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Designing Smart School Choice Recommendations: Heuristics for Sure Alternatives

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Designing Smart School Choice Recommendations: Heuristics for Sure Alternatives

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Abstract

I propose a school choice policy to recommend guaranteed school alternatives for students left unassigned under stable matching. By leveraging revealed preferences, I design a personalized recommendation mechanism that offers voluntary allocations to unlisted but potentially desirable nearby schools. Using rich administrative data from the Chilean school choice system, I simulate the proposed intervention across the full applicant pool to assess its general equilibrium effects on the resulting allocations. Results indicate that in the main round, the mechanism is able to (i) reduce the proportion of unmatched applicants by up to 50%, (ii) increase expected aggregate utility by 2-6%, and (iii) concentrate utility gains among applicants who apply to oversubscribed programs. To facilitate implementation, I develop a targeted submarket implementation that yields comparable improvements while preserving all original assignments. Overall, the policy offers a cost-effective and scalable solution to improve match outcomes by redistributing excess demand within centralized assignment systems.
Keywords: *school choice; market design; sure alternative*
JEL Classification: *C78; D47; I21; I28; D83*

I Introduction

Over the past two decades, there have been significant transformations in school assignment systems across the world. Many countries and cities have shifted away from decentralized application processes towards centralized and coordinated systems, that emphasize equity, transparency, and efficient allocation (Neilson, 2024). Effective reform requires close attention to the assignment mechanism itself, its set of rules, priority structure, and implementation strategies. Central to these reforms has been the transition from an Immediate Acceptance (or Boston) mechanism, towards a strategy-proof alternative, particularly the Deferred Acceptance (DA) algorithm (Gale & Shapley, 1962), which ensures that it is a dominant strategy for applicants to truthfully rank their school preferences, reducing strategic behavior, and improving transparency (Abdulkadiroğlu, Pathak, & Roth, 2005; Abdulkadiroğlu, Pathak, Roth, & Sönmez, 2005). A growing body of theoretical and empirical research highlights the benefits of such systems, including higher assignment rates,

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greater satisfaction, and improved student welfare (Abdulkadiroğlu, Agarwal, & Pathak, 2017; Arteaga, Kapor, Neilson, & Zimmerman, 2022; Chen & Sönmez, 2006; Elacqua, Jacas, Krussig, Méndez, & Neilson, 2024).

Yet integrating affirmative action into these frameworks poses important design challenges. In some cases, type-specific quotas no longer creates incentives for truth telling to be the dominant strategy (Abdulkadiroğlu, 2005; Hatfield & Milgrom, 2005); in others, even when maintaining the original DA properties, may unintentionally hurt the students it intends to support (Kojima, 2012). These considerations are particularly relevant to keep in mind, especially in the design and implementation of large-scale reforms, such as those in New York City, where a DA-based mechanism substantially reduced unassignment rates and administrative placements (Abdulkadiroğlu et al., 2017), and in Chile, which implemented in 2016 its nationwide *Sistema de Admisión Escolar* (SAE), that is also DA-based.

Despite the strategy-proof nature of the DA algorithm, recent evidence indicates that applicants frequently do not submit complete or well-informed preference lists. Arteaga et al. (2022) and Larroucau, Rios, Fabre, and Neilson (2024) show that even under strategy-proof mechanisms, applicants may stop their search prematurely, leaving feasible and potentially desirable options unranked. While the former examines primary and secondary education in Chile and the latter focuses on higher education, both studies, both cases highlight that many applicants in Chile face substantial information frictions and have overly optimistic beliefs about their chances of admission. As a result, many families/students list too few schools, increasing their risk of remaining unassigned. This paper addresses this problem by designing and evaluating a school choice policy that recommends guaranteed school alternative for students are left unassigned under stable matching.

My proposed approach leverages revealed preferences to generate a customized set of school recommendations for each student, effectively extending their submitted preference lists over potentially desirable schools. The goal of this policy is to increase placement rates and reduce congestion without placing a further burden on applicants nor creating incentives for them to adopt strategic behavior. This approach builds on and complements recent work on behavioral interventions by shifting the focus to platform-level design improvements and contributes to the literature on school choice design policies that can preserve strategy-proofness.

Evidence from Chile and other cities has shown that information frictions are a key constraint in school choice processes. Hastings and Weinstein (2008) contribution showed that information frictions have a direct effect in school choice decisions made by families, by stating that there are high search costs associated. Similarly, Kapor, Neilson, and Zimmerman (2020) show that in contexts where applicants are not fully informed, welfare outcomes vary depending on the assignment mechanism, suggesting that some designs are more robust to information constraints than others.

Building on this, Arteaga et al. (2022) proposes a direct intervention to reduce frictions: a “smart matching platform” that delivers live, personalized feedback on applicants’ admission chances. Implemented in Chile and New Haven, Connecticut, the platform provided real-time risk assessments as families filled out their applications. The intervention changed applicants behavior and significantly reduced their risk of nonplacement. The authors conclude that while strategy-proof mechanisms like DA simplify incentives, they are not enough for efficient allocation alone. Effective allocation also requires supporting families in the search process, where beliefs and information gaps influence outcomes.

Arteaga et al. (2022) identifies four key mechanisms behind these effects: (1) the search process is costly, as families must gather information across multiple school attributes; (2) applicants shorten their lists and stop searching when they believe they are likely to be admitted to one of their preferences; (3) families are often overoptimistic about their placement chances; and (4) substantial welfare gains can be achieved by improving the application process itself. Larroucau et al. (2024) applied a similar approach by examining Chile’s college admissions system which is also DA-based. They confirm earlier findings on overoptimism, but further document that families make systematic mistakes due to lack of awareness of options, misvaluation of school characteristics, and a lack understanding of admission rules. Both studies highlight that information frictions, particularly those linked to awareness and beliefs, play a central role in shaping outcomes.

The contributions of this paper to the literature on information frictions in school choice settings are threefold. First, on the policy front, this paper introduces a novel, personalized recommendation mechanism that is congestion-aware, compatible with the DA algorithm, and scalable to large centralized systems. Unlike prior work that focuses on real-time feedback interventions, this approach remains effective even when applicants are unwilling or unable to engage with dynamic information tools.

Second, the results reveal a positive general equilibrium impact: the intervention reduces unassignment rates by nearly 50% and increases aggregate expected utility by up to 6.7% on the main round, even after accounting for induced congestion. A detailed decomposition of the utility changes shows that gains are primarily driven by newly assigned students. Moreover, I develop a targeted version of the mechanism, applied only to unassigned students, which achieves comparable results while preserving original assignments for all others.

Third, I document strong heterogeneity in the policy’s impact across applicants. In particular, students exposed to excess demand benefit the most, suggesting that the mechanism effectively mitigates congestion in highly competitive markets. These findings offer a novel contribution by presenting a structural solution to excess demand in one-to-many matching markets without relying on modifications to the underlying mechanism nor active participation of the applicant.

The remainder of this paper is structured as follows. Section II provides an overview of the Chilean school admission system, detailing its design, implementation, and key features. Section III discusses the methodologies employed to estimate travel distances. Section IV introduces the preference extension mechanism. Section V presents the utility metrics and preference estimation techniques. Section VI examines the design and results of the simulations, focusing on extensive, intensive margins and heterogeneous results by excess demand. Finally, Section VII concludes.

II The Chilean School Admission System

A Context

Since 2016, Chile has adopted a centralized school admission system as part of the *Ley de Inclusión Escolar* (School Inclusion Law), which significantly changed how students are admitted to schools. Priorly, families would apply directly to individual schools, which was costly and time-consuming. Additionally, schools had the ability to establish their own admissions criteria, where evidence showed that school were highly socially segregated (Bellei C, 2013; Huerta Retamal, 2021; Valenzuela, Bellei, & Ríos, 2014), leading to discrimination based on sex and religion (Carrasco, Bogolasky, Flores, Gutiérrez, & San Martin, 2014). These practices contributed to widespread dissatisfaction and a growing concern for change.

The School Inclusion Law sought to address these inequities by prohibiting selective admissions in schools and creating a single, digital, and centralized platform to manage applications. This introduced the SAE system (an acronym for *Sistema de Admisión Escolar*) that defines a transparent set of rules and a priority-based assignment criterion (Correa et al., 2022). The law also eliminated co-payments in fully public schools and mandated equal access policies for voucher schools (i.e., private schools that receive public subsidies for each enrolled student), which together comprise approximately 95% of schools nationwide as of 2024. Another important aspect of this law is that it requires all data and algorithms used in the process to be publicly available.[1].

SAE was gradually implemented, starting in 2016 with the Magallanes region, and by 2020, it was nationwide. It applies nationally to all grades from pre-kindergarten through 12th grade. The system covers all public and voucher schools, but excludes fully private institutions. The assignment process is governed by a variation of the DA algorithm,

[1]All data used in this paper—including information on the admission process and schools—is publicly available through the Ministry of Education's *Open Data Website*. The original assignment algorithm can be requested directly from the Ministry. A publicly accessible version of the algorithm can be found in the *TetherEducation School Choice repository*.

adapted to meet Chile's specific priorities rules and quotas. A format definition of the Chilean school choice problem can be found in section . In all cases where there are more vacancies than applicants, students must be assigned to their highest preference, whereas in others, they are assigned given their order of priority (Biblioteca del Congreso Nacional, 2016).

A distinctive feature of the Chilean system is its detailed priority structure, designed to promote fairness and continuity in school assignments. Top priority is granted to applicants applying to their current school, followed by applicants with siblings already enrolled in a school, children of school staff and former students. The system also reserves quotas for students with disabilities, high academic achievement, and socioeconomically disadvantaged backgrounds. When demand exceeds capacity, applicants with equal priority are subject to a random lottery to break ties (Correa et al., 2022).

Given this priority structure, the joint sibling assignment introduce an additional complexity to the standard DA framework. To address this, the system employs family-level lotteries, which increase the probability that siblings are assigned to the same school. This design choice is particularly important in Chile, where there are no walk-zone priorities and public school transportation is limited.

The assignment process takes place in two main rounds. Families submit their applications through an online platform developed by the Ministry of Education, where they rank their preferred schools and programs. Families can list as many schools as they want, with a minimum of two. They may list as many options as they wish, with a minimum of two.[2].

In the main round, which covers the vast majority of applicants, families receive a single offer based on their submitted preferences and may choose to accept, conditionally accept, reject, or conditionally reject the assignment. Table 1 presents summary statistics for this round and its evolution over time. As shown in *Panel D*, slightly more than 50% of applicants accept their assignment on average, while approximately 8% reject it. The figure also shows that the average length of applicants' rank-ordered lists is 3.4 schools. Finally, *Panel C* illustrates that in the past four years, over 90% of applicants have received an assignment in the main round.

In the complementary round, unassigned applicants may reapply to schools with remaining vacancies. If no seat is available at any of their chosen schools, students are assigned to the nearest school to their residence with open slots. In this round, all applicants are required to accept the assignment they receive. Table 2 presents overall statistics for this phase. The data show that participation in the complementary round is roughly 20% of

[2]Exceptions apply in certain cases, such as families in rural areas or those applying to highly specialized programs without comparable alternatives, who may list only one school (Biblioteca del Congreso Nacional, 2016).

that in the main round. Applicants also tend to submit short rank-ordered lists, averaging fewer than three schools per application. Additionally, approximately 90% of students are assigned to a school from their submitted list, while 5.5% are placed through proximity-based assignment.

Although participation in SAE is voluntary, both students and schools are effectively required to participate. Students cannot enroll in a participating school unless they apply through SAE, and schools may not admit students outside the system without official approval. Those who fail to comply with SAE regulations are subject to significant penalties including fines and funding risks (Huerta Retamal, 2021). As a result, compliance is essential for schools to maintain operations and public financing.

B Timeline

The admission process follows a consistent timeline each year starting in July where schools report available slots to the Ministry of Education. For the main round, families typically have until August or September to submit their applications. During this period, they must provide documentation to validate according priorities (in case they apply) such as sibling or staff-member priority or disability status. It is also during this stage that most feedback reports are issued, including warnings about the risk of non-assignment and personalized recommendations (Arteaga et al., 2022).

Once applications are submitted, families have a limited time frame to modify their submissions. In October, the Ministry processes the applications and with those, generates a series of random numbers to serve as tiebreakers for oversubscribed slots and executes the assignments. Afterwards, families then have a specific window to accept, conditionally accept, reject, or conditionally reject their match. Those who do not respond to their assignment are assumed to have accepted their match. Families who reject their match, remain unassigned, or did not participate in the main round can take part in the complementary round. Matched families can begin the enrollment process with their assigned schools.

The complementary round, which usually takes place in November, allows families to reapply to schools with available vacancies. However, unlike the main round, families cannot remain unassigned; Those who are not matched to any of their preferred schools are, by law, assigned to the nearest school with available seats within a 17 km radius. If families are not satisfied with the assignment or receive no offer in this round, they can seek administrative placement from the Ministry in the next round.

Following the two rounds, a third phase, referred to as the regularization period, begins in January. During this phase, schools can marginally adjust their vacancies (that are conditionally approved by the Ministry), and families can apply to wait-lists for specific schools. Assignments during this phase are made on an in person first-come, first-served basis. This phase remains open throughout the school year to accommodate transfers and late enrollments. However, it is the only part of the assignment process not allocated by the formal algorithm.

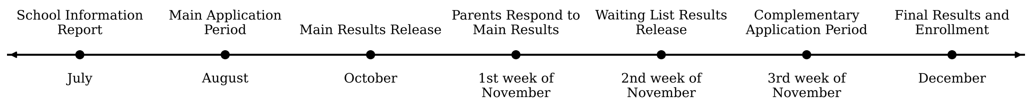


Figure 1: SAE 2023 Timeline

Figure 1 presents a timeline of the 2023 admission process, detailing the key phases from the release of school information to the final enrollment. The timeline begins in July with the publication of school characteristics and continues with the main application period in August. Results from the main round are released in October, after which parents have one week to accept or reject their offer. The second and third weeks of November are dedicated to the release of waitlist results and the complementary application period, respectively. Final results and enrollment take place in December. This timeline highlights the sequential structure of the process and the short response windows families face when making enrollment decisions.

III Distance Metrics

A Travel Distances and Times

In order to generate relevant and personalized school recommendations for students, it is essential to incorporate information about the educational options available in their vicinity. Prior research shows that applicants tend to have strong preferences for geographically proximate schools (Chumacero, Gómez, & Paredes, 2011).

To estimate travel distances between students' residences and nearby schools, I developed a custom API[3] built on the *Open Source Routing Machine* (OSRM), a widely used and reliable routing engine in both academic research and real-world applications. OSRM is an open-source routing engine designed to calculate optimal routes and travel times based on various transport profiles (e.g by foot, car, etc.) using geographic data. Its versatility and accuracy have made it a well-established method in recent economic and policy literature, with applications ranging from urban planning to school assignments. In Chile, the Ministry of Education employs OSRM during the complementary assignment round to

[3]The API interfaces with a locally hosted instance of the *Open Source Routing Machine* (OSRM), enabling fast and flexible distance calculations by travel mode. For more information on OSRM, see `http://project-osrm.org/`.

Table 1: Main Round Statistics

Year	2016	2017	2018	2019	2020	2021	2022	2023
Panel A: Markets								
Regions	1	5	15	16	16	16	16	16
Schools	63	2,172	6,421	8,064	8,014	7,979	7,941	7,893
Students	3,436	76,821	274,990	483,070	454,415	461,223	570,891	536,353
Panel B: Preferences								
Average Preference Longitude	3.5	3.6	3.4	3.5	3.3	3.3	3.4	3.4
Median Preference Longitude	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0
Min Preference Longitude	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Max Preference Longitude	16.0	32.0	45.0	119.0	70.0	94.0	124.0	93.0
Panel C: Assignment offered								
% Assigned 1st Preference	59.1	58.9	58.8	52.0	54.6	54.1	47.3	48.1
% Assigned Up to 3rd Preference	85.1	83.6	83.5	79.6	81.8	82.2	79.0	79.6
% Assigned Any Preference	91.2	91.3	91.1	89.6	90.6	91.5	91.2	91.9
% Unassigned	0.0	8.7	8.9	10.4	9.4	8.5	8.8	8.1
Average Preference Order Obtained	1.6	1.7	1.7	1.8	1.8	1.8	2.0	2.0
Median Preference Order Obtained	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Min Preference Order Obtained	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Max Preference Order Obtained	8.0	20.0	19.0	27.0	23.0	19.0	42.0	26.0
Panel D: Assignment choice								
% Accepts Assignment	63.2	57.5	53.8	51.9	56.5	54.7	49.2	50.2
% Conditionally Accepts Assignment	4.2	12.1	15.4	13.0	15.5	15.4	17.8	18.3
% Denies Assignment	8.2	1.9	7.0	7.2	5.8	6.4	8.0	7.6
% Conditionally Denies Assignment	7.2	4.6	0.0	0.0	0.0	0.0	0.0	0.0
% No Response	17.2	15.2	14.9	17.5	12.8	15.0	16.1	15.8
% Forced to Waitlist	0.0	8.7	8.9	10.4	9.4	8.5	8.8	8.1
% Left Process	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Notes: This table reports key statistics from Chile's main school admission round between 2016 and 2023. It is constructed with administrative data provided by the Ministry of Education. Panel A summarizes the expansion of the centralized system across regions, schools, and applicants over time. Panel B describes submitted preferences. Panel C shows assignment outcomes. Panel D describes the choice done on the given assignment.

allocate students who remain unassigned, using walking distance as the principal metric for determining school proximity. This institutional adoption emphasizes its validity as a robust and practical tool for estimating student-school proximity.

OSRM supports multiple routing profiles tailored to specific transport modes, each incorporating unique characteristics of mobility. The car profile uses road networks suitable for vehicles, accounting for speed limits, traffic patterns, and restrictions. It estimates driving times by considering the most efficient vehicular paths available while including additional constraints such as one-way streets, tolls, and restricted zones to provide realistic routing. In contrast, the foot profile focuses on pedestrian pathways, sidewalks, and walkways, emphasizing pedestrian accessibility. It estimates walking times by prioritizing shorter, safer, and more direct paths for individuals traveling on foot, excluding motorways or roads inaccessible to pedestrians.

For this analysis, I use both car and walking profiles to calculate travel times and distances between each student's residence and the schools on their ranked list, as well as all other available schools within a 5-kilometer radius. These calculations generate de-

Table 2: Complementary Round Statistics

Year	2016	2017	2018	2019	2020	2021	2022	2023
Panel A: Markets								
Schools	63	2,175	6,421	8,064	8,014	7,979	7,941	7,893
Students	439	9,507	46,698	87,604	74,111	108,119	110,155	97,593
Panel B: Preferences								
Average Preference Longitude	2.7	2.8	2.8	2.7	2.7	2.7	2.7	2.7
Median Preference Longitude	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0
Min Preference Longitude	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Max Preference Longitude	13.0	30.0	32.0	66.0	40.0	109.0	52.0	61.0
Panel C: Assignment offered								
% Assigned 1st Preference	83.4	83.0	46.4	65.0	72.1	72.0	67.4	72.1
% Assigned Up to 3rd Preference	96.6	97.4	64.0	86.4	90.9	91.5	88.5	91.2
% Assigned Any Preference	96.6	97.6	68.4	88.0	91.7	92.5	89.7	92.0
% Assigned by Distance	3.4	2.4	28.0	10.4	6.8	6.1	7.8	5.5
% Unassigned	0.0	0.0	3.6	1.6	1.6	1.3	2.4	2.5
Average Preference Order Obtained	1.1	1.2	1.6	1.4	1.3	1.3	1.3	1.3
Median Preference Order Obtained	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Min Preference Order Obtained	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Max Preference Order Obtained	3.0	5.0	18.0	17.0	11.0	12.0	12.0	9.0

Notes: This table reports key statistics from Chile's complementary school admission round between 2016 and 2023. It is constructed with administrative data provided by the Ministry of Education. Panel A summarizes the expansion of the centralized system across regions, schools, and applicants over time. Panel B describes submitted preferences. Panel C shows assignment outcomes.

tailed, student-level data that enable the inference of preferences and the construction of personalized school recommendations based on the educational options available in each student's neighborhood. The data for the OSRM calculations is based on the geographic maps of Chile available at July 2023, ensuring that estimates accurately reflect the state of the nation's transport and pedestrian infrastructure at the moment the students applied that year. section provides a more detailed definition on the computational mechanisms used and the assumptions made to make it computationally feasible.

A visual representation of the distance estimates, based on real geo-referenced data, is provided in Figure 2. Additionally, interactive estimates for a randomly selected student are available at the following link. Table 3 summarizes travel distances and times based on students' ranked preferences and recommended schools within a 5-kilometer radius. Median values in Panel A show that, despite some students listing faraway schools, most preferred options were within 2.6–5 km, depending on the mode. In contrast, Panel B highlights that recommended schools were consistently closer, with median distances and times tightly clustered around 3 km or 5 minutes, suggesting that the recommendation system effectively identifies nearby alternatives.

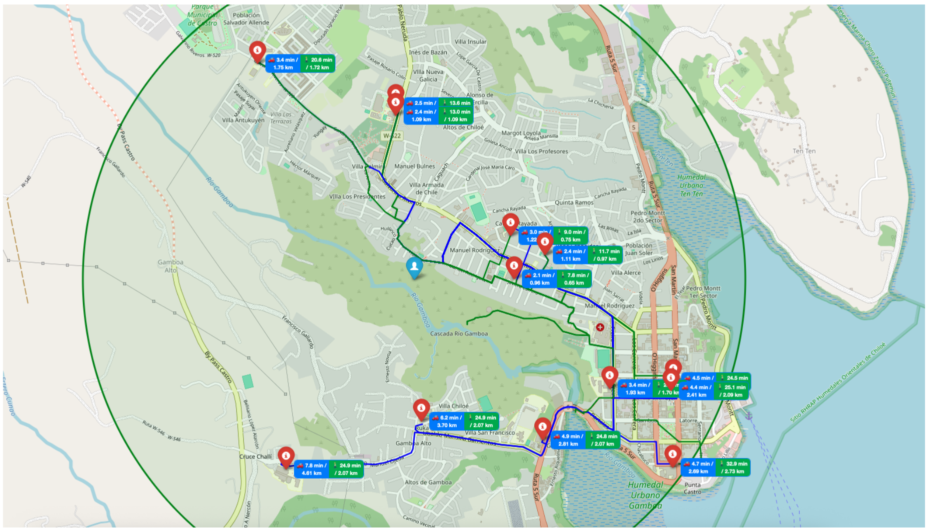


Figure 2: OSRM Routes for a Student in Chiloé, Chile

Table 3: Summary Statistics for Distance and Duration Metrics

Metric	Main Round		Complementary Round	
	Mean	Median	Mean	Median
Panel A: Preferences				
Foot distance (km)	12.69	2.42	20.27	2.60
Foot duration (minutes)	147.98	29.15	237.67	31.28
Car distance (km)	11.92	2.77	19.73	2.97
Car duration (minutes)	13.16	4.74	20.27	5.05
Panel B: Recommendations				
Foot distance (km)	2.76	2.82	2.71	2.77
Foot duration (minutes)	33.21	33.97	32.62	33.31
Car distance (km)	3.09	3.20	3.03	3.14
Car duration (minutes)	5.21	5.34	5.13	5.25

IV Preference Extension Design

A Formal Definition

The primary methodological contribution of this paper is the development of a student-personalized mechanism that extends applicants' ranked lists using aggregated revealed preferences from the applicant pool. The functional form of this mechanism is evidence-based, constructed in light of the findings in (Arteaga et al., 2022), which show that students are significantly more likely to include schools below their original preferences when presented with personalized recommendations. This mechanism modifies the original rankings, $R_{\succ_s,c}$ independently for each applicant,

$$\hat{R}_{\succ_s} = \begin{cases} R_{\succ_s}, & \text{if } R_{\succ_s} = \mathcal{C}_{s,D}, \\ R_{\succ_s} \cup \{c \in \mathcal{C}_{s,D} \setminus R_{\succ_s} \mid U_s(c; X_{s,c}) > U_s(c_{\text{last}}; X_{s,c_{\text{last}}})\}, & \text{otherwise.} \end{cases} \tag{1}$$

Where $c_{\text{last}} \in R_{\succ_s}$ denote the last school in the submitted ranking. I define the extended ranking $\hat{R}_{\succ_s}$ in Equation (1). If the submitted ranking $R_{\succ_s}$ includes all schools within a predefined geographic radius D, it is considered complete, and no modifications are made. Formally, this corresponds to the case where $R_{\succ_s} = \mathcal{C}_{s,D}$, where $\mathcal{C}_{s,D}$ denotes the set of feasible schools located within distance D from the centroid of student s's residence. In such cases, I set $\hat{R}_{\succ_s} = R_{\succ_s}$.

If $R_{\succ_s}$ is incomplete—that is, if there exist at least one school within $\mathcal{C}_{s,D}$ that the student did not rank—then the mechanism extends the list by appending all unranked schools $c \in \mathcal{C}_{s,D} \setminus R_{\succ_s}$ whose estimated utility exceeds that of the lowest-ranked school in the original list. I set this restriction to prevent making recommendation on undesirable schools and reduce the impact induced congestion. These additional schools are ordered by descending predicted utility and appended to the end of $R_{\succ_s}$, preserving the original order of preferences.

The utility function $U_s(c; X_{s,c})$ captures the expected benefit student s derives from being assigned to school c, conditional on observable characteristics of the student, the school, and their interaction.

Throughout the analysis, I set $D = 5\,\text{km}$ as the relevant radius for defining a student's local choice set. This choice is motivated by the distribution of travel distances reported in Table 3, which shows that 99% of students list at least one school within this distance. As such, a 5-kilometer radius captures the relevant search space for nearly all applicants, except in cases where families may anticipate changing their address. In Section VII, I evaluate the robustness of this choice by varying D continuously between 0 and 5 km[4], using a resolution of 10 meters.

B Preference Statistics

Table 4 presents the impact of extending preferences during the main round of the year 2023, following the mechanism defined in Equation 1.

Panel A presents the impact of the mechanism on the length of students' preference lists. The results show a substantial expansion: during the main round, the average number of

[4]While the utilitarian cutoff could, in principle, determine admissible schools without a radius limit, computational constraints require capping the search. Since over 99 % of baseline preferences lie within 5 km and utility gains exhibit concavity beyond this distance (see subsection VII.A), this restriction is unlikely to materially affect our results.

ranked programs increases from 3.44 to 14.14, while the median rises from 3 to 8. In other words, the typical applicant receives five additional programs with higher expected utility than their originally last-listed option. This notable increase underscores the mechanism's potential to broaden applicants' choice sets.

Table 4: Preferences Effects of the Preference Extension Mechanism: Main and Complementary Rounds

Metric	Main Round			Complementary Round		
	Original	**Extended (5 km)**	**Change (%)**	**Original**	**Extended (5 km)**	**Change (%)**
Panel A: Preferences						
Average Preference Extension	3.44	14.14	+311.05%***	2.69	14.14	+424.28%***
Median Preference Extension	3.00	8.00	+160%***	2.00	9.00	+350%***
Panel B: School Performance						
Average SIMCE Math Score	258.83	254.79	-1.56%***	260.10	257.88	-0.85%***
Panel C: Distance to School						
Walking Distance (km)	12.69	5.18	-59.18%***	20.27	6.06	-70.10%***

Notes: This table summarizes changes in student preferences and school characteristics before and after the implementation of the recommendation system, separately for the main and complementary application rounds. Panel A reports both the total number and the average number of new preferences generated by the preference extension mechanism. Panel B shows the average academic quality of all schools. Panel C reports the average walking distance between students and their preferred schools. Changes are expressed as percentage differences relative to the original values. Asterisks indicate statistical significance at the 1% level.

Panel B focuses on the performance of schools measured by the average SIMCE Math Score of the students from that school. A slight decrease of 1.56% is observed in the average score, suggesting that while more options become available, some of these options may correspond to schools with a slightly lower academic performance.

Finally, *Panel C* examines the walking distance to schools. The average walking distance decreases drastically by 59.18%, dropping from 12.69 km to 5.18 km on average. This substantial reduction demonstrates the spatial proximity advantage provided by the extension of preferences, improving the chances that the applicant accepts the recommendation. The sharp decrease is particularly relevant for aleviating access costs and reducing potential barriers related to commuting.

These results collectively illustrate the dual benefits of extending preferences: enhancing students' choice sets while improving geographic accessibility. However, the slight trade-off in school performance calls for additional measures to balance proximity with educational quality.

C Priorities extension

Extending school preferences for each student requires a corresponding reconstruction of their priority status at schools they did not originally rank. To do so, I infer the priority profile for each newly considered school based on observable student characteristics and previously submitted preferences. Reconstructing students' preference lists is relatively straightforward; however, recovering associated priority information, such as whether a sibling attends the school or a parent works there, requires additional data processing and inference.

In particular, I am able to incorporate two key priority-related conditions: (i) whether a sibling is currently enrolled in the school or is simultaneously applying to it, based on administrative enrollment records; and (ii) whether the student is applying to the school they currently attend.[5]

A potentially important source of variation in the simulations arises from the random tie-breaking vector assigned to students by the Ministry of Education, which is used to resolve ties among applicants with identical priority levels for oversubscribed programs. In practice, this vector is determined using a truly random number generator based on the magnitude of the last three earthquakes preceding the execution date of the assignment algorithm. To reflect this randomness in the simulations, I generate 500 distinct random seeds to assess the distribution and variability of outcomes under plausible tie-breaking realizations. Additionally, I include the actual seed used in the 2023 assignment cycle in order to recover the baseline estimates corresponding to the realized allocation.

In the robustness section (Subsection VII.F), I evaluate the sensitivity of the results to alternative tie-breaking realizations. This exercise ensures that the conclusions are not driven by a specific random draw but remain consistent across a wide range of plausible scenarios.

V Utility Metrics

A Preference Estimates

Following Fack, Grenet, and He (2019), I estimate student preferences using a rank-ordered logit model (Beggs, Cardell, & Hausman, 1981; McFadden, 1972; Train, 2009), under the assumption of a stable and strategy-proof environment in which submitted rankings reflect

[5]Unfortunately, administrative records do not allows me to identify whether a parent of the student works at a school unless that school was already included in the original preference list—either directly or through a sibling's application. Consequently, no students are assigned this type of priority in the simulations presented here. However, the likelihood that a student would omit a school where a parent works is presumed to be low, so this limitation is not expected to materially affect the results.

true preferences. This approach is well suited to settings like the Chilean school assignment system, where the DA mechanism removes incentives for strategic misreporting. It also aligns with the theoretical framework developed in Agarwal and Somaini (2020), which formalizes the conditions under which submitted rank-ordered lists can be interpreted as noisy but truthful signals of underlying utility.

The model assumes that the utility student s derives from school c is given by

$$v_{sc} = \delta_c + \boldsymbol{x}_c \bar{\gamma} \boldsymbol{z}_s - d_{sc} + \varepsilon_{sc} \tag{2}$$

where δ_c is a school fixed effect, $\boldsymbol{x}_c$ and $\boldsymbol{z}_s$ are vectors of observed school and student characteristics, respectively, and $\bar{\gamma}$ captures the interaction effects between them. The term d_{sc} represents the disutility from walking distance, and ε_{sc} is an i.i.d. Type I extreme value shock.

This specification allows preferences to be heterogeneous across students based on observed traits. For instance, a positive interaction between academic quality and prior achievement implies that high-performing students gain more utility from academically strong schools. The distance term d_{sc} enters negatively, capturing the empirical regularity that proximity plays a major role in school choice. The school fixed effect δ_c absorbs average unobserved desirability of school c after controlling for covariates and distance.

Under the rank-ordered logit framework, the model assigns a probability to each observed ranking $R_s = \{R_{s1}, R_{s2}, \ldots, R_{sK_s}\}$, where R_{sk} denotes the school ranked in position k by student s. This is computed as the product of conditional choice probabilities:

$$\mathbb{P}(R_s \mid \boldsymbol{x}, \boldsymbol{z}_s; \theta) = \prod_{k=1}^{K_s-1} \frac{\exp\left(\delta_{R_{sk}} + \boldsymbol{x}_{R_{sk}} \bar{\gamma} \boldsymbol{z}_s - d_{sR_{sk}}\right)}{\sum_{j=k}^{K_s} \exp\left(\delta_{R_{sj}} + \boldsymbol{x}_{R_{sj}} \bar{\gamma} \boldsymbol{z}_s - d_{sR_{sj}}\right)} \tag{3}$$

This likelihood reflects the assumption that each chosen school is preferred to all remaining options at the time of selection. This is the function that is maximized in order to obtain the parameters I needed. Once the parameters are estimated by maximum likelihood, I compute predicted utilities and implied probabilities of top-ranked choices. For any school $c \in \mathcal{C}_s$, the model-implied probability that student s ranks c first is given by

$$\mathbb{P}(c \text{ is top-ranked by } s) = \frac{\exp\left(\delta_c + \boldsymbol{x}_c \bar{\gamma} \boldsymbol{z}_s - d_{sc}\right)}{\sum_{k \in \mathcal{C}_s} \exp\left(\delta_k + \boldsymbol{x}_k \bar{\gamma} \boldsymbol{z}_s - d_{sk}\right)} \tag{4}$$

I compute the probabilities defined in Equation 4 to proxy $U_s(c; X_{s,c})$, i.e the expected utility of being assigned to c, for every $c \in \mathcal{C}_{s,D} \setminus R_{\succ_s}$. This allows me to define the set of extended preference and order them as defined in Equation 1. This is the key outcome I use to generate personalized recommendations, and conduct welfare analysis over the assignment in the simulations ahead.

A critical identifying assumption in this framework is that applicants submit rank-ordered lists that truthfully reflect their preferences. This assumption is justified in the Chilean context due to the use of a strategy-proof DA mechanism. However, informational frictions, behavioral biases, or search constraints may lead to incomplete or distorted lists. In such cases, although the full ranking is unobserved, the portion submitted may still reflect true preferences over the included alternatives, as argued in Arteaga et al. (2022).

The model also relies on the Type I extreme value assumption for the idiosyncratic error term ε_{sc}, which yields the familiar logit structure and closed-form expressions. However, this comes at the cost of imposing the Independence of Irrelevant Alternatives (IIA) property, which may be restrictive in the presence of correlated unobserved attributes across schools—such as similar schools in the same neighborhood or network.

Finally, the additivity of utility components imposes a linear structure on how covariates enter the model. While this supports tractability, it may overlook non-linearities or higher-order interactions. For example, the deterrent effect of distance may differ across income groups, or the value of school quality may depend on how accessible it is [6].

Table 5 presents the estimated coefficients of Equation 2 in the main round, which is based on students with high-precision georeferencing and school options within a 20 km radius. Estimates on the complementary round can be found in Table A-1. Additional robustness checks based on alternative distance cutoffs both for main and complementary round are reported in Table A-2 and Table A-3, respectively.

To capture heterogeneity in preferences, the model is estimated separately for students applying to (i) Pre-Kinder and Kindergarten, (ii) Lower Primary, (iii) Upper Primary, and (iv) Secondary levels. This stratification allows the model to flexibly account for life-cycle differences in school choice motivations.

Table 5 shows that walking time has a consistently negative and statistically significant effect on utility across all education levels. This finding confirms the importance of proximity in shaping school preferences and is consistent with the literature on Chilean school choice (Chumacero et al., 2011). The magnitude of the distance coefficient is larger for younger students, highlighting stronger proximity constraints in early education.

Similarly, the positive coefficients on the average SIMCE math scores suggest that families prefer higher-performing schools, confirming the role of academic quality in school choice. Variation in these coefficients across school levels reflects heterogeneity in how academic performance is valued. Finally, significant effects on other school attributes—including co-payment status, schedule type, and priority indicators—reveal that families take institutional features and eligibility rules into account when ranking schools.

[6] **??** presents the main-round results under alternative distance specifications (e.g quadratic distance, min between modes of transport). Across these specifications, I observe no statistically significant differences in key outcomes.

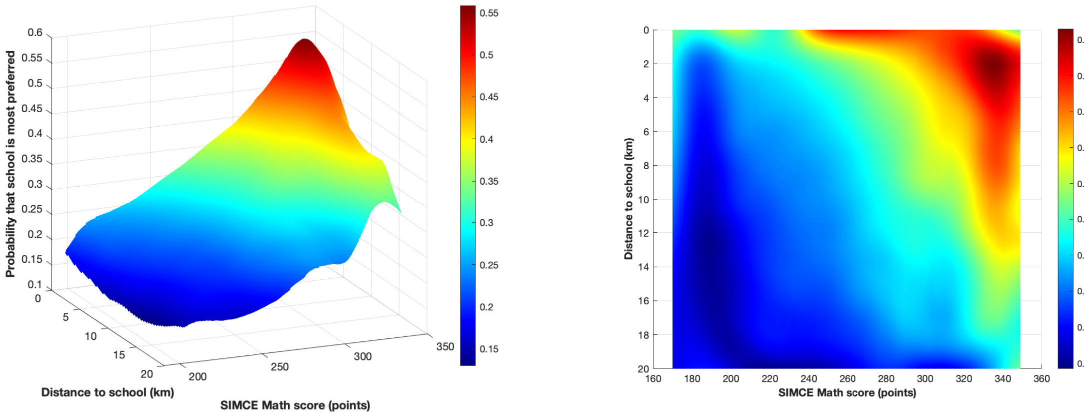
Table 5: Preferences Estimates and Grade Heterogeneity: Main round

	Stated Preference Rank				
	Within 20 km Top georef. quality All levels	Within 20 km Top georef. quality Pre-Kinder & Kinder	Within 20 km Top georef. quality Elementary-School	Within 20 km Top georef. quality Middle-School	Within 20 km Top georef. quality High-School
Walking travel time (minutes)†	-0.800***	-1.200***	-1.150***	-0.943***	-0.525***
	(1.000)	(2.700)	(2.600)	(2.600)	(1.300)
Average SIMCE Math Score†	0.706***	0.893***	0.768***	0.793***	0.527***
	(0.900)	(2.100)	(2.100)	(2.200)	(1.400)
Private School (Co-payment)	0.111***	0.229***	0.150***	0.102***	0.0332***
	(0.00497)	(0.0110)	(0.0106)	(0.0114)	(0.00811)
Afternoon	-0.105***	-0.160***	-0.0828***	-0.0972***	0.0638***
	(0.00626)	(0.00824)	(0.0129)	(0.0300)	(0.0209)
Full Day	0.0187***	0.0756***	0.0155	0.0619***	0.00573
	(0.00513)	(0.0108)	(0.0100)	(0.0128)	(0.00934)
Priority: Currently Enrolled	-5.061***	-3.854***	-4.977***	-5.416***	-5.070***
	(0.0312)	(0.0910)	(0.0539)	(0.0620)	(0.0583)
Priority: Sibling Attending	1.457***	1.810***	1.482***	1.295***	0.937***
	(0.0128)	(0.0199)	(0.0309)	(0.0417)	(0.0237)
Priority: Child of School Staff	1.154***	1.426***	1.163***	0.981***	0.663***
	(0.0481)	(0.0690)	(0.119)	(0.163)	(0.111)
Priority: Child of Alumni	0.146***	0.640***	0.168***	0.151***	0.162***
	(0.0183)	(0.126)	(0.0400)	(0.0326)	(0.0256)
Applications	975169	243739	228385	188120	314925
Applicants	272776	76772	63918	51365	80721
Pseudo-R2	0.193	0.0982	0.254	0.331	0.143
Min. preference length	2	2	2	2	2
Avg. preference length	3.575	3.175	3.573	3.662	3.901
Max. preference length	53	46	50	53	45

Notes: †Coefficient estimates and standard errors are multiplied by 100. Standard errors in parentheses and are clustered at the applicant level. Additional controls are included but omitted from the table to preserve space. This table reports estimates from the conditional logit model described earlier. The dependent variable is the stated rank order of school options. All models are restricted to alternatives located within 20 km of the student's residence and to students with the highest available georeferenced quality data. Column (1) considers all grades, and columns (2)–(5) further stratify the sample by educational level. Coefficients represent the marginal utility of school attributes: positive coefficients indicate higher likelihood of a school being ranked more favorably (i.e., earlier in the preference list), while negative coefficients reflect decreased preference. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

The panel (a) in Figure 3 provides a visual representation of the relationship between walking distance, SIMCE math scores (school performance), and the predicted probability of a school being the most preferred option for a student. The vertical axis approximates the expected utility of given a seat at that school, reflecting the combined influence of proximity and academic performance on that outcome. As walking travel time decreases, the probability of a school being most preferred rises significantly, emphasizing the importance of proximity in school choice. Similarly, schools with higher SIMCE Math scores exhibit higher predicted utilities, demonstrating the pivotal role of academic quality in shaping preferences.

The joint influence of proximity and school performance is clearly illustrated in panel (b), where the peaks represent schools that are both geographically close and high-performing. These peaks reflect the additive structure of the utility function, reinforcing the theoretical assumptions underlying the model. Additionally, the observed flattening of the red region as distance increases highlights the presence of diminishing returns to performance, illustrating the trade-offs families face when balancing academic quality against travel time. Notably, the extended reach of the red zone along the vertical axis, corresponding to high-performance schools located farther away, suggests that families are willing to tolerate longer commutes in exchange for better academic outcomes. This finding aligns with earlier evidence documented in (Chumacero et al., 2011), and further underscores the model's ability to capture key dimensions of revealed preferences in school choice.



(a) Angled View

(b) Overhead Plane

Figure 3: Predicted Probability of a School Being Most Preferred by Distance and School Performance

VI Preference Prediction Fit

To assess how well the proposed mechanism approximates families' stated school preferences, I conduct a predictive exercise that attempts to recover these preferences without directly observing them. To evaluate predictive performance under varying levels of stringency, I construct several complementary metrics that capture different dimensions of fit quality. These metrics are organized into two groups, corresponding to Panel A and Panel B of Table 6.

Panel A reports metrics based on exact matches in both school identity and ranking order. These results reveal that the mechanism predicts the first choice exactly for 36.4% of applicants, and matches the top two and top three preferences for 12.9% and 2.7% of applicants, respectively. While these rates may appear modest, they reflect a stringent standard: not only must the correct schools be identified, but their precise order must be recovered as well. These findings indicate that while rank-level prediction remains challenging, the mechanism captures meaningful information about top-ranked options.

Panel B offers a more flexible assessment, relaxing the requirement of correct ranking and focusing instead on the set of schools selected. Here, the mechanism correctly predicts at least one school preference for nearly half of the applicants (49.3%), and matches at

Table 6: Prediction Accuracy Metrics: Main and Complementary Rounds

Metric	Main Round	Complementary Round
Panel A: Exact Pairs, Strict Order		
First preference matches prediction	36.40%	25.02%
First two preferences match prediction	12.89%	9.55%
First three preferences match prediction	2.73%	1.13%
Last preference matches prediction	17.37%	14.91%
Panel B: Exact Pairs, Flexible Order		
At least one pair matches prediction	49.32%	31.58%
At least 25% of pairs match	43.15%	30.19%
At least 50% of pairs match	26.89%	23.65%
At least 75% of pairs match	11.56%	10.78%
All preference-program pairs match	11.25%	10.73%

Notes: Panel A shows the fraction of exact matching applicant-school pairs in a given preference order that are equal between the real preferences and the predicted preferences. Panel B relaxes preference order.

least 25% of preferences for 43.2%. The share of applicants for whom 50% or more of their preference list is recovered stands at 26.9%, and full list matches are achieved for 11.3%. These results suggest that even when rank order is not preserved, the mechanism reliably identifies relevant school alternatives within applicants' true consideration sets.

Taken together, these metrics show that the proposed mechanism performs well in approximating unobserved preferences—especially under relaxed criteria—suggesting its potential value for recommendation design.

It is importat to note that prediction performance in the complementary round, shown in Table 6, is consistently lower across metrics. This likely reflects the smaller scale of the round—just one-fifth of the applicant pool—as well as distinct search behaviors under tighter supply. While the model still captures meaningful patterns, the reduced accuracy underscores a key consideration for applying such mechanisms in smaller markets: limited data may hinder preference estimation and the effectiveness of recommendation tools.

VII Simulations

Building on the preference estimates presented earlier, this section outlines the implementation and results of simulations designed to assess the impact of extending parental preference lists in the primary round of the 2023 (2024 admission) school choice process. The goal is to quantify the potential benefits of implementing the proposed mechanism in terms of reducing unassignment rates and expected utility—thereby illustrating the practical value of preference recovery and recommendation tools.

The simulations proceed in the following steps. First, I construct the extended preference lists for each student based on the mechanisms described in Equation 1. Next, the DA mechanism is re-run using the extended preferences and priorities, producing a new set of assignments. Finally, the outcomes of the original and extended assignments are compared across key metrics, such as assignment rates, expected utility, distance traveled, and school quality, with an emphasis on understanding the net effects of introducing the mechanism.

The remainder of this section is structured as follows. Subsection VII.A presents the main results, focusing on assignment rates, transitions, and mechanisms underlying changes in unassignment. Subsection VII.B evaluates second-order outcomes, emphasizing utility and school performance. Subsection VII.E examines heterogeneous results based on exposition to excess demand on the applied schools. Finally, Subsection VII.F assesses the robustness of the results to variations in the lottery seed, highlighting the stability of the findings.

A Extensive Margin

Table 7 presents the primary results of the analysis. *Panel A* shows a significant reduction in the percentage of non-assigned students, from 8.07% in the original scenario to 4.20% when preferences are extended, corresponding to a 48.03% decrease in the fraction of non-assignment. This reduction highlights the effectiveness of the mechanism in increasing assignment rates. To contextualize the magnitude of these results, a similar improvement was documented by Abdulkadiroğlu et al. (2017), who reported a 45% increase in assignment rates following the transition from the Boston mechanism to Deferred Acceptance in a different setting.

Although smaller in magnitude, the complementary round also shows positive and statistically significant improvements from extending preferences. In this phase, students who remain unassigned are placed in their nearest school with available seats, thus smaller results are expected. The simulated extension reduces the unassignment rate by 5,6%.

Panel B illustrates the transitions in assignment outcomes. Approximately 73.26% of students retain the same assignment, while 5.28% of students who were previously unassigned, gain an assignment under the extended preferences. Interestingly, 17.27% of students are assigned to a different school, indicating notable changes in the allocation structure. However, only 1.40% of students lose their assignments, suggesting that the overall effect of the intervention is positive.

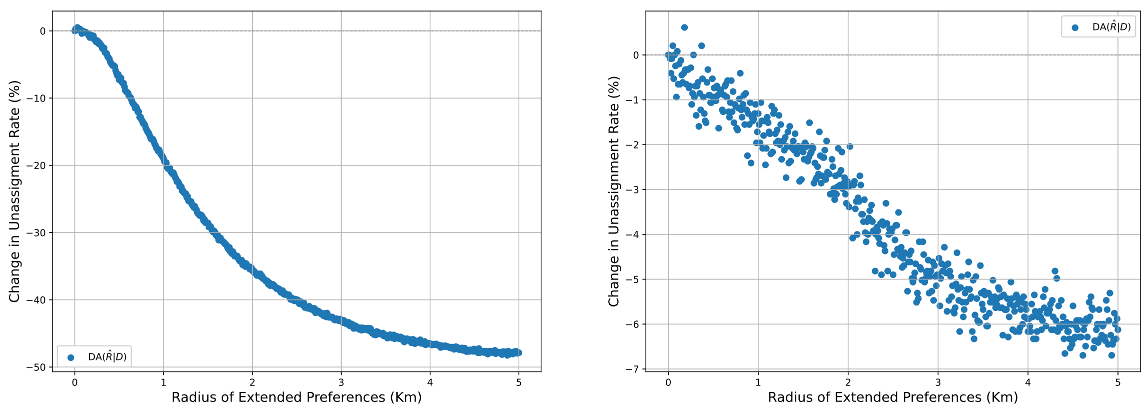
Figure 4 visualizes the percentage change in the fraction of unassigned students as the radius of extended preferences increases, that is as the set $\mathcal{C}_{s,D}$ gets bigger for each student. The figure shows a sharp decline in the unassignment rate with smaller radii, followed by a convergence as the radius continues to expand to 5 km. This pattern can be explained by two key mechanisms. First, expanding the radius increases the number of acceptable schools added to applicants' lists, which lowers the likelihood of remaining unassigned. Second, as the radius grows larger, the additional schools tend to be less desirable than

Table 7: Assignment Effects of the Preference Extension Mechanism: Main and Complementary Rounds

Metric	Main Round			Complementary Round		
	Original	Extended (5 km)	Change (%)	Original	Extended (5 km)	Change (%)
Panel A: Unassignment Rate						
Fraction of Unassigned Students	8.07%	4.20%	-48.03%***	2.50%	2.36%	-5.62%**
Panel B: Assignment Transitions						
Fraction with the same assignment	–	73.26%	–	–	83.78%	–
Fraction who gained an assignment	–	–	+5.28%	–	–	+0.65%
Fraction who lost an assignment	–	–	+1.40%	–	–	+0.51%
Fraction assigned to a different program	–	17.27%	–	–	13.22%	–

Notes: This table reports changes in student assignment outcomes before and after implementing the recommendation system, separately for the main and complementary rounds. Panel A shows the percentage of students left unassigned after the allocation process. Panel B tracks transitions in assignment status. Transition metrics are conditional on being assigned in either scenario. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

those already listed, making them unlikely to surpass the utility on the applicant's last-ranked option. As a result, the marginal benefit of further extending the list diminishes.



(a) Main Round

(b) Complementary Round

Figure 4: Percentage Change in Fraction of Unassigned Students Over Radius of Extended Preferences

Overall, the results demonstrate the potential of preference extension mechanisms to improve assignment rates within centralized school choice systems. The heterogeneity underlying these gains is explored in subsection VII.E, where effects are disaggregated by levels of excess demand. There, I find that a key mechanism driving the aggregate improvements is the ability of extended preferences to redirect demand away from oversubscribed schools, thereby alleviating congestion in high-demand institutions.

This naturally raises a concern: do students get diverted toward less preferred or lower-quality schools, potentially offsetting the benefits of assignment? To address this question, the following section examines intensive margin outcomes, in particular changes in net expected utility, resulting from the extension.

Together, these findings highlight the importance of addressing the limitations of short preference lists and illustrate how aggregate preference recovery can contribute to more equitable and efficient outcomes in large-scale assignment systems, particularly in contexts characterized by concentrated demand and limited capacity.

B Intensive Margin

This intensive margin section examines the changes in utility resulting from the preference extension mechanism. While the extensive margin focuses on first-order outcomes, such as assignment rates, the intensive margin delves deeper into expected utility and satisfaction of the resulting assignments.

Table 8 summarizes the main findings on changes in the model-implied expected utility of assigned schools, using the proxy defined in Equation 4. *Panel A* shows that mean expected utility increases under the extended preference scenario: by 2.38% when non-assigned students are assigned zero utility (a conservative specification), and by 6.70% when they are assigned a negative mean utility (an optimistic scenario). Additionally, excluding non-assigned students from the analysis allows for the estimation of the net cost associated with induced congestion, which amounts to 1.76%. These results suggest that the majority of the gains stem from assigning seats to previously unplaced students, although some applicants may lose access to their originally preferred schools. Importantly, we learn that the overall effect remains positive under the proposed recommendation mechanism. Although there are positive effects on the complementary round, these effects are much lower, ranging from 0.84% to 2.37%.

Equation 5 presents a decomposition of the observed net effect under the conservative scenario. The results indicate that the majority of utility gains are concentrated among students who were newly assigned to a school, while a smaller share of students incur marginal losses due to reallocation. This is why the "better school" and "worse school" almost net themselves. This trade-off highlights the redistributive nature of the mechanism: overall system utility improves through a more equitable allocation of seats, even if some students are reassigned from their initially preferred schools to accommodate those who were previously unassigned.

$$\overbrace{\underbrace{5.01\%}_{\text{Better school}} + \underbrace{4.48\%}_{\text{Gains seat}}}^{\text{Gross Gains: 9.49\%}} + \overbrace{\underbrace{-5.14\%}_{\text{Worse school}} + \underbrace{-1.97\%}_{\text{Loses seat}}}^{\text{Gross Losses: -7.11\%}} = \overbrace{\boxed{2.38\%}}^{\text{Net Effect}} \tag{5}$$

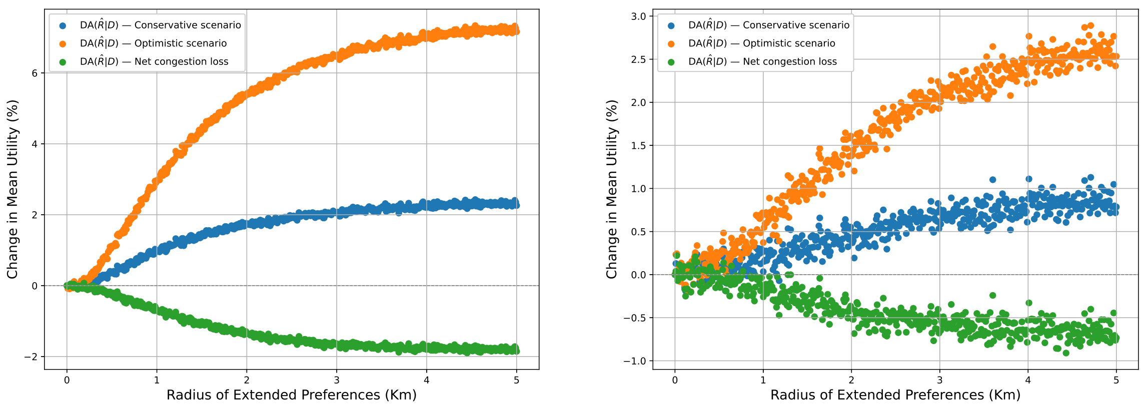
Panels B and *C* of the same table show that the changes in average academic performance and walking distance of assigned schools are small and statistically vaguely significant. These results help address the concern raised in the previous subsection—namely,

Table 8: Utility Effects of the Preference Extension Mechanism: Main and Complementary Rounds

		Main Round			Complementary Round		
Metric	**Interpretation**	**Original**	**Extended (5 km)**	**Change (%)**	**Original**	**Extended (5 km)**	**Change (%)**
Panel A: Mean Utility							
$U(\text{Unassigned}) = 0$	**Conservative scenario**	0.139	0.143	+2.38%***	0.147	0.148	+0.84%
$U(\text{Unassigned}) = -\bar{U}$	**Optimistic scenario**	0.128	0.137	+6.70%***	0.137	0.140	+2.37%***
$U(\text{Unassigned}) =$ NaN	**Net congestion loss**	0.230	0.228	−1.76%***	0.157	0.156	−0.65%
Panel B: School Performance							
SIMCE Math Score	Avg. Math at Assignment	251.12	251.04	−0.03%*	244.14	244.37	0.1%**
Panel C: Distance to School							
Walking Distance (km)	Avg. Distance to Assignment	12.84	12.56	-2.19%	11.41	11.38	-0.23%

Notes: This table reports average utility, school performance, and distance outcomes before and after implementing the recommendation system. Panel A presents three utility assumptions: (i) a **conservative scenario**, where unassigned students are assumed to experience no utility loss; (ii) an **optimistic scenario**, where unassigned students are assumed to lose utility equal to the average assigned utility; and (iii) a **NaN scenario**, where unassigned students are excluded from the calculation entirely. Negative utility changes in the NaN case reflect congestion effects among previously assigned students. Asterisks denote statistical significance at the 1% level.

whether the newly assigned schools are of lower quality or substantially farther away. The evidence suggests that the extended assignments do not systematically shift students toward lower-performing or less accessible schools.



(a) Main Round

(b) Complementary Round

Figure 5: Percentage Change in Utility Over Radius of Extended Preferences

Figure 5 illustrates the percentage change in mean utility as the radius to construct the set $\mathcal{C}_{s,D}$ expands. The figure shows that utility gains are initially steep as the radius increases, but they eventually plateau, demonstrating diminishing returns to additional preference extension. This behavior aligns with the mechanism seen in the unassignment rate outcomes: as the radius grows, additional schools are lees likely to increase utility since their distance outweighs other desirable characteristics.

Two key mechanisms drive these results. First, previously unassigned students that applied to oversubscriped programs gain utility by being matched to schools, transitioning from zero utility to a positive outcome. Second, there is a redistribution effect driven by the preference extension. Students with shorter original preference relatively apply to more schools closer to their neighborhoods, increasing their chances of displacing someone with lower priority. Despite this trade-off, the net effect is positive, as evidenced by the overall utility gains.

C Minimizing congestion loss

The previous simulations applied the preference extension mechanism universally to all students, including those who had already received an assignment. While this approach led to a substantial reduction in the share of unassigned students and an increase in overall utility, it also introduced a non-negligible level of congestion. Specifically, some applicants were displaced from their originally assigned programs to accommodate others who benefited from the expanded choice set. Although the aggregate welfare effects remained positive, this congestion implied that a subset of applicants could be made worse off by being matched to a less-preferred or entirely unranked option. This motivates the search for targeted applications of the recommendation mechanism that can be leveraged within specific submarkets.

To mitigate these drawbacks, I propose an alternative, targeted implementation of the preference extension mechanism. Rather than applying it globally, I restrict its application exclusively to students who remain unassigned after the main round. Under this variant, the original assignments are preserved. A new round, referred to here as the *aftermarket round*, is then conducted, in which the mechanism is applied solely to the remaining unassigned applicants. The procedure follows three steps: (i) determine the initial assignments based on the submitted preferences, (ii) update the seat availability based on those outcomes, and (iii) reassign the unplaced applicants using the extended preferences on their submarket.

This targeted implementation offers several key advantages. First, it preserves the integrity of the initial assignment; Table 9 shows that 91.93% of applicants (i.e all of those that had an assignment) retain their original school placement, which is significantly higher than the 73.26% observed under the universal mechanism. Second, no student is displaced from a previously assigned program, nor are any students reassigned to a different program. Third, the reduction in the share of unassigned students remains substantial, decreasing from 8.07% to 4.57%, a 43.34% improvement. These gains are statistically indistinguishable from those achieved under the full implementation, suggesting that similar aggregate benefits can be attained with substantially less disruption to existing assignments.

Table 10 presents the corresponding changes in expected utility. Under the conserva-

Table 9: Assignment Effects of the Preference Extension Mechanism: Aftermarket Round

Metric	Aftermarket Round Original	Extended (5 km)	Change (%)
Panel A: Unassignment Rate			
Fraction of Unassigned Students	8.07%	4.57%	-43.34%***
Panel B: Assignment Transitions			
Fraction with the same assignment	–	91.93%	–
Fraction who gained an assignment	–	–	+3.50%***
Fraction who lost an assignment	–	–	0.00%
Fraction assigned to a different program	–	0.00%	–

Notes: This table reports changes in student assignment outcomes in the Aftermarket Round for students unassigned in the Main Round, before and after implementing the recommendation system. Panel A shows the percentage of students left unassigned. Panel B tracks assignment transitions, conditional on being assigned in either scenario. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

tive scenario, mean utility increases by 2.51%, closely mirroring the gains observed under the full implementation. Notably, this improvement is not statistically distinguishable from that of the full-round application. Importantly, this aftermarket approach eliminates the need to decompose utility changes into gains and losses across groups. Since no students lose their assignment or are reassigned, the entire welfare improvement derives from previously unassigned students gaining placements. This provides a cleaner identification of the mechanism's net effect and avoids the equity concerns that can arise from reallocation-based gains.

Taken together, these results suggest that the aftermarket application of the preference extension mechanism provides a pragmatic and politically feasible pathway for implementation. It maintains the key benefits of increased assignment rates and improved expected utility, while minimizing potential resistance from stakeholders who might otherwise be adversely affected by reassignment. Given these properties, I argue that this constitutes a compelling submarket for operational deployment. More broadly, this approach could inform the design of similar interventions in submarkets where the benefits of preference extension can be realized without displacing or disadvantaging other applicant groups.

D Second-Best Policies

One potential barrier to real-world uptake of the preference-extension mechanism is its "black-box" nature: policy makers may object to using a model-implied ranking that is not transparent or rule-based. In practice, most centralized DA systems specify simple defaults for unlisted schools (e.g. nearest-distance), and practitioners may prefer clear, interpretable heuristics. To bridge this gap, I propose and evaluate a menu of *second-best* ordering policies on the same set of "desirable" schools $C_{s,D} = \{c : d(s,c) \leq D\}$ where

Table 10: Utility Effects of the Preference Extension Mechanism: Aftermarket Round

Metric	Interpretation	Aftermarket Round Original	Extended (5 km)	Change (%)
Panel A: Mean Utility				
$U(\text{Unassigned}) = 0$	**Conservative scenario**	0.1394	0.1429	+2.51%***
$U(\text{Unassigned}) = -\bar{U}$	**Optimistic scenario**	0.1281	0.1364	+6.42%***
Panel B: School Performance				
SIMCE Math Score	Avg. Math at Assignment	251.12	251.11	–0.06%
Panel C: Distance to School				
Walking Distance (km)	Avg. Distance to Assignment	12.84	12.44	-3.11%**

Notes: This table reports changes in student utility, academic quality, and distance outcomes in the Aftermarket Round for students unassigned in the Main Round, before and after implementing the preference extension mechanism. Panel A presents two utility scenarios: (i) a **conservative case** where unassigned students experience no utility loss; (ii) an **optimistic case** where they lose utility equal to the average assigned utility. No congestion-related loss is reported, as it is null. Asterisks denote statistical significance at the 1% level.

$D = 5$ km and $d(s, c)$ is walking distance (see Equation 1 on page 11). The optimal policy uses the estimated logit utilities $U_s(c; X_{s,c})$ from Equation 2 on page 14 to rank $C_{s,D}$ in descending order.

Maintain the cutoff set $C^*_{s,D} = \{c \in C_{s,D} : U_s(c) \geq U_s(c_{\text{last}})\}$ fixed. Let π^* denote the "true" (model-optimal) ordering of $C^*_{s,D}$, and let π^w be the exact reverse of π^* (the *worst* possible ordering). For any given ordering rule π, let us denote by $S_g(\pi)$ the set of students who gain a seat when preferences are reordered according to π. I further write $|S_g(\pi)|$ for the cardinality of this set. This plays two roles in our evaluation. First, it identifies the beneficiaries of each ordering policy, allowing us to compute the aggregate utility gained by all such students. Second, it accounts for differences in excess demand across orderings [7]. Then the *relative performance* of π from optimal is

$$\rho(\pi) = 1 - \frac{\sum_{s \in S_g(\pi^*)} U_s(\pi^*(s)) - \sum_{s \in S_g(\pi)} U_s(\pi(s))}{\sum_{s \in S_g(\pi^*)} U_s(\pi^*(s)) - \sum_{s \in S_g(\pi^w)} U_s(\pi^w(s))}, \tag{6}$$

so that $\rho(\pi) = 1$ for the optimal policy π^* and $\rho(\pi) = 0$ for the worst ordering π^w. I consider four simple heuristics as second-best candidates; i) Nearest-first, ii) Highest-SIMCE-first, iii) Distance-SIMCE hybrid ordered as given by Equation 2. For each policy

[7] Even a "worst-first" ordering can boost overall utility by placing students atop schools where they are most likely to be admitted, but such a rule may yield counter-intuitive or politically undesirable recommendations.

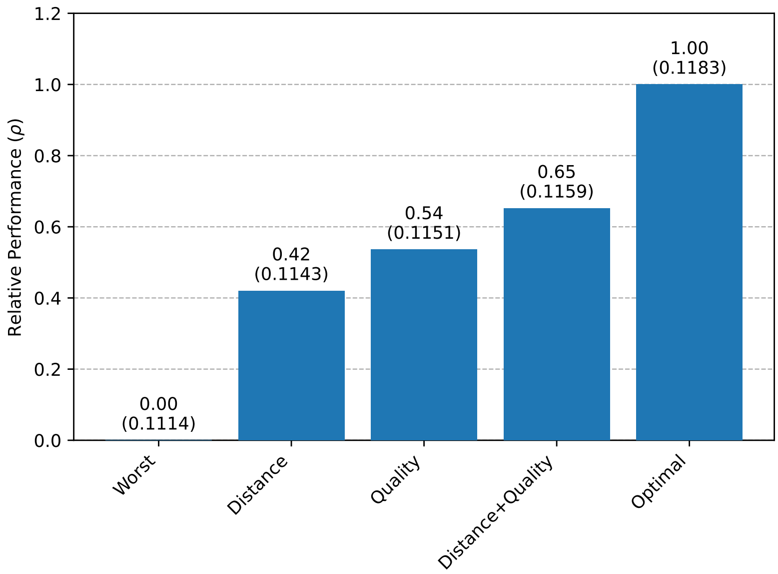


Figure 6: Second-Best Policies: Relative Performance and Avg. Utility per Seat Gained

π, I compute $d(\pi)$ via Equation 6 , and also report the *average absolute utility per seat gained*

$$\bar{U}(\pi) \;=\; \frac{1}{|S_g(\pi)|} \sum_{s \in S_g(\pi)} U_s(\pi(s))\,.$$

Figure 6 plots the normalized performance score $\rho(\pi)$ for each second-best ordering policy, with the average utility per seat gained in parentheses above each bar.

The simplest distance-based rule, recovers about 42% of the optimal welfare gain ($\rho \approx 0.42$), boosting average utility to 0.1143. Prioritizing school quality alone performs somewhat better, capturing roughly 54% of the model's gain ($\rho \approx 0.54$) and raising average utility to 0.1151. The disrance and quality hybrid combines these dimensions, letting families "run the extra mile" for higher-quality schools and delivers substantially better performance ($\rho \approx 0.65$), with average utility 0.1159. By explicitly balancing distance and SIMCE scores, this rule aligns more closely with what many parents prioritize: attending a strong school without unduly long commutes.

In sum, even simple heuristics that trade off proximity and quality can recover a large share of the welfare benefits of the full logit–based ordering, offering transparent, rule-of-thumb alternatives that better match families' own considerations. Nonetheless, the residual gap to the optimal ranking reflects other school and applicant-specific factors, such as voucher availability, shift schedules, and individual match, that these simple heuristics do not capture.

E Excess Demand

This section explores the heterogeneous effects of the preference extension mechanism observed in the simulation results. Specifically, I examine how the impact of the mechanism varies according to two indices of excess demand experienced by applicants in their submitted rank-ordered lists. The objective is to assess whether the mechanism helps mitigate excess demand from the applicant's perspective in oversubscribed school choice systems, thereby improving assignment outcomes in highly congested environments.

Let $s \in \mathcal{S}$ denote a student and $c \in \mathcal{C}$ denote a school program. Define $I_{sc} \in \{0, 1\}$ as an indicator variable equal to 1 if student s includes program c in their submitted preference list $R_{\succ_s}$, and 0 otherwise. Also, let $C_c \in \mathbb{N}$ denote the capacity (i.e., the number of available seats) at program c. It follows that the *Relative Excess Demand* (RED) for program c is then defined as the proportional difference between demand and supply, normalized by the program's capacity

$$\text{RED}(c) = \frac{1}{C_c}\left(\sum_{s \in \mathcal{S}} I_{sc} - C_c\right). \tag{7}$$

This measure quantifies excess demand in relative terms: it is positive if demand exceeds capacity, zero if demand matches capacity, and negative when the program is under-demanded. In practice, $\text{RED}(c)$ may be computed over the full applicant pool or conditional on specific subgroups (e.g., geographic region, priority type) to assess localized competition for seats.

Table 11: Exposure to Relative Excess Demand (RED) Across Applicants and Schools

Metric	Main Round	Complementary Round
Panel A: Applicants		
Share with at least one preference with RED > 0	95.6%	72.1%
Share with all preferences with RED > 0	65.2%	25.2%
Avg. share of preferences with RED > 0	84.0%	48.9%
Panel B: Schools		
Share of programs with RED > 0	50.8%	18.8%
Share of schools with at least one program with RED > 0	67.7%	48.7%
Share of schools with all programs with RED > 0	14.4%	1.3%
Avg. share of programs with RED > 0 per school	39.6%	16.6%

Notes: RED (Relative Excess Demand) measures whether demand for a program exceeds its capacity. A value of RED > 0 indicates excess demand. All metrics report the proportion of applicants or schools/programs meeting the specified condition in each round.

Table 11 presents summary statistics based on Equation 7, capturing exposure to excess demand across applicants and school programs in both the main and complementary rounds.

Panel A reports student-level exposure. In the main round, 95.6% of applicants included at least one program with positive excess demand (RED > 0), and 65.2% exclusively listed such programs, highlighting the intensity of competition faced by a majority of applicants. The average share of over-demanded preferences per applicant is 84.0%. In contrast, these values drop substantially in the complementary round, with only 72.1% of applicants listing any over-demanded program and just 25.2% listing only over-demanded programs. This reflects the lower levels of congestion and weaker competition in the second round.

Panel B reports school-level statistics. In the main round, 50.8% of programs face excess demand, and 67.7% of schools have at least one such program. Additionally, 14.4% of schools experience excess demand across all their offered programs. These figures drop significantly in the complementary round—only 18.8% of programs and 48.7% of schools face any excess demand, and just 1.3% of schools see it across all their programs. On average, only 16.6% of a school's programs are over-demanded in the complementary round, compared to nearly 40% in the main round.

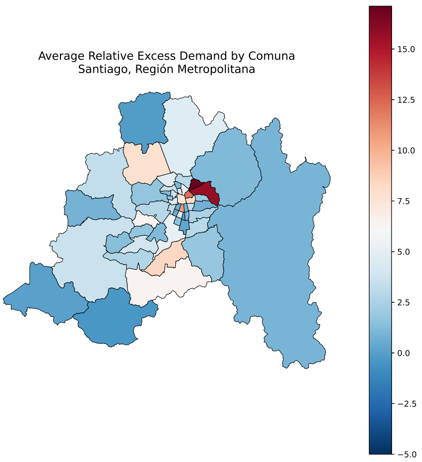
Together, these patterns underscore the high levels of congestion in the main round and suggest that the preference extension mechanism may be particularly effective in settings where demand is concentrated among a limited set of schools. To quantify the potential gains from such interventions, I define student-level measures of exposure to excess demand

$$\text{MRED}_s = \frac{1}{|R_{\succ_s}|} \sum_{c \in R_{\succ_s}} \text{RED}(c) \tag{8}$$

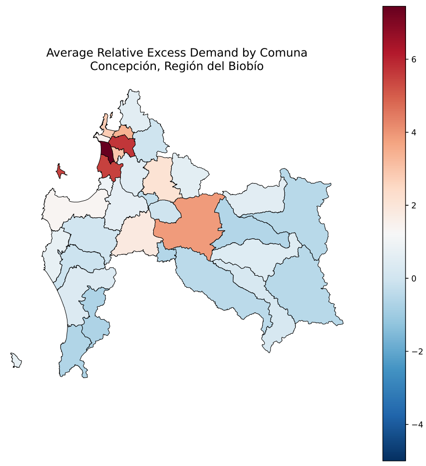
$$\text{CRED}_s = \sum_{c \in R_{\succ_s}} \mathbb{1}\{\text{RED}(c) > 0\} \tag{9}$$

Equation 8 defines the *Mean Relative Excess Demand* (MRED), which captures the average level of excess demand across all programs listed by student s. Higher values of MRED_s indicate that a student's preferences are concentrated in more oversubscribed programs. This provides a responsive measure of excess demand at the intensive margin. In the other hand, Equation 9 defines the *Count of Over-Demanded Preferences* (CRED), which measures how many of the programs in student s's list are over-demanded (i.e., $\text{RED}(c) > 0$). This discrete count provides an extensive margin measure of the competition faced by the student.

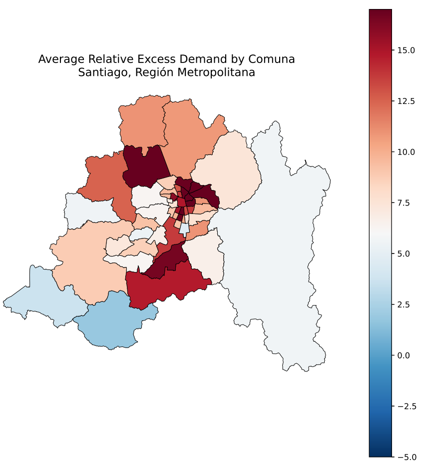
In order to graphically understand the distribution of these indexes, Figure 7 presents the average program-level MRED across *comunas* (administrative units comparable to counties) in Chile's two largest urban areas. The maps show that excess demand is geographically concentrated in the residential centers of these cities, particularly in higher-income neighborhoods. However, when the same statistic is computed at the applicant level, the spatial pattern changes: excess demand appears more evenly distributed across the urban landscape. This divergence suggests that applicants from a broad range of neighborhoods



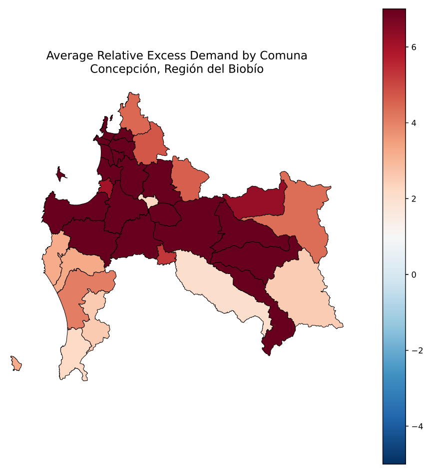
(a) Santiago: School-level MRED



(b) Concepción: School-level MRED



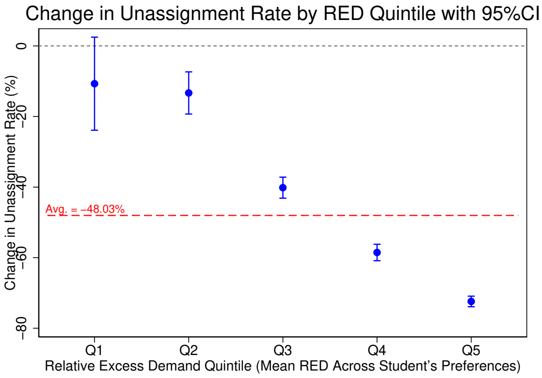
(c) Santiago: Student-level MRED



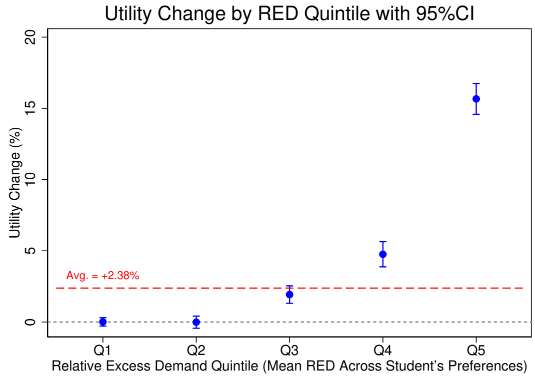
(d) Concepción: Student-level MRED

Figure 7: Average Relative Excess Demand (MRED) Across Schools and Students in Santiago and Concepción

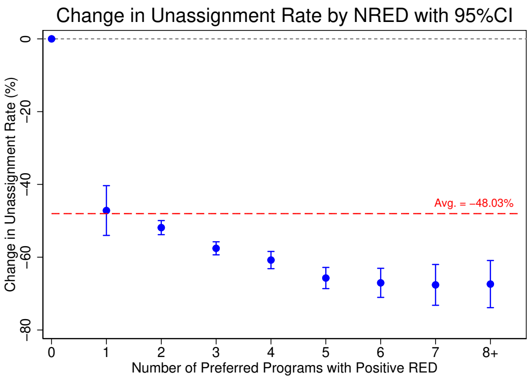
tend to apply disproportionately to schools located in central, affluent areas—likely attracted by perceived higher quality, stronger academic reputations, or better-funded programs.



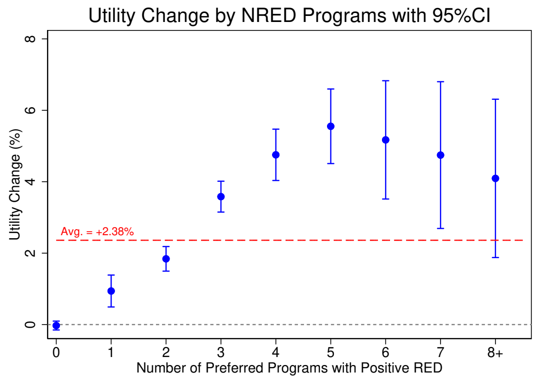
(a) Unassignment Rate Change by MRED Quintile



(b) Utility Change by MRED Quintile



(c) Unassignment Rate Change by NRED Programs



(d) Utility Change by NRED Programs

Figure 8: Changes in Unassignment and Utility Outcomes by Measures of Exposure to Excess Demand

Figure 8 presents the main outcomes—unassignment rates and expected utility—disaggregated by quintiles of MRED_s and by values of NRED_s of the main round.[8] The figure shows that both the reduction in unassignment and the gains in expected utility are concentrated among students who initially applied to highly oversubscribed programs. Consistent with this, (Arteaga et al., 2022) find that students who receive targeted warnings are more likely to add non-oversubscribed schools to their ranked choices. Panel (a) illustrates that students in the top quintile of MRED_s experience a reduction in unassignment of over 70%, which is nearly 50% higher than the average reduction of 48%. Similarly, panel (b) shows that utility gains are also concentrated in this upper quintile. Importantly, students in the lowest quintile—those whose submitted preferences included little to no excess de-

[8] The same set of outcome comparisons for the complementary round is shown in Figure A-2.

mand—do not exhibit statistically significant effects. Across quintiles, the differences in means are statistically significant.

Panels (c) and (d) replicate the analysis using NRED_s, an absolute count of over-demanded programs in each student's preference list. These panels reveal a pattern of diminishing returns: while students with a greater number of over-demanded choices benefit more from the extension mechanism, longer initial preference lists also reduce the probability of non-assignment through exhaustion alone. Thus, the effect of the mechanism is attenuated for those with already extensive preference submissions. Nonetheless, students who listed no over-demanded programs ($\text{NRED}_s = 0$) experience no measurable improvement in either outcome, as expected.

Because exposure to oversubscribed programs is highly correlated with the activation of the preference extension mechanism, utility gains are not evenly distributed across grade levels. Instead, they are systematically concentrated in entry points to the school system. In particular, students applying to kindergarten and 9th grade—both key transition stages—experience the largest improvements. As shown in Figure A-1, these two grades are the only ones with average utility gains that are significantly above the overall mean effect of 2.38%.

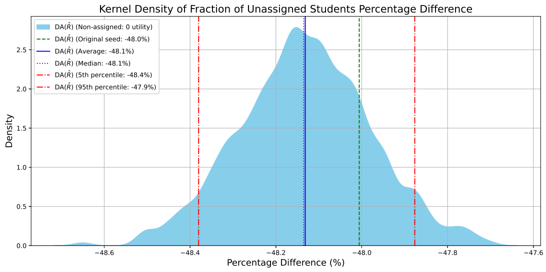
In sum, the results presented in this section offer strong evidence that the preference extension policy effectively alleviates excess demand in oversubscribed school choice markets. By expanding applicants' ranked lists with personalized, high-utility alternatives, the mechanism reduces the pressure on highly demanded schools and improves overall match efficiency. Importantly, it provides meaningful fallback options for students who are unlikely to secure admission to their originally oversubscribed preferred schools.

F Robustness to Random Tie-Breaking Orders

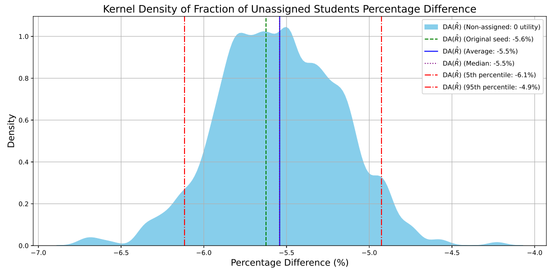
This section evaluates whether the results presented in section VII are robust to changes in the random priority vector assigned by the Ministry of Education, which is used to break ties among applicants with identical priority in oversubscribed programs.

To assess the stability of the main findings, I simulate 500 alternative priority orderings by varying the random seed used to generate tie-breaking vectors. This exercise allows for an evaluation of how sensitive the reduction in unassignment rates and the observed utility gains are to the randomness inherent in the DA algorithm's implementation.

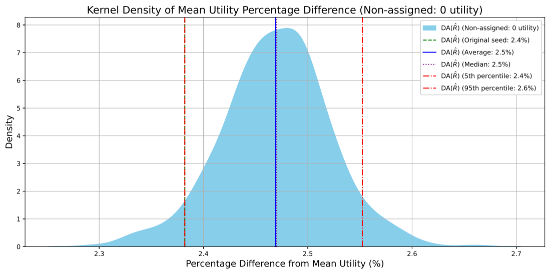
Figure 9 presents kernel density estimates of the outcome distributions across these 500 simulated scenarios, for both the main and complementary rounds. Each panel includes key summary statistics: the mean, median, baseline (actual) seed, and the 5th and 95th percentiles to capture the range of plausible outcomes.



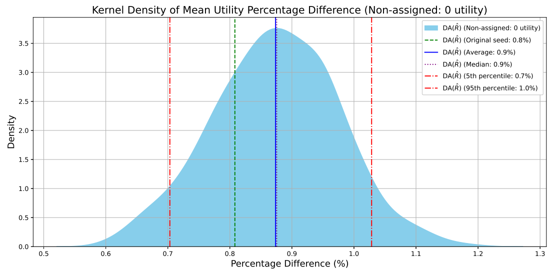
(a) Unassignment Rate – Main Round



(b) Unassignment Rate – Complementary Round



(c) Mean Utility – Main Round



(d) Mean Utility – Complementary Round

Figure 9: Distribution of Outcomes Under Random Priority Orderings: Unassignment Rates and Utilities

The results indicate a high degree of stability. For the unassignment rate, the distribution is tightly centered around the mean change of approximately -48%, with 95% of scenarios falling between -48.4% and -47.9%. Similarly, the distribution of expected utility gains is narrowly concentrated around a mean of 2.48%, with 95% of values ranging between 2.4% and 2.6%.

These findings demonstrate that both extensive-margin (assignment rates) and intensive-margin (expected utility) outcomes are highly robust to the randomness introduced through tie-breaking. The core results of the preference extension mechanism hold consistently, regardless of the specific seed used for priority ordering.

VIII Conclusion

This paper addresses a persistent challenge in centralized school assignment systems: the high rate of non-assignment caused by incomplete or misinformed preference submissions, particularly in settings with excess demand. Building on recent work that highlights the limitations of strategy-proof mechanisms in the presence of information frictions, I propose a preference extension mechanism that leverages revealed preferences and estimated utilities to recommend additional, desirable schools to applicants. This intervention operates ex-post, is DA-compatible, and is designed to be computationally feasible and scalable.

Simulation results from the Chilean school assignment system indicate that the proposed mechanism can significantly reduce the unassignment rate—by nearly 50% in the main round—while increasing expected utility at the system level. These gains are primarily concentrated among students who were previously unassigned or who applied to oversubscribed programs. Building on this, I propose a targeted application of the mechanism within a specific submarket that achieves equivalent benefits without displacing any previously assigned students. Importantly, the intervention does not systematically reassign students to lower-performing or more distant schools.

Several directions for policy and future research remain open. First, real-world implementation through field experiments could provide valuable evidence on behavioral responses, such as changes in truth-telling or assignment acceptance rates, that cannot be captured in the simulation. Second, this paper focuses on imputing preferences at the intensive margin, conditional on submitted lists. A natural extension is to develop mechanisms that generate recommendations at the extensive margin, for students who submit no preferences at all (e.g., transitions from pre-K to primary or from schools offering only basic levels to those with secondary education). Finally, further theoretical work is needed to characterize the types of submarkets in which this family of recommendation mechanisms may be particularly useful for addressing other policy-relevant objectives, such as affirmative action.

Overall, this study demonstrates that modest, data-driven improvements to the platform design can generate meaningful welfare gains in large-scale assignment systems, without requiring strategic sophistication or proactive engagement from applicants. By redistributing excess demand and expanding access to relevant options, the proposed mechanism offers a tractable and equitable path forward for education policy.

References

Abdulkadiroğlu, A. (2005, November). College admissions with affirmative action. *International Journal of Game Theory*, *33*(4), 535–549. Retrieved 2025-06-01, from `http://link.springer.com/10.1007/s00182-005-0215-7` doi: 10.1007/s00182-005-0215-7

Abdulkadiroğlu, A., Agarwal, N., & Pathak, P. A. (2017). The welfare effects of coordinated assignment: Evidence from the new york city high school match. *American Economic Review*, *107*(12), 3635–3689.

Abdulkadiroglu, A., Pathak, P., Roth, A., & Sonmez, T. (2006, January). *Changing the Boston School Choice Mechanism* (Tech. Rep. No. w11965). Cambridge, MA: National Bureau of Economic Research. Retrieved 2024-11-14, from `http://www.nber.org/papers/w11965.pdf` doi: 10.3386/w11965

Abdulkadiroğlu, A., Pathak, P. A., & Roth, A. E. (2005, April). The New York City High School Match. *American Economic Review*, *95*(2), 364–367. Retrieved 2024-12-07, from `https://pubs.aeaweb.org/doi/10.1257/000282805774670167` doi: 10.1257/000282805774670167

Abdulkadiroğlu, A., Pathak, P. A., Roth, A. E., & Sönmez, T. (2005, April). The Boston Public School Match. *American Economic Review*, *95*(2), 368–371. Retrieved 2024-12-07, from `https://pubs.aeaweb.org/doi/10.1257/000282805774669637` doi: 10.1257/000282805774669637

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

Agarwal, N., & Somaini, P. (2018). Demand Analysis Using Strategic Reports: An Application to a School Choice Mechanism. *Econometrica*, *86*(2), 391–444. Retrieved 2025-05-22, from `https://www.econometricsociety.org/doi/10.3982/ECTA13615` doi: 10.3982/ECTA13615

Agarwal, N., & Somaini, P. (2020, August). Revealed Preference Analysis of School Choice Models. *Annual Review of Economics*, *12*(1), 471–501. Retrieved 2024-12-07, from `https://www.annualreviews.org/doi/10.1146/annurev-economics-082019-112339` doi: 10.1146/annurev-economics-082019-112339

Agte, P., Allende, C., Kapor, A., Neilson, C., & Ochoa, F. (2024). Search and biased beliefs in education markets. *Econometrica*. (Revise and Resubmit)

Ajayi, K., & Sidibe, M. (2020, January). *School Choice Under Imperfect Information* [SSRN Scholarly Paper]. Rochester, NY. Retrieved 2025-05-22, from `https://papers.ssrn.com/abstract=3524535` doi: 10.2139/ssrn.3524535

Allende, C., Gallego, F., & Neilson, C. (2019). *Approximating the equilibrium effects of informed school choice* (Tech. Rep.).

Arteaga, F., Kapor, A. J., Neilson, C. A., & Zimmerman, S. D. (2022). Smart matching platforms and heterogeneous beliefs in centralized school choice. *The Quarterly Journal of Economics*, *137*(3), 1791–1848.

Aygün, O., & Turhan, B. (2020, July). Dynamic reserves in matching markets. *Journal of Economic Theory*, *188*, 105069. Retrieved 2024-12-07, from https://linkinghub.elsevier.com/retrieve/pii/S0022053120300661 doi: 10.1016/j.jet.2020.105069

Beggs, S., Cardell, S., & Hausman, J. (1981). Assessing the potential demand for electric cars. *Journal of Econometrics*, *17*(1), 1-19.

Bellei C, C. (2013). El estudio de la segregación socioeconómica y académica de la educación chilena. *Estudios pedagógicos (Valdivia)*, *39*(1), 325–345. Retrieved 2024-12-07, from http://www.scielo.cl/scielo.php?script=sci_arttext&pid=S0718-07052013000100019&lng=en&nrm=iso&tlng=en doi: 10.4067/S0718-07052013000100019

Bertelsmann Stiftung. (2020, October). Automating Society Report 2020. *AlgorithmWatch*. AlgorithmWatch. Retrieved 2025-05-22, from https://automatingsociety.algorithmwatch.org

Biblioteca del Congreso Nacional. (2016, August). *Decreto 152: Aprueba reglamento del proceso de admisión de los y las estudiante de establecimientos educacionales que reciben subvención a la educación gratuita o aportes del estado.* Retrieved 2024-12-07, from https://www.bcn.cl/leychile/navegar?idNorma=1093444

Bjerre-Nielsen, A., Christensen, L. S., Gandil, M. H., & Sievertsen, H. H. (2023). Playing the system: address manipulation and access to schools. *arXiv preprint arXiv:2305.18949*.

Bobba, M., & Frisancho, V. (2022). Self-perceptions about academic achievement: Evidence from mexico city. *Journal of Econometrics*, *231*(1), 58–73.

Calsamiglia, C., Haeringer, G., & Klijn, F. (2010). Constrained school choice: An experimental study. *American Economic Review*, *100*(4), 1860–1874.

Carrasco, A., Bogolasky, F., Flores, C., Gutiérrez, G., & San Martin, E. (2014). *Selección de Estudiantes y Desigualdad Educacional en Chile: ¿Qué tan coactiva es la regulación que la prohíbe?* (Tech. Rep.). CEPPE y Centro de Políticas Públicas, Universidad Católica de Chile. Retrieved from https://bibliotecadigital.mineduc.cl/handle/20.500.12365/18534

Chen, Y., & Sönmez, T. (2006). School choice: an experimental study. *Journal of Economic Theory*, *127*(1), 202-231. Retrieved from https://www.sciencedirect.com/science/article/pii/S0022053104002418 doi: https://doi.org/10.1016/j.jet.2004.10.006

Chumacero, R. A., Gómez, D., & Paredes, R. D. (2011). I would walk 500 miles (if it paid): Vouchers and school choice in chile. *Economics of Education Review*, *30*(5), 1103-1114. Retrieved from https://www.sciencedirect.com/science/article/pii/S0272775711000999 (Special Issue on Education and Health) doi: https://doi.org/10.1016/j.econedurev.2011.05.015

Correa, J., Epstein, N., Epstein, R., Escobar, J., Rios, I., Aramayo, N., … Subiabre, F. (2022, March). School Choice in Chile. *Operations Research*, *70*(2), 1066-1087. doi: 10.1287/opre.2021.2184

Correa, J., Epstein, R., Escobar, J., Rios, I., Bahamondes, B., Bonet, C., ... others (2019). School choice in chile. In *Proceedings of the 2019 acm conference on economics and computation* (pp. 325–343).

Delacrétaz, D. (2021). Processing reserves simultaneously. In *Proceedings of the 22nd acm conference on economics and computation* (pp. 345–346).

Department for Education UK. (2024, June). *Secondary and primary school applications and offers, Academic year 2024/25* [Explore education statistics]. Retrieved 2025-05-22, from https://explore-education-statistics.service.gov.uk/find-statistics/secondary-and-primary-school-applications-and-offers/2024-25 (publisher: Government UK)

Dubins, L. E., & Freedman, D. A. (1981). Machiavelli and the gale-shapley algorithm. *The American Mathematical Monthly*, *88*(7), 485–494. Retrieved 2025-05-26, from http://www.jstor.org/stable/2321753

Dur, U. M., Kominers, S. D., Pathak, P. A., & Sönmez, T. (2013). *The demise of walk zones in boston: Priorities vs. precedence in school choice* (Tech. Rep.). National Bureau of Economic Research.

Elacqua, G., Jacas, I., Krussig, T., Méndez, C., & Neilson, C. (2024). *The welfare effects of including household preferences in school assignment systems: Evidence from ecuador* (Discussion Papers No. 1110). Economic Growth Center, Yale University.

Fack, G., Grenet, J., & He, Y. (2019). Beyond truth-telling: Preference estimation with centralized school choice and college admissions. *American Economic Review*, *109*(4), 1486–1529.

Ferrand, E. (2021, June). *Affelnet: le rectorat de Paris se félicite de la réforme de la procédure d'affectation au lycée* [Etudes Supérieures]. Retrieved from https://etudiant.lefigaro.fr/article/affelnet-le-rectorat-de-paris-se-felicite-de-la-reforme-de-la-procedure-d-affectation-au-lycee_afe7b054-d7f3-11eb-9c31-47598425ca9d/

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

Hafalir, I. E., Yenmez, M. B., & Yildirim, M. A. (2013, May). Effective affirmative action in school choice: Effective affirmative action in school choice. *Theoretical Economics*, *8*(2), 325–363. Retrieved 2024-12-07, from http://doi.wiley.com/10.3982/TE1135 doi: 10.3982/TE1135

Hastings, J. S., & Weinstein, J. M. (2008, November). Information, School Choice, and Academic Achievement: Evidence from Two Experiments*. *Quarterly Journal of Economics*, *123*(4), 1373–1414. Retrieved 2025-06-01, from https://academic.oup.com/qje/article-lookup/doi/10.1162/qjec.2008.123.4.1373 doi: 10.1162/qjec.2008.123.4.1373

Hatfield, J. W., & Milgrom, P. R. (2005, September). Matching with contracts. *American Economic Review*, *95*(4), 913–935. Retrieved from https://www.aeaweb.org/articles?id=10.1257/0002828054825466 doi: 10.1257/0002828054825466

Hofflinger, A., Gelber, D., & Cañas, S. T. (2020). School choice and parents' preferences for school attributes in chile. *Economics of Education Review*, *74*, 101946.

Huerta Retamal, L. I. (2021). *Segregación y eficiencia en el Sistema de Admisión Escolar* (Master's thesis, Universidad de Chile). Retrieved 2024-12-07, from `https://repositorio.uchile.cl/handle/2250/181815`

Kapor, A. J., Neilson, C. A., & Zimmerman, S. D. (2020). Heterogeneous beliefs and school choice mechanisms. *American Economic Review*, *110*(5), 1274–1315.

Kojima, F. (2012). School choice: Impossibilities for affirmative action. *Games and Economic Behavior*, *75*(2), 685–693.

Kurata, R., Hamada, N., Iwasaki, A., & Yokoo, M. (2017, January). Controlled School Choice with Soft Bounds and Overlapping Types. *Journal of Artificial Intelligence Research*, *58*, 153–184. Retrieved 2025-06-02, from `https://jair.org/index.php/jair/article/view/11042` doi: 10.1613/jair.5297

Larroucau, T., Rios, I., Fabre, A., & Neilson, C. (2024). College application mistakes and the design of information policies at scale.

Laverde, M. (2024, June). *Distance to schools and equal access in school choice systems.* Retrieved from `https://drive.google.com/file/d/19HJFGmaf2HA56k3rNBgB_at4aSkG3Bpz/view`

McFadden, D. (1972). Conditional logit analysis of qualitative choice behavior.

My School DC. (2024). *Total Applicants and Results from 2014 - 2023.* Retrieved from `https://www.myschooldc.org/sites/default/files/dc/sites/myschooldc/page/attachments/SY23_24_Total_Applicants.pdf#:~:text=Unique%20applicants%20increased%20by%203,to%20the%20public%20health%20emergency`

Narita, Y. (2018). Match or mismatch? learning and inertia in school choice. *Learning and Inertia in School Choice (June 18, 2018)*.

Ndonga, W. (2014, January). Kenya: 200,000 Pupils to Miss Form One Places. Retrieved from `https://allafrica.com/stories/201401150132.html`

Neilson, C. (2024). *The rise of coordinated choice and assignment systems in education markets around the world* (Tech. Rep.). The World Bank.

Neilson, C., Arteaga, F., Kapor, A. J., & Zimmerman, S. D. (2021). Smart matching platforms and heterogeneous beliefs in centralized school choice.

Nielsen, R. S., & Andersen, H. T. (2019). Ethnic school segregation in copenhagen: A step in the right direction? *Urban Studies*, *56*(15), 3234–3250.

Otero, S., Barahona, N., & Dobbin, C. (2021). *Affirmative action in centralized college admission systems: Evidence from brazil.*

Pathak, P. A., & Sönmez, T. (2013). School admissions reform in chicago and england: Comparing mechanisms by their vulnerability to manipulation. *American Economic Review*, *103*(1), 80–106.

Train, K. E. (2009). *Discrete choice methods with simulation*. Cambridge university press.

Valenzuela, J. P., Bellei, C., & Ríos, D. D. L. (2014, March). Socioeconomic school segregation in a market-oriented educational system. The case of Chile. *Journal of Education Policy*, *29*(2), 217–241. Retrieved 2024-12-07, from https://www.tandfonline.com/doi/full/10.1080/02680939.2013.806995 doi: 10.1080/02680939.2013.806995

Chilean School Choice Problem Definition

The school assignment problem in Chile can be formally described using the standard one-to-many matching framework. Let $\mathcal{K}$ denote the set of educational levels, including pre-kindergarten and kindergarten (preschool), 1st through 8th grade (primary), and 9th through 12th grade (secondary). Each school program $c \in \mathcal{C}$ is offered at one or more levels in $\mathcal{K}$, and students can only apply to programs that correspond to their educational level. For clarity, the following exposition focuses on a single level; the interaction across levels, especially within family applications, is addressed later in the paper.

Let $\mathcal{S} = \{s_1, \ldots, s_N\}$ be the set of students and $\mathcal{C} = \{c_1, \ldots, c_M\}$ the set of school programs. Each program $c \in \mathcal{C}$ has a finite capacity denoted $C_c \in \mathbb{N}$, representing the number of available seats. Students are endowed with strict preference orderings over programs, denoted $\succ_s$ for each $s \in \mathcal{S}$, where $c \succ_s c'$ indicates that student s strictly prefers program c over c'. Students who submit a truncated preference list are interpreted as preferring to remain unassigned rather than be placed in an unlisted school.

Each school program $c \in \mathcal{C}$ has a weak priority ordering $\gtrsim_c$ over students, where $s \gtrsim_c s'$ means student s has weakly higher priority than s' at program c. These weak orderings are then refined into strict priority rankings $\succ_c$ through random tie-breaking mechanisms, resulting in strict profiles $\succ_{\mathcal{C}} = (\succ_{c_1}, \ldots, \succ_{c_M})$.

A matching μ is a function that maps students and programs to one another such that:

1. For each student $s \in \mathcal{S}$, $\mu(s) \in \mathcal{C} \cup \{\varnothing\}$, where $\mu(s) = \varnothing$ denotes that s is unassigned.
2. For each program $c \in \mathcal{C}$, $\mu(c) \subseteq \mathcal{S}$ and $|\mu(c)| \leq C_c$.
3. For all $s \in \mathcal{S}$ and $c \in \mathcal{C}$, $c = \mu(s)$ if and only if $s \in \mu(c)$.

This formalism ensures that matchings respect both capacity constraints and the one-to-one assignment constraint on students. That is, no school may admit more students than it has seats, and no student may be assigned to more than one program.

Travel Distances and Time Computation

To estimate travel distances and durations between students and school programs, I implement a multi-step process combining spherical approximations and network-based routing algorithms. The procedure begins by collecting geographic coordinates (latitude and longitude) for all students and schools from administrative datasets, which serve as the basis for all subsequent computations.

Using these coordinates, I calculate great-circle distances between each student-program pair by applying the Haversine formula. This approach yields a spherical approximation of the shortest distance between two points on the Earth's surface. Only pairs with distances under 5 kilometers, as measured by this method, are retained for further processing. This filtering step ensures computational feasibility and restricts the analysis to spatially relevant alternatives. The Haversine distance is computed using Equation 10.

For the filtered set of pairs, I compute precise travel distances and durations using the Open Source Routing Machine (OSRM), which enables mode-specific routing. Under the car profile, OSRM uses vehicular road networks to estimate travel times, incorporating constraints such as speed limits and traffic accessibility. Under the pedestrian profile, it emphasizes walking paths, sidewalks, and pedestrian-safe routes to yield realistic walking times.

In the rare cases where OSRM fails to return a valid estimate (fewer than 1% of cases), I fall back on the Haversine distance as a proxy. Travel times are then imputed assuming constant average speeds: 30 km/h for vehicle travel and 5 km/h for walking.

Haversine Formula for Great-Circle Distance

$$d = 2r \cdot \arcsin\left(\sqrt{\sin^2\left(\frac{\Delta\phi}{2}\right) + \cos(\phi_1)\cos(\phi_2)\sin^2\left(\frac{\Delta\lambda}{2}\right)}\right) \tag{10}$$

Here, r denotes the Earth's radius, ϕ_1, ϕ_2 are the latitudes, and λ_1, λ_2 are the longitudes of the two points, all expressed in radians. The terms $\Delta\phi = \phi_2 - \phi_1$ and $\Delta\lambda = \lambda_2 - \lambda_1$ represent the respective coordinate differences.

Preference estimation

Table A-1: Grade Heterogeneity on Preferences Estimates: Complementary round

	Stated Preference Rank				
	Within 20 km Top georef. quality All levels	Within 20 km Top georef. quality Pre-Kinder & Kinder	Within 20 km Top georef. quality Elementary-School	Within 20 km Top georef. quality Middle-School	Within 20 km Top georef. quality High-School
Walking travel time (minutes)†	-0.696***	-1.230***	-1.100***	-0.502***	-0.550***
	(0.0331)	(0.105)	(0.0990)	(0.0881)	(0.0404)
Average SIMCE Math Score†	0.634***	0.909***	0.401***	0.322***	0.744***
	(0.0399)	(0.0943)	(0.0941)	(0.100)	(0.0583)
Private School (Co-payment)	0.211***	0.216***	0.292***	0.320***	0.136***
	(0.0239)	(0.0504)	(0.0515)	(0.0706)	(0.0366)
Afternoon	0.0222	-0.0308	-0.00218	0.0413	0.188***
	(0.0262)	(0.0406)	(0.0535)	(0.0973)	(0.0589)
Full Day	0.00613	0.139***	0.00406	0.00442	-0.0160
	(0.0214)	(0.0508)	(0.0480)	(0.0516)	(0.0332)
Priority: Currently Enrolled	-1.870**	35.78***	-31.63***	-30.41***	-28.84***
	(0.758)	(0.758)	(0.737)	(0.777)	(0.544)
Priority: Sibling Attending	0.690***	1.077***	0.608***	0.427***	0.614***
	(0.0526)	(0.114)	(0.112)	(0.117)	(0.0893)
Priority: Child of School Staff	0.815***	1.228***	0.450	1.114***	0.538
	(0.195)	(0.332)	(0.326)	(0.416)	(0.465)
Priority: Child of Alumni	0.837***	1.259***	1.049***	0.890***	0.651***
	(0.0429)	(0.249)	(0.0819)	(0.0736)	(0.0721)
Applications	57904	11193	12344	9093	25274
Applicants	21667	4160	4771	3537	9199
Pseudo-R2	0.0308	0.0454	0.0487	0.0379	0.0222
Min. preference length	2	2	2	2	2
Avg. preference length	2.672	2.691	2.587	2.571	2.747
Max. preference length	46	46	34	21	17

Notes: Notes: †Coefficient estimates and standard errors are multiplied by 100. Standard errors in parentheses and clustered at the applicant level. Additional controls are included but omitted from the table to preserve space. This table reports estimates from the conditional logit model described earlier. The dependent variable is the stated rank order of school options. All models are restricted to alternatives located within 20 km of the student's residence and to students with the highest available georeferenced quality data. Column (1) considers all grades, and columns (2)–(5) further stratify the sample by educational level. Coefficients represent the marginal utility of school attributes: positive coefficients indicate higher likelihood of a school being ranked more favorably (i.e., earlier in the preference list), while negative coefficients reflect decreased preference. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

Preference estimation robustness

A-1 Radius selection

Table A-2: Radius Heterogeneity on Preferences Estimates: Main Round

	Stated Preference Rank					
	Within 100 km Only best quality All levels	Within 50 km Only best quality All levels	Within 20 km Only best quality All levels	Within 10 km Only best quality All levels	Within 50 km Only best quality All levels	Within 2 km Only best quality All levels
Walking travel time (minutes)†	-0.262***	-0.522***	-0.800***	-1.260***	-2.210***	-6.160***
	(0.00591)	(0.00920)	(0.0101)	(0.0140)	(0.0248)	(0.102)
Average SIMCE Math Score†	0.657***	0.689***	0.706***	0.723***	0.756***	0.847***
	(0.00874)	(0.00893)	(0.00917)	(0.00988)	(0.0121)	(0.0249)
Private School (Co-payment)	0.110***	0.107***	0.111***	0.134***	0.140***	0.137***
	(0.00476)	(0.00484)	(0.00497)	(0.00535)	(0.00669)	(0.0151)
Afternoon	-0.103***	-0.104***	-0.105***	-0.109***	-0.120***	-0.114***
	(0.00608)	(0.00616)	(0.00626)	(0.00658)	(0.00757)	(0.0136)
Full Day	0.0243***	0.0208***	0.0187***	0.0266***	0.0307***	0.0540***
	(0.00492)	(0.00501)	(0.00513)	(0.00554)	(0.00676)	(0.0133)
Priority: Currently Enrolled	-5.073***	-5.082***	-5.061***	-4.993***	-4.867***	-4.580***
	(0.0306)	(0.0309)	(0.0312)	(0.0322)	(0.0358)	(0.0574)
Priority: Sibling Attending	1.437***	1.444***	1.457***	1.494***	1.553***	1.793***
	(0.0124)	(0.0125)	(0.0128)	(0.0134)	(0.0151)	(0.0252)
Priority: Child of School Staff	1.092***	1.129***	1.154***	1.179***	1.177***	1.527***
	(0.0456)	(0.0467)	(0.0481)	(0.0525)	(0.0606)	(0.110)
Priority: Child of Alumni	0.179***	0.158***	0.146***	0.147***	0.147***	0.172***
	(0.0173)	(0.0177)	(0.0183)	(0.0196)	(0.0238)	(0.0453)
Applications	1040501	1016255	975169	865621	627171	194805
Applicants	287581	282481	272776	248407	191487	70499
Pseudo-R2	0.189	0.192	0.193	0.198	0.212	0.261
Min. preference length	2	2	2	2	2	2
Avg. preference length	3.618	3.598	3.575	3.485	3.275	2.763
Max. preference length	93	93	53	53	53	15

Notes: †Coefficient estimates and standard errors are multiplied by 100. Standard errors in parentheses, clustered at the applicant level. Additional controls are included in the model but omitted from the table for brevity. This table reports estimates from conditional logit models where the dependent variable is the stated preference rank of school options. All columns are restricted to alternatives with top-tier georeferencing quality. Each column varies the radius used to define the choice set, ranging from 100 km to 2 km. Coefficients represent the marginal utility associated with each attribute: positive values indicate higher likelihood of a school being ranked more favorably, while negative values imply reduced preference. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

Table A-3: Radius Heterogeneity on Preferences Estimates: Complementary Round

	Stated Preference Rank					
	Within 100 km Only best quality All levels	Within 50 km Only best quality All levels	Within 20 km Only best quality All levels	Within 10 km Only best quality All levels	Within 50 km Only best quality All levels	Within 2 km Only best quality All levels
Walking travel time (minutes)†	-0.318***	-0.445***	-0.696***	-1.050***	-1.780***	-3.810***
	(0.0241)	(0.0284)	(0.0331)	(0.0498)	(0.0939)	(1.120)
Average SIMCE Math Score†	0.599***	0.613***	0.634***	0.659***	0.689***	0.812***
	(0.0383)	(0.0386)	(0.0399)	(0.0436)	(0.0558)	(0.300)
Private School (Co-payment)	0.209***	0.205***	0.211***	0.212***	0.272***	0.447**
	(0.0229)	(0.0231)	(0.0239)	(0.0262)	(0.0335)	(0.193)
Afternoon	0.0157	0.0171	0.0222	0.0116	-0.0194	-0.0738
	(0.0255)	(0.0256)	(0.0262)	(0.0280)	(0.0338)	(0.188)
Full Day	-0.00214	-0.00155	0.00613	0.00483	-0.0000229	0.126
	(0.0207)	(0.0208)	(0.0214)	(0.0232)	(0.0292)	(0.158)
Priority: Currently Enrolled	-1.922**	-1.903**	-1.870**	-1.874**	-1.887**	0
	(0.757)	(0.757)	(0.758)	(0.754)	(0.750)	(.)
Priority: Sibling Attending	0.682***	0.684***	0.690***	0.717***	0.771***	0.684***
	(0.0518)	(0.0518)	(0.0526)	(0.0551)	(0.0641)	(0.263)
Priority: Child of School Staff	0.851***	0.881***	0.815***	0.834***	0.679***	1.102
	(0.183)	(0.188)	(0.195)	(0.206)	(0.242)	(0.780)
Priority: Child of Alumni	0.820***	0.826***	0.837***	0.848***	0.891***	1.018***
	(0.0418)	(0.0420)	(0.0429)	(0.0453)	(0.0521)	(0.217)
Applications	61084	60464	57904	50849	34485	1359
Applicants	22673	22442	21667	19406	13855	636
Pseudo-R2	0.0258	0.0275	0.0308	0.0341	0.0433	0.0818
Min. preference length	2	2	2	2	2	2
Avg. preference length	2.694	2.694	2.672	2.620	2.489	2.137
Max. preference length	46	46	46	46	15	5

Notes: †Coefficient estimates and standard errors are multiplied by 100. Standard errors in parentheses, clustered at the applicant level. Additional controls are included in the model but omitted from the table for brevity. This table reports estimates from conditional logit models where the dependent variable is the stated preference rank of school options. All columns are restricted to alternatives with top-tier georeferencing quality. Each column varies the radius used to define the choice set, ranging from 100 km to 2 km. Coefficients represent the marginal utility associated with each attribute: positive values indicate higher likelihood of a school being ranked more favorably, while negative values imply reduced preference. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

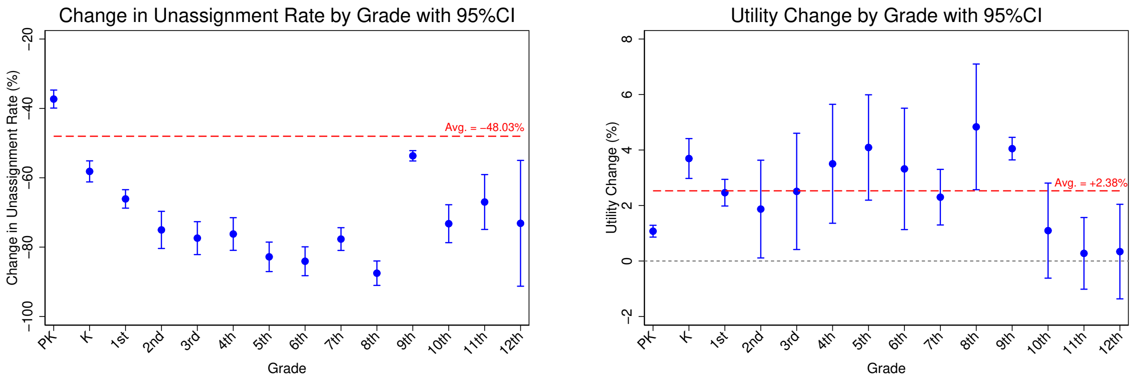
A-2 Alternative models

Table A-4: Main-Round Effects: Original vs. Alternative Models

	Foot-time (Baseline)			+Quadratic Foot-time		Car-time		Min(Foot-time,Car-time)		Foot distance (km)	
Metric	**Orig.**	**Ext.**	**Δ (%)**	**Ext.**	**Δ (%)**	**Ext.**	**Δ (%)**	**Ext.**	**Δ (%)**	**Ext.**	**Δ (%)**
Panel A: Unassignment Rate											
Fraction Unassigned	8.07%	4.20%	−48.03%***	4.09%	−49.32%***	4.06%	−49.70%***	4.06%	−49.70%***	4.17%	−48.32%***
Panel B: Assignment Transitions (conditional on being assigned)											
Same assignment	–	73.26%	–	73.31%	–	73.24%	–	73.12%	–	73.27%	–
Gained assignment	–	–	+5.28%	–	+5.37%	–	+5.38%	–	+5.38%	–	+5.28%
Lost assignment	–	–	+1.40%	–	+1.38%	–	+1.37%	–	+1.37%	–	+1.38%
Different program	–	17.27%	–	17.24%	–	17.32%	–	17.43%	–	17.28%	–
Panel C: Mean Utility											
Conservative, $U(\text{Unassigned}) = 0$	0.1500	0.1534	+2.28%***	0.1534	+2.28%***	0.1436	+2.48%***	0.1437	+2.49%***	0.1429	+2.50%***
Optimistic, $U(\text{Unassigned}) = -\bar{U}$	0.1378	0.1471	+6.74%***	0.1471	+6.74%***	0.1378	+6.96%***	0.1378	+6.96%***	0.1369	+6.85%***

Notes: This table presents the effects of implementing the preference-extension mechanism in the main round under five different travel-cost specifications. Foot-time is the baseline model; the remaining columns show results when I (i) add a quadratic term to walking time, (ii) use driving time costs, (iii) take the minimum of walking and driving time, and (iv) use the walking distance in kilometers. Panel A reports the fraction of students left unassigned before ("Orig.") and after ("Ext.") extension, along with the percent change. In Panel B tracks assignment-transition rates (same assignment, gained, lost, or switched program) conditional on being assigned under either scenario. Finally, Panel C reports changes in mean utility under two scenarios for unassigned students. Asterisks indicate statistical significance at the 1% level (***).

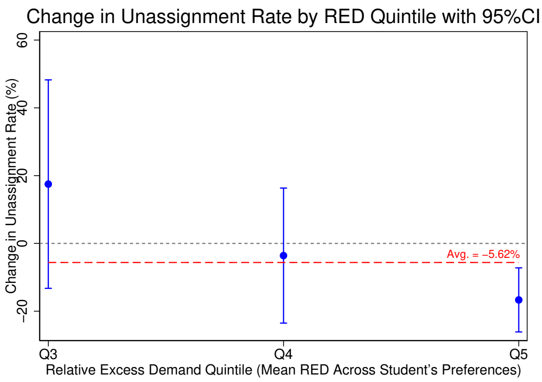
A-3 Heterogeneous Effects



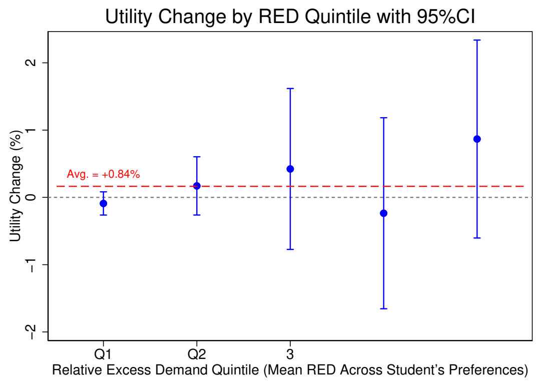
(a) Unassignment Rate Change by Grade

(b) Utility Change by Grade

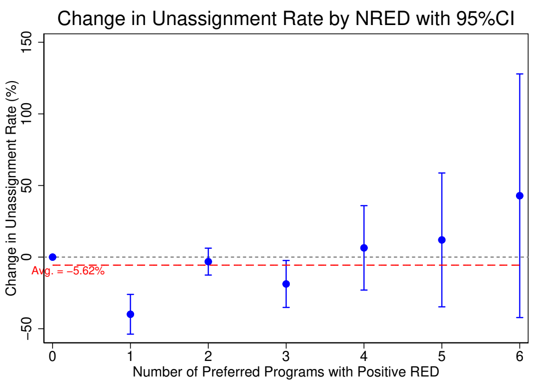
Figure A-1: Changes in Unassignment and Utility Outcomes by Grade: Main round



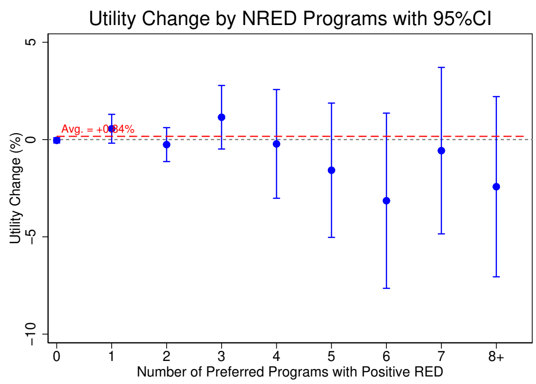
(a) Unassignment Rate Change by MRED Quintile



(b) Utility Change by MRED Quintile



(c) Unassignment Rate Change by NRED Programs



(d) Utility Change by NRED Programs

Figure A-2: Changes in Unassignment and Utility Outcomes by Measures of Exposure to Excess Demand: Complementary round