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Gregory Elacqua
Anne Sofie Westh Olsen
Santiago Velez-Ferro

Inter-American Development Bank
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The Market Design Approach to Teacher Assignment: Evidence from Ecuador

Gregory Elacqua*, Anne Sofie Westh Olsen†, Santiago Velez-Ferro‡

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Abstract

We study the advantages, trade-offs, and challenges of employing a centralized rule to determine the allocation of teachers to schools. Data come from the centralized teacher assignment program in Ecuador, "Quiero ser Maestro," conducted by the Ministry of Education. Notably, in 2019 the program transitioned from a priority based algorithm to a strategy proof mechanism, similar to the change introduced in Boston in 2005 to assign students to schools. Using the reported preferences, we conduct a counterfactual analysis and find substantive evidence that the adjustment in algorithm resulted in greater efficiency for the school system. However, in contrast to the Boston case, we find the benefits stem from increasing the competition for positions among teachers, rather than by the introduction of a strategy-proof mechanism.

*Principal Education Economist, Inter-American Development Bank email: gregorye@iadb.org
†email: fiewestholsen@gmail.com
‡email: svelez88@gmail.com

1 Introduction

In July 2005, the Boston School Committee started using the deferred acceptance algorithm to centrally assign students to schools (Gale and Shapley, 1962). This change was triggered by a critique of the previous algorithm in the seminal work of (Abdulkadiroğlu and Sönmez, 2003) and (Abdulkadiroglu, Pathak, Roth, and Sonmez, 2006). These scholars argued that the earlier approach provided strong incentives for parents to manipulate their reported preferences. In this paper, we discuss the advantages, trade-offs, and challenges of using a centralized rule to determine the allocation of teachers to schools. We show that a similar adjustment in algorithm introduced in Ecuador in 2019 generated significant gains in the overall efficiency of the teacher-school market.

We use data from the centralized teacher assignment system in Ecuador, "Quiero ser Maestro" (I Want to Be a Teacher), conducted by the Ministry of Education.[1]. Like student assignment, allocating teachers to schools is a *two-sided, many-to-one problem* (Roth and Sotomayor, 1992) It is two-sided in that there are two disjoint sets of agents, teachers and schools, that must be matched with each other; it is many-to-one in that several teachers can potentially be allocated to the same school. Centralized teacher assignment hence resembles student assignment, given that: i) it involves a high number of participants during the allocation process; ii) there is a high level of congestion since many teachers prefer the same schools; and iii) a significant number of teachers and positions are left unassigned.

Several countries have begun centrally assigning teachers with the objective of improving the efficiency, equity, and transparency of the allocation process. This is a crucial procedure, as teachers represent the most influential factor in improving student achievement (Chetty, Friedman, and Rockoff, 2014). They are also the most costly schooling input. Specifically, in a centralized system prospective teachers report their preferences to a central authority

[1]Information on the characteristics of the program can be found at `https://educacion.gob.ec/quiero-ser-maestro-6/`

and an algorithm is used to determine their allocation. In France, novice teachers who have just passed their certification exams are centrally assigned to a school under a one-year probationary period before they are granted tenure (Terrier, 2014). In Germany, each state centralized assigns teacher trainees to programs that incorporate practical teaching classes and then a teaching position (Klein and vom Baur, 2019). In Turkey (Özoglu and Beyazit, 2015), Ecuador (Drouet Arias and Westh Olsen, 2020), Peru (Bertoni, Elacqua, Méndez, Montalva, Munevar, Westh Olsen, and Román, 2020), and Portugal (Rodrigues, Dias, Gregório, Faria, Ramos, Miguéns, Félix, and Perdigão, 2019), teachers are centrally assigned to permanent (tenured) positions.

Study of the potential advantages of a centralized teacher allocation system is important for at least three reasons. First, many vacancies remain unfilled. Centralizing assignment can conceivably reduce search and information frictions faced by teachers when applying for positions. Indeed, while teachers in decentralized systems are required to file individual applications for each school, a centralized approach allows a teacher to apply to multiple schools with a single application. Reducing these frictions could increase the number of positions filled and thus enhance the efficiency of the allocations. This is particularly important for schools serving low-performing and disadvantaged students, characterized by the greatest number of unfilled vacancies. For example, in the 2015 Peru and the 2017 Ecuador (Drouet Arias and Westh Olsen, 2020) teacher allocation, respectively around 40% and 11% of low socioeconomic status (SES) school vacancies had no applicants during the teacher selection process.

A second reason relates to improving the quality of teachers. Most centralized school systems require teachers to pass an exam to be certified. In the case of Ecuador, the centralized test consists of three parts: a social-emotional exam, a standardized competency evaluation, and a practical class assessed by a panel. We assume here that the exam is a good measure of the relative quality of each teacher.[2] A centralized assignment that uses exam scores to determine teacher allocation could improve the average quality of the selected teachers. This point is especially relevant in Ecuador where not all of the applicants are assigned to a school at the end of the process. Therefore the centralized system not only affects the distribution of teachers with different attributes across schools but also the total average quality of the teachers in the system. This quality improvement stems from the fact that the new algorithm ensures that the most qualified teachers are the ones that get a vacancy, as opposed to the previous system in which some unassigned teachers had better qualifications than other teachers that were assigned a slot.

Finally, a centralized approach can result in more teachers being assigned to their preferred school, hence bettering allocative efficiency. This in turn can improve teacher welfare, arguably also enhancing their productivity. For example, Jackson (2013) shows that teacher-school match quality is a non-negligible part of the overall teacher quality. He uses panel data on schools in North Carolina and student outcomes to demonstrate that the effect cannot be explained by teachers moving to higher achieving schools, endogenous teacher effort, or student selection. Thus, if centralizing the assignment of teachers improves the teacher-school match by increasing its allocative efficiency, then teacher productivity will also improve, according to Jackson (2013). Centralizing assignment can therefore improve teachers' welfare while also improving their quality.

The above considerations are particularly relevant for low SES students. Highly effective teachers generate significant gains in achievement for all students, but it is especially lower-achieving students who benefit most from having an adept teacher (Rivkin, Hanushek, and Kain, 2005). This has been shown to be the case in Texas (Sanders and Rivers, 1996) and, more recently, in Ecuador (Araujo, Carneiro, Cruz-Aguayo, and Schady, 2016). In light of

[2]There is only weak evidence that centralized exams are precise tools for identifying the most effective teachers (Angrist and Guryan, 2008)

such findings, several policies have been implemented to attract teachers to disadvantaged schools (Elacqua, Hincapie, Hincapié, and Montalva, 2019). In this paper, we show how centralizing teacher assignment can benefit low SES students by reducing the number of vacant positions in their schools, improving teacher quality, and closing the placement gap with other more privileged schools.

The "Quiero ser Maestro" program was created in 2013 with the objective of centralizing the recruitment of new teachers (Drouet Arias and Westh Olsen, 2020). It consists of a *selection* and an *assignment* phase. In the selection phase, each teacher must take a centralized exam. In the allocation phase, their assignment to a school is determined using each teacher's reported preferences for schools and their scores on the centralized exam. The process attains wide coverage and includes all public schools with open positions. Historically, the main challenge of the program has been the number of positions left vacant at the end of the process. For example, in the 2016 and 2017 recruitment years, respectively 63% and 51% of the positions remained unfilled. The majority of these posts were in schools serving low SES populations.

In response to this problem, in 2019 several modifications were made to the "Quiero ser Maestro" recruitment process. First, teachers now apply directly to up to five schools, as opposed to three local school districts, or *circuitos*.[3] Second, the entry test score is now weighted higher than teacher preferences. Previously, the latter took precedence over the scores of teachers, e.g., a teacher with a lower score could be assigned to a given position over a higher scoring teacher because the former had ranked that specific school district higher in his/her reported preferences. In this paper, we discuss the impact of these two important adjustments.

This last change is, in fact, very similar to that introduced in Boston's student assign-

[3]School districts are known in Ecuador as *distritos*, comprised of smaller local school districts called *circuitos*

ment system (Abdulkadiroğlu and Sönmez, 2003). In both cases, centralized assignment - respectively of students and teachers - meant modifying the algorithm from immediate acceptance to deferred acceptance in order to improve the efficiency of assignments. The immediate acceptance algorithm is described by (Abdulkadiroğlu and Sönmez, 2003) in their seminal paper on the Boston centralized allocation of schools, while the *Deferred Acceptance* algorithm was formalized by (Gale and Shapley, 1962) in an abstraction aiming to describe how the marriage market works. Both have been extensively studied in the literature and used in practical applications. Though a conceptually similar change, the reasons for this decision were quite different between Boston (for students) and Ecuador (for teachers). In the case of Boston, the main motivation was that the algorithm used prior to 2002 generated incentives to misrepresent family preferences for schools. Meanwhile, in Ecuador, the high number of positions left vacant after the final assignment and the below average quality of allocated teachers drove the government to modify the previous algorithm. We show why a similar algorithm change worked in two very different choice scenarios.

In the 2019 "Quiero ser Maestro," 27,207 teachers competed for 15,718 positions. We compare the 2019 allocation to the counterfactual allocation using the previous algorithm and show that: i) schools, including schools serving low SES students, had fewer unfilled vacancies upon completion of the teacher recruitment; ii) the average scores of teachers assigned to a vacancy increased overall, as well as for schools serving low SES students; iii) the teacher-school match, or the allocative efficiency, improved. We find substantive evidence that the change of algorithm resulted in greater efficiency for the school system.

The remainder of the paper is organized as follows. Section 2 reviews the existing literature on the experiences in several countries that use centralized teacher assignment, and introduces the Ecuador case. Section 3 describes the theoretical framework and methodology employed to compare different allocation algorithms, mainly immediate acceptance and deferred acceptance. Section 4 describes Ecuador's teacher recruitment program, "Quiero

Ser Maestro". Section 5 analyses the consequences of changing the teacher assignment algorithm in Ecuador from one resembling immediate acceptance to a deferred acceptance version. Section 6 concludes with a discussion on policy implications.

2 Literature Review

In what follows, we discuss the main characteristics of centralized teacher assignment systems and the approaches implemented in different countries. Broadly, teacher assignment systems fall into three categories: (1) Teacher assignment to a temporary position, (2) Teacher assignment to a first permanent position, and (3) Teacher transfer between permanent positions. In this paper, we focus on teachers' first assignment to a permanent position. The other two types of assignments continue, in fact, to mainly be realized on an ad-hoc basis and not through a centralized assignment process.

In the majority of countries, teachers are hired in a decentralized fashion, often directly by schools, including many systems that use centralized exams. In Sao Paulo, for example, teachers' scores on a centralized test should, in theory, grant them priority access to vacant positions. Yet, in practice, teachers apply directly to each school. It has, in fact, been documented that schools have rejected teachers with higher scores in order to accommodate the hiring of candidates preferred by school principals, where the reporting of vacant positions is altered in order to influence the assignments (Rosa, 2017). Meanwhile, in Rio de Janeiro, teachers apply to local school districts (CREs) and district managers have discretion on which vacancies to show each applicant (Bertoni, Elacqua, Méndez, Montalva, Munevar, Westh Olsen, and Román, 2020).[4]

Countries that do use centralized teacher assignment can be classified into two groups:

[4]In focus groups with district managers in Rio, we learned that while high-scoring teachers were given first preference, managers do not always show them all the available vacancies. In fact, they often only show the hard-to-staff positions.

school systems that take into account teacher preferences and those that do not. In the first type of system, teachers report their preferences and a transparent rule is used to determine the allocation. Nations that implement this approach include Ecuador (Drouet Arias and Westh Olsen, 2020), Peru, France (Terrier, 2014), Germany (Klein and vom Baur, 2019), and Turkey (Özoglu and Beyazit, 2015). The second group includes countries such as Singapore and South Korea, where transparent rules and criteria are applied in carrying out the assignments, but where teachers do not report their preferences.

We focus here on the first group, i.e., when teachers report preferences and a transparent rule is used to assign them to schools. The main difference within these assignment systems is the rule or algorithm employed to determine the allocation. Specifically, there is notably variance across systems in how each school ranks teachers. Schools typically use a combination of *priorities*[5] and *merit-based scores*. This is the case in Ecuador, Germany, and France. In the latter two countries, priorities have precedence over the merit-based ranking, while in the case of Ecuador, priorities add bonus points to the merit-based scores. School systems also use different criteria to determine the merit-based scores. One of the most common is a standardized competency test for teachers, such as the assessments implemented in Ecuador and Peru. Other countries, such as Turkey, use grades from teaching institutes. France uses a combination of both exam scores and grades, while - in sharp contrast - the German state of Baden-Wurttemberg uses neither.

As discussed in the introduction, we explore the consequences of changing the centralized allocation algorithm from *immediate acceptance* to *deferred acceptance*. Both algorithms have been extensively studied in the literature and used in practical applications. In terms of the above-mentioned countries, France, Peru, and Ecuador are currently using the *deferred acceptance* algorithm to determine the allocation of teachers while the German state of

[5]This takes into account certain social circumstances such as disability, care of children, or proximity to work of other family members

Baden-Württemberg uses a variant of the *Immediate Acceptance* algorithm.

Recent studies have explored the welfare effect of the deferred acceptance and immediate acceptance mechanisms in centralized students-school allocation systems. Under the assumption that households have rational expectations and beliefs, previous studies have shown that mechanisms rewarding strategic play outperform deferred acceptance ((Calsamiglia, Fu, and Güell, 2020); (Agarwal and Somaini, 2018). On the other hand, (Kapor, Neilson, and Zimmerman, 2020) find that a deferred acceptance mechanism increases welfare when accounting for application mistakes they observe in the data. They also find that welfare gains are larger for low socioeconomic status households. However, the authors also argue that a model that does not incorporate subjective beliefs would have reached the opposite conclusion. In a slightly different approach, (De Haan, Gautier, Oosterbeek, and Van der Klaauw, 2015) quantify the advantages of each mechanism using information about students' actual choices as well as stated school preferences. They find that deferred acceptance with single tie-breaking provides higher welfare than the Boston mechanism.

In the next section, we develop a theoretical framework to analyze the immediate acceptance and deferred acceptance algorithms, and the similar algorithms employed in the "Quiero Ser Maestro" centralized teacher assignment system in Ecuador.

3 Theoretical Framework

Allocating teachers to schools is a two-sided, many-to-one problem (Roth and Sotomayor, 1992). There is a set of teachers seeking to be assigned and a pool of schools looking to fill their vacancies. In this setting, each school may have several vacant positions and each teacher can work at a maximum of one school.

Each teacher has a complete,[6] transitive,[7] and strict[8] preference over the set of schools and the possibility of not being assigned to any school.

All schools have the same complete and transitive preference for the individual teachers.[9] If two teachers have the same score, we assume the school is indifferent between those two teachers. Given that schools may need to hire more than one teacher, we assume that schools' preferences are a responsive extension of the preference for individual teachers such that two conditions hold. First, if a school quota has not been reached, it prefers to fill a position with a teacher rather than leaving it unfilled. Second, a school faced with two sets of teachers that differ in that only one teacher prefers the set of teachers that contains the most preferred teacher.[10]

The matches between teachers and schools can be compared in terms of their properties. The first of such properties is being **teacher efficient**, meaning that there is not another match such that each teacher is matched with something at least as preferred, and at least one teacher is matched with a school she strictly prefers. This property relates to the third motivation described in the introduction for centralizing assignment, i.e., to improve the allocative efficiency of the teacher-school matching.

The second property is being **stable**. A match is stable if there is no teacher-school pair such that they mutually (strictly) prefer each other, or the teacher prefers that school and the school has positions available. This property introduces a balance between the preferences of teachers and the welfare of schools as measured by the quality of teachers,

[6] Complete: a teacher can compare any two schools and knows which one is preferred

[7] Transitive: if a teacher prefers school y to school x and prefers school z to school y, then she prefers school z to school x

[8] Strict: Teachers are never indifferent between any two schools

[9] In the case of Ecuador, several priorities affect the rankings of schools for teachers. These priorities give additional points to the teacher's final score, though the latter are bounded to 5 points (66 points being the average for the final scores) and only about 2% of the teachers have any of those additional points.

[10] An example of the responsiveness of preferences makes the concept easier to understand. Suppose a school has two identical positions. We must make assumptions about its preferences for "pairs" of teachers, such that a school prefers x,y to x,z if and only if y is preferred to z.

which is directly related to the second motivation for centralizing teacher assignment i.e. to increase the average quality of teachers.

There are two mechanisms that have been extensively studied in the literature and used in practical allocations: *deferred acceptance* and *immediate acceptance* [11]. Both mechanisms are often presented as different algorithms (Abdulkadiroğlu and Sönmez, 2003). However, *immediate acceptance* can be defined as a special version of *deferred acceptance* when the preferences of schools for teachers are modified in a particular way (see appendix B for a complete proof). In fact, the main difference between *immediate acceptance* and *deferred acceptance* is that in the former, the preferences of schools for teachers give precedence to reported preference over scores, while in the latter, only the scores matter.

In terms of its properties, *Deferred acceptance* is *stable* while *immediate acceptance* is not. The fact that a tentatively assigned teacher can lose their assignment to a higher scoring teacher from another round is what makes deferred acceptance stable. It enhances competition among teachers based on their scores.

Immediate acceptance is *teacher efficient* when teachers report truthfully. In this case, the only way to make a teacher better off who was assigned in step 2 is for a teacher that was assigned in step 1 to not be assigned to their preferred position[12].On the other hand, *Deferred acceptance* is *teacher efficient* when all of the schools use common scores to determine their preferences (i.e have homogeneous preferences). If this is the case, the teacher with the highest score will always be assigned to her most preferred school.

4 Quiero Ser Maestro Program in Ecuador

The "Quiero ser Maestro" program was created in 2013 with the objective of centralizing the recruitment of new teachers (Drouet Arias and Westh Olsen, 2020). Since then, the Ministry

[11]Refer to appendix A for a complete description of these mechanisms

[12]Refer to appendix A for a full description of the steps in each algorithm

of Education has recruited teachers through a centralized, open, and transparent process. The program has wide coverage and all public schools with teaching vacancies participate.

The recruitment consists of a *selection* and an *assignment* phase. In the selection phase, each teacher must take a centralized exam, consisting of a personality test, a reasoning exam, and a field exam. The teachers then gain points based on their level of education, past experience as teachers, and score for their performance conducting a mock class. Overall, teachers go through a detailed screening that uses multiple measures to ensure that the final score they obtain is a good measure of their effectiveness as educators.

In the selection phase, each applicant indicates one or two fields in which they wish to obtain the status of *eligible*. In order to be able to apply to a given vacancy, the teachers need to be considered eligible first. To achieve this, they have to receive an adequate evaluation on the personality test, and at least a 70% on the knowledge test (which will depend on the field chosen by the teacher). Once a teacher is deemed eligible, she can apply to a maximum of five vacancies, as long as there are vacancies available in her field. Finally, once in service, the salary of the teacher is unique and independent of any credential. After four years, each teacher might be able to renegotiate her wage subject to budget availability. The vacancies that are not filled at the end of the process are occupied later by temporary teachers.

This paper mainly focuses on the allocation phase, i.e., teacher assignment to a school. This assignment is determined using teacher preferences for schools and the scores on the previously described centralized exam. We compare the algorithms used in "Quiero Ser Maestro" 2017 and 2019 in terms of their characteristics and performance. The algorithm used in the "Quiero Ser Maestro 2017" (henceforth QSM2017) closely resembles that of *immediate acceptance* while the "Quiero Ser Maestro 2019" (henceforth QSM2019) is very close to deferred acceptance. Appendix A provides a detailed description of each algorithm. As discussed in the previous section, these two algorithms differ in terms of the types of preferences schools are assumed to have. We use the 2019 allocation to conduct the counterfactual analysis. In this recruitment year, 27,207 teachers competed for 15,718 positions.

In this paper, we assume that all teachers report their preferences truthfully. Hence, we do not consider strategic incentives for reporting preferences. We use data from the QSM2019 allocation where, as we discuss below, teachers had strong incentives to report their true preferences.

In what follows, we show that *deferred acceptance*, *immediate acceptance*, and QSM2019 differ only in the types of preferences used by schools, while QSM2017 is a version of immediate acceptance at the local school district level[13]. Table 1 below summarizes the differences in terms of schools' preferences for teachers and the level at which preferences are reported by teachers for the four algorithms.

	Schools' Preference Type	Level of Teachers' Preference Report
Deferred Acceptance	scores	school
Immediate Acceptance	reported preference/ scores	school
QSM2017	reported preference/ scores	circuit
QSM2019	scores/reported preference	school

Table 1: Summary of Algorithms

As mentioned, the QSM2017 algorithm is an *immediate acceptance* algorithm at the school district level. Teachers therefore report their preferences over school districts. The algorithm is then used to determine the allocation of teachers to local school districts. Each local school district subsequently allocates the teachers to the schools in their district. We do not have accurate knowledge of the algorithms or rules used to determine the allocation within each school district in the second stage. For the counterfactual analysis, we thus

[13]In Ecuador, there are three administrative levels: zones, districts, and circuits. The highest level is zones, which are determined by geographical, cultural, and economic proximity. There are nine zones in the country. Each of them is comprised of districts, which at the same time are comprised of circuits. Each circuit is a collection of schools and related services. There are 140 districts and 1,117 educational circuits in the country. On average, there are approximately 14 schools in a circuit, with a standard deviation of 10. All circuits have at least one school, while the biggest circuits have as many as 66 schools in them.

make assumptions regarding the way in which school districts determine the allocations within their jurisdictions.

The QSM19 algorithm is similar to a deferred acceptance algorithm. In the same way that we define *reported preference/score preferences*, given that it is possible for teachers to have the same score, we define *score/reported preference preferences*. Under these preferences, when comparing two teachers, a school prefers the educator who has the highest score. Only if both teachers have the same score does the school prefer the one who ranked the school higher in her reported preferences. QSM2019 is a version of *deferred acceptance* where schools have *score/reported preference preferences*. Therefore, under QSM2019 scores have precedence over reported preferences in schools' preferences for teachers.

In the QSM2017 program, 51% of the positions remained vacant, the majority of which were in schools serving Low SES populations. The changes introduced in the QSM2019 were meant to solve this issue - the above-described first motivation for centralizing allocation. In the next section, we explore the impact of this change in the teacher assignment algorithm in Ecuador relative to the three reasons for centralizing allocation.

5 Counterfactuals

In what follows, we compare the performance of the QSM2017 and QSM2019 algorithms. Appendix C also reports the comparison of IA and DA algorithms through a counterfactual analysis. Our setting is of particular interest in that it shares many characteristics of centralized allocations. Specifically, it is a highly congested environment in which many teachers have preferences for the same vacancies. Moreover, the "Quiero Ser Maestro 2019" is ideal for analysis given that an algorithm very similar to deferred acceptance was used. This algorithm has the property that no teacher can obtain a preferred position by means of misrepresenting their preferences. Hence, teachers have the appropriate incentives to report their true preferences. Throughout this section, we thus assume that the teachers' reported preferences are their true preferences.

We use the preferences of teachers, their competency test results, and the information of the participating schools to simulate how the results of the allocations would vary when using different algorithms. We therefore not only assume that the settings in terms of the participants and their characteristics are the same, but also that the informational setting does not differ, i.e., teachers and schools had the same information available to make their decisions.

We use three different measures to compare the algorithms. These measures reflect the three reasons discussed in the Introduction for centralizing teacher allocation to public schools. The first motivation is reducing the number of unfilled vacancies. We therefore evaluate the number of unfilled vacancies under each algorithm as a measure of efficiency. The second motivation relates to improving the average quality of the assigned teachers. We thus evaluate the algorithms in terms of the allocated teachers' average exam scores. Finally, the third motivation regards assigning more teachers to more preferred schools. We consequently compare the number of teachers allocated to their n-th reported school.

We begin with efficiency relative to the percentage of positions filled. In Ecuador, the Ministry of Education recognizes those schools serving disadvantaged populations as belonging to a distinct category. These are usually hard-to-staff institutions. We compare the efficiency measure for both disadvantaged and other schools. Table 2 shows the performance of the algorithms in terms of the vacant positions.

	Low SES % Vacant Positions	Other Schools % Vacant Positions
QSM2017	22.5%	27.4%
QSM2019	19.6%	26.8%

Table 2: Efficiency Measures

The percentages show that QSM2019 fills more positions than QSM2017 in both types of schools. Note, however, that this may not always be the case when comparing IA and DA algorithms [14]. In the QSM2017 the teachers report preferences for local school districts. Since school districts can have several vacancies available in each subject, teachers are indirectly allowed to report more schools. As a result, the number of schools teachers would have applied to in the QSM2017 is significantly higher than the number of schools teachers effectively applied to in the QSM2019. Therefore, allowing teachers to report at the school district level can result in important efficiency gains. Teachers were not, however, informed of the different school options within the local school districts, such that they did not know which school that they would eventually be assigned to.

In Table 2, we observe that the QSM2017 allocation has about 3% fewer positions filled at low SES schools and 1% fewer positions filled at other schools. This result is explained by the fact that when teachers are allowed to only report three local school districts, there is greater congestion (i.e., teachers are applying to similar local school districts) than when teachers apply to five schools.

The second measure used is the average quality of the allocated teachers. Using the results from the teacher competency exam as a signal of teacher quality, we compare the sets of allocated teachers using the different algorithms. Previous literature shows that higher quality teachers have a greater impact on disadvantaged students. Therefore, we compare the average quality of the set of allocated teachers for both low SES schools and other schools. The result of this comparison can be found in Table 3.

We see that the QSM2019 algorithm allocates teachers with higher average quality. In fact, we observe an increase of 0.23 and 0.32 standard deviations in the quality of teachers. Since schools want to hire the highest performing teachers, we can translate the average

[14] This is is due to the fact that teachers with lower scores are more likely to report schools that have fewer applicants because they believe that they have a better chance of being assigned the vacancy.

	Low SES Avg. Exam Score	Other Schools Avg. Exam Score
QSM2017	0.18	0.18
QSM2019	0.41	0.50

Table 3: Avg. Quality of Teachers (Std deviations)

quality of teachers allocated as the average welfare of schools. The fact that the algorithms that do not give precedence to reported preferences over scores outperform the others is due to the fact that providing stated preferences undermines the competition on teacher scores for positions. This is a result of the allocation being *stable*. Figure 1 shows the distribution of scores between the QSM2019 and QSM2017 – that of QSM2019 almost dominates that of QSM2017.

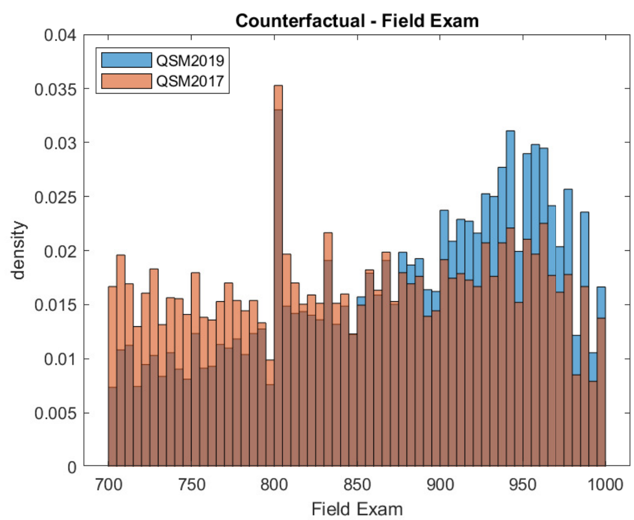

Figure 1: Histogram of Schools per Field per District

The final measure consists of comparing the allocative efficiency of each algorithm. Specifically, for each allocation, we compute the percentage of teachers that were allocated up to the (n-th) preferred school. Therefore, the distribution of the percentages will be a cumulative distribution. We then compare these distributions by stochastic dominance, i.e., an algorithm under this setting has a higher allocative efficiency than another if it allocates more teachers to their top n-th reported schools for any n. Figure 2 shows that QSM2019 has much higher allocative efficiency. Under the QSM2017 about 50% of teachers will be allocated to a school that is not reported as one of their preferred schools.

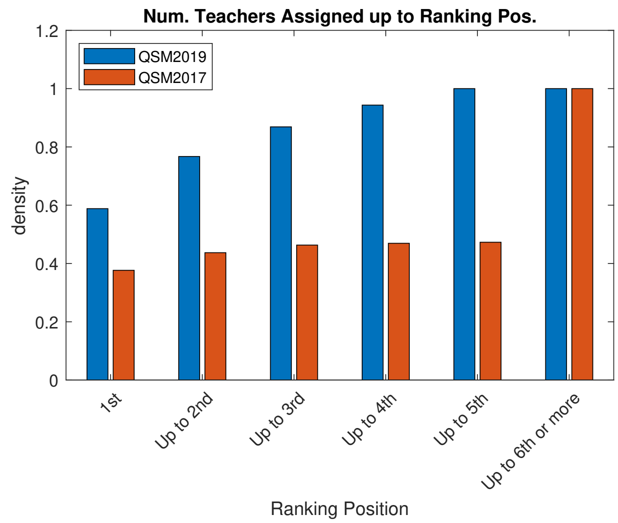

Figure 2: Allocative Efficiency — QSM2017 vs QSM2019

We thus show how the QSM2019 outperforms the QSM2017 both in terms of allocative efficiency and the quality of teachers selected. The QSM2019 is also more efficient because more positions are filled. In conducting the counterfactual, we assume that all of the schools within a district reported by a teacher are acceptable to them. Though there is no available evidence to this regard, this assumption improves the efficiency measure of the QSM2017, while not affecting the other measures. Overall, we show that the QSM2019 continues to outperform the QSM2017 even after making the strongest case possible for the QSM2017. This exercise allows us to conclude that the change in algorithm from QSM2017 to QSM2019 was welfare enhancing for teachers and schools.

6 Policy Discussion

In this paper we compare two centralized allocation systems, and in so doing show the importance of appropriately designing such assignment mechanisms. We demonstrate that a change in how to determine teacher allocations in Ecuador results in three significant benefits. Namely, this modification reduces the number of vacant positions, improves teacher welfare, and enhances the quality of educators. These dimensions are all crucial from a policy perspective; indeed, various countries have adopted interventions in an effort to impact them. For example, several school systems in Latin America use monetary incentives to attract teachers to hard-to-staff schools. The intervention discussed in this paper (algorithm change) not only had notable effects but offers a very low-cost option compared to other policies and programs.

We furthermore highlight that the change introduced in Ecuador had a significant impact on the equity of the allocation. This is particularly important, as recent studies show that allocating low SES students with above-average teachers can help to narrow achievement gaps. Not only do we observe an overall improvement in the three dimensions discussed but the gap between low and high SES schools in access to high scoring teachers is also reduced.

Finally, given that we compare two different centralized allocations, it is not possible to support centralizing the assignment of teachers from an empirical perspective. However, in centralized assignments like the one studied, an important flow of information is generated that can be used to increase the benefits of the system. The exercise conducted in this paper provides an example. Had the allocation not been centralized, it would be have been very difficult to obtain the preferences of teachers, the schools available, and the ways these schools select their teachers. The availability of this information enables a monitoring and evaluation that can guide different interventions to further improve the efficiency of the market at hand.

References

Abdulkadiroglu, A., P. Pathak, A. E. Roth, and T. Sonmez (2006): "Changing the Boston school choice mechanism," Discussion paper, National Bureau of Economic Research.

Abdulkadiroğlu, A., and T. Sönmez (2003): "School choice: A mechanism design approach," *The American Economic Review*, 93(3), 729–747.

Agarwal, N., and P. Somaini (2018): "Demand analysis using strategic reports: An application to a school choice mechanism," *Econometrica*, 86(2), 391–444.

Angrist, J. D., and J. Guryan (2008): "Does teacher testing raise teacher quality? Evidence from state certification requirements," *Economics of Education Review*, 27(5), 483–503.

Araujo, M. C., P. Carneiro, Y. Cruz-Aguayo, and N. Schady (2016): "Teacher quality and learning outcomes in kindergarten," *The Quarterly Journal of Economics*, 131(3), 1415–1453.

Bertoni, E., G. Elacqua, C. Méndez, V. Montalva, I. Munevar, A. S. Westh Olsen, and A. Román (2020): "Concurso docentes en Latinoamérica: Claves para mejorar calidad, eficiencia y equidad en educación," .

Calsamiglia, C., C. Fu, and M. Güell (2020): "Structural estimation of a model of school choices: The boston mechanism versus its alternatives," *Journal of Political Economy*, 128(2), 642–680.

Chetty, R., J. N. Friedman, and J. E. Rockoff (2014): "Measuring the impacts of teachers I: Evaluating bias in teacher value-added estimates," *American Economic Review*, 104(9), 2593–2632.

De Haan, M., P. A. Gautier, H. Oosterbeek, and B. Van der Klaauw (2015): "The performance of school assignment mechanisms in practice," .

Drouet Arias, M., and A. S. Westh Olsen (2020): ""Quiero Ser Maestro": Mejoras del concurso docente del Ministerio de Educación de Ecuador," .

Elacqua, G., D. Hincapie, I. Hincapié, and V. Montalva (2019): "Can Financial Incentives Help Disadvantaged Schools to Attract and Retain High-performing Teachers?: Evidence from Chile," .

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

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

Klein, T., and P. vom Baur (2019): "Matching Practices for Trainee Teachers – Germany," `http://www.matching-in-practice.eu/matching-practices-for-trainee-teachers-germany/` (Accessed 2020/05/21).

Özoglu, M., and Y. Beyazit (2015): "Teacher Allocation Policies and the Unbalanced Distribution of Novice and Senior Teachers across Regions in Turkey.," *Australian Journal of Teacher Education*, 40(10), n10.

Rivkin, S. G., E. A. Hanushek, and J. F. Kain (2005): "Teachers, schools, and academic achievement," *Econometrica*, 73(2), 417–458.

Rodrigues, A. M., A. Dias, C. Gregório, E. Faria, F. Ramos, M. Miguéns, P. Félix, and R. Perdigão (2019): "Regime de Seleção e Recrutamento do Pessoal Docente da Educação Pré-Escolar e Ensinos Básico e Secundário," .

Rosa, L. (2017): "Teacher Preferences in Developing Countries: Evidences from the City of São Paulo, Brazil," .

Roth, A. E., and M. Sotomayor (1992): "Two-sided matching," *Handbook of game theory with economic applications*, 1, 485–541.

Sanders, W. L., and J. C. Rivers (1996): "Cumulative and residual effects of teachers on future student academic achievement," .

Terrier, C. (2014): "Matching Practices for secondary public school teachers – France," `http://www.matching-in-practice.eu/matching-practices-of-teachers-to-schools-france/` (Accessed 2020/05/21).

A Algorithms

Algorithm 1 (Immediate Acceptance)**.**

*Step 1: Each teacher enrolls at their preferred school. Each school district assigns the positions to its proposers one at the time, following the preferences for teachers common to all schools. If the school is indifferent between two teachers (i.e., they have the same score), it randomly determines which one gets the position. The assigned positions at each school are **final**. All remaining proposers, if any, are rejected.*

⋮

*Step 2: Each teacher who was rejected in the previous step proposes to their next preferred school. Each school assigns their **remaining** positions following their preferences. If the school is indifferent between two teachers (i.e., they have the same score), it randomly determines which one gets the position. The assigned positions at each school are final. All remaining proposers, if any, are rejected. A teacher that is rejected by all his acceptable schools is left unassigned. The algorithm terminates once all teachers have been assigned to a school or left unassigned.*

Algorithm 2 (Deferred Acceptance)**.**

*Step 1: Each teacher applies their preferred school. Each school district assigns the positions to its proposers one at the time, following the preferences for teachers common to all schools. If the school is indifferent between two teachers (i.e., they have the same score), it randomly determines which one gets the position. The assigned positions at each school are **tentative**. All remaining proposers, if any, are rejected.*

⋮

*Step 2: Each teacher that was rejected in the previous step proposes to their next preferred school. Each school assigns **all of its positions** and considers the teachers that* *were tentatively assigned in the previous step and the new proposers from this period. The school tentatively assigns their positions to its considered teachers one at a time, following its preferences. If the school is indifferent between two teachers (i.e., they have the same score), it randomly determines which one gets the position. The assigned positions at each school are tentative. All remaining proposers, if any, are rejected. A teacher that is rejected by all his acceptable schools is left unassigned.*

A teacher that is rejected by all his acceptable schools is left unassigned. The algorithm terminates once each teacher is assigned to a school or left unassigned.

Algorithm 3 (Quiero ser Maestro 2017, QSM2017)**.**

Step 1.1: *Each teacher enrolls at their preferred school district. Each school district assigns the positions to its proposers one at the time, following the preferences for teachers common to all schools. If the school district is indifferent between two teachers (i.e., they have the same score), it randomly determines which one gets the position. Each school district assigns positions up to the sum of positions the schools in its district have. The assigned positions at each school district are **final**. All remaining proposers, if any, are rejected.*

$\vdots$

Step 1.2: *Each teacher that was rejected in the previous step proposes to their next preferred district. Each school district assigns their **remaining positions** to its proposers one at the time, following the preferences for teachers common to all schools. If the school district is indifferent between two teachers (i.e., they have the same score), it randomly determines which one gets the position. The assigned positions at each school district are **final**. All remaining proposers, if any, are rejected. A teacher that is rejected by all of his acceptable school districts is left unassigned.*

Step 1: Terminates once each teacher is assigned to a school district or left unassigned.

Step 2: Each school district determines the allocation of teachers to schools at their discretion.

Algorithm 4 (Quiero ser Maestro 2019, QSM2019)**.**

*Step 1: Each teacher lists their preferred school. Each school district assigns the positions to its proposers one at the time, following the preferences for teachers common to all schools. If the school is indifferent between two teachers (i.e., they have the same score), it gives priority to the teacher who lists the school higher in her ranking. Otherwise it randomly determines which teacher is assigned the position. The assigned positions at each school are **tentative**. All remaining proposers, if any, are rejected.*

⋮

*Step 2: Each teacher that was rejected in the previous step proposes their next preferred school. Each school assigns **all of its positions** and considers the teachers that were tentatively assigned in the previous step and the new proposers from this period. The school tentatively assigns their positions to its considered teachers one at a time, following its preferences. If the school is indifferent between two teachers (i.e., they have the same score), it gives priority to the teacher who listed the school higher in her ranking. Otherwise it randomly determines which teacher gets the position. The assigned positions at each school are **tentative**. All remaining proposers, if any, are rejected.*

A teacher that is rejected by all her preferred schools is left unassigned. The algorithm terminates once each teacher is assigned to a school or left unassigned.

B Immediate acceptance-Deferred acceptance parallel proof

Define new teacher preferences for schools called *reported preference/score preferences.* Under these preferences, when comparing two teachers, a school prefers the educators who ranked the school highest. Only where both teachers reported the school as k-th preferred, the school uses the teachers' scores to determine who gets the position. The next proposition proves that *immediate acceptance* is equivalent to *deferred acceptance* when schools have *reported preference/score preferences* instead of the usual *score preferences.*

Proposition 1. *For any set of teachers, teachers' reported preferences, teachers' scores, and schools, the allocation under immediate acceptance is the same as under deferred acceptance with reported preference/score priorities. Hence the two algorithms are the same.*

Proof by Induction. (Base case) Given the same reported preferences, the same teachers apply to the same schools in the first step. All the teachers apply to their preferred school, therefore any rejection will be based on scores. Any later applications will come from teachers who did not report the school as preferred. Therefore, all the teachers that were accepted in first step will be matched with that school (Induction step). After removing the teachers and schools that have been matched in previous steps, the same logic used in Step 1 applies. □

C Counterfactuals: Immediate acceptance and Deffered acceptance

This section compares the performance of the immediate acceptance and deferred acceptance algorithms, relative to QSM2017 and QSM2019 through a counterfactual analysis. For that, we use the same metrics presented in section 5 to compare the QSM2017 and QSM2019 allocations.

We begin by comparing the deferred acceptance and QSM2019 algorithms. The difference between these two algorithm is that reported preferences are used to break ties in scores. As the scores are constructed under a refined metric, ties in scores are not common. However, the resulting allocations differ for about 5.5% of the teachers. From Tables 4 and 5 we observe that in terms of efficiency and quality the differences in the results are small. However, deferred acceptance performs better for low SES schools while QSM2019 does better for other schools.

In terms of efficiency, notice from Table 4 that deferred acceptance results in a 2% higher filled vacancy rate for low SES schools and a 1% higher filled vacancy rate for other schools. Moreover, the average scores of the allocated teachers are 0.16 standard deviations higher for the disadvantaged schools and 0.18 standard deviations higher for the other schools. Giving precedence to the teachers' reported preferences over scores has strong consequences in terms of efficiency and the quality of the assigned teachers. The intuition behind this result is that only using scores enhances the competition for positions among teachers. This results in more positions being assigned and higher quality teachers obtaining vacancies. However, as shown in Figure 3, this competition has a cost in terms of allocative efficiency: about 20% more teachers are allocated to their preferred position under immediate acceptance than under deferred acceptance.

Now, we discuss the properties of QSM2017. This algorithm starts with immediate acceptance at the local school district level, then each school district determines the allocations within their jurisdiction. Unfortunately, we do not have information on the rules or algorithms used by the local school districts in the second stage. We assume henceforth that each school district assigns teachers within their school district using the deferred acceptance algorithm. Section D in the appendix conducts a robustness check of this assumption. When compared with alternative algorithms to be used in the second stage, QSM2017 performs best with the deferred acceptance algorithm. Therefore, in the counterfactual analysis, if an algorithm outperforms QSM2017 with deferred acceptance in the second stage, we are confident reporting it, as QSM2017 is performing at its best.

We also assume that teachers report the school district of their (k-th) preferred school as (next) preferred (if not already reported). In the QSM2017, teachers could report up to 3 local school districts. As a result, teachers effectively apply to about 7.44 schools. To put things in perspective, in the QSM2019 teachers were only allowed to report 5 schools and in practice teachers reported 4.72. Hence allowing teachers to report at the local school district level considerably increases the number of schools they report.

If teacher preferences satisfy the property of being school block preferences, the QSM2017 would be teacher efficient, which imply having a high allocative efficiency. Our next counterfactual analyzes whether the condition for QSM2017 to be teacher efficient is satisfied. If there are only a few schools available in each district, preferences would easily satisfy the school block property. The histogram of schools per district in Figure 4 shows that this is not the case; there are 2 schools per district on average. More than 60% of the school districts have positions available for a school in any given subject. Therefore, it is feasible that the teachers' preferences have the school district block property.

	Low SES % Vacant Positions	Other Schools % Vacant Positions
Immediate Acceptance	21.4%	27.8%
Deferred Acceptance	19.6%	26.7%

Table 4: Efficiency Measures IA, DA

	Low SES Avg. Exam Score	Other Schools Avg. Exam Score
Immediate Acceptance	0.25	0.32
Deferred Acceptance	0.41	0.50

Table 5: Avg. Quality of Teachers (Std deviations)

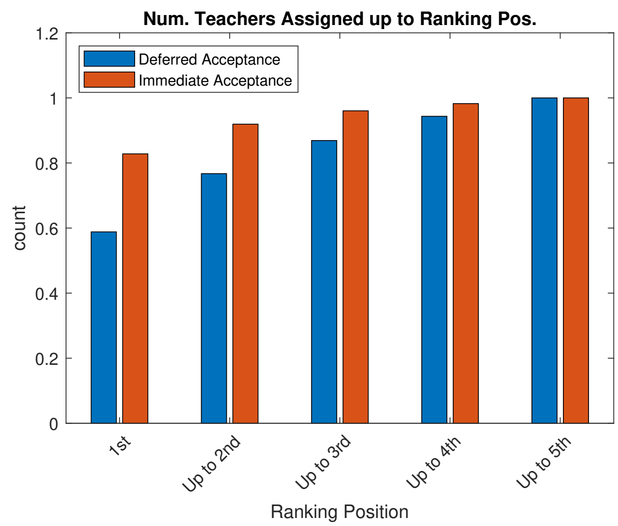

Figure 3: Allocative Efficiency — Deferred vs Immediate Acceptance

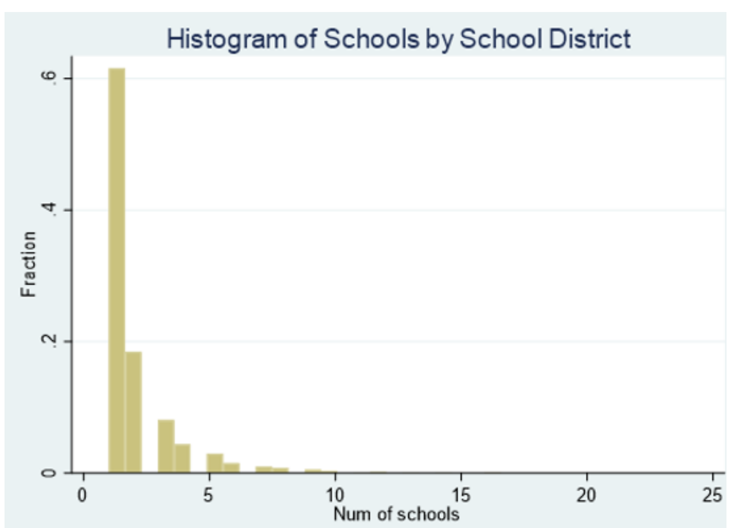

Figure 4: Histogram of Schools per Field per District

D Robustness Check: Second Stage of QSM2017

	Low SES Avg. Field Exam	Other Schools Avg. Field Exam
QSM2017 + Deferred Acceptance	22.5%	27.4%
QSM2017 + Immediate Acceptance	22.5%	27.4%
QSM2017 + Random Assignment	22.7%	27.4%

Table 6: QSM2017: Efficiency

	Low SES Avg. Field Exam	Other Schools Avg. Field Exam
QSM2017 + Deferred Acceptance	0.18	0.18
QSM2017 + Immediate Acceptance	0.17	0.17
QSM2017 + Random Assignment	−0.02	−0.03

Table 7: QSM2017: Avg. Quality of Teachers