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Teacher transfers and the disruption of teacher staffing in the City of Sao Paulo

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Abstract

This paper analyzes preferences for certain school attributes among in-service teachers. We explore a centralized matching process in the city of Sao Paulo that teachers must use when transferring schools. Because teachers have to list and rank their preferences for schools, we can estimate the desirability of school attributes using a rank-ordered logit model. We show that the school's distance from the teacher's home, its average test scores, and teacher composition play a central role in teacher preferences. Furthermore, we document that preferences vary according to teacher characteristics such as gender, race, age, and academic subject.

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1 Introduction

Teachers are the most crucial input in the education production function (Chetty et al., 2014) and their impact is greatest among the most disadvantaged students (Araujo et al., 2016). However, attracting and retaining qualified teachers to low-performing schools that serve low-income and minority students is one of the biggest challenges school systems face. Teachers often sort according to student socioeconomic level (Lankford et al., 2002), school racial composition (Hanushek et al., 2004), geographic location (Bertoni et al., 2022), and pupil achievement (Krieg et al., 2016). They also prefer establishments that have better working conditions (Boyd et al., 2005) and are closer to their homes or to where they went to college (Bertoni et al., 2022; Boyd et al., 2005). As a result of teacher sorting, disadvantaged and low-performing students are less likely to attend classes with qualified teachers (Jackson and Bruegmann, 2009), which has a negative impact on their learning (Araujo et al., 2016).

With few exceptions, research in this area focuses on how teachers sort according to specific school characteristics. While some studies use survey evidence to shed light on this topic, others explore the impact of teacher choices on sorting. The scant evidence on teachers' preferences in Latin America is largely related to the characteristics that drive the decisions of new teacher candidates (Bertoni et al., 2022; Rosa, 2019). Very little work has been done (Grissom et al., 2014 being a notable exception) on how teacher sorting is affected by the preferences of in-service teachers, who make up the majority of teachers in the labor market.

In this paper, we analyze the preferences of in-service teachers in the city of Sao Paulo. Using a rich administrative dataset that provides unique information on in-service teachers' exit decisions and ordered transfer preferences, we aim to answer the following questions: (i) what school factors are associated with teachers' desire to transfer away?; (ii) in searching for a new school, what characteristics do teachers look for? Using a rank-order logit model, we examine how in-service teacher transfer applicants evaluate different school characteristics in the establishments they leave and when ranking their preferred transfers.

Estimating worker preferences is challenging for any occupation, and teacher preferences are no different. In a competitive job market, teachers and school preferences interact, making it difficult to disentangle preferences when observing matches between teachers and schools. Analyzing this two-sided matching process requires some assumptions, which can limit understanding.

In a standard case, we observe the choices made by teachers, but we do not observe teacher choice sets. In other words, we do not know the options teachers have available to them and the factors they are considering when choosing a school, which makes it complicated to estimate teacher preferences. Furthermore, when considering the teacher labor market within a single education system, school characteristics tend to be homogeneous. The lack of variation in school features limits our ability to draw conclusions since we cannot estimate teacher preferences for many school factors (e.g., teacher wages). Finally, teacher preferences might differ between novice and in-service teachers. While novice teachers likely have considerably less information about school characteristics because they are not part of the workforce, in-service teachers have more experience in schools, presumably have more information about the local schooling market, and compare their current schools with other potential workplaces.

Our case study offers an interesting opportunity to address some of these challenges. While Sao Paulo is the largest city in Brazil – and one of the largest in the world – it has a highly centralized municipal school system. The Department of Education manages the transfer process across establishments, which we use to analyze teacher preferences. Once a year, teachers can request a transfer from their current school to another school in the municipal system. The Department of Education registers the teachers' requests and counts vacancies generated by attrition events (e.g., retirement or teacher leaves). The government publishes openings on an online platform and asks the teachers who requested a transfer to rank their school preferences. They can rank an unlimited number of vacancies. Finally, teachers are matched with their preferred schools using a deferred acceptance algorithm. If two teachers apply to the same school, the mechanism matches the school to the teacher with more points (based on a combination of experience and education level), with the matching process continuing over a series of rounds.

Arguably, this centralized process mitigates most concerns related to estimating teacher preferences. First, we do not need to disentangle teacher preferences and school preferences. The government standardizes school (or principal) preferences in the matching process. Second, because the entire matching process occurs on a centralized platform, we know the options available to teachers when they rank their preferences.

Thus, we can observe their choice sets in a competitive market. Third, the school system and the city are very large, with more than five hundred schools. Therefore, we observe considerable variation across school characteristics, including quality, average socioeconomic level, location, and monetary incentives. Finally, we consider in-service teachers and not novice teachers, meaning that the teachers in our sample are more informed and capable of observing and comparing school characteristics.

When analyzing in-service teachers asking for transfers, our results indicate that teachers are more likely to transfer out of schools with lower test scores, a higher percentage of low-SES students, and that are farther away from their homes.

We use a rank-ordered logit model to estimate teacher preferences for new schools. Our estimates show that distance from home to school is the strongest predictor for teacher preferences. However, other school characteristics are important as well: a school's average test scores are a very strong predictor of teacher preferences. School organization is another important factor behind teacher preferences, as teachers are more likely to avoid schools with many novice teachers and fewer classrooms. Interestingly, after controlling for distance and test scores, the average socioeconomic level of the student body is not related to teacher preferences.

Our study intersects with the growing literature on teacher preferences, teacher turnover, and an emerging body of work that explores teacher sorting in developing countries. In the teacher preference literature, most studies analyze cases where the teacher labor market might be classified as a two-sided matching (Bonhomme et al., 2016; Boyd et al., 2013; Engel et al., 2014), and the choice set for teacher preference ranking might not be very well-defined. One study mitigates this concern by analyzing a discrete-choice experiment with teachers, controlling the choice set environment and introducing variation in the school and job-contract features (Johnston, 2020). Here, we present a different case and address key challenges in the study of teacher preferences, as discussed above.

Our paper also contributes to understanding teacher turnover.[1] In this area, the most closely related study to ours is Boyd et al. (2011). The authors examine the teacher transfer system in New York City, which is centralized in a similar manner to Sao Paulo. We build on this research by exploring different school characteristics and

[1] Allen et al. (2018), C. Clotfelter et al. (2008), C. T. Clotfelter et al. (2008), and C. T. Clotfelter et al. (2004), Falch and Strøm (2005).

a different context. In contrast to Boyd et al. (2011) but consistent with other findings in the literature (Bonhomme et al., 2016), we show that average school test scores are important predictors of teacher transfers.

Finally, we build on the growing literature in developing countries that explores the factors that influence teacher sorting and the most effective policies for attracting and retaining teachers in hard-to-staff schools (Bertoni et al., 2022; Evans, Acosta, et al., 2021). Previous work focuses on the influence of new teacher preferences in sorting. For instance, Bertoni et al. (2022) analyze teacher preferences in the centralized teacher selection and assignment system in Peru and show that more experienced and higher-performing teachers prefer schools in more advantaged urban areas, located in places closer to where they attended college. Rosa (2019) studies the recruitment of teachers in Sao Paulo and documents that location and test scores are important determinants of initial teacher decisions. Unlike previous studies that examine the decisions of novice teachers, we look at in-service teachers and their decisions to transfer to a different school.

2 Teacher transfers in the city of Sao Paulo

Approximately 50,000 teachers work in primary and middle schools in the city of Sao Paulo. The Department of Education hires all teachers; schools do not participate in the hiring process. To be hired as an in-service teacher, candidates must pass a centralized assessment. Once they pass the exam, the department invites teachers to choose a school from a list of vacancies that they publish online. Teachers can decide to leave the school system at any time. At the end of each school year, in-service teachers can request a transfer to another school within the school system using the city's centralized system. In this transfer process, in-service teachers have priority over novice teachers as they are allowed to choose first. Our analysis focuses on these transfer processes.

Specifically, each year, managers in the Department of Education consolidate the number of teachers that exit the school system and the number of teachers requesting a transfer to compute the total number of vacancies per school. Then, they open the *concurso de remoção*, a process that allows teachers to request transfers across public municipal schools. Teachers who request a transfer must rank, using an online platform, their school preferences based on the official list of vacancies published by the Department of Education. They can list an unlimited number of vacancies. If a teacher who is requesting a transfer finds a school with a position available, then the department transfers the teacher. If the vacancy is due to a teacher requesting a transfer, the transfer to that teacher's position only goes through if they also find a vacancy.

The matching algorithm is straightforward and similar to a deferred acceptance (DA) algorithm. Teachers rank their preferences. Schools have homogeneous preferences (imposed by the Department of Education), preferring teachers with the highest scores based on a combination of experience and credentials. The process is interactive: in the first round, teachers propose a pair formation with the school. Schools prefer the candidate with the highest score, and teachers with lower scores are rejected. Any teacher whose offer is not rejected at this point is tentatively matched with the school they proposed. Similar to the DA algorithm, their current request might be rejected in the next iteration if the school receives a better offer at that time. In the next iteration, teachers whose proposal was rejected in the previous step make new proposals to the school on the other side based on the preference list. A teacher will continue to make proposals according to their preference list as long as there are acceptable schools on the other side that have vacancies. On the other side, schools continue to reject existing proposals if they receive one from a teacher with a higher score. The DA algorithm stops when there are no rejected agents that can make new proposals, at which stage the whole matching process terminates, and all the tentative matches become final.[2]

With respect to school characteristics, it should be noted that Sao Paulo is a very large city, both in terms of its population and its area. Therefore, aspects such as school quality vary considerably. However, teacher wages are similar across schools. While there are monetary incentives to work in selected neighborhoods, these incentives are small compared to the average teacher salary (Rosa, 2019). Altogether, non-pecuniary factors are probably the most important driver of teacher decisions.

[2]Adapted from Ren et al. (2021).

3 Methodology

3.1 Data

Our main data sets relate to teacher transfers for the year 2019-2020 in the city of Sao Paulo. Our first data set lists all teachers requesting a transfer, including their IDs, current school, the subject they teach, and their preference ranking of schools. We also have a second list that indicates the school to which the teacher was assigned.

We combined school transfer information with different administrative data sets. The following information was gathered from school administrative records: location, average test scores, average class size, number of classrooms, the share of novice teachers (teachers with less than 3 years of experience), retention rates, and average socioeconomic level of the student body. We also obtained teachers' zip codes from the city of Sao Paulo, which we geocoded and used to compute the distance from teacher homes to schools. Finally, we have the list of schools with monetary incentives.

3.2 Econometric model

Administrative records provide us with school characteristics, which we combine with teachers' ranked preferences from the transfer applications. This allows us to estimate a rank-ordered logit model and examine teacher preferences for school characteristics. This approach has been used in similar work to analyze teacher or parental preferences for school characteristics (Bertoni et al., 2022).

In our model, each teacher $i(i = 1, 2, 3..., I)$ has their own choice set C_i consisting of J_i schools that they list for transfer $(j = 1, 2, ..., J_i)$. We therefore define the utility function of teacher i for school j as:

$$U_{ij} = X_{ij}\beta + \varepsilon_{ij}, \tag{1}$$

where the matrix X contains the characteristics of schools in the teacher's choice set. We include the following school attributes in our model: distance from home to school, average test scores, the share of students of low socioeconomic status, a dummy indicating whether a school is in a *favela* (shantytown), percentage of novice teachers, number of classrooms, and monetary incentives.

In this framework, teachers will choose to rank the school $j*$ higher than any school j, if $U_{ij*} \geq U_{ij}$ for all $j \in C_i$. Considering the utility function is partially stochastic, we can write the probability of choosing $j*$ as:

$$P(U_{ij*} > U_{ij}, \forall j \in C_i) = P(\varepsilon_{ij*} > \varepsilon_{ij} \leq (X_{ij*} - X_{ij})\beta). \tag{2}$$

Assuming the error terms are identically and independently distributed, we can show that (McFadden, 1974):

$$P_{ij*} = \frac{\exp(X_{ij*}\beta)}{\sum_i^{J_i} \exp(X_{ij}\beta)} \tag{3}$$

Finally, the probability that teacher i has a particular school ranking such that $P(U_{i1} > U_{i2} > U_{i3}...)$ is a product of the standard conditional logit equation shown in 3. Teachers in Sao Paulo can rank as many schools as they desire. However, we limit the choice set of teachers, and our rank-ordered logit model considers up to twenty alternatives.[3]

4 Results

4.1 Descriptive analysis

We start by documenting some stylized facts through a descriptive analysis. Table 1 shows the frequency of teachers asking for a transfer. In total, there are nearly 47,000 teachers working in elementary and middle schools, of which nearly 8,000 teachers (17% of in-service teachers) requested a transfer in 2019. A high percentage (72%) of those asking were granted a transfer, with approximately 53% assigned to their first option and 77% to one of their top four schools.

[Table 1 about here.]

[3]We limited the choice set to avoid distortions in our estimates that might be caused by some teachers listing too many schools. In any case, only 27% of teachers listed more than 20 schools.

Focusing on the applicants, Table 2 describes the number of schools to which teachers applied for a transfer. Although teachers apply to an average of 39 schools, the median is 7, indicating that few teachers apply to many schools. Most teachers (60%) apply to at least five schools, and just 19% apply to only one school, which suggests that teachers are actively searching for and applying to new schools. Figure 1 rounds out this picture by showing the number of applicants per school. We see that many teachers apply to the same schools, indicating significant congestion in the transfer market. This partly explains why 28% of teachers were not granted a transfer at the end of the process.

[Table 2 about here.]

[Figure 1 about here.]

Finally, for the transferring teachers, we compare the characteristics of their current school, the schools they listed as their first preference, and the one to which they were ultimately assigned. We observe that teachers requesting transfers are often working in lower quality schools (-0.05 sd), that have a higher proportion of low-SES students, and a greater number of novice teachers. Their schools are also more likely to be in a favela, and to be located a greater distance from their homes. In contrast, the schools they list as their first choice have higher test scores (0.17 sd), a lower proportion of low-SES students and novice teachers, are not located in favelas, and are closer to their homes. Among teachers who receive a final assignment, the school to which they are assigned tends to be somewhere in the middle between their top choice and their current school, likely due to other teachers' preferences and market congestion. For example, schools in this last group have higher test scores than teachers' current school but lower test scores than their preferred schools. This pattern repeats with other school characteristics, such as distance from home to school.

[Table 3 about here.]

4.2 Estimates for teacher preference

To estimate teacher preferences for school attributes, when teachers are looking to transfer, we combine information about the teacher application and school characteristics. We use the same variables presented in Table 3 and add a variable indicating whether the school is located in a district where the Department of Education offers monetary incentives to attract and retain teachers.

Table 4 shows the estimates using a rank-ordered logit; standard errors are clustered at the school level. In each column, we add a different variable. We begin by analyzing the distance from the teacher's home to the school. Establishments that are farther away from teachers' homes are less desirable; the estimates are very stable, and the magnitude of the coefficient is large. Next, we consider school quality, measured by average student test scores. Teachers tend to prefer schools with higher test scores over low-performing schools. Interestingly, the estimates related to the percentage of low-SES students are not strongly related to teacher preferences. However, being in a favela does make schools less desirable.

[Table 4 about here.]

We also include variables that policymakers can control such as teacher composition, which appears to be very relevant to teacher preferences. Teachers are less likely to prefer schools with a high proportion of novice teachers. Large schools (number of classrooms) are preferred, which might indicate a preference for working in only one school and not splitting their workload across two schools, a common practice in Brazil (Elacqua & Marotta, 2020). The monetary incentives do not seem sufficient to change teacher preferences, a finding that is consistent with previous research on this policy in Brazil (Rosa, 2019).

4.2.1 Heterogeneity of preferences

We now turn to the heterogeneity of preferences across teacher characteristics. Table 5 shows the estimates for six different teacher characteristics: women, men, Black, White, under age 30, and over age 30. Men and women value distance to home and student SES differently: women prefer schools closer to their home and with a lower percentage of low-SES students compared to men. Women are also are less likely to prefer schools located in a favela. Black teachers are less likely to prefer schools in favelas than White ones, and they are more likely to prefer schools with greater monetary incentives. Older teachers are more likely to request a transfer to larger schools located closer to their homes but not in a favela, and with higher test scores. Younger teachers are more likely to request transfers to schools with more experienced teachers.

[Table 5 about here.]

Finally, we analyze teacher preferences by subject. Table 6 shows the estimates for elementary school and middle school teachers. We separate middle school teachers according to the subjects they teach: mathematics, language, sciences, and other (geography, history, arts, and physical education). Elementary school teachers care less about test scores than middle school teachers and more about the proportion of novice teachers. Math and language teachers in middle schools are more likely to prefer schools that are farther away from their homes. Language teachers are more likely to list schools with monetary incentives. Science teachers have similar preferences as the average elementary school teacher, with the exception of the proportion of novice teachers. Other middle school teachers are more likely to value distance and test scores and less likely to choose schools located in a favela. Similarly to elementary school teachers, they are also more likely to list schools with more experienced teachers.

[Table 6 about here.]

5 Discussion

In this paper, we explore how school characteristics drive preferences among in-service teachers seeking transfers within the school system of Sao Paulo, Brazil. To this end, we examine the rank-ordered preferences of 40,376 teachers who requested transfers during the city's 2019-2020 centralized teacher transfer process. We analyze the factors associated with teachers' desire to transfer out of their current school as well as the preferences for school characteristics when applying to a new school. Our study contributes to the emerging literature in developing countries on teacher preferences by focusing on in-service teachers, who make up the majority of teachers in the labor market. A better understanding of in-service teacher preferences for transfers can help to design effective policies that reduce teacher turnover and improve equity in teacher allocation by retaining and attracting teachers to the most hard-to-staff schools.

We find that, when transferring, teachers are more likely to leave schools with lower academic performance, a higher proportion of low-SES students, and a greater number of novice teachers, as well as establishments located in a favela and farther away from teachers' homes. In contrast, the schools that teachers ranked as their top choice in transfer requests tend to be larger ones with higher test scores, a lower proportion of low-SES students, and fewer novice teachers, as well as not located in a favela and closer to their homes. If ultimately assigned (28% were not granted a transfer, mainly due to market congestion), the school tends to be somewhere in the middle between their top preference and their current school in terms of the characteristics listed above.

We also find that preferences vary across different groups of in-service teachers: location is particularly important for female and older teachers (>30 years). Women are also more likely to choose schools with a lower percentage of disadvantaged students. Black teachers are less likely to choose to transfer to schools located in a favela and more likely to prefer schools that offer monetary incentives. In addition, we find that younger teachers (<30 years of age) are more likely to request transfers to schools with more experienced teachers.

More attractive wages at hard-to-staff schools, which are more likely to be low-performing and serve more disadvantaged students, may influence teacher transfer decisions. To address this issue, the City of Sao Paulo has introduced monetary incentives to work in specific neighborhoods. However, the wage bonus represents a small percentage of a teacher's salary and is thus unlikely to be sufficient to overcome teachers' dislike for the characteristics of schools located in disadvantaged neighborhoods. Indeed, only Black teachers, who may be more likely to reside in or close to neighborhoods with wage bonuses, are more likely to request transfers to schools with monetary incentives. The City of Sao Paulo may benefit from reviewing the current monetary incentive program. Further studies could evaluate the effect of the wage bonus more directly, as well as its impact on teacher retention and turnover and on the eligible schools and neighborhoods.

Governments in developing countries have adopted various strategies to increase the supply of teachers in hard-to-staff schools, including monetary incentives, faster tracks to promotion, and mandatory rotations (Evans, Acosta, et al., 2021). In light of the strong preference for establishments close to home, some school systems offer transportation and housing subsidies (Pugatch & Schroeder, 2014). More recently, governments in Latin America have been experimenting with behavioral nudges to attract teachers to disadvantaged schools (Ajzenman et al., 2020; Ajzenman et al., 2021). The research shows that simple low-cost interventions are effective at encouraging teachers to apply to hard-to-staff schools, offering a promising alternative to financial incentives at a time when economic growth is low and education budgets are tight. While this approach has shown some success in getting novice teachers to apply to hard-to-staff schools, future work might consider testing similar strategies to mitigate the sorting of more experienced teachers seeking transfers.

References

Ajzenman, N., Bertoni, E., Elacqua, G., Marotta, L., & Méndez Vargas, C. (2020). Altruism or money? reducing teacher sorting using behavioral strategies in peru. *Reducing Teacher Sorting using Behavioral Strategies in Peru (July 30, 2020)*.

Ajzenman, N., Elacqua, G., Marotta, L., & Olsen, A. (2021). Order effects and employment decisions: Experimental evidence from a nationwide program.

Allen, R., Burgess, S., & Mayo, J. (2018). The teacher labour market, teacher turnover and disadvantaged schools: New evidence for england. *Education Economics*, *26*(1), 4–23.

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

Bertoni, E., Elacqua, G., Hincapié, D., Méndez, C., & Paredese, D. (2022). Teachers' preferences for proximity and the implications for staffing schools: Evidence from peru. *Education Finance and Policy*, 1–32.

Bonhomme, S., Jolivet, G., & Leuven, E. (2016). School characteristics and teacher turnover: Assessing the role of preferences and opportunities. *The Economic Journal*, *126*(594), 1342–1371.

Boyd, D., Lankford, H., Loeb, S., Ronfeldt, M., & Wyckoff, J. (2011). The role of teacher quality in retention and hiring: Using applications to transfer to uncover preferences of teachers and schools. *Journal of Policy Analysis and Management*, *30*(1), 88–110.

Boyd, D., Lankford, H., Loeb, S., & Wyckoff, J. (2005). Explaining the short careers of high-achieving teachers in schools with low-performing students. *American economic review*, *95*(2), 166–171.

Boyd, D., Lankford, H., Loeb, S., & Wyckoff, J. (2013). Analyzing the determinants of the matching of public school teachers to jobs: Disentangling the preferences of teachers and employers. *Journal of Labor Economics*, *31*(1), 83–117.

Chetty, R., Friedman, J. N., & Rockoff, J. E. (2014). Measuring the impacts of teachers ii: Teacher value-added and student outcomes in adulthood. *American economic review*, *104*(9), 2633–79.

Clotfelter, C., Glennie, E., Ladd, H., & Vigdor, J. (2008). Would higher salaries keep teachers in high-poverty schools? evidence from a policy intervention in north carolina. *Journal of Public Economics*, *92*(5-6), 1352–1370.

Clotfelter, C. T., Glennie, E. J., Ladd, H. F., & Vigdor, J. L. (2008). Teacher bonuses and teacher retention in low-performing schools: Evidence from the north carolina $1,800 teacherbonusprogram.$ *Public Finance Review*, *36*(1), 63–87.

Clotfelter, C. T., Ladd, H. F., Vigdor, J. L., & Diaz, R. A. (2004). Do school accountability systems make it more difficult for low-performing schools to attract and retain high-quality teachers? *Journal of Policy Analysis and Management*, *23*(2), 251–271.

Elacqua, G., & Marotta, L. (2020). Is working one job better than many? assessing the impact of multiple school jobs on teacher performance in rio de janeiro. *Economics of Education Review*, *78*, 102015.

Engel, M., Jacob, B. A., & Curran, F. C. (2014). New evidence on teacher labor supply. *American Educational Research Journal*, *51*(1), 36–72.

Evans, D. K., Acosta, A. M., et al. (2021). *How to recruit teachers for hard-to-staff schools: A systematic review of evidence from low-and middle-income countries.* Center for Global Development.

Falch, T., & Strøm, B. (2005). Teacher turnover and non-pecuniary factors. *Economics of Education Review*, *24*(6), 611–631.

Grissom, J. A., Loeb, S., & Nakashima, N. A. (2014). Strategic involuntary teacher transfers and teacher performance: Examining equity and efficiency. *Journal of Policy Analysis and Management*, *33*(1), 112–140.

Hanushek, E. A., Kain, J. F., & Rivkin, S. G. (2004). Why public schools lose teachers. *Journal of human resources*, *39*(2), 326–354.

Jackson, C. K., & Bruegmann, E. (2009). Teaching students and teaching each other: The importance of peer learning for teachers. *American Economic Journal: Applied Economics*, *1*(4), 85–108.

Johnston, A. C. (2020). Teacher preferences, working conditions, and compensation structure.

Krieg, J. M., Theobald, R., & Goldhaber, D. (2016). A foot in the door: Exploring the role of student teaching assignments in teachers' initial job placements. *Educational Evaluation and Policy Analysis*, *38*(2), 364–388.

Lankford, H., Loeb, S., & Wyckoff, J. (2002). Teacher sorting and the plight of urban schools: A descriptive analysis. *Educational evaluation and policy analysis*, *24*(1), 37–62.

McFadden, D. (1974). The measurement of urban travel demand. *Journal of public economics*, *3*(4), 303–328.

Pugatch, T., & Schroeder, E. (2014). Incentives for teacher relocation: Evidence from the gambian hardship allowance. *Economics of Education Review*, *41*(1), 120–136.

Ren, J., Xia, F., Chen, X., Liu, J., Hou, M., Shehzad, A., Sultanova, N., & Kong, X. (2021). Matching algorithms: Fundamentals, applications and challenges. *IEEE Transactions on Emerging Topics in Computational Intelligence*, *5*(3), 332–350.

Rosa, L. (2019). *The organization of educational markets and effects on individuals' decisions: An empirical analysis using brazilian educational policies*. Stanford University.

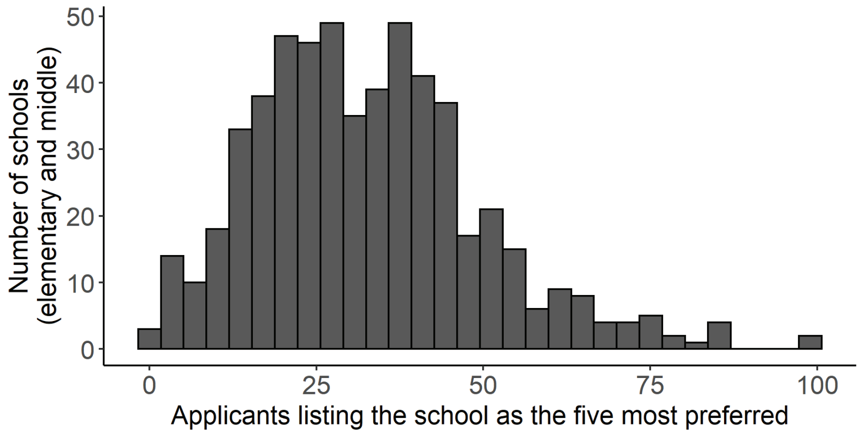

Figure 1: Market Congestion - Number of applicants per school

Table 1: Teacher transfers - Frequency

	Freq.	% total	% ask transf.	% got transf.
Total Number of Teachers	46755	-	-	-
Teachers asking for transfer	8072	17.3%	-	-
Teachers transferring	5804	12.4%	71.9%	-
Transfers by preference order				
1st	3057	-	-	52.7%
2nd	810	-	-	14%
3th	382	-	-	6.6%
4th	230	-	-	4%
5th or more	1324	-	-	22.8%

Note: The table shows the total number (frequency) of teachers registered in the department of education and the candidates for teacher transfers in the year 2019. The source of the data is the administrative records from the department of education in the city of Sao Paulo.

Table 2: Applicants - Statistics

	(1)
Average number of schools listed	38.8
Median number of schools listed	7.0
% of teachers listing only 1 school	19.2
% of teachers listing only 2 schools	9.0
% of teachers listing only 3 schools	6.9
% of teachers listing only 4 schools	5.7
% of teachers listing 5 schools or more	59.1

Note: The table shows the statistics of applications. First and second rows show the average and median number of schools listed by teachers in their preference list. Third to seventh rows show the percentage of schools that listed 1, 2, 3, 4, or more than 4 schools. The source of the data is the administrative records from the department of education in the city of Sao Paulo.

Table 3: School characteristics by current and transfer market

	Current	Transfer	
		First Best	Assigned
Test score (z-scr)	-0.052	0.174	0.013
SES	5.05	5.133	5.082
Low SES (%)	23.626	20.364	22.241
Class size	28.73	28.821	28.804
Novice teachers (%)	0.246	0.165	0.209
School is in favela	0.437	0.325	0.39
% of disability students	0.025	0.026	0.025
Number classrooms	30.568	30.179	30.272
Retention rates	0.037	0.044	0.039
Dist home-school (km)	9.011	6.46	7.024
N	4807	4458	3481

Note: The table shows the school characteristic by school type. First column shows the characteristics of the schools the teacher were currently working. Second column shows the characteristics listed as number one in the teacher preference order. Third column shows the school characteristics of the school the teachers were assigned.

Table 4: Rank-ordered logit estimates

	Teacher preferences						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dist home-sch (log)	0.488***	0.489***	0.489***	0.490***	0.486***	0.488***	0.489***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Test scores (z-score)		-0.095***	-0.080***	-0.072***	-0.047**	-0.056***	-0.054***
		(0.013)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Perc. low-ses			0.002	0.001	-0.000	0.001	0.001
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
School in favela				0.049**	0.047**	0.049**	0.047**
				(0.015)	(0.015)	(0.015)	(0.015)
Perc. novice teachers					0.725***	0.593***	0.589***
					(0.077)	(0.082)	(0.082)
Number of classrooms						-0.049***	-0.050***
						(0.008)	(0.008)
Monetary incentive - Low							0.043
							(0.027)
Monetary incentive - High							-0.016
							(0.050)
N	40376	40376	40376	40376	40376	40376	40376

Note: The table shows estimates from the rank-ordered logit model. Negative signals indicate the school attribute is preferred by teachers (teachers rank such schools first), and positive signals indicate that teachers dislike the attribute (ranking the schools lower on their preference list). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Estimates: rank-ordered logit by teacher characteristics

	Teacher preferences					
	Men	Women	Blacks	Whites	Age < 30	Age > 30
	(1)	(2)	(3)	(4)	(5)	(6)
Dist home-sch (log)	0.402***	0.521***	0.505***	0.522***	0.402***	0.499***
	(0.035)	(0.022)	(0.035)	(0.028)	(0.066)	(0.020)
Test scores (z-score)	-0.079**	-0.045**	-0.036	-0.052*	-0.018	-0.057***
	(0.030)	(0.017)	(0.023)	(0.021)	(0.046)	(0.016)
Perc. low-ses	-0.003	0.003*	0.001	0.002	-0.003	0.001
	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)
School in favela	0.039	0.050**	0.105***	0.026	-0.005	0.052**
	(0.028)	(0.018)	(0.026)	(0.022)	(0.049)	(0.016)
Perc. novice teachers	0.638***	0.560***	0.544***	0.577***	0.889***	0.558***
	(0.157)	(0.096)	(0.125)	(0.121)	(0.252)	(0.086)
Number of classrooms	-0.053***	-0.048***	-0.057***	-0.052***	-0.042	-0.051***
	(0.015)	(0.009)	(0.011)	(0.011)	(0.024)	(0.008)
Monetary incentive - Low	0.013	0.049	0.002	0.067	0.054	0.043
	(0.055)	(0.032)	(0.050)	(0.035)	(0.102)	(0.029)
Monetary incentive - High	-0.029	-0.020	-0.175*	0.089	-0.022	-0.016
	(0.092)	(0.057)	(0.077)	(0.070)	(0.168)	(0.052)
N	10341	30035	12470	20149	3253	37123

Note: The table shows estimates from the rank-ordered logit model by teacher characteristics. Negative signals indicate that teachers in the group show a preference for the school attribute (teachers rank the schools first), and positive signals indicate that teachers dislike the attribute (ranking the schools lower in their preference list). The "Black" category includes people who are classified as Black, mixed-race (*pardo*), and indigenous (*indigena*). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Estimates: rank-ordered logit by teacher subject

	Teacher preferences				
	Elementary	Middle School			
		Math	Language	Sciences	Other
	(1)	(2)	(3)	(4)	(5)
Dist home-sch (log)	0.514***	0.167*	0.287***	0.514***	0.529***
	(0.029)	(0.079)	(0.071)	(0.070)	(0.032)
Test scores (z-score)	0.007	-0.022	-0.099	-0.086	-0.104***
	(0.023)	(0.061)	(0.070)	(0.056)	(0.022)
Perc. low-ses	0.002	0.003	0.001	-0.003	0.000
	(0.002)	(0.004)	(0.004)	(0.004)	(0.002)
School in favela	0.040	-0.089	0.076	0.112	0.062**
	(0.024)	(0.066)	(0.071)	(0.058)	(0.023)
Perc. novice teachers	0.689***	0.554	0.606	0.580	0.514***
	(0.131)	(0.300)	(0.389)	(0.322)	(0.124)
Number of classrooms	-0.059***	-0.030	-0.091**	-0.062*	-0.037**
	(0.012)	(0.030)	(0.033)	(0.031)	(0.012)
Monetary incentive - Low	0.065	0.067	-0.412**	0.124	0.055
	(0.043)	(0.139)	(0.128)	(0.110)	(0.039)
Monetary incentive - High	-0.051	0.028	-0.286	0.117	0.013
	(0.077)	(0.233)	(0.180)	(0.163)	(0.078)
N	17470	2169	2015	2631	16091

Note: The table shows estimates from the rank-ordered logit model. Negative signals indicate that teachers in the group show a preference for the school attribute (teachers rank the schools first), and positive signals indicate that teachers dislike the attribute (ranking the schools lower in their preference list). The "other" category is comprised of history, geography, arts, and physical education teachers. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$