Application Mistakes and Information frictions in College Admissions

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Abstract

We investigate the prevalence and relevance of application mistakes in a seemingly strategyproof centralized college admissions system. Using data from Chile, we identify a common mistake: applying to programs without meeting all requirements. 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. Using nationwide surveys, we find that 2-3% of students do not list their true top preference and at least 1% would benefit from listing more programs. We also observe a pull-to-center effect on beliefs, with students underestimating the risk of not being assigned to the system. To address these issues, we design and implement a large-scale information policy, providing personalized information on admission probabilities to students. Results from a randomized controlled trial show that warning messages about listed programs significantly reduce application mistakes and improve outcomes. In collaboration with policymakers, we implement the policy at scale and show through an encouragement design that on-the-fly information about programs' cutoff scores has a causal effect on reducing students' biases, application mistakes, and improving students' outcomes. By measuring students' preferences and beliefs before and after the policy, we find that changes in outcomes are primarily driven by changes in beliefs over admission probabilities at the bottom of their preference orders, reducing the incidence of biases on students' applications. Our findings suggest that addressing information frictions can enhance the performance of centralized college admissions systems, even when strategic misreporting is not a primary concern, and that sequential implementations of assignment mechanisms or information policies implemented at scale can significantly reduce application mistakes and improve students' outcomes.

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. (2020a) 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 predict counterfactual behavior twhen students face changes to the system.

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); Arteaga et al. (2022)). 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 a significant fraction of students is not aware of their *admissibility* mistakes and does 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 adminis-

[1] For instance, Dreyfuss et al. (2019) show that some application mistakes can be rationalized if we account for loss aversion. Taking into account both biased beliefs about admission probabilities and optimization errors, de Haan et al. (2023) find that 8.3% of the secondary-school applicants in Amsterdam make strategic mistakes.

trative 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 information also helps us to identify which information frictions are the most relevant to explain students' mistakes and design effective information policies to address application mistakes.

We find that between 2% - 3% 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. 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 *rational expectations* beliefs. This pattern implies that students tend to under-predict the risk of not being assigned to the centralized system. Indeed, we estimate that at least 1% of students could have been better off by listing more programs in their application list. In addition, consistent with previous literature, we find substantial differences in the magnitude of the bias depending on students' characteristics, with studnets from public schools and lower scores having more biased beliefs.

In collaboration with MINEDUC and using partial information about students' applications, we created personalized websites with 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. Students who received safety messages significantly increased their chances of getting assigned to the centralized system (close 50% from their baseline value) and reduce the incidence of application mistakes.

In light of these findings and significant changes to the admission process, we collaborated on designing and implementing the policy on a larger scale. Employing an encouragement design through *WhatsApp* messages, we discovered that providing real-time personalized information about students' admission probabilities, alongside warning messages and cutoff scores for all programs in the centralized system—resembling sequential implementations of the Deferred Acceptance algorithm—causally improves students' outcomes, similarly to the RCT results. Furthermore, by evaluating students' preferences and beliefs before and after the policy implementation, we observed that the improvements in students' outcomes are primarily driven by changes in beliefs concerning admission probabilities at the bottom of their preference orders, rather than at the top, reducing the incidence of students' biases on their application decisions.

Our results suggest that information frictions significantly impact the performance of centralized college admissions systems, even when students lack clear strategic incentives to misreport their preferences. Implementing more robust mechanisms, such as dynamic implementations of DA, can mitigate these challenges. Moreover, our findings reveal that information policies can substantially improve college admissions system performance and can be effectively implemented at scale through personalized websites, ultimately reducing the incidence of application mistakes and improving students' outcomes.

Overall, we contribute to market design literature by empirically evaluating the effects of implementing at scale a sequential version of DA, on reducing information frictions and application mistakes. Our 2023 intervention, which offers students real-time information about current cutoff scores, can be considered an approximation of the first round of *iterative DA* (Bó and Hakimov (2022)).[2] This sequential implementation of the Deferred Acceptance algorithm seems to outperform DA when application mistakes are present. One possible explanation for this is that our interventions partially correct students' biased beliefs and considerably decrease uncertainty surrounding their admissions, subsequently reducing the influence of biased beliefs on students' application decisions. Our results complement the policy-counterfactual findings highlighted by Luflade (2017) for the sequential implementation of constrained-DA in Tunisia. Structurally, Luflade (2017) finds that this type of sequential implementation of DA can decrease the majority of students' welfare losses compared to the student-optimal allocation.

The paper is organized as follows. In Section 2, we describe the Chilean college admissions system and our sources of data. In Section 3, we 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 analyze their growth over time. In Section 5, we study the prevalence and relevance of *strategic* mistakes and shed light on their potential drivers. In Section 6, we describe the RCT information policy to reduce information frictions and application mistakes and report the results. Section 7 describes the implementation and evaluation of the information policy at scale and discusses the implications of our findings for Market Design. Finally, in Section 8 we conclude.

[2]In *iterative DA*, students are required to submit only their most preferred choice among the feasible options. Bó and Hakimov (2022) demonstrates that if students follow this simple strategy, the equilibrium allocation results in a student-optimal stable matching (see Gale and Shapley (1962)).

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.[3] From now on, we refer to this as the admission system.

To participate in the admissions process, 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,[4] the weights they will consider in each admission factor to compute application scores, and 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, they are not admissible, and thus their chances of admission to that program are equal to zero. In Table 19 (see Appendix A.1) we show all the admission requirements imposed in the application process of 2019.

After scores are published, students can access an online platform to submit their applications—which we referred to as Rank-Ordered List (ROL)—, where they can list up to ten programs in decreasing order of preference. 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 algorithm to perform the allocation. The mechanism is a variant of the DA algorithm, where ties on students' scores are not broken.[5] 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.

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

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

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

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 combine information on the admissions processes from 2004 to 2020. This dataset includes 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 program they applied to, whether the application was valid, and whether the student was assigned to that program or wait-listed).

Surveys. To learn about students' preferences, their beliefs and to characterize the drivers of application mistakes, we designed and conducted, in collaboration with MINEDUC, several nationwide surveys between 2020 and 2023. These surveys included three main modules: (i) preferences, (ii) beliefs, and (iii) understanding of the admission process. We include all the relevant questions of this survey in Appendix A.3.

In the preferences module, our goal was to elicit students' true preferences. Towards this end, we asked students about their true top preference, i.e., the program they prefer the most among all the programs in the system, assuming that their score was high enough to guarantee admission. In addition, we asked students about their true bottom preference, i.e., any program they did not list in their ROL and that they would prefer compared to being unassigned, assuming their score was high enough to guarantee admission.

In the beliefs module, we aimed to elicit students' beliefs about several relevant factors affecting their application, including admission probabilities, expected earnings, chances of retention and graduation, expected cutoffs, etc. We elicited this information for programs included in the students' preference list and others outside their ROL, including their true top and bottom preference and some random programs.

Finally, in the last module, our goal was to measure students' knowledge and understanding of the system's rules, the requirements of the programs they applied to, their awareness of potential admissibility mistakes, and also to learn the reasons behind some of their decisions.

To conduct the survey, in each admission process (between 2020 and 2023), MINEDUC/DEMRE contacted students via email using their official account, including a link to the survey in the message. MINEDUC/DEMRE sent these messages following the application deadline but before publishing the assignment results. Hence, when completing the survey, students knew their scores and reported preferences but did not know their assignments.

Finally, for the 2023 admissions process, we designed and implemented a baseline survey, administered after students took the admission exams but before they knew their results. Since students had not yet applied to the centralized system at the time of answering this survey, we asked them about their beliefs and preferences regarding hypothetical programs.

3 Framework

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 $\vec{u}_i = \{u_{ij}\}_{j \in M \cup \{\emptyset\}}$, a vector of scores $\vec{s}_i = \{s_i^k\}_{k \in \mathcal{K}}$, 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. To facilitate exposition, we drop index i in the remainder of this section, and we normalize the outside option so that $u_\emptyset = 0$ and $p_\emptyset = 1$.

Each program $j \in M$ is characterized by its number of vacancies $q_j \in \mathbb{N}_+$, by a vector of admission weights $\omega_j = \{\omega_j^k\}_{k \in \mathcal{K}}$, 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]

$$s_j = \sum_{k \in \mathcal{K}} \omega_j^k s^k. \tag{1}$$

These application scores are used by programs to rank their applicants in decreasing order. Let $\bar{s}_j$ be the cutoff of program j, and let $p \in [0,1]^M$ be the vector of admission probabilities of student i, i.e., for each $j \in M$, $p_j = \mathbb{P}\left(s_j \geq \bar{s}_j\right)$. Finally, let $\rho(R) := \prod_{j' \in R}(1 - p_{j'})$ be the probability of not getting assigned to any program in R, and let $\mathbb{E}_p\left[U(R)\right]$ be the expected utility a student submitting ROL R given their indirect utilities $\{u_j\}_{j \in M}$ and admission probabilities $\{p_j\}_{j \in M}$, i.e.,[7]

$$\mathbb{E}_p\left[U(R)\right] = u_1 \cdot p_1 + u_2 \cdot p_2 \cdot \rho(\{1\}) + \ldots + u_{|R|} \cdot p_{|R|} \cdot \rho(R). \tag{2}$$

3.1 Defining mistakes

Given a strategy-proof mechanism, any misreport in preferences is weakly dominated by truthful reporting, and we consider it as an application mistake. However, we can generalize this definition and consider an application mistake as submitting a ROL R that is

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

[7] In a slight abuse of notation, we assume that j is the program in the j-th position of ROL R.

weakly dominated in expected utility by another ROL R', as we formalize in the following definition.

Definition 1 (Application mistake)**.** $R \in \mathcal{R}$ involves an *application mistake* if $\exists R' \in \mathcal{R} \setminus R$ such that reporting R' weakly dominates reporting R in expected utility given admission probabilities p, i.e.,

$$\mathbb{E}_p \left[U \left(R' \right) \right] \geq \mathbb{E}_p \left[U \left(R \right) \right].$$

An important limitation of this definition is that it requires knowledge about the vector of admission probabilities that the student considered when submitting their application. To overcome this limitation, most field evidence on application mistakes involves obvious misrepresentations, whereby students could apply to a given program with and without scholarship but decide only to include the latter in their preference lists (see Rees-Jones and Shorrer (2023)). Skipping funded programs constitutes an application mistake for any vector of admission probabilities and thus can be considered an *obvious mistake*.

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

$$\mathbb{E}_p \left[U \left(R' \right) \right] \geq \mathbb{E}_p \left[U \left(R \right) \right], \quad \forall p \in [0,1]^M.$$

Our rich administrative and survey data allows us to extend the analysis to other mistakes not studied in previous literature. Given their empirical relevance, we focus on two categories: (i) *admissibility* mistakes, and (ii) *strategic* mistakes. We say that a student makes an admissibility mistake if they apply to a program where they do not fulfill all the application requirements. Thus, their application is invalid, and the student has zero chance of getting admitted into that program.

Definition 3 (Admissibility mistake)**.** $R \in \mathcal{R}$ involves an *admissibility mistake* if $\exists j \in R$ for which the student does not belong to A_j, and thus $p_j = 0$.

Admissibility mistakes are identifiable from the administrative data and quite common in the Chilean setting. For this reason, it is crucial to understand their drivers and whether these mistakes are payoff relevant to design policies to alleviate them. We focus on this in Section 4.

The second category of mistakes is *strategic* mistakes. Compared to *admissibility* mistakes, *strategic* mistakes are more subtle and complex to analyze since they require information about students' preferences and beliefs about their admission probabilities, which are not commonly available in administrative data. Nevertheless, our survey data allows us to characterize both dimensions (preferences and beliefs), enabling us to identify three types of *strategic mistakes*: (i) *underconfidence*, (ii) *overconfidence*, and (iii) *ordering* mistakes.

As we formalize in the following definitions, we say that a student makes an *underconfidence* (*overconfidence*) mistake if they do not apply to a program where they have a positive admission probability and that they strictly prefer compared to a program in their ROL (prefer to the outside option), leading the student to a higher expected utility.

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

$$\mathbb{E}_p \left[U(R \cup \{j'\})\right] > \mathbb{E}_p \left[U(R)\right].$$

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

$$\mathbb{E}_p \left[U(R \cup \{j'\})\right] > \mathbb{E}_p \left[U(R)\right].$$

Intuitively, a student may skip a program they prefer to a program on their list if they believe their chances of admission are low. Similarly, a student may decide to ignore a program they strictly prefer over not being assigned if they think they will get admitted in one of their reported preferences. However, if their beliefs are incorrect, these may lead to an *underconfidence* and a *overconfidence* mistake, respectively.

Finally, as we formalize in our last definition, the last type of *strategic* mistake we analyze is *ordering mistakes*, whereby students submit a ROL not ordered strictly according to their preferences.

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

$$\mathbb{E}_p \left[U(R_i')\right] > \mathbb{E}_p \left[U(R_i)\right].$$

4 Admissibility Mistakes

Since *admissibility* mistakes are directly observable in the administrative data, in this section, we focus on quantifying the prevalence and relevance of this type of mistake and later focus on understanding its drivers.

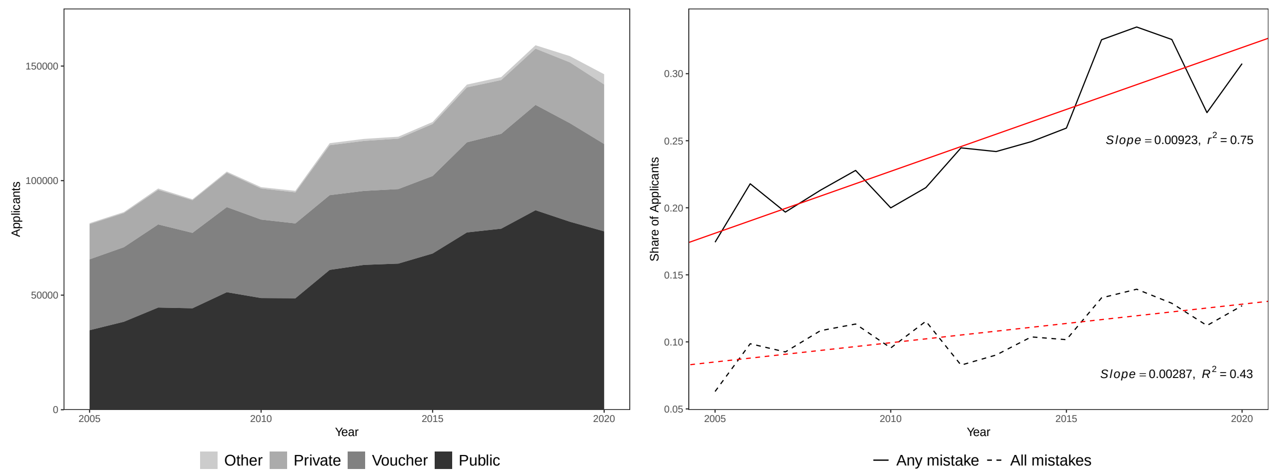
4.1 Prevalence and Relevance

In Figure 1, we show the evolution of the number of applicants by high-school type, and that of the number of students with admissibility mistakes, separating students who make at least one admissibility mistake from those who only include programs for which they are not eligible (i.e., have admissibility mistakes in all their preferences).

On the one hand, from Figure 1a we observe that the total number of applicants has increased over time, going from 70,000 in 2005 to 150,000 in 2020. In addition, we observe a change in the composition of applicants in terms of high-school type, with more students from public and less from voucher schools applying to the system. For instance, applicants from public and voucher schools represented 42.6% and 37.99% in 2005, respectively, while they accounted for 53.17% and 26.03% in 2020, respectively.

Figure 1: Evolution of Applicants and Mistakers

(a) Applicants (b) Mistakers



On the other hand, from Figure 1b, we observe that the share of students with at least one admissibility mistake (solid black line) and with admissibility mistakes in all their preferences (dashed black line) has also increased over time. Indeed, the fraction of students with at least one admissibility mistake has almost doubled (going from close to 17% to more than 33% in 2017), while the fraction of students with no valid preferences (all mistakes) has also doubled (going from 6.29% in 2005 to 12.69%). These results suggest that *admissibility mistakes* affect a significant fraction of applicants and have become more prevalent in recent years.

Although *admissibility mistakes* affect a significant fraction of applicants and their prevalence has increased in recent years, assessing whether these mistakes are payoff-relevant is essential. Admissibility mistakes could be payoff relevant for several reasons. First, since the Chilean system limits the number of programs students can apply to.[8] 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

[8]Before 2012, students were allowed to list no more than 8 programs, and this increased to 10 between 2012 and 2022. Finally, in 2023, students were allowed to list up to 20 programs.

assignment mechanism work, affecting how students decide to apply. However, it is also possible that *admissibility mistakes* are not payoff-relevant; for instance, if students still get assigned despite having an invalid preference, or if they have zero chance of admission to that program.

Indeed, most of the previous literature finds that mistakes are payoff irrelevant (Rees-Jones and Shorrer, 2023). Artemov et al. (2017) finds that most mistakes in their setting are payoff-irrelevant, as students do not rank funded programs that are either (i) "out-of-reach", i.e., programs for which their chances of admission are extremely low, or (ii) irrelevant, as they are worse than other listed options with very high admission chance (i.e., "within-reach"). Shorrer and Sóvágó (2017) and Hassidim et al. (2020b) also find that most mistakes are payoff-irrelevant. To accomplish this, the authors provide upper and lower bounds by comparing mistakers' assignment with the counterfactual assignment they would get assuming they add the skipped (funded) program as their top preference and right below the less preferred funded program, respectively. These bounds rely on the assumption that students strictly prefer to be assigned to the skipped program over their current assignment and the outside option. This assumption would not be reasonable in our setting, as students have heterogeneous and idiosyncratic preferences and there are no programs that clearly dominate others as in their settings (where students may apply to the same program with and without scholarship/funding).

To overcome this issue, we proceed as follows. First, we assume that an admissibility mistake is payoff relevant only if the student resulted unassigned and there are programs not listed in their ROL for which the student has a positive admission probability (ex-ante) or for which their score exceeds the realized cutoff (ex-post). Implicitly, we assume that the student would prefer to attend these programs over the outside option. To refine the analysis, we also focus on programs in the same area among the programs the student applied to and on programs sharing the same region of the programs the student applied to. Even though this is not a precise measure of welfare, resulting assigned to a program can significantly impact students' future outcomes due to the high returns of higher education Rodriguez et al. (2016). Second, we focus on students who made *admissibility* mistakes in all their reported preferences to provide a conservative estimate. In 2020, among the students that applied to at least one program (146,438), 18,605 students made application mistakes in all their submitted preferences and were unassigned. Hence, this is a large population, and MINEDUC has explicitly mentioned that they are interested in helping these students get assigned. Finally, note that a payoff-relevant admissibility mistake is necessarily an *underconfidence* or an *overconfidence* mistake, depending on whether there is a program not listed in the ROL that is more preferred than some program listed or the outside option, respectively.

In Table 1, we report the fraction of students likely to be making a payoff-relevant admissibility mistake among the set of students with no valid applications. Ex-ante captures students for whom there is at least one program for which they satisfy the requirements and have an admission probability above 1%.[9] Ex-post captures students for whom there is at least one

[9]To compute the distribution of cutoffs and the corresponding admission probabilities for each program,

program for which they satisfy the requirements, and their application score in that program exceeds its realized cutoff. We observe that between 17.2% and 24.2% of students with no valid applications make a payoff-relevant admissibility mistake. This result suggests that many of these students could have applied and gotten admitted to a program similar to the ones they included in their ROL.

Table 1: Admissibility mistakes

	Ex-ante		Ex-post	
	N	%	N	%
Any	4497	24.2	4497	24.2
Same region	4137	22.2	4121	22.1
Same area	4432	23.8	4431	23.8
Same region and area	3267	17.6	3209	17.2

Note: Sample includes all students with no valid preferences, i.e., students who make admissibility mistakes in all their reported preferences.

One limitation of this analysis is that it assumes that students would prefer to study any program (or any program in the same area/region they applied to) over being unassigned. However, it is possible that some students listed all the programs they would choose over the outside option. Thus, skipping other programs for which they have positive admission probability would not constitute an admissibility mistake. For this reason, the estimates in Table 1 should be considered as an upper bound and, in Section 6, we will discuss a lower bound for ex-ante and ex-post *admissibility* mistakes using the true bottom preference elicited in the 2022 survey.

Another limitation of this analysis is that there may be students who submit at least one valid application but also make *admissibility* mistakes and result unassigned. Assessing whether these students make a payoff-relevant *admissibility* mistake suffers from the same challenges mentioned above, i.e., we cannot unequivocally conclude that these students prefer the skipped programs over the outside option. For this reason, we will analyze this group of students using the true bottom preference in Section 6.

4.2 Drivers

Understanding the drivers of *admissibility* mistakes is crucial to design policies that prevent them from increasing in the future and consequently improve students' welfare. A natural

we follow a similar approach to that in Agarwal and Somaini (2019); Larroucau and Ríos (2018), i.e., we consider a bootstrap procedure where, in each simulation, we sample with replacement a set of students with their ROLS and solve the assignment, obtaining a cutoff for each program. Then, repeating this process, we get a vector of simulated cutoffs for each program, which we can later use to estimate a distribution of cutoffs and rational expectation admission probabilities.

solution would be to forbid invalid applications. However, DEMRE must allow students to submit invalid preferences because some of them may not have all their scores ready by the application period, and others request their scores be corrected, which may happen only after the application period.

Another solution could be to increase the salience of these mistakes so that students realize they are including invalid applications. Indeed, in 2019, DEMRE implemented changes to the application platform to increase the salience of *admissibility* mistakes. Specifically, they implemented a warning message that would notify students if they added a program for which they do not satisfy the admission requirements (see Figure 6b in Appendix 2.1). Nevertheless, as Figure 1b shows, the impact of this change had a limited effect in reducing *admissibility* mistakes, so it is unclear whether students (i) do not realize that they are making a mistake or (ii) do not understand the consequences of including invalid applications. We formalize this in the next two hypothesis.

Hypothesis 1. Students make *admissibility* mistakes because they do not realize they do not satisfy the program's requirements.

Hypothesis 2. Students make *admissibility* mistakes because they do not understand the consequences of submitting an invalid preference.

To test Hypothesis 1 and 2, we use the survey of 2020, where we also asked students with admissibility mistakes whether they knew they had invalid preferences and, if aware, why they insisted in applying to a program where they did not meet the requirements. Out of the total number of survey respondents, 29.85% (11370 respondents) made at least one *admissibility* mistake[10] and 16.75% (1905 respondents) of these students replied that they did not know that they were making a mistake, while 83.25% (9465 respondents) responded that they were aware. Hence, a large fraction of students does not know they are making admissibility mistakes, supporting Hypothesis 1.

In Table 2, we report the number of survey respondents by awareness of their mistakes and by reason of including invalid preferences (see Appendix A.3 for the detailed question). In each case, we report the number of survey respondents with *any* and *all* mistakes. Following the analysis in the previous section, we consider students who made *admissibility* mistakes in *all* their preferences as candidates for making payoff-relevant mistakes. Out of these students, we report the number and percentage of them who are *potentially* making payoff-relevant mistakes, i.e., all students with an average between their Math and Verbal scores above 450,[11], and also the number and fraction of them who are making a payoff relevant admissibility mistake *ex-ante* and *ex-post*.

[10] We do not observe significant differences in the incidence of admissibility mistakes among survey respondents compared to the general population of applicants.

[11] If this average is below 450, the student is not eligible for any program in the centralized system.

Table 2: Drivers of Admissibility Mistakes

		Adm. Mistake		Payoff Relevance					
				Potential		Ex-ante		Ex-post	
Aware	Reason	Any	All	N	%	N	%	N	%
No	Did not know	1905	901	140	15.5	128	14.2	128	14.2
Yes	Thought still had chances	6085	2548	698	27.4	686	26.9	686	26.9
	Does not affect my application	1481	271	60	22.1	58	21.4	58	21.4
	Expect change in scores	968	494	107	21.7	103	20.9	103	20.9
	Other	931	400	126	31.5	118	29.5	118	29.5

Note: Sample include all survey respondents with at least one admissibility mistake. Any reports the count by group, and All reports the count of survey respondents with admissibility mistakes in all their preferences. Potential reports the count of survey respondents with all mistakes and with an average between their Math and Verbal scores greater than or equal to 450. Ex-ante and ex-post report estimates for the number of payoff-relevant mistakes among students with all mistakes. Thus, all % are computed using as base the number in the column *All*.

First, we observe that many students who were unaware make a payoff-relevant mistake.[12] Second, 64.29% (6085 respondents) of students who were aware of their mistake (9465 respondents) replied that they thought they still had a positive admission probability. Of these students, 698 made an application mistake in all their reported preferences, and 26.9% of these made ex-ante and ex-post admissibility mistakes. Thus, this result suggests that many students are aware of their mistakes but do not understand the implication of including an invalid preference, supporting Hypothesis 2. Finally, from Table 2, we observe that the second most common reason among aware students is that their mistake would not affect their application.[13] Within this group, 18.30% ($= 271/1481$) have mistakes in all their preferences and thus have zero chances of admission. Therefore, their response implies they do not fully understand the consequences of their mistakes.

4.2.1 Admissibility Mistakes and changes in requirements

In this sub-section, we analyze whether knowledge about admission requirements and their changes over time can have an effect on *admissibility* mistakes.

[12]Note that the fraction is smaller than that in Table 1 and compared to that for students who were aware of their mistakes. This is because these students are less likely to have any program where they would be admissible, which is necessary for payoff relevance. In general, these students have lower scores, which explains why the fraction of them who are *potentially* making a mistake is smaller (15.5% vs. at least 21.7%) compared to the other groups.

[13]Note that the fraction of them who have at least one valid preference ($(1481 - 271)/1481 = 81.70\%$) is substantially larger than that for the other groups (at most $58.13\% = (6085 - 2548)/6085$ for students who thought they still had chances), so these students may be right in that their admissibility mistakes are not payoff relevant.

To understand whether students are aware of admission requirements, we asked them to report whether they knew the requirements for each program in the survey. In Appendix B.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, among 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.

Finally, to test whether changes in requirements over time can have an effect on *admissibility* mistakes, we estimate the following specification:

$$z_{jt} = \alpha_j + \lambda_t + \beta_1 z_{jt-1} + \beta_2 z_{jt-2} + \beta_3 \Delta_{jt} + \varepsilon_{jt} \tag{3}$$

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 3 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. Moreover, as a significant share of *admissibility* mistakes are payoff-relevant, this externality could affect students' outcomes.

Overall, we find that payoff-relevant admissibility mistakes are primarily explained by a

Table 3: Effect of Changes in Admission Requirements

	(1)	(2)	(3)	(4)
Applicants from public schools [%]	0.055	0.013	-0.006	-0.015
	(0.038)	(0.044)	(0.032)	(0.038)
Applicants from voucher schools [%]	0.088**	0.048	0.029	0.022
	(0.035)	(0.039)	(0.029)	(0.034)
Applicants with LM $\geq$ 450 [%]	-1.29***	-1.18***	-0.981***	-0.963***
	(0.073)	(0.064)	(0.060)	(0.052)
Avg. percentile LM	0.118*	-0.003	-0.029	-0.079
	(0.064)	(0.062)	(0.051)	(0.050)
Min. average score (P0)	0.023***	0.033***	0.028***	0.036***
	(0.006)	(0.006)	(0.005)	(0.004)
Min. average score (N0)	-0.026***	-0.033***	-0.043***	-0.045***
	(0.006)	(0.007)	(0.005)	(0.005)
Min. application score (P0)	0.021***	0.026***	0.034***	0.034***
	(0.005)	(0.007)	(0.005)	(0.006)
Min. application score (N0)	-0.007	-0.016	-0.018**	-0.025***
	(0.006)	(0.009)	(0.007)	(0.007)
Special test (N0)	-0.068	-0.105*	-0.260***	-0.339***
	(0.053)	(0.056)	(0.073)	(0.048)
Restricts application rank (P0)	0.048**	0.009	0.040***	0.009
	(0.019)	(0.021)	(0.009)	(0.017)
Restricts application rank (N0)	-0.034*	-0.024*	-0.042***	-0.041***
	(0.017)	(0.011)	(0.010)	(0.008)
Min. average score (P1)		0.017***	-	0.011***
	-	(0.003)	-	(0.003)
Min. average score (N1)	-	-0.032***	-	-0.029***
	-	(0.008)	-	(0.007)
Min. average score (P2)	-	0.010	-	0.004
	-	(0.006)	-	(0.004)
Min. average score (N2)	-	-0.020***	-	-0.015***
	-	(0.004)	-	(0.004)
Min. application score (P1)	-	0.015***	-	0.011***
	-	(0.005)	-	(0.004)
Min. application score (N1)	-	-0.006	-	-0.006
	-	(0.007)	-	(0.004)
Min. application score (P2) 2	-	0.017***	-	0.012***
	-	(0.003)	-	(0.004)
Min. application score (N2)	-	-0.003	-	-0.002
	-	(0.006)	-	(0.005)
Special test (N1)	-	-0.107	-	-0.120**
	-	(0.068)	-	(0.048)
Special test (N2)	-	-0.052	-	-0.011
	-	(0.089)	-	(0.058)
Restricts application rank (P1)	-	0.055*	-	0.045*
	-	(0.028)	-	(0.022)
Restricts application rank (N1)	-	-0.032***	-	-0.027***
	-	(0.009)	-	(0.005)
Restricts application rank (P2)	-	0.005	-	-0.006
	-	(0.015)	-	(0.012)
Restricts application rank (N2)	-	-0.034***	-	-0.023***
	-	(0.010)	-	(0.006)
Share mistakes (1)	-	-	0.394***	0.346***
	-	-	(0.026)	(0.038)
Share mistakes (2)	-	-	0.050***	0.092***
	-	-	(0.016)	(0.017)
Program	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Lags - Dependent	No	No	Yes	Yes
Lags - Others	No	Yes	No	Yes
Observations	17,548	13,545	15,481	13,545
R^2	0.889	0.916	0.927	0.935

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: $^*p < 0.1;^{**} p < 0.05;^{***} p < 0.01$

lack of understanding of the consequences of including invalid preferences, while there is also a large number of students who are not aware that they are making a mistake. These mistakes are correleted with lack of knowledge about admission requirements, and the effect of changes in admission requirements on the share of *admissibility* mistakes is positive and significant. These results suggest that students are not fully aware of the rules of the admission process, and that changes in admission requirements can have a negative externality in the centralized system.

Hence, simplifying complexities in the applciation process, providing more information about requirements, the consequences of including invalid preferences, and further increasing the salience of these mistakes, may help to reduce payoff-relevant *admissibility* mistakes in the system and improve students' assignment.

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*: A student makes an under-confidence mistake if they skip a program for which they have positive admission probability and they prefer more than other programs in their ROL. As there may be many programs that satisfy this condition, we focus on students that skip their true top preference (elicited through the survey), and we restrict the analysis to students for whom the constraint on the length of their list is not binding. We do the latter because skipping their true top preference may be optimal for students constrained by the length of the list, so we cannot directly label those as mistakes.

2. *Ordering*: A student makes 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 a different order. Since this could hold in any part of the preference list, we focus for simplicity on ordering mistakes involving the true top preference (elicited through the survey), i.e., we focus on students who apply to their true top preference but do not include it as their top reported preference.

3. *Over-confidence*: A student makes an over-confidence mistake if (i) they skip a program that they prefer more compared to being unassigned and for which they have a positive admission probability, and (ii) the constraint on the length of their list is not binding and they have a positive risk of being unassigned. As before, since there may be multiple programs that satisfy this condition, we focus on the true bottom preference (elicited through the survey).

Following a similar structure as in Section 4, we start analyzing the prevalence and relevance of each of these mistakes, focusing both on ex-ante (i.e., mistakes with positive probability) and ex-post (i.e., mistakes given the realized cutoffs) mistakes. Then, we study the drivers of the different types of *strategic* mistakes, focusing on the effect of beliefs and information.

5.1 Prevalence

Note that, by definition, *strategic* mistakes are payoff-relevant. Hence, in this section, we will focus on showing the prevalence of these types of mistakes using administrative and survey data from 2020.

5.1.1 Under-confidence and Ordering.

As previously discussed, we use the survey question about the true top preference to quantify the prevalence and relevance of *under-confidence* and *ordering* mistakes. However, students may skip or misplace their true top preference for other reasons that may not constitute a mistake. For instance, a student may skip it because they believe their chances of graduation are too small or because of the program's cost. As our intend was to elicit students' true top preference considering these factors, we need to rule out these possibilities and focus only on those students whose true top preference considers all these factors. To accomplish this, we included survey questions asking for the reasons behind their skipping decision (see Table 21 in Appendix B.2), and we focus our analysis on those students who provide consistent answers, i.e., students whose ROL is consistent with their response (see the discussion on Appendix B.2 for a precise definition of consistency).

Overall, 23,596 students (67.01% of survey respondents) provided consistent answers to the survey questions. In Table 4, we report summary statistics to characterize underconfidence and ordering mistakes these students, separating by whether the student is short-list or full-list (i.e., whether the constraint on the length of the application list is binding).

Table 4: Summary statistics for underconfidence and ordering mistakes

						Underconfidence mistake				Ordering mistake			
				Misreport		Ex-ante		Ex-post		Ex-ante		Ex-post	
	N	Truth	Total	Exclude	Order	*N*	%	*N*	%	*N*	%	*N*	%
Full-list	2627	1349	1278	904	374	39	1.5	30	1.1	47	1.8	39	1.5
Short-list	20969	12696	8273	6522	1751	501	2.4	420	2.0	387	1.8	318	1.5

Note: Sample includes all survey respondents who completed the survey, provided consistent answers regarding their true top preference, and are not PACE. The column *Truth* reports the number of respondents whose true top preferences matches their top reported preference. The columns below *Misreport* include the total number of students who misreport their preferences (*Total*), the number of respondents who exclude their true top preference (*Exclude*), and the number of respondents who include their true top preference in their list but not as their top preference. The columns below *Underconfidence mistakes* (*Ordering mistakes*) report the number and fraction of survey respondents who make ex-ante and ex-post underconfidence (ordering) mistakes.

First, we observe that 40.48% of these respondents misreport their true top preference, and most of these students are short-list. Since full-list students may optimally misreport their true top preference to satisfy the constraint on the length of their application list, we focus on short-list students, as these students could add their true top preference and weakly improve their expected utility. Second, we observe that most (short-list) misreporters (77.75%) exclude their true top preference, while the minority include it but not as their top preference. Third, we observe that 2.4% and 2.0% of respondents make ex-ante and ex-post underconfidence mistakes, respectively. Finally, we find that 1.8% and 1.5% of respondents make *ordering* mistakes.

In summary, many students make *underconfidence* and *ordering* mistakes. Since we characterize these mistakes based on misreports of true top preference, this analysis does not include students who may have zero chance of getting admitted to their true top preference but for whom there exist a program they prefer more than their top reported preference and where they could be admitted (ex-ante or ex-post). Hence, the results reported in Table 4 should be interpreted as lower bounds on the number of *underconfidence* and *ordering* mistakes.

5.1.2 Overconfidence mistakes.

As discussed in Section 4.1, in the 2020-survey we do not have information about programs that the student did not include in their list but would prefer over being unassigned, so we cannot fully characterize an over-confidence mistake. However, we can estimate in this sample the fraction of students likely to make an over-confidence mistake following a similar approach to that in Section 4.1. Namely, we assume that a student is likely to make an *over-confidence* mistake if they are unassigned but have at least one valid preference (to separate them from students with payoff-relevant admissibility mistakes) and there are programs not listed in their ROL for which they have a positive admission probability.

In Table 5, we report the fraction of students likely to be making an *overconfidence* mistake out of the total number of applicants.

Table 5: Overconfidence mistakes

	Ex-ante		Ex-post	
	N	%	N	%
Any	10772	7.4	10772	7.4
Same region	10692	7.3	10672	7.3
Same area	10699	7.3	10694	7.3
Same region and area	10322	7.0	10066	6.9

Note: Sample includes all students with no assignment.

As in the case of *admissibility* mistakes, the values in Table 5 provide an upper bound on the prevalence of over-confidence mistakes, since there may be students who prefer no other program to those listed in their ROL and would rather be unassigned. To refine this analysis and obtain a lower bound, in the 2022-survey, we asked students to imagine a hypothetical scenario in which they were not admitted to any program on their list. We then asked them whether there is any program in the centralized system that they have not included in their application, but they would prefer than being unassigned.[14]

This question allows us to measure lower and upper bounds on the percentage of students making an over-confidence mistake. Specifically, we compute the ex-ante lower bound by counting the number of students who faced a positive risk of not being assigned to the system ($> 1\%$) and have a strictly positive probability of being assigned to their *Bottom-true program*. Similarly, we compute the ex-post lower bound by counting the number of unassigned students who would have been assigned to their *Bottom-true* program if they had applied to it. We compute the ex-ante and ex-post upper bounds by counting all students who face positive risk (ex-ante) or result unassigned (ex-post) and reported a bottom-true program. Contrary to the lower bounds, we do not restrict the probability (ex-ante or ex-post) of being assigned to the bottom-true program. The reason is that students who report a bottom-true program may have other programs not listed that they prefer over being unassigned and for which they have a positive probability of being assigned (ex-ante or ex-post).

In Table 5, we report the bounds on the number of students making ex-ante and ex-post overconfidence mistakes out of the set of students who are short-listed and who completed the survey. Additionally, to mitigate potential sources of bias and have a representative sample of the applicants' population, we exclude from our analysis students who are assigned to the treatments. We do so for two reasons. First, treatment effects may influence the outcome variable, resulting in non-representative samples for students who open the intervention.

[14]See Appendix A.3 for the exact question.

Second, students who are assigned to the treatments and do not open the intervention may represent a non-random sample of the applicant population, and the decision to open the intervention may be correlated with application mistakes. By excluding these students from our analysis, we aim to obtain a more representative sample of the applicants' population.

Table 6: Over-confidence mistakes' bounds

Bounds	N	Ex-ante	Ex-post
Lower	5653	1.15%	0.64%
		(0.14)	(0.11)
Upper	5653	2.46%	1.79%
		(0.21)	(0.18)

Note: The sample is restricted to students who applied to less than 10 programs (short-list students), responded to the survey with 100% progress and, (i) who were not in the RCT sample, or (ii) who were in the RCT sample but in the control group. These two subsamples are pooled together to compute the bounds and the sample size is given in column *N*. Standard errors (in parenthesis) are multiplied by 100.

We observe that at least 1.1% and at most a 2.5% of applicants is making an over-confidence mistake. Because over-confidence mistakes are payoff relevant by definition, it is important to also understand the drivers of these mistakes. In the next section, we discuss the drivers of strategic mistakes and then evaluate how to reduce them.

5.2 Drivers

As in the case of *admissibility* mistakes, understanding the drivers of *strategic* mistakes is essential to provide students with tools to improve their applications. As discussed in Section 3, students' expected utilities depend on the value of getting assigned to each program and their admission probabilities. Hence, understanding the drivers of admissibility mistakes requires knowledge about students' preferences. Moreover, students do not know their actual admission chances and, thus, make their application decisions based on their beliefs about admission probabilities. Finally, even if we knew students' preferences and beliefs about their admission probabilities, some students may not be expected utility maximizers and have other considerations such as loss aversion or reference-dependent preferences, as proposed by recent literature Dreyfuss et al. (2019).

Given these challenges, we will focus on assessing to what extent (i) biases in beliefs and (ii) a lack of understanding explain *strategic* mistakes involving students' true top preference. We formalize this in the following two hypotheses.

Hypothesis 3. Students make *strategic* mistakes because they have biased beliefs about their admission probabilities.

Hypothesis 4. Students make *strategic* mistakes because they do not understand how the assignment mechanism works.

To test Hypotheses 3 and 4, we leverage the survey of 2020, where we also asked students their beliefs about their admission probability for some programs in their ROL and for their true top preference (even if they did not include it in their ROL). Then, by comparing these beliefs with the estimated rational-expectation probabilities, we can quantify biases in beliefs and assess whether these explain *strategic* mistakes. Formally, we will denote by $\tilde{p}_{ij}$ and p_{ij} the elicited belief and the rational-expectation admission probability of student i in program j, respectively, and we will denote the bias as $\eta_{ij} = p_{ij} - \tilde{p}_{ij}$. Similarly, let $\tilde{\rho}_i = 1 - \prod_{r \in R}(1 - \tilde{p}_r)$ and $\rho_i = 1 - \prod_{r \in R}(1 - p_r)$ the elicited and rational-expectation overall probability of student i getting assigned in any preference of their ROL R, and let $\bar{\eta}_i = \rho_i - \tilde{\rho}_i$ the bias on the overall admission probability.[15] When clear from the context, we may drop the indexes to facilitate exposition. Moreover, we asked students about their knowledge regarding previous year cutoffs and other elements of the assignment mechanism. Hence, we can use these responses to study the biases' drivers and to evaluate the impact of information friction on these mistakes.

5.2.1 Underconfidence and ordering.

As previously discussed, students may make underconfidence or ordering mistakes if they have a positive admission probability at their true top preference and either skip it or place it not as their top reported preference. Thus, any misreport regarding the true top preference among students with positive admission probability would lead to an *strategic* mistake.

To understand the effect of biases on these mistakes, in Table 7, we report the results of a multinomial logit model, in which the dependent variable is the type of ex-ante mistake (No mistake, Underconfidence, Ordering). The main variable of interest is the bias η at the true top preference, i.e., the difference between the ex-ante rational-expectations probability and the student's belief, and we control for demographics including gender, score and region stratas. To rule out misreports that may not constitute a *strategic* mistake, we exclude from the analysis students for which their true top preference is not valid and students for whom the constraint on the length of their ROL is binding.

We observe that the bias has a positive and significant effect on *underconfidence* and *ordering* mistakes. This result suggests that these *strategic* mistakes increase with students' pessimism, as larger bias values imply that students' beliefs are lower than their ex-ante admission probability. Overall, the results in Table 7 show that Hypothesis 3 is supported by the data for the case of *underconfidence* and *ordering* mistakes involving the true top preference.

[15] Implicitly, we assume that admission probabilities are independent.

Table 7: Effect of Bias on Misreporting Behavior

	Dependent variable: Strategic mistake	
	Underconfidence	Ordering
	(1)	(2)
Bias - True top	1.559^{***}	0.666^{***}
	(0.091)	(0.111)
Constant	-1.409^{***}	-1.559^{***}
	(0.118)	(0.142)
Demographics	Yes	Yes
Observations	10346	10346

Note: Sample includes all students who are not PACE, completed the survey, are short-list, and reported a top true preference for which they satisfy the application requirements. Significance: $^{*}p < 0.1;^{**} p < 0.05;^{***} p < 0.01$

5.2.2 Overconfidence mistakes

As we observe from Table 5.1.2, a large fraction of students who do not get assigned to any program may be making an *overconfidence* mistake. To understand the effect of biases on these mistakes, in Table 8, we report the results of logit regressions that consider as dependent variables whether the student made an overconfidence mistake and a payoff-relevant admissibility mistake involving any program, a program in their same region, area, and also sharing the same region and area as the programs the student included in their ROL. The main variable of interest is the bias on the overall admission probability $\bar{\eta}$, and we control for demographics including gender, region and score stratas. The sample considered in this analysis includes all students that are short-list, not PACE, and have an average between Math and Verbal greater than or equal to 450.[16]

Table 8: Effect of Bias on Overconfidence Mistakes

	Overconfidence mistake				Admissibility mistake			
	Any	Region	Area	Region and Area	Any	Region	Area	Region and Area
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Bias - Overall	-0.982^{***}	-0.960^{***}	-0.969^{***}	-0.730^{***}	0.982^{***}	0.925^{***}	0.970^{***}	0.781^{***}
	(0.089)	(0.088)	(0.088)	(0.084)	(0.091)	(0.092)	(0.091)	(0.095)
Constant	-0.674^{***}	-0.650^{***}	-0.648^{***}	-0.817^{***}	0.622^{***}	0.410^{***}	0.602^{***}	-0.556^{***}
	(0.072)	(0.072)	(0.072)	(0.072)	(0.073)	(0.072)	(0.073)	(0.080)
Observations	13,632	13,632	13,632	13,632	13,632	13,632	13,632	13,632

Note: Sample includes all students who are not PACE, are short-list and unassigned, and have an average score between Math and Verbal above 450. Significance: $^{*}p < 0.1;^{**} p < 0.05;^{***} p < 0.01$

[16]We include this filter to remove all students for whom there are no valid programs.

On the one hand, we observe that the bias on the overall admission probability has a negative and significant effect for all overconfidence mistakes. This result suggests that students that are more optimistic, i.e., students for whom their bias is smaller, are more likely to make an overconfidence mistake. Note that this effect goes in the opposite direction than the effect of biases on *underconfidence* mistakes, as in the latter more optimistic students are less likely to make a mistake. Nevertheless, all these results show that biases have a significant effect at explaining *strategic* mistakes, confirming Hypothesis 3. On the other hand, we observe that the bias has a negative and significant effect on payoff-relevant admissibility mistakes. The reason is that all students who make an admissibility mistake have zero overall probability of getting assigned. Hence, the bias can only take negative values, and thus a negative bias implies that the student assigns a higher probability of getting assigned (when in fact they have zero chance). Thus, negative biases imply a lower understanding of the consequence of their admissibility mistake, in line with our previous findings.

6 Field Experiment

The above results suggest that biased beliefs and information frictions could significantly affect students' applications and outcomes. In order to reduce these frictions and the resulting application mistakes, we designed an intervention providing students with key information at the time they were submitting their applications. This section describes the intervention and reports its effects on students' application behavior and admission outcomes.

6.1 Description

6.1.1 Background.

In collaboration with MINEDUC, we designed and implemented an intervention to provide information and recommendations to students during the application process in 2022. Specifically, we created a personalized website for each student that submitted their application within the first two days of the five-day application window.[17] MINEDUC sent emails, including a link to their personalized website, inviting students to open their personalized websites at the beginning of the third day of applications.

Our intervention exploits the fact that students are allowed to modify their list as many times as they want within this time window, so we can measure the effectiveness of the intervention provided by comparing the preferences reported before and after it. Moreover,

[17]Students could submit their application list from January 11 to January 15, 2022, and we use January 12 at 8 pm as the cutoff to collect all applications and create the personalized websites.

as we discuss next, we randomize the information provided to each student, allowing us to study the effect of each part of the intervention.

6.1.2 Information.

The information included in the personalized websites was carefully tailored to address the causes of mistakes outlines in the above sections: (i) biased beliefs and (ii) lack of information. Specifically, the intervention had four main modules:

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

M2: Personalized information about scores for programs included in the applicant's list.

M3: Personalized alerts depending on the admission probabilities.

M4: Personalized recommendations about other majors of potential interest.

General information about programs. Figure 12 in Appendix shows an example of module M1. It displays the application list of the student. When clinking on a particular program, the student can access detailed information including the program's address, the number of years that the institution is accredited for[18], benefits and types of financial aid for which the student is eligible to when enrolling in that program, its formal duration, measured in semesters, as well as yearly tuitions fess in pesos.

Personalized information about scores. Figure 2 shows the design of module M2. As in M1, students first see a list of the programs they applied to (Figure 2a). Clicking on a given program gives them access to personalized information about two elements. First, we show the application score of the first and last student admitted in the processes of 2020 and 2021. We also include a graphical representation of where the student stands relative to these scores.[19] Second, if the student does not fulfill the requirements of the program (i.e., makes an admissibility mistake), we display an alert including the following message:[20] *"Please verify that you satisfy the admission requirements for this program."*

[18]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/`.

[19]To provide more relevant information, the score of the last admitted student displayed depends on the admission tracks where the student is participating in. Hence, if the student is BEA, we display the score of the last admitted student in the BEA process. See Figure 10 in Appendix C for a detailed zoom on this element.

[20]As requested by MINEDUC, we display the application score if it can be computed, despite the admissibility mistake. However, if one of the scores is missing (and thus we cannot compute the application score), then we display the message *Score not computed*.

Figure 2: Feedback on Programs' Admission Chances

(a) General (b) Detailed

Personalized alerts depending on admission probabilities. Considering the application lists and scores of all students who applied before January 12 at 8 pm CT, this module displays the probability for the student to be admitted to each of the listed programs. Appendix C.2 describes in details how these probabilities are computed. In particular, we estimate two sets of probabilities: interim and adaptitve.[21] Interim probabilities are computed using the applications received before January 12 at 8 pm CT. To do so, we first estimate the total number of applicants that will apply during the application process, and then use this information to estimate the admission probabilities via bootstrap. Adaptive probabilities are constructed via bootstrap, using students' applications in the admission process of 2021.

These probabilities determine the personalized alerts received by each applicant on their personalized website, aimed at helping them avoid strategic mistakes. As shown in Figure 3, these alerts are embedded in M2, adding the following information:

- Program-level alert: when both estimated probabilities are below 1%,[22] we display the red alert in Figure 3a (see Figure 11 in Appendix C for detailed zoom) including the following message:

[21]We consider these two sets of probabilities to reduce the risk of displaying misleading information to students.

[22]Admission probabilities are bimodal and highly concentrated in the two extremes (i.e., probability equals to 0 or 1). Hence, any threshold between 1% and 99% leads to similar results. Nevertheless, MINEDUC opted to use 1% to be more conservative.

Based on the applications received up to January 12th at 11 pm, 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.

- Overall alert: depending on the admission probabilities of the top preference and overall,[23] we display an alert nudging students to consider additional programs in their application list. Figure 14 shows the different message types. There are three groups:

  1. If the overall probability of being assigned is below 99%, we recommend students to add *safety* programs, i.e., programs for which the student faces a positive admission probability (Figure 14a, in Appendix);
  2. If the estimated probability of being assigned to the top preference is above 99%, we recommend students to add *reach* programs to their lists, i.e., programs that are generally more preferred, that the student may be interested in[24], and for which the student faces positive admission probability (Figure 14b, in Appendix).
  3. Otherwise, we display a message inviting students to *explore* and get information about other programs.

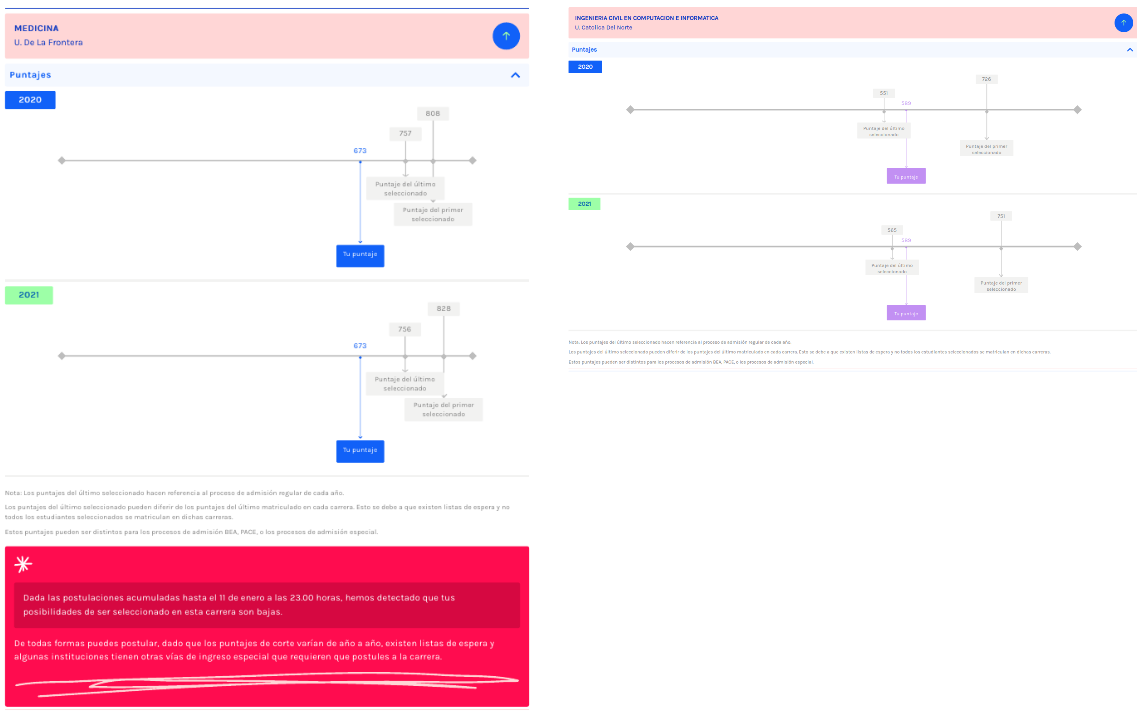
Notice that we recommend students to add *safety* programs to reduce over-confidence mistakes, while we recommend adding *reach* programs to reduce under-confidence mistakes. As requested by MINEDUC, none of our interventions encourages students to remove programs from their lists (even in the presence of admissibility mistakes) or alter the order of the programs initially included.

[23]Notice that this probability considers all programs included in the list. More specifically, if the student applied to a subset R of programs and p_r represents the probability of being assigned to program $r \in R$, then this probability can be computed as $1 - \prod_{r \in R}(1 - p_r)$.

[24]To determine potential *reach* programs, we use the information on students' top-true preferences in the survey of 2021. We compute transition matrices for programs that are typically declared to be top-true preferences conditional on the top-reported preference submitted by the student.

Figure 3: Feedback on Programs' Admission Chances

(a) Red Alert (b) No Alert



Personalized recommendations. Based on students' scores and their reported preferences, we compute four personalized major recommendations to encourage students to consider other options. Appendix C.3 describes how these recommendatios are obtained in more details. We recommend 1) the most preferred major predicted based on the student's list, 2) the second most preferred major predicted based on the student's list, 3) the major with the highest expected wage among all majors belonging to IPs or CFTs, and 4) the major with the highest expected wage among all feasible[25] majors considering the transition matrix previously computed.

For each recommended major, we include information on the average duration of the programs belonging to that major, as well as on the minimum and maximum application score of the last admitted student to any of the programs belonging to that major. We also provide information related to labor market outcomes of students enrolling in this major: we show the average employment rate and average wages four years after graduation among programs belonging to that major. An example of this module can be found in Appendix (Figure 13).

Note that the recommendations are made at the major level, while students apply to specific

[25] A feasible major is a major for which the student has a positive probability of assignment

programs.[26] However, by providing a range of scores for the last admitted students, we aim to extend students' consideration sets and encourage them to find more information about these majors. Hence, we believe that the recommendation module serves two purposes: (i) reduce potential information frictions about programs' characteristics and (ii) affect students' beliefs on admission probabilities for programs that are not in their consideration sets.

6.1.3 Experimental Design

To properly evaluate the impact of each module, we build four treatment groups which differ with respect to the modules displayed in the applicant's personalized website. We assign each student selected in the intervention to one of four groups:

- T1 General information: only M1 is displayed.
- T2 General information + scores: M1 and M2 are displayed.
- T3 General information + scores + alerts: M1, M2 and M3 are displayed.
- T4 General information + recommendations: M1 and M4 are displayed.

We perform the assignment of students to treatments in a stratified way to achieve balance on observables across groups. In Appendix C.4 we describe the variables used for stratificationn and we report the results of several balance checks.

As previously discussed, each student that applied before January 12 at 8pm CT received an email with a link to their personalized website. In addition, using the same stratification discussed in Appendix C.4, we randomly chose 30,000 students and sent them an SMS encouraging them to open their personalized website.

6.2 Effect on Application Behavior and Assignment Outcomes

In this section, we evaluate the results of the intervention. Table 9 shows aggregate statistics by group. Among the four treatment groups of interest, we observe that about 25,000 students received the email, and around 28% of them opened their personalized website. As expected, we do not observe significant differences across groups in opening the email. We use T1 as a control group, as this group only observes module M1, which is also displayed in the other treatment arms.

[26]MINEDUC did not allow us to make program-specific recommendations to avoid favoring some schools/universities.

We observe that close to 78% of the students in each group are assigned to the system. In addition, students in T2 and T3 increase the length of their application lists more than students in T4 and T1. This translates into more students entering the centralized system or changing their program of assignment after the intervention.

Table 9: Summary Statistics by Group

			Application		Assignment	
Treatment	Total	Opened [%]	Modified [%]	Increased [%]	Assigned [%]	Entered [%]
T1	25337	28.097	10.862	4.156	78.079	2.614
		(0.282)	(0.195)	(0.125)	(0.26)	(0.21)
T2	25459	28.281	11.359	4.47	77.921	3.21
		(0.282)	(0.199)	(0.13)	(0.26)	(0.23)
T3	25456	28.048	11.687	4.529	78.037	3.432
		(0.282)	(0.201)	(0.13)	(0.259)	(0.239)
T4	25407	28.417	11.304	4.306	77.947	3.178
		(0.283)	(0.199)	(0.127)	(0.26)	(0.229)

Note: Opened is a binary variable equal to 1 if the student opened the personalized website, 0 otherwise. Modified is a binary variable equal to 1 if the student modified its application after the personalized websites were sent, 0 otherwise. Increased is a binary variable equal to 1 if the student increased the number of valid applications in their list, 0 otherwise. Assigned is a binary variable equal to 1 if the student resulted assigned at the end of the process, 0 otherwise. Entered is a binary variable equal to 1 if the student resulted unassigned given their list of preferences before the intervention and assigned given their preferenes after the intervention, 0 otherwise. Standard errors reported in parenthesis.

Of course, any effect of the treatment on students' application behavior and assignment outcomes should be driven by students who actually accessed their personalized website. To understand which interventions have the largest impact, we thus restrict the analysis to the sample of students who opened their personalized website. This restriction allows us to estimate the ATT of *seeing* the information displayed within a given treatment arm.

Table 10 summarizes these results. We observe that students in T2 — who received information about their scores, cutoffs, and admissibility mistakes — and students in T3 — who in addition received personalized alerts — are 14%-16% more likely to modify their application list after receiving the intervention relative to the control group. Specifically, it seems by students increase the length of their application lists: students in T3 are 14% more likely to do so.

Through these changes, the intervention significantly improves students' assignment outcomes. The effect of T3 is particularly large: students who would not have been assigned given their initial list are 60% more likely to be assigned to a program at the end of the procedure compared to students in the control group. Providing information about scores and previous years' cutoffs, together with warning messages about students' risk, is thus particularly effective at allowing students to match to a program within the centralized program.

Table 10: Regression Results among Openers

Treatment	Application				Assignment			
	Modified		Increased		Entered		Changed program	
	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error
Intercept	-1.90	(0.035)	-2.97	(0.055)	-3.47	(0.150)	-3.13	(0.059)
Treatment 2	0.13	(0.048)	0.10	(0.076)	0.28	(0.198)	-0.03	(0.084)
Treatment 3	0.15	(0.048)	0.13	(0.076)	0.47	(0.191)	0.13	(0.081)
Treatment 4	0.06	(0.049)	0.02	(0.077)	0.07	(0.207)	-0.08	(0.085)
				Odd-ratios				
Intercept	0.15		0.05		0.03		0.04	
Treatment 2	1.14		1.10		1.33		0.97	
Treatment 3	1.16		1.14		1.60		1.14	
Treatment 4	1.06		1.02		1.08		0.93	
Observations	28679		28679		6221		28679	

Note: This table presents estimated coefficients, odds ratios, and standard errors for logistic regression models. *Modified* is a binary variable equal to 1 if the student modified its application after the personalized websites were sent, 0 otherwise. *Increased* is a binary variable equal to 1 if the student increased the number of valid applications in their list, 0 otherwise. *Entered* is a binary variable equal to 1 if the student resulted unassigned given their list of preferences before the intervention and assigned given their preferences after the intervention, 0 otherwise. Changed program is a binary variable equal to 1 if the student changed their program of assignment considering the list of preferences submitted before and after the intervention. We exclude PACE students and misfits from the sample. The sample size is reported in the *Observations* row.

6.3 Effect on Application Mistakes

We now analyze the effects of the information intervention on *admissibility* and *strategic* mistakes.

6.3.1 Admissibility mistakes.

Our previous results show that the intervention is effective at increasing the number of valid applications (see Table 10). To further analyze this, we estimate the effect of the intervention on eliminating *admissibility* mistakes in the application lists of students who opened their personalized website. Table 11 shows the results of two logit models where the dependent variable is whether student eliminated at least one *admissibility* mistake in their initial application list. The sample is restricted to students who opened their personalized website and had at least one ex-ante *admissibility* mistake in their application list (before the intervention). The first model considers all students in the sample, while the second one restricts attention to students who had valid scores. We observe that students in T3 who had valid scores are significantly more likely to eliminate *admissibility* mistakes in their application lists, increasing their odds by 1.25. However, we do not observe significant effects for students in T2. This suggests that the effect of the intervention is driven primarily by the warning messages, which are only displayed to students in T3.

Table 11: Treatment effects on admissibility mistakes

Dependent Variable: Decreasing Admissibility Mistakes				
	Model 1		Model 2	
	Coeff.	Std. Error	Coeff.	Std. Error
Intercept	-4.16	(0.256)	-4.02	(0.264)
Treatment 2	0.15	(0.084)	0.06	(0.103)
Treatment 3	0.17	(0.084)	0.23	(0.101)
Treatment 4	-0.02	(0.087)	0.00	(0.105)
Odd-ratios				
Intercept	0.02		0.02	
Treatment 2	1.16		1.06	
Treatment 3	1.18		1.25	
Treatment 4	0.98		1.00	
Observations	30000		17188	

Note: Logistic regression results. The sample is restricted to students with at least one admissibility mistake (model 1) or at least one admissibility mistake and valid scores (model 2). We exclude PACE students and misfits from the sample. The dependent variable is a dummy variable equal to 1 if the student eliminated at least one program with an admissibility mistake and 0 otherwise. Gender, scores, region, and general message (risk) are used as controls. Standard errors are reported in parenthesis.

6.3.2 Strategic mistakes.

To analyze the causal effect of the intervention on *strategic* mistakes, we estimate the effect of the intervention on the probability of making an ex-ante *strategic* mistake in the application lists of students who opened their personalized website and had at least one ex-ante *strategic* mistake in their initial application list before the intervention (*Mistake Exante Interim*

Table 12 shows the results of four logit models. Models 1 and 2 consider students who had at least one *strategic* mistake in their list before the intervention (Mistake Exante Interim). Models 3 and 4 consider all students in the sample and add an interaction term with the variable *Mistake Exante Interim*. Models 1 and 3 consider all survey respondents, while even models 2 and 4 focus on consistent respondents.

We observe that students in T3 who had had at least one ex-ante *strategic* mistake in their initial application list before the intervention, reduce their odds of making at least one ex-ante *strategic* mistake by 0.12 (Model 3) and 0.18 (Model 4). Due to lack of power, results are marginally significant only when considering increasing the sample size and considering both consistent and inconsistent answers in the survey.

Table 12: Treatment effects on strategic mistakes

Dependent Variable: Mistakes Exante Final								
	Model 1		Model 2		Model 3		Model 4	
	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error
Intercept	1.60	(0.896)	1.06	(0.931)	-8.15	(1.233)	-8.69	(1.273)
Treatment 2	0.34	(0.377)	0.40	(0.385)	1.59	(1.096)	0.68	(1.225)
Treatment 3	-0.36	(0.329)	-0.37	(0.344)	1.79	(1.081)	1.36	(1.119)
Treatment 4	0.16	(0.355)	0.13	(0.365)	1.40	(1.119)	1.10	(1.155)
Mistake Exante Interim					9.79	(1.032)	9.37	(1.034)
Treatment 2 * Mistake Exante Interim					-1.24	(1.158)	-0.28	(1.284)
Treatment 3 * Mistake Exante Interim					-2.15	(1.130)	-1.73	(1.170)
Treatment 4 * Mistake Exante Interim					-1.25	(1.173)	-0.97	(1.211)
Odd-ratios								
Intercept	4.96		2.90		0.00		0.00	
Treatment 2	1.41		1.49		4.91		1.97	
Treatment 3	0.70		0.69		5.97		3.88	
Treatment 4	1.17		1.14		4.06		3.01	
Mistake Exante Interim					17924.10		11716.85	
Treatment 2 * Mistake Exante Interim					0.29		0.75	
Treatment 3 * Mistake Exante Interim					0.12		0.18	
Treatment 4 * Mistake Exante Interim					0.29		0.38	
Observations	654		486		9742		8801	

Note: This table presents estimated coefficients, odds ratios, and standard errors for two logistic regression models. The dependent variable *Mistake Exante Final* is a binary variable indicating whether a participant made any ex-ante strategic mistake in their final portfolio. *Mistake Exante Interim* is a binary variable indicating whether a participant made any ex-ante strategic mistake in their interim portfolio. The sample is restricted to students who responded to the survey, and opened the intervention. We exclude PACE students and misfits from the sample. Gender, scores, region, and general message (risk) are used as controls. The sample size is reported in the *Observations* row.

6.4 Drivers

Effect on Beliefs' Bias. To test whether the intervention affects behavior through changes in beliefs, we compute a measure of bias in admission probabilities by taking the difference between students' subjective beliefs (elicited in the survey of 2022) and the rational expectations admission probabilities. We report the absolute value of the bias in beliefs over the top-reported, bottom-reported, true top, and true bottom programs.

Table 13 presents the results of OLS regressions of the absolute bias in beliefs over each program on the treatment group, controlling for stratification variables. Since both the Control and Treatment 4 provided no information regarding cutoffs nor admission probabilities, we pooled the data from these two groups.[27]. Our results indicate that students in Treatment 3, who receive warning messages, exhibit lower bias in beliefs over their bottom-reported program. Additionally, students in Treatment 2 and Treatment 3 exhibit lower bias in beliefs

[27]We perform Welch Two Sample t-tests for each outcome variable and reject the null hypothesis that T1 and T4 have different means.

over their true bottom program. However, we do not observe significant differences in the bias in beliefs over the top-reported and true top programs.

These results support our hypothesis that the intervention affects students' application behavior by changing their beliefs over their admission probabilities. Notably, the effects are concentrated on programs that are not ranked at the top of students' preferences, which are programs for which students have higher baseline biases. Furthermore, our findings suggest that the treatment effects on outcomes primarily impact students who were initially at a high risk of being unassigned to the system, potentially due to over-confidence mistakes.

Finally, we observe that the intervention reduces biases for programs that were initially included in students' applications (bottom-reported programs), as well as for programs that were not included in their applications (true bottom programs). The mechanisms driving these spillover effects require further research. For instance, students might start searching for more information after receiving the intervention and learning about programs' cutoffs. Alternatively, they may update their beliefs using a correlated model of learning.

Table 13: Treatment effects on absolute bias on admission probabilities

	Dependent Variable: Absolute bias			
	Top-reported	Top-true	Bottom-reported	Bottom-true
Intercept	0.20	0.30	0.29	0.33
	(0.028)	(0.028)	(0.030)	(0.056)
Treatment 2	-0.01	-0.01	-0.01	-0.07
	(0.011)	(0.011)	(0.011)	(0.021)
Treatment 3	-0.00	-0.00	-0.02	-0.05
	(0.010)	(0.010)	(0.011)	(0.021)
Observations	4910	5082	4164	1141

Note: Note: The analysis employs OLS regression models to examine the absolute value of each student's subjective bias towards admission probabilities for a given program. The sample is limited to students who responded to the survey and opened the intervention, with exclusions for PACE students and misfits. Programs with well-defined cutoff scores are included in the sample. Gender, scores, region, and general message (risk) are used as controls. Standard errors are reported in parentheses.

7 Policy implementation

Given the positive results reported in the previous section, MINEDUC decided to implement the information policy nationwide. In this section, we describe the implementation and its results.

7.1 Description

In general, the implementation of the policy followed similar guidelines to those described in Section 6, namely, we generated personalized websites for students who applied in the first half of the application period and provided them with personalized alerts to improve their application. However, there are some relevant differences compared to the field experiment. In this section we discuss these differences in detail.

7.1.1 Background

As in the previous year, students participated in a national exam that provided them with test scores that the system uses to compute their application scores in each program they listed in their preference list. However, MINEDUC introduced a series of changes to the admission process. First, they completely redesigned the admission exam by changing its focus (moving from knowledge-based to attitude-based) and adding a math-specific exam. In addition, MINEDUC changed the normalization rules and, more importantly, the range of possible scores, moving from a $[210, 850]$ to a $[100, 1000]$ scale.

Second, MINEDUC introduced the option to take the national exam twice per year and changed the rules on how to compute application scores for students that took the exam several times and thus have multiple pools of scores.[28] Specifically, they moved from a pool-based approach, in which the application score is computed considering the best pool among all the ones available, to a test-specific approach, in which the application score is computed considering the best score for each specific exam, potentially combining different pools of scores.

Finally, given all the changes mentioned above and the advice from the research team, MINEDUC decided to increase the constraint on the length of preference lists from ten to twenty programs.

A critical consequence of all these changes is that the previous year's cutoffs were not as informative as in previous years. Indeed, many students had no idea how to assess their chances of admission, as they had no reference point, and the uncertainty was considerably higher. In addition, the high level of changes in requirements and the new exam could have induced students to make payoff-relevant *admissibility* mistakes, as shown in Section 4.2.1. As a result, MINEDUC decided it was crucial to provide students with as much guidance as possible, and thus decided to implement our information policy for all students nationwide. Hence, students who opened their personalized websites received the same information fields, so we do not have proper treatment and control groups as described in Section 6. Nevertheless, as we later discuss, we can still estimate the effect of the intervention using an

[28]Moreover, MINEDUC had to introduce conversion tables to transform scores from the previous scale to the new one.

encouragement design.

7.1.2 Information

In general, the information policy implemented in 2023 considered the same four modules described in Section 6.1.2. However, we modified modules M2, M3, and M4 in some important ways. First, instead of displaying the application score of the first and last student admitted to the programs in previous years, we displayed the score of the last student that would be admitted to each program considering the applications received so far (see Figure 4). Given all the changes to the system described above, MINEDUC thought it would be more confusing to provide information about previous years. Moreover, they argued that giving students the "current" cutoff (given the applications received so far) would be more helpful in guiding them to assess their admission probabilities.

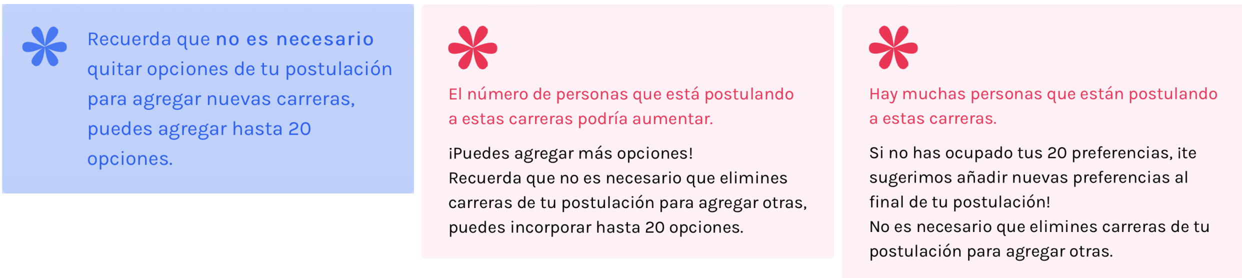
Figure 4: General

(a) (b) (c)

Second, in line with the previous point, we modified M3 to condition the personalized alerts only on the interim probabilities, and we slightly modified the messages displayed in each case (see Figure 5).

Figure 5: Messages

(a) (b) (c)



Finally, given the lack of effect of recommending specific majors (see Section 6), we modified module M4 and offered students a search engine to find new programs based on location, major, university, and other filters (see Figure 15 in Appendix C.6). For each program resulting from their search, we showed students the same information as that described in M2, i.e., the score of the last student that would be admitted to each program considering the applications received so far and relevant information about the program (e.g., tuition, duration, benefits, etc.).

7.2 Results

As discussed in Section 6.2, our goal is to measure the effect of the information policy on two sets of outcomes: (i) application-related outcomes, namely, the length of applicants' lists and how many valid preferences they included; and (ii) admission-related outcomes, namely, their overall probability of admission, the status of their application, and whether they enrolled or not in the centralized system. For each set of outcomes, we compare the results that students would have obtained with their interim reported preferences (i.e., preference lists submitted before the intervention) with those they obtained with their final preferences.

Recall that all students who applied in the first half of the application time window (close to 70% of the total number of applicants) received an email inviting them to open their personalized website. Still, many of them did not open it, so we can quantify the effect of the intervention by comparing students who opened it with those who did not. In Table 14, we report the aggregated results for both application and admission related outcomes, separating by whether the student opened the intervention and by risk group.

First, we observe that opening the personalized website is correlated with an increased in the length of applications and in the number of valid preferences, specially among students in the high and medium risk groups. In addition, compared to the number of students who increased their number of applications and their number of valid preferences, the number of students who decreased them is substantially smaller.

Table 14: Summary Statistics across Groups

			Applications				Admission					
			Length		Valid		Prob. Admission			Status		
Open	Risk Group	N	Inc.	Dec.	Inc.	Dec.	Inc.	Dec.	Change	Enter	Leave	Enroll
No	High	14179	0.116	0.016	0.102	0.017	0.056	0.003	0.043	0.043	0.001	0.020
	Medium	6310	0.113	0.022	0.094	0.194	0.066	0.060	0.011	0.032	0.072	0.385
	Low	35830	0.108	0.035	0.063	0.525	0.003	0.031	-0.005	0.000	0.004	0.742
Yes	High	16153	0.239	0.024	0.214	0.026	0.129	0.003	0.100	0.097	0.002	0.050
	Medium	7541	0.181	0.036	0.145	0.215	0.117	0.071	0.024	0.047	0.072	0.418
	Low	52880	0.132	0.058	0.072	0.564	0.003	0.033	-0.007	0.000	0.006	0.771

Note: Includes all students eligible to receive the intervention, i.e., who applied during the first half of the application time window. Inc. (Dec.) is short for increased (decreased).

Second, we observe that opening the intervention is correlated with an increased in the overall probability of admission for the high and medium-risk groups, while it did not affect the low-risk group. In addition, we observe no major effect on decreasing the overall probability of admission.

Third, we observe that opening the intervention is correlated with an increase on the number of students who entered the assignment (i.e., who would not have been admitted given their interim preferences but get assigned with their final preferences) among students in the high and medium risk groups. Moreover, we do not observe differences in the fraction of students who leave the assignment (i.e., who would have been admitted given their interim preferences but do not get assigned with their final ones) for any risk groups. Finally, students who open the intervention are more likely to enroll in the centralized system, conditional on being assigned.

Overall, these results align with the results reported in Section 6 and confirm that the intervention had a positive impact on helping students improve their applications. However, it is possible that the effect of the intervention is due to some unobserved differences between students who open the intervention and those who do not. For instance, students who received the intervention may be more aware of how the mechanism work or may be more engaged with the process, which may explain the effects mentioned above.

To address this potential endogeneity issue, we use an encouragement design whereby we randomly select a group of students and send them a WhatsApp message motivating them to open their personalized website. Then, we can use the fact of receiving encouragement as an instrument to measure the causal effect of opening the intervention. In Appendix C.8 we show that receiving the WhatsApp had a positive and significant effect on encouraging students to open their personalized websites and receive the intervention, and we also provide several robustness checks testing the relevance of the instrument.

In Table 15, we report the second-stage results of our IV estimation strategy considering application-related outcomes as the dependent variable. Consistent with the results reported in Table 14, we observe a positive and significant effect of opening the intervention in increasing the total and valid number of applications, and no effect on decreasing them.

Table 15: Regression results: Instrumental Variables (Application)

	Dependent variable:			
	Length		Valid	
	Increased	Decreased	Increased	Decreased
	(1)	(2)	(3)	(4)
Open	0.084^{***}	0.009	0.065^{***}	-0.021
	(0.012)	(0.007)	(0.010)	(0.015)
Constant	0.139^{***}	0.016^{***}	0.128^{***}	0.033^{***}
	(0.006)	(0.004)	(0.005)	(0.008)
Risk group	Yes	Yes	Yes	Yes
Observations	132,896	132,896	132,896	132,896

Note: Significance reported: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

In Table 16 we report the results of our IV approach considering admission-related outcomes as dependent variable. As previously discussed, we observe that receiving the intervention significantly increased the number of students who increased their overall probability of admission and also the magnitude of the increment. Moreover, we observe a marginally significant positive effect on entering the assignment.

Table 16: Regression results: Instrumental Variables (Admission)

	Dependent variable:					
	Prob. admission			Status		
	Increased	Decreased	Diff.	Enter	Leave	Enroll
	(1)	(2)	(3)	(4)	(5)	(6)
Open	0.020^{***}	-0.010^{*}	0.016^{***}	0.009^{*}	-0.0002	0.015
	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)	(0.014)
Constant	0.084^{***}	0.008^{***}	0.065^{***}	0.066^{***}	0.011^{***}	0.028^{***}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.008)
Risk group	Yes	Yes	Yes	Yes	Yes	Yes
Observations	132,893	132,893	132,893	132,893	132,893	132,893

Note: Significance reported: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

To further understand the effect on entering the assignment, in Table 17, we report the results separating by group of risk. As suggested by the results in Table 14, we observe a positive and significant effect on entering for students in the high risk group, while we observe no significant effect for the medium and low risk groups. This result is intuitive, as medium and low risk students get assigned with almost full certainty, and thus there is no way to increase their overall probability of assignment. Moreover, we observe that opening the intervention had no effect on students leaving the assignment.

Table 17: Regression results: Instrumental Variables (enter vs. leave by risk level)

	Dependent variable:								
	Enter			Leave			Enroll		
	High (1)	Medium (2)	Low (3)	High (4)	Medium (5)	Low (6)	High (7)	Medium (8)	Low (9)
Open	0.039^{**}	-0.002	0.0003	-0.0002	0.025	-0.004	0.040^{***}	0.072	0.001
	(0.017)	(0.022)	(0.001)	(0.0004)	(0.025)	(0.003)	(0.012)	(0.046)	(0.019)
Constant	0.050^{***}	0.054^{***}	0.00004	0.0002	0.058^{***}	0.008^{***}	0.013^{*}	0.278^{***}	0.755^{***}
	(0.009)	(0.012)	(0.0004)	(0.0002)	(0.014)	(0.002)	(0.007)	(0.025)	(0.012)
Observations	28,387	13,354	91,152	28,387	13,354	91,152	28,387	13,354	91,152

Note: Significance reported: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

In summary, we find that the intervention had a positive and significant causal effect on both application and admission-related outcomes.

7.3 Drivers

Effect on Beliefs' Bias. To examine whether the policy influences behavior through changes in beliefs, we use the panel of respondents from the baseline and endline surveys conducted in 2023. For each student in the panel, we calculate a measure of bias in expected cutoffs and a measure of bias in admission probabilities by taking the difference between students' subjective beliefs (elicited in the baseline and endline surveys) and the rational expectations of expected cutoffs and admission probabilities. We then compute the difference between the absolute value of the bias in beliefs for baseline and endline measures across the top-reported, bottom-reported, and true top programs declared in the baseline survey, and over their overall admission probability.

Table 18 presents the results of OLS regressions for our measure of reduction in absolute bias. We include students' risk group, their baseline beliefs about their expected PAES scores, and their realized PAES scores as controls. Our identification assumption posits that after controlling for individual risk levels, baseline beliefs, and baseline biases, the policy's effect on students' beliefs is uncorrelated with their decisions to access the personalized website. We find that the policy has a positive effect on reducing bias in expected cutoff scores across all three programs. Notably, the effects appear to be larger—relative to the baseline reduction in absolute bias—for students' top-reported and true top programs. However, when examining the reduction in absolute bias concerning admission probabilities, results are only significant for the bottom-reported program and students' beliefs about overall admission probabilities. These findings are consistent with the outcomes of the 2022 intervention, indicating that providing personalized warnings and real-time information about admission probabilities effectively reduces biases in beliefs at the bottom of students' preferences, even under high levels of uncertainty and when implementing the policy on a large scale.

Table 18: Regression results: OLS Before-After (Biased beliefs)

	Dependent variable: reduction in absolute bias						
	Cutoffs			Adm. Probs.			
	Top-true	Top-reported	Bottom-reported	Top-true	Top-reported	Bottom-reported	Overall
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Open	12.798**	12.324**	12.543**	−0.711	−0.689	3.078**	3.914***
	(5.344)	(5.292)	(5.453)	(1.494)	(1.507)	(1.535)	(1.043)
Constant	31.215**	31.241**	52.138***	6.109	9.376**	−2.561	−6.988**
	(13.958)	(13.852)	(14.311)	(3.903)	(3.945)	(4.028)	(2.753)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,345	2,324	2,266	2,347	2,324	2,267	3,320

Note: Significance reported: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

7.4 Implications for Market Design

Our previous results indicate that information frictions significantly impact the performance of centralized college admissions systems, even in the absence of clear strategic incentives for students to misreport their preferences. Our findings have three main implications that could apply to other setting with strategy-proof mechanisms in place and that could be of interest for market designers.

First, given that strategy-proof mechanisms are not immune to application mistakes and the prevalence of payoff-relevant mistakes is significant, policymakers may want to implement mechanisms that are more robust to information frictions and behavioral biases. This can be accomplished with obviously strategy-proof (OSP) mechanisms (Li (2017)) or dynamic implementations of DA (Bó and Hakimov (2022)). Although the literature suggests that OSP mechanisms are limited to markets organized by serial dictatorship, as discussed by Rees-Jones and Shorrer (2023), sequential assignment procedures can serve as viable alternatives in real-world two-sided matching markets. For example, sequential assignment procedures can enhance the performance of these markets when students lack full information about their preferences (Grenet et al. (2022)) or when behavioral biases lead to misrepresentations of preferences (Meisner and von Wangenheim (2021) and Dreyfuss et al. (2022)).

Second, our findings indicate that information policies can substantially enhance the performance of centralized college admissions systems. If the primary goal is to support students in their information acquisition process, then the policy interventions discussed in this paper can be implemented at scale.[29] For instance, the personalized website we designed and implemented in 2022 can be easily adapted for use in other countries. In this context, if policymakers prefer not to implement sequential mechanisms like *iterative DA*, they can still introduce information policies that accomplish similar objectives.

Finally, our analyses demonstrate that increasing complexities in admission requirements and changing rules over time can have a causal effect on raising the incidence of application mistakes. The implications for policymakers and market designers are clear. They should either simplify admission requirements or provide students with more information about the rules and consequences of their application decisions.

8 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 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, a share of admissibility mistakes are likely welfare-relevant, as students are not fully aware of admission requirements and 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% - 3% of students do not list their top-true preference of program, even though they face a strictly positive admission probability.

In addition, using our survey data, 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. Indeed, we estimate that at least 1% of students could have been better off by listing more programs in their application list. Finally, we also find that the magnitude of the bias considerably changes depending on

[29] See Immorlica et al. (2020) for a related discussion on this topic.

students' characteristics, with studnets from public schools and lower scores having more biased beliefs.

Using the previous insights, we collaborated with policy makers in the design and implementation of a multi-year outreach policy to reduce information frictions and application mistakes. By using a Randomized Control Trial, we find that showing personalized information about admission probabilities for listed programs, 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 application mistakes.

With the positive results of the RCT, and in the context of severe changes to the admission process with an increase in the uncertainty students might face, we collaborated in the design and implementation of the policy at scale. By exploiting an encouragement design, we find that showing on-the-fly personalized information about students' admission probabilities, though warning messages and cutoff scores for all programs in the centralized system—akin to sequential implementations of the Defered Acceptance algorithm—has a causal effect on improving students' outcomes, similarly to the RCT results. Moreover, by measuring students' preferences and beliefs before and after the policy, we find that changes in students' outcomes seem to be primarily driven by changes in beliefs over their admission probabilities at the bottom of their preference orders but not at the top.

Our results suggest that information frictions significantly impact the performance of centralized college admissions systems, even when students lack clear strategic incentives to misreport their preferences. Implementing more robust mechanisms, such as dynamic implementations of DA, can mitigate these challenges. Our 2023 intervention, which offers students real-time information about current cutoff scores, exemplifies the potential benefits of a sequential implementation of the Deferred Acceptance algorithm in reducing information frictions and application mistakes. Moreover, our findings reveal that information policies can substantially improve college admissions system performance, and can be effectively implemented at scale through personalized websites, ultimately reducing the incidence of application mistakes and improving students' outcomes.

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Appendix

A Appendix to Section 2.1

A.1 Additional Information

Table 19: 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

A.2 Application Platform

The platform that students use to submit their preferences displays three types of information:

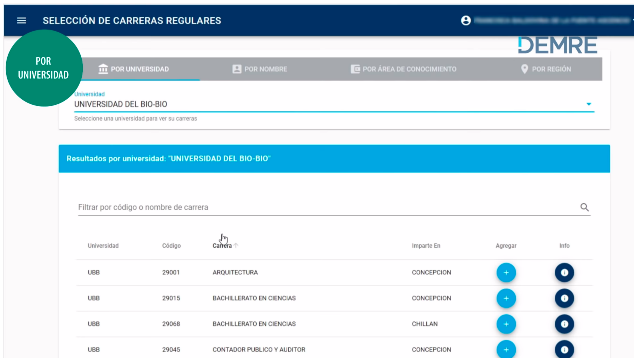
1. **Academic information:** students receive information about their scores, high-school grades, and other academic credentials.

2. **Information about programs:** students can search for information about the programs' characteristics and requirements, as illustrated in Figures 6a and 6b.

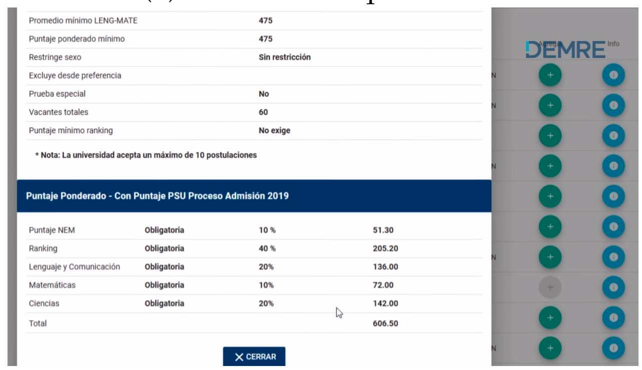
3. **Information about application:** for each of the programs included in their list, students can see their application score and whether they satisfy the requirements imposed by the program.

   Starting from 2019, DEMRE includes a message to warn students if they do not meet an admission requirement when adding a program to their application list, as illustrated in Figure 7a, specifying the admission requirements not satisfied by the student while students are adding and sorting their options, as shown in Figure 7b.

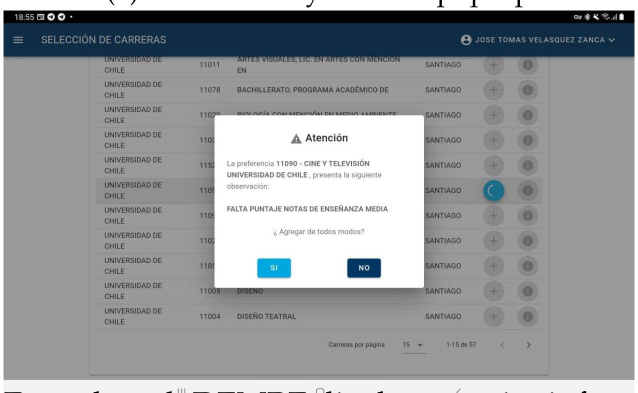
(a) Searching stage



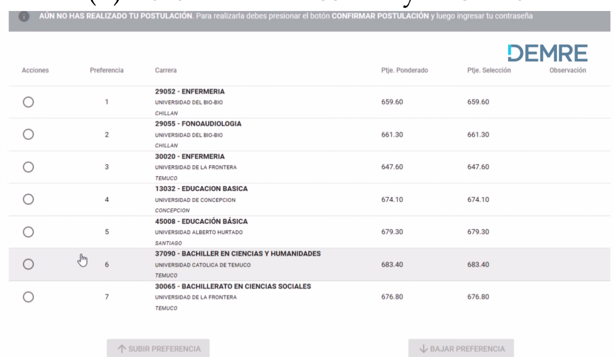
(b) Admission requirements



(a) Admissibility mistake pop-up



(b) Potential admissibility mistake



Even though DEMRE displays precise information about admission requirements, it still allows students to include programs for which they do not meet the admission requirements. As we will show in Section 5, this feature contributes towards generating confusion and introducing biases on students' beliefs. Moreover, the system does not provide information about cutoffs in previous years or students' admission probabilities, potentially increasing the biases on students' beliefs.

A.3 Surveys

A.3.1 Questions

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".

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?

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?

Imagine a HYPOTHETICAL scenario in which you were NOT admitted to any program in your application list. Is there any program in the centralized system that you have NOT included in your application but you would prefer than being unassigned?

A.3.2 Survey respondents

B Appendix to Section 4

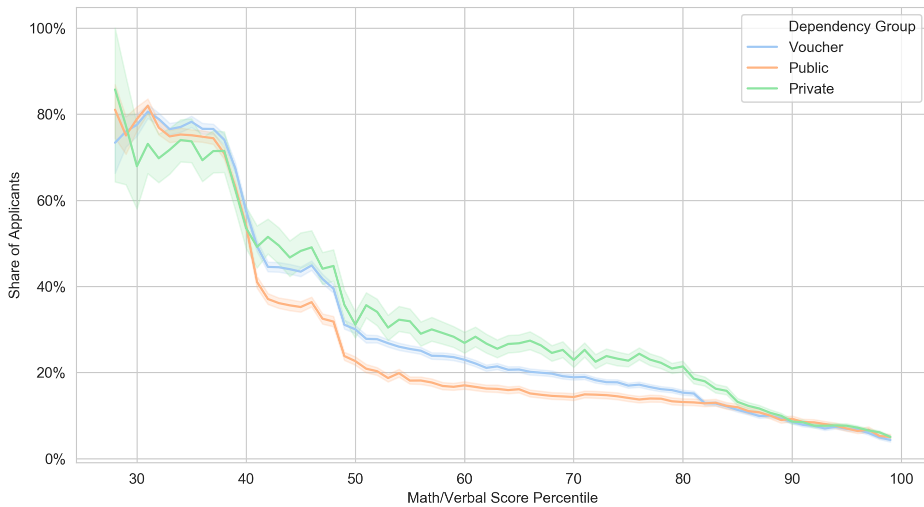
B.1 Admissibility Mistakes

Table 20: Evolution of Mistakers

	Any (1)	All (2)
Slope	0.009***	0.003***
	(0.001)	(0.001)
Constant	−18.330***	−5.674***
	(2.717)	(1.644)
Observations	16	16
R^2	0.770	0.469

Note: Significance reported: *p<0.1; **p<0.05; ***p<0.01

Figure 8: 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.

B.2 Misreporting

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 21 in Appendix B.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 is intended to elicit students' ideal program taking into account their 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.[30]

[30] 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).

Table 21: 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.

Table 22: 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 23: 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

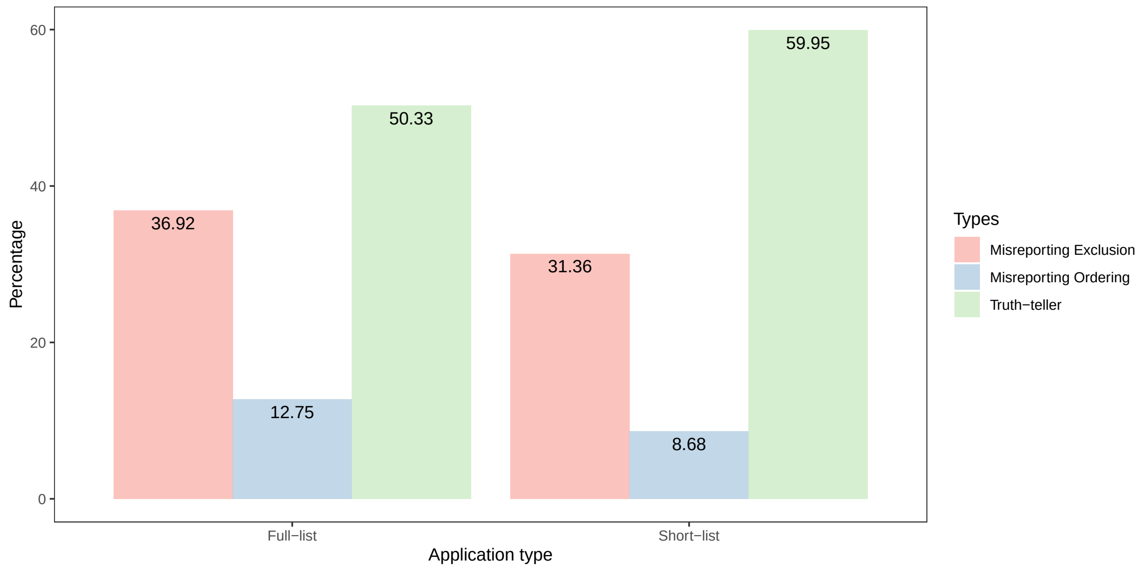
Note: respondents can choose multiple reasons. Percentages are computed among the fraction of consistent respondents.

Appendix to Section 5

Figure 9, 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.

Figure 9: Application types



C Appendix for Section 6

C.1 Intervention Design

Figure 11: Feedback on Programs' Admission Chances: red warning

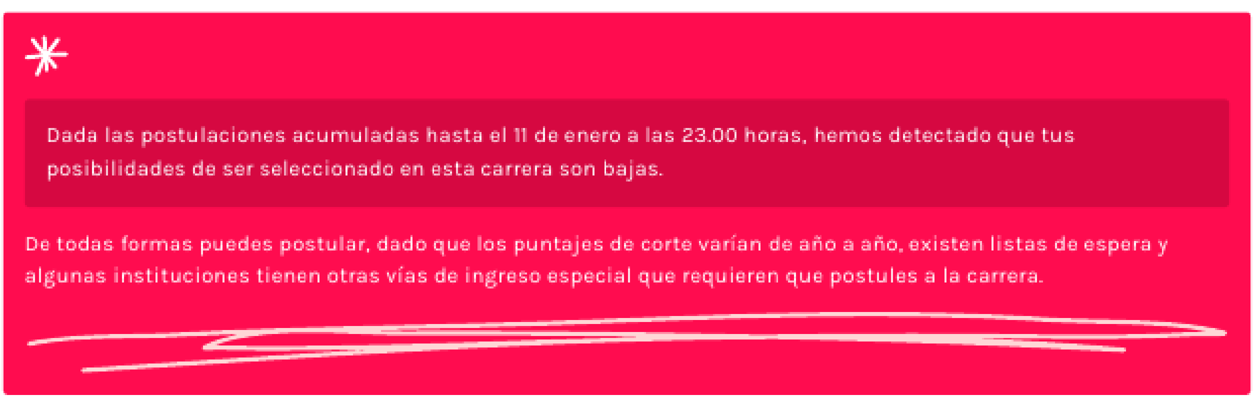


Figure 10: Detailed zoom

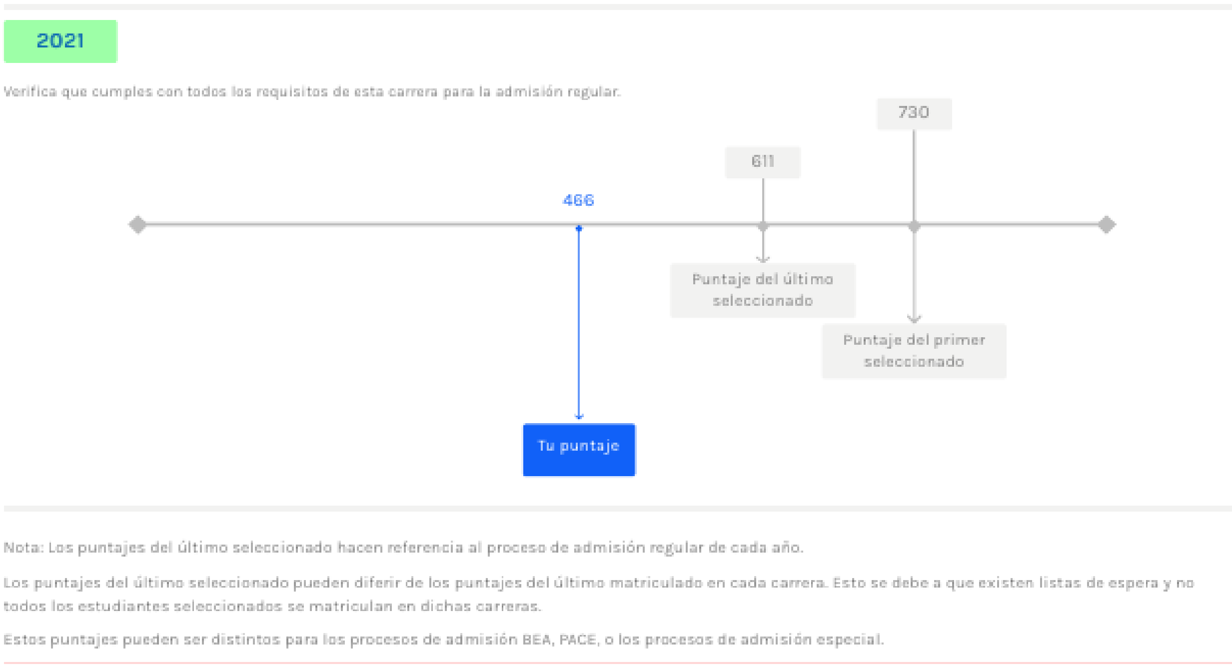


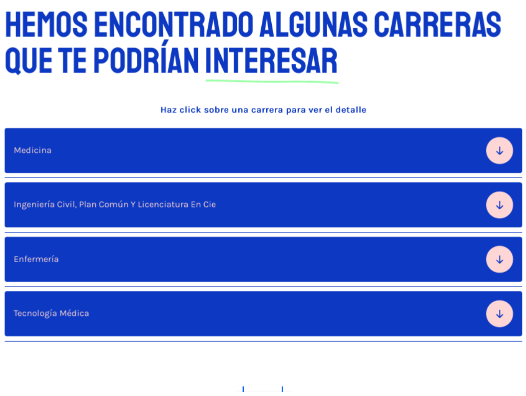
Figure 12: Information on Programs Included in Application

(a) General

(b) Detailed

Figure 13: Recommendation of Other Majors

(a) General

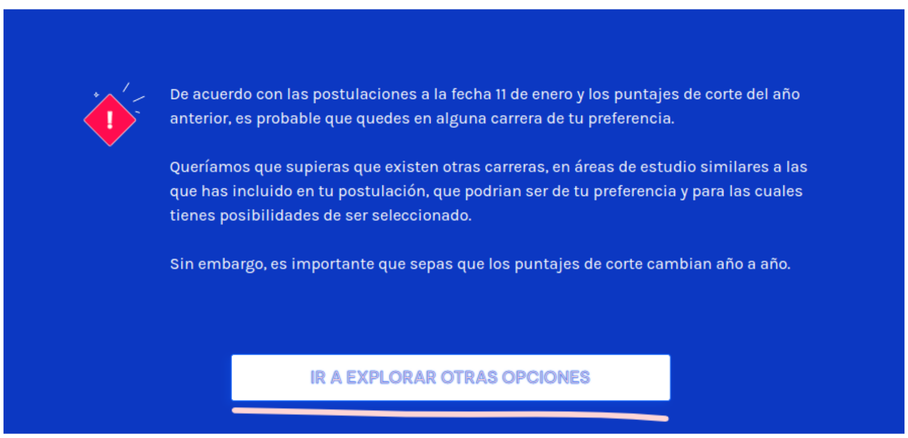


(b) Detailed

Figure 14: Feedback on Application list's and potential strategic mistakes

(a) Add Safety

(b) Add Reach



C.2 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 2022 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 2020 and 2021, 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.

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.

C.3 Recommendations

The recommendation algorithms works 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[31] 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.

C.4 Treatment Assignment and Stratification

As discussed in Section 6.1.3, we assign students to treatments in a stratified way to achieve balance. For the stratification we consider the following observables:

- Female: dummy variable equal to 1 if the student is female, and 0 otherwise.
- Region: categorical variable that takes four 3 levels depending on the region where the student graduated from high-school. Specifically, this variable is equal to 1 for students graduating in the north (regions I, II, III, IV and XVII); 2 for students graduating in the center (regions V, XIII, VI, VII); and 3 for students graduating in the south (regions VIII, IX, X, XI, XII, XIV and XVI).

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

- Score: categorical variable that takes 4 levels depending on the average score between the PDT tests in Math and Verbal. Specifically, this variable is equal to 1 for students with average score below 450; 2 for students which average score between 450 and 600; and 3 for students with score above 600.

- Overall alert: as discussed in Section 6.1.2, there are three types of overall alerts: (i) reach, (ii) safety, and (iii) more information. Each student can be assigned to one of these groups, and thus we also use this assignment as part of the stratification.

- Opened scores' intervention: when the scores of the PDT were published, MINEDUC ran an experiment aiming to provide information regarding the relative position of students among their peers (their high-school and their region). Hence, we use a dummy variable equal to 1 if the student received that intervention (and 0 otherwise) as part of our stratification.

- SMS: dummy variable equal to 1 if the student received an SMS encouraging them to open their personalized website, and 0 otherwise.

In Table 24 we report the results of a multinomial regression models that consider the treatment assigned as dependent variable and the aforementioned variables as controls. The first three columns report the results considering all observations, while the last three columns report the resulting excluding misfits. We observe that none of the variables considered is significant, which confirms that our treatment assignment is balanced in terms of these covariates.

Table 24: Treatment Assignment: Balance Checks

	Dependent variable: Treatment					
	All observations			Excluding misfits		
	(1)	(2)	(3)	(4)	(5)	(6)
Region - Center	−0.011	−0.007	−0.003	−0.010	−0.007	−0.003
	(0.026)	(0.026)	(0.026)	(0.027)	(0.027)	(0.027)
Region - South	−0.007	−0.004	−0.002	−0.005	−0.004	−0.002
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Female	−0.002	−0.001	−0.001	−0.002	0.00002	−0.0001
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Score - Medium	−0.008	−0.004	−0.002	−0.006	−0.004	−0.002
	(0.032)	(0.032)	(0.032)	(0.033)	(0.033)	(0.033)
Score - High	−0.003	−0.001	−0.001	−0.001	0.0004	0.0001
	(0.036)	(0.036)	(0.036)	(0.037)	(0.037)	(0.037)
Overall Alert - Safety	−0.014	−0.008	−0.004	−0.012	−0.008	−0.004
	(0.038)	(0.038)	(0.038)	(0.039)	(0.039)	(0.039)
Overall Alert - Information	−0.017	−0.010	−0.005	−0.017	−0.011	−0.007
	(0.031)	(0.031)	(0.031)	(0.032)	(0.032)	(0.032)
Received SMS	0.007	0.005	0.003	0.007	0.005	0.002
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Received Previous Intervention	0.037	0.023	0.011	0.034	0.022	0.010
	(0.036)	(0.036)	(0.037)	(0.038)	(0.038)	(0.039)
Constant	0.031	0.018	0.010	0.029	0.018	0.010
	(0.049)	(0.049)	(0.049)	(0.051)	(0.051)	(0.051)
Observations	107,837	107,837	107,837	106,100	106,100	106,100

C.5 Additional Results

Table 25: Summary Statistics by Group and Reception

			Application			Assignment			
Treatment	Opened	N	Modified [%]	Increased [%]	Decreased [%]	Entered [%]	Left [%]	Changed status [%]	Changed program [%]
T1	No	18462	9.999	3.884	1.316	2.498	0.887	1.267	3.618
			(0.221)	(0.142)	(0.084)	(0.236)	(0.079)	(0.082)	(0.137)
T1	Yes	7296	12.966	4.852	1.796	3.173	0.682	1.22	4.126
			(0.393)	(0.252)	(0.155)	(0.442)	(0.109)	(0.129)	(0.233)
T2	No	18495	10.024	4.098	1.319	2.909	0.851	1.341	3.412
			(0.221)	(0.146)	(0.084)	(0.253)	(0.077)	(0.085)	(0.133)
T2	Yes	7437	14.576	5.338	2.098	4.25	0.846	1.6	4.034
			(0.409)	(0.261)	(0.166)	(0.497)	(0.12)	(0.146)	(0.228)
T3	No	18547	10.476	4.146	1.483	3.01	0.74	1.272	3.661
			(0.225)	(0.146)	(0.089)	(0.259)	(0.072)	(0.082)	(0.138)
T3	Yes	7342	14.792	5.598	1.975	4.687	0.93	1.771	4.672
			(0.414)	(0.268)	(0.162)	(0.522)	(0.127)	(0.154)	(0.246)
T4	No	18416	10.339	4.045	1.558	3.129	0.819	1.368	3.312
			(0.224)	(0.145)	(0.091)	(0.263)	(0.076)	(0.086)	(0.132)
T4	Yes	7410	13.738	4.953	1.849	3.301	0.849	1.39	3.873
			(0.4)	(0.252)	(0.157)	(0.442)	(0.121)	(0.136)	(0.224)

Note: Opened is a binary variable equal to 1 if the student opened the personalized website, 0 otherwise. Modified is a binary variable equal to 1 if the student modified its application after the personalized websites were sent, 0 otherwise. Increased (decreased) is a binary variable equal to 1 if the student increased (decreased) the number of valid applications in their list, 0 otherwise. Entered (left) is a binary variable equal to 1 if the student resulted unassigned (assigned) given their list of preferences before the intervention and (un)assigned given their preferenes after the intervention, 0 otherwise. Changed status (program) is a binary variable equal to 1 if the student changed their status (program) of assignment considering the list of preferences submitted before and after the intervention. Standard errors reported in parenthesis.

Table 26: Summary Statistics by Treatment, Reception and Message Group

				Application			Assignment				
Treatment	Open	Group	N	Modified [%]	Increased [%]	Decreased [%]	Assigned [%]	Entered [%]	Left [%]	Changed status [%]	Changed program [%]
T1	No	1	1544	8.031	3.044	1.101	99.87	0	0.195	0.194	2.979
				(0.692)	(0.437)	(0.266)	(0.092)	(0)	(0.112)	(0.112)	(0.433)
		2	4271	7.82	2.95	0.468	11.192	2.231	7.034	2.599	0.258
				(0.411)	(0.259)	(0.104)	(0.482)	(0.235)	(1.416)	(0.243)	(0.078)
		3	12647	10.975	4.301	1.629	96.513	5.036	0.809	0.949	4.831
				(0.278)	(0.18)	(0.113)	(0.163)	(1.072)	(0.081)	(0.086)	(0.191)
T1	Yes	1	604	10.43	4.636	1.987	99.834	0	0.166	0.166	2.98
				(1.245)	(0.856)	(0.568)	(0.166)	(0)	(0.166)	(0.166)	(0.692)
		2	1529	11.118	4.186	0.327	11.511	2.593	10.784	3.139	0.392
				(0.804)	(0.512)	(0.146)	(0.816)	(0.421)	(3.086)	(0.446)	(0.16)
		3	5163	13.81	5.075	2.208	97.211	8.844	0.538	0.775	5.365
				(0.48)	(0.305)	(0.205)	(0.229)	(2.35)	(0.103)	(0.122)	(0.314)
T2	No	1	1538	7.932	3.706	1.105	99.74	0	0.326	0.325	1.886
				(0.689)	(0.482)	(0.267)	(0.13)	(0)	(0.145)	(0.145)	(0.347)
		2	4290	8.065	3.17	0.186	11.538	2.619	5.643	2.844	0.21
				(0.416)	(0.268)	(0.066)	(0.488)	(0.253)	(1.294)	(0.254)	(0.07)
		3	12667	10.942	4.46	1.729	96.376	5.621	0.792	0.955	4.681
				(0.277)	(0.183)	(0.116)	(0.166)	(1.116)	(0.08)	(0.086)	(0.188)
T2	Yes	1	688	10.174	3.779	1.599	100	0	0	0	2.762
				(1.153)	(0.728)	(0.479)	(0)	(NA)	(0)	(0)	(0.625)
		2	1591	14.205	4.525	0.566	13.074	3.992	6.195	4.148	0.126
				(0.875)	(0.521)	(0.188)	(0.845)	(0.509)	(2.278)	(0.5)	(0.089)
		3	5158	15.277	5.797	2.637	96.51	6.548	0.842	1.028	5.409
				(0.501)	(0.325)	(0.223)	(0.256)	(1.914)	(0.129)	(0.14)	(0.315)
T3	No	1	1577	9.702	4.502	1.141	99.873	0	0.064	0.063	2.917
				(0.746)	(0.522)	(0.268)	(0.09)	(0)	(0.064)	(0.063)	(0.424)
		2	4273	7.559	2.996	0.398	11.233	2.68	5.346	2.879	0.164
				(0.404)	(0.261)	(0.096)	(0.483)	(0.257)	(1.263)	(0.256)	(0.062)
		3	12697	11.554	4.489	1.89	96.771	6.361	0.707	0.882	4.93
				(0.284)	(0.184)	(0.121)	(0.157)	(1.233)	(0.076)	(0.083)	(0.192)
T3	Yes	1	627	12.759	5.104	2.552	99.681	NaN	0.319	0.319	3.987
				(1.333)	(0.88)	(0.63)	(0.225)	(NA)	(0.225)	(0.225)	(0.782)
		2	1582	12.705	4.804	0.506	12.705	4.15	12.5	4.741	0.19
				(0.838)	(0.538)	(0.178)	(0.838)	(0.52)	(3.139)	(0.534)	(0.109)
		3	5133	15.683	5.903	2.357	96.571	9.249	0.746	1.033	6.137
				(0.508)	(0.329)	(0.212)	(0.254)	(2.209)	(0.122)	(0.141)	(0.335)
T4	No	1	1508	9.682	4.907	0.862	100	16.667	0	0.066	2.586
				(0.762)	(0.556)	(0.238)	(0)	(16.667)	(0)	(0.066)	(0.409)
		2	4260	7.793	3.31	0.305	11.667	2.634	5.788	2.864	0.446
				(0.411)	(0.274)	(0.085)	(0.492)	(0.255)	(1.326)	(0.256)	(0.102)
		3	12648	11.275	4.19	2.064	96.497	7.565	0.793	1.02	4.364
				(0.281)	(0.178)	(0.126)	(0.163)	(1.287)	(0.08)	(0.089)	(0.182)
T4	Yes	1	667	10.495	4.348	1.499	99.85	0	0	0	2.699
				(1.188)	(0.79)	(0.471)	(0.15)	(0)	(0)	(0)	(0.628)
		2	1569	11.09	3.314	0.637	11.217	2.802	10.377	3.314	0.319
				(0.793)	(0.452)	(0.201)	(0.797)	(0.432)	(2.976)	(0.452)	(0.142)
		3	5174	14.959	5.528	2.261	96.637	7.647	0.759	0.986	5.102
				(0.496)	(0.318)	(0.207)	(0.251)	(2.044)	(0.123)	(0.137)	(0.306)

Note: Opened is a binary variable equal to 1 if the student opened the personalized website, 0 otherwise. Modified is a binary variable equal to 1 if the student modified its application after the personalized websites were sent, 0 otherwise. Increased (decreased) is a binary variable equal to 1 if the student increased (decreased) the number of valid applications in their list, 0 otherwise. Assigned is a binary variable equal to 1 if the student resulted assigned at the end of the process, 0 otherwise. Entered (left) is a binary variable equal to 1 if the student resulted unassigned (assigned) given their list of preferences before the intervention and (un)assigned given their preferenes after the intervention, 0 otherwise. Changed status (program) is a binary variable equal to 1 if the student changed their status (program) of assignment considering the list of preferences submitted before and after the intervention. Standard errors reported in parenthesis.

C.5.1 Effect of Specific Warnings.

Students in T3 were receiving different types of messages depending on their probabilities to be admitted to a specific programn, and overall. What are the warnings driving the above results?

Safety. Students facing an application risk greater than 1% are 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 and that which might preferred to the outside option. The purpose of recommending *safety* programs is to decrease their likelihood of making an overconfidence mistake. As Table 26 shows, students in the *safety* group have a significantly lower probability of being assigned, ranging from 11% to 13%.

Table 27 highlights that the increase in the share of students who get assigned to a program while it was not the case given their initial lost is driven by students in the *safety* group. Such students have 53% and 62% higher odds to enter the centralized system when assigned to T2 and T3 compared to students in T1.

Reach. Students facing an admission probability to their top-reported preference above 99% are eligible to receive a message recommending them to include additional *reach* programs. 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 shown in the column Assigned [%] in Table 26. We do not find any statistically significant effect of the treatments on the outcomes of interest.

Explore. Students facing an application risk below 1% and a probability of not being assigned to their top-reported preference below 99% are eligible to receive a message recommending them to explore additional programs. Table 28 shows that students in T3 have close to 16% higher odds to modify their lists relative to the control group. In addition, students in T3 have close to 17% higher odds to increase the length of their lists and 15% higher odds to change their assigned program.

Table 27: Regression Results among Openers in Safety group

	Application			Assignment			
Treatment	Modified	Increased	Decreased	Entered	Left	Changed status	Changed program
T2	0.280***	0.082	0.550	0.422*	−0.605	0.289	−1.141
	(0.109)	(0.176)	(0.559)	(0.218)	(0.504)	(0.193)	(0.817)
T3	0.151	0.144	0.438	0.485**	0.167	0.429**	−0.729
	(0.111)	(0.174)	(0.571)	(0.217)	(0.428)	(0.188)	(0.708)
T4	−0.003	−0.243	0.670	0.025	−0.043	0.056	−0.209
	(0.114)	(0.190)	(0.549)	(0.234)	(0.451)	(0.203)	(0.607)
Constant	−2.079***	−3.131***	−5.720***	−2.738***	−2.113***	−3.429***	−5.537***
	(0.081)	(0.128)	(0.448)	(0.170)	(0.319)	(0.147)	(0.409)
Odd-Ratios							
T2	1.324	1.085	1.734	1.525	0.546	1.335	0.319
T3	1.164	1.155	1.549	1.624	1.182	1.536	0.482
T4	0.997	0.785	1.955	1.026	0.958	1.058	0.319
Observations	6,271	6,271	6,271	2,545	433	6,271	6,271

Note: Logistic regression results. Modified is a binary variable equal to 1 if the student modified its application after the personalized websites were sent, 0 otherwise. Increased (decreased) is a binary variable equal to 1 if the student increased (decreased) the number of valid applications in their list, 0 otherwise. Entered (left) is a binary variable equal to 1 if the student resulted unassigned (assigned) given their list of preferences before the intervention and (un)assigned given their preferences after the intervention, 0 otherwise. Changed status (program) is a binary variable equal to 1 if the student changed their status (program) of assignment considering the list of preferences submitted before and after the intervention. Significance reported: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 28: Regression Results among Openers in Explore group

Treatment	Application			Assignment			
	Modified	Increased	Decreased	Entered	Left	Changed status	Changed program
T2	0.118**	0.141	0.182	−0.325	0.378	0.285	0.009
	(0.056)	(0.087)	(0.129)	(0.426)	(0.251)	(0.210)	(0.087)
T3	0.149***	0.160*	0.067	0.049	0.330	0.290	0.143*
	(0.056)	(0.087)	(0.132)	(0.391)	(0.254)	(0.210)	(0.085)
T4	0.093*	0.090	0.024	−0.158	0.319	0.243	−0.053
	(0.056)	(0.088)	(0.133)	(0.409)	(0.254)	(0.212)	(0.088)
Constant	−1.831***	−2.929***	−3.791***	−2.333***	−5.204***	−4.853***	−2.870***
	(0.040)	(0.063)	(0.095)	(0.290)	(0.193)	(0.159)	(0.062)
				Odd-Ratios			
T2	1.125	1.151	1.199	0.722	1.459	1.33	1.009
T3	1.161	1.173	1.069	1.05	1.391	1.336	1.153
T4	1.098	1.095	1.025	0.854	1.375	1.275	1.009
Observations	20,628	20,628	20,628	658	19,664	20,628	20,628

Note: Logistic regression results. Modified is a binary variable equal to 1 if the student modified its application after the personalized websites were sent, 0 otherwise. Increased (decreased) is a binary variable equal to 1 if the student increased (decreased) the number of valid applications in their list, 0 otherwise. Entered (left) is a binary variable equal to 1 if the student resulted unassigned (assigned) given their list of preferences before the intervention and (un)assigned given their preferences after the intervention, 0 otherwise. Changed status (program) is a binary variable equal to 1 if the student changed their status (program) of assignment considering the list of preferences submitted before and after the intervention. Significance reported: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Appendix to Section 7

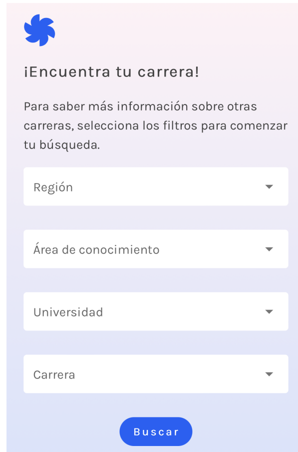
C.6 Policy implementation

C.7 Search tools

In this section, we analyze the effect of the search engine embedded in the personalized websites. To make a fair comparison, we focus on students who opened the information policy, and evaluate the effect of the variable *Search*, which is equal to 1 if the student used the search engine (i.e., did a search) and zero otherwise.

In Table 29 we report summary statistics for the same outcomes of interest discussed in Section C.6, separating by risk level and by whether the student did any search. We observe that using the search engine is correlated with increasing the number of applications, valid applications, and also is positively correlated with increasing the overall probability of admission and entering the assignment. These results suggest that using the search is correlated with

Figure 15: Search module



improving application and admission outcomes.

Table 29: Summary Statistics across Groups

			Applications		Valid Applications		Overall probability			Assignment	
Risk level	Search	N	Inc.	Dec.	Inc.	Dec.	Inc.	Dec.	Change	Enter	Leave
High	No	13075	0.193	0.022	0.171	0.024	0.099	0.003	0.078	0.076	0.002
Medium	No	6255	0.148	0.032	0.117	0.216	0.091	0.070	0.017	0.042	0.072
Low	No	44345	0.109	0.053	0.059	0.568	0.002	0.032	-0.006	0.000	0.005
High	Yes	3078	0.438	0.034	0.393	0.038	0.257	0.005	0.195	0.187	0.001
Medium	Yes	1286	0.342	0.056	0.278	0.205	0.240	0.075	0.057	0.072	0.075
Low	Yes	8535	0.251	0.082	0.141	0.545	0.006	0.039	-0.010	0.001	0.009

Note: Each unit of observation is a subject.

One possible explanation for the aforementioned effect is that student who use the search engine may be more likely to add new programs to their application, increasing its length and their chances of admission. To rule out this effect, in Table 30 we analyze the results on admission outcomes considering only students who opened the intervention and added a program, and we analyze the outcomes of interest separating by whether the student did any search and also by whether the student added at least one program that resulted from their search.

We observe that adding a program that resulted from the search is positively correlated with increasing the overall chances of admission and entering the assignment.

Table 30: Summary Statistics across Groups (among students who add programs)

				Overall probability			Assignment	
Risk	Search	Add from search	N	Inc.	Dec.	Change	Enter	Leave
High	No	No	2500	0.460	0.008	0.367	0.356	0.000
High	Yes	No	870	0.423	0.008	0.312	0.294	0.001
High	Yes	Yes	970	0.561	0.007	0.424	0.407	0.001
Medium	No	No	1031	0.518	0.084	0.144	0.168	0.057
Medium	Yes	No	282	0.550	0.074	0.154	0.174	0.046
Medium	Yes	Yes	321	0.583	0.084	0.158	0.181	0.075
Low	No	No	6594	0.015	0.045	-0.017	0.001	0.017
Low	Yes	No	1510	0.016	0.042	-0.013	0.001	0.014
Low	Yes	Yes	1718	0.017	0.051	-0.019	0.002	0.019

Note: Each unit of observation is a subject.

C.8 Robustness checks

For an instrument to be valid, we need to satisfy two conditions: (i) relevance, and (ii) exclusion. The former states that the instrument is correlated with the endogeneous variable of interest. In our case, we need to confirm that receiving a whatsapp is correlated with opening the intervention. To check these, there are two possible approaches: (i) check the F-statistic of the first stage regression

$$O_i \sim W_i + X_i + \epsilon_i$$

where $O_i = 1$ if the student opens the intervention and zero otherwise; $W_i = 1$ if student i receives a Whatsapp encouragement message and zero otherwsie; X_i is a vector of control variables (in this case, the risk level group); and ϵ_i is an error term. The results of this first-stage regression are reported in the next table:

Table 31: Regression results: First Stage

	Dependent variable:
	Open
Receive Whatsapp	0.184***
	(0.003)
Constant	0.463***
	(0.003)
Risk group	Yes
Observations	132,894
R^2	0.030
F Statistic	1,373.088*** (df = 3; 132890)
Note:	$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

As we observe from this table, the variable W_i is positive and significant, and the F-statistic is well above 10, so this provides evidence that our first-stage is significant and that the instrument is relevant. To get further evidence, we cna perform a Weak instruments' test, which results in a p-value < $1e^{-6}$, rejecting the null-hypothesis that the instrument is weak. Hence, we conclude that the instrument considered is relevant.

To assess whether the instrument satisfies the exclusion condition, we must ensure that the variable W_i is exogenous. This condition holds by design since we randomized who receives the encouragement message. In Table 32, we report regression results that consider whether the student received the encouragement as the dependent variable, and we control for the risk group, score variables (different categories of average between Verbal and Math), demographics (including gender, region of residence, whether they have NEM score) and whether the student participated in the BEA/PACE processes. We observe that none of the controls significantly affected all cases, confirming that the encouragement messages were properly randomized.

Table 32: Randomization of Encouragement

	Dependent variable: Receive Whatsapp		
	(1)	(2)	(3)
Risk - Medium	-0.001	-0.001	-0.001
	(0.005)	(0.005)	(0.005)
Risk - High	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)
$LM \in (545, 574]$	-	0.0002	0.0002
	-	(0.004)	(0.004)
$LM \in (574, 604]$	-	0.0004	0.0003
	-	(0.004)	(0.004)
$LM \in (604, 640]$	-	-0.0002	-0.0003
	-	(0.004)	(0.004)
$LM \in (640, 685]$	-	-0.0003	-0.0003
	-	(0.004)	(0.004)
$LM \in (685, 758]$	-	-0.001	-0.001
	-	(0.004)	(0.004)
$LM \in (758, 1000]$	-	-0.001	-0.001
	-	(0.005)	(0.005)
No NEM	-	-0.0002	-0.0001
	-	(0.003)	(0.003)
Female	-	-0.00001	-0.00003
	-	(0.003)	(0.003)
Region - Center	-	-0.0004	-0.0004
	-	(0.004)	(0.004)
Region - South	-	-0.0004	-0.0004
	-	(0.004)	(0.004)
BEA	-	-	0.001
	-	-	(0.005)
PACE	-	-	-0.0003
	-	-	(0.004)
Constant	0.270^{***}	0.271^{***}	0.271^{***}
	(0.003)	(0.005)	(0.005)
Risk group	Yes	Yes	Yes
Demographics	No	Yes	Yes
Bea/PACE	No	No	Yes
Observations	132,896	132,896	132,896

Note: LM represents the average between the highest Verbal and Math scores obtained by the student. Significance reported: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$