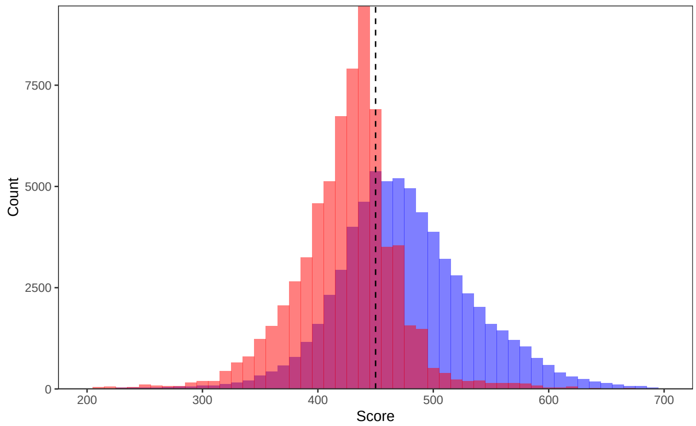
In this section, we analyze the relevance of *admissibility mistakes*, i.e., whether making this type of mistake can affect students' outcomes and welfare.

Admissibility mistakes could be payoff relevant for several reasons. First, since the Chilean system only allows students to apply to at most ten programs, making an admissibility mistake results in a wasted preference, which could potentially limit students' chances of applying to other programs where they are admissible. Second, even for students who apply to less than the maximum number of programs allowed, a high fraction of admissibility mistakes reflects a poor understanding of how the application process and the assignment mechanism work, affecting how students decide to apply.

To analyze the relevance of admissibility mistakes, we consider the probability of being assigned to the centralized system as a proxy for welfare. Even though this is not a precise measure for welfare, resulting assigned to a program can have a significant impact on students' future outcomes due to the high returns of higher education (Rodriguez et al., 2016). We say then that an admissibility mistake is payoff relevant if it reduces a student's admission probability to a program. As previously discussed, not all admissibility mistakes are payoff relevant. For instance, if a student applies to a program where she faces low admission probability (*reach* program) and then includes programs with high admission probability (*safety* programs), making an admissibility mistake would have no impact on her admission chances.

One case in which admissibility mistakes are likely to be payoff relevant is when they affect all student applications. In 2020, among the students that applied to at least one program (146,438), 18,586 students made application mistakes in all their submitted preferences. In Figure 4.9 we plot the distribution of the average score between Math and Verbal (in red) and the application scores (in blue) among students who made mistakes in all their applications. We observe that 25.05% of these students have scores that would

Figure 4.9: Distribution Average Math-Verbal and Weighted Score for Students with All Mistakes



enable them to be admissible in some programs, which would be enough for them to be admitted. Hence, these students could have applied to different programs and being assigned to the centralized system.

Discussion. Welfare-relevant mistakes may also be present among students that submit valid applications. For instance, students may include valid applications but may result unassigned, and thus not including more valid preferences prevented them from obtaining a better assignment. However, it is difficult to estimate the causal effect of an admissibility mistake on the probability that the student is assigned, as students who make admissibility mistakes may not be comparable to those who do not.

For this reason, it may be the case that two students with similar scores and observable characteristics but different eligibility statuses differ on unobservable characteristics that push them to apply. For instance, students who make admissibility mistakes may have a lower understanding of the system's rules than students with similar characteristics but who do not make admissibility mistakes. Then, identifying the effect of the mistake from the unobservable characteristics is not possible using observational data.

Overall, although we cannot directly estimate the effect of admissibility mistakes, we know that an important fraction of students is not aware of their mistakes. Also, a significant fraction of students make admissibility mistakes in all their applications when they could have included programs for which they are eligible. Hence, we conclude that admissibility mistakes play an important role, and reducing their incidence is a relevant goal that can be achieved by providing students more information.

appropriately

5 Strategic Mistakes

In this section, we focus on *strategic mistakes*. As discussed in Section 3, we focus on three types of strategic mistakes:

1. *Under-confidence*: students make an under-confidence mistake if, despite having valid applications, they do not apply to their top-true choice as their top-reported preference, even though their score is high enough to be admitted with positive probability and the constraint in the length of the list is not binding.
2. *Over-confidence*: students make an over-confidence mistake if, despite having valid applications, they do not apply to programs they: (i) prefer to be unassigned and (ii) face a positive probability of assignment, even though they face a positive probability of being unassigned to the centralized system and the constraint in the length of the list is not binding.
3. *Ordering*: students make an ordering mistake if they do not rank programs with a positive admission probability in decreasing order of utility. As a result, the student would benefit from submitting a ranked ordered list with the same subset of programs but in different order.

Notice that both types of mistakes are, by definition, payoff relevant. In addition, to properly analyze these mistakes, we need to understand students' application behavior and, more specifically, how they form their beliefs on admission probabilities and the expected utilities from attending each program. For this reason, we start by characterizing the application behavior of students and their subjective beliefs. Then, we document the prevalence and relevance of strategic mistakes and analyze their main drivers.

5.1 Application behavior

As part of our surveys, we ask students about their most desired program, aiming to elicit their top-true preference and to understand their application behavior.[9] This question allows us to classify students into three groups: (i) *Truth-tellers*, i.e., students who include their top-true preference as their top-reported preference in their application list, (ii) *Misreporting Exclusion*, i.e., students who do not include their top-true preference in their list, and (iii) *Misreporting Ordering*, i.e., students who include their top-true preference in their list but not as their top reported preference.

To properly classify students into these groups, we analyze the reasons why students did not include their top-true preference as top-reported preference. Table 8.1 in Appendix

[9] In particular, we ask students the following question:
This question aims to know where you would have applied to in the hypothetical case in which your admission did not depend on your scores. We remind you that this is only a hypothetical question and will not affect your application or admission probabilities. If the Admissions Process did not depend on your PSU scores, nor your NEM or Ranking scores. To which program would you have applied?

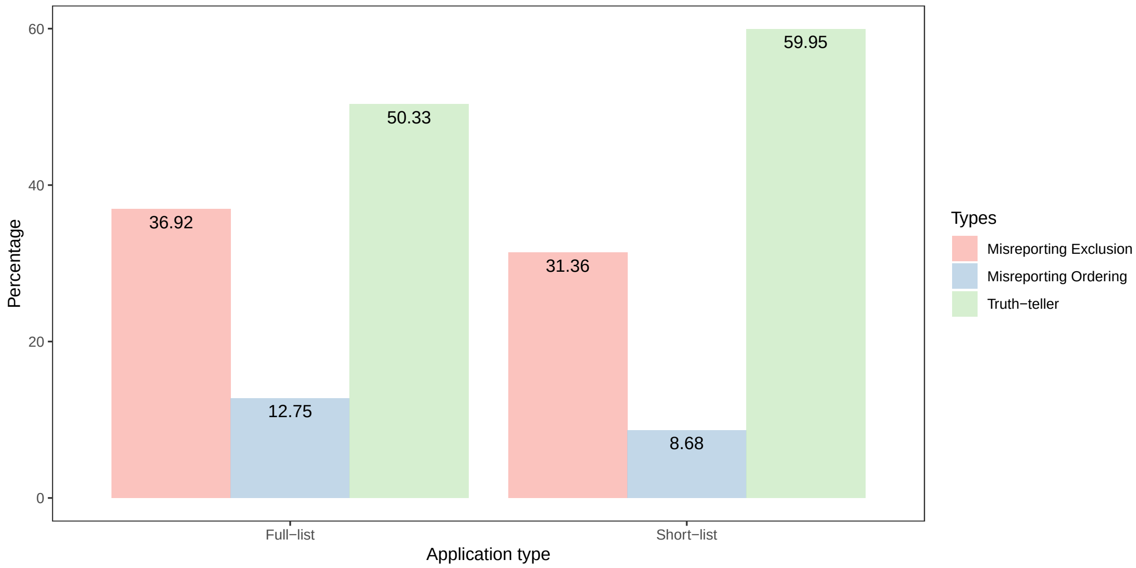
8.2, shows the reasons students give to not list their top-true preference as top-reported preference. We observe that a significant fraction of students give inconsistent answers to this question. For instance, close to 14% of *truth-tellers* do not declare to have listed their top-true preference as top-reported preference. In addition, a significant fraction of students who are classified as *misreporting exclusion* or *misreporting ordering* declare to not list their top-true preference as top-reported preference because they do not have the monetary resources to pay for that program (26% and 20%, respectively). However, the survey question we are analyzing does not ask students to choose their ideal program abstracting from monetary costs. To avoid over-estimating the share of students who misreport their preferences, we consider only students who give consistent answers regarding their application type.[10]

Figure 5.1, shows the percentage of students in each group who give consistent answers. We further divide these groups between *short-list* (students who report less than 10 programs) or *full-list* (students who list exactly 10 programs). We observe that, among *short-list* students (88% of applicants), close to 60% of applicants report their top-true preference as their top-reported preference, and 31% exclude this program from their application list. This statistic contrasts to the close to 50% for *full-list* students who include their top-true preference as their top-reported preference. A potential explanation for these differences is that students who submit full lists might face strategic incentives to exclude their top-true preferences if their beliefs assign a low admission probability to that program.

In addition, we observe that a significant fraction of students misreports the order of their top-true preference (*Misreport Ordering*). This percentage is close to 8% for *short-list* students, while it is close to 13% for full-list students. One potential explanation for this result is that these students do not understand how the mechanism works, and therefore do not order the programs in their ROL appropriately.

[10] We consider as inconsistent answers, students who are classified as *truth-tellers* and do not give reason (a) or give reasons (c) or (d), and students who are classified as *misreporting exclusion* or *misreporting ordering* and give reason (a) or reasons (c) or (d).

Figure 5.1: Application types



5.1.1 Subjective beliefs

We now characterize students' subjective beliefs on admission probabilities. We ask students in the survey about their beliefs over the realization of cutoff scores and the probability they assign to their application score being above the cutoff score for every program in their application list.[11]

Rational expectations and biased beliefs. To understand if students have correct beliefs regarding their admission chances, we compute their Rational expectation beliefs (*Ratex*) for every listed preference and also for their top-true preference. *Ratex* beliefs are computed following the approach described in Larroucau and Ríos (2018)[12].

Figure 5.2a shows the distribution of *Ratex* beliefs for the first and fourth reported preferences. We observed peaks around 0% and 100%, with little mass in the middle of the distribution's support. This pattern is explained by the fact that a significant fraction of students faces almost degenerate admission probabilities for the programs listed in their

[11]In particular, we asked the following question:

We show you now a list of the programs you applied to, in strict order of preference. For each of them, please tell us which do you think will be the value of the cutoff score for the CURRENT Admission Process and how likely do you think your application score will be above the cutoff score. We remind you that this is only a survey, and it DOES NOT affect in any way your application nor your admission probabilities. What do you think will be the value of the cutoff score for the current Admission Process for each of these programs?
How likely do you think your application score for the following programs will be above the current admission process's cutoff score?
On a scale from 0 to 100, where 0 is "completely sure that your application score WILL NOT be above the cutoff score for this program" and 100 is "completely sure that your application score WILL BE above the cutoff score for this program".

[12]The only difference to the approach followed by Larroucau and Ríos (2018), is that after obtaining the marginal distribution of cutoffs for every program, we smooth these distributions by fitting Truncated Normal distributions doing a standard MLE procedure.

application lists.

Figure 5.2b shows the distribution of subjective beliefs for the first and fourth reported preferences. We observe peaks at 0%, 50%, and 100%, and we also observe a significant mass between these points of the distribution. The mass at 50% suggests that students' subjective beliefs could be subject to a pull-to-the-center effect, i.e., students' beliefs are biased towards the middle, assigning an attenuated probability to extreme outcomes compared to *Ratex* beliefs.[13]

Figure 5.2: Distribution of Ratex and subjective beliefs by preference

(a) Ratex beliefs (b) Subjective beliefs

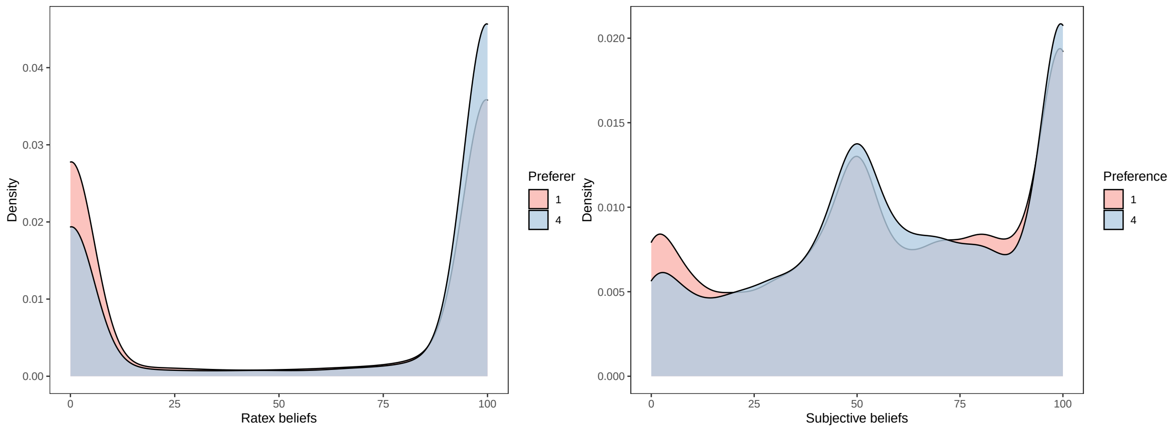
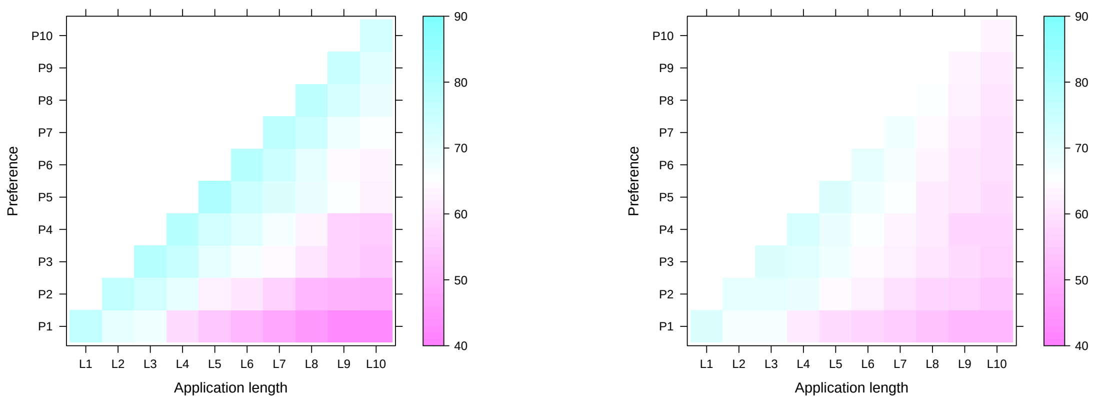


Figure 5.3 shows the average *Ratex* (panel (a)) and average subjective beliefs (panel (b)) by preference and application length. We observe that under *Ratex* beliefs, students face on average higher admission probabilities in lower-ranked programs compared to subjective beliefs, especially for students with long lists. Under subjective beliefs, there is less dispersion on average admission probabilities by preference and application length.[14]

Figure 5.3: Average Ratex and Subjective beliefs by preference and application length

(a) Ratex (b) Subjective



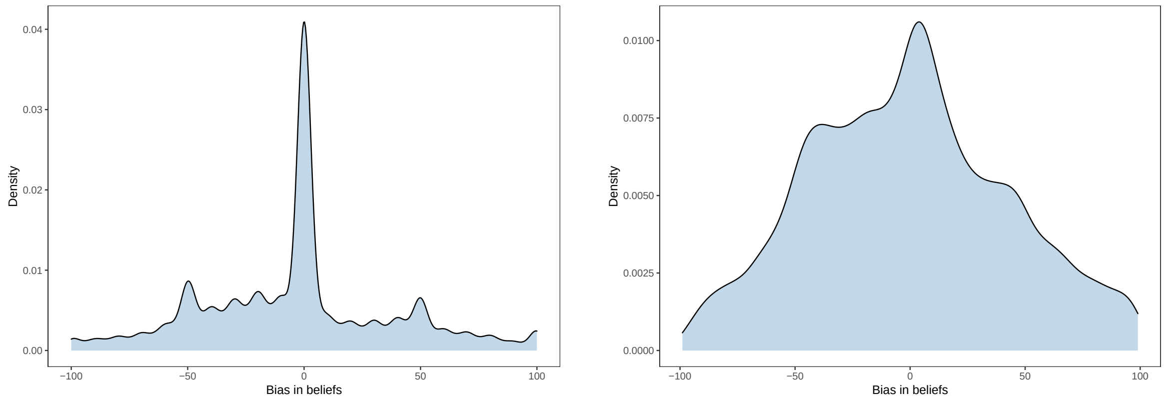
[13]Similar pull-to-center effects are found in more general belief elicitation tasks, and also in newsvendor problems (see Bostian et al. (2008)).

[14]In Appendix 8.3, we analyze these correlation patterns in detail.

Ratex bias. We compute a measure of bias in beliefs by taking the difference between the value of students' subjective beliefs and their *Ratex* beliefs. Figure 5.4a shows the distribution of the *Ratex* bias. We observe a large mass at zero, suggesting that most students are correct about their admission chances on average. However, there is slightly more mass in the negative values than in the positive values. To understand if most of the mass at zero is driven by degenerate admission chances, Figure 5.4b shows the previous distribution but including only observations for which students face between 1% and 99% admission probability according to the *Ratex* beliefs. The distribution of bias is still centered around zero and relatively symmetric.

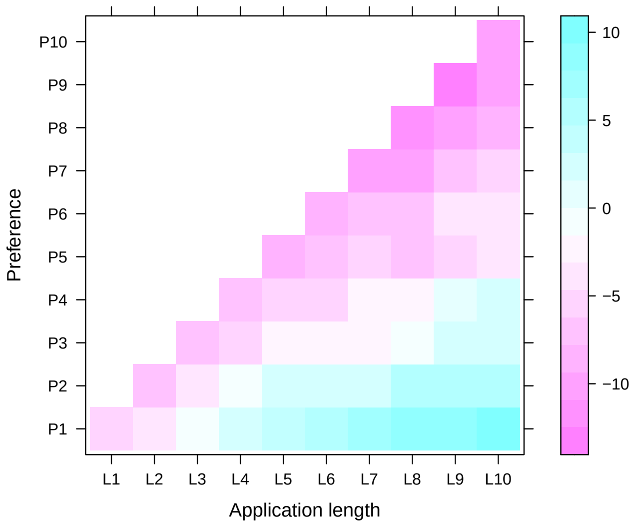
Figure 5.4: Distribution of Ratex bias

(a) Distribution of Ratex bias (b) Ratex bias (non-degenerate)



To understand if there is any correlation between students' bias and their application lists, Figure 5.5 shows the distribution of *Ratex* bias by preference and application length. We observe that students, on average, tend to be slightly optimistic for their top-reported preferences and more pessimistic for their bottom-reported programs, especially considering students who submit long lists. These correlation patterns are consistent with the pull-to-the-center effect.

Figure 5.5: Average bias in beliefs by preference and application length



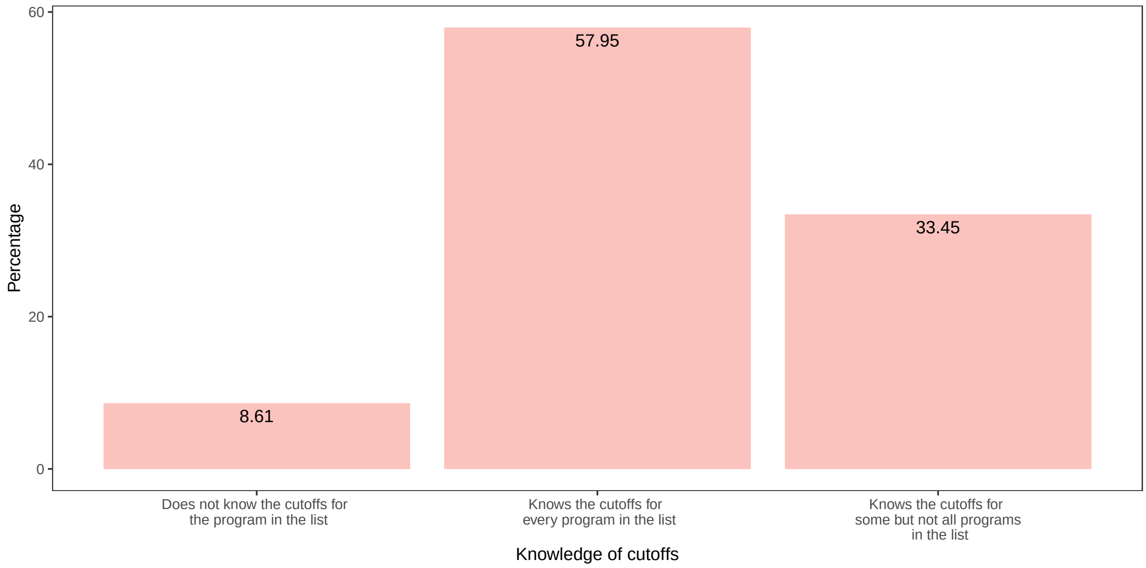
Knowledge of cutoffs. To understand whether students' knowledge about cutoff scores could explain biased beliefs, we ask students in the survey whether they know the value of cutoff scores for the previous year.[15] Figure 5.6 shows students' knowledge level about the previous year's cutoff scores. Close to 58% declare to know the previous year's cutoff scores for all of the programs listed in their application lists. In contrast, close to 9% declare to ignore the previous year's cutoff scores of all the programs listed in their application.[16]

Although previous year cutoffs are informative for the current process, cutoffs are random variables that may vary from year to year. To assess if students know this and understand how they use past information to build their beliefs, we ask them to predict the expected cutoff for the current admission process for every program listed in their application list. On the one hand, Figure 5.7a shows the distribution of the difference between the standardized expected cutoff (subjective) and the standardized realized cutoffs (*Ratex*) by position in the preference list. First, we observe that bias distributions are centered around zero. Second, we observe that students tend to be more accurate about the expected cutoffs of their top-reported preferences, as the distributions become significantly more spread for programs listed in lower reported preferences. This heterogeneity implies that there is a significant fraction of students with high positive bias, and a signif-

[15] In particular, we ask the following question: *It is referred to a cutoff score as the application score of the last admitted students to a given program. Each student is assigned to the highest reported preference for which her application score is greater than or equal to the cutoff score that realizes in the current Admission Process. Do you know which was the cutoff score for the PREVIOUS YEAR for each of the programs you applied to?*

[16] DEMRE does not provide any information about programs' cutoffs during the application process. However, this information can be typically found on universities' websites. One reason behind the lack of centralized information about cutoff scores is the concern that some students might not understand what a cutoff score exactly means. For instance, they might believe that cutoffs are predetermined by programs and do not understand that they may vary from year to year. This discussion stresses the importance of providing not only information that is necessary for students to forecast their admission chances but also to educate them about the meaning of this information.

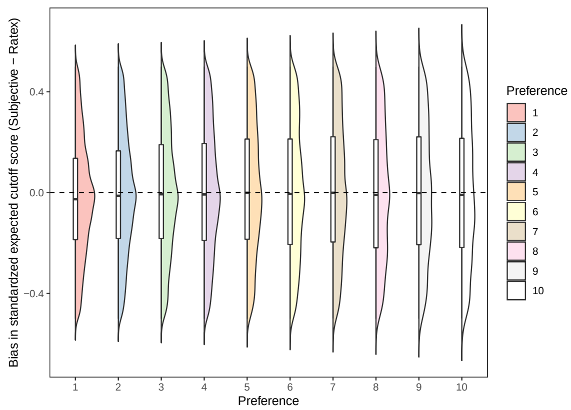
Figure 5.6: Knowledge of previous year's cutoff scores



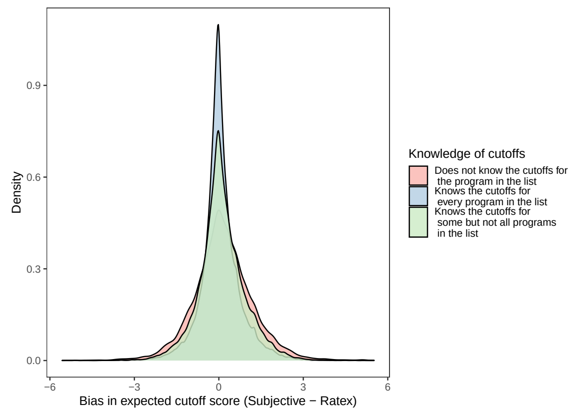
icant share with a high negative bias. We refer to these groups of students as *pessimistic* and *optimistic*, respectively. On the other hand, Figure 5.7b shows that the distribution of bias is more spread for students who do not know the previous-year cutoffs for some or all of the programs in their lists. This pattern suggests that giving information to students about previous year cutoff scores could be an effective policy to decrease their bias.

Figure 5.7: Distributions of bias in standardized expected cutoff

(a) By preference



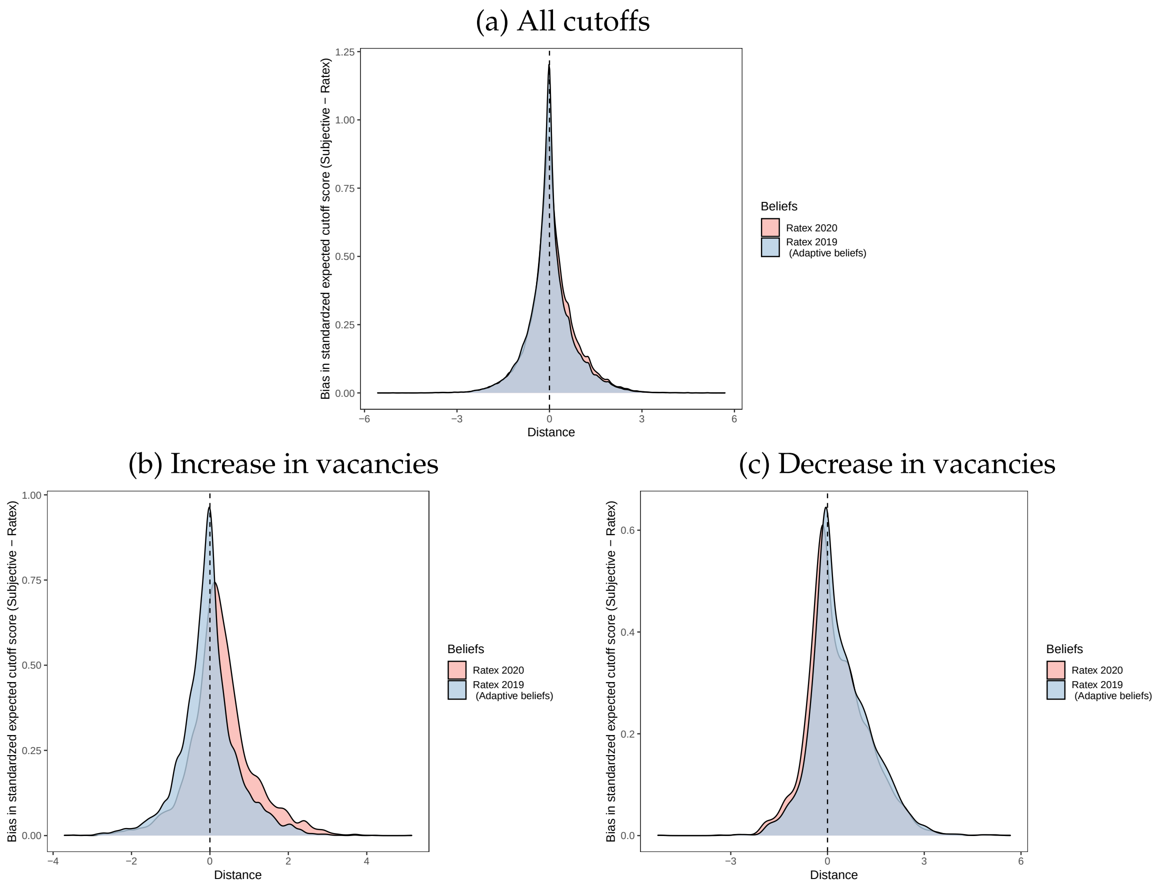
(b) By knowledge of cutoff scores



Adaptive beliefs. We now analyze whether students anticipate current changes in the distribution of admission cutoffs (*Ratex* beliefs) or believe that cutoff distributions for the current admission process are the same as the distributions of the previous admission process (*Adaptive* beliefs). Shedding light on this difference is important for modeling assumptions and policy evaluations. Suppose students do not anticipate current changes in cutoff distributions. In that case, changes in admission policies such as admission requirements, admission weights, and vacancies, could increase the bias in students' beliefs, which can translate into payoff-relevant strategic mistakes.

Figure 5.8 shows the distributions of the difference between subjective expected cutoffs–for every listed program–and expected cutoffs given by *Ratex* (red) and *Adaptive* beliefs (blue). We measure the difference in expected cutoffs in standard deviations of application scores. Panel 5.8a shows these distributions for all programs. We observe that both distributions are centered around zero, i.e., there is no evidence of aggregate *optimism* or *pessimism*. However, the distribution with *Adaptive* beliefs is more concentrated towards zero. To analyze whether students' beliefs are closer to *Ratex* or *Adaptive* beliefs, Panel 5.8b shows the distribution of bias for programs that increased their vacancies in at least 25% compared to the previous year, and Panel 5.8c for programs that decreased their vacancies in at least 25%. In both cases we observe that the distributions of bias with *Adaptive* beliefs are more centered around zero, even though the distribution of bias with *Ratex* beliefs are more displaced to the sides. This suggests that students do not correctly anticipate changes in cutoffs, even for programs that change significantly their vacancies from year to year, and that their beliefs are closer to *Adaptive* than *Ratex* beliefs.

Figure 5.8: Distributions of the standardized difference between subjective expected cutoffs and *Ratex* and *Adaptive* beliefs



Modeling bias. We consider a simple model of subjective beliefs to capture the previous data patterns, i.e., (i) that students have biased beliefs that are centered around *Adaptive* beliefs, (ii) that beliefs are subject to the pull-to-the-center effect, and (iii) that students are more biased if they do not know previous years' cutoff scores. Formally, we introduce the following definitions and assumptions:

Definition 7 (Consideration sets)**.** For each student $i \in N$, define by $M_{it} \subseteq M$ the set of programs such that the student knows the cutoff for year $t-1$, $\bar{s}_{jt-1}$.

Assumption 1 (Subjective beliefs as a deviation)**.** We denote by $\tilde{p}_{ijt}$ the subjective belief of student i in program j in period t, and we compute it as

$$\tilde{p}_{ijt} \equiv \mathbb{P}\left(s_{ij} \geq \tilde{s}_{ijt}\right) \tag{5.1}$$

where s_{ij} is the application score of student i in program j, and $\tilde{s}_{ijt}$ is a random variable given by

$$\tilde{s}_{ijt} = \begin{cases} \bar{s}_{jt-1} + \nu_{ijt} & \text{if } j \in M_{it} \\ \eta_{ijt} & \text{otherwise} \end{cases} \tag{5.2}$$

where $\bar{s}_{jt-1}$ is the realized cutoff score for program j in year $t-1$, $\nu_{ijt} \sim g_{ijt}\left(\nu_{ijt}\right)$ is an idiosyncratic shock that induces bias over the cutoff distribution for program j in year t, and $\eta_{ijt} \sim h_{ijt}(\eta_{ijt})$ is the prior beliefs of student i when she is uninformed about the expected cutoff score for program j in year $t-1$.

To capture the pull-to-the-center effect, we allow the bias to depend on the distance between students' application scores and the cutoff score of the previous year. For instance, if students above the previous year cutoff scores tend to be pessimistic, and students below tend to be optimistic, we would observe gravitation to the middle.

To test whether students' bias are correlated with their preferences and whether the pull-to-the-center effect is driven by differences in the mean of the bias shock, we decompose students' bias on admission probabilities relative to *Adaptive* beliefs and estimate the following regression:

$$\underbrace{\frac{\mathbb{E}\left[\tilde{s}_{ijt}\right] - \bar{s}_{jt-1}}{\bar{s}_{jt-1}/100}}_{\text{Bias in expected cutoff}} = \alpha_i + \beta_1 \underbrace{\left[\frac{s_{ij} - \bar{s}_{jt-1}}{\bar{s}_{jt-1}/100}\right]^{+}}_{\text{Distance (if positive)}} + \beta_2 \underbrace{\left[\frac{s_{ij} - \bar{s}_{jt-1}}{\bar{s}_{jt-1}/100}\right]^{-}}_{\text{Distance (if negative)}} + \gamma_{rank} rank\left(R_i(j)\right) + \epsilon_{ijt}, \tag{5.3}$$

where $\mathbb{E}\left[\tilde{s}_{ijt}\right]$ is the subjective expectation of the cutoff score $\bar{s}_{jt}$ by student i, α_i is a student fixed-effect, s_{ijt} is the application score of student i in program j, $rank_{R_i(j)}$ is a vector with a one in the position of program j in student's i ROL, and zero otherwise, and ϵ_{ijt} is an i.i.d error term. The function $[\cdot]^{+}$ ($[\cdot]^{-}$) returns the absolute value of the argument if positive (negative), and returns zero otherwise.

Column (1) in Table 5.1 reports the estimation results. We observe that students whose application scores are above the previous year's cutoffs have, on average, an additional upward bias of near 0.5 percentage points per unit of distance (per one percentage point above the cutoff). This statistic suggests that students above the cutoffs tend to be more pessimistic as the distance from the cutoff increases. Similarly, students who are below the previous year's cutoffs have on average an additional downward bias of near 0.4 percentage points per unit of distance, i.e., students below the previous year's cutoffs tend to be more optimistic. These effects are consistent with the pull-to-the-center effect. In addition, we observe a negative correlation between the preference rank and the proportional bias in expected cutoffs relative to the top-reported preference. For instance, programs listed in the fifth reported preferences exhibit 1.1 additional percentage points of downward bias than programs listed in the top-reported preference. This result suggests that students tend to be slightly more optimistic for programs listed at the bottom of their application lists.

To understand how the magnitude of the bias differs with students' observable characteristics, in column (2) of Table 5.1 we report the results of considering the logarithm of the norm 2 of the bias as a dependent variable and replacing the fixed effects with students' observable characteristics, including their gender, normalized application score, the type of high school they graduated from (relative to Private schools), whether the program is their most desired preference, whether they know someone at the program, among others. First, we find that females are significantly more biased than males. Second, we observe that students from public and voucher schools are significantly more biased than students from private schools. Third, we observe that the application score has a negative and significant effect. These results are consistent with previous literature and suggests that students with high SES might have more accurate beliefs than students with low SES (potentially due to differential access to information). Fourth, we observe that students' beliefs about their admission chances in their most desired program are significantly more accurate than in other programs. This result is intuitive, as students may collect more information regarding their most desired preference. Finally, we observe that knowing someone at the program also helps students to have more accurate beliefs.

Discussion: For every student i, we elicited a measure for $\mathbb{E}\left[\tilde{s}_{ijt}\right]$ and $\tilde{p}_{ijt}$ at her application score s_{ij} but only for programs that were listed in the application or declared as top-true preference. We then face a selection problem: the sample of observed beliefs might not come from a random sample of programs from within the consideration set of the student. The potential bias could come from at least two sources: (i) correlation between preferences and bias and (ii) correlation between bias and the decision to rank a program in the list. In the first case, students' preferences could be correlated with their bias if they follow a search process to form their subjective beliefs and tend to search more information for programs they like the most. In the second case, the ranking strategy could be correlated with bias if, for instance, students maximize their expected utility over their assignment and face–even small–application costs. Under this scenario, if a student has a positive bias in her subjective beliefs for a given program that she likes, she may be more likely to include that program in her list than a similar program where she has a negative bias in her beliefs.

To address this selection issue, we redo our previous analysis considering only the bias for students' top-true preference. We obtain similar results concerning the pull-to-the-center effect.

Table 5.1: Regression Results on Bias

	(1)	(2)
Distance score to cutoff (positive)	0.546***	0.055***
	(0.005)	(0.0005)
Distance score to cutoff (negative)	-0.412***	0.062***
	(0.010)	(0.001)
Score	-	-0.377^{***}
	-	(0.005)
Female	-	0.058***
	-	(0.010)
Public	-	0.111***
	-	(0.015)
Voucher	-	0.123***
	-	(0.013)
Most Preferred	-	-0.106^{***}
	-	(0.019)
Knows Someone	-	-0.099^{***}
	-	(0.012)
Preference 2	-0.418***	0.114***
	(0.050)	(0.017)
Preference 3	-0.692***	0.237***
	(0.061)	(0.018)
Preference 4	-1.042***	0.326***
	(0.071)	(0.019)
Preference 5	-1.169***	0.403***
	(0.089)	(0.021)
Preference 6	-1.167***	0.467***
	(0.105)	(0.023)
Preference 7	-1.068***	0.522***
	(0.129)	(0.026)
Preference 8	-0.840***	0.540***
	(0.154)	(0.030)
Preference 9	-1.017***	0.605***
	(0.182)	(0.034)
Preference 10	-1.588***	0.626***
	(0.227)	(0.039)
Constant	-	0.113***
	-	(0.019)
Observations	78,095	77,409

Note: In column (1), the dependent variable is the bias, and we include student fixed-effects. In column (2), the dependent variable is the log of the norm 2 of the bias, and we do not consider student fixed-effects.

5.2 PREVALENCE AND RELEVANCE

UNDER-CONFIDENCE AND ORDERING. As previously defined, we say that students make an under-confidence mistake if, despite them having valid applications, they do not apply to their top-true choice as their top-reported preference, even though their score is high enough to be admitted with positive probability and the constraint in the length of the list is not binding. In addition we say that students make an ordering mistake if by changing the order of a program in their list they can improve their expected utility.

Table 5.2 shows the percentage of students who make under-confidence and ordering mistakes. We compute this statistic by the level of knowledge the student declares about last year's cutoff scores. Overall, we observe that between 1.7% and 3.2% of students make an under-confidence mistake *ex-post* and that between 0.9% and 2.0% of students make an ordering mistake *ex-post*, i.e., they do not include their top-true preference as their top-reported preference, and their application score was above the realized cutoff score for that program. This percentages increase to 2.3%-4.2% if we consider *ex-ante* under-confidence mistakes and to 1.8%-3.5% if we consider *ex-ante* ordering mistakes, i.e., all students who face a strictly positive probability of admission to their top-true preference but did not include that program as their top-reported preference. We also observe that students who do not know any of the cutoff scores for their listed programs experience a higher prevalence of under-confidence and ordering mistakes, suggesting that a driver of these mistakes could be the lack of information about past cutoff scores.

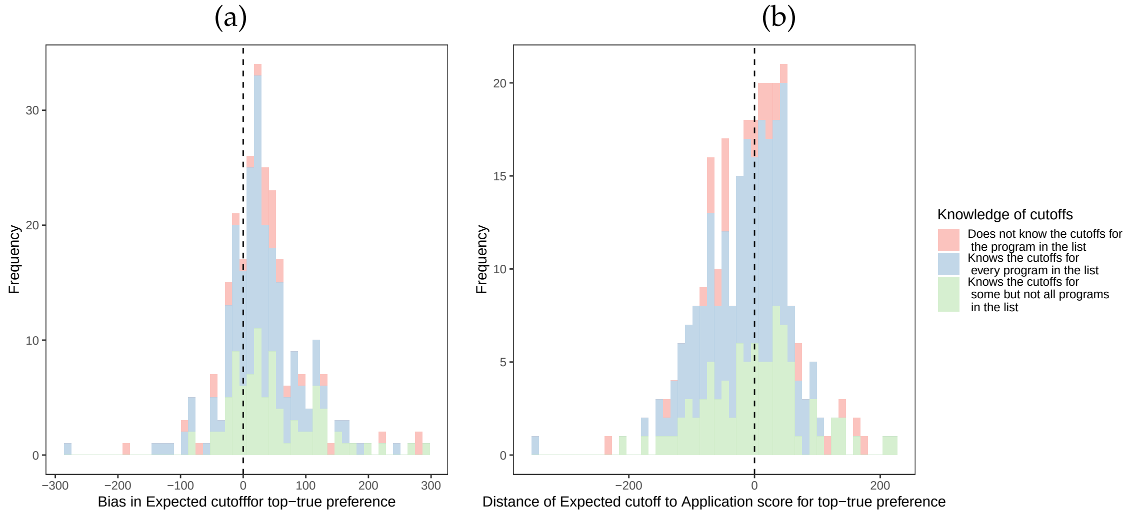
Table 5.2: Under-confidence and Ordering mistakes

	Under-confident mistake		Ordering mistake	
Knowledge of cutoffs	Ex-post [%]	Ex-ante [%]	Ex-post [%]	Ex-ante [%]
Does not know the cutoffs	3.19	4.16	1.94	3.47
for the program in the list	(0.65)	(0.74)	(0.51)	(0.68)
Knows the cutoffs for	1.73	2.34	0.94	1.82
every program in the list	(0.17)	(0.19)	(0.12)	(0.17)
Knows the cutoffs for some	2.00	2.74	1.35	2.55
but not all programs in the list	(0.25)	(0.29)	(0.2)	(0.28)

Note: standard errors are computed in parenthesis.

We now analyze whether students' subjective beliefs can fully explain under-confidence mistakes. Figure 5.9 shows frequency histograms for the bias in expected cutoffs for the top-true preference relative to *Ratex* beliefs (panel (a)), and the distance between the application score of the student and his subjective expected cutoff (panel (b)). We compute these distributions only for students who made an *ex-ante* under-confidence mistake and give consistent answers to the survey (see Section 5.1). From panel (a) we see that close to 75% of the observations fall at the right of zero, i.e., students who make an under-confidence mistake tend to be pessimistic about the expected cutoff for their top-true preference. From panel (b) we observe that only close to 50% of students declare to believe that the realization of the cutoff—for the current admission process—will be higher than their application score. This last result implies that only 50% of under-confidence mistakes could be explained by bias in subjective beliefs about admission cutoffs (without considering potential measurement errors).[17]

Figure 5.9: Distributions of bias in expected cutoff by knowledge of cutoffs for under-confidence mistakes



OVER-CONFIDENCE. Students make an over-confidence mistake if, despite having valid applications, they do not apply to programs they: (i) prefer to being unassigned, and (ii) face a positive probability of assignment, even though they face a positive probability of being unassigned to the centralized system and the constraint in the length of the list is not binding. Over-confidence mistakes are not directly observed in our data. The reason behind this is that, in the surveys, we do not elicit information about programs that the student might prefer to be unassigned. For this reason, we must resort to the information contained in students' reported preferences and their subjective beliefs.

To understand the prevalence and relevance of these mistakes without directly observing them, we must understand their potential drivers. For any student i, a necessary condition for making an over-confidence mistake given her application list R_i, is that $\exists j \in M \notin R_i$, such that i prefers to be assigned to j than to be unassigned, i.e., $j \succ_i \emptyset$. If such a program exists, over-confidence mistakes could result from students having biased beliefs and facing small application costs. For instance, suppose students face small application costs. In this scenario, a student might not include a program of her preference if her subjective beliefs : (i) assign a low admission probability to that program or (ii) assign a low risk of being unassigned to the centralized system given her application list. If these beliefs are biased, these mistakes could then be payoff relevant. We focus then on the risk of the application list.

It is crucial to analyze the risk of the application lists and not only individual biases. Even if students have biased beliefs on their admission chances, these biases could have no implications on their assignment results. For instance, suppose students are optimistic about their admission probabilities and that they include programs at the bottom of their

[17]In Appendix 8.2, Table 8.3, we detail the reasons students–with *ex-ante* under-confidence mistakes–give for not listing their top-true preference.

application lists to ensure being assigned to the centralized system. In this scenario, there would be no changes in students' assignments if, instead, they had correct beliefs.[18] However, if students face a positive cost of including additional programs in their lists and they tend to underestimate the risk of their application lists, these biases could be payoff-relevant and result in *over-confidence* mistakes.

Figure 5.10 shows the distributions of *Ratex* and subjective application *Risk*. Panel 5.10a shows the histograms for the risk of application lists given *Ratex* and subjective beliefs, and Panel 5.10b shows boxplots of *Risk* given *Ratex* beliefs by level of subjective beliefs. We compute these statistics for all students who face a non-zero risk given *Ratex* beliefs and whose average scores are above the minimum required to be admitted to a program in the centralized system. These students are likely to face a strictly positive probability of admission to some program in the centralized system.

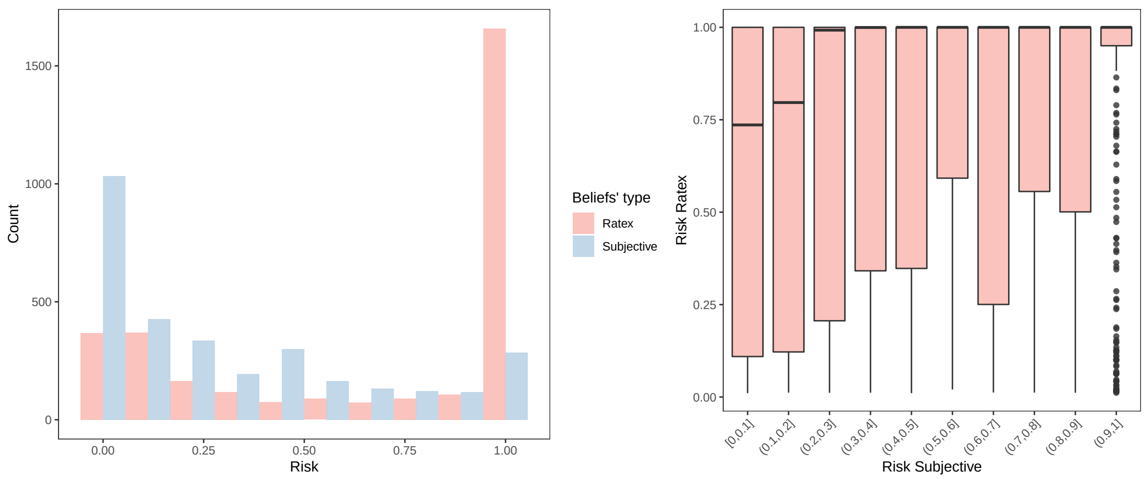
We observe that students who face some risk tend to under-predict how risky are their application lists. In fact, close to 10% of the sample faces a $Risk$ given *Ratex beliefs* greater than 1%, and close to 80% of this group under-predicts their $Risk$. This pattern is particularly severe at the extremes, where only a small fraction of students believe to be facing a risk equal to 1 relative to what *Ratex* beliefs predict. Indeed, close to 20% of students with positive $Risk$ and average scores above the minimum requirements believe they have a $Risk$ lower than 10% when they face a $Risk$ given $Ratex$ greater than 70%.

These results suggest that biased beliefs result in payoff-relevant *over-confidence* mistakes. In Section 6, we analyze if it is possible to reduce these mistakes by giving information to students about the correct risk of their application lists.

Figure 5.10: Distribution of Subjective and Ratex application Risk

(a) Histograms of Risk by beliefs' type

(b) Ratex Risk by Subjective Risk levels



[18] Assuming the constraint in the length of the list is not binding.

6 Reducing the Incidence of Mistakes

Based on the results in Sections 4 and 5, admissibility and strategic mistakes have different causes. The former are due to a lack of information about requirements, while biased beliefs mostly cause the latter. In this section, we report the design and results of an intervention aiming to reduce these two types of mistakes.

6.1 Description

In collaboration with MINEDUC, we designed and implemented an intervention to provide information to students during the application process. Specifically, using partial information about the applications, we created a personalized website for each student, which included information about the programs in the student's preference list and recommendations to improve the application.

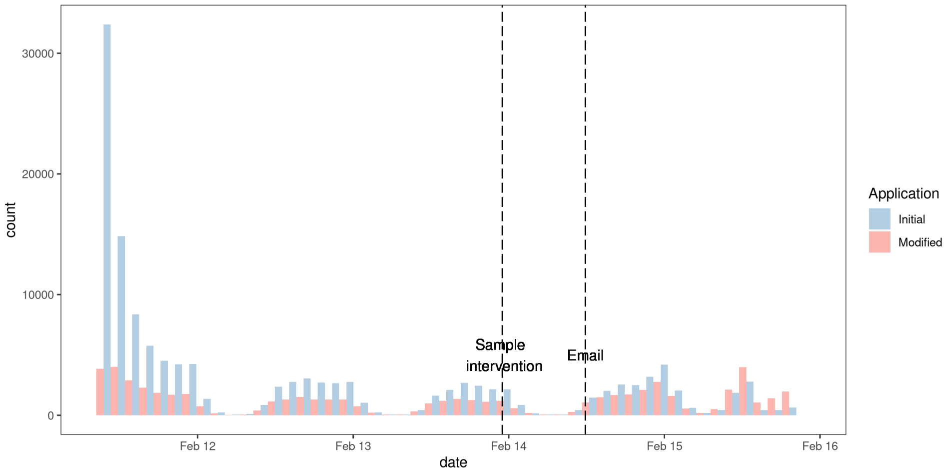
6.1.1 Background

As discussed in Section 2.1, the application process starts when the scores of the PSU/PDT are published. Students have five days to submit an application list—in the admission process of 2021, from February 11th to February 15th—and they are allowed to modify and update it as many times as they want.

To personalize the information provided, we use the applications received up to February 13th at 8 pm CT, which included 89,429 students, representing 66.16% of the total number of students that applied. We created a personalized website for each student using this information, and we sent them an email on February 14th at 9 am CT. The email included each student's personalized link and a general message inviting them to open it and get more information to improve their application.

Figure 6.1 shows histograms of applications' date, grouping by initial versus modified applications. We observe that a large share of applications happens during the first hours of the application window (blue histogram). However, a significant amount students update their initial applications (red histogram). The two dashed lines represent the time of the last application considered before the intervention and when the emails were sent, respectively.

Figure 6.1: Histogram of applications' date



6.1.2 Information

The information included was carefully designed to address the causes of mistakes outlined in the previous section, namely, lack of information and biased beliefs. Specifically, the intervention had three main modules:

M1: General information about programs included in the applicant's list

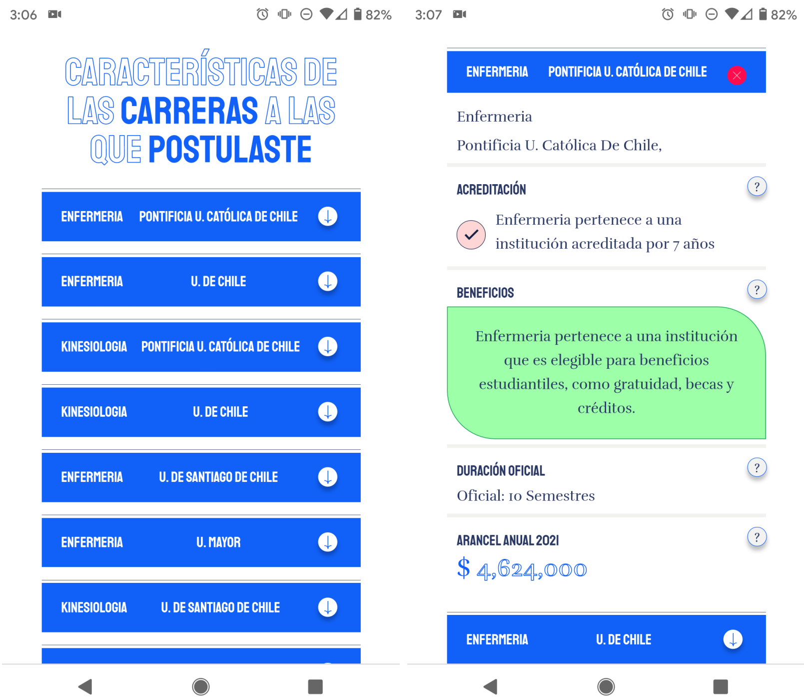
M2: Personalized information on admission probabilities for programs included in the applicant's list and personalized information about the application list's risk

M3: Personalized recommendations about other majors of potential interest

General information about programs. In Figure 6.2 we show an example of this module. Figure 6.2a shows how the list of programs included in the student's list is displayed. Students had the option to click on each of the programs listed, displaying a view like the one shown in Figure 6.2b.

Figure 6.2: Information on Programs Included in Application

(a) General (b) Detailed



For each program included in the applicant's list, we provide general information about the program, including:

- *Location*: campus and university to which the program belongs.
- *Accreditation*: number of years that the institution is accredited.[19]
- *Benefits*: benefits and types of student aid for which the student is eligible in that program.
- *Duration*: formal duration of the program, measured in semesters.
- *Tuition*: yearly tuition measured in Chilean pesos.

This information is provided to all students who received the intervention, i.e., who applied before February 13th at 8 pm CT.

PERSONALIZED INFORMATION ON ADMISSION PROBABILITIES. In Figure 6.3 we show an example of this module. Figure 6.3a shows the list of programs included in the student's list. As before, students can click on each of the programs they included to see their personalized information, which includes:

[19]The years of accreditation is a signal of the quality of the institution. If the institution is not accredited, enrolled students cannot receive public student aid. See details in `https://www.cnachile.cl/`.

- *Cutoffs*: application score of the last student admitted in the regular processes of 2019 and 2020, and graphical representation of where the student stands relative to these cutoffs.

- *Alert by program*: if the estimated admission probability is below 1% and the student's application score is below the cutoffs of the past two admission processes, we display a red alert that includes the following message:

  > *Based on the applications received up to February 14th at 8 am, we find that your admission probability in this program is low. Nevertheless, you can still apply, as the cutoff of this program may change from year to year and also there are waitlists.*

  This information is illustrated in Figure 6.3b. In contrast, if the aforementioned conditions are not met , the alert is not included (see Figure 6.3c). Finally, if the student made an *admissibility* mistake in a given program, we do not display information about students' application scores, and we add the following message:

  > *Based on our records you do not satisfy all admission requirements for this program, please review your application.*

- *Alert by application list*: depending on the risk of the application list, we display a message nudging students to consider additional programs in their application list if their lists were not full. Figure 6.4 shows the different message types. There are four cases: (i) if the estimated probability of not being assigned to the top preference is lower than 1% , we recommend students to add *reach* programs to their lists, i.e., programs which are more preferred and for which the student faces positive admission probability (Figure 6.4b); (ii) if the risk is higher than 30%, we recommend students to add *safety* programs, i.e., programs that are less demanded and for which the student faces a high admission probability (Figure 6.4a); (iii) if the computed risk falls between 1% and 30%, we recommend students to add both *safety* and *reach* programs (Figure 6.4c); and (iv) if none of the cases above holds, we display a generic message inviting students to get more information about their options.

Discussion. MINEDUC required us that the information provided should only nudge students to add additional programs and not swap or eliminate programs from their application lists (even if the application list contained *admissibility* mistakes). As a result, we recommend students adding *safety* programs to reduce the prevalence of over-confidence mistakes and adding *reach* programs to reduce the incidence of under-confidence mistakes.

Figure 6.3: Feedback on Programs' Admission Chances

(a) General (b) Red Alert (c) Green Alert

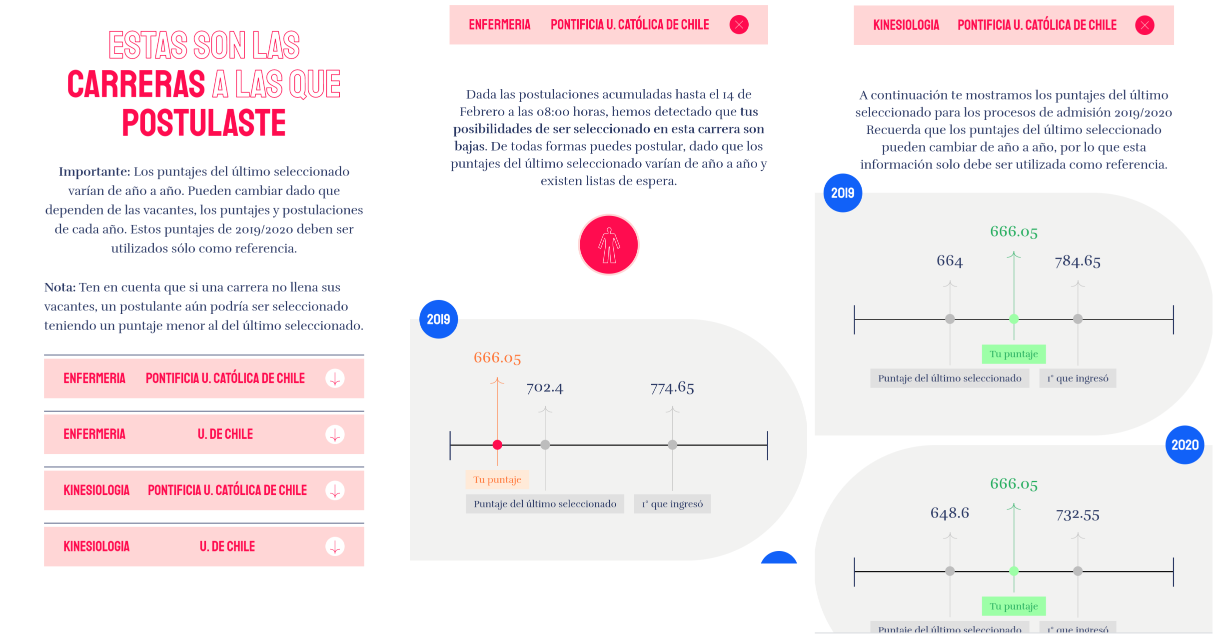
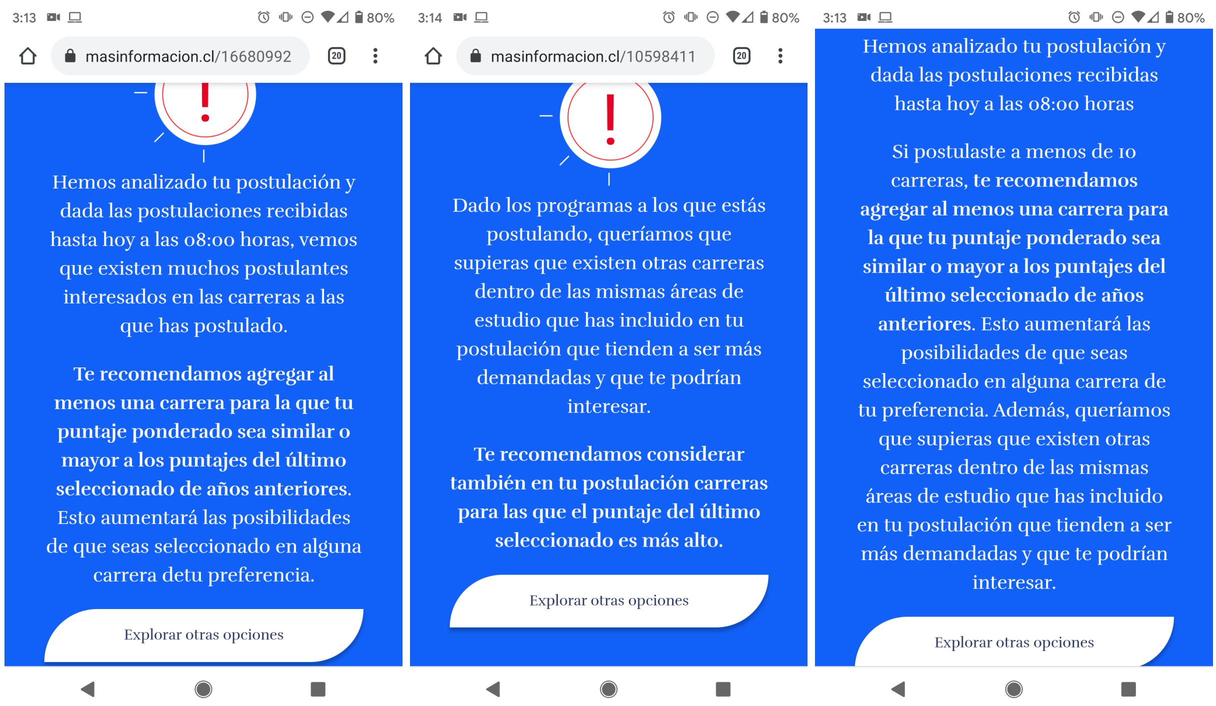


Figure 6.4: Feedback on Application list's and potential strategic mistakes

(a) Add Safety (b) Add Reach (c) Add Safety and Reach



Admission probabilities. To compute the admission probabilities, we use a bootstrap procedure similar to that in Agarwal and Somaini (2018) and Larroucau and Ríos (2018). The main difference is that these approaches use complete information regarding the applications. In our case, we only have the application list of close to 2/3 of the students that ended up applying, so running the bootstrap procedure on this sample would considerably underestimate the cutoffs. For this reason, our first task is to estimate the total number of students that would apply in 2021 based on the applications received so far. To accomplish this, we divide the population into three segments based on their average score between Math and Verbal (the two mandatory exams of the PSU/PDT). Then, using data from 2019 and 2020, we estimate which fraction of all students that take the national exam would apply to at least one program in the centralized system taking the average between these two years. Finally, comparing this number with the actual fraction of students in each score bin that have applied so far, we quantify the number of students that have not applied yet. This information is summarized in Table 6.1.

Table 6.1: Applications Received and Comparison to Previous Processes

	2019			2020			2021			Bootstrap	
	Participate	Apply	%	Participate	Apply	%	Participate	Apply	%	Target	Added
Low	148787	33170	0.223	119830	19213	0.160	75549	13248	0.175	0.192	1229
Medium	73468	47551	0.647	69082	29426	0.426	66336	31974	0.482	0.537	3620
High	83797	73645	0.879	119623	97826	0.818	92122	59747	0.649	0.848	18402

Note: Low includes students with average in Math/Verbal below 450. Medium includes students with an average in Math/Verbal greater than or equal to 450 and less than 600. High includes students with an average in Math/Verbal greater than or equal to 600. Data for 2021 considers all applications received up to February 13th at 8 pm CT. Target is the average between the % for 2020 and 2021 for each group. Added is the number of students sampled in each group to achieve the target.

Based on the number of applicants missing, we perform 1000 bootstrap simulations, each consisting of the following steps:

1. Sample with replacement the number of students missing in each bin score, and incorporate the sampled students to the pool of applications received so far.

2. Run the assignment mechanism used in the Chilean system. See Rios et al. (2020) for a detailed description of the mechanism used in Chile to solve the college admissions problem.

3. Compute the cutoff of each program for both the regular and BEA admission processes.

As a result of this procedure, we obtain two matrices (for the regular and BEA processes) with 1000 cutoffs for each program. Hence, the next step is to estimate the distribution of the cutoff of each program in each admission track. To accomplish this, we estimate the parameters of a truncated normal distribution for each program and admission track via maximum likelihood. Then, using the estimated distributions, we evaluate the CDF on the application score of the student to obtain an estimate of the admission probability, taking into account whether the student participates only in the regular process or also in the BEA track.

Personalized recommendations of other majors. For each student, we recommend four majors, which are computed considering the student's scores and reported preferences. Specifically, our recommendation algorithm proceeds as follows:

1. Find the most and the second most popular majors based on the preferences included in the student's ROL.
2. For each pair of majors, and considering the most and the second most preferred major of each student, compute a transition matrix that returns the probability that a given major is followed by another major as the most preferred ones.
3. For each student, compute the set of feasible majors considering the student's scores and her admission probabilities (obtained as described in the previous section).
4. For students with high scores (i.e., average between Math and Verbal above 600), choose four majors according to the following rule:
   (a) Choose most preferred major according to the student's list of preferences,
   (b) Choose the second most preferred major according to the student's list of preferences,
   (c) Choose the major with the highest average wage[20] among all majors considering the transition matrix previously computed,
   (d) Choose the major with the highest average wage among all feasible majors (i.e., majors for which the student has a positive probability of assignment) considering the transition matrix previously computed.
5. For students with low scores (i.e., average between Math and Verbal below 600), choose four majors according to the following rule:
   (a) Choose the most preferred major according to the student's list of preferences,
   (b) Choose the second most preferred major according to the student's list of preferences,
   (c) Choose the major with the highest expected wage among all majors belonging to IPs or CFTs,
   (d) Choose the major with the highest expected wage among all feasible majors (i.e., majors for which the student has a positive probability of assignment) considering the transition matrix previously computed.

In Figure 6.5 we provide an example of the recommendations' module.

[20] Average wages are measured at the fourth year after graduation. This statistic is computed by SIES and provided to us by MINEDUC.

Figure 6.5: Recommendation of Other Majors

(a) General (b) Detailed

Discussion. The recommendation module has two purposes: (i) to reduce potential information frictions about programs' characteristics and (ii) to affect students' beliefs on admission probabilities for programs that are not in their consideration sets. A program is defined to be in the consideration set of a student if the student knows the program's cutoff of the previous year (see Definition 7). Even though we were not allowed to recommend specific programs to students, we could show information about programs' cutoffs for specific majors, such as the cutoffs' range. After students observe the cutoffs' range for a given major of their preference, they might realize that some majors are not out of their reach. Knowing that some majors are not out of their reach, could increase incentives to search for information about admission cutoffs and update their beliefs on admission probabilities, reducing their potential bias and the probability of making a strategic mistake.

6.1.3 Intervention design

The intervention was considered by MINEDUC as an outreach policy and, due to equity concerns, we were not allowed to randomize the group of students that received the email. In addition, all students that opened their personalized website received general information about programs included in their lists (Module M1). However, we randomized which additional modules to show to each student. There were three treatment groups:

T0 : Warning and recommendation modules (M1 + M2 + M3)

T1 : Warning module (M1 + M2)

T2 : Recommendation module (M1 + M3)

Blocking. To achieve a balance between the treatment groups, we stratified the randomization considering (i) the application score, (ii) the major of the top-reported preference, (iii) whether the student graduated from a private High-school, and (iv) the type of general message the student would receive if she were in treatment groups T0 or T1. The stratification allows us to compute the treatment effect in balanced populations of different characteristics without adding these covariates as exogenous regressors.

Sample. We excluded from the randomization a group of students for which the information provided was not well-tailored: (i) students with average scores below 450 points,[21] (ii) students participating in the PACE program,[22] and (iii) students with *admissibility* mistakes in their top preference. We leverage the latter to provide additional information about the potential effects of the information intervention in the group of students with *admissibility* mistakes. The group of students removed from the sample is labeled as T3. This group also received an email from MINEDUC, but their personalized websites had only general information about financial aid. In this sense, even though this group of students is not a proper control group, we can leverage this group to analyze whether there are significant differences in outcomes for students in T3 that opened the website versus students who received the email but did not open their website.

6.2 RESULTS

In this section, we evaluate the results of the intervention. Table 6.2 shows aggregate statistics by group. Among the three treatment groups of interest (T0, T1, and T2), we observe that close to 29,800 students received the email, and 26% of them opened their personalized website. As expected, we do not observe significant differences across groups.

[21]This group of students is likely to face zero admission probability in any program in the centralized system.

[22]This group of students faces a different set of admission requirements and admission probabilities than students who are participating only on the regular admission process.

Table 6.2: Aggregate statistics by treatment groups

Treatment	Total	Opened website [%]	Modified [%]	Increased length [%]	Decreased length [%]	Assigned [%]	Changed assignment state [%]	Changed program of assignment [%]
T0	29816	26.49	12.49	4.99	1.64	89.68	0.22	4.79
	(-)	(0.26)	(0.19)	(0.13)	(0.07)	(0.18)	(0.06)	(0.12)
T1	29797	26.28	12.61	5.24	1.61	89.52	0.11	4.81
	(-)	(0.26)	(0.19)	(0.13)	(0.07)	(0.18)	(0.06)	(0.12)
T2	29816	26.28	12.33	4.84	1.61	89.54	0.18	4.38
	(-)	(0.25)	(0.19)	(0.12)	(0.07)	(0.18)	(0.05)	(0.12)
T3 (out of sample)	17731	21.33	15.81	6.93	2.73	79.08	1.22	6.93
	(-)	(0.31)	(0.27)	(0.19)	(0.12)	(0.31)	(0.11)	(0.19)

Note: standard errors are computed in parenthesis.

To assess the effect of our intervention, we consider two types of analysis: (1) across treatments, to compare the effects of different information policies; and (2) within treatment, to compare students that opened the email and visited their personalized website with those who did not. For the latter analysis to be causal, it must be the case that the students who opened the email are comparable to those who did not. However, this may not be the case. For instance, students who are more aware of the requirements and their admission probabilities may also be more likely to open the website than less knowledgeable students.

SELECTION ON OBSERVABLES. To account for differences in observable characteristics that may predict the exposure to our intervention and address the potential selection problem mentioned above, we use propensity score matching to balance observable characteristics among students who did not open their website. More specifically, we first estimate the propensity score of each student, which captures the probability that they will open the email and receive our intervention. We estimate these probabilities using the following specification:

$$e_i(X_i) = X_i\beta_0 + \epsilon_i,$$

where e_i is the propensity score of user i. In other words, $e_i(X_i,) = Pr(W_i = 1|X_i)$, where W_i is the binary treatment indicator that is equal to 1 if user i received our intervention and 0 otherwise. X_i is a matrix of pre-treatment observable characteristics of user i that includes: (1) scores (for both the PSU/PDT tests and NEM and Rank); (2) location (including the region, province, and municipality); (3) characteristics of the school the student graduated from (including whether it is public/voucher/private and scientific/humanistic); and (4) whether the student is BEA and PACE. Let $\hat{e}_i(X_i)$ be the estimated propensity score for student i. Then, for each student in the treatment group (i.e., students who received the intervention), we find the student in the control group that shares the same strata, and that is closest in terms of propensity score (without replacement). As the treatment assignment is random conditional on the propensity score, this procedure rules out any potential concerns regarding selection on observables.

GENERAL RESULTS. In Table 6.3 we replicate Table 6.2 using the matched sample and separating students who did and did not open their personalized website. First, comparing students within each group, we observe significant effects of the intervention on several outcomes. In particular, between 17% and 18% of students who received warning messages (T0 and T1) and opened their websites modified their applications, compared to only 11% for the group that did not open their websites. This effect is slightly smaller (16.01% vs. 11.43%) for students who received only recommendations (T2). In addition, treated students who modified their applications increased more the length of their lists than students who did not open their websites. As the last two columns show, these changes had a significant impact on students' assignments. Second, considering only those students that opened their website across groups, we assess which interventions have the largest impact on student outcomes. Specifically, comparing groups T0 and T1—who received information about cutoffs and admissibility mistakes—with T2—who only received recommendations—we observe that the former modified considerably more their applications (16.81% and 17.66% vs. 15.67%). In addition, we observe that the effects of only showing warnings (T1) tend to be slightly bigger than showing warnings and recommendations (T0). In addition, the effects of showing only recommendations (T2) on these outcomes tend to be smaller than showing only warnings or warnings and recommendations. Overall, these results suggest that providing more information nudges students to change their applications, which changes their outcomes. Moreover, we observe that providing information about admissibility mistakes and previous cutoffs has a bigger effect than providing recommendations about majors.

Table 6.3: Aggregate statistics by treatment groups

Treatment	Opened website [%]	Total	Modified [%]	Increased length [%]	Decreased length [%]	Assigned [%]	Changed assignment state [%]	Changed program of assignment [%]
T0	No	6223	10.94	4.5	1.37	89.47	0.08	4.11
			(0.4)	(0.26)	(0.15)	(0.39)	(0.11)	(0.25)
T0	Yes	6240	17.24	6.57	2.39	91.14	0.62	6.07
			(0.48)	(0.31)	(0.19)	(0.36)	(0.14)	(0.3)
T1	No	6162	11.51	4.77	1.44	89.47	-0.02	4.51
			(0.41)	(0.27)	(0.15)	(0.39)	(0.12)	(0.26)
T1	Yes	6186	17.98	7.39	2.55	90.88	0.45	6.37
			(0.49)	(0.33)	(0.2)	(0.37)	(0.14)	(0.31)
T2	No	6213	11.43	4.54	1.5	89.68	-0.05	3.81
			(0.4)	(0.26)	(0.15)	(0.39)	(0.11)	(0.24)
T2	Yes	6198	16.01	5.99	2.18	89.95	0.31	5.37
			(0.47)	(0.3)	(0.19)	(0.38)	(0.12)	(0.29)

Note: standard errors are computed in parenthesis.

EFFECT OF SPECIFIC WARNINGS. To understand the effect of the different warning messages, in Table 6.4 we show the previous statistics conditional on opening the personalized website and grouping by message type. We now analyze the results for each type of warning.

Reach. Students who faced an application risk below 1% were eligible to receive a message recommending them to include additional *reach* programs, i.e., programs that are more selective than the ones listed in their application, but that the students might prefer to their outside option. The purpose of recommending *reach* programs is to decrease their likelihood of making an underconfidence mistake. By design, this group of students faces a low risk of not being assigned to the centralized system, as the column Assigned [%] in Table 6.4 shows.

First, we do not observe major changes in the probability of being assigned (second to last column). However, comparing students who opened their website with those who did not, we observe that the former are significantly more likely to modify their application. Second, notice that only those in the treatment groups T0 or T1 received the message among the students in the *Reach* group. Comparing these two groups with those in T2 (among students who opened their website), we do not observe significant differences in the assignment across groups. In addition, warning messages that suggest adding *reach* programs do not seem to be particularly effective in inducing students to modify their initial application lists. These results confirm that receiving the intervention significantly increased the fraction of students who modified their list and motivated students to add more programs. However, their chances of admission remained relatively unchanged.

Safety. Students who faced an application risk greater than 70% were eligible to receive a message recommending them to include additional *safety* programs. *Safety* programs are less selective programs than the ones listed in the student's application—where the student faces positive admission probability—but that the student might prefer to her outside option. The purpose of recommending *safety* programs is to decrease their likelihood of making an overconfidence mistake. As the middle part of Table 6.4 shows, students in the *safety* have a significantly lower probability of being assigned, ranging from 15.34% to 23.53%.

First, similar to our previous results, we observe that the probability of modifying the application significantly increases among students who opened their website. From columns *Increased length* and *Decreased length*, we observe that most students added programs to their preference list. Second, comparing the students who received the message (i.e., students from treatment groups T0 and T1 and who opened the website) with those who did not, we observe that the *safety* warning message vastly increased the probability of modifying the application. For instance, between 19%-21% of students changed their initial application lists after observing this message, compared to less than 10.12% among students in treatment groups T0 and T1 who did not open the website. Moreover, we observe that getting the *safety* message also increases the probability of updating the application compared to other students who opened their website but did not receive it (13.24% among students in group T2). Third, we observe that students who received the *safety* message significantly increased their admission probabilities. For instance, close to 23.53% of students who received the warning and the recommendation modules (group T0) were assigned to the centralized system, compared to 17.5% for students who opened their website and received only the recommendation module (group T2). These results show that providing *safety* warning messages can dramatically increase the number of students who modify their preferences and that are assigned due to this change.

Explore. Students who faced an application risk between 1% and 30% were eligible to receive a message recommending them to explore additional programs. As before, we observe that students who opened their website included more programs in their lists compared to students with similar risks who did not receive this message (T2). Due to the low risk of their initial applications, close to 98% of students who could receive the

Explore message are assigned to the centralized system. Thus, the effects on changing assignment state (changing from not being assigned to being assigned) are almost zero for the different treatment groups. However, we do observe a more significant effect on changing the program of assignment. Close to 9% of students who receive both warnings and recommendations changed their assigned program because they changed their application lists after the intervention, and close to 7% do so if they only received the recommendation module.

Safety and Reach. Students who faced an application risk between 30% and 70% were eligible to receive a message recommending them to include both *safety* and *reach* programs. This group of students had very few observations per treatment group, and most effects are not statistically significant when comparing differences across treatment groups.

Table 6.4: Aggregate statistics by treatment groups and message type

Message type	Treatment	Opens	Total	Modified [%]	Increased length [%]	Decreased length [%]	Assigned [%]	Changed assignment state [%]	Changed program of assignment [%]
Reach	T0	No	3007	9.18	3.53	1.13	98.97	-0.1	2.16
				(0.53)	(0.34)	(0.19)	(0.18)	(0.06)	(0.27)
Reach	T0	Yes	3048	13.12	4.99	1.97	99.48	-0.07	2.85
				(0.61)	(0.39)	(0.25)	(0.13)	(0.05)	(0.3)
Reach	T1	No	2994	10.02	4.61	1.2	98.83	-0.03	2.91
				(0.55)	(0.38)	(0.2)	(0.2)	(0.07)	(0.31)
Reach	T1	Yes	3012	13.48	5.98	1.73	98.94	-0.07	3.32
				(0.62)	(0.43)	(0.24)	(0.19)	(0.08)	(0.33)
Reach	T2	No	2976	9.71	3.76	0.94	99.06	-0.07	2.49
				(0.54)	(0.35)	(0.18)	(0.18)	(0.05)	(0.29)
Reach	T2	Yes	3041	14.67	5.89	1.71	98.85	-0.07	3.88
				(0.64)	(0.43)	(0.24)	(0.19)	(0.07)	(0.35)
Safety	T0	No	692	10.12	5.35	1.3	17.63	2.6	5.06
				(1.15)	(0.86)	(0.43)	(1.45)	(0.79)	(0.83)
Safety	T0	Yes	629	19.08	11.29	0.79	23.53	7.31	8.59
				(1.57)	(1.26)	(0.35)	(1.69)	(1.11)	(1.12)
Safety	T1	No	670	8.51	5.22	0.45	17.91	1.79	4.63
				(1.08)	(0.86)	(0.26)	(1.48)	(0.82)	(0.81)
Safety	T1	Yes	602	20.76	12.62	1.66	21.59	7.48	10.3
				(1.65)	(1.35)	(0.52)	(1.68)	(1.17)	(1.24)
Safety	T2	No	652	9.97	6.29	0.46	15.34	1.99	4.45
				(1.17)	(0.95)	(0.27)	(1.41)	(0.76)	(0.81)
Safety	T2	Yes	657	13.24	7.46	0.76	17.5	4.11	5.78
				(1.32)	(1.03)	(0.34)	(1.48)	(0.89)	(0.91)
Explore	T0	No	2401	13.45	5.41	1.62	98.67	-0.37	5.91
				(0.7)	(0.46)	(0.26)	(0.23)	(0.12)	(0.48)
Explore	T0	Yes	2460	21.83	7.2	3.41	98.86	-0.28	9.31
				(0.83)	(0.52)	(0.37)	(0.21)	(0.16)	(0.59)
Explore	T1	No	2366	14.07	4.69	2.07	98.44	-0.3	6.3
				(0.72)	(0.43)	(0.29)	(0.26)	(0.13)	(0.5)
Explore	T1	Yes	2457	22.71	7.49	3.87	98.45	-0.57	8.95
				(0.85)	(0.53)	(0.39)	(0.25)	(0.16)	(0.58)
Explore	T2	No	2447	13.85	4.94	2.45	98.61	-0.33	4.86
				(0.7)	(0.44)	(0.31)	(0.24)	(0.13)	(0.43)
Explore	T2	Yes	2383	18.25	5.71	3.06	98.83	-0.21	7.01
				(0.79)	(0.48)	(0.35)	(0.22)	(0.13)	(0.52)

Note: standard errors are computed in parenthesis.

In Table 6.4 we analyze the characteristics of the programs that students added when they modified their initial application list, separating by treatment and message group. First, we observe that students who received *reach* messages (i.e., students in treatment groups

T0 and T1) added programs that lead to a higher wage and also added programs with a slightly higher cutoff, in line with the recommendation. In contrast, we do not observe substantial differences between the initial and the added programs for the group T2 (i.e., students that only received recommendations of majors and that do not receive the *reach* message). Second, we observe that students who received *safety* messages (i.e., students in treatment groups T0 and T1) added programs with substantially lower cutoffs and also with lower wages. Finally, we observe no substantial differences among students in the *explore* group. These results suggest that students follow the advice provided in the messages and that students, on average, improve their initial applications after receiving the outreach intervention.

Table 6.5: Characteristics of added programs for students who modified their application lists

			Average Cutoff		Average Wage	
Message type	Treatment	Total	Initial	Added	Initial	Added
Reach	T0	493	585.87	598.96	1322.99	1413.14
			(3.26)	(5.1)	(20.3)	(32.19)
Reach	T1	507	585.29	595.03	1316.9	1368.78
			(3.05)	(4.48)	(20.12)	(30.81)
Reach	T2	534	586.59	589.5	1317.79	1316.64
			(2.97)	(4.64)	(19.14)	(29.92)
Safety	T0	149	651.54	609.96	1598.9	1479.55
			(6.3)	(8.51)	(47.32)	(58.43)
Safety	T1	163	643.17	592.66	1547.57	1357.01
			(6.31)	(7.62)	(46.04)	(47.82)
Safety	T2	113	647.51	607.59	1580.61	1427.12
			(7.3)	(9.61)	(57.86)	(56.98)
Explore	T0	657	613.74	607.76	1424.58	1451.32
			(2.57)	(4.39)	(16.67)	(29.34)
Explore	T1	686	613.69	610.5	1468.14	1505.52
			(2.67)	(4.55)	(17.62)	(30.76)
Explore	T2	550	615.13	606.3	1456.23	1446.18
			(3.02)	(5.06)	(20.32)	(32.92)

Note: Initial considers the programs included in the last application received before the intervention. Added considers the additional programs added in the last application received (i.e., excluding those that were part of the initial application). Average wages at the fourth year after graduation (thousands of Chilean pesos, nominal 2021). Average cutoffs consider the cutoffs for the regular admission process of 2020. Standard errors are computed in parenthesis.

Finally, we analyze the effects of the information intervention on *admissibility* mistakes. Table 6.6 shows statistics for students with at least one *admissibility* mistake in their initial application lists. We observe that students who opened their websites are more likely to reduce their *admissibility* mistakes when they modify their applications, compared to students who did not open their websites. In addition, as students tend to add programs when they modify their initial applications, they also significantly reduce the share of *admissibility* mistakes in their lists. We do not observe significant differences for students out of the sample depending on whether they opened their websites.

Table 6.6: Statistics for mistakers by treatment groups conditional on opening

Treatment	Opened website [%]	Total	Modified [%]	Reduced Adm. Mistakes [%]	Reduced share Adm. Mistakes [%]
T0	No	195	13.85	4.62	7.69
		(-)	(2.48)	(1.51)	(1.91)
T0	Yes	204	16.18	7.84	8.82
		(-)	(2.58)	(1.89)	(1.99)
T1	No	190	10.53	5.26	6.32
		(-)	(2.23)	(1.62)	(1.77)
T1	Yes	173	15.03	5.78	8.67
		(-)	(2.72)	(1.78)	(2.15)
T2	No	214	8.88	3.27	5.14
		(-)	(1.95)	(1.22)	(1.51)
T2	Yes	166	16.87	4.22	7.83
		(-)	(2.92)	(1.56)	(2.09)

Note: standard errors are computed in parenthesis.

It is important to notice that the number of observations in the analysis reported in Table 6.6 is considerably smaller than the number of students who make application mistakes (see Section 4). This result is expected since we removed from treatments T0, T1, and T2 all students who made an admissibility mistake in their top reported preference. We are planning to remove this constraint and repeat our intervention in the following admission process to increase the sample of students with admissibility mistakes and better understand the effect of our intervention in that group.

7 Conclusions

We analyze the prevalence and relevance of application mistakes in the Chilean centralized college admissions system. We exploit institutional features to identify a common type of application mistake: applying to programs without meeting all requirements (*admissibility* mistakes). We exploit the fact that *admissibility* mistakes are observed in the Chilean data. Moreover, there is a significant variation in admission requirements and *admissibility* mistakes over time.

We find that the growth of *admissibility* mistakes over time is driven primarily by growth on active score requirements. Also, we find that changes in admission requirements over time increase *admissibility* mistakes. However, this effect fades out over time, suggesting that students might adapt to the new set of requirements but not immediately. In addition, admissibility mistakes are likely welfare-relevant. Indeed, close to 25% of students who only list programs with *admissibility* mistakes could have been assigned in the centralized system if they had included programs in which they were eligible. As students are not fully aware of admission requirements and *admissibility* mistakes can be welfare-relevant, changes in requirements can affect students' outcomes. In this sense, increasing the complexity of the admission process can generate a negative externality in the system.

To analyze application mistakes not directly observed in the data, we design nationwide surveys and collect information about students' true preferences, their subjective beliefs about admission probabilities, and their level of knowledge about admission requirements and *admissibility* mistakes. Using this data, we shed light on which information frictions are the most relevant to explain students' mistakes.

We find that between 2% - 4% of students do not list their top-true preference of program, even though they face a strictly positive admission probability, and only a fraction of this skipping behavior can be rationalized by bias on students' subjective beliefs. In addition, we find that students' subjective beliefs are closer to *adaptive* beliefs than rational expectations, i.e., they do not anticipate changes in cutoffs due to changes in current vacancies or other admission factors. Also, we find a pull-to-center effect on beliefs, i.e., students tend to attenuate the probability of extreme events. This effect translates into students under-predicting the risk of being unassigned to the system. Finally, we also find that the magnitude of the bias considerably changes depending on students' characteristics. High-score students from private schools have significantly more accurate beliefs than students from public schools or low-score students.

Using the previous insights, we design and implement a large-scale outreach policy to reduce application mistakes. We find that showing personalized information about admission probabilities and information about the risk of application lists has a causal effect on improving students' outcomes, significantly reducing the risk of not being assigned to the centralized system and the incidence of *admissibility* mistakes.

Our results suggest that information frictions play a significant role in affecting the performance of centralized college admissions systems, even when students do not face clear strategic incentives to misreport their preferences. In this sense, policy interventions that reduce these frictions can significantly reduce application mistakes and improve students' welfare.

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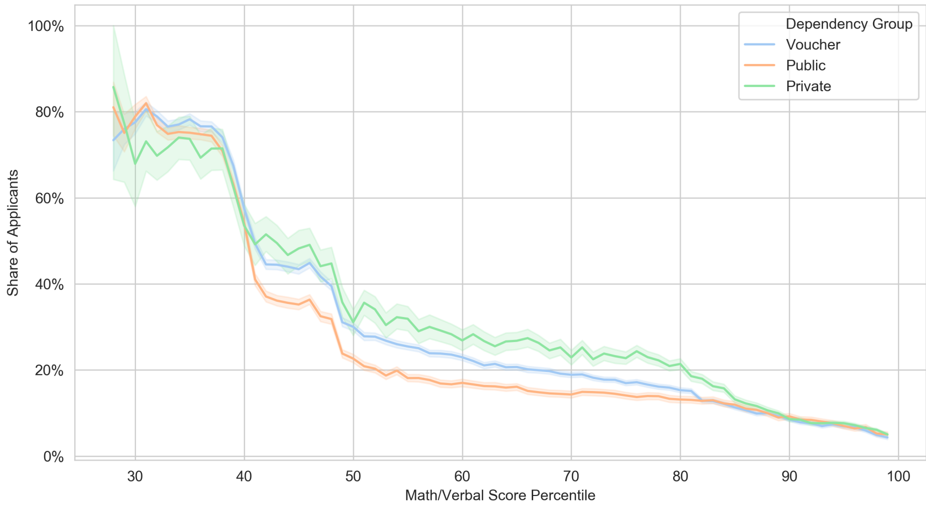
Appendix

8 Appendix

8.1 Appendix Admissibility Mistakes

Figure 8.1: Share of students with *admissibility* mistakes by average score and school type



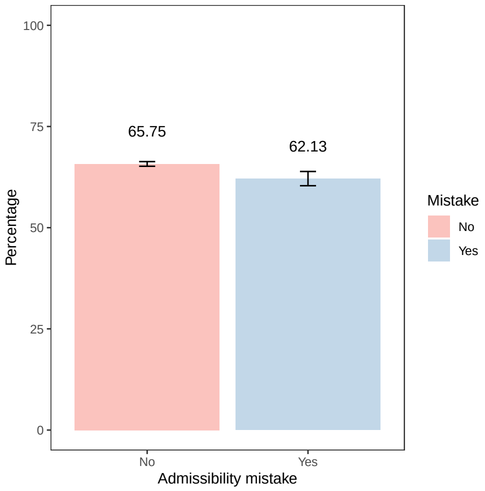
Notes: The share is computed as the total number of students in admission process 2005-2018 who submitted a ROL with at least one *admissibility* mistake, over the total number of applicants per bin of score percentiles and school type. The solid line is a conditional mean computed with a bandwidth of 1 score percentiles and shaded region corresponds to its 95% confidence interval. The score percentiles are computed with respect to the population of students who participated in the admission process and had a valid average Math/Verbal score.

Figure 8.2 shows the percentage of students who declare to know the admission requirements for a subset of the programs listed in their applications. We compute this statistic only for programs with an active requirement and group it by different admission requirements and whether the student made an *admissibility* mistake or not. Overall, we observe heterogeneity in the level of knowledge by requirement type and significant differences between the group of students who made an *admissibility* mistake or not. Between 60% to 75% of students who did not make an *admissibility* mistake declare to know the minimum scores' requirements and specific tests. However, close to 50% to 60% declare to know these requirements from the group who made an *admissibility* mistake.

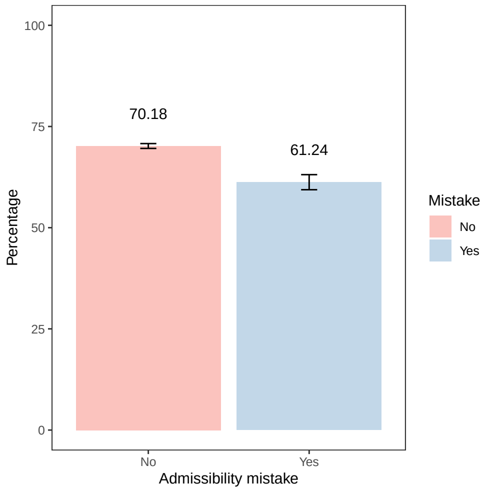
Figure 8.3 shows the percentage of students who gave a correct answer for each requirement where they declared to have the correct knowledge. We observe a low level of correct knowledge about requirements and heterogeneity by requirement type. The requirements for the restriction in the preference ranking and number of vacancies are the lowest.

Figure 8.2: Knows admission requirements

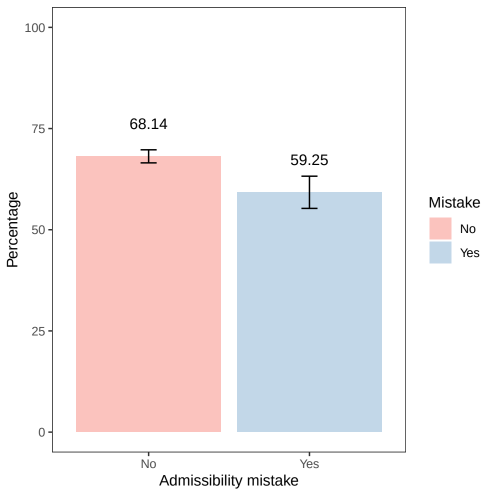
(a) Minimum Math-Verbal Score



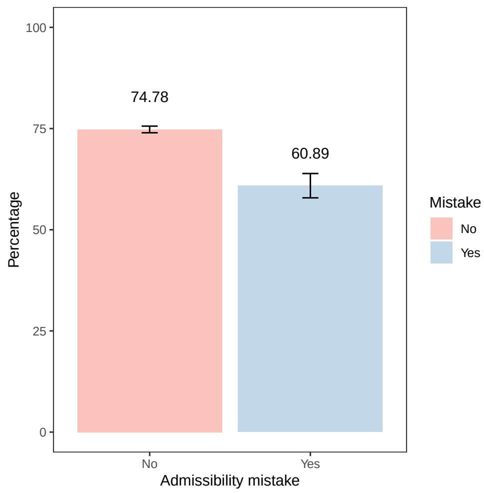
(b) Minimum Weighted Score



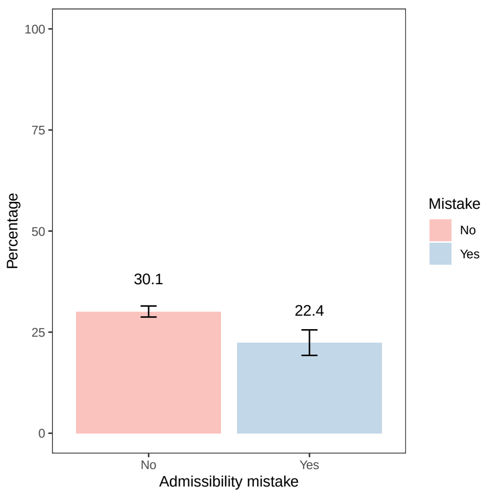
(c) Requires History



(d) Requires Science



(e) Restricts Preference Ranking



(f) Number of Vacancies

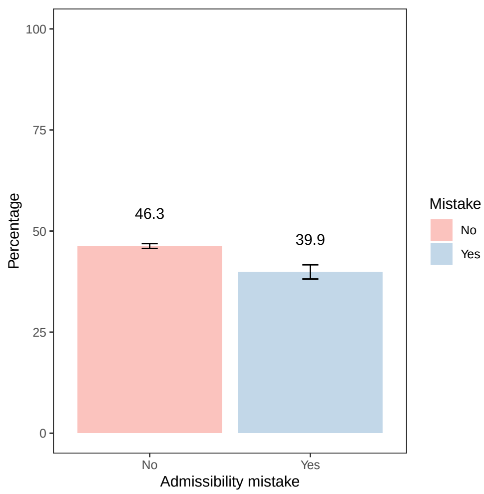
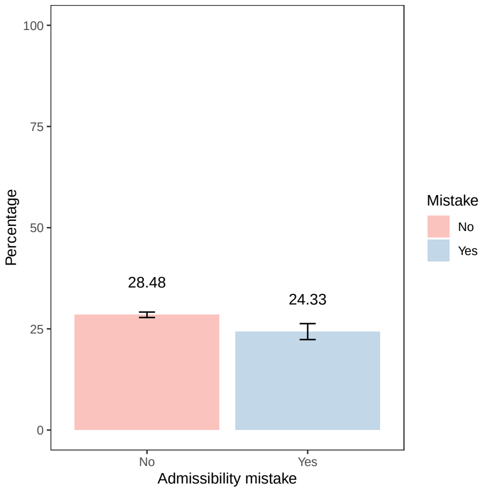
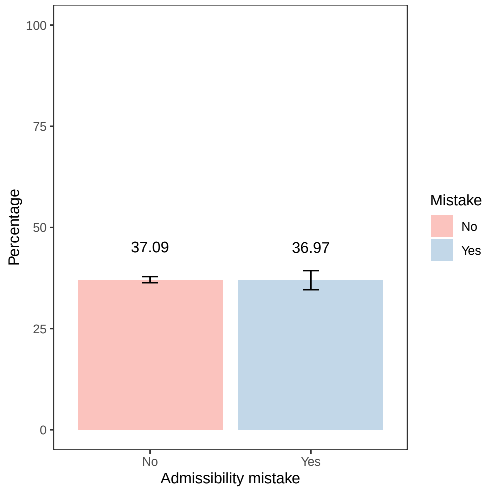


Figure 8.3: Knows correctly admission requirements

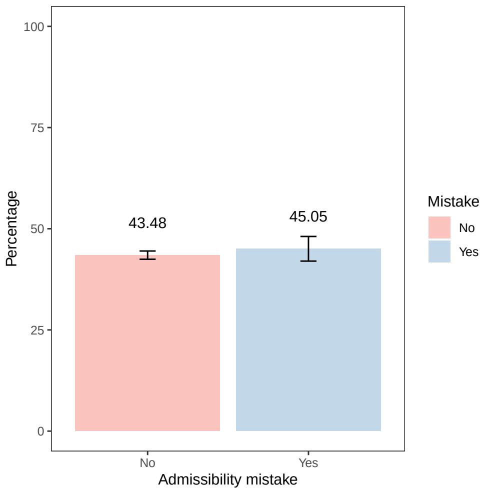
(a) Minimum Math-Verbal Score



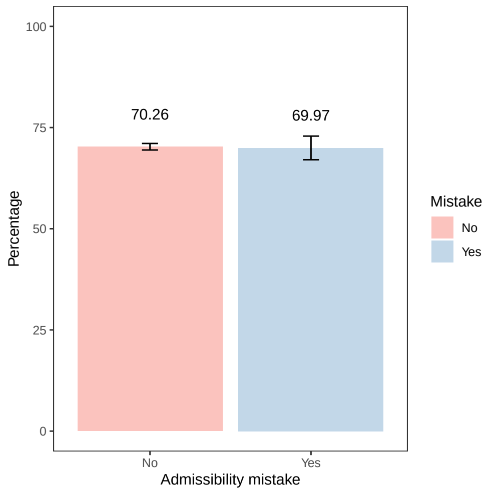
(b) Minimum Weighted Score



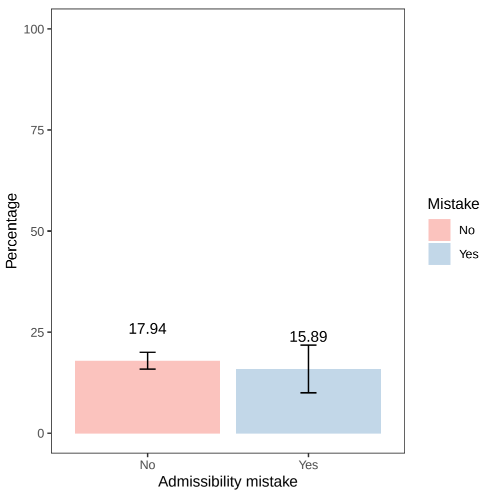
(c) Requires History



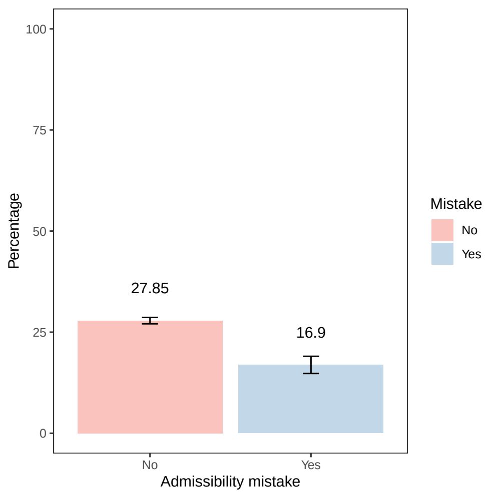
(d) Requires Science



(e) Restricts Preference Ranking



(f) Number of Vacancies



Discussion: the low levels of correct knowledge might suggest a high measurement error in the survey, mainly because the questions about the survey requirements were at the end of the survey. Doing an in-depth analysis of the responses about the admission requirements, we observe that a significant fraction of students seems to confuse the requirement types. For instance, (i) responding to the value of the minimum weight score requirement when asked about the value of the minimum average math-verbal score requirement; (ii) responding to the current preference of the program in the list instead of the preference restriction of the program, and (iii) confusing when a program allows the student to take the Science (History) test with when the program requires that one of these tests is taken. In this sense, we attribute these low levels of correct knowledge to be a combination of students not understanding the system's rules and misinterpreting the survey question. However, we do not find evidence that responses are randomly selected.

8.2 Appendix Misreporting

Table 8.1: Reasons for misreporting

Application type	Misreporting Exclusion [%]	Misreporting Ordering [%]	Truth-teller [%]
Reasons			
(a) YES, I did apply to my ideal program as a top-reported preference	20.33	29.02	86.22
(b) My admission probability to that program is too low	50.21	46.53	9.08
(c) The program is too hard and I don't think I would be able to graduate from it	3.06	1.56	0.37
(d) I do not have the monetary resources to pay for the program	25.44	20.2	4.73
(e) To include my ideal program, I would have to exclude some program from my list	2.2	2.53	0.36
(f) The decision to where to apply did not depend only on me, and it was influenced by other people (family, friends, etc.)	6.5	8.28	1.17
(g) I thought that by including this program in my list I would have reduced my chances of being admitted to the other listed programs	6.6	4.78	0.53
(h) Given that my admission chances are too low, I prefer to do not list this program and being assigned to a higher reported preference	36.3	14.02	1.22
Other	13.91	12.74	1.74
Total	6184	1861	6939

Note: respondents can choose multiple reasons.

8.3 Appendix Subjective beliefs

Figure 8.4a shows a heat-map of the average subjective beliefs on admission probabilities by preference (P1-P10) and application length (L1-L10). We observe that given an application length, there is a positive gradient in the average admission probability by preference (position of the program in the list). This pattern could be explained if students tend to list programs with low admission probabilities as their most preferred ones

Table 8.2: Reasons for misreporting (consistent responses)

Application type	Misreporting Exclusion [%]	Misreporting Ordering [%]	Truth-teller [%]
Reasons			
(b) My admission probability to that program is too low	64.2	70.92	-
(e) To include my ideal program, I would have to exclude some program from my list	2.12	3.43	-
(f) The decision to where to apply did not depend only on me, and it was influenced by other people (family, friends, etc.)	5.77	9.66	-
(g) I thought that by including this program in my list I would have reduced my chances of being admitted to the other listed programs	7.58	5.36	-
(h) Given that my admission chances are too low, I prefer to do not list this program and being assigned to a higher reported preference	46.98	18.99	-
Other	18.51	19.74	-
Total	3257	932	5983

Note: respondents can choose multiple reasons. Percentages are computed among the fraction of consistent respondents.

Table 8.3: Reasons for misreporting conditional on making an ex-ante under-confidence (consistent responses)

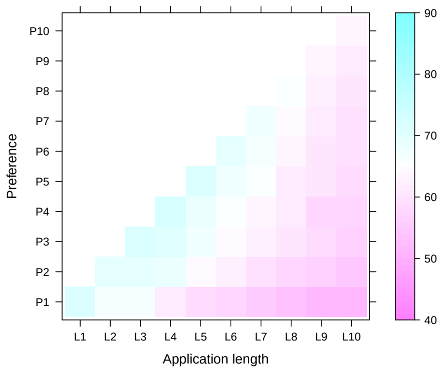
Application type	Misreporting Exclusion [%]
Reasons	
(b) My admission probability to that program is too low	28.52
(e) To include my ideal program, I would have to exclude some program from my list	1.9
(f) The decision to where to apply did not depend only on me, and it was influenced by other people (family, friends, etc.)	21.29
(g) I thought that by including this program in my list I would have reduced my chances of being admitted to the other listed programs	7.22
(h) Given that my admission chances are too low, I prefer to do not list this program and being assigned to a higher reported preference	17.11
Other	49.81
Total	263

Note: respondents can choose multiple reasons. Percentages are computed among the fraction of consistent respondents.

(*reach*) and programs with high admission probabilities at the bottom (*safety*). Furthermore, students who submit longer application lists tend to face lower admission chances at the top and the bottom of their application lists. To understand if students' scores explain this pattern, Figure 8.4b shows the distribution of application scores by the length of application lists. We observe a non-monotonic relation between the median application score and the length of the application list, showing its peak for lists of length equal to 4. In addition, we observe that within the length of application lists, there is significant variation in the average application score. These data patterns suggest that the correlations observed in Figure 8.4a cannot be explained only by systematic differences in scores for students who submit lists of different lengths.

Figure 8.4: Subjective beliefs and preference of assignment

(a) Average subjective beliefs by preference and application length



(b) Distribution of application scores (standardized) by application length