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Matteo Bobba
Tim Ederer
Gianmarco Leon-Ciliotta
Christopher Neilson
Marco G. Nieddu

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ABSTRACT

This paper studies how increasing teacher compensation at hard-to-staff schools can reduce inequality in access to qualified teachers. Leveraging an unconditional change in the teacher compensation structure in Peru, we first show causal evidence that increasing salaries at less desirable locations attracts better quality applicants and improves student test scores. We then estimate a model of teacher preferences over local amenities, school characteristics, and wages using geocoded job postings and rich application data from the nationwide centralized teacher assignment system. Our estimated model suggests that the current policy is helpful but both inefficient and not large enough to effectively undo the inequality of initial conditions that hard-to-staff schools and their communities face. Counterfactual analyses that incorporate equilibrium sorting effects characterize alternative wage schedules and quantify the cost of reducing structural inequality in the allocation of teacher talent across schools. Overall our results show that a policy that sets compensation at each job posting using the information generated by the matching platform is more efficient and can help reduce structural inequality in access to learning opportunities. In comparison, a rigid system that ignores teacher preferences will indirectly reinforce such inequalities.

Matteo Bobba
Toulouse School of Economics
University of Toulouse Capitole
1, Esplanade de l'Université
Toulouse Cedex 06 31080
France
matteo.bobba@tse-fr.eu

Tim Ederer
Toulouse School of Economics
University of Toulouse Capitole
1, Esplanade de l'Université
Toulouse Cedex 06 31080
France
tim.ederer@tse-fr.eu

Gianmarco Leon-Ciliotta
Department of Economics and Business
Universitat Pompeu Fabra
Barcelona GSE, IPEG and BREAD
Carrer Ramon Trias Fargas 25-27
Barcelona 08005
Spain
gianmarco.leon@upf.edu

Christopher Neilson
School of Public and International Affairs
Princeton University
Firestone Library, Room A2H
Princeton, NJ 08544
and NBER
cneilson@princeton.edu

Marco G. Nieddu
Department of Economics
University of Cagliari and CRENoS
Viale Sant'Ignazio da Laconi 17
Cagliari 09123
Italy
mgnieddu@unica.it

An online appendix is available at http://www.nber.org/data-appendix/w29068

1 Introduction

Children born in remote and rural communities face significant disadvantages in achieving comparable levels of human capital as their peers born in urban areas (World Bank, 2018). Part of these wide inter-regional disparities reflect underlying differences in the distribution of opportunities across geographic areas that is a result of past policies and historical inequities. However, current policies can also contribute to further widening the gap in opportunities if the pre-existing inequality is not compensated for (Glewwe and Muralidharan, 2016).

In this paper, we study how inequality in the access to learning opportunities is amplified or reduced by policies that determine teacher compensation and shape the geographic distribution of teacher talent.[1] We study this question in the context of Perú, a developing country with a heterogeneous geography and a population that is characterized by different languages, cultures, and ethnicities. After documenting inequality in the access to schooling inputs across rural and urban communities, we evaluate the impact of a recent policy reform that significantly increased compensation at hard-to-staff schools in rural Perú. We use a combination of a regression discontinuity design and an empirical model of teacher school choice, to characterize the effects of the policy and the mechanisms through which it operated. We provide evidence that higher compensation at rural schools can increase the supply of qualified teachers and improve student learning outcomes. Despite the positive effects of increased compensation, we further show that the current policy is both inefficient in terms of the spatial distribution of increased compensation and not large enough to effectively undo the inequality of initial conditions that hard-to-staff schools and their communities face.

We then consider the design of the optimal policy in our setting by asking what alternative compensation schemes could reduce inequality in the access to learning opportunities. To do so, we use the estimates of teacher preferences and information on school vacancies to implement a matching-with-contracts algorithm that delivers the cost-efficient wage schedule that is consistent with a given social objective (Hatfield and Milgrom, 2005). We finally explore how the optimal allocation changes with the introduction of complementary policies such as investing in rural school/community infrastructure or by increasing the supply of teachers from different ethnic and geographic backgrounds.

We begin our empirical analysis by presenting descriptive evidence on the structural divide in school inputs and academic outcomes between rural and urban areas. Administrative data on school infrastructure and teacher qualifications show large gaps between rural and urban schools, and these gaps persist when comparing student achievement. Job

[1] There is ample evidence that teacher quality is important for student outcomes in e.g., the US (Chetty et al., 2014; Jackson, 2018), Ecuador (Araujo et al., 2016), Pakistan (Bau and Das, 2020) and Uganda (Buhl-Wiggers et al., 2017).

amenities, or the lack thereof, could be one explanation for these large differences in teacher qualifications. Because teachers indicate their preferences over available positions through a centralized application system, we are able to measure this empirically. We show that job applications are highly skewed towards vacancies in urban areas, and the school system is hard-pressed to staff many small rural public schools scattered throughout the poorest parts of the country. The lack of teachers applying for jobs at rural schools could be due to several factors, including insufficient compensation (Jackson et al., 2014).

Against this backdrop, the government implemented a policy that increased compensation at teaching positions in rural public schools based on a coarse set of school and community attributes. We exploit discrete jumps in teacher wages at specific thresholds of the local population to show causal evidence that higher wages significantly increase the demand at vacancies in rural locations. Teachers who chose bonus-eligible positions have higher scores (0.45σ) on the national teacher competency test compared to those who chose lower-paying positions in otherwise similar teaching positions. Importantly, these effects are observed only for contract-teachers for whom the assignment mechanism follows a transparent and strict-priority assignment rule based on teacher competency scores and their preferences.[2]

We also show that the increase in teacher compensation led to significantly higher student academic achievement in math and language (0.3σ and 0.35σ, respectively). This is only true for schools that had an available teaching position in the recruitment drives we analyze, even though incumbent teachers were also paid more. This evidence suggests that there is no effort response of incumbent teachers, which mirrors recent findings that establish little or no effects of unconditional wage increases in contexts where most teachers are public servants with permanent contracts (de Ree et al., 2018).[3]

To evaluate the policy away from the eligibility cutoffs, we estimate an empirical model of teacher school choice and construct counterfactual assignments in the absence of the policy. We estimate the model parameters taking advantage of teachers' revealed preferences observed in the contract-teacher assignment system. Together with detailed information on every school vacancy, teacher characteristics, and final assignments, this setting is ideal for estimating a flexible model of heterogeneous teacher preferences over wages and job attributes (see Agarwal and Somaini (2020) for a review). The model is able to replicate the main features of the data in terms of spatial sorting of teachers, including the local effects around

[2] As found in other settings (Duflo et al., 2015; Estrada, 2019), the local institutions determining how teachers are evaluated and assigned might be an important necessary condition for the effectiveness of policies that provide incentives in the public sector.

[3] In our context, instead, a large proportion of the school vacancies targeted by the wage reform are filled by contract teachers, which is a common feature of teacher labor markets in most Latin American and African countries.

the wage discontinuity as well as broader trends along the support of the variables that characterize rural areas (locality population and remoteness to the provincial capital). The estimated preference parameters quantify key trade-offs between wages and local amenities, school characteristics, teacher-school match effects, and commuting/migration costs. Importantly, teachers from rural areas and ethnic minorities are more willing to work at schools in communities similar to their hometown and thus require a lower compensation to staff those positions.

The model of teacher school choice provides a rich perspective on the effects of the wage policy on the spatial distribution of teachers. By comparing simulated assignment outcomes with and without the wage bonus, we can characterize the policy effects on teacher sorting away from the discontinuities generated by the eligibility cutoffs of the recent policy reform. We show that, while most of the effect of the wage bonus policy on teacher quality happens close to the population threshold, the effect of the wage bonus on the share of filled vacancies seems spatially concentrated in less desirable locations that are farther away from the cutoffs.

Having established the effects of the policy that increased compensation, we turn to the evaluation of the equilibrium effects of alternative compensation policies. We use the estimated model to characterize counterfactual wage schedules that are consistent with two independent objectives: (i) filling all vacancies with any teacher irrespective of their quality, and (ii) recruiting in every school a teacher who is at least as qualified as the average teacher in urban areas. We encode these objectives into schools' preferences over contracts and use the matching-with-contracts algorithm to uncover the associated cost-efficient wage schedules. The algorithm is akin to an ascending auction where schools increase the wages they offer sequentially until the social objective is attained.

Our results show that a policy that sets compensation at each job posting using the information generated by the matching platform is more efficient and can help reduce structural inequality in access to learning opportunities. In comparison, a rigid system that ignores teacher preferences will indirectly reinforce such inequalities. We show that relative to the current compensation policy, the budget neutral optimal policy increases the share of filled vacancies by 7 percentage points and the share of schools with higher quality teachers by 4 percentage points. We find that filling every job vacancy with the current stock of teachers would require twice the current budget (in terms of the total wage bill). However, shifting the supply of highly qualified teachers towards hard-to-staff schools is significantly more costly. Given the existing stock of teachers and schools, it would take six times the current budget to equalize access to teacher quality across the country.

We then repeat this exercise by implementing complementary policies such as investing in school infrastructure or increasing the pool of teachers in locations where the supply is relatively scarce. We find that if differences in school infrastructure were completely eliminated, the share of filled vacancies and the share of schools with higher quality teachers both rise an additional six and 7 percentage points respectively. We get larger increments in equity if, instead of equalizing school infrastructure, the number of teachers from rural locations were to increase by just 3%. This targeted teacher training policy would lead to significant cost savings for policies that seek to eliminate inequality. Filling every job vacancy would cost 30% less and providing equal access to high quality teachers would cost 35% less than the optimal policy with the existing stock of teachers. These results show that there are large potential gains from complementary policy levers beyond wage incentives.[4]

This paper brings new data and market design tools to a growing literature that studies the role of compensation policy in the context of equilibrium models of the labor market for teachers and their implications for the distribution of teacher quality (Tincani, 2021; Biasi et al., 2021). Our results are relevant for the literature evaluating policies that vary teachers' compensation in both developed and developing countries. There is large body of work studying the effectiveness of pay-for-performance schemes.[5] Relatively fewer studies consider policy effects of unconditional wage increases on teacher turnover (Clotfelter et al., 2008) and student outcomes (de Ree et al., 2018; Pugatch and Schroeder, 2018; Cabrera and Webbink, 2020).

More broadly, we contribute to the recent literature on the personnel economics of the state (Finan et al., 2017). For instance, Ferraz and Finan (2009) find that higher wages for politicians in Brazil attracted more educated candidates and improved politician performance, Dal Bo et al. (2013) show that increased compensation for public sector positions in Mexico led to a larger pool of applicants, and a higher quality of hired employees. We bridge this literature with an empirical market design approach that leverages matching platforms to study the sorting patterns of public school teachers and their effects on structural inequality in the access to educational opportunities.

2 Data

In this paper, we combine several administrative data sources from the Ministry of Education of Perú over the period 2015-2018. While the resulting dataset spans the universe of public-sector teachers and schools throughout the country, we restrict our analysis to primary

[4]In addition to targeted teacher training or policies that equalize schooling inputs, Ajzenman et al. (2021) show evidence that teacher applications to hard-to-staff schools can also be influenced by information interventions or behavioral nudges.

[5]See for example Muralidharan and Sundararaman (2011); Barrera-Osorio and Raju (2017); Gilligan et al. (2018); Leaver et al. (2020); Brown and Andrabi (2020).

schools for two reasons. First, secondary schools are much less prevalent in rural areas.[6] To the extent that the geographic distribution of schools is key to understanding disparities in access to competent teachers, we need to focus on primary schools that are well represented throughout the country. Second, in primary schools, all students in a classroom are taught by a single teacher—instead of having a separate teacher for each subject. This setup allows us to pin down the effect of the newly assigned teachers on student achievement in our empirical analysis.

Our first data source is the *centralized teacher job application and assignment system*. This dataset includes information on all job vacancies posted at every public school in the country during the first two rounds of the national recruitment of public sector teachers (2015 and 2017), the scores in the subject competency evaluations for every applicant in the centralized test, and detailed information on the job application process that we discuss in Section 3.2. During the first (second) national recruitment drive, 77,500 (79,000) applicants competed for 18,000 (25,500) vacancies in primary schools. Of those, about one-fifth report no prior teaching experience (novice teachers).

Our second administrative data source is the *teacher occupation and payroll system (NEXUS)*. This is an official dataset collected and maintained by the Ministry of Education, which contains the complete records of all teachers employed in the public sector. In particular, the dataset includes individual identifiers for all teachers, the school in which they work (but not the specific grade), and the type of contract/position (permanent or contract, number of hours, etc.). This information is collected at the start, middle, and end of each school year, allowing us to precisely trace both the school of origin (if any) and the school of destination (if any) for each applicant to the national recruitment drives. Overall, 58% of applicants had previously been employed as public sector teachers.

We obtain school and locality characteristics data from the *school census*. These data include the number of pupils, libraries, computers, classrooms, sports facilities, and staff (teaching and administrative) at each school. They also include information on local amenities, such as access to basic services (electricity, sewage, water source) and infrastructure (community phone, internet, bank, police, public library). This information is reported annually by the principals of each school. Table A.1 in the Online Appendix reports basic descriptive statistics for some of these characteristics for schools in urban and rural areas,

[6]Secondary schools represent 27% of the total number of schools in the country. Only 14% of secondary schools are located in *Extremely Rural* areas (as defined in Section 3.3). Peruvian public primary schools serve 74% of the primary school enrollment countrywide. The majority of private schools target middle-class students in urban areas. In rural communities, defined as localities with less than 2,000 inhabitants, public schools are generally the only option, with more than 6,000 schools catering to 98 percent of the school-aged children in 2015.

respectively.

Our fourth data source is the administrative records on *student academic outcomes*. The *Evaluación Censal de Estudiantes* (ECE) is a national standardized test that covers curricular knowledge of math and language (Spanish). The test is administered by the Ministry of Education at the end of every school year at selected grades at both public and private schools whose enrollment exceeds five pupils (coverage is around 98%). We have access to individual test scores from 2014–2018 for fourth grade students in public primary schools.[7]

Finally, in collaboration with the Ministry of Education, we administered an online survey during the centralized job application process in 2015. Among several questions about the application decisions, the survey asked applicants to rank the most important characteristics of their chosen school. As shown in Table A.2, forty-four percent of teachers rank "being close to home" as the most important characteristic. The two most often cited characteristics are "prestige" and "cultural reasons".[8] Other characteristics that drive decision-making for some teachers include quality of school infrastructure, quality of students, and safety. In addition, there is heterogeneity in the characteristics that are most important to teachers, with teachers who score in the top quartile of the teacher evaluation test ranking characteristics differently. These survey results partly motivate the empirical model that we propose and estimate in Section 5.

3 Context and Institutions

3.1 Inequality of Education Inputs

Perú's colonial history has affected current institutions, governance, public good provision, and welfare (Acemoglu et al., 2001; Dell, 2010). The country spans a vast and varied geography made up of mountainous, jungle, and coastal regions, with a population of culturally and linguistically diverse groups who have lived for centuries under extractive systems of governance as a colony of the Spanish empire. The legacy of colonial institutions and policies is one of the root causes of current structural inequalities. These policies were often targeted to the highlands and jungle regions, where most of the natural resources were located. These areas, in turn, have high poverty rates and a large concentration of indigenous population.

[7] In 2017 there were a large number of floods and landslides throughout the country due to the El Niño natural calamity. This emergency led the Minister of Education at the time to take the (unfortunate) decision to cancel the achievement test for that year.

[8] While "prestige" is admittedly a somewhat vague concept, "cultural reasons" mainly refer to ethnolinguistic similarities between teachers and the communities where the schools are located.

Over the last decade, the government has undertaken several efforts to improve educational outcomes in poorer rural areas, such as implementing a large-scale conditional cash transfer program, investing in school infrastructure projects, and improving access to drinking water and sewage (Bertoni et al., 2020). However, large differences still exist in the access to education inputs such as school and locality infrastructure. Schools in rural areas predominantly hold (90%) mixed classes, with a single teacher attending to students of different grades, and relative to urban schools they are 30% more likely to lack access to basic services such as running water or electricity. See Table A.1 in the Online Appendix for urban-rural differences across a broader set of indicators of schools, teachers, students, and community characteristics.

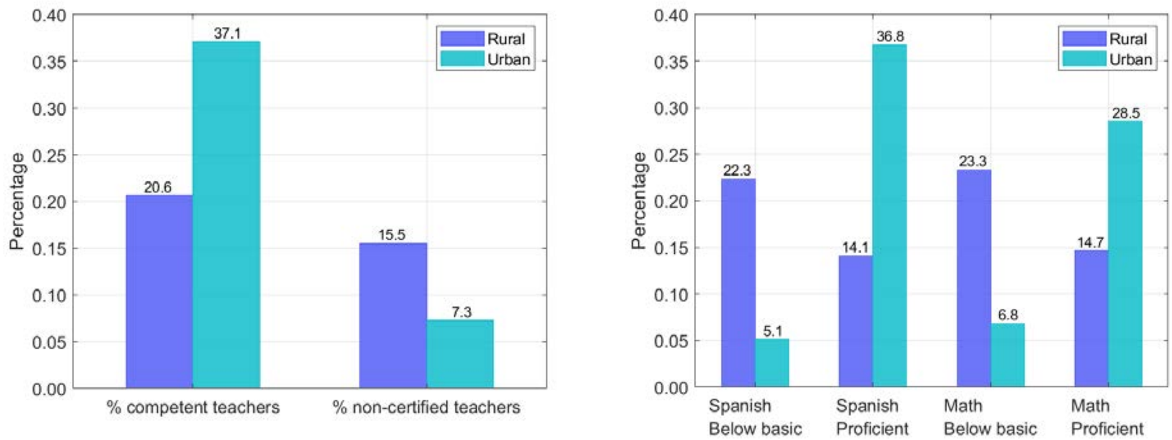
Figure 1 documents the stark differences in teacher quality and student achievement between urban and rural schools. Panel A shows that teachers at rural schools are 20% less likely to pass the requirements set by the government for permanent teachers (competent teachers) and are twice as likely to lack teaching credentials (non-certified teachers).[9] Panel B of Figure 1 displays students' academic performance on the national standardized evaluation in two subjects – Spanish and math. Approximately one in four students enrolled in rural schools are classified as performing below the basic curricular requirements in either of the two subjects, whereas the corresponding shares in urban schools are around 5%.

We report additional stylized facts about the distribution of teacher quality in Online Appendix A. Figure A.2 shows the geographic distribution of competent teachers across provinces alongside the corresponding distribution of student test scores. Competent teachers are heavily concentrated in the richer, coastal cities, while they are nearly absent in the highlands and the inner amazonian regions (Panel A). The spatial variation in students' achievement outcomes, shown in Panel B, is highly correlated with the concentration of competent teachers across the country.

We document inequality in schooling inputs and outputs across Perú. While local amenities and school infrastructures likely reflect structural differences between urban and rural areas, the unequal spatial distribution of teacher quality suggests a margin where policy can play an important role. To better understand the reasons behind the allocation of teachers across different geographic areas, we now describe the institutions surrounding the labor

[9] Competency is assessed by teachers' performance on the curricular and pedagogical knowledge module of the standardized test used to both screen and recruit teachers (see Section 3.2). Subject competency test have shown to correlate with teacher value added and other dimensions of teacher quality in several contexts (Bold et al., 2017; Estrada, 2019; Gallegos et al., 2019; Araujo et al., 2020). In Perú in particular, Bertoni et al. (2021) document strong correlations between various measures of teaching effectiveness and the score in the curricular and pedagogical knowledge module of the evaluation test. Competent teachers are defined in Figure 1 as those who attain a score of at least 60% in that module of the test. Figure A.1 in the Online Appendix depicts a few individual-level correlates of performance in the standardized test.

Figure 1: Teachers and Students in Urban Vs. Rural Areas



a) Teachers **b) Students**

Notes: These figures show different summary statistics about teachers and students in urban and rural areas. Panel A shows that teachers in rural schools are less likely to be classified as competent and are more likely to lack teaching certifications. Panel B shows how academic performance in the Spanish and math modules of the national standardized evaluation differs between students of urban and rural schools. See A.1 in the Online Appendix for a broader set of indicators for school and community-level characteristics across urban and rural areas.

market for public school teachers.

3.2 Contracts, Wages, and Sorting of Public School Teachers

Public school teachers in Perú are hired under two distinct types of contracts. Permanent teachers (*docentes nombrados*) are civil servants with indefinite contracts and very stable employment. Teachers can also be hired by the central administration to work at a specific school for an academic year as contract teachers (*docentes contratados*). This contract can be renewed for up to one more year subject to the approval of the school's administration. Short-term contracts are routinely used in most education systems around the world and are often designed as entry-level positions in the teaching career.[10] In our setting, about one out of five primary school instructors in urban areas is hired as a contract teacher. Short-term contracts are more widespread in rural areas, reaching almost half of the labor force in the most remote schools.

The compensation of public-school teachers in Perú depends on (i) the type of contract (permanent or contract), (ii) seniority, and (iii) some specific location or school characteristics. In 2015, the base monthly wage for primary-school teachers under a short-term

[10] Research in India and Kenya shows that students taught by locally hired teachers on annual contracts have higher test scores (Muralidharan and Sundararaman, 2011; Duflo et al., 2015), although in Kenya those gains tend to vanish when the contracts are administered by the government rather than by a non-government organization (Bold et al., 2018).

contract was S/ 1,550 (US$ 510). This amount corresponds to the starting monthly wage of permanent teachers, although more experienced permanent teachers can earn up to S/ 3,110 (US$ 1023). Additional wage bonuses are given to all teachers (irrespective of the contract) working in specific types of schools, such as multi-grade or single-teacher schools, or schools located in disadvantaged communities.[11] While teacher compensation in the public sector in Perú is lower (Mizala and Ñopo, 2016; Evans et al., 2020), they are higher than comparable teaching positions in private schools.[12]

The recruitment process of permanent and contract teachers in Perú was decentralized until 2015. As in most countries, regional and local level officials often had significant discretion in teacher hiring and allocation decisions (Bertoni et al., 2019; Estrada, 2019). In an effort to make the process more transparent and meritocratic, the Ministry of Education established a nation-wide recruitment process in which school-level job postings and teacher job applications are processed on a single, centrally-managed platform. The first national recruitment drive took place in 2015, followed by another round in 2017. Teachers recruited through the 2015 and 2017 drives started teaching in the 2016 and 2018 academic years (March-December), respectively.

The process consists of two phases. In the first phase, every vacancy for permanent teachers across all education levels are posted in the centralized system. Interested applicants must have earned a teaching accreditation and taken a standardized competency evaluation. The test is divided into three modules, which carry different weights in the total score: logical reasoning (25 percent), reading comprehension (25 percent), and curricular and pedagogical knowledge (50 percent). Those who correctly answer at least 60 percent of the questions in each part of the test are eligible to apply for a permanent position by submitting a ranked-order list of school preferences for up to five available positions in a given school district.[13] Each school evaluates a short-list of the highest scoring teachers who express a preference

[11]Figure A.3 in the Online Appendix shows the different wage bonuses, which vary between 3% (bilingual school) and 30% (extremely rural locations, as defined in Section 3.3) of the monthly base wage. Schools can satisfy multiple criteria (e.g. multi-grade and bilingual), in which case the bonuses are cumulative. Accredited bilingual teachers are eligible for an additional bonus of S/ 100. There are also some compensation adjustments throughout the year, such as a holiday bonus, which usually represents less than 5% of the total monthly wage.

[12]According to the national household survey (ENAHO 2016), the earnings of primary school teachers are ranked second to last among the liberal professions in Perú, followed only by translators and interpreters. Nationally representative survey data on teachers (ENDO 2014) document that the average monthly wage for teachers working in primary schools in the private sector is approximately S/ 950. Only private school teachers in the top ten percent of the distribution earn more than the base wage of a teacher in the public sector (S/ 1,550).

[13]In total there are 218 school districts participating in the assignment with substantial within-district variation in the rural status of the school vacancies. For the average district, 71 percent of vacancies are in rural locations. All available vacancies are in urban locations for 33 school districts (15 percent).

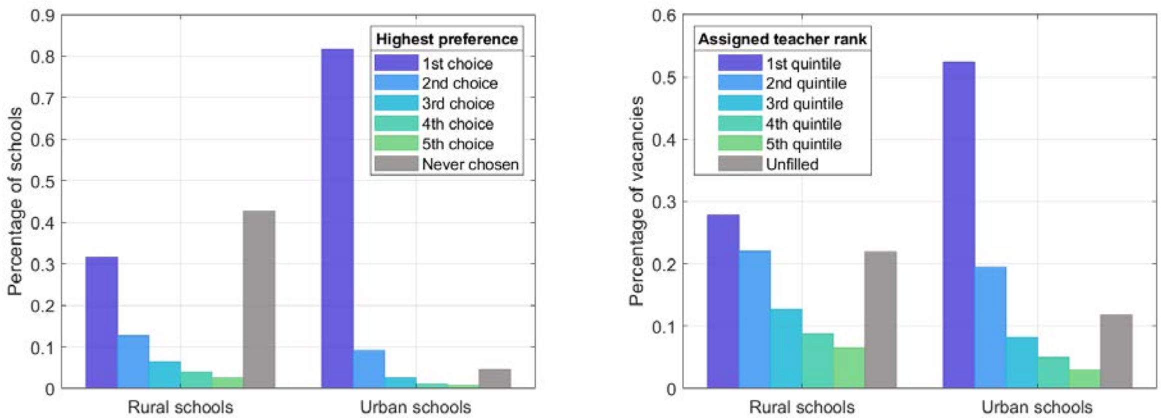
for that vacancy based on an in-class demonstration, their experience, and an interview. At the end of the process, positions are allocated according to an overall score in both the competency test and the school-based evaluation.[14]

The short-term vacancies are assigned through the platform in a second phase, which aims to fill most of the vacancies that remain unfilled after the first phase. In contrast to the assignment of permanent teachers, short-term teaching positions are allocated through a serial dictatorship algorithm where schools' preferences are taken to be a strict ranking of the teacher competency scores. Applicants are sequentially allowed to choose from the list of open vacancies in a given school district. Once a vacancy is filled, it is eliminated from the list of the available options in that district, and the next lower-ranked teacher is allowed to pick her preferred option. This iterative process continues until all vacancies are filled, or until the lowest-ranked teacher in each school district is allowed to choose among the remaining vacancies. After the first round of the matching process, unassigned applicants are given another chance to choose among the remaining open vacancies from other districts. The remaining teaching positions are eventually filled through a decentralized secondary market, which includes teachers without accreditation.

Figure 2 shows the data on applications to primary-school vacancies. While 80% of schools in urban areas are ranked first by at least one permanent-job applicant, vacancies posted in rural areas receive significantly fewer applications – nearly half of the rural schools are never ranked by applicants. As a result, more than two-thirds of job vacancies for permanent positions remain unfilled in rural schools, while three-fourths of vacancies are filled in urban schools through the centralized assignment mechanism. Panel B considers the sample of temporary positions by plotting the quintiles of the rank-order in which positions get filled in the serial dictatorship algorithm. Again, short-term teaching vacancies in urban areas are in higher demand: on average as more than half of those postings get filled by teachers ranked in the top 20% of the pool of applicants in their respective school districts. Overall, the centralized assignment process fills almost 90 percent of short-term vacancies in urban areas and 80 percent of short-term vacancies in rural areas.

[14] In the 2015 screening and recruitment process, candidates were allowed to rank a maximum of five schools. This constraint was removed from 2017 onwards, and applicants were free to submit an unlimited number of options.

Figure 2: Teacher Choices over Job Postings



a) Permanent Teachers **b) Contract Teachers**

NOTES: This figure depicts the demand for teaching positions in rural and urban schools. Panel a plots the relative share of schools depending on the highest preference received, so that each blue bar indicates the proportion of schools that were included in the applicants' ranked-order lists (as first, second, third, fourth or fifth choice, respectively). Similarly, the grey bar indicates the relative share of schools that were not mentioned in any of the permanent teacher rankings. Panel b plots the rank order (grouped in quintiles) in which a contract teaching position is filled, together with the share of vacancies that remained unfilled (not filled by a certified teacher). The rank order is defined based on the applicants' distribution within each school district and teaching field, and is normalized so that it takes the value of zero when the position is chosen first and one when the position is filled last. The numbers are obtained by pooling the data from the two recruitment drives from 2015 and 2017.

We conclude that the spatial inequality in access to qualified teachers displayed in Panel A of Figure 1 can be at least in part explained by teachers preferences and choices over locations. Teachers in poor rural areas face numerous challenges: scarcity of basic school inputs, lack of services and public goods, few local amenities, and (for some) being far from friends and family. To the extent that wage-setting policies do not adequately compensate for the lack of these amenities, those jobs will be less attractive. The micro-data on job postings and teacher rank-order applications show that applications are concentrated at positions in urban areas, and the system is hard-pressed to staff the roughly 14,000 positions in rural public schools scattered throughout the poorest parts of the country. While some of these vacancies are eventually filled using short-term contracts, many remain unfilled until significantly less-qualified teachers fill the position through the decentralized secondary market. On average, teachers that are assigned to rural schools have competency scores that are 0.5 standard deviations lower than those assigned to urban schools.

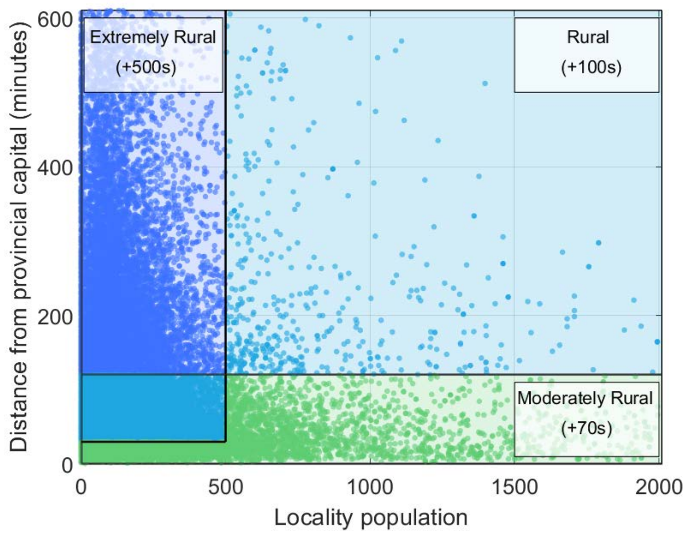
3.3 Policy Changes to Compensation in Rural Locations

The government recently implemented a reform to the wage bonus that significantly increases teacher compensation at positions in select rural schools. The new policy establishes three distinct categories of rurality according to the school's locality population and its proximity to the provincial capital: *Extremely Rural*, *Rural*, and *Moderately Rural* (see Figure 3). The population of the locality is measured by population counts in the latest available census (2007). Travel time from the locality to the provincial capital is used as a proxy for how remote a community is, and it is measured on the basis of GPS coordinates, after taking into account usual modes of transport and the roads available at the time of the measurement. The first category of *Extremely Rural* schools are in localities with less than 500 inhabitants, and for which it takes more than 120 minutes to reach the province capital. The second category of *Rural* schools is reserved for either: (a) schools in localities with less than 500 inhabitants and which are located between 30 and 120 minutes from the province capital, or (b) schools in localities with 500–2,000 inhabitants that are farther than 120 minutes from the province capital. The third category of *Moderately Rural* schools are either: (a) in localities with 500–2,000 people that are closer than 120 minutes, or (b) in localities with less than 500 inhabitants that are less than 30 minutes away from the province capital. All other schools are classified as Urban and are not entitled to the wage bonus.

The policy was first implemented in January 2014. At the time of implementation, permanent teachers in *Extremely Rural*, *Rural*, and *Moderately Rural* schools were eligible for the monthly wage bonuses of S/ 200, S/ 100, and S/ 70, respectively. In August 2015, the wage bonus for *Extremely Rural* schools was increased to S/ 500 and bonus eligibility was extended to include contract teachers. These changes were not announced until they were implemented (in August, i.e. in the middle of the school year) and thus right before the first centralized recruitment drive that took place in October 2015, which marks the start of our study period. The bonus for *Extremely Rural* schools is fairly generous – it is equivalent to 30 percent of contract teachers' monthly earnings, and between 20 and 30 percent of earnings of permanent teachers.

Figure 3 displays a scatter plot of the distribution of the 25,000 rural primary schools in Perú over the population (x-axis) and remoteness of the communities where the schools are located (y-axis). There is a large mass of schools around both the time cutoffs (30 minutes and 120 minutes from the provincial capital) and the population cutoff (500 inhabitants) for the rural wage bonuses. As the localities become more remote, schools are more likely to be located in communities that are small and predominantly fall into the *Extremely Rural* category. Likewise, for localities with populations above 1,000 inhabitants, there are more communities that are closer to the provincial capitals (*Moderately Rural*).

Figure 3: The Distribution of Rural Schools over Population and Remoteness



NOTES. This figure shows the spatial distribution of rural primary schools along the two dimensions that determine assignment of the rural wage bonus. *Extremely Rural* schools are the dark blue dots, *Rural* are light blue and *Moderately Rural* schools are green.

4 Causal Effects of the Increase in Compensation

4.1 Identification and Estimation

Offering higher wages for positions at rural locations could attract more and higher-quality teachers, which may lead to better student outcomes. On top of these effects at the extensive margin, additional compensation may also increase the quality of instruction through potential changes in effort and motivation for both new and existing teachers in rural schools. In the empirical analysis, we exploit the classification rules of the rural wage bonus to identify the causal effects of unconditional wage increases on teachers' application behavior and assignment outcomes. We also study how student outcomes change in response to the wage reform throughout the study period (2015-2018). Comparing schools with and without open vacancies in the national recruitment drives of 2015 and 2017 allows us to discern whether changes at the extensive or the intensive margin of teacher quality can explain the effect of the wage reform on students' academic achievement.[15]

The introduction of the rural wage bonus may generate incentives for school principals and administrators to manipulate the information used to determine bonus eligibility. The population threshold is based on census data, and as such, it is difficult to manipulate,

[15]Table B.3 in the Online Appendix shows that there is no effect of the wage bonus on the probability that a school has an open position for permanent or contract teachers. Figure A.4 in the Online Appendix displays scatter plots similar to the one reported in Figure 3 for schools with and without vacancies in the national recruitment drives of 2015 and 2017, respectively.

whereas the time-to-travel measure is gathered by inspectors from the Ministry of Education, who physically go to the schools and take a GPS measurement of the school's location. The procedure was repeated in 2017 in order to account for possible changes in the transportation network. By that time, the previous measurement had become public information, and hence some schools located just below the 120-minute threshold may have then gained eligibility to the S/ 500 wage bonus by slightly manipulating the GPS measurement. The data shows that there is a significantly larger mass of schools that falls just above the time-to-travel threshold for the assignment process that took place in 2017, while there are no significant jumps in the density of schools at the population threshold for either of the years of interest.[16]

We thus rely on the population-based assignment rule as the only source of variation in teacher wages for this part of the analysis. Contract teachers in localities that are just below the 500 inhabitants cutoff earn on average almost S/.250 more than those in localities that are just above the cutoff, which represents an increase in the monthly wage of about 15 percent. The corresponding average increase in wages for newly recruited permanent teachers (i.e. no experience) due to the rural bonus reform is S/.240, or 14 percent of their monthly wage. These effects are unconditional weighted averages of the different wage increases induced by crossing from above the population cutoff for different values of the time-to-travel variable.[17]

Given continuity of potential outcomes around the population cutoff, the following specification identifies the effect of a higher wage bonus:[18]

$$y_{jt} = \gamma_0 + \gamma_1 \mathbf{1}(pop_{jt} < pop_c) + g(pop_c - pop_{jt}) + \delta_t + u_{jt}, \tag{1}$$

[16] Figures B.1, B.2, and B.3 in the Online Appendix display the densities for each of the assignment variables by year of the assignment mechanism based on local-quadratic density estimators with the corresponding confidence intervals (Cattaneo et al., 2020) along with the bias-corrected t-statistics (and associated p-values) for the null hypothesis of no difference in height between the two density estimators for the time-to-travel discontinuity. While the locality population is a good predictor for the eligibility to the rural wage bonus in both years, time-to-travel in 2015—which we observe to be less prone to manipulation—does not help predict the policy eligibility status in 2017 and therefore doesn't provide useful variation for estimating the effects of the wage bonus in 2017 (see Figure B.4 in the Online Appendix).

[17] Table B.1 in the Online Appendix shows the RD estimates of the increase in wages for the two different sub-samples that define the rural categories according to the values of the time-to-travel variable as well as the weighted average effects reported in the text. Another strategy for dealing with the concern of partial manipulation would be to limit the sample to observations that are above the 120-minute time-to-travel cutoff, thereby comparing schools located in *Rural* and *Extremely Rural* localities. We don't pursue this approach for two reasons. First, restricting the sample to schools above the time-to-travel cutoff would imply conditioning on a partially manipulated variable. Second, this sample restriction would imply leaving out a large portion of schools, and in particular, schools that are located in the lower-right quadrant of Figure 3, thereby missing relevant variation in wages in the data, i.e. from *Moderately Rural* to *Extremely Rural*.

[18] Table B.2 in the Online Appendix shows that pre-determined school and locality-level covariates are smooth around the population threshold, with point estimates that are very small and not statistically different from zero in all but five cases for 2015, and in all cases for 2017 (out of the 29 covariates considered).

where y_{jt} is an outcome variable for school j at time t, $g(\cdot)$ is a flexible polynomial in the negative distance from the population cutoff, δ_t denotes time indicators for the specific year of the recruitment drive (for teachers) or the school year (for students), and u_{jt} is an error term clustered at the school-year level. The parameter of interest is γ_1, which represents the average outcome difference between schools, teachers, or students in localities that are just above or below the population cutoff, and therefore that are marginally eligible to receive (or not) a 15% increase in teacher wages. We estimate γ_1 non-parametrically using the robust estimator proposed by Calonico et al. (2014) through local-linear regressions that are defined within the mean squared error optimal bandwidths.

We exclude from the estimation sample all urban and rural schools in localities within 30 minutes of the province capital since for those crossing the population cutoff does not imply an increase in the rural bonus. We further restrict the sample to schools with non-missing observations for the different outcome categories considered in our analysis discussed in this section.[19]

4.2 Teacher Choices over Job Postings

We start by showing graphical evidence of threshold crossing effects separately by job applications for permanent and short-term teaching positions. This analysis provides direct evidence on the effects of wage increases on teachers' labor supply decisions. In all panels of Figure 4, the horizontal axis is the difference between the 500-inhabitants cutoff and the population of the community where the school is located: crossing the cutoff from left to right implies moving to the high bonus area.

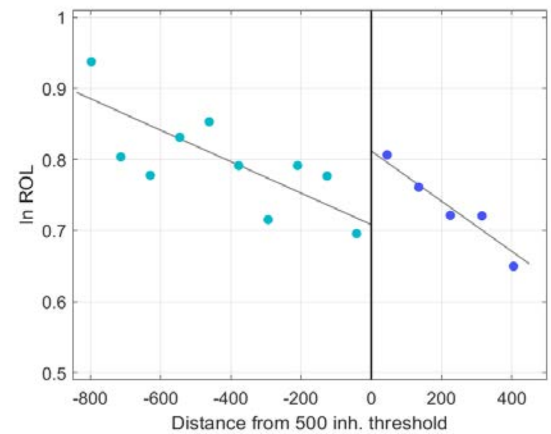
Panel A documents clear evidence that applicants for permanent teaching positions are more likely to include in their rank-order lists (ROL) schools in localities with a population just below the cutoff (eligible for wage bonus), as opposed to options just above (not eligible for wage bonus). Away from the cutoff, the observed positive correlation between teachers' choices over job postings and the population of the community is consistent with the notion that the population captures some valuable amenities in the locality.[20]

Panel B considers the choices over job posting for contract teachers. As in Section 3.2,

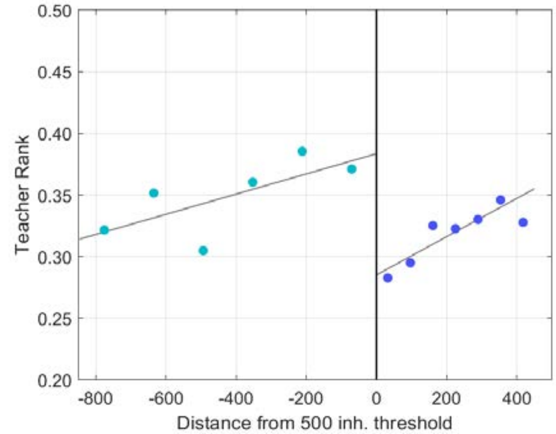
[19] As mentioned in Section 2, student test scores data are collected only for public schools with five or more students enrolled in the grade under evaluation. We present all the results pooling the data from the two recruitment drives from 2015 and 2017. The results split by year are shown in Tables B.4 and B.5 in the Online Appendix and they are broadly consistent with the patterns described here.

[20] The two-sided matching mechanism in place for permanent teachers does not ensure that the preference rankings submitted are strategy-proof. Indeed, teachers may submit ROLs that take into account their beliefs about getting an offer for each specific job opening (see also Section 5). For this reason, we only focus on the effect of the wage bonus on whether or not a given school was included in the ROL, thereby deliberately discarding additional information on the relative intensity of teachers' stated preferences.

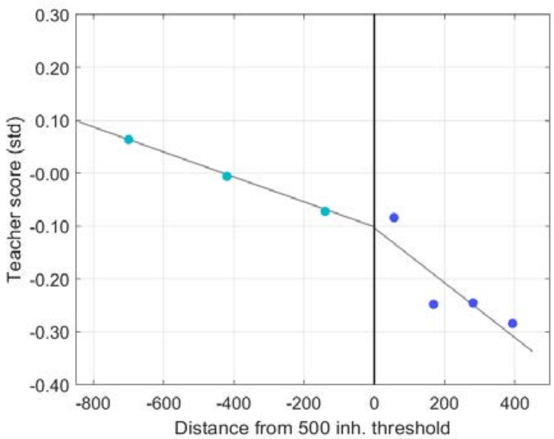
Figure 4: Teacher Choices over Job Postings



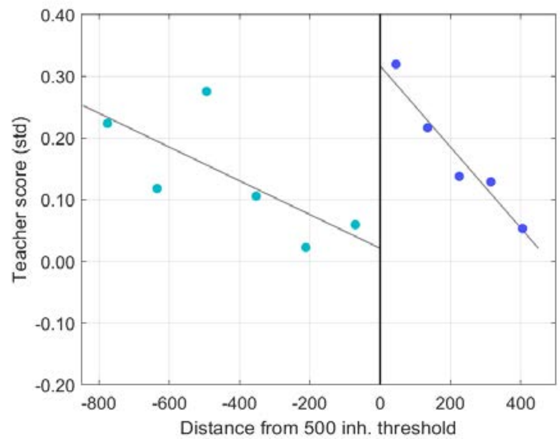
a) ln ROL, Permanent teachers



b) Teacher rank, Contract teachers



c) Teacher score, Permanent teachers



d) Teacher score, Contract teachers

Notes. This figure shows how applicants' preferences and quality vary based on the difference between the 500-inhabitants cutoff and the population of the community where the school is located. Panels A and C focus on the assignment process of permanent teachers. In Panel A the outcome variable is a dummy equal to one if a school was mentioned in at least one application, while in Panel C the outcome variable is the standardized (total) score obtained in the centralized test by the newly-assigned permanent teacher. Panels B and D are analogous to A and C for the assignment process of contract teachers. Panel B uses as outcome variable the rank in which a vacancy was chosen in the serial dictatorship mechanism (normalized so that it takes value from zero to one), while Panel D uses the standardized score obtained in the centralized test by the newly-assigned contract teacher. Each marker indicates the average of the outcome variable within each bin, defined following the IMSE-optimal evenly spaced method by Calonico et al. (2015). Solid lines represent the predictions from linear regressions estimated separately for observations to the left and to the right of the cutoff.

we back out the intensity of teachers' preferences by the rank order in which a position is filled. We normalize the rank between zero (if the position is chosen first) and one (if the position is filled last) in order to make the rank order comparable between school districts. Short-term positions that are just below the population cutoff (higher wage) get filled at higher priority order (lower rank) when compared to those above the cutoff, which again indicates that the wage bonus increases the demand for these positions, largely offsetting the observed negative gradient by rurality on teachers' preferences over job postings.

Table 1 reports the regression-discontinuity estimates from the empirical specification depicted in equation (1) using data at the school/vacancy level. In Column (1) the dependent variable is either an indicator that takes the value of 1 if a school was mentioned in at least one application for a permanent teaching position (Panel A) or the normalized rank at which a short-term position is filled (Panel B). In a neighborhood of the population discontinuity, the average school is mentioned in 76% of permanent teacher rankings. This proportion increases by 23% for schools that offer higher wages. Similarly, the average short-term position in localities with a population close to 500 inhabitants is filled by a teacher ranked in the 37^{th} percentile of the score distribution of applicants, while schools that offer a wage bonus manage to fill the position with an applicant in the 25^{th} percentile.[21]

Overall, the evidence presented suggests that vacancies at schools that receive a wage bonus become more desirable. They are requested more often by applicants for permanent positions and are filled faster by contract teachers. Increased competition for vacant positions can lead to an increase in the quality of applicants who select into higher-paying teaching jobs either by attracting a larger pool of prospective teachers into the public sector or by pure sorting *within* the system, whereby competent teachers who would have otherwise accepted offers in other rural or urban schools are instead choosing positions in *Extremely Rural* schools due to the wage incentives. We explore some of these potential margins of response to the wage reform in the next subsection.

4.3 Teacher Sorting Patterns

A first-order dimension of the centralized assignment system is whether or not a position is filled. If the vacancy goes unfilled, schools either recruit teachers without credentials or increase the workload for the existing teachers at the school, presumably reducing their effectiveness. Column (2) of Panel A in Table 1 presents regression-discontinuity estimates for the probability that a vacancy is filled in the selection process of permanent teachers, while Panel B shows analogous estimates for contract teachers. For contract teachers, we find a positive but not statistically significant effect of higher wages on the probability that a vacancy is filled. Increased compensations in extremely rural schools do not seem to significantly affect the probability of filling vacancies within the assignment mechanism for permanent or contract teachers.

[21]Teacher rank reported in Column (1) and teacher scores for both permanent and contract teachers reported in Column (3) of Table 1 are defined for the subset of the open vacancies that got filled in the centralized stages of the matching process (see Section 3.2). To deal with potential endogenous selection into the sample, we report RD bounds below the point estimates using the approach outlined in Gerard et al. (2020). The bounds are in general quite tight, thereby suggesting that the censorship in the density of the observations due to the fact that some vacancies remain unfilled is inconsequential for the RD estimates.

Table 1: Teacher Choices and Sorting

Panel A: Permanent teacher			
	(1)	(2)	(3)
	In ROL	Vacancy filled	Competency score
Above cutoff	0.177	-0.001	-0.014
	(0.068)	(0.071)	(0.175)
Bounds	[.154; .28]	[-.005; .041]	[-.271; .201]
Mean dep. var. (LHS)	0.759	0.372	-0.099
BW	173.292	165.291	205.787
Schools	860	830	601
Observations	1038	1697	864
Panel B: Contract teacher			
	(1)	(2)	(3)
	Teacher rank	Vacancy filled	Competency score
Above cutoff	-0.121	0.045	0.451
	(0.035)	(0.045)	(0.123)
Bounds	[-.132; -.109]	[.048; .048]	[.396; .472]
Mean dep. var. (LHS)	0.372	0.900	0.068
BW	157.271	157.103	161.830
Schools	881	925	909
Observations	2010	2183	2069

NOTES. This table reports the effect of crossing the population threshold on different outcomes. Panel A uses the sample of permanent teachers. In Column (1) the outcome variable is a dummy equal to one if a school was mentioned in at least one application, while in Column (2) is an indicator for whether the vacancy was filled by a certified teacher in the assignment process for permanent teachers. The regression displayed in the last column uses the standardized total score obtained by the teachers in the centralized test as outcome variable. In Columns (3) the sample is restricted to vacancies that were actually filled by a certified teacher. Panel B focuses on the selection process of contract teachers. Column (1) shows the effects on the rank in which a vacancy was chosen in the deferred acceptance mechanism (normalized so that it takes values from zero to one), while Columns (2) and (3) are analogous to those from Panel A. Cells report the bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014) and their bounds estimated using the procedure developed in Gerard et al. (2020). Regressions are defined within a mean-square error optimal bandwidth (BW), reported at the bottom part of the table. The table also reports the mean of the dependent variable computed within the interval $(-BW, 0]$ (left-hand-side of the cutoff). Standard errors are clustered at the school×year level.

In Panels C and D of Figure 4 we evaluate whether the observed boost in competition for high-paying positions in extremely rural locations leads to an increase in teacher quality, as measured by the competency score used to define priorities in the assignment algorithm. The two-sided nature of the assignment process for permanent teachers may explain the lack of an effect of a higher wage bonus on scores for the assigned permanent teachers, which is consistent with the small and noisy estimate reported in Column (3) of Panel A in Table 1.[22]

Both the graphical evidence and the RD estimates show that contract teachers who select into schools that offer a higher wage bonus have higher competency scores, on average, than those who choose a position in another rural school. The point estimate reported in Column (3) of Panel B in Table 1 is 0.45 standard deviations, which is a very large effect that points

[22] We provide supporting evidence for this interpretation in Figure B.5 of the Online Appendix, where we report the estimated threshold-crossing effects for different quintiles of the teacher score distributions separately for permanent and contract teachers. This evidence is consistent with recent findings reported in Bertoni et al. (2021), which point toward the discretionary role of the decentralized stage of the assignment mechanism in potentially undoing the meritocratic aspect of the recruitment process for permanent teachers.

toward quantitatively important sorting implications within the assignment system. To put this magnitude in perspective, the average gap in the teacher competency score between *Extremely Rural* schools and other rural schools is approximately 0.3 standard deviations, whereas the average gap between rural and urban schools is about 0.5 standard deviations.[23]

We document additional evidence on teacher sorting in Online Appendix B. In Table B.6 we compare individual characteristics between applicants who select into higher paying positions and those that do not. Overall, there does not appear to be systematic differences in the pool of applicants and hence no composition effects triggered by the rural bonus at the margin. One potential concern with our estimates is that the observed threshold-crossing effect is due to the fact that higher-quality teachers who sort into schools right below the population cutoff would have otherwise chosen schools just above the cutoff. The estimates reported in Table B.7 seem to suggest that the observed sorting effects are not the result of a zero-sum game among schools located around the population cutoff.

In sum, a higher wage bonus targeted at disadvantaged locations shifted applications toward schools offering both permanent and short-term positions. This change in teachers' labor supply leads to a large inflow of more competent teachers for short-term positions. To the extent that contract teachers account for nearly half of the teaching positions in the RD sample (with 3 teachers per school on average), the increased quality of new teachers may generate substantial improvements in student outcomes. The analysis that we discuss in the next subsection digs into this issue.

4.4 Student Achievement

We document the effect of a higher wage bonus on learning outcomes by comparing student test scores in schools that are located just above and just below the population cutoff. In Table 2 we report separate results for standardized test scores in Spanish (Panel A) and math (Panel B) administered to fourth graders three years after the policy change. We focus on test scores collected during the 2018 academic year since this increases the likelihood that any given cohort of students in the fourth grade was exposed to teachers recruited through the centralized system after the introduction of the rural wage bonus.[24]

Wage bonuses apply to all teachers in an eligible school. To the extent that higher wages affect the behavior of incumbent teachers, we should observe that student outcomes improve in schools that did not have an open teaching vacancy to fill in the 2015 or 2017 recruitment

[23]The main estimates reported in Table 1 are robust to alternative specifications and estimation choices. The results of these specification checks are reported in Figure B.6 in the Online Appendix.

[24]As mentioned in Section 2, the data available does not allow us to precisely link teachers to classes within a school, and hence we are unable to isolate the precise effect of having a better teacher (due to higher wages) in the classroom.

Table 2: Wage Bonus and Student Achievement

Panel A: Spanish Test (z-score)				
	(1)	(2)	(3)	(4)
	No vacancy	Any vacancy	Permanent vacancy	Short-term vacancy
Above cutoff	0.014	0.298	-0.057	0.317
	(0.157)	(0.127)	(0.190)	(0.137)
Mean dep. var. (LHS)	-0.471	-0.470	-0.382	-0.491
BW	124.095	108.453	175.257	114.883
Schools	372	691	292	622
Observations	3948	9700	3409	8966
Panel B: Math Test (z-score)				
	(1)	(2)	(3)	(4)
	No vacancy	Any vacancy	Permanent vacancy	Short-term vacancy
Above cutoff	0.039	0.350	-0.047	0.470
	(0.174)	(0.142)	(0.248)	(0.159)
Mean dep. var. (LHS)	-0.416	-0.416	-0.296	-0.417
BW	126.632	112.196	163.972	101.761
Schools	381	710	275	561
Observations	4046	10013	3205	8146

Notes. This table reports the effect of crossing the population threshold on student achievement in Math and Spanish. In all columns, the outcome variable is the standardized 2018 test scores in Spanish (Panel A) and Math (Panel B) for students in fourth grade. The sample in Columns (1) and (2) is split based on whether the school had an open vacancy (of any type) in the 2015 and/or 2017 centralized recruitment drives. In Column (3) and (4), the sample is further restricted to schools that had vacancies for permanent or contract teachers, respectively. Each cell reports the bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014). Regressions are defined within a mean-square error optimal bandwidth (BW), reported at the bottom of the table. The table also reports the mean of the dependent variable computed within the intervals $(0, +BW)$ (right-hand-side of the cutoff) and $(-BW, 0]$ (left-hand-side of the cutoff). Standard errors are clustered at the school×year level.

drives. Column (1) shows the RD estimate of the total policy effect for this sample of schools. The point estimates are very small and statistically insignificant, suggesting that there is no effort response to higher wages of incumbent teachers. In Column (2), we focus on the subsample of schools with an open vacancy in 2015 and/or 2017, for either permanent or contract teacher positions. Students in these bonus-eligible schools performed much better in Spanish and math, with effect sizes of 0.3-0.35 standard deviations.

The evidence in Columns (1) and (2) of Table 2 suggests that the recruitment effects of the wage bonus documented in Section 4.3 are the main drivers of the observed increase in student test scores. Accordingly, Column (3) documents that the effect of higher wages on student performance is very small and statistically insignificant for schools with open vacancies only for permanent teachers, for whom there is no evidence of a higher wage on assignment outcomes (see Panel A of Table 1).[25]

Finally, in Column (4) of Table 2 we consider the sample of schools with an open vacancy for short-term teaching positions in the 2015 and/or 2017 centralized recruitment

[25] As most of the permanent positions that remain unfilled in the assignment process are later posted as vacancies for a contract teacher (see section 3.2), the sample that we use in Column (3) of Table 2 excludes schools that, besides having had a vacancy for a permanent position, also had an opening for a short-term position.

drives. Consistent with the substantial increase in the competency level of newly recruited contract teachers, students in schools that receive higher wages perform much better in the Spanish and math achievement tests relative to students in schools that had contract teacher vacancies but were not eligible for the wage bonus. The effect sizes on student performance are very similar to the effect of higher wages on teacher competency scores, as shown in Panel B of Table 1.[26]

We report additional evidence on the channels through which the wage bonus may affect student outcomes in Online Appendix B. While there may still be an effort margin due to the wage incentives for the newly recruited teachers, the evidence reported in Table B.6 on the lack of selection effects along observable characteristics suggests that selection based on unobserved traits such as intrinsic or extrinsic motivation is unlikely to operate in this setting. In principle, wage bonuses could also affect student achievement by changing the size of the teaching staff. However, Table B.8 shows that the wage reform has small and statistically insignificant effects on the number of teachers, the relative share of permanent and contract teachers, and student-to-teacher ratios. Teachers' retention may be another channel through which schools with higher wages improve learning outcomes, although Table B.9 shows that wage bonuses do not have an effect on retention rates during the study period.

The analysis presented in this Section documents causal evidence that higher wages increase the number of teachers interested in working at those positions, which in turn leads to a substantial increase in the average quality of the newly recruited teachers. This inflow of more competent teachers mostly explains the large improvements in learning outcomes for the students enrolled in higher-paying schools. We do not find evidence for other channels through which higher wages may affect the behavior of teachers and hence student outcomes in our setting, such as efficiency wages or other margins of adjustment at the school-level.

5 An Empirical Model of Teacher Preferences

The RD estimates discussed in the previous Section provide only a partial assessment of the effect of higher wages on the allocation of public-sector teachers in Perú. The evidence on teacher sorting is necessarily "local" and hence difficult to extrapolate away from the population cutoffs that partly determine eligibility for the rural bonus. This feature may

[26] Additional evidence displayed in Figure B.7 in the Online Appendix documents that the results shown in Columns (2) and (4) of Table 2 are robust to alternative specifications. Figure B.8 in the Online Appendix displays the estimated RD coefficients and the confidence intervals for separate regressions where the dependent variables are indicators for whether or not students belong to discrete categories of achievement used by the Ministry of Education to classify students based on their scores in the standardized test. For Spanish scores, the effects of a higher wage bonus are more pronounced for students at the bottom of the ability distribution. For math scores, instead, the size of the effect is symmetric along the ability distribution.

be important in our setting given the heterogeneity across locations within the *Extremely Rural* category of schools. Relatedly, the wage bonus policy currently in place does not take into account teachers' heterogeneous preferences across job postings and hence it can be modified to further incentivize teacher sorting toward disadvantaged locations. We need to better understand how teachers trade off school and local amenities with the compensation offered at every specific job postings throughout the country in order to appreciate the potential limitations of the recent reform to the wage bonus, as well as to be able to propose and simulate the impact of alternative wage policies.

5.1 Teachers' Preferences

We specify an empirical model of teachers' preferences to predict how sorting patterns across job postings would evolve under counterfactual wage policies or different configurations of school and local characteristics. We start by defining the (indirect) utility that teacher i gets from being matched with school j as:

$$v_{ij} = \alpha_i w_j + \boldsymbol{\beta}_i' \boldsymbol{z}_j + \boldsymbol{\delta}' \boldsymbol{d}_{ij} + \boldsymbol{\lambda}' \boldsymbol{m}_{ij} + \epsilon_{ij}, \tag{2}$$

where w_j is the wage posted at school j in thousands of Peruvian Soles and $\boldsymbol{z}_j$ is a vector of locality and schools' characteristics that generate variation in preferences across teaching positions. The vector $\boldsymbol{z}_j$ contains a poverty index, an infrastructure score at the locality level capturing the overall level of amenities associated to a given area, a flexible polynomial in the population of the locality of the school and the time-to-travel (in hours) between the locality of the school and the province's capital that jointly determine eligibility to the rural wage bonus, as well as indicator variables for whether a given school belongs to specific regimes such as multi-grade, single-teacher, bilingual, and/or to the specific geographic areas that determine eligibility for the other wage bonuses.[27]

We allow teachers' labor supply to be more or less elastic with respect to wages and other school or locality characteristics depending on a variety of individual-level dimensions. For example, men may be more sensitive to wages than women due to gender norms and/or gender differences in outside options. Similarly, teachers at an early stage of their professional life might be more or less sensitive to wages and other local amenities due to life cycle considerations or career concerns. We flexibly capture such patterns through the parameters

[27]The poverty index is an asset-based measure of poverty at the individual level (poverty score) computed by the Ministry of Economy and Finance that we aggregate at the locality level. The infrastructure score collapses a set of indicators measuring infrastructure quality at the locality level through a multiple correspondence analysis (see Panel D of Table A.1).

α_i and $\boldsymbol{\beta}_i$, which are defined as:

$$\boldsymbol{\beta}_i = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1' \boldsymbol{x}_i,$$
$$\alpha_i = \alpha_0 + \boldsymbol{\alpha}_1' \boldsymbol{x}_i + \sigma \nu_i,$$

where $\boldsymbol{x}_i$ is a vector of indicator variables for teachers' characteristics such as gender, experience, residential location, and competency. We also include ν_i, a log-normally distributed random coefficient capturing unobserved preference heterogeneity for wages which would not be accounted for by $\boldsymbol{x}_i$. The presence of heterogenous preferences in our model generates flexible substitution patterns between wages and other school and locality characteristics that are key to interpreting the role of alternative wage schedules, as well as different values of school and locality amenities in generating the counterfactual sorting patterns that will be shown in Section 6.

In addition to this fairly rich structure of preferences for the different school-level factors specified above, the discrete choice model described by equation (2) features two different sources of match-specific preference heterogeneity. Moving costs are captured by $\boldsymbol{d}_{ij}$, a vector of linear splines in the geodesic distance between school j and the current location of teacher i, as measured by the location of the school where this teacher was working in 2015 from the NEXUS data. For novice teachers we use the location of the university/institute from which they recently graduated. For the remaining non-novice teachers who were not working in a public school in 2015 we use the locality of residence in 2013. The vector $\boldsymbol{m}_{ij}$ contains ethnolinguistic match effects, indicating whether teacher i's indigenous native language and school j's secondary language of instruction (if any) coincide. These capture language barriers that teachers might face when working in a school from a different ethnolinguistic group and, more broadly, any specific taste for living in a community from teacher i's own ethnic group.

All residual unobserved tastes of teacher i for school j are captured in the ϵ_{ij} term, which is assumed to be distributed *iid* across i and j through a Gumbel distribution with normalized scale and location. Finally, we include all private schools that are not part of the centralized assignment mechanism in the outside option, as well as any other labor market opportunity that we do not observe in the data. We specify the utility of the outside option as:

$$v_{i0} = \boldsymbol{\eta}_0 + \boldsymbol{\eta}_1' \boldsymbol{q}_i + \epsilon_{i0}, \tag{3}$$

where $\boldsymbol{q}_i$ is a rich set of characteristics for teacher i. These characteristics include gender, experience in both the public and the private sector, ethnicity, the competency score, the population of the place of residence, and the time-to-travel between the provincial capital and the place of residence.

5.2 Identification and Estimation

We observe data on teachers' revealed preferences over job postings from two sources. The first data source is the rank-order lists of applications for permanent positions. The second source of information is the realized match for short-term positions given teachers' competency scores and choice of school district. We choose to focus our analysis on the allocation of short-term contracts for several reasons. First, the large majority of teachers are not eligible for a long-term position and most of the vacancies in rural schools end up being filled by short-term contract teachers. Additionally, wage bonuses had no effect on the sorting outcomes of permanent positions, both at the extensive margin (i.e. whether or not the vacancy is filled) and at the intensive margin (i.e. the competency score of the assigned teacher). These arguments suggest that short-term contract teachers would be the most relevant group to target in order to design a wage schedule that would be effective at reducing inequalities in the allocation of public-sector teachers. Finally, the design of the assignment mechanism for permanent positions gives rise to incentives for teachers not to report their preferences truthfully. Our survey of teachers elicits preferences over job postings that are unconditional on the constraints of the application system. Almost one third of the surveyed teachers do not apply to their most preferred school, which clearly indicates the presence of strategic considerations in our setting (see Table A.2 in the Online Appendix).[28]

Recall from Section 3.2 that within each administrative unit (school district), teachers are ranked based on their competency score and are sequentially assigned to their preferred school among the options that still have open vacancies. This procedure is iterated until all vacancies are filled and/or all teachers are assigned. Teachers who end up being unmatched at the end of this first round can then re-apply through the centralized platform for the remaining unfilled vacancies located in other administrative units. Given the structure of the assignment mechanism, we assume that the realized matching equilibrium is stable, meaning that teachers would not be accepted by a school that they strictly prefer with respect to their current match. This implies that the observed match between schools and teachers can be interpreted as the outcome of a discrete choice model with individual-specific

[28]Learning about preferences from the available data on the ranked ordered lists would require a model of teachers' application decision coupled with a model of schools' preferences. In addition, one would need to take into account that teachers might have biased beliefs regarding their admission chances due to the complex nature of the assignment process (Kapor et al., 2020). One would also need to model the dynamic strategic considerations that would arise due to the sequential nature of the assignment mechanism. This more involved exercise is left for future research.

choice sets that only depend on teachers' competency scores (Fack et al., 2019).[29]

Under the distributional assumptions stated above (see Section 5.1), we can write the following log-likelihood function:

$$L(\boldsymbol{\theta}) = \frac{1}{n}\sum_{i=1}^{n} \log\left\{\int_0^{\infty}\left(\frac{\exp \tilde{v}_{i\mu(i)}}{\sum_{k\in\Omega(s_i)\cup\{0\}} \exp \tilde{v}_{ik}}\right) dF(\nu_i)\right\}, \tag{4}$$

where $\mu(i)$ is the school assignment of each teacher i, $\Omega(s_i)$ is the feasible choice set, which depends on teacher i's competency score s_i, and $\tilde{v}_{ij}$ is the deterministic component of the indirect utility function in (2). The term inside the brackets of equation (4) is the conditional probability that teacher i chooses schools j from her feasible choice set, which is also a function of the cumulative distribution function of the log normal distribution, $F(\cdot)$. We compute the integral in (4) numerically using a Gaussian-Hermite quadrature (Conlon and Gortmaker, 2020).

In this model, preference parameters $\boldsymbol{\theta}$ are identified if (i) the observable characteristics $(w_j, \boldsymbol{z_j}, \boldsymbol{d_{ij}}, \boldsymbol{m_{ij}}, \boldsymbol{x_i}, \boldsymbol{q_i})$ are independent of both taste shifters ϵ_{ij} and the random coefficient ν_i and (ii) the feasible choice sets $\Omega(s_i)$ are independent from the taste shifters ϵ_{ij} conditional on observables. The first condition implies that the set of observables has to be rich enough such that residual preference heterogeneity can be modeled as an exogenous shock. This might be problematic if, for instance, we believe that we are omitting a set of relevant variables that would be correlated with wages. However, given that wages are set exogenously via deterministic rules and that we are controlling flexibly for all relevant wage determinants, we are confident that this assumption is reasonable in our setting. The second condition may not hold if there is a possibility that the decision by teacher i to accept or reject a given job posting may trigger a chain of acceptance or rejections by other teachers that may feed back into teacher i's set of feasible schools (Menzel, 2015). Preference cycles of this sort are ruled out in our setting, since schools rank applicants according to the same criterion (i.e. the competency score).[30]

[29]The assignment mechanism directly implies that the match will be stable within each administrative unit. Overall stability might be compromised if teachers do not correctly predict in which school district their preferred feasible school will be. However, the presence of an aftermarket that assigns the remaining unfilled vacancies mitigates these concerns.

[30]Vertical preferences of the schools over applicants imply that if teacher i decides to rematch and displaces teacher l who would in turn be matched with another school, then teacher l is by definition ranked below teacher i. All the subsequent displacements will only affect the teachers who are ranked below teacher i.

5.3 Teacher Preference Estimation Results

Panel A of Table 3 reports selected preference estimates for relevant school and locality characteristics such as wages, poverty, infrastructure, and indicators for whether a school is multigrade or single teacher. We present the full set of estimated parameters of the model described in Equation (2) in Table C.1 in the Online Appendix. The estimated preferences for wages are heterogeneous along both observed and unobserved dimensions. Men applicants are much more responsive to compensations than women. Applicants living in urban areas and competent teachers (as defined in Section 3.1) are also more wage sensitive, which is consistent with the higher cost of living in cities as well as with unobserved heterogeneity in ability and/or effort that likely determines the competency score. The large and significant standard deviation of the random coefficient indicates the presence of substantial unobserved taste heterogeneity with respect to wages that is not explained by the observed teacher characteristics included in the model.[31]

To put the magnitude of these estimates into perspective, Figure 5 displays the wage elasticities implied by the estimates of the model. These estimates combine both observed and unobserved sources of preference heterogeneity with respect to the wages posted at each vacancy, and they range from close to 0 to 6 with a global average of 2.19. Several interesting patterns emerge from these distributions. For instance, increasing wages seems to be a more prominent "pull" factor for attracting teachers in rural schools than in urban schools. This can be explained by the fact that amenities are in general lower at rural schools and hence wages enter more prominently into teachers' compensating differentials.

Preference estimates for other job characteristics show that, while on average teachers have a strong distaste for localities with high levels of poverty as well as for schools that are multigrade or have a single teacher, competent and more experienced teachers seem to be particularly sensitive to school-level characteristics. Although a combination of factors likely explain these patterns of heterogeneity, this evidence suggests that complementary policies aiming at improving school infrastructure may be effective in reducing spatial inequalities in the allocation of public-sector teachers.

Panel B displays the ethnolinguistic match effects and the effect of the geodesic distance between teachers and schools. The magnitudes of the estimated parameters suggest that both play a very important role in teachers' choices over schools. Figure C.1 in the Online Appendix plots the implied wages needed to compensate teachers from moving farther away

[31] We do not find any significant heterogeneity with respect to experience, suggesting that many different channels may be at play that are potentially cancelling each other out. For instance, career concerns for novice teachers may push down the wage coefficient while at the same time life-cycle considerations are consistent with a positive correlation between experience and the wage coefficient.

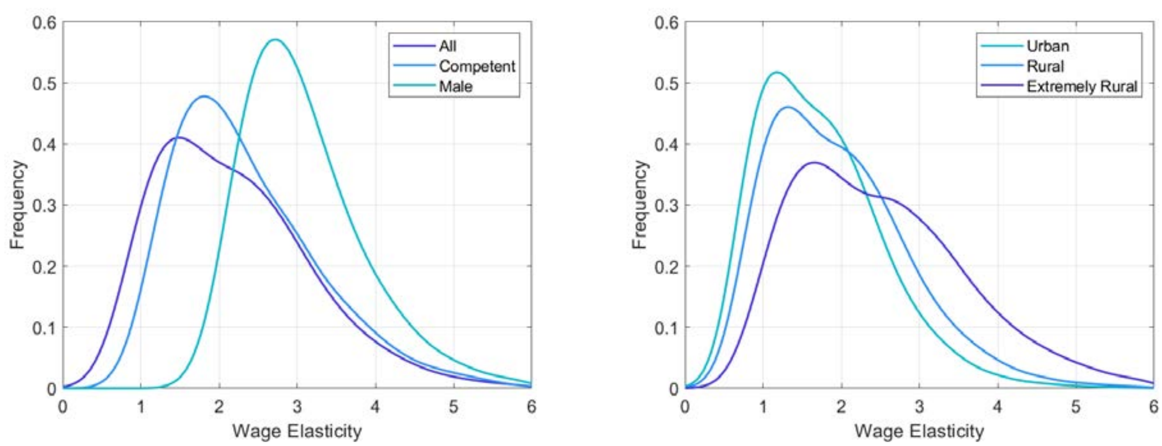
Table 3: Preference Estimates – Selected Parameters

Panel A: School/Locality Characteristics										
	Wage		Poverty Score		Infrastructure		Multigrade		Single Teacher	
	0.815	(0.120)	-0.201	(0.035)	-0.054	(0.054)	-0.237	(0.119)	-0.786	(0.192)
$\times$ Male	0.611	(0.157)	0.115	(0.032)	-0.060	(0.048)	0.019	(0.099)	0.519	(0.137)
$\times$ Exp ≥ 4	0.070	(0.053)	0.097	(0.036)	0.132	(0.052)	-0.284	(0.118)	0.020	(0.181)
$\times$ Urban	0.115	(0.061)	-0.060	(0.044)	0.036	(0.068)	0.009	(0.170)	-0.125	(0.242)
$\times$ Competent	0.170	(0.067)	-0.065	(0.047)	0.198	(0.076)	-0.782	(0.185)	-0.752	(0.351)
Std. Deviation (σ)	0.560	(0.053)								

Panel B: Teacher-School Match Effects					
	Ethnolinguistic Match		Geographical Proximity (Spline)		
Quechua $\times$ Quechua	1.488	(0.158)	Distance < 20km	-0.187	(0.003)
Aimara $\times$ Aimara	1.375	(0.537)	20km < Distance < 100km	-0.033	(0.001)
Ashaninka $\times$ Ashaninka	2.243	(0.558)	100km < Distance < 200km	-0.018	(0.001)
Awajun $\times$ Awajun	2.086	(1.020)	200km < Distance < 300km	-0.017	(0.002)
Amazonas $\times$ Amazonas	0.995	(0.113)	Distance > 300km	-0.002	(0.000)

Notes. This table displays selected estimates and standard errors (in parentheses) of the parameters of the model described in Equation 2. Panel A shows the estimated coefficients associated to a selected set of schools/locality characteristics while Panel B shows estimated preferences for geographical proximity as well as the interaction between schools' language of instruction and teachers' own native language. The data used contains choices of the pool of 59,949 applicants (note that 500 applicants are left out due to missing data) that participated in the allocation of short-term contracts for public primary schools in 2015. Estimation is done via maximizing the likelihood described in Equation (4) where the integral is computed numerically in an inner loop via a Gaussian-Hermite quadrature. Table C.1 in the Online Appendix displays the full set of the estimated coefficients.

Figure 5: Estimated Wage Elasticities



a) Teacher Characteristics **b) School Characteristics**

Notes. This figure depicts the distribution of the wage elasticities which are computed using the estimates from Table 3. These elasticities give the % change in the conditional probability that teacher i chooses school j, which we denote P_{ij}, resulting from a 1% increase in the wage proposed in school j: $\frac{\partial P_{ij}}{\partial w_j}\frac{w_j}{P_{ij}} = \alpha_i w_j(1-P_{ij})$. Panel A plots the distribution of this elasticity for different groups of teachers (all, competent, and male) while Panel B displays heterogeneity of this distribution with respect to the rurality of schools' locality.

from where they live (Panel A) and from being assigned to a school offering a bilingual education that corresponds to their own ethnolinguistic group (Panel B). Moving costs are estimated to be substantial in our context. This is consistent with previous evidence drawn from the rank-order lists of permanent teachers in Perú (Bertoni et al., 2019). Our estimates indicate it would take on average 2.75 times the current base wage to make teachers willing to move 50 km away from where they live.

Similarly, Panel B shows that teachers from an ethnolinguistic minority would be willing to pay up to the amount of the base wage in order to teach in a school from their own ethnic group. Interestingly, we can see that the estimated willingness-to-pay is higher for minority ethnic groups, such as Ashaninka and Awajun. To the extent that these ethnic minorities are mostly located in rural areas with school vacancies that are in excess demand for bilingual teachers, place-based policies aimed at leveraging these strong match-specific effects (both ethnic and geographic) might be a promising alternative to wage incentives as a way to enhance the local supply of teachers.

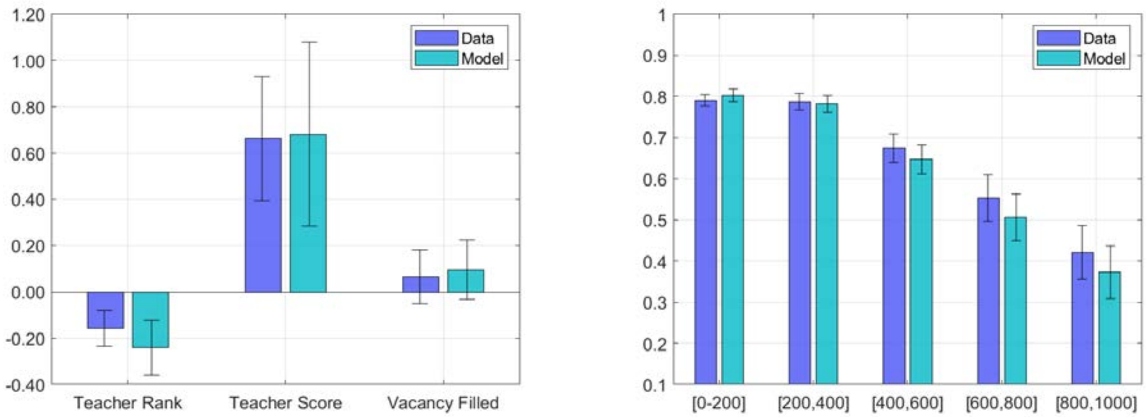
5.4 Model Validation

We close this Section by assessing how well our model predicts some key moments in the data. In particular, it is important to test the empirical plausibility of the estimated wage elasticity given that the counterfactual exercises will rely on that parameter. We check the consistency between the sorting patterns predicted by the model and the estimated effects at the 500-inhabitant population threshold for eligibility of the rural bonus discussed in Section 4. The predicted size of the effects in teacher sorting outcomes can be used for model validation since its magnitude would be entirely explained by the estimated wage elasticity. We thus simulate teachers' choices using the estimated preference parameters, replicate the RD analysis on simulated data, and compare the resulting estimates with those obtained with the actual data. In addition, we assess the overall fit of the model in terms of the global sorting patterns across school attributes.[32]

Figure 6 shows the corresponding estimates of this exercise along with the associated 95% confidence intervals. The evidence reported in Panel A documents that the estimated model seems to predict very well the different sorting patterns triggered by the policy effects due to the rural bonus that we observe in the data. This is even more reassuring given that the rural bonus policy explains only a small portion (less than 10%) of the total variation in wages across job postings that is used to identify the wage elasticity in the choice model. The evidence shown in Panel B further confirms that our model seems to precisely replicate the negative gradient by the degree of remoteness of the locality on the share of filled vacancies.

[32] Additional measures of model fit are available in Figure C.3 and Figure C.4 in Online Appendix C.

Figure 6: Comparing RD Estimates, Observed Sorting and Simulated Data



a) Threshold Crossing Effects (pop.=500) **b) Share of Filled Vacancies by Remoteness**

NOTES. Panel A in this figure shows the estimated RD jump in vacancy filled, teacher score and teacher rank at the 500 locality population threshold both in the actual data and in the simulated data. The simulated assignment is generated by running the serial dictatorship algorithm using predicted utilities computed from the estimates of Table 3 as well as a randomly drawn set of taste shocks ϵ_{ij}. Panel B compares the share of vacancies filled observed in the actual data and the simulated data depending on how far the schools posting the vacancies are located from the provincial capital.

6 Counterfactual Analysis

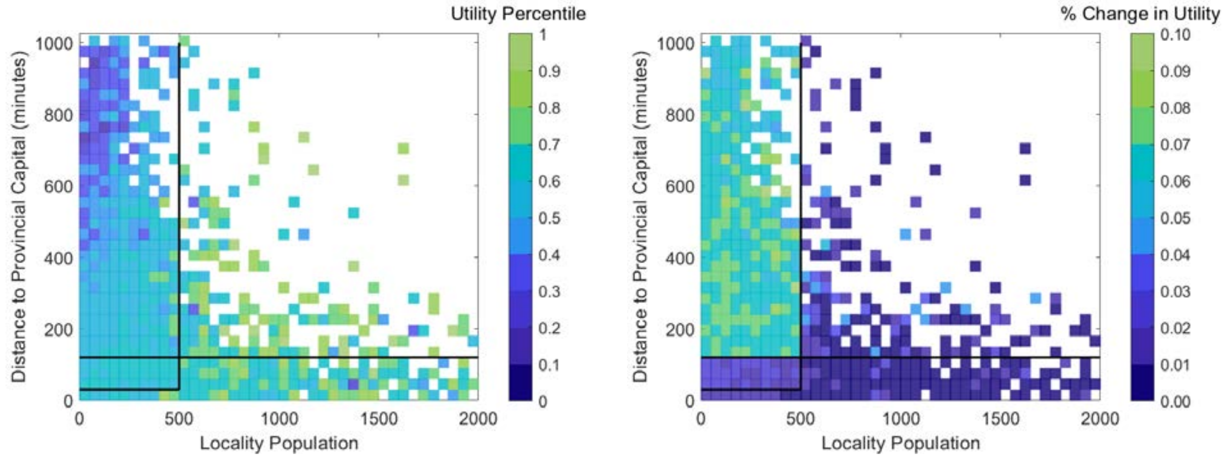
6.1 Evaluation of the Wage Bonus

Public-sector teachers who work in schools with a specific set of locality and school characteristics receive additional compensations that vary between 3% and 30% of the base wage (see Figure A.3 in the Online Appendix). The rural wage bonuses studied in Section 4 are part of this larger incentive scheme. We use the estimated preference parameters of the model discussed in the previous Section to evaluate the effects of the overall system of wage bonuses currently in place in Perú. The structure of the model allows us evaluate the policy effects away from the population threshold and hence gain a broader perspective on how wage bonuses affect teacher sorting globally.

We run the serial dictatorship algorithm that is used to assign teachers into short-term jobs under a counterfactual scenario where all wage bonuses are set to zero, including those that are not specifically tied to rurality.[33] Panel A of Figure 7 plots the percentile of desir-

[33] The school-specific and locality-specific determinants of the other wage bonuses are highly correlated with both dimensions of rurality (distance to provincial capital and population). Figures C.5-C.6 in the Online Appendix separately show the impacts of the other wage bonuses (vis-a-vis the no-bonus scenario) and those of the rural bonus (vis-a-vis the other-bonus scenario) along the support of the univariate distributions of population and the time to the provincial capital. Results suggest that the bulk of the policy effects on sorting outcomes are driven by the rural bonus.

Figure 7: Fitted Teacher Utility



a) No Bonus **b) Wage Bonus**

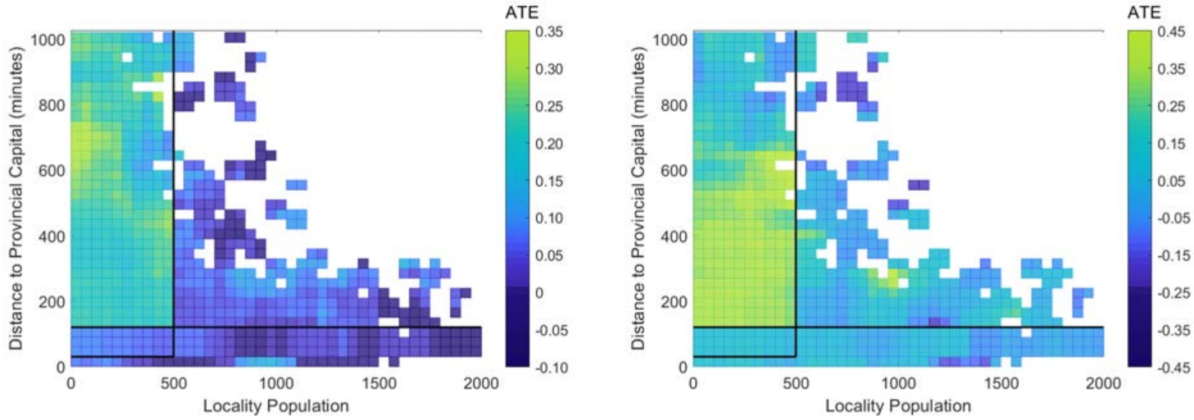
NOTES. Panel A plots the average percentiles of the median predicted utility associated with each vacancy from the estimates reported in Table C.1 for a fine grid in the population and distance to provincial capital space (each cell is 50×30). Panel B reports the average percentage changes in the median utility between the status quo and the counterfactual scenario with no wage bonuses.

ability, as measured by local averages in the median utility predicted by the model without any wage bonus in each school.[34] The desirability index monotonically decreases with the distance to the provincial capital whereas it is only weakly correlated with the population of the locality. The figure shows that schools located close to the cutoffs for eligibility to the rural bonus are not the least desirable, suggesting that some (if not most) of the effect of the wage bonus may actually manifest away from these cutoffs. This is confirmed by Panel B, which displays the cell-averages of the percentage changes in predicted utility between the status quo and the ”no bonus” counterfactual scenario. Changes in utility are heterogenous within the *Extremely rural* category, indicating large differences in the initial conditions of the schools that receive the same S/ 500 rural bonus.

Figure 8 displays heat plots of the simulated policy effects of the wage bonuses. In each cell, defined by discrete values of population and time-to-travel, we compute the average difference in the share of filled vacancies (Panel A) and the difference in the average standardized competency scores of the assigned teachers between the counterfactual scenario (where we remove all wage bonuses) and the status quo (with the usual wage bonuses in place). Consistent with the targeting and the magnitudes of the rural bonus, most of the positive effects of the wage-incentive policy seem to manifest in schools that are in localities

[34]The difference in predicted utility between a school located in the first and the last percentiles of desirability is around 3.9. It would take an amount that is 3.5 times larger than the base wage in order to compensate teachers for such a gap.

Figure 8: Policy Effects on Teacher Sorting



a) Share of Filled Vacancies **b) Teacher Competency Score**

NOTES. This Figure uses simulated assignment data that is generated by running the serial dictatorship algorithm with predicted utilities computed from the estimates from Table 3 as well as a randomly drawn set of taste shocks ϵ_{ij}. Panel A plots cell-average differences in the share of filled vacancies in the population and distance-to-provincial-capital space (each cell is 100×60) between the assignment simulated under the current policy and a counterfactual scenario with no wage bonuses. Panel B plots the mean differences in the standardized competency score at the vacancy level in the population and distance to provincial capital space between the assignment simulated under the current policy and a counterfactual scenario with no wage bonuses.

with less than 500 inhabitants and that are farther than 120 minutes away from provincial capitals. However, while for teacher scores most of the effect is concentrated in localities that are just below the population cutoff and near the time-to-travel cutoff, much of the effect on the share of filled vacancies is actually located away from the discontinuities induced by the rural bonus policy, which is consistent with the evidence shown in Figure 7.[35]

The analysis presented here confirms previous estimates shown in Section 4 that the wage bonuses have been partly effective in reducing the large inequality in the allocation of public-sector teachers across different areas of the country. However, it also shows some limitations of the current wage bonus policy, which features limited variation for all schools that are categorized as *Extremely Rural*. As such, it may be too rigid to appropriately incentivize teacher sorting at the extensive margin.

[35] Figure C.2 in the Online Appendix documents the selection effects of the wage bonus policy. Panel A shows the CDF of the wage elasticities for the assigned teachers under the no-bonus scenario and the corresponding CDF for the "marginal" teachers (i.e. those who choose a position within the assignment mechanism under the current system of wage bonuses while they would have chosen the outside option under the no-bonus scenario). As expected, the latter distribution first order stochastically dominates the former, indicating that the applicants who are drawn into short-term teaching jobs due to the wage incentives are more sensitive to compensations. Panel B illustrates the composition effects of the wage bonus policy in terms of observable teacher characteristics.

6.2 Optimal Wage Policies

We combine the estimated preference parameters of the teachers' school choice model with a wage-setting protocol that allows us to flexibly characterize a menu of counterfactual wage schedules aimed at reducing inequality in the allocation of public-sector teachers in our context. In particular, we consider two independent objectives: (i) to fill every vacancy with any teacher irrespective of her/his quality, and (ii) to assign in each school with one or more open vacancies one teacher that is at least as competent as the average urban teacher (as measured by the competency score).[36]

We define contracts as teacher-wage pairs and embed our two redistributive objectives into the preferences of schools over contracts. We next use the estimated teacher preferences to implement a school-proposing generalized deferred-acceptance algorithm (Hatfield and Milgrom, 2005) that works as follows. First, schools propose to the highest ranked teacher at the lowest wage. This teacher is tentatively assigned to her preferred school. Depending on the objective, all schools with unfilled vacancies—or, alternatively, that are not filled with a more competent teacher—start proposing to either the next ranked teacher at the same wage or at the highest ranked teacher at a slightly higher wage, if the first option is not possible. We then iterate this procedure until each objective is reached. Given the structure of the algorithm, each iteration gives the allocation of teachers that maximizes our redistributive objectives under the constraint that wages cannot exceed the proposed wages at that round.[37]

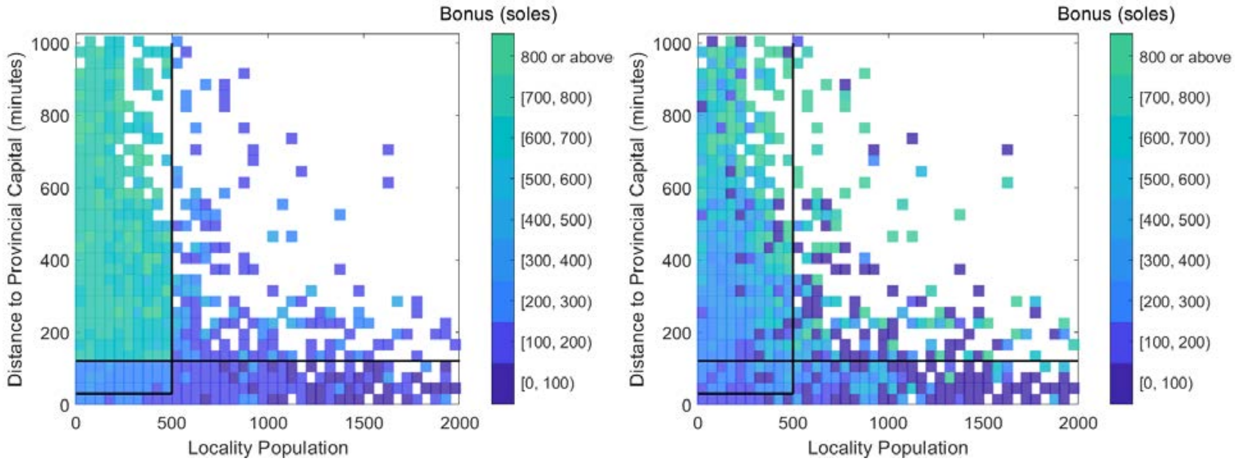
Figure 9 shows the distribution of wage bonuses under the current policy (Panel A) and the distribution of the wage bonuses that maximizes the share of filled vacancies under the same budget as the current policy (Panel B). The optimal wage schedule puts relatively more weight on the remoteness of the locality and relatively less weight on its population. This takes into account that school vacancies in localities that are far away from the provincial capital are much harder to fill irrespective of the population of the locality (see Figure 7).

Figure 10 quantifies the total cost, in terms of the wage bill, of reaching our redistributive objectives. The shaded area illustrates the set of feasible allocations, while the dots show the allocation achieved under the current policy. The wage bonus policy lies inside the area of feasible contracts and is therefore sub-optimal compared to the optimal compensation achieved by the algorithm described above (purple lines). The gap with a balanced budget is approximately 7 percentage points for the share of filled vacancies (Panel A), whereas it is 4 percentage points for the share of schools with more competent teachers (Panel B). This result is consistent with previous evidence shown in Figure 8 that documents that most of

[36] About 25% of the applicants for short-term teaching positions satisfy this criterion.

[37] See Online Appendix D for a more formal discussion.

Figure 9: Current Vs. Optimal Wage Bonus Policy



a) Current Policy **b) Optimal Policy**

NOTES. This figure shows the distribution of wage bonuses under the current policy (Panel A) and the distribution of the wage bonuses resulting from our algorithm that maximizes the share of filled vacancies under the same budget as the current policy (Panel B).

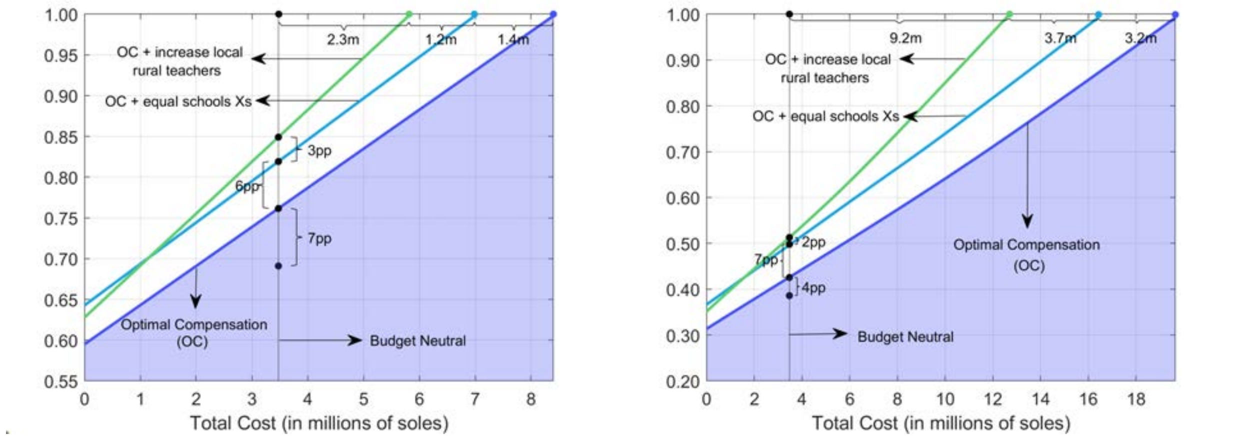
the policy effect at the intensive margin of teacher sorting lies close to the population threshold, suggesting that the current rural bonus is sufficiently well targeted in that dimension. Regarding the objective of filling vacancies, the current policy is less effective and hence there is a clear margin of improvement for the optimal policy.

Attracting competent teachers is significantly more costly than merely filling vacancies. With approximately double the current budget in terms of the total wage bill (eight million Soles), the algorithm is able to fill almost every vacancy but at best it can fill a bit more than half of the schools with a more competent teacher. It would take a total wage bill that is 6 times the current budget to equalize teacher quality across the country.

We finally use our matching with contract framework to assess the relative cost-effectiveness of additional policy instruments that may complement wage incentives in reducing spatial inequalities in the allocation of public-sector teachers. We remove all structural inequalities by considering a scenario where all the locality and school characteristics that potentially explain teachers' preferences are equalized across the country. The blue lines in Figure 10 show that the cost-efficiency frontiers are significantly shifted outwards due to these demand-side incentives, reaching more than 80% of vacancies filled and about half of the schools with a competent teacher at the same wage bill as the current policy. Investing in local infrastructures in our setting would entail saving almost 20% of the wage bill in order to achieve either of the two redistributive objectives.

An alternative policy consists in training prospective teachers so as to increase the pool

Figure 10: Cost Efficiency Frontiers



a) Share of Filled Vacancies **b) Share of Schools with Competent Teachers**

NOTES. The Figure plots the cost-efficiency frontiers derived by the algorithm described in the text (see also Online Appendix D) for both the objective of filling every vacancy with any teacher irrespective of quality (Panel A) and filling every school with a teacher who is at least as competent as the average teacher in urban areas (Panel B). The shaded area represents the set of feasible allocations. The purple lines show the optimal allocations under the current distribution of teachers and local amenities. The blue lines refer to a counterfactual scenario where all the locality/school characteristics are equalized across all the job postings throughout the country. Finally, the green lines refer to a different counterfactual scenario where we increase the local pool of applicants by 3% in a neighborhood of the most disadvantaged communities.

of local applicants in the most disadvantaged locations. The counterfactual depicted by the green lines in Figure 10 mimics this policy by duplicating the four teachers who are most closely located to each of the 500 schools that propose the highest wages according to our algorithm, which results in a total of 2000 new teachers. A small and targeted increase in the supply of teachers (3% increase with respect to the overall number of applicants) would outperform at balanced budget the counterfactual with no structural inequalities. Place-based incentives aimed at enhancing the local supply of teachers would entail saving between 30% and 35% of the wage bill that is necessary to achieve our two redistributive objectives. This last result highlights the predominant roles of moving costs and of the ethnolinguistic match effects in explaining teachers' preferences over job postings in our setting.[38]

7 Conclusion

Teachers are a central input to the education production function and better teachers can have long-term influences on students' labor market outcomes. Therefore, interventions that reduce inequality in access to qualified teachers should be a crucial component of any policy agenda aimed at reducing structural inequality overall. In this paper, we use a combination

[38] Table C.2 in the Online Appendix shows the realized sorting across ethnolinguistic groups of the newly matched teachers for different percentage increases in the local supply of applicants.

of methods, rich administrative data, and policy changes to empirically assess the role of teachers' compensation on teacher sorting in equilibrium and its potential effects on student outcomes. Moreover, we show how to use application and assignment data to incorporate information from demand and supply and set wage bonuses more efficiently.

There are four distinctive features of our setting in Perú that makes it a unique context to study teacher compensation policies and their potential to mitigate structural inequalities. First, the government uses a centralized matching platform that acts as a market clearinghouse between prospective teachers and school vacancies. Second, high-quality administrative data that link information on (i) job openings for all public schools in the country, (ii) detailed records on job applications for the universe of public-sector teachers, and (iii) student achievement in standardized tests allow us to study the matching mechanism. Third, the introduction of a wage bonus policy for positions in hard-to-staff areas with replicable and arbitrary cutoff rules provides a credible source of variation to study the effects of financial compensation on geographic sorting. Fourth, the context of Perú provides a wide array of heterogeneity in geography, language, and ethnicity and has significant historical inequality dating back to colonial times.

Our first contribution is to show causal evidence that increasing teacher pay at disadvantaged locations has both recruitment and productivity effects. Specifically, we find that unconditional wage increases are successful in effectively attracting more competent contract teachers to public schools. We also document that students in schools that pay higher wages perform better in standardized achievement tests. The observed increase in productivity is highly correlated with the inflow of new teachers across schools. In fact, the policy effect on student outcomes is entirely driven by students in schools that had openings during the period when the policy was in place, while it is estimated to be a precise zero in schools where no new openings were available.

Our second contribution is to quantify the way teachers trade off wages with local school and community amenities by leveraging geocoded data on applications and job postings from a centralized assignment system. The model estimates shed light on the channels through which teachers sort across locations and provide key insights on alternative policy levers beyond wage incentives that may be highly effective in reducing inequality in access to qualified teachers. Teachers are allowed to have heterogeneous preferences for locality and school amenities that are unequally distributed throughout the country. While wage profiles are rigid and do not fully take take into account these trade offs, more competent teachers seem to be more sensitive to compensation. These features suggest that policymakers can increase equity in the market for public-sector teachers through wage policies that take into account teachers' heterogenous preferences.

We empirically implement this insight by recasting the current matching algorithm in a more general framework in which schools can sequentially post higher wages in order to attract more qualified teachers or to fill their vacancies irrespective of teacher quality. This allows us to characterize the wage schedule that would maximize the allocation of teachers across schools under a given redistributive objective while keeping the same budget as the current policy. Targeting less desirable places more accurately, this alternative wage schedule would increase the share of filled vacancies by 7 percentage points and the share of schools with higher quality teachers by 4 percentage points.

The presence of high moving costs for teachers and the sizable ethnolinguistic match effects between schools and teachers imply that other place-based policies can act as complements to wage incentives in order to reduce the spatial inequality in the allocation of public-sector teachers. We show that policies that increase the local supply of teachers at specific job postings (e.g., by providing scholarships and training to prospective teachers) may be highly effective when compared to other targeted demand-side interventions such as investments in school infrastructure.

The evidence we have presented has important implications for teacher compensation policy. Unconditional wage increases targeted at specific job postings can significantly spur teacher sorting and productivity over a relatively short time span. This effect seems to be explained by the fact that a large proportion of the school vacancies targeted by the wage reform are filled by contract teachers. This feature generates significant flexibility in the labor market through which the sorting channel of wage incentives can play an important role in improving the quality of teachers and, consequently, student outcomes. This result is promising as it complements the existing evidence on pay-for-performance incentive schemes, which are in general less politically viable in the public sector than unconditional wage increases.

Finally, we have shown how the estimated model of teacher preferences can be used to inform effective wage policies. We believe that this procedure can be fruitfully implemented in a variety of market-design applications in which policymakers can leverage knowledge of preferences of one side (or both sides) of the market in order to design effective policies that incentivize sorting along specific dimensions.

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Appendices

A Descriptive Evidence

Table A.1: School and Locality Characteristics

	Rural schools		Urban Schools	
	Mean	Std. Dev.	Mean	Std. Dev.
Panel A: School characteristics				
Number of students	40.16	(45.89)	339.9	(262.0)
Bilingual school	0.249	(0.432)	0.00864	(0.0926)
Single-teacher school	0.393	(0.488)	0.0151	(0.122)
Multigrade school	0.466	(0.499)	0.0868	(0.282)
Number of teachers	5.092	(4.050)	24.59	(13.58)
% of permanent teachers	0.677	(0.468)	0.807	(0.394)
% of certified contract teachers	0.164	(0.371)	0.114	(0.317)
% of non-certified contract or other teachers	0.158	(0.365)	0.0790	(0.270)
% of competent teachers	0.210	(0.407)	0.386	(0.487)
Panel B: Student characteristics				
Math test scores (std)	-0.438	(1.005)	0.125	(0.962)
Math test scores: % Below basic	0.233	(0.423)	0.0681	(0.252)
Math test scores: % Proficient	0.147	(0.354)	0.285	(0.452)
Spanish test scores (std)	-0.568	(0.924)	0.162	(0.961)
Spanish test scores: % Below basic	0.223	(0.416)	0.0513	(0.221)
Spanish test scores: % Proficient	0.141	(0.348)	0.368	(0.482)
Panel C: School infrastructure				
No water	0.311	(0.463)	0.0355	(0.185)
No electricity	0.233	(0.423)	0.0127	(0.112)
Cafeteria	0.284	(0.451)	0.211	(0.408)
Computer	0.619	(0.486)	0.932	(0.252)
Kitchen	0.392	(0.488)	0.372	(0.483)
Internet	0.186	(0.389)	0.912	(0.283)
Library	0.207	(0.405)	0.564	(0.496)
Sport facility	0.190	(0.392)	0.614	(0.487)
Gym	0.0126	(0.111)	0.118	(0.323)
Stadium	0.00268	(0.0517)	0.0419	(0.200)
Panel D: Locality infrastructure				
Electricity	0.803	(0.398)	0.997	(0.0553)
Sewage	0.259	(0.438)	0.915	(0.279)
Library	0.0166	(0.128)	0.430	(0.495)
Doctor	0.324	(0.468)	0.869	(0.338)
Internet access point	0.0554	(0.229)	0.845	(0.362)
Village phone	0.0498	(0.218)	0.0928	(0.290)
Drinking water	0.582	(0.493)	0.945	(0.228)

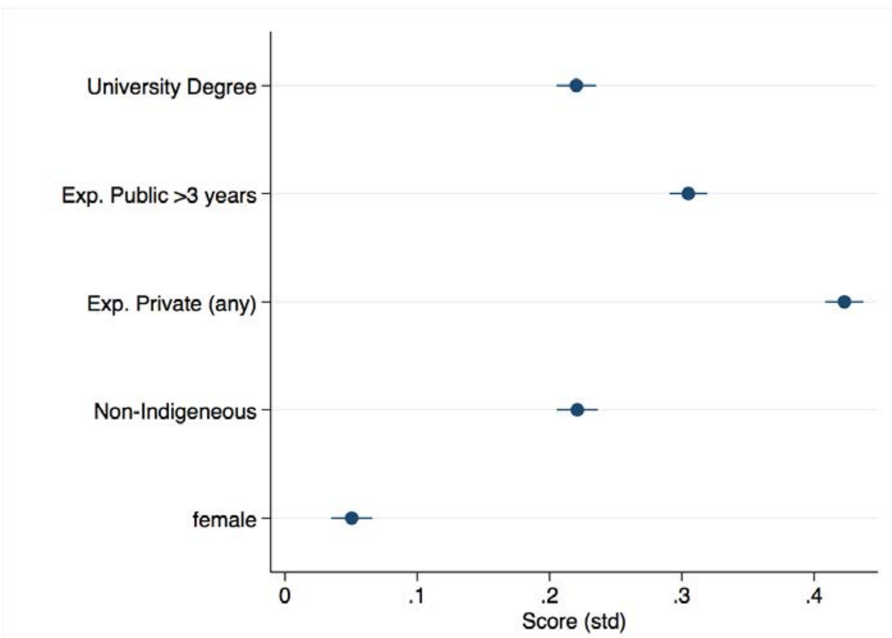
Notes. This table reports the summary statistics for the universe of rural and urban primary schools in Peru over the period 2016-2018. The first panel describes the baseline characteristics of each type of school (size, bilingual spanish/indigenous language curriculum) for the year 2016, and the teaching staff composition (pooling together the post-recruitment drives years 2016 and 2018). The second panel summarizes students' achievement in the 2016 and 2018 standardized test. The third and the fourth panel describes the quality and quantity of school infrastructures and locality amenities, as measured by the 2016 school census.

Table A.2: Applicant Survey (Most Relevant Attributes)

	All Teachers Rank				Score in Top Quartile Rank			
	1^{st}	2^{nd}	3^{rd}	In Top 3	1^{st}	2^{nd}	3^{rd}	In Top 3
Question A: Most important characteristic?								
Close to House	44.17	11.66	8.00	63.83	49.77	13.22	8.76	71.75
Safe	10.66	24.19	19.25	54.10	7.65	24.50	19.35	51.50
Well Connected	9.69	20.62	20.20	50.51	8.23	18.70	19.67	46.60
Prestige	17.92	14.12	12.29	44.33	21.13	15.77	12.68	49.58
Cultural Reasons	10.61	9.67	12.31	32.59	7.58	9.45	12.61	29.64
Good Infrastructure	2.02	8.40	12.86	23.28	1.81	7.23	11.83	20.87
Good Students	1.24	4.52	6.08	11.84	0.84	4.36	5.95	11.15
Possibility other Jobs	1.93	3.72	4.90	10.55	1.62	4.10	4.71	10.43
Career	1.76	3.10	4.09	8.95	1.36	2.67	4.44	8.47

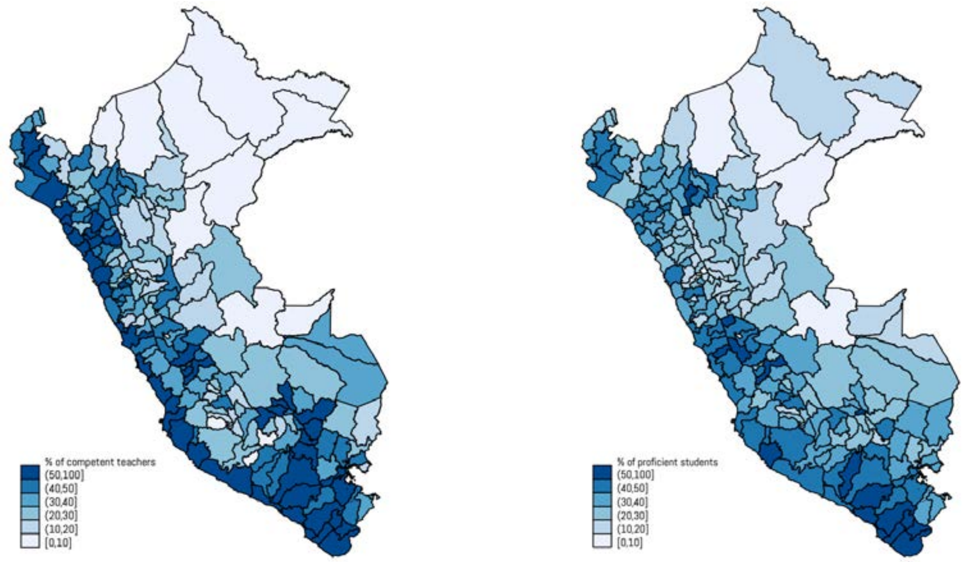
Notes. This table displays the share of the 5,553 survey respondents that chose the corresponding answers to Question A. The first three columns show which answer they chose and how they ranked them (by order of importance) while column 4 shows the share of respondents that listed the corresponding choice in their top 3 reasons. The last four columns display the same results for respondents that scored above the top quartile of the test score distribution for tenured teachers.

Figure A.1: Determinants of Teacher Competency



Notes: This figure shows OLS estimates and the associated 95 percent confidence intervals of the effect of individual teacher characteristics on the standardized competency score undertaken by all the applicants for a primary school vacancy in the context of the national recruitment drive in 2015 (see Section 3.2).

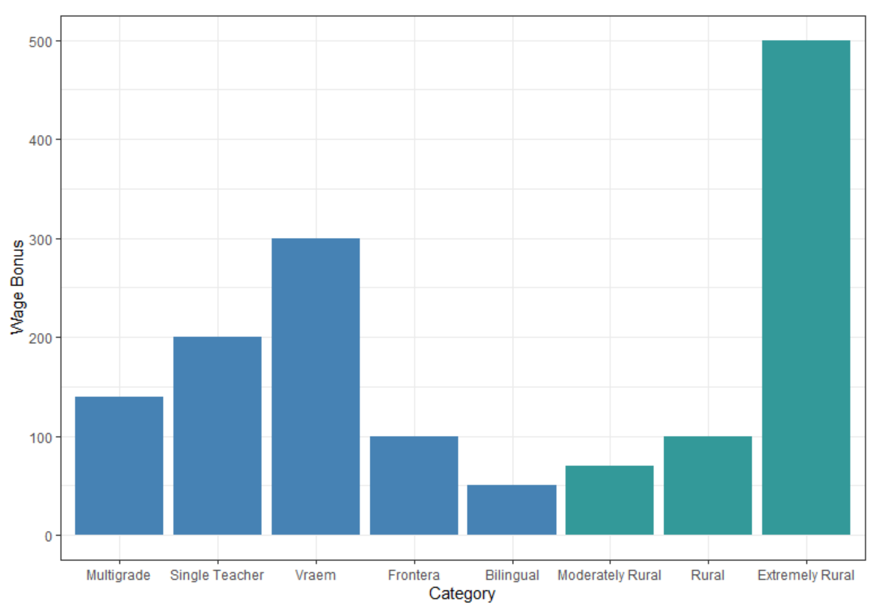
Figure A.2: Geographic Distribution of Teacher Competency and Student Achievement



a) % Competent Teachers **b) % of Proficient Students**

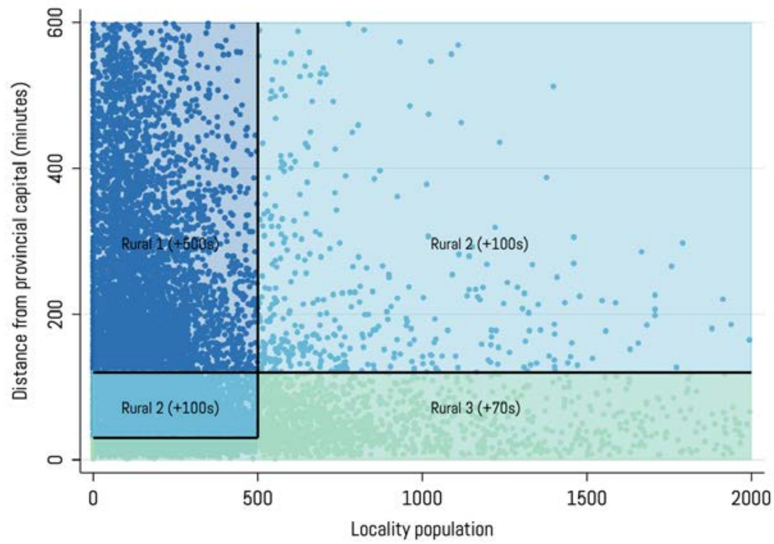
Notes: This figure depicts the geographical variation in the share of competent teachers (panel A) and the share of proficient students (panel B) within each province of Peru. Proficient students are defined as those who attain a proficient (*Satisfactorio*) achievement level in Math and/or Spanish. Similarly, competent teachers are defined as those who attain at least 60% of correct answers in the curricular and pedagogical knowledge module of the standardized test. The reported shares are obtained by pooling the data across two school years (2016 and 2018).

Figure A.3: The Different Wage Bonuses for Disadvantaged Schools

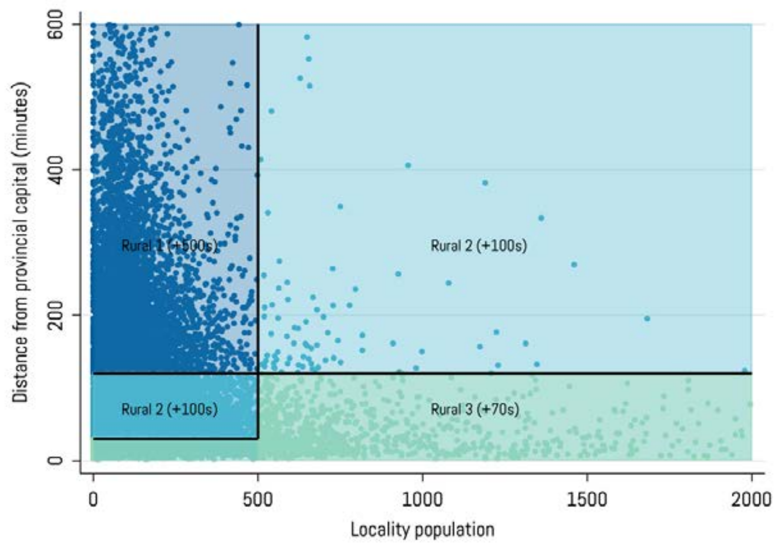


Notes. This figure shows the monetary amount in Peruvian Soles for the different wage bonuses implemented by the Government as of December 2015. Vraem correspond to schools located in the Valle de los Rios Apurimac, Ene y Mantaro which is extremely poor and under the control of drug cartels. Frontera categorizes schools that are close to the frontier of the country.

Figure A.4: The Distribution of Rural Schools over Population and Remoteness



a) Schools with Vacancies in 2015-2017

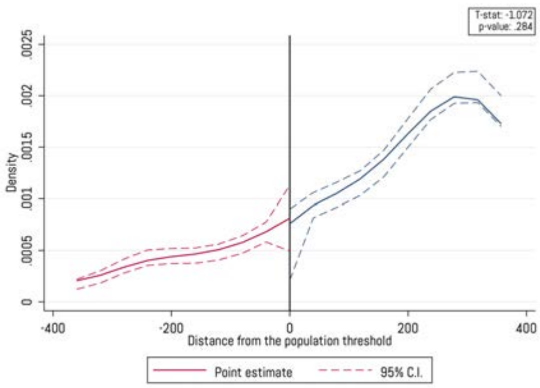


b) Schools without Vacancies in 2015-2017

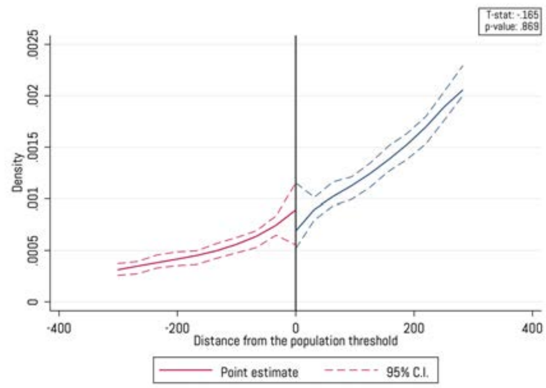
NOTES: This figure shows the spatial distribution of rural primary schools along the two dimensions that determine the assignment of the wage bonus. *Extremely Rural* schools are the purple dots, *Rural* are light blue and *Moderately Rural* schools are green.

B RD Evidence

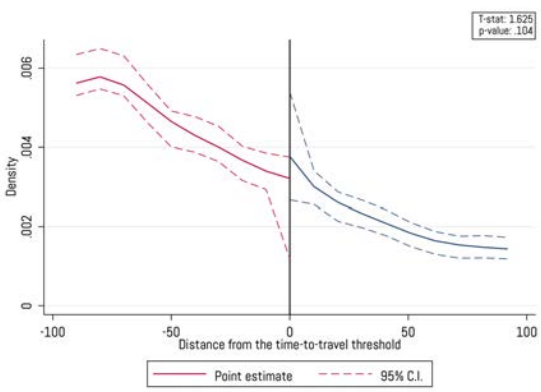
Figure B.1: Manipulation charts



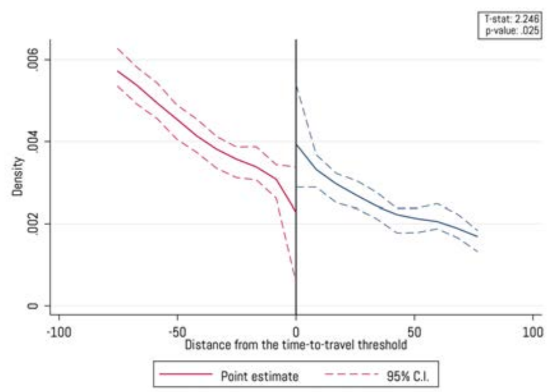
a. Population (2015)



b. Population (2017)



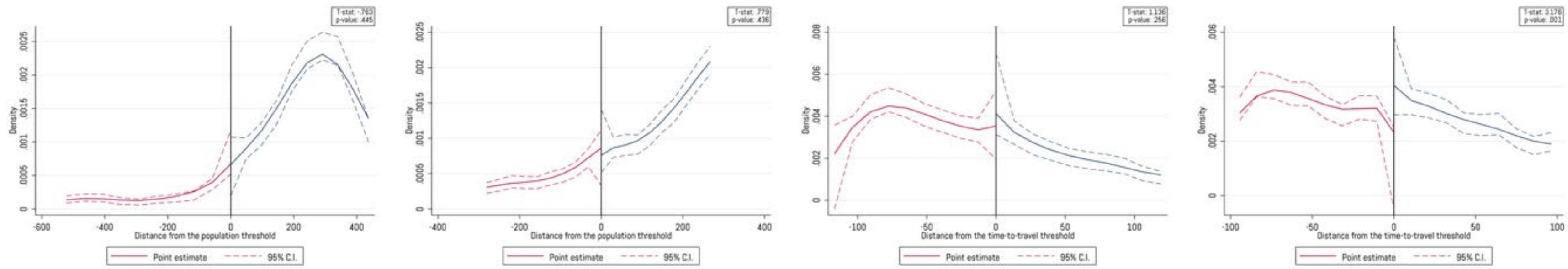
c. Time-to-travel (2015)



d. Time-to-travel (2017)

NOTES. The figure displays the empirical densities with the corresponding confidence intervals for two running variables (population and time-to-travel) for each of the years in which the teacher recruitment drive was conducted (2015 and 2017). The density is computed using the local-polynomial estimator proposed in Cattaneo et al. (2020), and the figures show the 95% confidence intervals. The sample includes all schools with a permanent or contract teacher opening in the corresponding year.

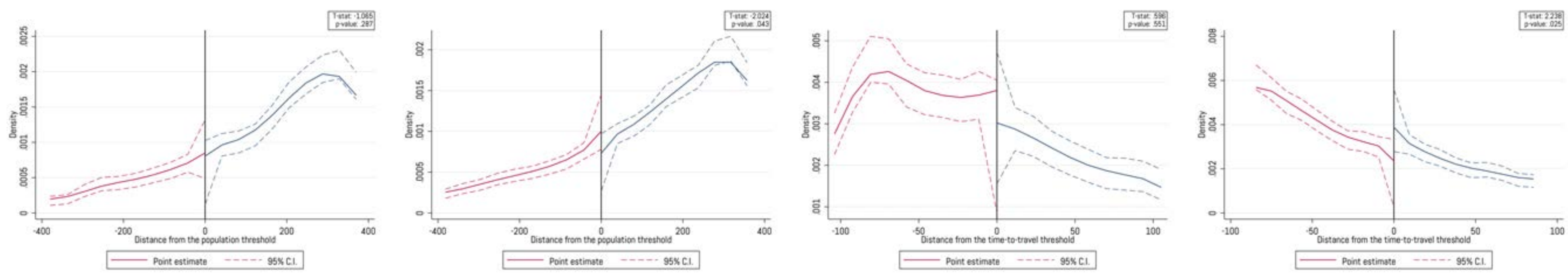
Figure B.2: Manipulation Charts - Schools with a Vacancy for Permanent Teachers



a. Population (2015) *b.* Population (2017) *a.* Time-to-travel (2015) *b.* Time-to-travel (2017)

Notes. The figure displays the empirical densities with the corresponding confidence intervals for two running variables (population and time-to-travel) for each of the years in which the teacher recruitment drive was conducted (2015 and 2017). The density is computed using the local-polynomial estimator proposed in Cattaneo et al. (2020), and the figures show the 95% confidence intervals. The sample includes only schools with a permanent teacher opening in the corresponding year.

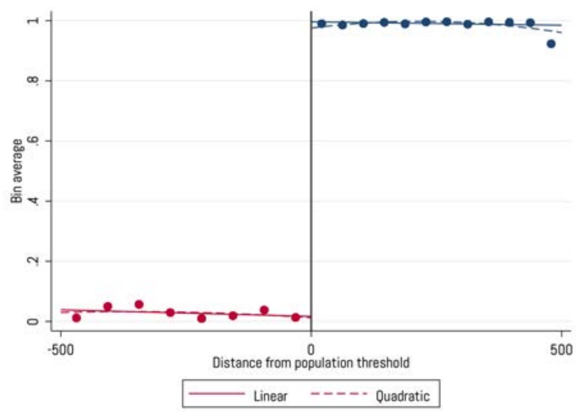
Figure B.3: Manipulation Charts - Schools with a Vacancy for Contract Teachers



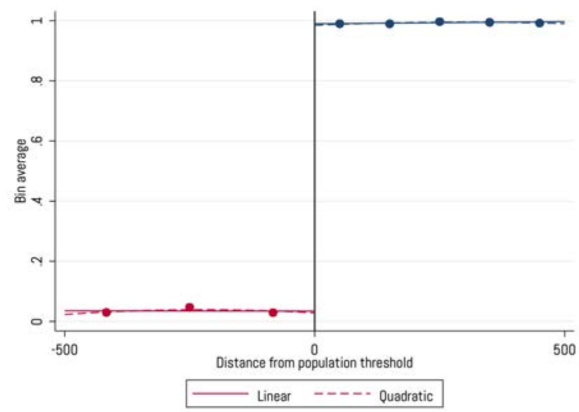
a. Population (2015) *b.* Population (2017) *a.* Time-to-travel (2015) *b.* Time-to-travel (2017)

Notes. The figure displays the empirical densities with the corresponding confidence intervals for two running variables (population and time-to-travel) for each of the years in which the teacher recruitment drive was conducted (2015 and 2017). The density is computed using the local-polynomial estimator proposed in Cattaneo et al. (2020), and the figures show the 95% confidence intervals. The sample includes only schools with a contract teacher opening in the corresponding year.

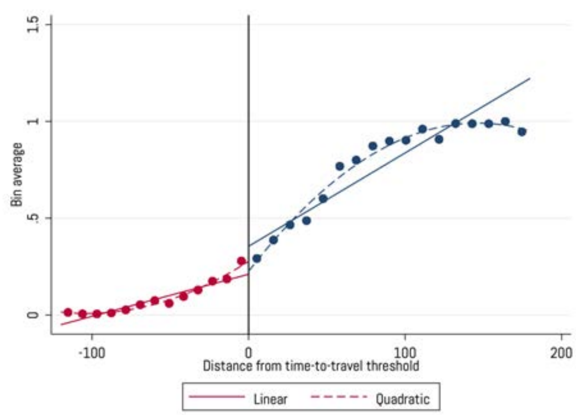
Figure B.4: First Stage for Different Years and Treatment Status



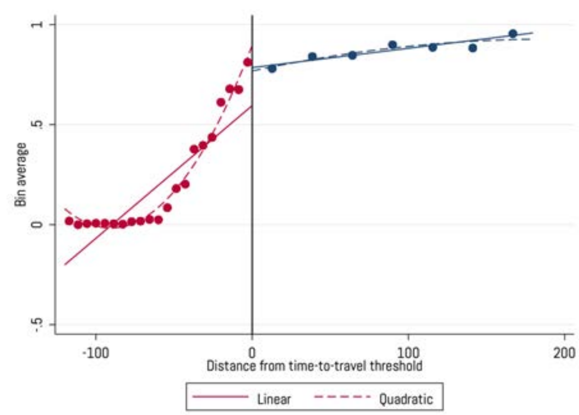
a. Treatment 2017; RV: population 2015



b. Treatment 2015; RV: population 2017



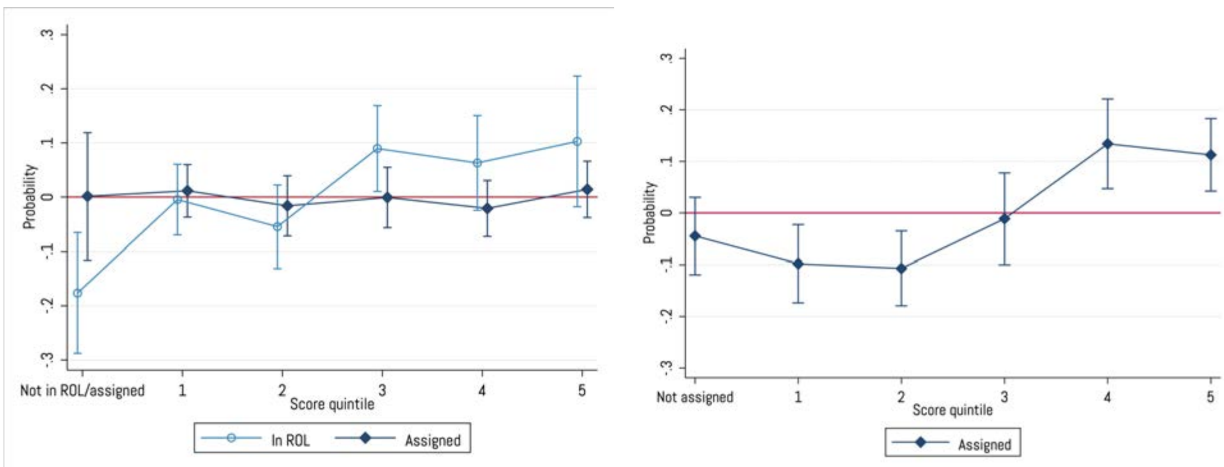
c. Treatment 2015; RV: time-to-travel 2017



d. Treatment 2017; RV: time-to-travel 2015

Notes. The figures show the probability that a school is classified as *Extremely Rural* in each year (2015 and 2017) plotted against the two different running variables (Population and time-to-travel) for the opposite year (2017 and 2015, respectively). The regression lines are computed using linear and quadratic polynomials.

Figure B.5: Wage Bonuses and the Selection of Quality Teachers

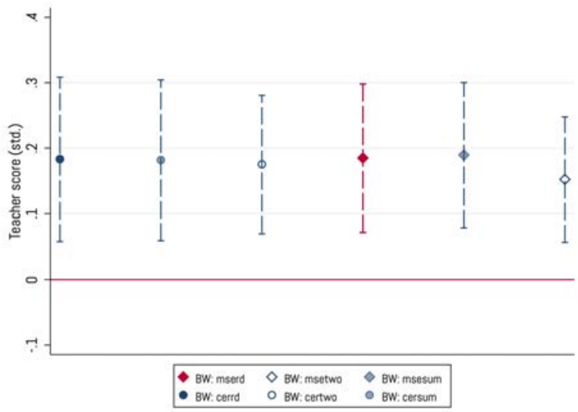


a. Permanent teacher

b. Contract teacher

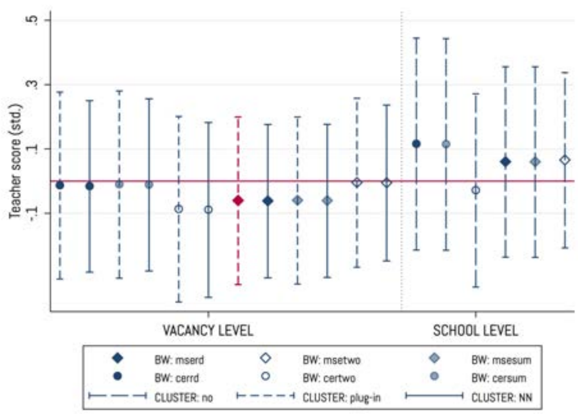
Notes. The figure displays the effect of crossing the population threshold on different measures of the demand for teaching positions and the quality of recruited teachers. Circles in panel (a) indicate the point estimates from a set of regression of the form of Equation 1 where the dependent variable is either a dummy equal to one if a school was not mentioned in any application for a permanent teaching position or a set of binary indicators for whether the school was mentioned by at least a teacher whose score falls into the quintile of the test score distribution reported on the x-axis. Similarly, diamonds in panel (a) and (b) are the point estimates from a set of regressions where the dependent variable is either a dummy equal to one if a teaching position remained unfilled, or was filled by a non-qualified teacher, or a set of binary indicators for whether the vacancy is filled by a teacher whose score falls into the decile of the score distribution reported on the x-axis. Non qualified teachers are defined as teachers who did not pass the minimum required grade for a permanent position (panel a), and teachers without a score in the standardized test (panel b). Markers and vertical lines indicate the robust bias-corrected regression-discontinuity estimates and confidence interval (at the 90% level) obtained using the robust estimator proposed in Calonico et al. (2014). Regressions are defined within a mean-square error optimal bandwidth.

Figure B.6: Robustness to Alternative RD Specifications – Preferences and Sorting

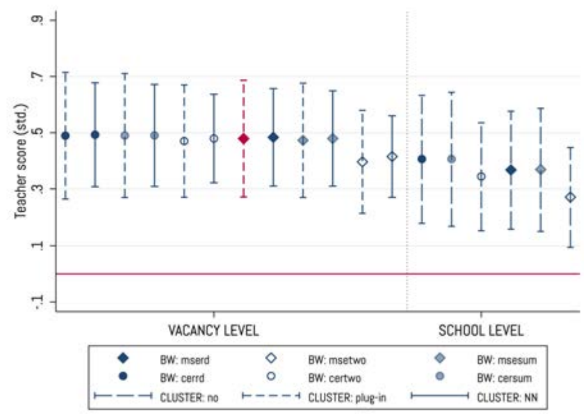


a. In ROL, Permanent teachers

b. Teacher rank, Contract teachers



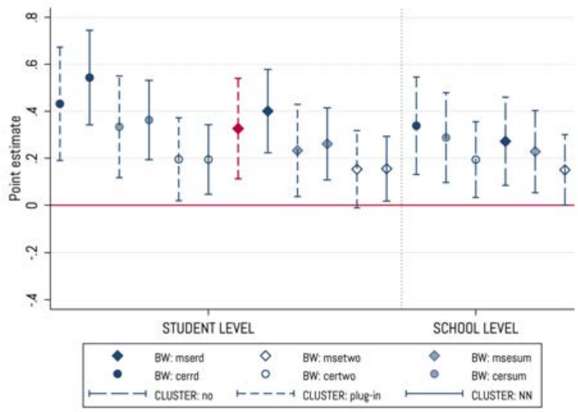
c. Teacher score, Permanent teachers



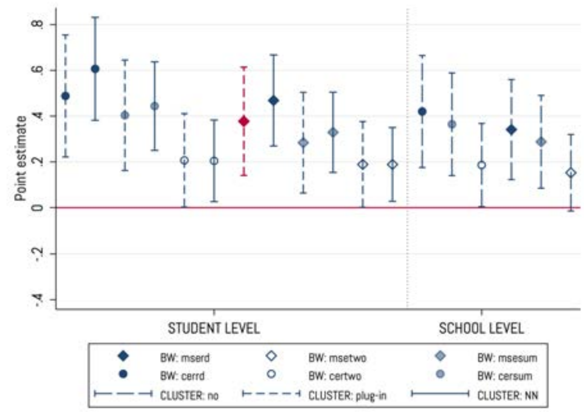
d. Teacher score, Contract teachers

Notes. The figure shows how the applicants' preferences and quality vary based on the distance from the population threshold. Panels A and C focus on the assignment process of permanent teachers. In Panel A the outcome variable is a dummy equal to one if a school was mentioned in at least one application, while in Panel C the outcome variable is the standardized (total) score obtained in the centralized test by the newly-assigned permanent teacher. Panels B and D are analogous to A and C for the assignment process of contract teachers. Panel B uses as outcome variable the rank in which a vacancy was chosen in the serial dictatorship mechanism (normalized so that it takes value from zero to one), while Panel D uses the standardized score obtained in the centralized test by the newly-assigned contract teacher. Markers indicate the robust bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014). Regressions are defined within different specifications for the optimal bandwidths. These are: *i.* one common mean-square error (MSE) optimal bandwidth (BW: mserd); *ii.* two different MSE-optimal bandwidths, above and below the cutoff (BW: msetwo); *iii.* one common MSE-optimal bandwidth for the sum of regression estimates (BW: msesum); *iv.* one common coverage error rate (CER) optimal bandwidth (BW: cerrd); *v.* two different CER-optimal bandwidths, above and below the cutoff (BW: certwo); *vi.* one common CER-optimal bandwidth for the sum of regression estimates (BW: cersum). Vertical lines indicate confidence intervals (at the 95% level) obtained from different estimation procedures: heteroskedasticity-robust plug-in residuals (CLUSTER: no); cluster-robust plug-in residuals (CLUSTER: plug-in); cluster-robust nearest neighbor (CLUSTER: NN). The vertical dotted line separates estimates based on whether they are obtained from regressions where the unit of observation is the student (on the left) or the school (on the right). In the latter case, the outcome variables are school-level averages

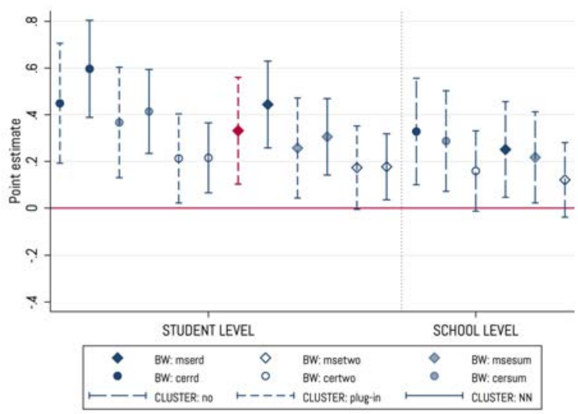
Figure B.7: Robustness to Alternative RD Specifications – Student Achievement



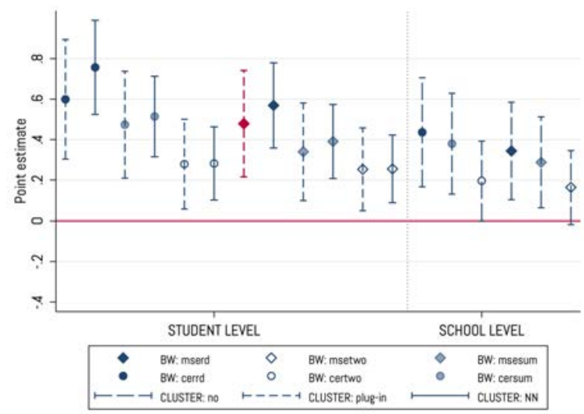
a. Spanish scores, Any vacancy



b. Math scores, Any vacancy



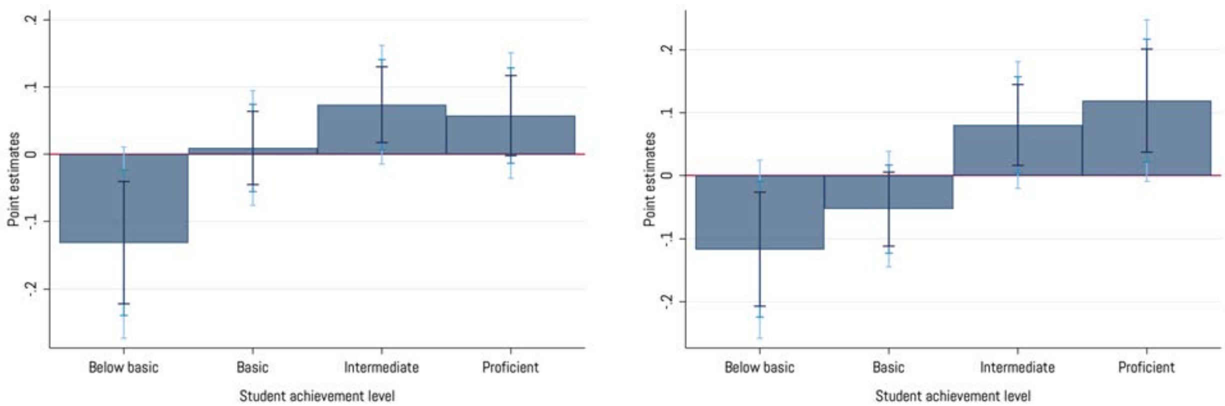
c. Spanish scores, Short-Term vacancy



d. Math scores, Short-Term vacancy

Notes. This figures shows the effect of crossing the population threshold on student achievement under different specifications. The outcome variable is the average of the standardized 2018 test scores in Math and Spanish for students in the fourth grade. The sample includes schools that had an open vacancy for contract teachers the 2015 or 2017 centralized recruitment drive. Markers indicate the robust bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014). Regressions are defined within different specifications for the optimal bandwidths. These are: *i.* one common mean-square error (MSE) optimal bandwidth (BW: mserd); *ii.* two different MSE-optimal bandwidths, above and below the cutoff (BW: msetwo); *iii.* one common MSE-optimal bandwidth for the sum of regression estimates (BW: msesum); *iv.* one common coverage error rate (CER) optimal bandwidth (BW: cerrd); *v.* two different CER-optimal bandwidths, above and below the cutoff (BW: certwo); *vi.* one common CER-optimal bandwidth for the sum of regression estimates (BW: cersum). Vertical lines indicate confidence intervals (at the 95% level) obtained from different estimation procedures: heteroskedasticity-robust plug-in residuals (CLUSTER: no); cluster-robust plug-in residuals (CLUSTER: plug-in); cluster-robust nearest neighbor (CLUSTER: NN). The vertical dotted line separates estimates based on whether they are obtained from regressions where the unit of observation is the student (on the left) or the school (on the right). In the latter case, the outcome variables are school-level averages

Figure B.8: Wage Bonus and Students' Achievement Level



a. Spanish *b.* Math

Notes. This table reports the effect of crossing the population threshold on student achievement in Spanish (on the left side) and Math (on the right side) classified according to four categories. These are below basic (*Previo al inicio*), basic (*En inicio*), intermediate (*En proceso*), and proficient (*Satisfactorio*). Bars and vertical lines indicates the estimated regression-discontinuity coefficients and confidence intervals (at the 90, 95 and 99% level) from a set of regression where the outcome variable is a dummy equal to one if a (fourth-grade) student falls into the corresponding category. The sample includes schools with an open position for contract teachers. Point estimates and confidence intervals are obtained using the robust estimator proposed in Calonico et al. (2014). Standard errors are clustered at the school×year level.

Table B.1: Wage increases around the population cutoff

Panel A: Permanent teacher			
	(1) Low bonus	(2) High bonus	(3) Average
Above cutoff	26.108***	397.479***	241.171***
	(6.796)	(5.540)	(20.553)
Mean dep. var. (LHS)	1702.391	1754.379	1726.681
BW	155.394	186.237	233.538
Schools	380	536	1263
Observations	625	1194	2536
Panel B: Contract teacher			
	(1) Low bonus	(2) High bonus	(3) Average
Above cutoff	29.885***	406.376***	248.968***
	(1.816)	(2.844)	(22.646)
Mean dep. var. (LHS)	1681.324	1757.923	1711.724
BW	115.300	90.887	197.547
Schools	377	255	1184
Observations	683	758	2759

Notes. This table reports the effect of crossing the population threshold on the wages of permanent (Panel A) and contract teachers (Panel B). In all columns, the outcome variable is the gross salary, which includes both the baseline wage and the bonuses. In Column (1), the sample includes only schools in rural locations whose travel time to the provincial capital is between 30 and 120 minutes, so that crossing the 500 inhabitant cutoff from above implies moving from a Moderately Rural to a Rural area. Similarly, in Column (2) the sample includes only schools in rural locations whose travel time to the provincial capital is above 120 minutes, so that crossing the 500 inhabitant cutoff from above implies moving from a Rural to an Extremely Rural area. In Column (3), the sample is the union of that in Column (1) and (2): it includes all schools in rural locations whose travel time to the provincial capital is above 30 minutes. Cells report the bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014). Regressions are defined within a mean-square error optimal bandwidth (BW), reported at the bottom part of the table. The table also reports the mean of the dependent variable computed within the intervals $(0, +BW)$ (right-hand-side of the cutoff) and $(-BW, 0]$ (left-hand-side of the cutoff). SE are clustered at the school level. *** p< 0.01, ** p<0.05, and *p<0.10.

Table B.2: Covariate Smoothness around the Population Cutoff

	2015			2017		
	(1) Any vac.	(2) Permanent	(3) Contract	(4) Any vac.	(5) Permanent	(6) Contract
School characteristics						
Number of students	-2.912	5.555	-18.543	-1.045	-4.498	-3.479
	(10.290)	(11.990)	(11.635)	(6.499)	(8.513)	(6.736)
Indigenous language students	-0.038	-0.052	-0.056	0.017	-0.042	0.014
	(0.097)	(0.143)	(0.108)	(0.067)	(0.087)	(0.075)
% indigenous language students	-0.022	0.028	-0.030	-0.008	-0.040	0.015
	(0.085)	(0.112)	(0.103)	(0.046)	(0.066)	(0.065)
% proficient students (math)	3.863	-0.939	4.796	1.331	-4.160	2.993
	(3.144)	(7.601)	(3.305)	(3.477)	(3.511)	(3.722)
% proficient students (spanish)	6.294	5.182	8.202**	-2.264	-5.437	0.278
	(4.070)	(5.609)	(4.114)	(3.775)	(4.073)	(4.049)
Village amenities						
Electricity	0.062	0.011	0.012	0.026	-0.043	0.058
	(0.090)	(0.126)	(0.083)	(0.053)	(0.064)	(0.068)
Drinking water	0.260**	0.231	0.309**	0.110	0.174	0.144
	(0.132)	(0.173)	(0.150)	(0.083)	(0.115)	(0.101)
Sewage	0.179	0.067	0.171	-0.022	-0.030	-0.001
	(0.115)	(0.153)	(0.127)	(0.070)	(0.097)	(0.080)
Medical clinic	0.056	0.030	0.066	0.000	-0.069	0.001
	(0.107)	(0.151)	(0.122)	(0.082)	(0.100)	(0.091)
Meal center	0.186**	0.246**	0.146	0.069	0.113	0.075
	(0.087)	(0.117)	(0.101)	(0.081)	(0.093)	(0.085)
Community phone	-0.007	-0.059	-0.036	-0.034	-0.033	-0.086
	(0.093)	(0.135)	(0.114)	(0.069)	(0.091)	(0.075)
Internet access point	0.054	0.153*	0.070	0.022	-0.004	0.024
	(0.058)	(0.084)	(0.079)	(0.051)	(0.059)	(0.062)
Bank	0.023*	0.000	0.031*	0.010	0.005	0.013
	(0.013)	(0.000)	(0.016)	(0.007)	(0.008)	(0.009)
Public library	0.018	-0.059	0.019	-0.004	0.002	0.006
	(0.032)	(0.049)	(0.043)	(0.023)	(0.030)	(0.016)
Police	-0.079	-0.161	-0.094	-0.056	-0.124	-0.078
	(0.082)	(0.118)	(0.097)	(0.063)	(0.089)	(0.067)
School amenities						
Distance from district municipality (min.)	-27.579	99.432	-17.468	78.389	83.076	101.385
	(112.029)	(171.377)	(128.940)	(138.805)	(173.709)	(169.936)
Teachers room	-0.033	0.016	-0.095	-0.074	-0.177**	-0.069
	(0.072)	(0.095)	(0.084)	(0.066)	(0.075)	(0.072)
Sport pitch	-0.033	0.023	-0.041	0.002	-0.033	0.020
	(0.087)	(0.098)	(0.090)	(0.059)	(0.067)	(0.069)
Courtyard	-0.061	-0.010	-0.096	-0.116	-0.074	-0.104
	(0.092)	(0.107)	(0.100)	(0.080)	(0.087)	(0.081)
Administrative office	-0.010	-0.130	-0.094	0.056	0.032	0.048
	(0.101)	(0.155)	(0.128)	(0.077)	(0.102)	(0.094)
Courtyard	0.002	0.001	0.001	-0.009	-0.025	0.002
	(0.004)	(0.001)	(0.005)	(0.014)	(0.023)	(0.004)
Computer lab	-0.004	-0.023	-0.048	0.050	0.006	0.070
	(0.087)	(0.122)	(0.113)	(0.074)	(0.099)	(0.083)
Workshop	-0.002	-0.006	-0.020	0.010	-0.013	0.002
	(0.036)	(0.066)	(0.037)	(0.029)	(0.033)	(0.033)
Science lab	0.030	0.043	0.029	0.040	0.006	0.049
	(0.062)	(0.090)	(0.076)	(0.042)	(0.043)	(0.050)
Library	0.044	-0.115	0.007	0.094	0.076	0.044
	(0.104)	(0.159)	(0.134)	(0.071)	(0.102)	(0.095)
At least a personal computer	0.030	0.045	0.043	0.075	0.125	0.103
	(0.082)	(0.118)	(0.094)	(0.073)	(0.091)	(0.074)
Electricity	0.173	0.145	0.179	0.106	0.072	0.124
	(0.114)	(0.147)	(0.132)	(0.075)	(0.093)	(0.083)
Water supply	0.276**	0.239	0.346**	0.079	0.050	0.132
	(0.128)	(0.168)	(0.144)	(0.077)	(0.084)	(0.095)
Sewage	0.183*	0.089	0.214	-0.007	0.029	0.058
	(0.102)	(0.120)	(0.131)	(0.070)	(0.107)	(0.081)

Notes. This table studies whether schools in localities just above or below the population threshold differ in terms of village and school amenities (as of 2013). Columns (1) to (3) focus on the 2015 assignment process, with schools split based on whether they had at least a permanent (column 2) or contract (column 3) vacancy (the sample in column 1 is the union of column 2 and 3). Columns (4) to (6) are the analogous of columns (1)-(2) but focus on the 2017 assignment process. Cells report the bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014). Regressions are defined within a mean-square error optimal bandwidth. Robust SE in parentheses.*** p< 0.01, ** p<0.05, and *p<0.10.

Table B.3: Probability of Openings around the Population Cutoff

	All		Permanent teacher		Contract teacher	
	(1)	(2)	(3)	(4)	(5)	(6)
	Vacancy	N. of vacancies	Vacancy	N. of vacancies	Vacancy	N. of vacancies
Above cutoff	-0.007	-0.114	0.008	-0.042	-0.007	-0.113
	(0.040)	(0.138)	(0.041)	(0.091)	(0.044)	(0.135)
Mean dep. var. (LHS)	0.476	0.960	0.252	0.463	0.397	0.764
BW	245.255	185.331	166.599	172.265	221.811	184.597
Observations	6196	4244	3793	3904	5365	4221

NOTES. This table reports the effect of crossing the population threshold on the probability that vacancy is posted (and their number) in the 2015 or 2017 assignment process. In column (1) the outcome variable is a dummy equal to 1 if the school had at least a vacancy (of any type), while in column (2) is the number of open vacancies. Columns (3)-(4) and (5)-(6) are the analogous of columns (1)-(2) but focus only on permanent and contract teachers vacancies, respectively. Cells report the bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014). Regressions are defined within a mean-square error optimal bandwidth (BW), reported at the bottom part of the table. The table also reports the mean of the dependent variable computed within the intervals $(0, +BW)$ (right-hand-side of the cutoff) and $(-BW, 0]$ (left-hand-side of the cutoff). SE are clustered at the school level. *** p< 0.01, ** p<0.05, and *p<0.10.

Table B.4: Monetary Incentives and Teacher Selection (2015)

Panel A: Permanent teacher			
	(1)	(2)	(3)
	In ROL	Vacancy filled	Teacher score (std)
Above cutoff	0.071	-0.182	0.419
	(0.083)	(0.122)	(0.414)
Bounds	[.085; .194]	[-.149; -.07]	[.266; .266]
Mean dep. var. (LHS)	0.795	0.508	0.277
BW	247.770	219.949	134.609
Schools	590	488	148
Observations	590	661	189
Panel B: Contract teacher			
	(1)	(2)	(3)
	Teacher rank	Vacancy filled	Teacher score
Above cutoff	-0.132**	0.097	0.644***
	(0.060)	(0.068)	(0.196)
Bounds	[-.166; -.097]	[.089; .089]	[.482; .722]
Mean dep. var. (LHS)	0.391	0.869	-0.104
BW	170.605	198.155	150.920
Schools	441	583	392
Observations	720	971	651

NOTES. This table reports the effect of crossing the population threshold on different outcomes. Panel A uses the sample of permanent teachers. In Column (1) the outcome variable is a dummy equal to one if a school was mentioned in at least one application, while in Column (2) is an indicator for whether the vacancy was filled by a certified teacher in the assignment process for permanent teachers. The regression displayed in the last column uses as outcome variable the standardized total score obtained by the teachers in the centralized test. In Columns (3) the sample is restricted to vacancies that were actually filled by a certified teacher. Panel B focuses on the selection process of contract teachers. Column (1) shows the effects on the rank in which a vacancy was chosen in the deferred acceptance mechanism (normalized so that it takes value from zero to one), while Columns (2) to (3) are analogous to those from Panel A. Cells report the bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014) and their bounds estimated using the procedure developed in Gerard et al. (2020). Regressions are defined within a mean-square error optimal bandwidth (BW), reported at the bottom part of the table. The table also reports the mean of the dependent variable computed within the interval $(-BW, 0]$ (left-hand-side of the cutoff). Standard errors are clustered at the school×year level. *** p< 0.01, ** p<0.05, and *p<0.10.

Table B.5: Monetary Incentives and Teacher Selection (2017)

Panel A: Permanent teacher			
	(1)	(2)	(3)
	In ROL	Vacancy filled	Teacher score (std)
Above cutoff	0.252***	0.069	-0.085
	(0.087)	(0.082)	(0.209)
Bounds	[.199; .382]	[.035; .113]	[-.508; .402]
Mean dep. var. (LHS)	0.743	0.330	-0.177
BW	157.073	170.460	164.311
Schools	626	681	338
Observations	626	1261	456
Panel B: Contract teacher			
	(1)	(2)	(3)
	Teacher rank	Vacancy filled	Teacher score
Above cutoff	-0.121***	0.021	0.375**
	(0.042)	(0.056)	(0.150)
Bounds	[-.113; -.113]	[.021; .021]	[.362; .362]
Mean dep. var. (LHS)	0.361	0.911	0.166
BW	165.878	155.386	185.069
Schools	815	787	906
Observations	1401	1407	1545

Notes. This table reports the effect of crossing the population threshold on different outcomes. Panel A uses the sample of permanent teachers. In Column (1) the outcome variable is a dummy equal to one if a school was mentioned in at least one application, while in Column (2) is an indicator for whether the vacancy was filled by a certified teacher in the assignment process for permanent teachers. The regression displayed in the last column uses as outcome variable the standardized total score obtained by the teachers in the centralized test. In Columns (3) the sample is restricted to vacancies that were actually filled by a certified teacher. Panel B focuses on the selection process of contract teachers. Column (1) shows the effects on the rank in which a vacancy was chosen in the deferred acceptance mechanism (normalized so that it takes value from zero to one), while Columns (2) to (3) are analogous to those from Panel A. Cells report the bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014) and their bounds estimated using the procedure developed in Gerard et al. (2020). Regressions are defined within a mean-square error optimal bandwidth (BW), reported at the bottom part of the table. The table also reports the mean of the dependent variable computed within the interval $(-BW, 0]$ (left-hand-side of the cutoff). Standard errors are clustered at the school×year level. *** p< 0.01, ** p<0.05, and *p<0.10.

Table B.6: Monetary Incentives and the Selection of Contract Teachers

						Years as public school teacher		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Female	Age	Other language	University	Novice Teacher	0	1-3	> 3
Above cutoff	0.098*	-1.309	-0.006	0.078	0.035	0.053	0.075	-0.145**
	(0.059)	(0.849)	(0.064)	(0.053)	(0.031)	(0.035)	(0.047)	(0.059)
Mean dep. var. (LHS)	0.581	37.363	0.348	0.294	0.083	0.151	0.389	0.388
BW	147.765	157.516	131.986	182.385	129.025	152.043	210.154	128.455
Schools	854	925	757	1072	742	893	1278	738
Observations	1890	2108	587	2306	1658	2084	2891	1752

Notes. This table reports the effect of crossing the population threshold on several teachers' characteristics. These are a female dummy (column 1), age (column 2), a dummy equal to 1 if the teacher speaks a Peruvian indigenous language (column 3), an indicator for university or technical institute education (column 4), and a dummy equal to 1 if the teacher has no previous teaching experience, neither in the public nor private sector (column 5). In column 6 the outcome variable is a binary indicator for the number of years the teacher was observed in the teacher occupation and payroll system (*NEXUS*) before the assignment process. The sample includes all contract teacher vacancies assigned in the 2015 and 2017 processes, regardless of whether they were assigned to a certified or non-certified teachers. In column (3) the sample includes only vacancies assigned to certified teachers in 2015, as the same information is not available for the 2017 assignment process. Cells report the bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014). Regressions are defined within a mean-square error optimal bandwidth (BW), reported at the bottom part of the table. The table also reports the mean of the dependent variable computed within the intervals $(0, +BW)$ (right-hand-side of the cutoff) and $(-BW, 0]$ (left-hand-side of the cutoff). SE are clustered at the school×year level. *** p< 0.01, ** p<0.05, and *p<0.10.

Table B.7: Monetary Incentives and the Origin of Newly Recruited Teachers

	Unfilled v.	Filled vacancy											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
		New entr.	Same sch.	0-99	100-199	200-299	300-399	400-499	500-599	600-699	700-799	800-2000	Urban
Above cutoff	-0.043	0.049	-0.002	-0.023	-0.009	0.037	0.032	0.006	0.003	-0.027	-0.035*	0.026	-0.008
	(0.045)	(0.041)	(0.039)	(0.027)	(0.035)	(0.032)	(0.026)	(0.019)	(0.022)	(0.018)	(0.018)	(0.019)	(0.028)
Mean dep. var.	0.102	0.216	0.154	0.051	0.075	0.087	0.047	0.044	0.049	0.025	0.024	0.056	0.066
BW	160.098	122.583	163.318	144.407	129.042	154.888	124.410	211.734	173.911	162.758	123.568	155.949	143.211
Schools	943	693	969	826	742	905	711	1281	1018	961	700	911	822
Observations	2218	1692	2278	1975	1795	2146	1729	2962	2366	2263	1708	2154	1966

Notes. This table reports the effect of crossing the population threshold on a set of indicators for the teachers' location in the year before the assignment process. These are a dummy equal to one if the vacancy is filled by a teacher already in the same school (column 3), or is filled by a teacher whose previous location falls into the population bin indicated in the column header (columns 4-13). Urban schools are those in localities above 2000 inhabitants. The table also reports the effect of crossing the population threshold on the probability that the vacancy remains unfilled (column 1), or is filled by a new entrant in the public education system (column 2). Teachers' previous school is determined based on the teacher occupation and payroll system (*NEXUS*). The sample includes all contract teacher vacancies assigned to a certified teacher in the 2015 and 2017 processes. Cells report the bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014). Regressions are defined within a mean-square error optimal bandwidth (BW), reported at the bottom part of the table. The table also reports the mean of the dependent variable computed within the intervals $(0, +BW)$ (right-hand-side of the cutoff) and $(-BW, 0]$ (left-hand-side of the cutoff). SE are clustered at the school×year level. *** p< 0.01, ** p<0.05, and *p<0.10.

Table B.8: Monetary Incentives and Teaching Staff Composition

	Permanent Vacancy			Short-term Vacancy		
	(1)	(2)	(3)	(4)	(5)	(6)
	N. of teachers	Student/Teacher	% of permanent t.	N. of teachers	Student/Teacher	% of contract t.
Above cutoff	0.189	-0.111	0.082*	-0.541	0.048	-0.039
	(0.352)	(0.184)	(0.043)	(0.373)	(0.184)	(0.038)
Mean dep. var. (LHS)	6.617	2.667	0.543	6.548	2.598	0.409
BW	177.285	145.189	243.788	145.863	168.266	182.564
Observations	1068	841	1648	1120	1304	1441

Notes. This table reports the effect of crossing the population threshold on the number and the composition of teaching staff in schools that had an open vacancy in the 2015 or 2017 assignment process. The sample in columns (1) to (3) includes schools that had vacancies for permanent teachers. In column (1) the outcome variable is the total number of teachers, in column (2) is the students to teachers ratio, while in column (3) is the share of permanent teachers. Columns (4) to (6) are the analogous of columns (1)-(3) for schools that had vacancies for contract teachers. Cells report the bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014). Regressions are defined within a mean-square error optimal bandwidth (BW), reported at the bottom part of the table. The table also reports the mean of the dependent variable computed within the intervals $(0, +BW)$ (right-hand-side of the cutoff) and $(-BW, 0]$ (left-hand-side of the cutoff). SE are clustered at the school level. *** p< 0.01, ** p<0.05, and *p<0.10.

Table B.9: Monetary Incentives and Teachers' Retention

	Permanent teachers		Contract teachers	
	(1)	(2)	(3)	(4)
	Within-year	Between-years	Within-year	Between-years
Above cutoff	0.013	0.010	0.004	-0.003
	(0.020)	(0.026)	(0.007)	(0.013)
Mean dep. var. (LHS)	0.905	0.098	0.970	0.919
BW	198.481	149.719	170.668	143.062
Schools	1354	989	1974	1624
Observations	5572	4161	19142	16015

Notes. This table reports the effect of crossing the population threshold on the within- and between-years retention of contract and permanent teachers. In column (1) the outcome variable is a dummy equal to one if the teaching position is filled by the same permanent teacher at the beginning (March) and the end (December) of a school year. In column (2) it is a dummy equal to one if the position is filled by the same teacher for two consecutive years (the teacher in school year t is the same teacher observed in year $t-1$). Columns (3) and (4) are the analogous of columns (1) and (2) for contract teaching positions. The sample includes all the teaching positions in rural Peru over the period 2016-2018 that are observed for at least two consecutive years. Cells report the bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014). Regressions are defined within a mean-square error optimal bandwidth (BW), reported at the bottom part of the table. The table also reports the mean of the dependent variable computed within the interval (?BW,0] (left-hand-side of the cutoff). SE are clustered at the school×year level. * p¡ 0.01, p¡0.05, and *p¡0.10.

C Evidence from the Model of Teacher Sorting

Table C.1: Preference Estimates

Panel A: School/Locality Characteristics										
	Wage		Poverty Score		Infrastructure		Multigrade		Single Teacher	
	0.815	(0.120)	-0.201	(0.035)	-0.054	(0.054)	-0.237	(0.119)	-0.786	(0.192)
× Male	0.611	(0.157)	0.115	(0.032)	-0.060	(0.048)	0.019	(0.099)	0.519	(0.137)
× Exp $\geq$ 4	0.070	(0.053)	0.097	(0.036)	0.132	(0.052)	-0.284	(0.118)	0.020	(0.181)
× Urban	0.115	(0.061)	-0.060	(0.044)	0.036	(0.068)	0.009	(0.170)	-0.125	(0.242)
× Competent	0.170	(0.067)	-0.065	(0.047)	0.198	(0.076)	-0.782	(0.185)	-0.752	(0.351)
Std. Deviation	0.560	(0.053)								
	Bilingue		Vraem		Frontera					
	-0.747	(0.123)	-0.409	(0.284)	-0.747	(0.123)				
× Male	0.011	(0.113)	-0.234	(0.187)	0.270	(0.142)				
× Exp $\geq$ 4	-0.290	(0.112)	0.009	(0.247)	0.047	(0.155)				
× Urban	-0.050	(0.166)	0.017	(0.404)	-0.135	(0.319)				
× Competent	-0.732	(0.473)	-0.233	(1.063)	-0.048	(0.299)				
× Lives in Vraem			0.521	(0.208)						
			Rural Wage Bonus Determinants (polynomial)							
log(Pop)	0.228	(0.301)			Time^3			-0.000	(0.000)	
Time	-0.207	(0.097)			Time × log(Pop)			-0.002	(0.028)	
$\log(\text{Pop})^2$	-0.054	(0.031)			Time^2 × log(Pop)			-0.002	(0.000)	
Time^2	0.011	(0.003)			Time × $\log(\text{Pop})^2$			0.007	(0.002)	
$\log(\text{Pop})^3$	0.002	(0.001)								
Panel B: Teacher-School Match Effects										
	Ethnolinguistic Match				Geographical Proximity (spline)					
Quechua × Quechua	1.488	(0.158)			Distance < 20km			-0.187	(0.003)	
Aimara × Aimara	1.375	(0.537)			20km < Distance < 100km			-0.033	(0.001)	
Ashaninka × Ashaninka	2.243	(0.558)			100km < Distance < 200km			-0.018	(0.001)	
Awajun × Awajun	2.086	(1.020)			200km < Distance < 300km			-0.017	(0.002)	
Other × Other	0.995	(0.113)			Distance > 300km			-0.002	(0.000)	
Panel C: Outside Option										
Constant	2.740	(1.197)			Quechua			0.527	(0.116)	
Male	0.840	(0.271)			Aimara			0.214	(0.454)	
Score	-0.205	(0.036)			Ashaninka			-0.564	(0.646)	
Age	0.019	(0.005)			Awajun			-0.026	(0.913)	
Experience	-0.043	(0.005)			Other Amazonas			-0.473	(0.067)	
Private Exp > 0	0.195	(0.054)			Time			-0.059	(0.008)	
					log(Pop)			0.115	(0.011)	

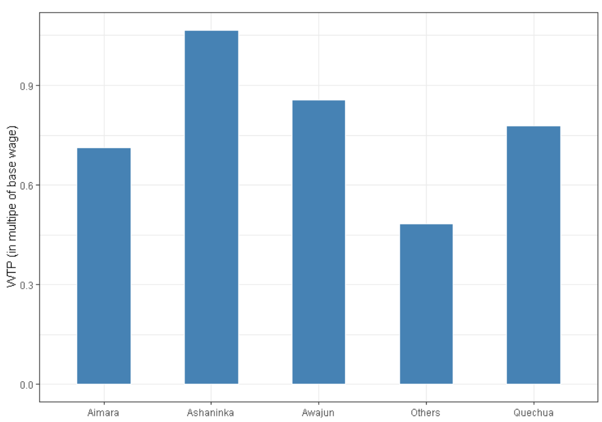
Notes. This table displays estimates and standard errors (in parentheses) of the parameters of the model described in Equation 2. Panel A shows the estimated coefficients associated to a selected set of schools/locality characteristics while Panel B shows estimated preferences for geographical proximty as well as the interaction between schools' language of instruction and teachers own native language. The data used contains choices of the pool of 59,949 applicants (note that 500 applicants are left out due to missing data) that participated in the allocation of short-term contracts for public primary schools in 2015. Estimation is done via maximizing the likelihood described in Equation 4 where the integral is computed numerically in an inner loop via a Gaussian-Hermite quadrature.

Table C.2: Counterfactuals: Increase in Local Supply

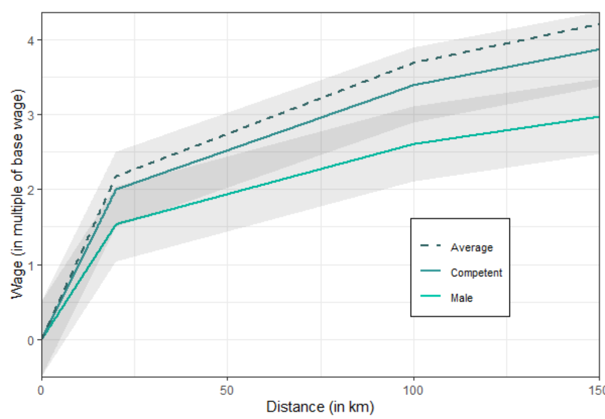
	Castel-lano	Quechua	Aimara	Ashaninka	Awajun	Other Ama-zonas
Objective 1: At least one competent teacher in each school						
New Teachers (1% increase)	0.666	0.016	0.002	0.004	0.000	0.312
New Teachers (3% increase)	0.814	0.013	0.001	0.001	0.000	0.171
Overall Pool	0.710	0.235	0.030	0.004	0.003	0.017
Objective 2: Fill every vacancy						
New Teachers (1% increase)	0.424	0.034	0.002	0.040	0.124	0.376
New Teachers (3% increase)	0.438	0.038	0.001	0.046	0.112	0.365
Overall Pool	0.819	0.151	0.026	0.001	0.000	0.003

Notes. This table displays in which ethno-linguistic groups the new teachers selected to augment the total pool of applicants belong to. These teachers are selected based on their proximity to the schools for which we need to pay the most in order to attract either a high quality teacher (social objective 1) or to fill its vacancies (social objective 2).

Figure C.1: Match Effects



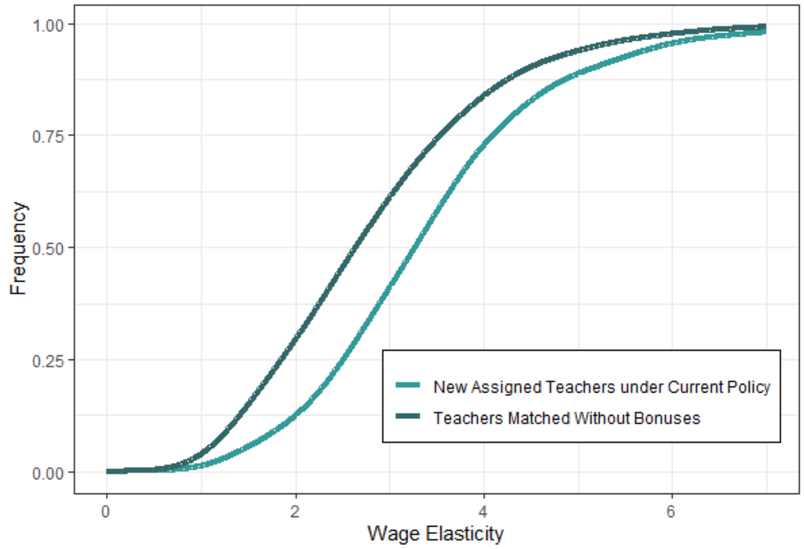
a) Ethnolinguistic Match



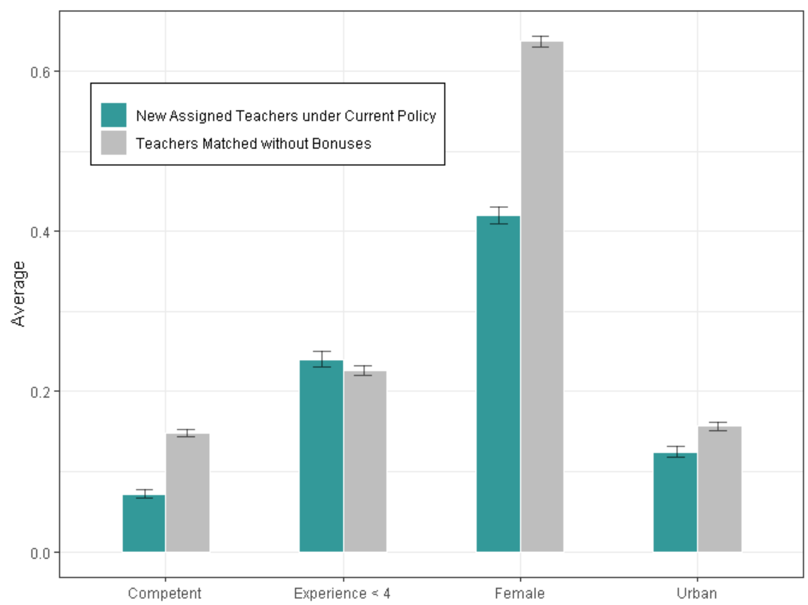
b) Disutility of Distance

Notes. Panel A interprets the estimates of Table 3 in terms of moving cost. It shows how much money we would need to give teachers on average in order to make them indifferent between a school located where they live and school located x km away keeping other observables constant. The dashed line displays this relationship for the average teacher. The other lines display the average for specific groups of teachers (male and competent). The shaded areas around each line displays how the unobserved wage preference heterogeneity affects this relationship by showing confidence bands of the size of one standard deviation of the wage coefficient. Panel B reinterprets the estimated match effects in terms of willingness to pay.

Figure C.2: The Effect of the Wage Bonus on the Selection of Teachers



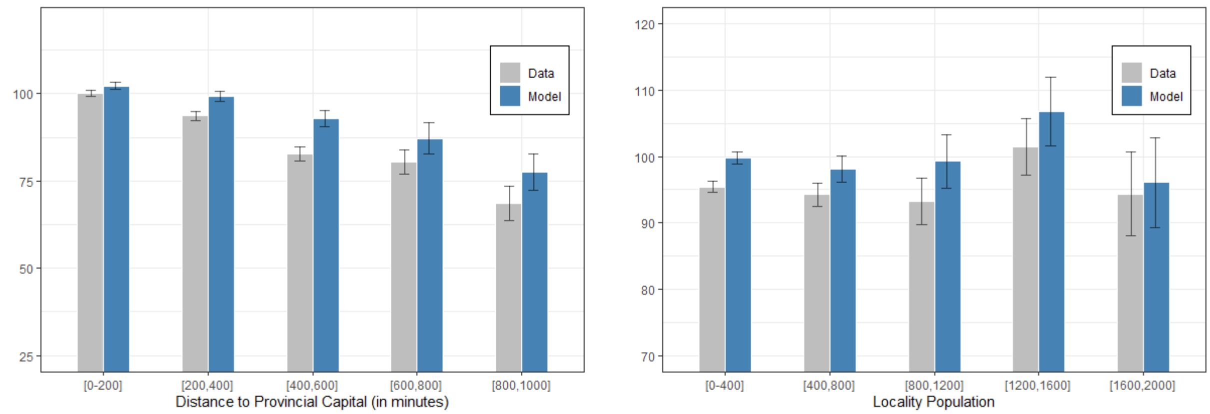
a) CDF of Wage Elasticities



b) Teacher Characteristics

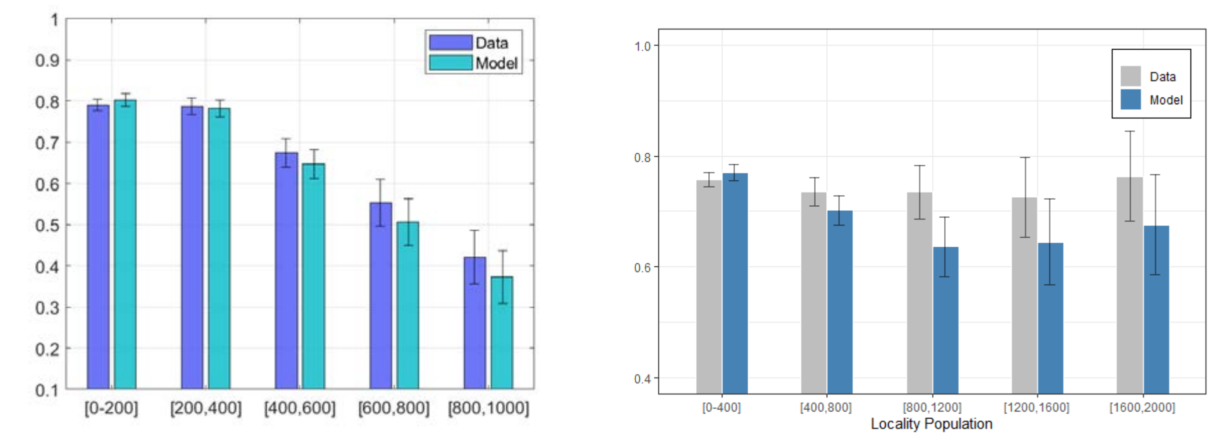
NOTES. Panel A of this Figure plots the CDF of the wage elasticity for the assigned teachers in the counterfactual scenario where all wage bonuses would be removed along with the distribution of the wage elasticity of the new teachers that chose to be matched rather than the outside option under the current policy. Panel B then plots the average characteristics of the individuals belonging to these two groups.

Figure C.3: Model Fit: Teacher Score



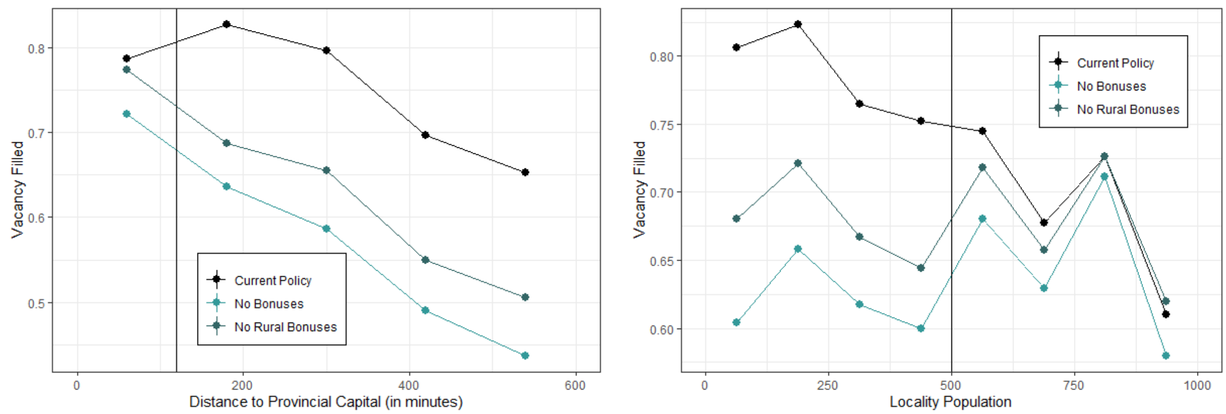
NOTES. This figure uses simulated assignment data which is generated by running the serial dictatorship algorithm using predicting utilities computed from the estimates from Table 3 as well as a randomly drawn set of taste shocks ϵ_{ij}. It then compares the average score of teachers assigned to vacancies observed in the actual data and the simulated data depending on the associated school's distance to the provincial capital and locality population.

Figure C.4: Model Fit: Vacancy Filled



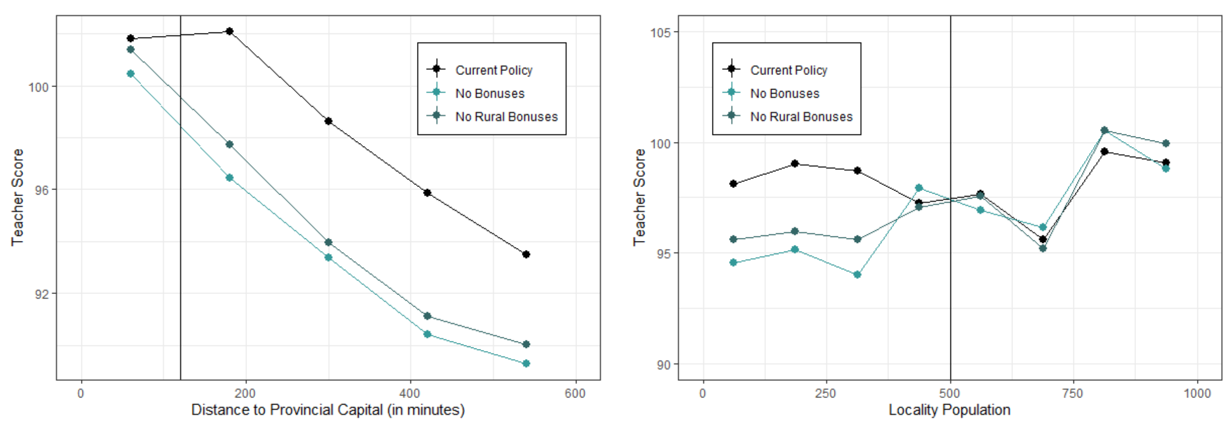
NOTES. This figure uses simulated assignment data which is generated by running the serial dictatorship algorithm using predicting utilities computed from the estimates from Table 3 as well as a randomly drawn set of taste shocks ϵ_{ij}. It then compares the share of vacancies filled observed in the actual data and the simulated data depending on the associated school's distance to the provincial capital and locality population.

Figure C.5: Global Policy Evaluation: Vacancy Filled



Notes. This figure uses simulated assignment data which is generated by running the serial dictatorship algorithm using predicting utilities computed from the estimates from Table 3 as well as a randomly drawn set of taste shocks ϵ_{ij}. It then compares, along the population and distance to provincial capital dimension, the average score of teachers assigned to vacancies under three counterfactual scenarios: (a) under the current policy, (b) in the absence of all wage bonuses, (c) in the absence of rural wage bonuses only.

Figure C.6: Global Policy Evaluation: Teacher Score



Notes. This figure uses simulated assignment data which is generated by running the serial dictatorship algorithm using predicting utilities computed from the estimates from Table 3 as well as a randomly drawn set of taste shocks ϵ_{ij}. It then compares, along the population and distance to provincial capital dimension, the share of vacancies filled under three counterfactual scenarios: (a) under the current policy, (b) in the absence of all wage bonuses, (c) in the absence of rural wage bonuses only.

D Matching with contracts: Theory

Let us consider a framework where we have a set of teachers T, a set of schools S and a set of possible wages W. We define a contract as a school, a teacher and a wage where the set of possible contracts is denoted $X = T \times S \times W$. We leverage the seminal result in Hatfield and Milgrom (2005) that, under some regularity conditions on preferences, a stable set of contracts always exist. This means that there exists an allocation such that there is no pair of school and teacher that would want to deviate and break their current match to match together instead, whatever the wage proposed. In a traditional labor market, this framework would typically be used in order to take into account that other dimensions such as wages or amenities can be leveraged as an additional market clearing device. However, in most labor markets for public servants, wages usually act as a tool for the central planner to achieve a given social objective. There is thus scope for using this framework to guide policy makers in finding the most cost effective way to achieve such an objective. We will thus show that, by encoding a given social objective in schools' preferences, the matching with contracts framework can indeed be used to find the most cost effective stable set of contracts which would reach this objective.

We start by defining agents' preferences over contracts. Teachers' preferences over each school-wage pair were already identified and estimated in the previous section. We thus need to specify schools' preferences such that the school proposing matching with contracts algorithm will give us the most cost effective wage schedule that would reach our social objective under the assignment mechanism currently in place in Peru. We define our social objective as reaching an allocation under the current assignment mechanism in place in Peru where every school would have at least one teacher with a score above a given threshold $\bar{s}$. We thus assume that all schools rank contracts for their first open slot such that:

- $\{(i, w_1) : s_i \geq \bar{s}\} \succ \{(l, w_2) : s_l < \bar{s}\} \quad \forall (i, l, w_1, w_2) \in T^2 \times W^2$
- $\{(i, w_1) : s_i \geq \bar{s}\} \succ \{(l, w_2) : s_l \geq \bar{s}\} \quad \forall (i, l) \in T^2$ and for any $w_1 < w_2$
- $\{(i, w_1) : s_i < \bar{s}\} \succ \{(l, w_2) : s_l < \bar{s}\} \quad \forall (i, l) \in T^2$ and for any $w_1 < w_2$
- $\{(i, w)\} \succ \{(l, w)\} \quad \forall (i, l, w) \in T^2 \times W \iff s_i > s_l$

The first requirement states that a school would prefer any teacher with a score above $\bar{s}$ to a teachers below $\bar{s}$ irrespective of the wage. This makes sure that schools will increase wages until at least one good quality teacher is willing to accept their offer. The second and third requirement state that among teachers with a score above $\bar{s}$ and among the teachers below $\bar{s}$ schools would always prefer to hire at the cheapest cost. The fourth requirement allows to break ties by stating that for a given wage, schools would prefer the highest quality teacher. This last requirement also makes sure that the final allocation can be reached by using the same assignment mechanism as the one currently used in Peru. For the remaining slots, we assume that schools instead use the following ranking:

- $\{(i, w_1)\} \succ \{(l, w_2)\} \quad \forall (i, l) \in T^2$ and for any $w_1 < w_2$
- $\{(i, w)\} \succ \{(l, w)\} \quad \forall (i, l, w) \in T^2 \times W \iff s_i > s_l$

This makes sure that schools will stop increasing wages to compete for good quality teachers once they managed to attract one. Given that good quality teachers are scarce, schools would never stop increasing wages without this requirement and the algorithm will never converge. Of course this can be adjusted depending our the objective function. An alternative objective that we will consider will be to fill every vacancy with any teacher irrespective of quality. In that case, schools' preferences need to be adjusted such that they would be willing to increase wages until they fill all their vacancies irrespective of the quality of the teachers they attract. We can now state our main result.

Proposition 1. *Under the preferences and social objectives described above: (i). The outcome of the school-proposing matching with contracts algorithm gives the lowest wage schedule that achieves these social objectives.*
(ii). Each iteration of the algorithm gives the allocation maximizing our social objectives under the constraint that wages cannot exceed the proposed wages at this round.

Sketch of Proof:

Proposition 1.(i) is a direct implication of stability and that the outcome reached is school-optimal. Given how schools' preferences are defined, stability implies that a given school would always prefer to pay less to attract a teacher irrespective of its quality. This implies that in a stable allocation schools cannot lower their wages or they will lose their current match. If they could lower their wages and still keep their slots filled, this would contradict stability. On top of this, we know from that the school-optimal set of contracts maximizes schools' surplus which implies, given schools' preferences that it will minimize the equilibrium wages. Following the same argument, Proposition 1.(ii) is a direct implication of stability under the constraint that the wages proposed cannot exceed a given threshold.

Let us now describe the school-proposing matching with contracts algorithm:

Round 1: Each school proposes to its most preferred teacher-wage pair. Teachers are tentatively assigned to the proposing schools at the wage specified in the contract. All schools which did not fill at least one vacancy move to the next round.

Round k: Each unassigned school proposes to its next preferred teacher-wage pair. Teachers choose their preferred offer from those made in all rounds up to k. All unfilled schools move to the next round.

The algorithm stops once all schools are filled or once all unfilled schools run out of offers. However, given our assumptions on schools' preferences, we can show that we can rewrite this algorithm and simplify it significantly. Indeed, given that all schools have the same preferences and that, for a given wage, teachers with a score below $\bar{s}$ are dominated by teachers with a score above $\bar{s}$, we can decompose the algorithm in two stages. First, start by running the algorithm only with above $\bar{s}$ teachers. Then run the serial dictatorship algorithm with the remaining slots and the remaining teachers using the wages resulting from the first round. We thus describe here the algorithm which allocates the n teachers which have a score above $\bar{s}$.

Round 1: Each school proposes to the highest quality teacher at the lowest wage possible. This teacher is tentatively assigned to its preferred school. All schools which still have an unfilled vacancy move to the next round.

Round n: Each school with remaining vacancies proposes to the lowest quality teacher at the lowest wage possible. This teacher is tentatively assigned to its preferred school. All schools which still have an unfilled vacancy move to the next round.

Round $n+1$: Each school with all vacancies empty start proposing to the highest quality teacher at a slightly higher wage. This teacher chooses its preferred offer from those made in all rounds up to $n+1$. All schools which still have an unfilled vacancy move to the next round.

Round $k > n+1$: Each school with all vacancies empty start proposing either to their next preferred teacher at the same wage or to the highest quality teacher at a slightly higher wage. Teachers choose their preferred offer from those made in all rounds up to k. All schools which still have an unfilled vacancy move to the next round.

The algorithm stops once every school has at least one of its slot filled. We can also show that this algorithm is equivalent to iterating the serial dictatorship algorithm taking teachers' score as priorities and only letting the unfilled schools increase their proposed wages at each round which makes it very easy to implement.

From the description of the algorithm, we can see that at each iteration the sum of the wages proposed is weakly increasing while the share of unfilled school is weakly decreasing. We can thus use Proposition 1 to draw a cost efficiency frontier showing us, for a given budget, what would be the allocation minimizing the share of schools without a good quality teacher or, for a given objective, what would be the cheapest way of reaching it.