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Rodrigo Icaran S.

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Icaran, Sagaceta, Rodrigo Ignacio

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Rodrigo Ignacio Icaran Sagaceta

Comisión

Nicolás Figueroa
Kenzo Asahi

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Worthwhile or Not? Estimating the Impacts of AI-based Recommendation Systems on Chile's School Choice System*

Rodrigo Icaran†
Instituto de Economía
Pontificia Universidad Católica de Chile

Abstract

This paper studies the effects of implementing a recommender system in the context of the Chilean School Choice System. We develop an artificial intelligence-based algorithm for suggesting schools to students. Using these suggestions as input, and conjecturing different levels of acceptance rates by the population, we evaluate the general equilibrium effects of this policy. If, on average, students accepted one suggestion each, this technology could decrease the percentage of non-assigned students by 1.5pp. However, since good schools are a scarce resource, not everyone benefits from this policy. We find minor effects on commuting distances and assigned schools' SIMCE scores. Also, we show that this technology has small but negative impacts on social welfare from a utilitarian perspective. Our results offer powerful insight for public policy and suggest that the impacts of a recommender system in a context of rival goods may be counterintuitive.

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†Mail:riicaran@uc.cl

1 Introduction

Humans make decisions, based on their available information, all the time. However, there is strong evidence that people do not necessarily translate information into usable knowledge to make decisions (Handel and Schwartzstein, 2018). For instance, people may choose a health insurance plan that costs $500 per year more in premiums in order to obtain a deducible that is $250 lower (Bhargava et al., 2017). Similarly, consumers tend to demand the wrong cell phone plans given their previous usage patterns (Grubb and Osborne, 2015). The research literature has identified one possible explanation for this phenomenon: friction gaps. Essentially, they are related to the costs of acquiring and processing information. Exploring more options in a choice set and assessing them is not cost-free, so agents may not do it even if, ex-post, it would be optimal for them. These gaps are not homogeneously present within the population. Poor people might have additional difficulties in estimating the returns to investments (Banerjee and Duflo, 2012; Jensen, 2010). Furthermore, and more relevant to this paper's context, low SES students face a high cost in acquiring information about academic choices (Hastings and Weinstein, 2008).

In many aspects, technology has made our lives easier. One technological innovation that has started to gain more importance in the last decades is artificial intelligence. Taking advantage of the increasing availability of data, algorithms have begun to help us in decision-making processes on our daily-basis. Recommender Systems have been widely implemented in internet applications to reduce information costs. When we search for a movie on Netflix, an intelligent algorithm is behind the scenes trying to suggest the best film. Likewise, at the moment we get tired of a particular song, Spotify recommends a song an algorithm predicts is suitable for us. Amazon does the same thing when it tries to sell us articles that people like us frequently buy. The list goes on and on. However, interestingly, all these examples belong to private companies. Almost no recommendation system has been implemented in a public service context (Cortés-Cediel et al., 2017).

This paper studies the effects of implementing a recommender system in the Chilean School Choice System. We first start reviewing the most popular recommendation system algorithms and argue which of them are appropriate in our context. Later, we implement them and report suggestive evidence of the quality of our suggestions. At least three of the most popular algorithms fail in generating reasonable recommendations, making them non-viable.

Then, we implemented an alternative artificial intelligence algorithm that delivered reasonable suggestions. Indeed, its recommendations are not only reasonable but also optimal. In 17.91% of the cases, our best suggestion is closer than the student's farthest application and has a better SIMCE score than his best application. In other words, it is not only closer but also academically better than all of the student's applications. We present evidence that suggests that our algorithm is correctly inferring students' revealed preferences, based on school-student distance, schools' yearly tuition, and SIMCE scores.

Distinguishing between Priority (low SES) and Non-Priority students (middle-high SES), we find that our recommender system might be giving extra utility gains for the latter. Although unlike a traditional econometric method, our approach does not provide us causal tools to explain this difference, we postulate some hypotheses. We suggest that this is likely related to the fact that, on average, Priority students tend to apply better, in terms of their preferences, than Non-Priority students. Indeed, Non-Priority Students do not apply, on average, to 7.6 schools with higher utility levels than their best application. In contrast, for Priority Students, this number stands at 5.9 schools. However, given that the Chilean School Choice System is based on a Deferred Acceptance algorithm, these ex-ante differences are not necessarily reflected in the final assignations.

Finally, using our suggestions as input and conjecturing different levels of acceptance rates by the population, we evaluate the general equilibrium effects of this system under a Gale-Shapley algorithm. We estimate that if students accepted, on average, one suggestion each, this technology could decrease the percentage of non-assigned students during the first stage by 1.5pp. We evaluate our algorithm's effects on observable outcomes, and characterize winners and losers. We find minor effects on school-student commuting distances and assigned schools' SIMCE scores. However, we do find small but negative impacts on social welfare, which can be mainly explained by the competition created by the introduction of our system. Winners start to harm other students in a magnitude that may be higher than the gain of the former. These results offer powerful insight for public policy and may be interpreted broadly. In a context of rival goods, the aggregate impacts of a recommendation system may be counterintuitive since individuals start to compete for scarce goods. Moreover, we show that our system reduces the standard deviation of utility levels, which may be interpreted as a measure of inequality between agents.

In practice, our algorithm could have, at least two useful applications. First, it might help to reduce the number of unassigned students during the main phase, which in 2018 was roughly 18% of all the applicants.[1] Second, it may help to assign students that never entered the application system. Our system is capable of recommending schools only with a few attributes of a student, even if he did not apply to any school.

This work contributes to the literature in several dimensions. First, to the best of our knowledge, no recommendation system has been implemented in a school choice process. In

[1]That entered the application system during this phase.

fact, Rivera et al. (2018) found that there is a lack of research in the use of intelligent algorithms to improve academic choices. Second, it suggests new strategies to enhance academic choices in centralized application systems like the one presented by Neilson et al. (2019). Still, in contrast to this work, they evaluate a program that provides personalized information to applicants using a video and a report card. They show that capacity constraints in the supply-side may severely affect the positive impacts of a personalized information provision intervention. Despite using a different approach, their results are along the same lines as ours. Third, as far as we know, it is the first paper that evaluates the impact of a recommender system in a context of rival goods. The impacts of recommending rival goods may be different from the ones observed in internet applications since agents start competing for them. Fourth, it contributes to the insufficient literature that evaluates the impact of recommendation systems in public service contexts (Cortés-Cediel et al., 2017).

This paper is organized as follows. Chapter 2 presents a brief description of the Chilean education system and its recent reforms. Chapter 3 presents basic data sources. Next, Chapter 4 reviews recommendation systems and presents our final model. Later, Chapter 5 analyzes our suggestions and studies the differences between SES groups. Then, Chapter 6 studies the general equilibrium effects of our policy on observable outcomes. Chapter 7 evaluates the impact of our technology on social welfare. Chapter 8 presents a robustness test. Finally, Chapter 9 briefly concludes.

2 The Chilean Context

Until 1981, the Chilean Educational System consisted of three types of schools: public, paid private and free private schools. The first ones were funded and managed by the central government and enrolled most of the population. Paid private schools, on the contrary, were run by privates and charged high tuition fees, making them unaffordable for the majority of the students. Free private schools were also run by privates but received partial public funding and donations.

The 1981 educational reform radically changed the structure of the Chilean Educational System. It introduced a voucher system and resulted in the emergence of the following types of schools: publicly owned schools (now funded and managed by local governments), voucher schools (owned by private agents), and non-voucher private schools. The latter do not receive public funding and are not included in the centralized admission system, so they are totally excluded from our analysis.

Chile has one of the lowest levels of social inclusion in their schools among OECD countries. Students with similar socioeconomic status tend to study in the same schools. (OECD, 2016). Partly due to this, the Chilean educational system has experienced multiple reforms during the last decades. In 2008, the Preferential School Subsidy Law (SEP) was passed by congress, which introduced important changes to the voucher system. This reform introduced an additional subsidy for Priority Students (low SES), which are roughly in the 40th percentile of the income distribution. Also, schools with a high concentration of low-SES students started receiving a special bonus. These economic incentives recognized that educating low-SES students implies higher costs. To be part of this program, schools have to fulfill several requirements. First, they are not allowed to charge any tuition to Priority students, aiming to attract a larger number of low-SES students to these types of schools. Second, they are not allowed to select their students based on their academic achievement. Third, they must share their accounting records with the government to ensure the correct use of the additional public funding.

Despite these reforms, the Chilean Educational System continues to be highly segregated (Valenzuela et al., 2014; Elacqua, 2012). Attempting, again, to reduce educational inequality, the Chilean congress passed another educational reform during 2016. It involved three main points. First, it banned for-profit schools from receiving public funding. Second, it prohibited that private voucher schools charged any tuition to students if they received public funding. The third point - and the most relevant to this work - involved the implementation of a centralized admission system for public and private voucher schools. Based on evidence that indicated that student selection was a widespread practice among private voucher schools (Contreras et al., 2010), this new system aimed to centralize all admissions, not giving any chance to schools to select their students.

The new admission system is called Sistema de Admisión Escolar (from now on, SAE). It is based on the famous Deferred Acceptance (DA) algorithm proposed by Gale and Shapley (1962). Basically, families must apply to their most-preferred schools with a rank-order logic through a government-run website. The matching process is entirely managed by the government and does not involve any intervention by schools, except informing their available vacancies every year. This ensures schools do not have any space for selecting their future students.

The school-student matching process is simple. If the number of applicants is lower than the number of available vacancies in one school, all students get accepted. However, if the number of applicants exceeds the number of vacancies, the law establishes a tiebreaker criteria. It gives the highest priority to applicants whose sibling is already enrolled in that school. It also prioritizes Priority students, students that have parents working in that school, and students that were previously enrolled in a certain school. Finally, applicants with the same priority level are randomly selected. Students that are not selected during the main phase may apply again in a complementary stage. Those that are not matched to any school during the latter, are assigned to their closest school with available seats.

3 Data

We only consider Pre-Kindergarten (PK) applications that took place during 2019 in the city of Santiago.[2] We work exclusively with Chile's capital city since it concentrates roughly half of the Chilean population and therefore, general equilibrium effects may be easily identified. Additionally, Santiago offers a high diversity of school options in each district, which may be recommended to each student. In rural contexts, schools might be more distant and hence, difficult to recommend. Both reasons make this city ideal for evaluating the general equilibrium effects of a Recommendation System. It is worth specifying that we only give recommendations to students that applied exclusively to schools in Santiago.[3] Students who applied to schools in Santiago but also to schools in other parts of the country were not considered since they could eventually confuse our algorithm.[4] Also, our system would not know where to give them a recommendation.

SAE's database has information about students and schools. From students, we know their rank-ordered school choices, gender, geographic coordinates,[5] siblings in the system, and if they are part of the Priority group (low SES group). In addition, we know their final assignment in the centralized system. On the other hand, from schools, we have data about their offered vacancies, religion type, geographic coordinates, and their tuition. Nonetheless, in our dataset, schools' tuition is expressed in intervals of payments. Following previous work on SAE (e.g., Baloian, 2019; Tagle, 2018) we take the median value of each interval as the numeric value of it.

We also combine SAE's database with other publicly available datasets. The SEP dataset allows us to identify schools that have an economic agreement with the Chilean government. In our context, this characteristic is relevant since Priority students are exempt from paying tuition in these types of schools, even if the general fee is positive. We consider this interaction in our statistics that involve payments. Additionally, we use SIMCE's 2018 results

[2]Being more specific, we work with the Metropolitan Region, which apart from Santiago includes some rural towns that have a high level of interconnection with Santiago.

[3]Also, when studying general equilibrium effects, only these students are taken into account.

[4]These students are evidently different from the rest. Likely they are moving house.

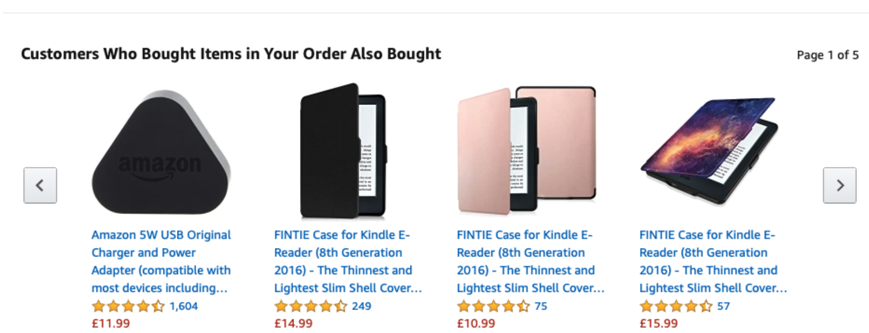
[5]For privacy concerns, these coordinates include a normal error. A reasonable geographic location is available only for 73% of the students. For the remaining percentage, we assumed they lived in the applied school that minimized the distance between the first three applications of each student. As a reference, for well-located students, this imputation procedure, on average, produced a difference of 2.10 Km. (but with high variance, median value: 1.10 Km.) between the imputed and the real address. Additional statistics are available in Table A1 in Appendix B.

as a proxy of the academic performance of each school. Specifically, we define the average between Maths and Spanish in fourth grade as a proxy. Finally, we calculate the percentage of Priority students in each school with public administrative records from the Chilean government.

4 Recommendation Systems

Recommendation Systems have been widely used for a long time. Goldberg et al. (1992) was one of the first papers that presented an intelligent algorithm to provide personalized suggestions to each user. Briefly, the authors realize that many users began to be inundated with hundreds of electronic messages each day with the introduction of email, which they seldom read. To tackle this issue, they developed a system that delivers only messages that each user will likely read. At first, this scheme sounds quite simple. However, their novel contribution consisted of using information retrieved from the interactions of all users to give each person a personalized set of messages. In today's world, recommendation systems are present in almost any application or device we use. For example, Netflix is famous for implementing a precise algorithm that suggests movies to each user, based on user's characteristics and movies he previously watched but also on information provided by the community (Gomez-Uribe and Hunt, 2016). Similarly, Amazon recommends products to its customers, considering past purchases (Linden et al., 2003). Analogous systems have been developed by Spotify, for recommending new songs and by Facebook, for suggesting new friends; among others.[6]

Figure 1: Example of a Recommender System by Amazon



Even though there is plenty of research about recommender systems in AI and Data Science Journals, not too much has been done in Economics. Taking this into account, the

[6] Many applications have been implemented in diverse contexts.

present chapter firstly presents a general theoretical framework of Recommender Systems. Then, it characterizes the algorithm that is used in the rest of this paper and its results.

4.1 Basic Definition

Karlgren (1990)[7] was the first paper to formulate a definition of recommender systems. Although his definition is essentially informal, it has been extensively accepted for its simplicity. He basically claims that in a typical bookcase, similar books tend to be found near to each other. However, this does not happen by chance. Akin books are often close since someone sorted them in this way. Hence, it is likely that when someone goes to a library and looks for a book, he will also like the nearest ones. In this context, the user is given a recommendation. The bookcase, indirectly, suggests books based on the user's preferences. In that line, a recommendation system's role is to be a digital bookcase and give personalized recommendations to users based on their preferences.

More formally, according to Lu et al. (2015) recommendation systems can be defined as "programs which attempt to recommend the most suitable items to particular users[8] by predicting a user's interest in an item based on related information about the items, the users, and the interactions between items and users". In other words, recommender systems try to "guess" a user's preferences based on his behavior and other users to provide personalized recommendations. Apart from behavior, they can also use metadata[9] as input, depending on the algorithm type.

Mathematically, the concept can be expressed using a matrix (from now on, an *interaction matrix*) which summarizes the relations between users and items. Figure 2 represents an interaction matrix, in which rows are users and columns are items. The matrix's values are the particular rating each user gives to each item. Only for illustrative purposes, we will assume ratings can take a value between 1 and 100. However, not all users score every item, so there are blank values inside the matrix.[10]

[7] Anecdotally, this paper was never published. It was rejected by the referees since - according to them - a recommender system could interfere with users' privacy.

[8] In the context of this paper, items are schools. Analogously, users are students.

[9] Users' and items' features.

[10] To be clearer, blank values were filled with dots.

Figure 2: 4 (users) × 6 (items) Interaction Matrix

$$\begin{array}{cc} & \begin{array}{cccccc} i_1 & i_2 & i_3 & i_4 & i_5 & i_6 \end{array} \\ \begin{array}{c} u_a \\ u_b \\ u_c \\ u_d \end{array} & \begin{bmatrix} 50 & . & 99 & . & . & . \\ 30 & 80 & . & . & . & 20 \\ 20 & 15 & 49 & . & . & 11 \\ 15 & 19 & . & . & . & . \end{bmatrix} \end{array}$$

For example, in the interaction matrix presented in Figure 2 user u_a scored items i_1 and i_3 with 50 and 99, respectively. But he did not rate items i_2, i_4, i_5 and i_6. As explained above, a recommendation system's goal is to give every user a personalized suggestion. For this, it fills the matrix's blank values using AI-based prediction tools that will be explained later. Filling our interaction matrix with predicted ratings (in bold), we get the matrix in Figure 3.

Figure 3: 4 (users) × 6 (items) Predicted Matrix

$$\begin{array}{cc} & \begin{array}{cccccc} i_1 & i_2 & i_3 & i_4 & i_5 & i_6 \end{array} \\ \begin{array}{c} u_a \\ u_b \\ u_c \\ u_d \end{array} & \begin{bmatrix} 50 & \mathbf{35} & 99 & \mathbf{29} & \mathbf{67} & \mathbf{80} \\ 30 & 80 & \mathbf{29} & \mathbf{15} & \mathbf{91} & 20 \\ 20 & 15 & 49 & \mathbf{9} & \mathbf{7} & 11 \\ 15 & 19 & \mathbf{1} & \mathbf{6} & \mathbf{56} & \mathbf{40} \end{bmatrix} \end{array}$$

Next, for every user items are sorted in descending order, according to their predicted ratings. Finally, it suggests to every user his first **N** items.[11] Evidently the algorithm will not consider the items the user already rated, since the goal is to produce suggestions.

For instance, with N=3, the sorted recommendation set for user u_a is:
$R_{u_a} = \{i_6, i_5, i_2\}$

4.2 Main Types of Algorithms

Recommendation Systems are usually classified into two types:[12] Collaborative filtering algorithms (CF) and Content-based algorithms (CB) (Almazro et al., 2010). Nevertheless, a third type has emerged during the last years, mixing CF and CB models: Hybrid algorithms.

[11] N is a parameter fixed by the programmer. Some recommendation systems give many recommendations simultaneously, while others only offer one.

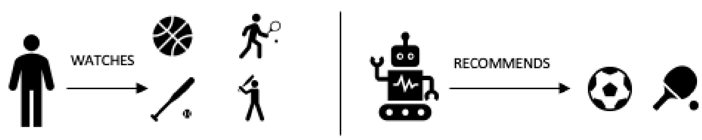
[12] Other types do exist. Here we present only the most popular ones, which are, besides, the only relevant to this paper.

4.2.1 Content-Based Models (CB)

Content-based models use the observable attributes (metadata) of items and/or users to generate recommendations. Typically, they first analyze the characteristics of the items a user previously rated well[13] and try to conclude the shared attributes between them. Subsequently, using these common characteristics, they calculate the similarity index[14] between the items which the user has already interacted with and the ones he has not seen (based on its attributes). Afterward, using this similarity index, they suggest to each user the most similar items to the ones they previously rated well. Notice that the similarity index in this algorithm is equivalent to a predicted rating.

Figure 4 illustrates this logic. If a user frequently watches sports movies, a CB model will recommend him more sports movies.

Figure 4: Intuition Behind a Content-Based Model



As opposed to Collaborative filtering models, which are reviewed below, there is no collaboration between users. This implies a model of this type can even be run in settings with few users and many items. Albeit, for giving optimal suggestions is crucial that there is abundant information (many attributes) available about items. We discuss later this is not possible in the context of this paper.

4.2.2 Collaborative Filtering Models (CF)

Collaborative filtering models build suggestions using information retrieved from all users. Basically, they infer that two users have common interests if they rate the same items with an equivalent score. After identifying a user's closest group, it recommends him the items the others have rated well, but the user has not seen.

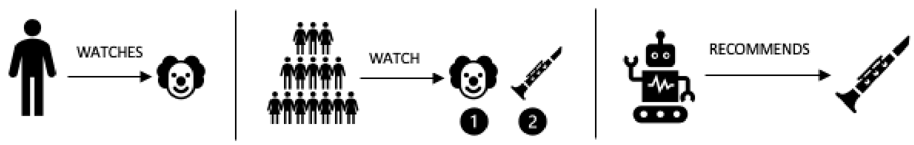
This idea is exemplified in a simplified way in Figure 5. Suppose a certain user watches comedy shows often. Besides, most of the people who watch comedy shows tend to view also musicals. Using statistical tools a CF model will conclude that our specific user is similar to the other people who also watch comedy shows. Thus, it will recommend him to watch musicals.

[13] Or bought/watched, depending on the context.

[14] Several similarity measures are available. The most popular one is the cosine similarity, which computes the distance between two vectors.

Notice that to accomplish its goal, it never needed the use of metadata. Neither from users nor items. This makes this type of algorithm ideal when there is a huge amount of interaction data between users and items and little information about attributes.

Figure 5: Intuition Behind a Collaborative Filtering Model



Moreover, inside collaborative filtering models, two major approaches can be distinguished:

- User-based: Algorithms identify similar users from their interactions with items. Similar users should rate the same items analogously. Then, each user is given suggestions considering well-rated items by - previously recognized - similar users.
- Item-based: Algorithms identify similar items. Generally, they recognize common patterns. For example, if two items are frequently well-rated by the same users, the model will conclude both items are similar. On the contrary, if two items are commonly rated oppositely, it will infer they are quite different. After identifying similar items, it recommends - every user - items similar to the ones he rated positively.

There is empirical evidence that item-based approaches get the same or even better results than user-based ones (Deshpande and Karypis, 2004; Sarwar et al., 2001). Furthermore, generally, the item-based approach demands fewer computer resources,[15] making it ideal for big-data contexts. Indeed, this method was first popularized by Amazon when they faced a big-dimension problem of millions of users and items (Linden et al., 2003).

4.2.3 Hybrid Models

A hybrid recommender system combines multiple recommendation techniques together to produce suggestions (Burke, 2007). Several hybrid models have been developed. Some of them run two or more models and combine their predictions only in the last step. Others, on the contrary, include content-based characteristics in a collaborative filtering approach - and vice versa. Netflix's recommendation system (Gomez-Uribe and Hunt, 2016) is one of the

[15]Usually, there are more users than items, so calculating the relationships between items requires fewer computations. Additionally, in dynamic contexts, relationships between items tend to be more static.

most popular hybrid algorithms. Mixing content-based and collaborative filtering algorithms to provide accurate suggestions, it has been crucial to Netflix's business value.

Hybrid algorithms have proven to be effective for dealing with pure CF and CB models' limitations (Pazzani, 1999; Balabanović and Shoham, 1997; Claypool et al., 1999). These issues are discussed in the next point.

4.2.4 Known Problems and Challenges

Despite their benefits, recommendation systems are not perfect. Three problems or challenges have been widely documented: cold start, sparsity and scalability.

Cold start: At the beginning, new users have not rated even a single item. Thus, without using additional methods, it is almost impossible to give them accurate, personalized recommendations. The same is also valid for new items, which have no rating when introduced in a system.

Diverse solutions have been proposed. Most of them imply using hybrid models. Schein et al. (2002) developed a hybrid model in which items and/or users are expressed in function of their attributes. In this way, the model does not learn directly from the interaction between users and items, but rather from the interaction between attributes. Assuming that attributes are known in advance, there should not exist a cold start problem with this technique. Alternatively, Rashid et al. (2002) propose different smart-sorting methods to show items to new users, gaining some insight into their preferences when they rate them.

Sparsity: Recommender Systems are designed to predict a big number of ratings using only a few interactions as input. However, if the number of interactions per user is extremely small, it can be very difficult to train a model to give useful suggestions. A small number of interactions makes it hard to extract users' preferences. Notice that in some way, Cold Start may be interpreted as a special case of sparsity, in which there is absolutely no interaction information about a user or item.

Again, like with cold start, one way to mitigate this problem is the use of Hybrid Systems, mixing collaborative functions with metadata of users and/or items. Pazzani (1999), for example, use - apart from their ratings - demographic information (gender, age, education, employment information, among others) to conclude that two users are similar. Huang et al. (2004) apply an associative retrieval framework, which considers transitive associations, to diminish sparsity problems.

Scalability: The execution time of a Recommender System is highly sensitive to the number of users and items. In many contexts, the amount of data increases exponentially in the short term. Additionally, with big databases, computational resources demand may go beyond acceptable levels. This high dimensionality makes delivering personalized real-time suggestions a practical challenge (Xin, 2015). For instance, in the case of a user-based CF, all user-user similarities have to be computed. As a result, the execution time is quadratic in the number of users.

Several methods to make algorithms scalable have been developed. As stated previously, Linden et al. (2003) popularized using a CF item-based approach instead of a user one. Other techniques to tackle this issue involve using clustering (Su and Khoshgoftaar, 2009) and Singular Value Decomposition (Billsus and Pazzani, 1998) methods.

4.3 The Model

Implementing a Recommendation System for the Chilean School Choice System is far away from being a simple task. As detailed previously in the Data Section, there is little information from students and schools. From the students, we only know - apart from their applications - their address,[16] gender, grade and if they are part of the high academic performance and/or the Priority group. On the other hand, for schools, we only have information about their tuition costs, location, available quotas and some proxies about their previous academic performance, like SIMCE. Considering this lack of attributes - and the absence of many others that families may take into account when making decisions - a Content-Based algorithm would likely not be capable of extracting user preferences' (Lops et al., 2011). Hence, at first, we developed Collaborative Filtering algorithms since they only need interaction information as input.

Nevertheless, the way in which people apply to schools - i.e., directly ranking their preferences - is non-standard for recommendation systems. Most recommender systems are designed for working either with explicit or implicit feedback. In explicit feedback, users are explicitly asked to rate items with a score. These scores are used by the algorithm to make predictions. On the other hand, in implicit feedback, the algorithm only knows if a user bought/chose/watched an item. It is implicit because the system only knows if a user interacted with an item, but not if he actually liked it.

In SAE, users are asked to inform an ordered ranking of their preferred schools. Even though this could sound similar to explicit feedback, it has significant differences. First, users are asked to inform strict[17] preferences relations, so it is not possible that - for the

[16]However, as noted in the Data Section, this variable is imperfect.

[17]In the sense that they are not allowed to rank two schools in the same position.

same user - two items have the same score. This constraint does not exist in a usual explicit feedback context, where users may rate two items with the same score. Second, there is no restriction on the number of schools a user may rank.[18] In consequence, the maximum score given by each user, is different and dependant on the number of schools applied. For instance, the maximum score given by a user who applied to two schools is 2, whereas, for one that applied to 8, it is 8. As a result, the scale of the scores may be quite different between users. Despite the fact that in explicit feedback, some users could be stricter than others,[19] ex-ante all users have the possibility of assigning scores using a common scale. This common scale is usually fixed by the programmer, asking users to give a rating between a lower and an upper limit. [20]

To the best of our knowledge, no recommendation system has been implemented in a context similar to this one. In addition to the above challenges, three empirical facts make this task more difficult. First, the interaction matrix of our dataset is very sparse. On average, each student only applies to 3.36 schools. This number is quite small, considering that there is no restriction on the number of applications per student and also that in our dataset, there are 1213 possible schools. As discussed previously, CF models might have difficulties in extracting users' preferences if the interaction matrix is too sparse. Second, there is no clear interpretation of the absence of a school in a student's application. In a conventional explicit feedback model, users may poorly rate an item if they do not like it. On the contrary, in SAE, students probably do not apply to a school if they dislike it. But a student might have also not applied to a school because he did not know it. Then, it is not clear how to interpret this absence. Finally, recommendation systems that are run on-demand may gain some insight from the answers students give to suggestions. For example, it may learn additional facts about a student's preferences[21] if he rejects certain types of recommendations. Evidently, since this is an offline and theoretical exercise, it is not possible to update recommendations using this kind of feedback.

In the following points, we present several algorithms that failed in generating reasonable recommendations. Then, we describe the final model that is used in the rest of this paper and its results.

[18] The only restriction is applying at least to 2 schools.

[19] In the context of this paper, it is difficult to argue that users that apply to fewer schools - having a lower average score - are stricter in rating items.

[20] Additionally, in SAE, the interpretation of scores is upside down. In a typical explicit feedback context, a higher score is equal to being "more" preferred. Yet, in SAE students are asked to rank their applications in descending order. Therefore, smaller numbers mean stronger preferences. Ranking a school in the first position (score=1) is the strongest preference possible.

[21] Strictly speaking, since parents apply on behalf of their children, they are the parents' preferences. For simplicity, in this paper, we use both concepts indistinctly.

4.3.1 First Attempts

We started implementing the most classic Collaborative Filtering algorithms: K-Nearest Neighbors, Co-clustering and Singular Value Decomposition (SVD). They were implemented using Python with the help of Surprise library (Hug, 2020). The results for these models are presented in Appendix A, since they are, in short, weak. In Appendix A, we present evidence that suggests that CF models are not capable of inferring students' preferences in this context.

Considering the disappointing results and following the suggestions of Pazzani (1999), we added content-based characteristics to a collaborative model, resulting in a hybrid one.

4.3.2 Final Model: Theoretical background

We implemented our Hybrid Model using Python and the LightFM Library. The model, presented in Kula (2015), was specially designed to work in contexts with sparse datasets. The following description is entirely based on their paper.

It is essential to highlight that this model, unlike the previous ones, uses implicit feedback. Therefore, it will not matter the order in which each student applied to each school. What only matters if he applied.

Let U be the set of students, I be the set of schools, F^U be the set of user features and F^I be the set of school features. Specifically, F^U includes the imputed district[22] of the student, his gender, and if he belongs to the Priority group. On the other hand, F^I contains the school's district, its religious type, and monthly tuition.

Each student interacts with a number of schools. The only interaction possible is applying. Students and schools are fully described by their features, which are known in advance. Each student is described by a set of features $f_u \subset F^U$. Equivalently, each schools is described by a set of features $f_i \subset F^I$. The model is parametrised in terms of d-dimensional feature embeddings (latent vectors), e_f^U and e_f^I for each feature. Each feature is also described by scalar bias terms: b_f^U for students and b_f^I for schools. Both, feature embeddings and biases, are calculated by the model during the optimization process.

Also, the latent representation of the student u is given by the sum of its feature's latent vectors.

$$q_u = \sum_{j \in f_u} e_j^U \tag{1}$$

[22]We do not have the real district of each student. We calculated the distance between each student and all municipalities and assumed they lived in the district of the nearest one.

Analogously for schools:

$$p_i = \sum_{j \in f_i} e_j^I \tag{2}$$

Similarly, the bias term for student u is given by the sum of the features' biases:

$$b_u = \sum_{u \in f_u} b_j^U \tag{3}$$

The same holds for schools:

$$b_i = \sum_{i \in f_i} b_j^I \tag{4}$$

The predicted rating given by the student u for school i is given by:

$$\widehat{r}_{ui} = f\left(q_u \cdot p_i + b_u + b_i\right) \tag{5}$$

Which is a function of the interaction between the student's and the school's latent vectors, adjusted by their biases. Considering that we are facing a binary prediction model, we define $f()$ as the sigmoid function.

$$f(x) = \frac{1}{1 + \exp(-x)} \tag{6}$$

Finally, the optimization problem maximises the likelihood of the data.

$$L\left(e^U, e^I, b^U, b^I\right) = \prod_{(u,i) \in A^+} \widehat{r}_{ui} \times \prod_{(u,i) \in A^N} \left(1 - \widehat{r}_{ui}\right) \tag{7}$$

Being A^+ the observed student-school applications in dataset and A^N the unobserved (not applied) ones.

4.3.3 Final Model: Results

On average, the best (first recommendation) is 3.05 Km. away from each student. Remembering that in the observed data, students - on average - apply to a school that is at most 3.15 Km. away from their homes, this is evidence that our model's suggestions are capturing users' preferences. At least, in terms of distance. Table 1 presents the average school-student distance for every suggestion, being #1 the best one.

Table 1: Suggestions' School-Student Distance: Hybrid Matrix Factorization Model

	Suggestion N°									
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10
Average	3.05	3.13	3.19	3.24	3.25	3.29	3.42	3.65	3.65	3.81
Std. Dev	9.47	9.43	9.56	9.62	9.52	9.54	8.68	9.97	10.05	10.07
Median	2.30	2.38	2.35	2.31	2.36	2.38	2.48	2.60	2.59	2.68
75th percentile	3.43	3.55	3.60	3.67	3.60	3.59	3.76	3.99	3.94	4.09
99th percentile	12.37	13.41	13.89	14.24	15.36	15.20	15.61	19.53	22.68	26.50

Notes: Distances in kilometers and computed only for students with a reasonable address in dataset.

It is quite surprising that our suggestions are perfectly monotonous in the distance, given that our model does not know this distance, but only the student's and school's district. This is evidence that the model is learning not only from metadata yet also from the observed applications.

Table 2 presents the school-student distance minus the maximum distance applied by each student. On average, our best suggestion is 0.10 Km. closer to the student's home than his farthest observed application. Furthermore, at least until suggestion number 2, we are suggesting closer schools.

Table 2: Difference Between Suggestions' School-Student Distance and Furthest Applied School: Hybrid Matrix Factorization Model

	Suggestion N°									
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10
Average	-0.10	-0.04	0.01	0.07	0.08	0.12	0.27	0.47	0.48	0.66
Std. Dev	5.34	5.24	5.30	5.38	5.32	5.47	5.68	5.93	5.95	6.15
Median	0.20	0.28	0.24	0.21	0.24	0.29	0.37	0.49	0.50	0.60
75th percentile	1.41	1.53	1.57	1.54	1.54	1.56	1.72	1.93	1.89	2.06
99th percentile	7.92	10.80	11.47	11.51	11.93	11.99	12.26	13.87	16.39	21.09

Notes: Distances in kilometers and computed only for students with a reasonable address in dataset.

When we look at proxies of academic performance the situation is similar. Table 3 shows the SIMCE scores of our recommended schools. Again, we observe a monotonic relationship. The first suggestions have a better SIMCE score than the next ones. Our model does not have any academic performance proxy as input, so this is evidence we are correctly inferring students' preferences from their applications if parents pay attention to this aspect when evaluating schools.

Table 3: Suggested Schools' SIMCE Scores: Hybrid Matrix Factorization Model

	Suggestion Nº									
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10
Average	285.55	281.90	280.31	277.46	275.66	272.27	271.08	269.76	268.14	267.71
Std. Dev	15.53	18.69	20.43	19.84	20.19	19.55	19.14	18.46	19.02	19.32
Median	286	283	280	278.5	277	272.5	272	270.5	269	269
75th percentile	295	294	293	291.5	289.5	285.5	284.5	284	282.5	282
99th percentile	313.5	334.5	334.5	314.5	337	314.5	314.5	308.5	308.5	308.5

Notes: SIMCE Score was calculated as the average of Math and Spanish Tests applied in 2018 for 4th grade.

Table 4 presents the difference between our suggestions' SIMCE scores and the average applied SIMCE score,[23] for each student. On average, our first recommendation is 15.78 points higher than the average applied SIMCE score of each student. Moreover, at least until suggestion #8, we are suggesting better schools, in terms of SIMCE, than the applied ones.

Table 4: Difference Between Suggestions' SIMCE Scores and Average Applied SIMCE: Hybrid Matrix Factorization Model

	Suggestion Nº									
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10
Average	15.78	12.26	10.66	7.78	5.93	2.59	1.44	0.15	-1.43	-1.65
Std. Dev	21.53	23.41	24.96	24.77	25.37	24.35	24.65	24.05	24.18	24.56
Median	16.5	11.5	9.16	6.83	4.36	0.84	0.75	0	-1.5	-2.16
75th percentile	30.5	27.87	26.75	24.33	23.25	18.66	18	17	14.81	15.16
99th percentile	66.25	67.66	75.5	69.66	72.5	62	60.25	54.25	53.21	54.5

Notes: SIMCE Score was calculated as the average of Math and Spanish Tests applied in 2018 for 4th grade.

Combining distance and SIMCE statistics, we observe that in **17.91%** of the cases, our first suggestion is closer than the student's furthest application and has a better SIMCE score than his best application, in terms of SIMCE. In other words, is not only closer, but also academically better that all of his applications. Only observing at SIMCE, our first suggestion is better than all the student's applications, in 52.13% of the cases. Besides, in

[23]Average SIMCE scores of all the schools applied by each student.

76.74% of the students, our first suggestion has a higher SIMCE than their average applied SIMCE. In regard to distance only, in 44.81% of the cases our first suggestion is closer than the student's furthest application.

Finally, when we observe our suggestions' yearly tuition, we have once more an almost perfect monotonic relationship. The first suggestions have a higher tuition than the following ones. Although it goes beyond the scope of this paper, this likely is related to our algorithm's bias to recommend first high SIMCE schools, that tend to have a higher price. Indeed, in our dataset the correlation between SIMCE scores and yearly tuition is very high: 0.58.

Table 5: Suggestions' Yearly Effective Tuition: Hybrid Matrix Factorization Model

	Suggestion N°									
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10
Average	388	283	272	250	232	224	222	216	203	203
Std. Dev	434	398	383	355	337	355	362	368	372	365
Median	0	0	0	0	0	0	0	0	0	0
75th percentile	974	493	493	493	493	487	487	487	233	233
99th percentile	980	980	980	980	980	980	980	1298	1298	1298
% students tuition-free	50.22	60.06	60.71	60.64	61.69	66.34	66.98	69.53	72.04	71.60

Notes: Yearly Tuition was calculated adding up base fee plus monthly fee multiplied by 10. All prices in USD (Change rate: 770 CLP/USD). Original tuition data was expressed in intervals, median value of each interval was considered to calculate numeric values. We consider that Priority students are exempt from paying in SEP Schools.

Table 6 presents the yearly tuition difference between our suggestion yearly tuition and the most expensive applied school by each student. On average, our first suggestion is only 39 USD above than the most expensive applied school of each student. From suggestion number 2, our recommendations, on average, are even cheaper than each student most expensive applied school. However, on every suggestion, there exists a high variance. We try to explain this distribution in the next chapter.

Overall, if we combine distance, SIMCE and yearly tuition, in 3.84% of the cases, our first suggestion is closer than the student's farthest application, has a better SIMCE score than his best application, and is cheaper than the student's most expensive application. Moreover, in 9.76% of the cases our first suggestion is closer than the student's farthest application, has a better SIMCE score than the average of his applications, and is cheaper than the student's most expensive application.

Table 6: Difference Between Suggestions' Yearly Effective Tuition and Most Expensive Applied School: Hybrid Matrix Factorization Model

	Suggestion Nº									
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10
Average	39	-66	-76	-97	-118	-125	-127	-132	-141	-133
Std. Dev	547	518	505	508	497	505	508	523	527	513
Median	0	0	0	0	0	0	0	0	0	0
75th percentile	487	0	0	0	0	0	0	0	0	0
99th percentile	980	980	980	980	980	980	980	980	980	980

Notes: Yearly Tuition was calculated adding up base fee plus monthly fee multiplied by 10. All prices in USD (Change rate: 770 CLP/USD). Original tuition data was expressed in intervals, median value of each interval was considered to calculate numeric values. We consider that Priority students are exempt from paying in SEP Schools.

In our opinion, there is enough suggestive evidence that our model is truly learning from students' preferences and thus, giving reasonable suggestions. Even more, our model is providing suggestions that involve significant academic improvements from the observed applications. Albeit, it is still not clear if we are giving similar suggestions to Priority and non Priority students. Of course, this is a relevant matter for public policy since our algorithm might be benefiting a particular group. Therefore, the next chapter goes deep into our suggestions and formulates hypotheses that may explain the differences we find.

5 Suggestions' Analysis

We showed previously that our recommendation system was providing reasonable suggestions. However, we did not study if it was giving the same kind of suggestions to different groups of students. In this chapter we study if Priority (low SES) and Non-Priority (high SES) students are receiving similar suggestions, in terms of distance, SIMCE, tuition and utility. As stated before, this might be crucial for public policy. If we are giving better recommendations, in terms of SIMCE, to Non-Priority students, our algorithm may be increasing the gap between low and high-SES students. This would not be desirable.

In any case, notice that because the final assignment depends on a DA algorithm, differences in applications (suggestions) do not necessarily result in the same differences in the final assignation. For example, if our algorithm frequently recommended a popular school, it is unlikely that many students would be able to enroll in it. Students would start to compete for available vacancies and since they are limited, not all of them would be selected. Apart from that, remember that our suggestions are intended to be added after the original (observed) applications, not before them, so the final impact should be limited. Thus, the present chapter aims to study the differences in our suggestions deeply, but not in the final assignments.

5.1 Distance

Table 7 reports the difference between our suggestion's school-student distance and the maximum distance applied by each student for Non-Priority and Priority students, respectively. For Non-Priority students, on average, we are recommending closer schools (negative sign) at least until suggestion #7. In contrast, for Priority students, all our suggestions imply further schools, on average.

Nevertheless, when we look only at distance distributions (without taking into account the maximum applied distance of each student), this difference does not hold. Table A6 in Appendix C presents the average school-student distance, distinguishing between Non-Priority and Priority, respectively. On average, our recommendations imply almost the same effective distance, either for Priority or Non-Priority. Then, the differences in Table 7 between both groups, can be explained by the fact that Non-Priority have, on average, a higher maximum applied distance than Priority. On average, Non-Priority students apply to a school that is 3.52 Km. away at most. By contrast, Priority apply to a school that is, on average, 2.64 Km. at most. Although not conclusive,[24] this may suggest that our recommendation system is not perfectly capturing heterogeneous distance preferences between Priority and Non-Priority. Alternatively, given that Priority students tend to apply to closer schools, our algorithm might be recommending further schools - relative to their applications - to them since they already applied to their closest options.

[24] Our algorithm, for example, may be giving a higher weight to other attributes or non-observable variables.

Table 7: Difference Between Suggestions' School-Student Distance and Furthest Applied School: Hybrid Matrix Factorization Model

	Suggestion N°									
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10
Non-Priority Students										
Average	-0.40	-0.28	-0.23	-0.24	-0.23	-0.23	-0.05	0.15	0.19	0.37
Std. Dev	5.11	5.25	5.18	5.20	5.25	5.41	5.60	5.85	5.86	6.06
Median	0.04	0.12	0.12	0.05	0.04	0.07	0.17	0.31	0.32	0.48
75th percentile	1.24	1.42	1.51	1.36	1.37	1.28	1.47	1.74	1.75	1.95
99th percentile	6.80	10.90	11.32	10.84	11.12	11.49	11.57	13.64	14.44	16.38
Priority Students										
Average	0.43	0.39	0.46	0.67	0.65	0.79	0.87	1.04	1.00	1.14
Std. Dev	5.68	5.21	5.47	5.64	5.39	5.51	5.77	6.02	6.06	6.29
Median	0.46	0.51	0.43	0.52	0.56	0.69	0.74	0.79	0.76	0.79
75th percentile	1.65	1.70	1.66	1.78	1.77	1.99	2.08	2.24	2.13	2.22
99th percentile	10.15	10.56	11.74	12.04	12.87	12.44	12.61	14.17	18.72	25.77

Notes: Distances in kilometers and computed only for students with a reasonable address in dataset.

5.2 SIMCE

Table 8 shows the difference between our recommendations' SIMCE scores and the average applied SIMCE scores for Non-Priority and Priority students, respectively. In every suggestion, the score gain is significant and similar between both groups. Notice, however, that Non-Priority tend to apply, on average to schools with higher SIMCE (average applied SIMCE: 271) than Priority (average applied SIMCE: 264).

When we look at the absolute SIMCE scores of our suggestions, we find that we are suggesting better schools to Non-Priority students, in terms of SIMCE. These statistics are presented in Table A7 in Appendix C. Our algorithm does not give us causal tools for explaining these differences. Albeit, it is reasonable to argue that since our algorithm uses students' applications as input and Priority students tend to apply to lower SIMCE schools, it is recommending them these types of schools. In this sense, our algorithm would be replicating students' bias. Still, it is relevant to highlight that one of our goals is to recommend schools based on revealed preferences. Therefore, if our algorithm is suggesting worst schools to Priority students, because they applied in this way, this is not necessarily unwanted. Besides, Priority are anyway having a significant score gain in every suggestion and in most of them slightly higher than the one observed in Non-Priority students.

Table 8: Difference Between Suggestions' SIMCE Scores and Average Applied SIMCE: Hybrid Matrix Factorization Model

	Suggestion N°									
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10
Non-Priority Students										
Average	14.25	12.22	10.04	5.83	3.49	0.12	0.11	-1.39	-2.70	-1.99
Std. Dev	20.48	23.31	24.41	23.65	23.82	23.42	24.97	23.91	23.60	24.27
Median	14.83	11.25	8.5	5	1.83	-1.87	-1.25	-2.25	-2.87	-2.66
75th percentile	28.66	27.72	25.60	22.33	20	15.20	16.5	14.75	13	14.5
99th percentile	60.25	67	73.75	61.75	61.75	58.68	62.75	53.5	53	54.75
Priority Students										
Average	18.33	12.34	11.70	11.02	9.93	6.70	3.64	2.72	0.65	-1.11
Std. Dev	22.94	23.59	25.82	26.23	27.26	25.31	23.94	24.06	24.98	25.02
Median	19.5	12.25	10.37	10.10	9	6.5	4	3.5	0.5	-1
75th percentile	33.39	28.25	29	28.25	28.33	24	20	19.75	18.66	16.25
99th percentile	74	68	77.83	76	82	64.75	58	55.33	53.5	53.75

Notes: SIMCE Score was calculated as the average of Math and Spanish Tests applied in 2018 for 4th grade.

5.3 Tuition

Table 9 reports the difference between our suggestion's yearly tuition and the most expensive applied school for Non-Priority and Priority students, respectively. It is interesting that, at first, we are - relative to their most expensive applied school - suggesting cheaper schools to Non-Priority students. Nonetheless, the high standard deviations suggest that the average might not be the appropriate measure for comparing between both distributions. The median is not suitable either since in both is equal to 0.

Table 9: Difference Between Suggestions' Yearly Effective Tuition and Most Expensive Applied School: Hybrid Matrix Factorization Model

	Suggestion N°									
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10
Non-Priority Students										
Average	4	-121	-109	-157	-193	-195	-194	-208	-216	-197
Std. Dev	577	545	551	548	525	537	542	554	564	553
Median	0	0	0	0	-6	0	0	0	-6	-6
75th percentile	487	6	6	6	0	0	0	0	0	0
99th percentile	980	981	980	980	980	980	980	980	980	1298
Priority Students										
Average	98	24	-21	2	4	-10	-17	-7	-18	-31
Std. Dev	488	455	409	415	418	422	423	440	434	421
Median	0	0	0	0	0	0	0	0	0	0
75th percentile	233	0	0	0	0	0	0	0	0	0
99th percentile	980	980	980	980	980	980	980	980	980	980

Notes: Yearly Tuition was calculated adding up base fee plus monthly fee multiplied by 10. All prices in USD (Change rate: 770 CLP/USD). Original tuition data was expressed in intervals, median value of each interval was considered to calculate numeric values.

To learn more about the dispersion of the previous distributions, we calculated the percentage of students, in each suggestion, that would be paying at most the same as their most expensive applied school. Equivalently, the percentage of students that are paying either the same or less than their most expensive applied school. Results are presented in Table 10

Table 10: Percentage of Students Paying at Most the Same Than Their Most Expensive Applied School: Hybrid Matrix Factorization Model

	Suggestion N°									
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10
% all students	66.89	77.06	77.77	77.55	77.99	80.81	80.62	81.11	83.18	84.09
% Non-Priority	63.25	74.59	73.19	74.88	76.73	79.12	78.75	79.44	80.55	81.70
% Priority	72.94	81.18	85.39	82.00	80.06	83.63	83.74	83.89	87.52	87.93

In all suggestions, the percentage is higher on Priority students. This implies that, although, on average, we are suggesting more expensive options to Priority, this number is being mostly affected by an small group of the distribution. Most Priority students are getting suggestions that have at most the same cost than their most expensive applied school. However, a small percentage of them is getting much more expensive schools, rising the average.

But, why the majority of the averages in Table 9 are negative for Non-Priority students and positive for Priority? The answer is quite simple. In the original applications, for 79.93% of Priority students their most expensive applied school was free (i.e., yearly tuition was 0 USD). Obviously, yearly tuition is bounded on the left by 0, so our algorithm can not give these students a cheaper school. On the other hand, only 37.92% of Non-Priority students had - in their original applications - a free school as their most expensive applied one. These facts give our system more space to recommend, relatively, cheaper schools to Non-Priority students and explain the sign differences observed in the previous tables.

5.4 Utility Levels

We formerly studied relative gains in distance, SIMCE scores and tuition but only in isolation. This kind of analysis, despite it helped us to understand more about our suggestions and their heterogeneity, does not allows us to conclude if students are, overall, better. To compare including all observable factors, between our suggestions and the observed applications, we need to define a utility function for each student.

Following Tagle (2018), we defined the observable utility that the student A receives for being enrolled in school Y as:

$$\begin{aligned} U_{A,Y} = {} & \beta_1 * dist_{A,Y} + \beta_2 * dist_{A,Y} * P_A + \gamma_1 * SIM_Y + \gamma_2 * SIM_Y * P_A \\ & + \theta_1 * YT_{A,Y} + \theta_2 * YT_{A,Y} * P_A + \alpha_1 * VUL_Y + \alpha_2 * VUL_Y * P_A \end{aligned} \tag{8}$$

Where $dist_{A,Y}$ is the euclidean distance between the student A and the school Y, in logs. P_A is a dummy that takes a positive value if the student A is member of the Priority group and helps to capture the heterogeneity between Priority and Non-Priority students. SIM_Y represents the SIMCE score obtained by the school Y. On the other hand, $YT_{A,Y}$ is the effective yearly tuition paid by student A in the school Y. Finally, VUL is the percentage of Priority students enrolled in school Y.

Tagle (2018), using an Exploded Logit estimated these coefficients, which are available in Table A8 in Appendix C. Using equation 8 and these coefficients, we calculated the utility differences between our suggestions and the last applied school for every student. Table 11 reports these differences for Non-Priority and Priority students, respectively. It is worth noting that suggestions, for both groups, are perfectly monotonous in utility levels. The first suggestions imply a higher utility gain on average.

Table 11: Difference Between Suggestions' Utility and Last Applied School's Utility: Hybrid Matrix Factorization Model

	Suggestion N°									
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10
Non-Priority Students										
Average	0.18	0.05	-0.04	-0.23	-0.36	-0.47	-0.49	-0.59	-0.67	-0.71
Std. Dev	1.68	1.72	1.74	1.73	1.73	1.76	1.77	1.77	1.75	1.78
Median	0.32	0.18	0.07	-0.11	-0.22	-0.33	-0.38	-0.46	-0.53	-0.58
75th percentile	1.13	1.04	0.97	0.78	0.63	0.53	0.54	0.42	0.36	0.33
99th percentile	3.47	3.40	3.37	3.16	3.02	2.90	2.95	2.86	2.76	2.79
Priority Students										
Average	-0.27	-0.48	-0.48	-0.56	-0.60	-0.73	-0.84	-0.93	-1.00	-1.06
Std. Dev	2.02	2.04	2.07	2.05	2.07	2.08	2.08	2.06	2.07	2.07
Median	-0.02	-0.23	-0.20	-0.25	-0.32	-0.43	-0.55	-0.62	-0.71	-0.79
75th percentile	0.75	0.58	0.62	0.55	0.52	0.41	0.27	0.16	0.11	0.04
99th percentile	3.30	3.00	2.86	2.83	2.88	2.71	2.62	2.44	2.45	2.44

Besides, in every suggestion, Non-Priority are experiencing higher utility gains than Priority students. Indeed, Priority students are having utility losses. While we can not give a conclusive answer to why this is happening, we can conjecture some hypotheses. We took a random sample [25] of 1000 Non-Priority Students and 1000 Priority Students and calculated the utility levels they could get by applying to any school located in Santiago.[26] Afterwards, we compared these potential utility levels with the utility level given by the best application[27] of each student. We found that Priority Students, on average, do not apply to 5.9 schools that give them a higher utility level than their best application. In contrast, Non-Priority students do not apply to 7.6 schools with this characteristic. These numbers suggest that Priority tend to apply better. Thus, our system might not be offering utility gains to Priority Students because they already applied to their best options, in terms of utility. If most of them already applied to their best options, there is no way to improve their utilities. For instance, given that 79.93% of Priority applied only to free schools, it is impossible to raise their utility by suggesting them cheaper schools, ceteris paribus.

[25] We did not have the computational capacity required for doing it for all the students.

[26] We did not consider schools that were located more than 10 Km. away from each student. However, our conclusions are robust to this assumption.

[27] We defined the best application as the one with the highest utility level for each student.

6 General Equilibrium

The previous chapter analyzed our suggestions in detail. However, as mentioned before, differences in applications may not necessarily reflect in final assignations. Consequently, this chapter evaluates the general equilibrium effects of this policy.

Evaluating the general equilibrium effects of our system is not a simple task. Equilibrium effects will highly depend on the acceptance rate of our suggestions, which we do not observe. Even more, this acceptance rate likely varies substantially between students. Assuming this empirical challenge, we conjecture different acceptance rates according to observable utility gains. This will allow us to establish lower and upper bounds of the impacts our technology would have if implemented by the authorities.

6.1 Acceptance Rate

Even though we calculated the utility gains our suggestions imply, there is still a non-observable part in them. Therefore, even if one of our suggestions involves a positive utility gain, we can not be sure that students are going to accept them. This forces us to work within a stochastic framework. Particularly, we will assume that the utility that student A receives for being enrolled in school Y follows this structure:

$$u_{A,Y} = U_{A,Y} + \varepsilon_{A,Y} \tag{9}$$

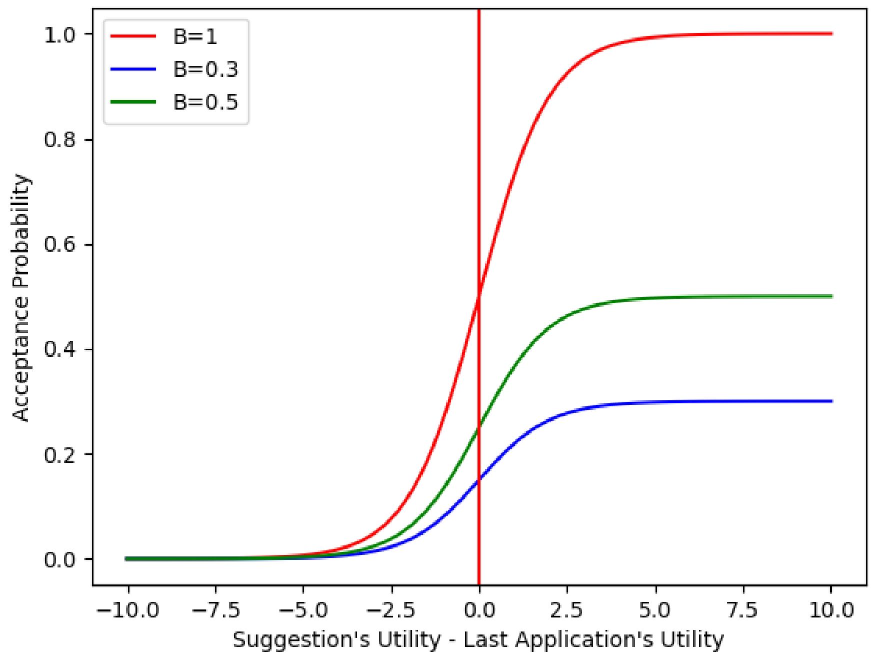
Where $U_{A,Y}$ is the observable component defined in equation 8 and $\varepsilon_{A,Y}$ is a non-observable component. For simplicity, we will assume that the non-observable component distributes logistic. Although there is no observable evidence to choose between distributions, most of the literature makes this assumption (Greene, 2007). Given this, the acceptance probability of the suggestion S is defined as:

$$P(U_0, U_s, B) = \frac{B}{1 + e^{U_0 - U_s}} \tag{10}$$

Which depends on the difference between the utility level of our suggestion U_s and the utility level of the last application of each student U_0. Basically, if our suggestion is better than the student's last application; i.e., $u_s > u_0$; we assume it would likely accept it. The probability also depends on the parameter B, which we will calibrate to evaluate our model in different scenarios. As explained later, this parameter will be calibrated based on the average number of accepted suggestions.

Figure 6 shows the acceptance probability of a certain suggestion, with different values of A. Higher values of B, imply higher acceptance probabilities.

Figure 6: Acceptance Rate



6.2 Calibration and Effective Acceptance Rates

We calibrate the value of B according to different values of the average number of accepted suggestions. Notice that we use this approach because the likelihood of accepting suggestions should vary between students, based on their utility gains. If we directly supposed every student accepted the same number of suggestions, we would not capture this heterogeneity. Using a probabilistic approach and calibrating the parameters of the function considering the average number does capture this heterogeneity, at least on observable variables.

Considering an average number of accepted suggestions between 0.5 and 7 per student, we get the following values for B:

Table 12: Corresponding B to Each Value of Average Number of Accepted Suggestions per Student

	Approximate average of accepted suggestions							
	0.5	1	2	3	4	5	6	7
B value	0.09	0.18	0.34	0.55	0.72	0.9	1.08	1.28

Which involve the following average number of accepted suggestions, distinguishing between Priority and Non-Priority students.

Table 13: Average Number of Accepted Suggestions, Distinguishing Between Priority and Non-Priority Students

	Approximate average of accepted suggestions							
	0.5	1	2	3	4	5	6	7
Accepted by Non-Priority	0.51	1.03	1.92	3.11	4.08	5.11	6.13	7.13
Accepted by Priority	0.48	0.96	1.76	2.87	3.75	4.70	5.63	6.60

As expected, since Non-Priority students undergo higher utility gains with our suggestions, these students have a higher acceptance rate than Priority students, for every value of A.

6.3 Methodology

Our simulations were run in the following way, for each average of accepted suggestions:

1. For each student A, we calculated the acceptance probability using equation 10[28]for his best 10 suggestions. This determined the set of accepted suggestions for each student. Notice that it could happen that suggestion n, in the order defined by our algorithm, is not included but $n+1$ it is.

2. We sorted the set of accepted suggestions of each student, following the order given by our recommending system.

3. For each student A, we added his sorted set of accepted suggestions, immediately after his observed applications.

4. We run the matching algorithm developed by the Chilean government *à la* Gale-Shapley. Considering that in the original application each student had been given a random number in each one of the schools he applied, we followed the next logic for adding new applications: the first new applicant for each school was given a random number between 0 and the original number of applicants for that school. All students that originally applied to that school and had a position equal or below the new applicant's obtained number, were displaced in one place. Next, the second new applicant for each school was given a new random number between 0 and the original number of applicants for that school, plus one. All students that after the first iteration were

[28]Setting B in the corresponding level for each average of accepted suggestions.

in that school's list and had a position equal or below the new applicant's obtained number, were displaced in one position. And so on until adding all the new applicants to each school. Conceptually, adding the new applications following this procedure allows us to simulate what would have happened if the students had accepted our recommendations

6.4 Final Results

6.4.1 Percentage of Non-Assigned Students During Main Phase

As mentioned before, SAE involves two main stages: the main (or first) one and a complementary one. Most students are assigned to a school during the first stage. However, an important percentage of them - 12.55%[29] in 2019 - are not assigned in the first stage. This may happen mainly for two reasons: applying to few schools or only to highly demanded ones (or a combination of both). Students that are not matched to a school during the main phase must apply again in the complementary stage. This situation is not desirable for several reasons. First, families have to take part again of the application process, which involves information and time costs. Second, in this stage, many schools already filled all their vacancies or have only a few left, so it is less likely to find a preferred school. In addition, non-assigned students also have to compete with students that rejected their first-stage assignation and with ones that did not take part of the first stage and entered the system during this phase. Third, there is a high probability of not participating in the complementary stage if not selected in the first one. In fact, 48% of the students that were not selected during the main stage, did not participate in the complementary phase. Even more, 28% of the students that were not assigned in the first stage and did not participate in the complementary stage, did not enroll to any school, including private ones. In other words, they abandoned the formal education system.

Table 14 shows the impact of our suggestions on the percentage of non-assigned students. On the original (observed) application 12.55% of the students were not assigned to any school. However, this problem is more serious for Non-Priority students: 15.37% of them are not selected. In contrast, only 7.85% of Priority students are not selected in the first stage.

[29] Calculated taking into account only students that applied exclusively to schools located in Santiago.

Table 14: Percentage of Non-Assigned Students During The First Stage of the Application Process, Considering Suggestions

		Approximate average of accepted suggestions							
	Original	0.5	1	2	3	4	5	6	7
Non-Priority	15.37%	14.52%	13.83%	13.00%	12.36%	11.79%	11.48%	11.25%	10.82%
Priority	7.85%	7.01%	6.42%	5.83%	5.22%	5.04%	4.82%	4.70%	4.42%
Overall	12.55%	11.71%	11.05%	10.31%	9.68%	9.26%	8.98%	8.80%	8.42%

Notes: Original column represents the observed application. Percentages calculated only for students of Santiago.

Column "0.5" represents the hypothetical results if, each student accepted, on average, .5 suggestions given by our system. This would reduce the number of non-selected students. Overall, the percentage of non-assigned students goes down from 12.55% to 11.71%. This represents a decrease of 0.84 pp (6%). Non-Priority students experience a similar decrease (0.85 pp) to the one observed in Priority (0.84 pp). Nevertheless, proportionally, effects are much higher for Priority (10.7% Priority v/s 5.5% Non-Priority). Previously, this result was not expected, since Priority have a lower acceptance rate than Non-Priority.

The number of non-assigned students decreases monotonously in the average of accepted suggestions. In the limit, if we assumed that each student accepted, on average, 7 suggestions this number would converge to 8.4%.

Unfortunately, this improvement can not be considered a zero-sum game. Part of the new student-school matches are being made at the expense of other students that were originally assigned to a school. Table A9 in Appendix D shows the percentage of net losers[30] for every average number of accepted suggestions, distinguishing between Priority and Non-Priority students. The overall percentage of net losers increases while students accept a higher number of suggestions, on average. Nonetheless, the observed gains in assigned students presented in Table 14 imply that, for every number of accepted suggestions, net winners[31] are higher than net losers. Moreover, the percentage of Non-Priority net losers is more than twice the one of Priority, for every level of accepted suggestions. This result is striking since proportionally the observed gains in assigned students are higher in Priority students. Despite not being causal, this fact suggests that, on average, Non-Priority students apply to more congested schools than Priority.[32] Since our algorithm uses observed applications as

[30]We define net losers as students that in the original process had a school assigned, but due to the effect of our suggestions on the general equilibrium, they finally are not assigned to any school during the main phase.

[31]Net winners correspond to students originally not assigned to any school during the main phase, that with our suggestions would be assigned to one.

[32]Within Santiago, 57.02% of Non-Priority Students are assigned to their first application, while on

input, it recommends overcrowded schools to these students. In consequence, Non-Priority are experiencing smaller gains in assigned students, while having a higher percentage of net losers.

Other students are also affected, although to a lesser extent, by the inclusion of our suggestions. Table A10 in Appendix D reports the percentage of collaterally affected students for every average number of accepted suggestions, distinguishing between Priority and Non-Priority students. Collaterally affected students are students originally assigned - that with our suggestions would be assigned to a different school, compared to the original process.[33] Similar to net losers, the overall percentage of collaterally affected students increases while applicants accept a higher number of suggestions, on average. Besides, Non-Priority are more collaterally affected than Priority. This strengthens our suggestive evidence that Non-Priority apply in greater proportion to overcrowded schools. In any case, in the next sections, we study if collaterally affected students end assigned in worse schools in terms of SIMCE, yearly tuition and distance than their original assignations.

6.4.2 Distance

Table 15 presents the effects of our suggestions in the assigned school-student distance, only for students assigned during the main phase. In the real assignation students, on average, are assigned to a school that is 2.07 Km away from their homes. Our suggestions imply an increase in this distance. However, the difference is absolutely marginal. At most, if students accepted 7 suggestions on average, this would imply a 50 meters increase in the average school-student distance.

Table 15: Assignations' School-Student Distance, Considering Suggestions

		Approximate average of accepted suggestions							
	Original	0.5	1	2	3	4	5	6	7
Average	2.07	2.08	2.09	2.09	2.11	2.11	2.13	2.12	2.12
Std. Dev	9.70	9.66	9.62	9.45	9.52	9.40	9.44	9.41	9.38
Median	1.05	1.06	1.08	1.10	1.12	1.14	1.14	1.15	1.16
75th percentile	2.13	2.15	2.19	2.21	2.25	2.27	2.28	2.29	2.30
99th percentile	15.31	15.23	15.20	15.04	15.04	14.76	15.02	14.79	14.53
% of assigned students	87.45	88.29	88.95	89.69	90.32	90.74	91.02	91.20	91.58

Notes: Distances in kilometers and computed only for students with a reasonable address in dataset.

Priority Students this number stands at 72.30%. Similarly, this suggests that Non-Priority Students apply to more congested schools.

[33]Net losers are not included in this group.

Albeit, Table 15 has to be interpreted with caution. Comparing column "7" with "Original" implies a 50 meters increase in the average distance. However, at the same time, we are having a huge rise in the number of assigned students. "7" implies a 4.13pp improvement in the percentage of assigned students in the first stage. It is relevant to highlight that each column considers distances only from students that were matched to a school during the main phase. For example, column "Original" does not consider 12.55% of students. Column "7", on the contrary, does not consider only 8.42% of students.

Table A14 in Appendix D shows the school-student distance for net winners, for every number of accepted suggestions. Net winners are being assigned to schools, that are, on average, around 2.50 Km away from their homes. Yet, they are being assigned to further schools than originally assigned students (2.07 Km). However, since net winners would not be assigned during the main phase if it was not for our suggestions, the actual benchmark should be their final enrollment in the system (outside option). Table 16 reports the average school-student distance for students that participated in the main phase but were not assigned to any school. On average, they enrolled[34] in a school that is 2.85 Km away from their homes.

Table 16: Final Assignations' School-Student Distance, Students Not Assigned During First Stage

	Observed non-assigned students
Average	2.85
Std. Dev	4.27
Median	1.54
75th percentile	3.14
99th percentile	22.50

Notes: Distances in kilometers and computed only for students with a reasonable address in dataset.

Thus, on average, with our suggestions, students are being assigned to schools that are 350 meters closer to their homes.

Table 17 shows the effects of our suggestions in the assigned school-student distance, but now distinguishing between Non-Priority and Priority students, respectively. The conclusions are similar to the ones derived from the previous tables. Both groups are improving their percentage of assigned students, while experiencing marginal increases in the average distance.

[34]During later phases like the complementary phase. They could also have been assigned to their closest school with available vacancies, if not assigned in the complementary phase; or have gone to the private sector, not included in SAE.

Table 17: Assignations' School-Student Distance, Considering Suggestions

		Approximate average of accepted suggestions							
	Original	0.5	1	2	3	4	5	6	7
Non-Priority Students									
Average	2.27	2.28	2.29	2.30	2.32	2.32	2.33	2.33	2.32
Std. Dev	11.45	11.40	11.35	11.30	11.25	11.21	11.21	11.18	11.14
Median	1.17	1.18	1.20	1.23	1.26	1.27	1.28	1.29	1.30
75th percentile	2.36	2.38	2.42	2.44	2.49	2.52	2.53	2.53	2.54
99th percentile	15.88	15.81	15.76	15.73	15.62	15.54	15.61	15.58	15.52
% of assigned students	84.63	85.48	86.17	87.00	87.64	88.21	88.52	88.75	89.18
Priority Students									
Average	1.74	1.75	1.75	1.74	1.77	1.76	1.78	1.77	1.78
Std. Dev	5.68	5.66	5.64	5.03	5.47	5.02	5.19	5.19	5.18
Median	0.88	0.90	0.91	0.91	0.93	0.94	0.95	0.94	0.95
75th percentile	1.77	1.81	1.83	1.85	1.86	1.89	1.91	1.90	1.92
99th percentile	13.28	13.28	13.26	13.07	13.18	13.07	13.07	13.02	12.96
% of assigned students	92.15	92.99	93.58	94.17	94.78	94.96	95.18	95.30	95.58

Notes: Distances in kilometers and computed only for students with a reasonable address in dataset.

Table A15 in Appendix D shows the school-student distance for Non-Priority and Priority net winners, respectively; for every number of accepted suggestions. On average, they end assigned in similar schools, in terms of distance. This is not surprising since in the previous chapter we concluded that concerning distance we were offering similar suggestions to both groups.

Nevertheless, as shown in Table 18, Priority students face a relatively worse outside option if not selected during the first stage. On average, Priority students experience a 0.88 Km (2.62-1.74) increase in distance if not selected during the main phase. On the other hand, Non-Priority students face a 0.35 Km (2.62-2.27) rise. Hence, our algorithm, regarding distance, is giving better improvements to Priority students. This is even more important if we consider that Priority give a higher weight to commuting distances (Tagle, 2018).

Table 18: Final Assignations' School-Student Distance, Students Not Assigned During First Stage, Distinguishing Between Priority and Non-Priority Students

	Overall	Non-Priority	Priority
Average	2.85	2.93	2.62
Std. Dev	4.27	4.11	4.74
Median	1.54	1.59	1.40
75th percentile	3.14	3.28	2.65
99th percentile	22.50	22.40	22.40

Notes: Distances in kilometers and computed only for students with a reasonable address in dataset.

On the other side, collaterally affected students face an increase[35] in their school-student distances, as reported in Table A11 in Appendix D. Withal, the difference is marginal and at most of 160 meters.

Finally, Table 19 shows the impact of our suggestions in the enrolled school-student distance, considering all phases. Taking into account all phases is relevant because, in this way, we capture the added effect of net winners, net losers and collaterally affected students. Some assumptions had to be made.[36] At most, our suggestions result in a 80 meters decrease in the average school-student distance. Table A16 reports these impacts, but only for Non-Priority and Priority students, respectively. Both groups undergo similar but small decreases in school-student distances.

[35]Except when the average number of accepted suggestions is 0.5.

[36]Since in our simulations we do not know if students would enroll in the school they had assigned during the main phase, in the original assignation we assumed they did it; even if we knew they finally enrolled in another school. This is the only way to make the numbers comparable. Additionally, in our simulations, we imputed the median values reported in Table 18 as the school-student distance for students not assigned during the main phase, distinguishing between Priority and Non-Priority students. This was not necessary for the original process, because we do know where non-assigned students finally ended enrolled. Besides, we did not consider students that lived and applied to schools of Santiago but ended enrolled in other regions of the country, for being outliers. Finally, we supposed that the characteristics of the outside option remained constant even if the percentage of non-selected students during main phase changed. This may be considered a weakness of our approach.

Table 19: Final Assignations' School-Student Distance, Considering All Phases

		Average number of accepted suggestions							
	Original	0.5	1	2	3	4	5	6	7
Average	2.14	2.06	2.07	2.08	2.10	2.10	2.12	2.12	2.11
Std. Dev	6.49	9.04	9.05	8.93	9.03	8.94	8.99	8.98	8.97
Median	1.10	1.32	1.32	1.33	1.33	1.34	1.35	1.34	1.34
75th percentile	2.24	1.98	2.02	2.05	2.10	2.13	2.14	2.17	2.18
99th percentile	17.67	15.73	15.61	15.61	15.72	15.47	15.76	15.60	15.54

Notes: Distances in kilometers and computed only for students with a reasonable address in dataset.

All in all, our results suggest that our algorithm would not have major impacts in commuting distances, either considering only the main phase or all stages. If anything, taking into account all phases, there is a improvement for Non-Priority and Priority students, negligible in size.

6.4.3 SIMCE

Table 20 reports the effects of our suggestions in the assigned schools' SIMCE scores. In the real assignation students, on average, are assigned to a school that scores 266.31 in SIMCE. Our suggestions imply a slight decrease in these scores. At most, if students accepted 7 suggestions on average, this would result in a 0.49 points fall.

Table 20: Assignations' SIMCE Scores, Considering Suggestions

		Average number of accepted suggestions							
	Original	0.5	1	2	3	4	5	6	7
Average	266.31	266.27	266.23	266.12	266.04	265.97	265.92	265.89	265.82
Std. Dev	22.79	22.79	22.79	22.79	22.80	22.80	22.80	22.89	22.83
Median	264.5	264.5	264	264	264	264	264	264	263.5
75th percentile	282.3	282.5	282.5	282.5	282.5	282.5	282.5	282.5	282.5
99th percentile	314.5	314.5	314.5	314.5	314.5	314.5	314.5	314.5	314.5
% of assigned students	87.45	88.29	88.95	89.69	90.32	90.74	91.02	91.20	91.58

Notes: SIMCE Score was calculated as the average of Math and Spanish Tests applied in 2018 for 4th grade.

Nonetheless, the most relevant comparison should be between the final assignation, considering our suggestions and the student's outside option. Table A17 in Appendix D presents assignations' SIMCE scores for net winners, for every number of accepted suggestions. Net winners end assigned in better schools (average across columns: 276.13 points), in terms of SIMCE, than originally assigned students (266.31 points). Table 21 presents the final assignation's SIMCE Score for students that participated in the first stage but were not assigned to any school; i.e., their outside option. On average, these students are assigned to a school that gets 268.57 in SIMCE, which is worse than the average from students originally matched during the main stage. Considering their outside option, our suggestions involve, on average, 7.56 SIMCE points gain for net winners.

Table 21: Final Assignation's SIMCE Score, Students Not Assigned During First Stage

	Observed non-assigned students
Average	268.57
Std. Dev	24.58
Median	269.5
75th percentile	287
99th percentile	319

Notes: SIMCE Score was calculated as the average of Math and Spanish Tests applied in 2018 for 4th grade.

Despite the fact that net winners are assigned to schools better than the ones from students originally matched, averages presented in Table 20 experience a mild decrease. At first, this fall could be explained by two groups affected by our suggestions: net losers and collaterally affected students. Nonetheless, since net losers were displaced by net winners and gave their places to them, they can not explain this difference. In other words, SIMCE scores from their original assignations are included in the new averages, since their vacancies were taken by net winners. This leaves us only with collaterally affected students for explaining this decline. In fact, as shown in Table A12 in Appendix D, with our suggestions these students end assigned to schools with lower SIMCE scores compared to their original assignations. On average, this fall is roughly of 8 points. As reference, this fall is 0.44 points higher than the gain observed for net winners.

Table 22 reports the effects of our suggestions in the assigned schools' SIMCE scores, for Non-Priority and Priority students, respectively. There are no major differences between both groups in the small losses observed in average SIMCE scores.

Table 22: Assignations' SIMCE Scores, Considering Suggestions

	Average number of accepted suggestions								
	Original	0.5	1	2	3	4	5	6	7
Non-Priority Students									
Average	269.11	269.04	269.01	268.87	268.76	268.69	268.62	268.61	268.56
Std. Dev	22.48	22.48	22.46	22.52	22.50	22.48	22.49	22.50	22.55
Median	269	268.5	268.5	268	268	268	268	268	268
75th percentile	285	285	285	285	284.5	284.5	284.5	284.5	284.5
99th percentile	314.5	314.5	314.5	314.5	314.5	314.5	314.5	314.5	314.5
% of assigned students	84.63	85.48	86.17	87.00	87.64	88.21	88.52	88.75	89.18
Priority Students									
Average	262.04	262.02	261.96	261.84	261.85	261.76	261.73	261.65	261.54
Std. Dev	22.60	22.60	22.61	22.56	22.62	22.65	22.65	22.66	22.60
Median	260	260	260	259.5	259.5	259.5	259.5	259.5	259
75th percentile	277	277	277	277	277	276.5	276.5	276.5	276.5
99th percentile	314.5	314.5	314.5	314.5	314.5	334.5	314.5	314.5	314.5
% of assigned students	92.15	92.99	93.58	94.17	94.78	94.06	95.18	95.30	95.58

Notes: SIMCE Score was calculated as the average of Math and Spanish Tests applied in 2018 for 4th grade.

At the same time, when we distinguish net winners between types of students, we observe that, for every level of accepted suggestions, Non-Priority end assigned in schools with better SIMCE than Priority students. On average, this difference is about 6 points, as expected since our suggestions involve better schools, in terms of SIMCE, for Non-Priority students. Disaggregated results for net winners are presented in Table A18 in Appendix D.

Relative to their outside options, Priority net winners experience a higher gain in SIMCE scores. Table 23 reports the final assignation's SIMCE Score for students that participated in the main stage but were not assigned to any school, differentiating between Non-Priority and Priority students. We observe a 6.84 SIMCE points average gain[37] in Non-Priority net winners. In contrast, this gain is 11.31 for Priority net winners.

[37]This result corresponds to the difference between the average SIMCE score for Non-Priority net winners; among different level of accepted suggestions; and Priority's outside option.

Table 23: Final Assignations' SIMCE Scores, Students Not Assigned During First Stage, Distinguishing Between Priority and Non-Priority Students

	Overall	Non-Priority	Priority
Average	268.57	271.01	261.39
Std. Dev	24.58	24.55	23.25
Median	269.5	272	260
75th percentile	287	289.5	279
99th percentile	319	321.5	313.5

Notes: SIMCE Score was calculated as the average of Math and Spanish Tests applied in 2018 for 4th grade.

Lastly, Table 24[38] reports the impact of our suggestions in the enrolled schools' SIMCE scores, considering all phases. As mentioned before, this exercise is important since it captures the added effect of net winners, net losers and collaterally affected students. Our suggestions have a negative but negligible effect on average SIMCE scores. Besides, this fall is monotonous in the number of accepted suggestions. Negative effects are marginally higher for Non-Priority students, as shown in Table A19 in Appendix D.

Table 24: Final Assignations' SIMCE Scores, Considering All Phases

		Average number of accepted suggestions							
	Original	0.5	1	2	3	4	5	6	7
Average	266.68	266.63	266.58	266.47	266.38	266.31	266.25	266.21	266.14
Std. Dev	22.63	21.49	21.57	21.66	21.73	21.79	21.82	21.85	21.91
Median	265	267.5	267	266.5	266	266	266	266	265.5
75th percentile	282.5	280.5	280.5	280.5	280.5	280.5	280.5	280.5	280.5
99th percentile	314.5	314.5	314.5	314.5	314.5	314.5	314.5	314.5	314.5

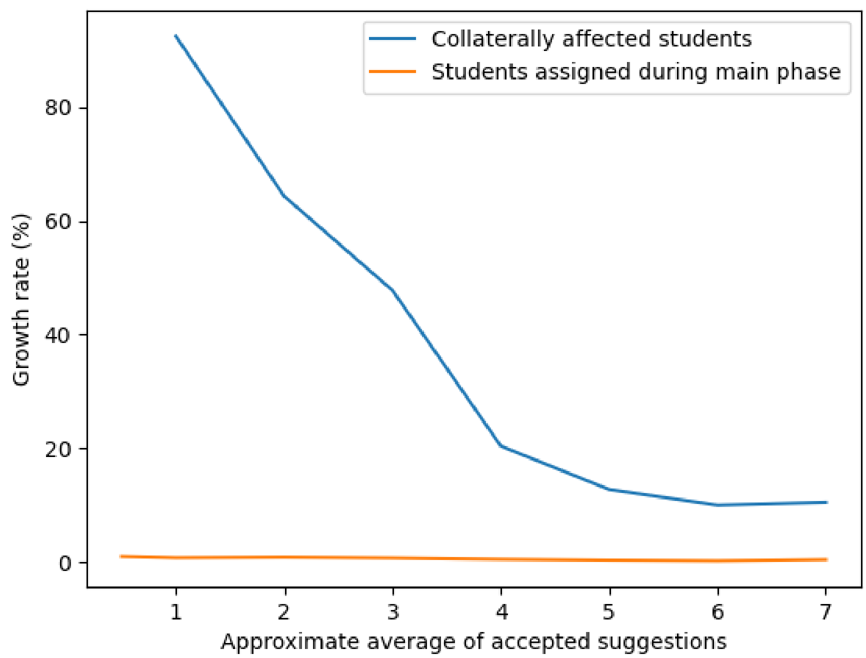
Notes: SIMCE Score was calculated as the average of Math and Spanish Tests applied in 2018 for 4th grade.

Overall, we find that the implementation of our algorithm would have negative but insignificant effects in overall SIMCE scores. These negative impacts can be explained by the fact that collaterally affected students experience significant negatives impacts in their assigned schools' SIMCE scores, as shown in Table A12. In addition, the percentage of collaterally affected students is higher when more suggestions are accepted on average and

[38] Analogous assumptions of footnote 36 apply.

grows at a higher rate than the percentage of students assigned during the main phase, who are the main beneficiaries of our system. Growth rates for assigned students during main phase and collaterally affected students are presented in Figure 7. In consequence, average SIMCE scores fall when the number of accepted suggestions is higher. Intuitively, when students start accepting too much suggestions, we create congestion in the system. When this happens, some students (collaterally affected students) start being matched to poor schools, that can be some times even worse than the outside option.

Figure 7: Growth Rates for Collaterally Affected Students and Students Assigned During Main Phase



Anywise, we observe that due to our system, at first, increases the median SIMCE score in 2.5 SIMCE points. This effect is stronger at the beginning, although always positive and economically significant.

6.4.4 Tuition

Table 25 presents the effect of our suggestions in the assigned school's yearly tuition fees. Our suggestions involve a slight decrease in these fees. At most, if students accepted 7 suggestions, this would result in a 2 USD fall. Table A20 in Appendix D disaggregates these statistics between Non-Priority and Priority students, respectively. Non-Priority students experience, on average, a fall, although insignificant. In contrast, for Priority the average goes up, but the change is of negligible magnitude.

Table 25: Assignations' Yearly Tuition, Considering Suggestions

		Average number of accepted suggestions							
	Original	0.5	1	2	3	4	5	6	7
Average	177	177	177	177	176	176	175	175	175
Std. Dev	335	335	335	334	334	333	333	333	332
Median	0	0	0	0	0	0	0	0	0
75th percentile	227	227	227	227	227	227	227	227	227
99th percentile	980	980	980	980	980	980	980	980	980
% of assigned students	87.45	88.29	88.95	89.69	90.32	90.74	91.02	91.20	91.58

Notes: Yearly Tuition was calculated adding up base fee plus monthly fee multiplied by 10. All prices in USD (Change rate: 770 CLP/USD). Original tuition data was expressed in intervals, median value of each interval was considered to calculate numeric values. We consider that Priority students are exempt from paying in SEP Schools.

Table A21 in Appendix D reports the yearly tuition for net winners, for every number of accepted suggestions. Net winners are being assigned to schools, that effectively charge around 260 USD per year. This amount of money is much higher than the one for originally assigned students (177 USD per year). Also, they are being assigned to schools that are cheaper than their outside option, shown in Table 26.

Table 26: Final Assignations' Yearly Tuition, Students Not Assigned During First Stage

	Observed non-assigned students
Average	307
Std. Dev	463
Median	0
75th percentile	487
99th percentile	1298

Notes: Yearly Tuition was calculated adding up base fee plus monthly fee multiplied by 10. All prices in USD (Change rate: 770 CLP/USD). Original tuition data was expressed in intervals, median value of each interval was considered to calculate numeric values. We consider that Priority students are exempt from paying in SEP Schools.

Despite the fact that net winners are matched to more expensive schools than the ones from students originally assigned, averages presented in Table 25 experience a mild decrease. This fall is explained by the change observed for collaterally affected students. As reported in Table A13 in Appendix D, our suggestions cause that them end up assigned to schools that are, at least, 51 USD cheaper than their original assigned school.

Furthermore, when we distinguish net winners between type of students, we observe that, for every level of accepted suggestions, Non-Priority net winners end matched to schools that are much more expensive than the ones for Priority. These disaggregated results are available in Table A22 in Appendix D. This was expected since we previously concluded that our algorithm suggests cheaper schools to Priority students. Relative to their outside options, shown in Table 27, Priority net winners undergo increases in yearly tuition. On average, Priority net winners face a 66 USD increase in yearly tuition with our suggestions. For Non-Priority students, there is a 77 USD fall.

Table 27: Final Assignations' Yearly Tuition, Students Not Assigned During First Stage, Distinguishing Between Priority and Non-Priority Students

	Overall	Non-Priority	Priority
Average	307	385	77
Std. Dev	463	493	2242
Median	0	0	0
75th percentile	493	974	0
99th percentile	1396	1396	980

Notes: Yearly Tuition was calculated adding up base fee plus monthly fee multiplied by 10. All prices in USD (Change rate: 770 CLP/USD). Original tuition data was expressed in intervals, median value of each interval was considered to calculate numeric values. We consider that Priority students are exempt from paying in SEP Schools.

Finally, Table 28[39] reports the impact of our suggestions in the enrolled school's yearly tuition, considering all phases; which captures the total effect of net winners, net losers and collaterally affected students. Our suggestions result in a fall of the average yearly fees. Albeit, the effect is stronger initially. When students start accepting more suggestions average fees start going up. Interestingly, this result is mainly explained by the change observed in Non-Priority students. Table A23 in Appendix D reports the final assignation's,

[39] Analogous assumptions of footnote 36 apply.

considering all phases, yearly tuition for Non-Priority and Priority students, respectively. We do not find major impacts in the average for Priority students. By contrast, Non-Priority students experience significant decreases in their average fees.

Table 28: Final Assignations' Yearly Tuition, Considering All Phases

		Average number of accepted suggestions							
	Original	0.5	1	2	3	4	5	6	7
Average	184	157	159	159	160	160	161	161	161
Std. Dev	346	320	321	322	322	322	322	323	323
Median	0	0	0	0	0	0	0	0	0
75th percentile	227	0	0	0	0	0	0	0	0
99th percentile	1298	980	980	980	980	980	980	980	980

Notes: Yearly Tuition was calculated adding up base fee plus monthly fee multiplied by 10. All prices in USD (Change rate: 770 CLP/USD). Original tuition data was expressed in intervals, median value of each interval was considered to calculate numeric values. We consider that Priority students are exempt from paying in SEP Schools.

All things considered, we find that the implementation of our algorithm would have significant impacts in the average fee paid by students. On average, it would reduce this fee around 25 USD per year. This fall is perceived essentially by Non-Priority students. We do not find major impacts in Priority, which is reasonable since they never pay tuition in SEP schools.

7 Social Welfare

We formerly evaluated the effects our suggestions would have, considering the general equilibrium, in relevant observable variables such as commuting distances, SIMCE scores and tuition fees. Albeit, studying these variables individually does not allow us to directly conclude if our system improves the social welfare, in terms of utilities, or not. Considering this fact, in this chapter we analyze the impact of our technology in social welfare from a utilitarian perspective. We only focus in social welfare calculated with the final assignation considering all phases,[40] since conceptually it does not make sense to evaluate the main phase isolatedly.

[40]Since in our simulations we do not know if students would enroll in the school they had assigned during the main phase, in the original assignation we assumed they did it; even if we knew they finally enrolled in another school. This is the only way to make the numbers comparable. Additionally, in our simulations, we imputed the average values reported in Table A29 as the utility level for students not assigned during

We define social welfare based on a classical utilitarian approach, as follows:

$$S_I = \sum_{n=1}^{m} U_{n,Y(X)} \tag{11}$$

Where I is the approximate average number of accepted suggestions and takes values between 0 (original observed application) and 7. The parameter m is the total number of students that participated in the main stage; not distinguishing if they finally got matched to a school or not. On the other hand, $U_{n,Y(X)}$ is the observable utility level, defined in equation 8, that the student n receives for being enrolled in the school X. The enrolled school also is a function of the average number of accepted suggestions X. It is important to highlight that our definition of social welfare does not include the utility of students that did not participate in the SAE in the main phase; e.g., students that directly apply to private schools outside of the system. However, our algorithm should not affect them at all, so their utilities remain constant within any number of accepted suggestions.

The impact of our suggestions in social welfare is reported in Table 29. All percentage changes are relative to the observed application.

Table 29: Social Welfare, Considering All Phases

	Average number of accepted suggestions							
	0.5	1	2	3	4	5	6	7
Relative change in total social welfare (%)	-0.29	-0.61	-1.05	-1.42	-1.71	-1.88	-1.97	-2.20
Relative change in S.D. (%)	-2.46	-2.79	-3.29	-3.55	-3.92	-3.90	-4.11	-4.21

Notes: All percentage changes are relative to the observed application.

In terms of social welfare, our technology has small but negative impacts. Besides, negative impacts are higher when students accept, on average, more suggestions. This result may be explained, on one side, by the impact perceived by collaterally affected students, who are matched to schools that can be even worse than the outside option. Table A25 in Appendix D reports the negative impact, in terms of welfare, for collaterally affected students. Roughly 65% of them have a negative impact in their utility levels. On the other side, counterintuitively, many net winners are negatively impacted by our suggestions. Table

the main phase, distinguishing between Priority and Non-Priority students. This was not necessary for the original process, because we do know where non-assigned students finally ended enrolled. Besides, we did not consider students that lived and applied to schools of Santiago but ended enrolled in other regions of the country, for being outliers. Finally, we supposed that the characteristics of the outside option remained constant even if the percentage of non-selected students during main phase changed. This may be considered a weakness of our approach.

A26 in Appendix D reports the impact, in terms of welfare, for net winners. Surprisingly, on average, net winners are having a negative impact. Although this negative impact is insignificant compared to the one experienced by collaterally affected students, it is striking that almost half of net winners would have been better with their outside option.

Our evidence suggests that this negative impact on net winners is not explained by the quality of our suggestions. Instead, it is explained by the high quality of the outside option. As previously shown in Table 11, our suggestions are quite similar, in terms of utility, to the last applied school by each student. For Non-Priority students, our first recommendations can be even better. Table A28 in Appendix D reports the difference between the last applications' utility levels and the outside option's utility level.[41] On average, for Non-Priority students the outside option is better than their last application. While for Priority students, the last application is, on average, better than their outside option, both groups show a negative median. This implies that at least for half of the students of each group, the outside option is better than their last application. These results are counterintuitive: why these students did not apply to this outside options if it was better than their last application? Although further research is needed, we can propose three possible explanations. First, our utility calculations only consider observable variables. It is likely that people pay attention to other non-observable attributes at the moment of applying. If this was not true, we could simply recommend schools based on these calculated utility levels, instead of using an intelligent algorithm. Consequently, students may not be applying to their outside option because the total utility of it (including non-observable components) is smaller than their last application's utility level. Second, students could be not be applying to their outside option because of friction gaps. Essentially, they are related to the costs of acquiring and processing information. Exploring more options in a choice set and assessing them is not cost-free, so agents may not do it even if, ex-post, it would be optimal for them. Third, the utility level of the outside option may be capturing the one of students that enrolled in private schools. These institutions are not included in SAE, so students can not apply to them through this system. Table A29 in Appendix D reports the outside option's utility level, without taking into account students that ended enrolled in private schools. There are no signs that for Priority Students the outside option' utility level is being influenced by private schools. However, this does not hold for Non-Priority, since the utility level of their outside option worsens without considering private schools. Moreover, only 1.19% of Priority Students that were not assigned during the main phase ended enrolled in a private school. On the contrary, 10.60% Non-Priority Students did it.

[41] Also, the difference between our suggestions' utility levels and the outside option's utility level is presented in Table A27 in Appendix D, but the results are similar.

In addition, the growing negative changes observed in social welfare can be attributed to the fact that collaterally affected students grow at a higher rate than net winners. Growth rates for both groups were previously shown in Figure 7.

Welfare losses are significantly higher for Non-Priority students. Table A24 in Appendix D disaggregates welfare changes between Non-Priority and Priority students. Losses for the former are much higher than the ones for the latter. This is not surprising, since as shown in Table A9 in Appendix D, proportionally, Non-Priority Students have a higher number of collaterally affected students, who are the most harmed by our system.

Furthermore, our algorithm has negative effects in the standard deviation, which can be interpreted as a measure of inequality levels.

In sum, our algorithm is specially harming collaterally affected students, resulting in net losses.

8 Robustness Test

In this chapter we follow an alternative methodology for evaluating the impact of our suggestions on the general equilibrium and social welfare. The main difference with our previous exercise is that, in this chapter, suggestions are not necessarily added in the last places of the students' list of applications. Now, they can even take the first place, as detailed in the following lines:

8.1 Methodology

1. For each student A, we calculated the initial acceptance probability for his best 10 suggestions using the following equation:

$$P(U_{out}, U_s, B) = \frac{B}{1 + e^{U_{out} - U_s}} \tag{12}$$

   Which depends on the difference between the utility level of our suggestion U_s and the utility level of the student's outside option U_{out}.[42] The probability also depends on the parameter B.[43] This determined the set of accepted suggestions for each student. Notice that it could happen that suggestion n, in the order defined by our algorithm, is not included but $n+1$ it is.

[42]Since we are not able to know exactly each student's outside option, we considered the utilities presented in Table A28 in Appendix D as the outside option's utility level, distinguishing between Priority and Non-Priority Students.

[43]Similar to our previous exercise, B was calibrated for each average of accepted suggestions.

2. Each recommendation of the student's set of accepted suggestions was temporarily added immediately after his observed applications, i.e., in the last place. However, each of them had the following probability of moving up one position:

$$P(U_j, U_s, B) = \frac{B}{1 + e^{U_j - U_s}} \tag{13}$$

   Where U_s is the utility level of suggestion s and U_j is the utility level of the student's last application.

3. Suggestions that previously advanced one place, had now the chance of moving up another position, with an analogous probability:

$$P(U_{j-1}, U_s, B) = \frac{B}{1 + e^{U_{j-1} - U_s}} \tag{14}$$

   Notice that now, the probability depends on the utility level of the student's observed[44] penultimate application.

4. The previous procedure was repeated n times, being n the number of schools originally applied by each student. In this way, one suggestion could even take the first place. More generally, the conditional probability that suggestion s advances from position *T* to *T-1* can be defined as:

$$P(U_{T-1}, U_s, B)|(place = T) = \frac{B}{1 + e^{U_{T-1} - U_s}} \tag{15}$$

5. Suggestions that finally ended in the same position were sorted following the order given by our recommendation system.

6. We run the matching algorithm developed by the Chilean government *à la* Gale-Shapley. Considering that in the original application each student had been given a random number in each one of the schools he applied, we followed the next logic for adding new applications: the first new applicant for each school was given a random number between 0 and the original number of applicants for that school. All students that originally applied to that school and had a position equal or below the new applicant's obtained number, were displaced in one place. Next, the second new applicant for each school was given a new random number between 0 and the original number of applicants for that school, plus one. All students that after the first iteration were in that school's list and had a position equal or below the new applicant's obtained

[44]Not considering our suggestions.

number, were displaced in one position. And so on until adding all the new applicants to each school. Conceptually, adding the new applications following this procedure allows us to simulate what would have happened if the students had accepted our recommendations.

8.2 Results

8.2.1 Percentage of Non-Assigned Students During Main Phase

Table 30 reports the effects of our algorithm, under our alternative approach, on the percentage of non-assigned students during the first stage. Compared to our original strategy, the impacts are less significant. Moreover, when students start accepting too much suggestions, the impacts are much lower. Intuitively, this may be explained by the fact that our suggestions generate too much distortion in the whole system.

Table 30: Percentage of Non-Assigned Students During The First Stage of the Application Process, Considering Suggestions - Alternative Approach

		Approximate average of accepted suggestions							
	Original	0.5	1	2	3	4	5	6	7
Non-Priority	15.37%	14.84%	14.50%	13.86%	14.08%	14.23%	14.69%	15.19%	15.62%
Priority	7.85%	7.33%	6.80%	6.41%	5.96%	6.28%	6.52%	6.51%	6.87%
Overall	12.55%	12.03%	11.61%	11.05%	11.04%	11.25%	11.63%	11.94%	12.34%

Notes: Original column represents the observed application. Percentages calculated only for students of Santiago.

8.2.2 Distance

Table 31 presents the effects of our algorithm, under our alternative approach, on the final assignations' School-Student distance. The effects are similar in magnitude to the ones we observed with our original strategy.

Table 31: Final Assignations' School-Student Distance, Considering All Phases - Alternative Approach

		Average number of accepted suggestions							
	Original	0.5	1	2	3	4	5	6	7
Average	2.14	2.05	2.06	2.06	2.05	2.03	2.02	2.00	2.01
Std. Dev	6.49	9.04	9.04	9.04	9.01	8.99	8.97	8.94	8.93
Median	1.10	1.23	1.33	1.34	1.35	1.37	1.4	1.4	1.4
75th percentile	2.24	1.96	1.98	2.03	2.04	2.06	2.05	2.07	2.08
99th percentile	17.67	15.60	15.54	15.23	15.02	14.19	13.62	13.30	13.39

Notes: Distances in kilometers and computed only for students with a reasonable address in dataset.

8.2.3 SIMCE

Table 32 shows the effects of our algorithm, under our alternative approach, on the final assignations' SIMCE Scores. The effects are similar in magnitude to the ones we observed with our original strategy. Still, interestingly, when students start accepting too much suggestions, our algorithm has positive insignificant impacts. We did not observe this situation with our original approach.

Table 32: Final Assignations' SIMCE Scores, Considering All Phases - Alternative Approach

		Average number of accepted suggestions							
	Original	0.5	1	2	3	4	5	6	7
Average	266.68	266.61	266.56	266.50	266.56	266.62	266.71	266.76	266.82
Std. Dev	22.63	21.45	21.50	21.56	21.52	21.48	21.39	21.35	21.30
Median	265	267.5	267	266.5	266.5	267	267.5	267.5	268
75th percentile	282.5	280	280	280.5	280.5	280.5	280.5	280	280
99th percentile	314.5	314.5	314.5	314.5	314.5	314.5	314.5	314.5	314.5

Notes: SIMCE Score was calculated as the average of Math and Spanish Tests applied in 2018 for 4th grade.

8.2.4 Tuition

Table 33 reports the effects of our algorithm, under our alternative approach, on the final assignations' yearly effective tuition. The effects are very close to the ones we found in our previous exercise.

Table 33: Final Assignations' Yearly Tuition, Considering All Phases - Alternative Approach

		Average number of accepted suggestions							
	Original	0.5	1	2	3	4	5	6	7
Average	184	157	157	158	158	158	158	157	157
Std. Dev	346	320	320	321	321	321	321	320	320
Median	0	0	0	0	0	0	0	0	0
75th percentile	227	0	0	0	0	0	0	0	0
99th percentile	1298	980	980	980	980	980	980	980	980

Notes: Yearly Tuition was calculated adding up base fee plus monthly fee multiplied by 10. All prices in USD (Change rate: 770 CLP/USD). Original tuition data was expressed in intervals, median value of each interval was considered to calculate numeric values. We consider that Priority students are exempt from paying in SEP Schools.

8.2.5 Social welfare

Table 34 presents the effects of our algorithm, under our alternative approach, on social welfare. The effects are smaller than the ones we previously found but, anyway, similar.

Table 34: Social Welfare, Considering All Phases - Alternative Approach

	Average number of accepted suggestions							
	0.5	1	2	3	4	5	6	7
Relative change in total social welfare (%)	-0.36	-0.57	-0.99	-1.14	-1.28	-1.41	-1.45	-1.51

Notes: All percentage changes are relative to the observed application.

9 Conclusions

In this paper we studied the effects of implementing a recommender system in the context of the Chilean School Choice System. We showed that artificial intelligence-based recommendation algorithms are capable of inferring students' preferences to suggest schools similar to the applied ones. Even more, this suggestions may be optimal in terms of observable variables.

However, when we evaluated the impact of our suggestions in a general equilibrium framework, we did not find major impacts in average school-student distances and assigned schools' SIMCE scores. We also found small negative impacts in social welfare. These results may be explained by the fact that our suggestions create congestion in the system, hurting a significant number of students. Strikingly, the number of damaged students may be higher than the number of the benefited ones. Besides, the negative impact made to collaterally affected students may be similar in magnitude to the positive impact on net winners. As a result, our algorithm, in the aggregate, may create social net losses. Despite having a different approach, our results are similar to the ones found by Neilson et al. (2019), that shows that capacity constraints in the supply-side may severely affect the positive impacts of a personalized information provision intervention. If all students have similar preferences and good schools are a scarce resource, overall improvements may be impossible. There is no such thing as a free lunch.

Albeit, we also demonstrated that our system is able to reduce the number of non-assigned students during the main phase. In consequence, if the authority's goal is to tackle this issue, it may be useful in this line. Additionally, our algorithm may be used for assigning students who never apply during the first phase. Both effects are not included in our welfare calculations and the society might value them. For example, not being matched during the main phase, involves additional information costs, among other things.

Our results may be interpreted broadly. In contexts of rival goods, like schools, the aggregated impacts of a recommendation system may be counterintuitive, since individuals start to compete for goods. The level of competition is highly influenced by a recommendation system, since, by construction, they tend to suggest popular items. Evidently, this conclusion does not hold for internet applications, because they do not offer rival goods. For instance, all Netflix's users may be watching the same movie at the same time, without hurting each other. With rival goods, only a limited number of people can consume them simultaneously.

Finally, we have to make explicit that our approach has some weaknesses. Particularly, for calculating impacts considering all phases, we had to assume that the characteristics of the outside option remained constant when the number of non-assigned students during the main stage varied. Empirically, it is unlikely that these characteristics remain constant, since, if more students are matched during the main phase, fewer schools end with available vacancies. However, because the final enrollment is not fully based on SAE, in our opinion, this was the most reasonable way to tackle this problem. Future research should take into account this issue.

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Appendices

A Model: First Attempts

K-Nearest Neighbors

This algorithm follows a classical nearest neighbours approach. Predicted ratings are calculated using a weighted average of ratings of similar schools.[45] Mathematically, the predicted rating of school i for student u is equal to:

$$\hat{r}_{ui} = \mu_i + \frac{\sum_{j \in N_u^k(i)} \text{sim}(i,j) \cdot (r_{uj} - \mu_j)}{\sum_{j \in N_u^k(i)} \text{sim}(i,j)} \tag{16}$$

Where u_i is the average rating of school i given by all the students. Analogously, u_j is the average rating for the neighbor j $\forall j$ and r_{uj} $\forall u, j$ corresponds to the observed rating the student u gave to school i. Finally, $\text{sim}(i,j)$ is the cosine similarity between school i and j which can be defined as:

$$\text{sim}(i,j) = \frac{\sum_{u \in U_{ij}} r_{ui} \cdot r_{uj}}{\sqrt{\sum_{u \in U_{ij}} r_{ui}^2} \cdot \sqrt{\sum_{u \in U_{ij}} r_{uj}^2}} \tag{17}$$

Notice that we are computing similarities between schools, so it is an item-based approach. We were not able to run the user-based approach since - given the dimensions of our dataset - it was extremely demanding in terms of computer resources.[46] Considering that in our context smaller numbers imply stronger preferences, for each user, schools were recommended ascending in their predicted ranking. In other words, the school with the smallest predicted ranking was recommended first.[47]

On average, the best (first) recommendation is 12.40 Km. away from each student. In the observed data, students - on average - apply to a school that is at most 3.15 Km. away from their homes. Detailed statistics are available in Table A2 in Appendix B. Therefore, we assumed that in a real implementation, most of them would simply not accept our suggestion. Running simulations with this model did not make sense. Thus, we then tested a Co-clustering model, achieving similar results. Next, we developed a SVD algorithm, whose results are presented below.

SVD

Matrix Factorization models - like SVD - are superior to classic nearest-neighbor techniques for producing suggestions (Koren et al., 2009). Moreover, they tend to give better results in sparse contexts like ours. Basically, the predicted rating of school i for student u is defined

[45] The effective k is different for every student, taking values between 1 and 40. Neighbors with a negative correlation are not taken into account.

[46] Still, item-based had to be run in Amazon's EC2 128 GB RAM servers.

[47] Fearing that the algorithm could be misinterpreting this uncommon ranking method, we also transformed ratings. With this transformation, for every user, the first preferred school had the higher observed rating. Results varied only slightly and are available in Table A3 in Appendix B.

as:

$$\hat{r}_{ui} = \mu + b_u + b_i + q_i^T p_u \tag{18}$$

Where μ is an overall average ranking. $b_u + b_i$ denote the bias for student u and school i, respectively. These biases make an adjustment for students that tend to give higher ratings or analogously, for schools that regularly are given better scores. Finally, $q_i^T p_u$ is the interaction between a certain student and a particular school. Specifically, q_i is a vector that contains latent factors inferred from observed patterns for school i, while p_u represents the importance that student u gives to each factor. All these parameters, except μ,[48] are computed in the following optimization problem:

$$\min_{b_i, b_u, q_i, p_u} \underbrace{\sum_{r_u \in R_{\text{train}}} (r_{ui} - \hat{r}_{ui})^2}_{①} + \underbrace{\lambda \left(b_i^2 + b_u^2 + \|q_i\|^2 + \|p_u\|^2 \right)}_{②} \tag{19}$$

Where ① minimizes the prediction error, fitting the observed ratings. However, only with this term, the model would overfit the observed data, not being able to generalize to new - unobserved - combinations. In that sense, ② penalizes the magnitude of the parameters, preventing overfitting. λ is the regularization constant and it is fixed by the programmer. This optimization problem is solved using a Stochastic Gradient Descent Algorithm, which goes far beyond the scope of this paper.[49]

On average, the best (first) recommendation is 25.28 Km. away from each student.[50] More detailed statistics are available in Table A4 in Appendix B. Unexpectedly, the obtained results are even worse, in terms of distance, than the previous ones. We assume that given the extreme sparsity of our dataset, pure CF models are not able to learn underlying preferences. As mentioned before, there is evidence that pure CF models tend to perform poorly in these contexts (see e.g., Adomavicius and Tuzhilin, 2005).

[48] Which is observed in the data.

[49] See Zhang (2004) for more details.

[50] Again, results virtually do not vary using transformed ratings. Presented in Table A5 in Appendix B.

B Additional General Statistics

Table A1: Geographic Imputation for Reasonably Located Students. Distance Between Imputed and Real Location.

	Distance (Km.)
Average	2.10
Std. Dev	9.08
Median	1.10
75th percentile	2.20
99th percentile	15.50

Notes: Computed only for students with a reasonable address in dataset.

Table A2: Best Suggestion's Statistics: K Nearest Neighbors Algorithm (Original Rating)

	Distance (Km.)
Average	10.71
Std. Dev	12.44
Median	8.03
75th percentile	13.41
99th percentile	45.29

Notes: Distance computed only for students with a reasonable address in dataset. Best suggestion was defined as the school with the lowest predicted rating.

Table A3: Best Suggestion's statistics: K Nearest Neighbors Algorithm (Transformed Rating)

	Distance (Km.)
Average	12.40
Std. Dev	15.44
Median	8.42
75th percentile	14.84
99th percentile	78.55

Notes: Distance computed only for students with a reasonable address in dataset. Observed ratings where transformed in a way that the first preference, for each student, had the highest rating. Best suggestion was defined as the school with the highest predicted rating.

Table A4: Best Suggestion's Statistics: SVD Algorithm (Original Rating)

	Distance (Km.)
Average	25.28
Std. Dev	18.81
Median	21.25
75th percentile	35.03
99th percentile	75.39

Notes: Distance computed only for students with a reasonable address in dataset. Best suggestion was defined as the school with the lowest predicted rating.

Table A5: Best Suggestion's Statistics: SVD Algorithm (Transformed Rating)

	Distance (Km.)
Average	25.22
Std. Dev	18.95
Median	21.00
75th percentile	34.56
99th percentile	76.96

Notes: Distance computed only for students with a reasonable address in dataset. Observed ratings where transformed in a way that the first preference, for each student, had the highest rating. Best suggestion was defined as the school with the highest predicted rating.

C Differences Between Priority and Non-Priority

Table A6: Suggestions' School-Student Distance: Hybrid Matrix Factorization Model

	Suggestion N°									
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10
Non-Priority Students										
Average (Km.)	3.05	3.19	3.24	3.23	3.23	3.22	3.38	3.64	3.67	3.85
Std.Dev (Km.)	10.79	10.81	10.84	10.91	10.96	10.87	9.59	11.27	11.32	11.47
Median (Km.)	2.32	2.45	2.48	2.35	2.37	2.33	2.45	2.61	2.60	2.75
75th percentile (Km.)	3.50	3.67	3.70	3.73	3.62	3.53	3.76	3.99	4.00	4.21
99th percentile (Km.)	11.65	13.35	13.68	14.07	14.73	15.03	15.26	18.99	20.56	23.11
Priority Students										
Average (Km.)	3.05	3.02	3.08	3.27	3.27	3.41	3.49	3.66	3.63	3.75
Std.Dev (Km.)	6.41	6.21	6.63	6.67	6.15	6.47	6.72	7.03	7.22	7.00
Median (Km.)	2.26	2.27	2.15	2.26	2.33	2.48	2.53	2.58	2.56	2.58
75th percentile (Km.)	3.33	3.35	3.38	3.54	3.57	3.68	3.76	4.00	3.82	3.90
99th percentile (Km.)	14.25	13.91	15.26	15.08	16.23	15.54	16.47	20.19	25.87	27.40

Notes: Distance computed only for students with a reasonable address in dataset.

Table A7: Suggested Schools' SIMCE Scores: Hybrid Matrix Factorization Model

	Suggestion N°									
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10
Non-Priority Students										
Average	286.86	284.70	282.52	278.34	276.13	272.64	272.59	271.06	269.66	270.15
Std.Dev	14.83	18.26	19.53	18.91	19.26	19.31	19.37	18.43	18.80	19.32
Median	287.5	285	283	280	277.5	272.5	272.5	271	270.5	270.5
75th percentile	297	297	295	292	289.5	285.5	285.5	284.5	283	284
99th percentile	313.5	334.5	334.5	314.5	314.5	314.5	314.5	311.5	310	308.5
Priority Students										
Average	283.37	277.25	276.64	275.99	274.89	271.65	268.56	267.61	265.65	263.79
Std.Dev	16.40	18.47	21.34	21.22	21.59	19.92	18.49	18.30	19.11	18.68
Median	285	275.5	276	275	276	272.5	269	269	266	264.5
75th percentile	292.5	290.5	289.5	290	289.5	285.5	282.5	282	280.5	276
99th percentile	337	334.5	334.5	337	337	314	303.5	303.5	302	304

Notes: SIMCE Score was calculated as the average of Math and Spanish Tests applied in 2018 for 4th grade.

Table A8: Exploded Logit Estimated Coefficients by Tagle (2018)

Variable	Value
β_1	-.7119
β_2	-.1528
γ_1	.02465
γ_2	.00073
θ_1	-8.13e-07
θ_2	-4.42e-07
α_1	-4.1714
α_2	1.8573

D General Equilibrium and Social Welfare

Table A9: Percentage of Net Losers, Considering Suggestions and Distinguishing Between Priority and Non-Priority Students

	Average number of accepted suggestions							
	0.5	1	2	3	4	5	6	7
Non-Priority	1.20%	1.96%	2.69%	3.25%	3.50%	3.78%	3.85%	3.95%
Priority	0.47%	0.87%	1.16%	1.45%	1.62%	1.67%	1.66%	1.68%
Total	0.91%	1.53%	2.09%	2.54%	2.76%	2.95%	2.99%	3.05%

Notes: Net losers correspond to students that in the original process had a school assigned, but due to the effect of our suggestions on the general equilibrium, they finally are not assigned to any school. Percentages were calculated within each category. Total does not distinguish between Priority and Non-Priority students.

Table A10: Percentage of Collaterally Affected Students, Considering Suggestions and Distinguishing Between Priority and Non-Priority Students

	Average number of accepted suggestions							
	0.5	1	2	3	4	5	6	7
Non-Priority	1.89%	3.63%	5.88%	8.55%	10.30%	11.51%	12.72%	13.97%
Priority	1.16%	2.23%	3.81%	5.83%	7.01%	8.06%	8.77%	9.82%
Total	1.60%	3.08%	5.06%	7.48%	9.00%	10.15%	11.16%	12.33%

Notes: Collaterally affected students correspond to students - originally assigned - that with our suggestions would be assigned to a different school, compared to the original process. Percentages were calculated within each category and do not include net losers, which are reported in Table A9. Total does not distinguish between Priority and Non-Priority students.

Table A11: Distance Difference Between New and Original Assignation for Collaterally Affected Students

	Average number of accepted suggestions							
	0.5	1	2	3	4	5	6	7
Average	-0.07	0.13	0.12	0.15	0.16	0.14	0.10	0.10
Std. Dev	2.39	2.80	2.79	3.08	3.02	3.06	3.25	3.13
Median	0.04	0.14	0.14	0.15	0.19	0.17	0.18	0.19
75th percentile	0.74	0.93	0.95	1.00	1.04	1.06	1.07	1.09
99th percentile	5.90	5.76	5.90	8.24	7.24	6.37	6.81	6.73

Notes: Distances in kilometers and computed only for students with a reasonable address in dataset.

Table A12: SIMCE Score Difference Between New and Original Assignation for Collaterally Affected Students

	Average number of accepted suggestions							
	0.5	1	2	3	4	5	6	7
Average	-8.35	-8.07	-8.64	-7.94	-7.92	-7.96	-8.01	-7.92
Std. Dev	28.12	27.71	28.27	27.94	28.01	28.00	28.14	27.89
Median	-8.5	-8.5	-9.5	-8.5	-8.5	-8.5	-8.5	-8.5
75th percentile	8.75	9	9	9	10.5	10	10	10
99th percentile	64	63.5	60	64	58.5	60	60.5	57

Notes: SIMCE Score was calculated as the average of Math and Spanish Tests applied in 2018 for 4th grade.

Table A13: Tuition Difference Between New and Original Assignation for Collaterally Affected Students

	Average number of accepted suggestions							
	0.5	1	2	3	4	5	6	7
Average	-52	-51	-74	-60	-71	-73	-73	-68
Std. Dev	411	412	407	419	419	419	425	427
Median	0	0	0	0	0	0	0	0
75th percentile	0	0	0	0	0	0	0	0
99th percentile	980	980	980	980	980	980	980	980

Notes: Yearly Tuition was calculated adding up base fee plus monthly fee multiplied by 10. All prices in USD (Change rate: 770 CLP/USD). Original tuition data was expressed in intervals, median value of each interval was considered to calculate numeric values. We consider that Priority students are exempt from paying in SEP Schools.

Table A14: Assignations' School-Student Distance, Considering Suggestions. Only for Net Winners

	Average number of accepted suggestions							
	0.5	1	2	3	4	5	6	7
Average	2.56	2.54	2.49	2.46	2.45	2.48	2.46	2.41
Std. Dev	2.10	2.08	1.96	1.96	1.89	2.39	2.00	1.90
Median	2.09	2.08	2.02	2.02	2.02	2.04	2.03	2.01
75th percentile	3.26	3.29	3.22	3.17	3.17	3.12	3.17	3.10
99th percentile	12.04	11.89	10.86	10.97	11.48	10.38	10.94	9.37

Notes: Net winners correspond to students originally not assigned to any school during the main phase, that with our suggestions would be assigned to one. Distances in kilometers and computed only for students with a reasonable address in dataset.

Table A15: Assignations' School-Student Distance, Considering suggestions. Only for Net Winners

	Average number of accepted suggestions							
	0.5	1	2	3	4	5	6	7
Non-Priority Students								
Average	2.51	2.52	2.52	2.51	2.49	2.52	2.50	2.44
Std. Dev	1.95	1.94	1.95	1.87	1.88	2.53	1.95	1.87
Median	2.07	2.08	2.06	2.09	2.06	2.05	2.08	2.03
75th percentile	3.21	3.31	3.27	3.24	3.30	3.18	3.20	3.15
99th percentile	10.79	10.32	9.76	10.94	10.94	10.94	11.08	9.37
Priority Students								
Average	2.67	2.61	2.40	2.34	2.34	2.36	2.32	2.31
Std. Dev	2.46	2.42	1.90	2.15	1.91	1.96	2.13	1.97
Median	2.13	2.09	1.91	1.85	1.91	2.03	1.83	1.92
75th percentile	3.35	3.26	3.08	2.95	2.93	2.88	3.03	2.92
99th percentile	14.77	14.02	11.76	11.48	11.48	9.94	10.07	9.23

Notes: Net winners correspond to students originally not assigned to any school during the main phase, that with our suggestions would be assigned to one. Distances in kilometers and computed only for students with a reasonable address in dataset.

Table A16: Final Assignations' School-Student Distance, Considering All Phases.

		Average number of accepted suggestions							
	Original	0.5	1	2	3	4	5	6	7
Non-Priority Students									
Average	2.31	2.20	2.27	2.23	2.26	2.26	2.28	2.28	2.28
Std. Dev	6.89	10.50	10.50	10.50	10.51	10.51	10.53	10.52	10.50
Median	1.21	1.40	1.40	1.40	1.40	1.40	1.40	1.40	1.40
75th percentile	2.48	2.11	2.16	2.21	2.26	2.30	2.31	2.34	2.35
99th percentile	18.72	15.97	15.96	15.90	15.97	15.87	16.02	16.03	15.97
Priority Students									
Average	1.85	1.80	1.80	1.79	1.82	1.80	1.82	1.81	1.82
Std. Dev	5.73	5.49	5.49	4.94	5.37	4.94	5.11	5.11	5.11
Median	0.92	1.02	1.02	1.02	1.02	1.03	1.04	1.02	1.03
75th percentile	1.87	1.72	1.75	1.79	1.82	1.85	1.87	1.86	1.89
99th percentile	15.92	14.27	14.29	14.35	14.29	14.12	14.12	13.61	13.49

Notes: Distances in kilometers and computed only for students with a reasonable address in dataset.

Table A17: Assignations' SIMCE Scores, Considering Suggestions. Only for Net Winners.

	Average number of accepted suggestions							
	0.5	1	2	3	4	5	6	7
Average	276.39	276.32	275.93	275.76	275.98	275.98	276.59	276.14
Std. Dev	21.01	20.97	20.89	20.46	20.02	20.58	20.12	20.53
Median	276	276.5	276.5	277	277	277	277	277
75th percentile	292	291.5	290	289.5	289.5	289.5	290	289.5
99th percentile	334.5	334.5	334.5	334.5	334.5	334.5	334.5	334.5

Notes: Net winners correspond to students originally not assigned to any school during the main phase, that with our suggestions would be assigned to one. SIMCE Score was calculated as the average of Math and Spanish Tests applied in 2018 for 4th grade.

Table A18: Assignations' SIMCE Scores, Considering Suggestions. Only for Net Winners.

	Average number of accepted suggestions							
	0.5	1	2	3	4	5	6	7
Non-Priority Students								
Average	277.85	278.32	278.14	276.87	277.11	276.88	277.57	277.30
Std. Dev	20.82	20.02	20.28	19.94	19.43	19.99	19.22	20.04
Median	278.5	279	278.5	277.5	277.5	277.5	278.5	278.5
75th percentile	293	292.5	292.5	290.5	290.5	290.5	291.5	291.5
99th percentile	334.5	334.5	334.5	334.5	334.5	334.5	334.5	334.5
Priority Students								
Average	272.83	271.54	270.37	273.06	273.11	273.65	274	273.08
Std. Dev	21.10	22.40	21.36	21.45	21.20	21.89	22.12	21.51
Median	272	270.5	269.75	272	272	272	272.5	272
75th percentile	286.5	287	285	287	286.5	287.5	287.5	287
99th percentile	334.5	334.5	334.5	337	337	337	337	337

Notes: Net winners correspond to students originally not assigned to any school during the main phase, that with our suggestions would be assigned to one. SIMCE Score was calculated as the average of Math and Spanish Tests applied in 2018 for 4th grade.

Table A19: Final Assignations' SIMCE Scores, Considering All Phases

		Average number of accepted suggestions							
	Original	0.5	1	2	3	4	5	6	7
Non-Priority Students									
Average	269.57	269.48	269.42	269.31	269.16	269.08	269.01	269.00	268.94
Std. Dev	22.33	20.80	20.87	21.01	21.08	21.13	22.10	21.21	21.31
Median	270.5	272	272	272	266.5	272	272	272	272
75th percentile	285	282.5	282.5	282.5	282.5	282.5	282.5	282.5	283
99th percentile	314.5	314	314	314.5	314.5	314	314.5	314.5	314.5
Priority Students									
Average	262.06	261.88	261.83	261.73	261.75	261.67	261.65	261.57	261.47
Std. Dev	22.34	21.79	21.88	21.89	22.02	22.07	22.10	22.12	22.09
Median	260	260	260	260	260	269	260	260	260
75th percentile	277	275.5	276	276	276	276	276	275.5	275.5
99th percentile	314.5	314.5	314.5	314.5	314.5	314.5	314.5	314.5	314.5

Notes: SIMCE Score was calculated as the average of Math and Spanish Tests applied in 2018 for 4th grade.

Table A20: Assignations' Yearly Tuition, Considering Suggestions

	Average number of accepted suggestions								
	Original	0.5	1	2	3	4	5	6	7
Non-Priority Students									
Average	252	252	251	250	249	248	247	247	246
Std. Dev	375	374	374	373	372	372	371	371	371
Median	0	0	0	0	0	0	0	0	0
75th percentile	487	487	487	487	487	487	487	487	487
99th percentile	1071	1071	1071	1071	1071	1071	1071	996	996
% of assigned students	84.63	85.48	86.17	87.00	87.64	88.21	88.52	88.75	89.18
Priority Students									
Average	63	64	64	64	64	64	64	64	64
Std. Dev	218	219	219	220	220	220	220	220	221
Median	0	0	0	0	0	0	0	0	0
75th percentile	0	0	0	0	0	0	0	0	0
99th percentile	980	980	980	980	980	980	980	980	980
% of assigned students	92.15	92.99	93.58	94.17	94.78	94.06	95.18	95.30	95.58

Notes: Yearly Tuition was calculated adding up base fee plus monthly fee multiplied by 10. All prices in USD (Change rate: 770 CLP/USD). Original tuition data was expressed in intervals, median value of each interval was considered to calculate numeric values. We consider that Priority students are exempt from paying in SEP Schools.

Table A21: Assignations' Yearly Tuition, Considering Suggestions. Only for Net Winners

	Average number of accepted suggestions							
	0.5	1	2	3	4	5	6	7
Average	282	269	262	250	259	256	264	249
Std. Dev	384	380	376	369	375	373	379	370
Median	0	0	0	0	0	0	0	0
75th percentile	493	493	493	487	493	493	493	493
99th percentile	980	980	1298	980	980	980	980	980

Notes: Net winners correspond to students originally not assigned to any school during the main phase, that with our suggestions would be assigned to one. Yearly Tuition was calculated adding up base fee plus monthly fee multiplied by 10. All prices in USD (Change rate: 770 CLP/USD). Original tuition data was expressed in intervals, median value of each interval was considered to calculate numeric values. We consider that Priority students are exempt from paying in SEP Schools.

Table A22: Assignations' Yearly Tuition, Considering Suggestions. Only for Net Winners

	Average number of accepted suggestions							
	0.5	1	2	3	4	5	6	7
Non-Priority Students								
Average	322	322	317	293	306	299	312	294
Std. Dev	388	392	388	378	385	381	389	381
Median	0	0	0	0	0	0	0	0
75th percentile	493	493	493	493	493	493	493	493
99th percentile	980	980	1298	980	1298	980	1298	980
Priority Students								
Average	184	143	124	145	140	142	137	132
Std. Dev	355	318	301	323	318	324	317	309
Median	0	0	0	0	0	0	0	0
75th percentile	0	0	0	0	0	0	0	0
99th percentile	980	980	980	980	980	980	980	980

Notes: Net winners correspond to students originally not assigned to any school during the main phase, that with our suggestions would be assigned to one. Yearly Tuition was calculated adding up base fee plus monthly fee multiplied by 10. All prices in USD (Change rate: 770 CLP/USD). Original tuition data was expressed in intervals, median value of each interval was considered to calculate numeric values. We consider that Priority students are exempt from paying in SEP Schools.

Table A23: Final Assignations' Yearly Tuition, Considering All Phases

		Average number of accepted suggestions							
	Original	0.5	1	2	3	4	5	6	7
Non-Priority Students									
Average	260	216	218	219	219	220	220	221	220
Std. Dev	387	358	359	359	359	359	359	359	359
Median	0	0	0	0	0	0	0	0	0
75th percentile	487	487	487	487	487	487	487	487	487
99th percentile	1298	966	996	996	996	996	996	996	996
Priority Students									
Average	62	59	60	60	61	61	61	61	62
Std. Dev	215	211	213	214	215	215	215	215	216
Median	0	0	0	0	0	0	0	0	0
75th percentile	0	0	0	0	0	0	0	0	0
99th percentile	980	980	980	980	980	980	980	980	980

Notes: Yearly Tuition was calculated adding up base fee plus monthly fee multiplied by 10. All prices in USD (Change rate: 770 CLP/USD). Original tuition data was expressed in intervals, median value of each interval was considered to calculate numeric values. We consider that Priority students are exempt from paying in SEP Schools.

Table A24: Social Welfare, Considering All Phases

	Average number of accepted suggestions							
	0.5	1	2	3	4	5	6	7
Non-Priority Students								
Relative change in welfare (%)	-0.34	-0.77	-1.26	-1.69	-1.94	-2.16	-2.25	-2.46
Priority Students								
Relative change in welfare (%)	-0.22	-0.39	-0.79	-1.06	-1.40	-1.52	-1.62	-1.85

Notes: All percentage changes are relative to the observed application.

Table A25: Utility Difference Between New and Original Assignation for Collaterally Affected Students, Considering All Phases

	Average number of accepted suggestions							
	0.5	1	2	3	4	5	6	7
Average	-0.58	-0.76	-0.91	-0.86	-0.88	-0.76	-0.85	-0.86
Std. Dev	2.45	2.35	2.40	2.35	2.35	2.34	2.31	2.31
Median	-0.49	-0.52	-0.57	-0.56	-0.55	-0.56	-0.56	-0.56
75th percentile	0.50	0.33	0.29	0.27	0.26	0.26	0.29	0.27
99th percentile	7.43	6.28	5.54	5.85	5.76	5.62	5.43	5.62
% worse	63.54	65.57	66.72	67.35	67.50	67.51	67.35	67.22

Table A26: Utility Difference Between New and Original Assignation for Net Winners, Considering All Phases

	Average number of accepted suggestions							
	0.5	1	2	3	4	5	6	7
Average	-0.08	-0.09	-0.14	-0.17	-0.11	-0.11	-0.10	-0.17
Std. Dev	1.84	1.78	1.74	1.81	1.77	1.77	1.74	1.80
Median	0.026	0	0	-0.02	0	0	0	-0.02
75th percentile	0.89	0.87	0.86	0.83	0.87	0.87	0.88	0.80
99th percentile	3.71	3.31	3.27	3.41	3.47	3.49	3.34	3.36
% better	51.85	50.57	50.61	49.28	51.01	50.47	50.39	49.45

Table A27: Utility Difference Between Suggestions and Outside Option

	Suggestion N^o									
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10
Non-Priority Students										
Average	0.15	0.02	-0.07	-0.26	-0.39	-0.49	-0.52	-0.61	-0.70	-0.74
Std. Dev	0.90	0.94	0.98	0.98	0.97	1.02	1.00	0.97	1.00	1.00
Median	0.27	0.13	0.01	-0.14	-0.25	-0.37	-0.36	-0.48	-0.59	-0.62
75th percentile	0.74	0.66	0.60	0.43	0.26	0.23	0.19	0.08	0	-0.05
99th percentile	1.99	2.00	1.89	1.68	1.55	1.44	1.34	1.29	1.29	1.36
Priority Students										
Average	-0.15	-0.36	-0.36	-0.43	-0.48	-0.60	-0.72	-0.81	-0.88	-0.93
Std. Dev	0.92	0.96	1.00	0.96	0.99	1.00	0.96	0.92	0.96	0.94
Median	-0.12	-0.35	-0.29	-0.37	-0.40	-0.51	-0.61	-0.74	-0.83	-0.88
75th percentile	0.38	0.24	0.28	0.17	0.13	0.05	-0.10	-0.20	-0.22	-0.30
99th percentile	2.15	2.01	1.93	1.69	1.74	1.51	1.32	1.21	1.14	1.17

Table A28: Utility Difference Between Last Application and Outside Option

	Non-Priority Students	Priority Students	
Average	-0.12	0.31	
Std. Dev	2.02	2.79	t
Median	-0.34	-0.25	
75th percentile	0.43	0.57	
99th percentile	8.26	12.01	

Table A29: Utility Difference Between Last Application and Outside Option

	Overall	Non-Priority Students	Priority Students
Including Private Schools			
Average	5.13	4.95	5.63
Median	5.01	4.92	5.30
Not including Private Schools			
Average	5.05	4.83	5.64
Median	4.90	4.72	5.30