Increasing Teacher Pay To Help Dismantle Structural Inequality Evidence from Centralized Teacher School Choice in Peru[†]

Camila Alva Matteo Bobba Tim Ederer Gianmarco León-Ciliotta
Christopher Neilson Marco Nieddu

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Abstract

This paper studies the inequality in access to teacher quality in the context of Perú and evaluates whether teacher compensation policies can contribute to reducing it. We evaluate the recruitment and productivity effects of a large increase in the salary of public-sector teacher jobs in rural Perú. Using a regression discontinuity design induced by arbitrary cutoffs in the policy we show that school vacancies offering 25 percent higher wages attract better teachers, and that students in those primary schools have better performance on standardized test scores three years after the policy change. We then estimate a model of teacher school choice with preferences over school attributes using data on teachers' realized choices from the country-wide assignment of school vacancies. Counterfactual policy experiments allow us to benchmark the cost-effectiveness of the current wage-bonus policy against alternative policy levers aimed at reducing structural inequalities in the access to high-quality teachers.

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1 Introduction

The level and structure of public sector compensation play a key role in the ability of governments to attract, retain and motivate high-quality employees. However, contracts in the public sector typically feature quite rigid wage profiles, often exclusively based on seniority, which lead to workers sorting on non-pecuniary aspects of employment (Rosen 1986). This issue is particularly important for the provision of services in jobs or locations where working conditions can be less attractive, which therefore end up attracting low-quality applicants. In the education sector, this translates into large and persistent differences in teacher quality between regions. This is particularly worrying given the recent evidence that teacher quality at all levels has long-term consequences on adult labor market outcomes (Araujo et al. 2016, Chetty et al. 2014). In spite of how potentially important this aspect of teacher compensation could be, the evidence on the effectiveness of wage policies in the teacher labor market or the mechanisms through which they may operate is scarce.

In this paper, we study the recruitment and productivity effects of a policy that raised public-sector teacher salaries by about 25% at 50,000 teaching positions in over 17,000 rural schools spread across Perú. Arbitrary cutoff rules for policy eligibility tied to population counts generate local quasi-experimental variation in wages across schools. We also take advantage of the fact that starting in 2015 the Ministry of Education introduced biannual centralized recruitment drives for the allocation of contract (fixed-term) teachers across the entire country. These two institutional features represent a unique setting to study teachers' preferences from realized choices, and to analyze their sorting patterns across schools/locations with different wage levels. Importantly, the transparent and meritocratic nature of the allocation system provides us with a reliable and standardized measure of competence by means of the scores in the teacher evaluations that are used to determine priorities in the assignment mechanism.

We start by comparing schools with vacancies in locations around the population threshold of the wage policy. Regression-discontinuity estimates show that teachers who took a position at a rural school with higher wages score higher by 0.7 of a standard deviation in the competency test when compared to teachers who choose a position in lower paying but otherwise similar schools. Teachers in higher paying schools are also more effective, as their students perform significantly better in national standardized achievement tests three years after the policy change. These effects on student outcomes are very large in magnitude and they are even larger in schools that had an open vacancy in the previous recruitment drive, suggesting a link with the sorting pattern by teacher quality. In fact, we show that the treatment effects on achievement are very small and not different from zero for schools that had no vacancies throughout the period while they are entirely concentrated among schools that had multiple vacancies and hence that are more likely to experience a prolonged inflow of new (higher-quality) teachers.

This first set of results suggests that there is no meaningful direct effect of wages on productivity of individual teachers already hired in the system, which is consistent with a recent and related paper studying a large unconditional salary increase in Indonesia by de Ree et al. (2018). The authors show that increases in wages have a precise zero effect on student outcomes, and therefore conclude that wage policies are not likely to affect the quality of education. However, in the Indonesian context most teachers are public servants with permanent contracts, thus the selection channel is unlikely to yield relevant effects in the short or medium run. The Peruvian educational system, on the other hand, is similar to the one in other Latin American or African countries, where a large proportion of public sector teaching jobs are staffed by contract, fixed-term teachers. This generates a significant flexibility in the labor market for teachers and a large turnover where the selection margin of wage incentives can play an important role in improving the quality of teachers and student outcomes within a relatively short time pan. As found in other settings (Duflo et al. 2015), the local institutions determining how teachers are evaluated and assigned could be an important necessary condition for increased wages to lead to a meritocratic sorting of talent. The fact the Peruvian system allows for some teacher jobs to be flexible, paired with the fact the assignments are done in a transparent, meritocratic way may play an important role in explaining the observed policy effect.

We next estimate a discrete choice model in order to better quantify the channels through which the structure of wage incentives shape sorting by quality across space. To the extent that in the assignment mechanism teachers choose their school sequentially based on their ranking in the score distribution, the observed positive effect of wage incentives on the quality of the newly-assigned teachers is consistent with a positive wage elasticity. The estimated model allows us to quantify the magnitude of such elasticity and compare it with the other determinants of teachers' demand for job postings, such as their willingness to move/commute away from their current residence and the value of local amenities. The model ability to correctly pin down the wage elasticity and hence to predict counterfactual changes in the wage schedule is validated by replicating the observed changes in teachers' score at the population cutoff of the wage policy. Counterfactual experiments suggest that wage bonuses may be an effective policy to level the playing field for children attending schools that are located close to densely populated (urban) areas. However, it is unlikely that wage bonuses would be an efficient instrument to affect sorting at a national scale. Teachers have a strong distaste for moving far away from where they live, which largely outweighs the implied wage elasticity. Alternative place-based policies such as investments in teacher training or in school infrastructures in remote, less desirable locations may be more cost-effective in reducing spatial inequalities in the quality of education provision.

These results contribute to the recent and rapidly growing literature on the personnel economics of the state (see Finan et al. (2017) for a review). In particular, Dal Bo et al. (2013) show that increased compensation for public sector positions in Mexico lead to a larger pool of applicants, and a higher quality of hired employees. Deserranno (2019) finds that higher financial incentives attract more applicants and increase the probability of filling a vacancy, while crowding out pro-socially motivated agents.

We also add to the literature on teacher compensation and "pay for performance" schemes (Muralidharan and Sundararaman 2011, Fryer 2013, Barrera-Osorio and Raju 2017, Berlinski and Ramos 2020), showing that relative pay differences can have significant effects on the re-allocation of talent across jobs. In the Peruvian context, teachers compensation is low relative to other college graduates and at baseline there are issues with staffing rural positions with talented teachers. Increasing salaries in this setting is found to generate positive productivity effects through improved ability to recruit relatively more talented teachers. From a policy perspective this evidence seems particularly appealing to the extent that pay-for-performance reforms are in general less politically viable in the public sector than unconditional wage increases targeted at specific job postings.

More generally, our results are relevant for the design and the evaluation of policies that aim at increasing teacher compensation. Several global policy think tanks have recommended for years to increasing teacher pay in low-income countries as a way to attract talents toward the education sector (McKinsey 2010, UNICEF 2011, UNESCO 2014). Prior evidence seems to suggest a positive relationship between teacher earnings and school productivity in the long-run (Card and Krueger 1992a,b). However, de Ree et al. (2018) note that while increasing teacher compensation can improve the overall talent pool through the extensive margin eventually, it may take a long time to see the effects and it will be very costly during the transition if higher earnings do not translate into higher productivity for current teachers as well. This paper addresses a different aspect of teachers' incentive schemes and highlights the notion that not only the level of compensation matters, but also the way it varies within job postings. We show that this channel can have significant effects on the re-allocation of teachers across schools, with crucial implications for the distribution of the quality of education provision.

2 Context and Data

2.1 The Labor Market for Teachers in Perú

In 2015, the Peruvian education system employed about 180,000 teachers in roughly 110,000 public schools. Teacher's wage scales mostly ignore local amenities of the job, thereby generating geographical differences on how local labor markets clear, i.e. while there is large demand for highly attractive positions (e.g. large cities and well equipped schools), it is challenging to staff some of the roughly 17,000 small rural public schools scattered all over the country. Figure 1 depicts the regional inequalities in school inputs and outputs. The map in the left shows the proportion of teachers who score in the upper quartile in each district in the national evaluation tests of 2015 and 2017, and present it side by side with a similar map showing the proportion of students scoring in the upper quartile in the national standardized test in 2018. These maps are a mirror image of each other, showing that the poor provision of schooling inputs may be a major factor in reproducing historical inequalities between regions in Perú.

Teachers in public schools are hired under two distinct types of contracts: on the one hand, permanent teachers (*docentes nombrados*) work in conditions similar as in other countries: they are civil servants with permanent contracts, and in practice, the chances of dismissal are close to zero; on the other hand, contract teachers (*docentes contratados*) can also be hired by the central administration to work on a specific school for an academic year, with the option of renewing the contract for a total of two years. Contract teacher positions are typically opened when the local administration can't secure a long term source of funding to hire a permanent teacher and are usually conceived as entry-level positions in the teaching career. [1] In Perú, by 2015, 15% of all primary school teachers were hired under this regime, with a much higher share in the most rural schools (46%, see Table 1). These teachers are required to have a teaching diploma (certification), either from a university or technical institute. In cases in which the teaching vacancy remains unfilled, the school is allowed to hire adults from the local community without teaching certifications.

Not unlike other countries in the world, public school teachers in Perú are paid a fixed wage, and the scale of these wages reward seniority, rather than merit (Bau and Das 2018). Teachers' wages depend on (i) whether they are permanent or contract teachers, (ii) their seniority, and (iii) the location where they work.[2] In 2015, contract teachers received a

[1] This is a common strategy used in other public educations systems around the world, especially in developing countries. Some notable exceptions are some countries in Southeast Asia, where teachers are included as part of the wider body of civil servants.

[2] On top of the fixed wages, some teachers receive additional bonuses for taking specific responsibilities as e.g. deputy principals, or for teaching in special education or bilingual schools.

monthly wage of S/ 1,550 (approximately, 515 USD using the exchange rate of S/ 3 per USD, from January 2015) in primary school, whereas the wages of permanent teachers increase with experience, starting at S/ 1,451 and reaching S/ 2,902. Overall, public school teachers' compensations are low: the unobserved wage gap between teachers and other professionals with comparable characteristics and educational levels are 30 to 40 percent lower (Mizala and Ñopo 2016).[3]

Traditionally, the recruitment of permanent and contract teachers in Perú was done in a decentralized fashion. Each year, the central government decided the number of open positions in each of the 220 administrative education units (Unidad de Gestión Educativa Local, UGEL), which were expected to organize recruitment at the local level. Little supervision of the process and wide institutional heterogeneity between local administrations rose concerns about lack of transparency, corruption and political patronage in the hiring of public school teachers. In an effort to make the process more transparent and meritocratic, the Ministry of Education (MINEDU) introduced nation-wide, centralized, recruitment drives, where teacher job postings and teacher job applications were processed on a single, centrally managed, platform.

The first national recruitment drive took place in October 2015, followed by another round in May 2017. More than 200,000 teachers applied for a position each year for a total of about 56,000 contract teaching positions available in 2015 and 73,000 in 2017. These numbers also include unfilled permanent positions, which were later re-posted as contract teaching positions. Teachers recruited through the 2015 and 2017 drives started teaching in the 2016 and 2018 academic years (March-December), respectively.[4] The application process included a standardized teacher evaluation in which all applicants took a knowledge test on their specific field of expertise, e.g. primary education, secondary math, secondary history and social sciences, etc. Those who passed the minimum required grade were eligible for a permanent position, and went through to participate in a two-sided matching mechanism, which includes an in-school (subjective) evaluation.[5] Instead, contract teaching positions

[3]This stands in contrast with institutional settings in other countries in South East Asia, such as India, Pakistan or Indonesia, where public teachers tend to earn more than other comparable professionals. See de Ree et al. (2018) for references.

[4]At the end of 2016 (and 2019) academic year, contract teachers had the option to re-apply to their current positions, and their contracts were renewed for an additional year subject to the approval of the school's administration. If the position was not allocated through this mechanism, it is filled by applicants from the 2015 drive following the serial dictatorship mechanism. These teachers worked in the chosen positions during the 2017 (and 2020) academic year.

[5]Teachers first choose an UGEL and their field of expertise, and are asked to list their preferences for available positions. Based on the rank in the centralized test, schools receive a list of up to twenty teachers who are then evaluated at the local level. In this second phase, they are scored based on an in-class demonstration, their experience, and an interview. At the end of the process, the grade in the centralized test and the decentralized evaluation are added, and positions are allocated to the highest scoring teacher

are filled using a one-sided matching mechanism. Applicants first choose an UGEL and field, and then they are sequentially assigned to the available vacancies according to a serial dictatorship algorithm. The highest scoring teachers within each UGEL/Field got to choose first among the available teaching vacancies. Once a position is assigned, it is eliminated from the list of available options. The next highest scoring teacher makes a choice, and so on until either all teaching positions are filled or all teachers are allocated to a position. Teaching vacancies that are not filled through this mechanism are allocated by the UGEL in a decentralized fashion, progressively relaxing the requirements until the vacancy is filled. As a result, those vacancies are often taken by teachers who are potentially less qualified.[6]

2.2 Wage Bonuses in Rural Locations

Many factors may be playing a part in determining the lack of quality teachers being recruited in rural areas. Rural schools have lower levels of infrastructure and other teaching inputs. Teachers in rural areas face a number of challenges, from scarcity of very basic school inputs and lack of services, public goods and local amenities, to simply being isolated from friends and family. If wage setting policies do not adequately compensate for the lack of amenities in rural areas, those jobs will be less attractive. As a consequence, vacancies in rural schools will be both harder to fill and may be filled with lower quality applicants.

These considerations motivated the government to introduce a reform to the way public school teachers are paid, significantly increasing wages for those who choose to take a position in a rural school. A new classification of schools was used to allocate wage bonuses based on two pre-established criteria: (i) the population of the locality where the school is located (measured by population counts in the latest available census), and (ii) the time it takes to travel from the locality to the province capital (measured on the basis of GPS coordinates taken by an inspector after taking into account usual modes of transportation and types of roads available each year.) The most rural schools (henceforth, *Rural 1*) were those located in localities with less than 500 inhabitants, and for which it takes more than 120 minutes to reach the province capital. The second category *(Rural 2)* is reserved for those schools in localities with less than 500 inhabitants and which are located between 30 and 120 minutes from the province capital, or those in localities with 500-2,000 inhabitants and are farther

who chose each position. In 2015 and 2017 there were 19,500 and 37,000 vacancies for permanent teachers, respectively. The two-sided nature of the assignment mechanism of permanent teachers may induce some strategic incentives on the teachers' side and hence complicates inferring teacher preferences over schools from the observed choices and assignment. In this study, we thus focus on *contract teachers*.

[6]More precisely, unfilled vacancies are first assigned to certified teachers from a different UGEL, again using a deferred acceptance matching mechanism based on their scores in the standardized test. Vacancies that are still unfilled after the first two rounds are later assigned in a third round, to (i) certified teachers from different specialities, or (ii) teachers without certifications.

than 120 minutes from the province capital. The final set of rural schools (*Rural 3*) are those in localities with 500-2,000 people and are closer than 120 minutes, or those with less than 500 inhabitants, and that are less than 30 minutes away from the capital. All other schools are classified as Urban.

The policy was first implemented in January 2014 providing only *permanent teachers* in *Rural 1*, *2*, and *3* schools with wage bonuses of S/ 200, S/ 100, and S/ 70, respectively. In August 2015, the bonus for teachers in *Rural 1* was increased to S/ 500, and wage bonuses were extended to contract teachers as well. Importantly, these changes were announced and introduced in August (the middle of the school year) and thus can't affect the selection of teachers prior to the centralized recruitment drive of 2015. The bonus for *Rural 1* is fairly generous, as it represents 30-40% of the earnings of contract teachers and 20-30% of the earnings of permanent teachers. Figure 2 displays the rural categories and the associated wage bonuses as a function of population and time-to-travel as well as the timeline of the implementation of the policy.

Figure 3 shows how teacher wages vary depending on the travel distance from the school to the province capital (left), and on the number of inhabitants in the locality. The Figure is based on teachers payroll data (contract teachers) for December 2015, and shows that teacher wages exhibit a large discrete jump when crossing from the left the 120 minutes threshold, and from the right the 500 inhabitants threshold, that is the two criteria used to identify *Rural 1* schools. The average wage for teachers in schools which are within two hours from the province capital are about S/ 300 lower than in schools which are slightly further away. Similarly, the wages drop by S/ 200 when the population of the school locality is under 500 inhabitants. When considering both criteria simultaneously (the diamonds in both panels), the observed wage difference between schools missing either of the two criteria and schools meeting both of them is approximately S/ 380. This number matches closely the "theoretical" S/ 400 (S/ 430) difference in the wage bonus between *Rural 1* and *Rural 2* (*Rural 3*) schools.

2.3 Data

In this paper, we use a large array of administrative datasets from the Ministry of Education, which are linked through unique identifiers at either the teaching position level, or at the school level, for each year of our analysis.

Teacher employment records and payrolls (NEXUS). This is an official dataset used by the Ministry of Education that records all teachers in the Ministry's payroll. It identifies teachers, the school to which she/he is assigned (but not the grade), the type of contract/position (permanent or contract, number of hours, etc.), the base wage and any additional wage bonuses. This information is available for every year between 2012–2018, at the start, middle and end of each school year (March, August and December, respectively.)

Teachers' nation-wide recruitment drives. For the centralized processes that took place in the October 2015 and 2017, these datasets include information on the scores for every applicant in the centralized test, the chosen UGEL, and field of expertise. Additionally, the information from these recruitment drives include the list of all positions available for permanent and contract teachers, as well as the locality-level values of the population and time-to-travel criteria used in each year to assign the wage bonuses.[7]

School Characteristics. The school census provides information on a number of school characteristics: number of pupils, libraries, computers, classrooms, sport facilities, staff (teachers by status, administrative staff), as well as village-level characteristics: access to basic services (electricity, sewage, water source) and infrastructure (community phone, internet, bank, police, public library). This information is reported yearly by school principals.

Student outcomes. The *Evaluación Censal de Estudiantes* (ECE) is a national standardized test administered at the end of every school year at selected grades by the Ministry of Education to almost all public and private schools throughout the country (coverage is around 98%). We use information on ECE 2016 and 2018 for students in the fourth grade in public primary schools, covering curricular knowledge of math and language (Spanish).[8]

2.4 Sample Description

Our sample contains the universe of rural primary schools included in the ECE evaluation process, that is, schools with five or more students enrolled in fourth grade. While positions in secondary schools were also open in the two rounds of the national recruitment drive, there are far less secondary schools in rural areas, and the majority of teaching positions available in these schools are permanent, rather than contract teaching positions. Urban schools, defined as those in localities with more than 2,000 inhabitants are not considered in the analysis, since this population threshold is also used to target other social and education policies.

To study the effects of the wage bonus on the selection of teachers, we limit our sample to primary schools that had an open vacancy for a contract teacher. Importantly, the

[7]These criteria have changes over time due to the construction of new roads, new measurements of the schools' locations, and changes in population counts.

[8]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.

probability that a school has such an open vacancy depends on budgetary decisions, and as such, there is no effect of the wage bonus on the probability that a school has an open position, as shown in Appendix Table B.2. The final sample for the empirical analysis is comprised of 8,368 teaching positions over the two recruitment drives in 3,829 rural primary schools, which respectively represent 8% (14%) of the universe of teaching positions in rural areas and 22% (38%) of the universe of rural public primary schools in Perú in 2016 (2018).

The scatter plot in Figure 4 shows the distribution of primary schools in our sample along the two dimensions that determine the assignment of the rural wage bonus, where the size of the dots is proportional to the total number of open vacancies in each school over the two recruitment drives. The distribution of vacancies reflects fairly well the distribution of schools along both targeting criteria of the policy – i.e. locality population size and time-to-travel distance to the provincial capital. There is clearly a large mass of data around both thresholds that define *Rural 1* schools, with relatively more mass concentrated around the distance threshold.

Panel A of Table 1 reports means and standard deviations of school characteristics, separately for the schools classified as *Rural 1*, *Rural 2* or *3*, and Urban. Consistent with the policy, teachers' wages are on average 24% higher in *Rural 1* schools when compared to less rural schools, and 39% higher when compared to urban schools. *Rural 1* schools also serve a smaller population of students, have less teachers (albeit a higher share of contract teachers), and they are more likely to have one teacher in multiple grades (multi-grade), lack access to basic infrastructures, such as electricity or water.

Some basic facts about the within-school dynamics of teachers measured during the period 2016-2018 are reported in Panel B of Table 1. The average school in the sample has 1.5 open vacancies, which correspond to half of the teaching positions in each school. This reflects the high turnover rate in rural schools, a by product of the large proportion of contract teachers working in rural primary schools. As expected, *Rural 1* schools have a much higher turnover, compared to other rural and urban schools. Finally, not all vacancies are filled. About 9% of them remain vacant at the end of the recruitment drive, and end up either going unfilled or occupied by a non-certified teacher.

Panel C of Table 1 reports descriptive statistics for socio-demographic characteristics of contract teachers participating in at least one of the two centralized recruitment drives and recruited in the primary schools in our sample. When compared to applicants who got a position in urban or less rural schools, applicants who ended up in *Rural 1* schools are on average more likely to be male, they are one year older and they are less likely to be new entrants to the teaching sector in public schools (novice teachers). Importantly, the average applicant who ended up in a *Rural 1* school performs 0.3 of a standard deviation worse in centralized admission test than the average applicant hired in a less rural school, and 0.9 worse when compared to applicants ending up in urban schools.

Evidence from other settings shows that skill and content knowledge tests administered in the context of merit-based teacher selection procedures are strong predictors of teacher quality (Araujo 2020). In our context, the data on test scores for students in primary schools available from the Peruvian setting does not allow us to compute teacher value added measures (see Section 2.3), and the simple cross-school correlation between teacher scores and student achievement test scores may not be very informative as it is likely to reflect sorting through the assignment mechanism of better teachers into schools with better students. We thus exploit matched teacher-classroom observations for a subset of the available data on primary schools, which allow us to focus on the within-school variation between teachers' scores in the centralized test (2015) and the test scores obtained by their students at the end of the school year.[9] Figure 5 shows that there is indeed a significant and positive relationship between the the two (residualized) scores, which is suggestive of the fact that the performance in the screening test used for the centralized assignment may indeed capture some information about teaching effectiveness.

3 Evidence on the Effects of Increased Teacher Wages

3.1 Identification and Estimation

We estimate the causal effect of unconditional wage increases on (i) the selection of teachers, and (ii) student outcomes. To identify these causal effects, we use the assignment rules of the rural wage bonus in a regression discontinuity design (RDD) framework by comparing teacher characteristics and student outcomes at both sides of the cut-off points. Our main estimating equation is as follows:

$$y_{ijt} = \beta_0 + \beta_1 Rural1_{jt} + f(pop_{jt}, time_{jt}) + \delta_t + \epsilon_{ijt}, \tag{1}$$

where y_{ijt} is the outcome variable for teacher (or student) i in school j at time t. The treatment is defined by *Rural1*, an indicator variable equals to one school j's locality has less than 500 inhabitants ($pop_{jt} < pop_c$) *and* it is located more than 120 minutes away from the province capital ($time_{jt} > time_c$). In our main specification, we control for flexible polynomials $f(\cdot)$ of the running variables. The parameter of interest is β_1, which captures

[9] CHECK (Marco): Explain here the SIAGIE data and why we are able to match only a subset of the primary schools. Give sample size for the matched observations that we use in Figure 5 (including urban schools) and explain why we cannot use this data for the RD analysis.

the effect of wage bonuses on teacher outcomes or student outcomes. We pool data from the two centralized recruitment drives (and subsequent school years), therefore δ_t is a time dummy indicating the specific year of the recruitment drive (for teachers) or the school year (for students), and the error term ϵ_{ijt} is clustered at the level of the assignment of the wage bonus, that is school$\times$year.

The policy under study may have generated incentives for school principals and administrators to partly manipulate some of the information required for the assignment rule, thereby leading to a violation of the continuity assumption of the RDD framework. We test this empirically in Figure 6, where we display the empirical densities based on local-quadratic density estimators with the corresponding confidence intervals for each of the assignment variables. The population threshold is based on census data, and as such it is very hard to manipulate. The figure in the left shows that indeed, there is no significant discontinuity at the 500-inhabitants threshold for neither of the years of interest. The panel at the right hand side of Figure 6 shows the empirical density of observations around the time-to-travel distance threshold. There is a significantly larger mass of schools that fall just into the *Rural1* category. The formal manipulation tests (McCrary 2008) confirm these visual patterns.[10] Time-to-travel information is gathered by inspectors from the Ministry of Education, who physically go to schools and take a GPS measurement of the school's location. The GPS measurement was updated in 2017, and by that point, the previous measurement was public information, which provides larger incentives for schools close to the threshold to manipulate the measurement and gain access to the wage bonus for all of their teachers.

In sum, the data shows that schools may be sorting endogenously across the time-to-travel distance threshold, whereas there seems to be no strategic manipulation of the population assignment variable. To further support this claim, in Appendix Table B.1 we show that school and locality-level covariates are smooth around the population threshold. Column (1) reports RD estimates of the empirical specification in Equation (1) for the population discontinuity. The point estimates for the β_1 coefficient are very small and not statistically different from zero in all but two cases (out of the 34 covariates considered).[11] We therefore only rely on the exogenous variation provided by the population threshold for our main estimation. Given continuity of potential outcomes around the population cutoff, the following

[10]The estimated (robust) t-statistic for the null hypothesis of no difference in height between the two interpolating kernel density estimators for the time-to-travel discontinuity is 2.08 (p-value=0.037) in 2018 and 1.39 (p-value=1.16) in 2016. T-stats are much lower in size and are not statistically significant for the population discontinuities: 0.37 in 2016 and 0.49 in 2018.

[11]We get a similar result when limiting the sample to schools that had an open position for a contract teacher in 2016 or 2018, which are displayed in columns 2 and 4, respectively, of Appendix Table B.1.

reduced-form equation identifies an Intention-To-Treat (ITT) effect of the policy:

$$y_{ijt} = \gamma_0 + \gamma_1 \mathbf{1}(pop_{jt} < pop_c) + g(pop_c - pop_{jt}) + \delta_t + u_{ijt}, \tag{2}$$

where, as before, $g(\cdot)$ is a flexible polynomial in the distance from the population cutoff and u_{ijt} is an error term clustered at the school-level. We estimate γ_1 non-parametrically using the robust estimator proposed in Calonico et al. (2014) through local-linear regressions that are defined within mean-square error optimal bandwidths. The γ_1 parameter, scaled by the unconditional effect of crossing from above the population thresholds on the probability that schools are classified as *Rural 1* defines a Local Average Treatment Effect (LATE) of the policy (Hahn et al. 2001). We first show the compliance effect (first stage) in Figure 7. Schools in villages with less than 500 people are 42% more likely to be eligible for the wage bonus, compared to those in a locality with more than 500 people. These considerations motivate the use of a fuzzy regression discontinuity (FRD) approach, whereby an indicator function for crossing from above the population threshold, $\mathbf{1}(pop_{jt} < pop_c)$, can be used as a valid instrument for the schools being in the *Rural 1* category.[12]

3.2 Wage Bonuses and the Demand for Teaching Positions

As shown in Section 2, the average contract teacher in a *Rural 1* school earn S/ 380 more than those in a school in a locality that is just above the 500 inhabitants threshold, which on average represents an increase in the unconditional wage of 23%. This wage increase makes positions more desirable, increasing the demand and potentially leading to a better selection of personnel (Deserranno 2019, Dal Bo et al. 2013). We analyze these margins of response in Table 2. In these regressions, the level of observation is the vacancy, and we therefore limit the analysis sample to those schools that had an open position. We display for different outcome variables both the direct effect of crossing the population threshold (ITT) and the effect of the wage bonus (LATE) associated to the γ_1 coefficient in Equation (2).

About 13% of the open teaching positions do not get filled through the centralized recruitment process, and therefore are filled either by other certified teachers in the additional assignment rounds (3.4%), by a non-certified teachers (7.6%), or go unfilled (2%) increasing the workload of other teachers. Recall that positions filled outside the centralized recruitment drive are (almost by definition) not assigned in a meritocratic fashion, therefore raising concerns about the quality of these teachers and potentially having negative consequences

[12] Alternatively, we could use a sharp RD limiting the sample to schools located above the time-to-travel threshold – see Figure 4. However, this would imply conditioning on a variable that also vary with the treatment (time-to-travel), and leaving out a large portion of schools that cross the threshold in the diagonal, i.e. from *Rural 3* to *Rural 1* , thereby missing relevant variation in the data.

on the quality of education. The first panel of Figure 8 shows that crossing the population threshold does not lead to a significant change in the probability that a vacancy gets filled by a certified teacher. This result is also shown in a regression format in Column (1) of Table 2. The point estimate of the LATE of the wage bonus is 8.6 percentage points and it is statistically indistinguishable from zero.[13]

Even though the number of filled vacancies do not significantly change due to the wage increases in *Rural 1* schools, higher financial compensation could still be increasing the demand for some positions, leading to higher competition and potentially improving the quality of new teachers. We explore these issues in Columns (2)-(4) of Table 2. Recall that the vacancy allocation mechanism uses a serial dictatorship mechanism, therefore we are unable to directly observe stated preferences over teaching positions. Instead, we can directly infer the demand over teaching positions by looking at the other side of the market, i.e. the relative ranking in which the vacancy was filled. Given that there is a different number of total applicants in each UGEL×field, we normalize the ranking so that it takes values from zero to one, with one indicating the last teacher who applied in the UGEL×field.[14] The average vacancy is filled by the applicant in the 35^{th} percentile in the UGEL×field, and just below the population threshold, positions are filled by candidates who rank 10 percentage points higher. The average vacancy in a school classified as *Rural 1* because it is just below the population threshold (LATE) gets filled by candidates who rank 19 percentage points higher than comparable vacancies in schools just above the population threshold. This evidence suggests that higher paying positions are more desirable among applicants, as this demand effect spurs competition for those vacancies within the assignment mechanism.

3.3 Wage Bonuses and Teacher Quality

More competition for positions could lead to an increase in the quality of applicants who select into higher paying teaching jobs. This effect can potentially be explained by two different mechanisms. On the one hand, higher wages attract new high-quality applicants, increasing the average quality of the marginal applicant who takes a position in a school

[13]In the Appendix (Tables B.4 and B.5), we show that the magnitude of the effect is similar for each of the two recruitment drives, although we have more limited statistical power to identify these effects.

[14]Note that in these regressions we limit our sample to those vacancies that were actually filled by certified teachers through the centralized recruitment drives (about 90% of the original sample). While the point estimate in Column (1) of Table 2 is not significant, there may be concerns that the density of observations for these regressions is not continuous at the threshold. Appendix Figure A.2 shows that this is not the case. While there is a slight discontinuity, the statistical test shows that we can reject the null with a p-value of 0.18. Furthermore, columns (3) and (5) of Appendix Table B.1 show that the vast majority of the predetermined covariates are smooth around the population cutoff even when considering the sample of schools with a vacancy filled by a certified teacher.

offering higher wages. Alternatively, an increase in the quality of the marginal candidate taking a position at a *Rural 1* school could be explained by pure sorting within the system, whereby higher ability teachers who would have otherwise gone to *Rural 2* or *Rural 3* schools are instead choosing *Rural 1* positions due to the wage incentives.

Wage bonuses cause a large average increase in teacher quality, as measured by the standardized scores in the centralized test. The second Panel of Figure 8 shows that there is a sizable discrete jump in quality of teachers at the population threshold. Teachers who choose a position in a locality with less than 500 inhabitants score 0.35σ higher than those who choose to go a to a rural school in a locality with slightly more people. Importantly, this is not a marginal increase in quality, as we show in the third Panel of Figure 8: the probability that the newly recruited teacher comes from the top half of the teacher quality distribution also increases in about 26 percentage points (42 percent). Columns (3) and (4) of Table 2 show the regression results corresponding to the graphical evidence. Teachers who select into a *Rural 1* school have a score that is 0.65σ higher and are 46 percentage points more likely to be in the top half of the distribution.

In Table 3 we study whether higher wages systematically attract teachers with specific characteristics. Our (imprecisely estimated) effect sizes suggest that teachers who select into higher paying positions are more likely to be female (column 1), about two years younger (column 2), and 6.3 percentage points more likely to be novice teachers in the public school system (column 3). This is consistent with the fact that the probability that these teachers have more than 3 years of experience drops by about 16 percentage points (column 5). Taken together, these different pieces of evidence suggest that the vacancies in higher paying positions are partly being filled by new comers that are drawn into the public education system by the wage incentives rather than a pure reallocation effect of the policy within existing teachers.

Having teachers who take positions at the left-hand side of the population threshold being those who would have otherwise chosen a school just at the other side of the threshold is problematic as it would imply a SUTVA violation (Rubin 1986) in the context of our RD design. We address this issue in Figure 9 – and its companion Table B.6 in the Appendix. We run the regression model depicted in equation (2) using as dependent variable an indicator variable which takes the value of one if a teacher who accepts a position at a school just below the population threshold was previously teaching at a school in a location within a certain population range or whether or not she/he was a new comer to the public school system. In the first panel of Figure 9 we plot the left- and the right-hand side intercepts from each regression, while in the second panel we plot the difference between the two, corresponding to the ITT effect of the wage bonuses. Most coefficients reported in the second panel are close to zero, and the large majority of them are not statistically significant. The relatively larger coefficients (though not statistically significant) are concentrated among the population bins to the left of the population cutoff, suggesting that some of the teachers who accept a position at a school just below the population threshold would have otherwise gone to a *more rural* school. Additionally, the size of the effect on the share of new comers to the public school system who end up occupying a vacancy at a school just below the population threshold is not trivial (0.2). This evidence suggests that the observed increase in teacher quality is not the result of a zero-sum game among schools located across the population cutoff, but rather that the wage bonus attracts a quite diverse pool of applicants either coming from schools in localities of a wide range of population size (including urban areas) or new entrants in the education system.

Intensive and Extensive Margins of Selection So far, we have shown that unconditional wage bonuses for teachers choosing a position at a *Rural 1* school cause more competition for higher paying positions, increasing the average quality of recruited teachers. However, this may seem inconsistent with the finding that the probability of vacancies being filled does not change significantly (see column 1 of Table 2). We now turn to explore this issue by showing that cross-posting variations in amenities generate different margins of response to the wage increase. To do this, we use a large array of school and locality characteristics to generate an amenity index of a teaching position.[15]

Table 4 dives into the heterogeneity of the response to the wage bonus across more or less desirable teaching positions (those above or below the median of the principal component of the amenity index.) In Column (1) of Table 4 we show that vacancies in less desirable locations that are allocated with a wage bonus are 43% more likely to be filled out of a baseline probability of 74%. In Column (2) we analyze the effects of the wage bonus on the quality of teachers recruited in less desirable positions. The results show an increase in teacher quality, but the effect is statistically insignificant. However, note that this effect can't be interpreted as causal, since the large and statistically significant effect on the probability of filling a vacancy (column 1) implies that the sample in which this regression is estimated is endogenously selected. In Column (3) we study the different selection effects of the wage

[15] We include school characteristics like whether the school has a science lab, a library, computers, internet access, access to basic services (electricity, drinking water, sewage, etc.), among others. Likewise, to measure village-level amenities, we use access to public services at the village level like electricity, sewage, medical clinics, banks, police stations, etc. The descriptive statistics of all these variables can be found in Appendix Table B.1, where we further show that the large majority (32 out of 35) of these variables is balanced across the threshold. Our desirability index is then generated by taking the first principal component of these variables. In Appendix Figure A.1, we show that there is a strong unconditional correlation between the amenity index and (i) the probability that the vacancy is filled, and (ii) teacher quality as measured by the school-average score in the centralized admission test.

bonus for more desirable positions, i.e. job postings with above median amenity index. In the absence of the wage bonus, these positions are filled 90% of the time by a certified teacher, and an increase in the unconditional wage does not generate a statistically significant change in this probability. However, there is a large and statistically significant gain in the quality of the average teacher recruited in these positions, as shown in Column (4).

To sum up, the introduction of the wage bonus generates a sizable response along the extensive margin of the assignment of teachers into schools among less desirable locations that are, at baseline, less likely to be filled. In more desirable locations, instead, an increase in the unconditional wages spurs more competition along the intensive margin, which in turn causes a large increase in the average quality of recruited teachers.

3.4 Wage Bonuses and Student Achievement

In this subsection, we ask whether the improved selection of teachers due to higher wages lead to improvements in students' academic achievement. While the average school in our sample has few teachers (about 3), the data available does not allow us to match teachers with a specific class, and hence we are unable to pin down the direct effect of having a better teacher (due to higher wages) in the classroom. Instead, we show the 'total policy effect' of higher wages for teachers on students' achievement *in schools that got a new teacher* through the centralized recruitment drive. To do this, we focus on the sample used in Table 2, namely schools that had a chance of attracting a new teacher through an open vacancy in the 2015 or 2017 recruitment drives. We then compare the standardized test scores of students in the 4^{th} grade in 2016 and 2018, between children in *Rural 1* schools and those in *Rural 2* and *3*.

Columns (1) and (2) of Table 5 show RD estimates from pooling student outcomes from 2016 and 2018. We find positive estimates of the effects of the wage bonus on test scores. The average student in a school where teachers receive an unconditional wage increase score 0.37-0.44σ higher in Spanish and Math, respectively. In columns (3)-(6) of Table 5, we split the sample by year, and show that for 2016 there are positive and non-trivial point estimates for both Math and Spanish, but these effects are not statistically significant. In 2018, two years after the introduction of the wage bonus for teachers, we see larger effects of the wage policy: students taught by better paid teachers score are 0.46σ and 0.62σ higher in Spanish and Math, respectively, although the estimates for Spanish are nosier and not statistically different from zero.[16]

Figure 10 corroborates visually the results in columns (5) and (6) of Table 5 by displaying the relationship between the distance to the population cutoff for the locality in which

[16]Importantly, these effects can't be attributed to changes in the teacher-student ratio, which would go in the opposite direction (see Appendix Table B.3).

the school is situated and local averages of 2018 Math score (top charts) or Spanish score (bottom charts), for schools with an open vacancy for a contract teacher in either of the two recruitment drives. As it was the case for teacher scores (see Figure 8), there is a clear negative relationship indicating that student scores monotonically deteriorate as the size of the locality gets smaller. Crossing the population threshold seems to clearly shift up that relationship.

The Ministry of Education classifies students into four categories according to their responses in these standardized achievement tests. The lowest category correspond to students who have below basic knowledge (*Previo al inicio*), and the top category corresponding to outstanding students (*Satisfactorio*). Figure 11 displays the estimated ITT coefficients and the confidence intervals corresponding to our main specification using as dependent variables indicator functions for whether a specific student falls into one of these four categories (the corresponding point estimates and standard errors of the ITT effects and LATEs are also reported in Tables B.8 and B.7 in the Appendix.) The results show that the effects are driven by relative changes in the two tails of the achievement distribution. The proportion of students who are below basic decreases by about 25% both in Math and Spanish in schools that receive the wage bonuses, showing that there is a strong focus on the students at the bottom of the distribution. For the case of Math test scores, there is also a large increase in the relative proportions of competent and outstanding students.

Recall that wage bonuses to teachers in rural schools are not restricted to those who are recruited through the centralized recruitment drive, but rather they affect all teachers in the school. Hence, these bonuses could potentially affect student achievement through two main mechanisms: (i) increased teacher effort due to a higher compensation, or (ii) improvements in the quality of selected teachers. We explore these mechanism in Table 6. If wage increases cause an increase in teachers' effort, which in turn lead to improvement in student achievement, we should observe that student outcomes also improve in schools that didn't have an open vacancy. Column (1) in Table 6 explores this hypothesis by looking at students' achievement in 2018 in the sample of schools that didn't have an open vacancy in the 2015 or 2017 recruitment drives. For these schools, the wage bonus does not significantly affect student achievement. Both in Spanish and Math, the estimated coefficients are very small and statistically insignificant.[17]

One potential explanation for the patterns observed in Table 5 is that in order to improve academic achievement, it is not sufficient for a school to have a temporary influx of a high

[17] This result is consistent with the findings in de Ree et al. (2018), where they show that doubling the wages received by teachers who were already working in Indonesian schools at the time of the reform didn't cause any improvements in students' outcomes (but increased teachers' life satisfaction outcomes).

quality teachers, but rather that the quality of teachers has to be consistently high. This could happen, for example, through the diffusion of teaching techniques, or a change in social norms and attitudes toward new pedagogical practices within the school. If this were the case, we should expect the effects to be concentrated on schools that had an open vacancy *both* on 2015 and 2017, and little or no effects on those that only had an influx of potentially high quality teachers in one year only.[18] In Column (2) of Table 6 we focus on those schools with an open vacancy for a contract teacher either in the 2015 or 2017 recruitment drives (but not both). In this sample, the effects of the policy on 2018 standardized tests are small in magnitude and they are imprecisely estimated. In Column (3) we instead consider the sample of schools that had a longer exposure to the new (potentially higher quality) teachers, i.e. those that had an open position in *both* recruitment drives. The estimated coefficients of the impact of the wage bonus are large and statistically significant, with effect sizes of 0.64σ and 0.59σ in Math and Spanish, respectively.

4 Policy Implications of Teachers Revealed Preferences

The evidence reported in the previous section documents that, in the context of a meritocratic and transparent assignment mechanism of teaching positions, higher wages increase the demand for schools in remote locations, which in turn leads to an increase in the average quality of newly recruited teachers and subsequent improvements in students' academic achievement. In this section, we benchmark the cost-effectiveness of the wage-bonus policy currently implemented with respect to alternative wage incentive schemes as well as alternative policy levers aimed at reducing regional inequalities in the access to high-quality teachers. In order to accomplish this objective, we first estimate a simple demand model over school attributes using data on teachers' realized choices across vacancies available within the two centralized recruitment drives. We then use the estimated preference parameters to evaluate alternative policy scenarios and compare the resulting counterfactual sorting patterns with those observed under the actual policy.

[18] Alternatively, given that we can't match students and teachers, having two consecutive draws of new, highly paid teachers increases the chances that a 4^{th} grade student is effectively taught by a higher-quality teacher recruited through the centralized assignment mechanisms. While theoretically plausible, recall that the average school in our sample has three teachers and it has 1.5 open vacancies, therefore the probability of getting a newly teacher in the tested grade is already quite high.

4.1 An Empirical Model of Teachers' Sorting

We start by defining the utility of teacher i for being matched with school j as:

$$
\begin{aligned}
u_{ij} &= v_{ij} + \epsilon_{ij} \\
&= \alpha \mathbf{D_{ij}} + \beta w_j + \theta \mathbf{X_j} + \epsilon_{ij}
\end{aligned} \tag{3}
$$

where $\mathbf{D_{ij}}$ is a vector of distance dummies that measure the geographic proximity between school j and the municipality of origin of teacher i as well as between school j and the previous school in which teacher i worked. We interpret both distance measures as a proxy for movement costs, which we think include both the costs of travel as well as a broader set of concerns including a preference for remaining in the school where contract teachers are located at the moment of applying for a new job. Next, w_j is the wage posted at school j in thousands of Peruvian Soles while $\mathbf{X_j}$ is a vector of locality and school characteristics that are meant to generate variation in the individual valuations across the teaching positions. These include the natural logarithm of the population of the locality of the school, the time to travel (in hours) between the locality of the school and the province's capital, the natural logarithm of the number of students in the school, an indicator variable of whether the school is bilingual (Spanish and Quechua) or not, a poverty index at the locality level, the principal component of a subset of the indicator variables for whether or not the schools has access to school infrastructures (water, electricity, internet, library, room for teachers, lecture room, kitchen) that constitute the amenity index discussed in Section 3.3. Finally, we assume that ϵ_{ij} is an unobserved Gumbel distributed taste shock that is *iid* across i and j with normalized scale and location.

4.2 Identification and Estimation

Leveraging data on teachers' assignment in the assignment mechanism to learn about their preferences requires us to impose some structure on the underlying data generating process. As discussed in Section 2, within administrative units (UGEL) and for a given field of study, teachers are ranked based on their score and they are sequentially assigned to their preferred school among the ones that still have open vacancies. This procedure is iterated until all vacancies are filled and/or all teachers are assigned. We assume that teachers have full information, meaning that they know ex-ante the scores of the other teachers they will compete with in each UGEL. This implies that, in equilibrium, teachers choose the UGEL in which their preferred feasible school is located. In that case, the matching equilibrium between school vacancies and teachers is globally stable, and it can be easily recovered from the data as the solution of a standard discrete choice model with individual-specific feasible choice sets (Fack et al. 2019).[19] We thus maximize the following log-likelihood function:

$$L(\beta) = \frac{1}{n} \sum_{i=1}^{n} \log \frac{\exp v_{i\mu(i)}}{\sum_{j \in S_i} \exp v_{ij}}, \tag{4}$$

where S_i is the set of feasible schools of teacher i and $\mu(i)$ is the school where teacher i ends up being assigned according to the centralized mechanism.

In this model, preferences are identified if (i) teachers' test scores are independent from the taste shifters, ϵ_{ij} in equation (3), and (ii) the feasible choice sets are also independent from these taste shifters. The first condition is typically violated if teachers intentionally under-perform at the centralized competency test, which is unlikely to happen in this context. 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 which may feed back into teacher i's set of feasible school alternatives (Menzel 2015). Preference cycles of this sort are ruled out in our setting since school preferences are homogeneous, which imply monotonicity along the applicants' (score-based) ranking with respect to any possible chain of acceptances or rejections.

4.3 Estimation Results

We use the sample of teachers that are assigned in the first round of the assignment mechanism for both the estimation and counterfactual analysis. To illustrate the role of heterogeneous preferences, we augment the estimates of the baseline model for various groups/types of teachers. In the counterfactual analysis we use the estimates of such a more flexible model with interaction terms and polynomials for the different teachers' types in order to better fit the choices observed in the data.

Table 7 shows how the average estimated preference parameters across teachers vary across model specifications that include an increasing set of observed school and locality characteristics. The bare-bone model displayed in Column (1) shows that teachers seem to prefer relatively more populated places and schools situated in localities that are close to large cities. As discussed in Sections 2 and displayed in Figure 3 posted wages are strongly correlated with both of these characteristics, hence the estimated negative coefficient of the wage coefficient reported in Column (2) partly capture the unexplained negative valuation

[19] The fact that teachers can choose the UGEL in which they will compete for open positions through the assignment system may potentially invalidate the stability assumption of the realized match between vacancies and teachers. However, the vast majority of the applicants in our sample select the UGEL where they currently work and/or where they reside (84% in the recruitment drive of 2015 and 86% in 2017). These figures point toward a limited role of strategic considerations in application behaviors.

for remote and small locations. Adding school characteristics helps to better pin down average preferences for school quality and remoteness such that the wage coefficient becomes positive (Column 3), which is in line with what we expect given the evidence discussed in Section 3.[20] Our preferred specification is displayed in Column (5), which features all the previous school characteristics plus the complete set of distance dummies where the omitted reference category is an indicator variable for whether or not the locality of the school is situated less than one kilometer away from teachers' residence/previous job location. The magnitude of the estimated wage elasticity increases significantly in Columns (4) and (5), which suggests that moving costs act as negative amenities that partly confound the role of monetary compensation in the model specifications displayed in Columns (1)-(3).

The very large magnitude of the distance coefficients in Column (4) and (5) implies that moving costs are key in explaining teachers' preferences over schools. Figure 12 plots the implied wages needed to compensate teachers from moving far away from where they live or from where they previously worked. For instance, it would take a wage that is approximately 7 times higher than the current wage in order to make teachers indifferent between working in the same school where they they currently are located and another school situated 100 kilometers away. To the extent that higher-quality teachers are mostly located in urban areas, as shown in Figure 1, public policies aimed at enhancing the local supply of teachers in remote areas might be a promising alternative to wage incentives in order to reduce regional inequalities in the quality of teachers.

Table 8 and 9 document how the model estimates of column (5) of Table 7 vary with individual teacher characteristics. Female teachers seem to value much less the wage of the job postings than male teachers (Columns 2-3 of Table 8). There seems to be a U-shape relationship between wage elasticity and the population density of the locality of origin (columns 4-7 of Table 8). Teachers who reside in very rural and very urban areas appear as the most sensitive to wages. Interestingly, most of the other school and locality characteristics, including the distance dummies, do not vary much across the different sub-populations of applicants defined by gender and population density of the locality of origin. In terms of teachers' age and experience, the estimates displayed in Table 9 show that wages seem to mostly matter for teachers that are in the mid-range of the age distribution (between thirty and forty, see Column 2), who are also more likely to have some previous experience in the public education system (column 5). Instead, younger and newly certified teachers are found to be much less sensitive to the monetary compensations of the job postings. In

[20]Controlling for the size of the school seems to partly confound the effect of population density as the sign of the estimated coefficient of the locality population (log(Pop) in Table 7) changes from positive to negative from Column (2) to Column (3).

contrast to the estimates of Table 8, the different sub-populations of teachers defined by age and experience seem to value quite differently other school and locality amenities, such as the poverty-level of the locality, the total size of the school in terms of enrolled students, and the access to basic infrastructures. These sources of preference heterogeneity are very important since they determines which teachers will be more likely to respond to counterfactual wage incentive schemes as well as alternative recruitment policies. The estimated coefficients of the distance dummies are instead always very large and remarkably stable across the different groups of applicants considered in Table 9.

Model Fit In order to bolster the credibility of the model-based counterfactual experiments discussed in the next section, it seems necessary to first assess how well the model predicts some key moments in the data. In particular, it is important to corroborate the validity of the estimated wage elasticity estimated off the observed cross-school variation in posted wages. To do so, we check the consistency between the model estimates and the RD estimates presented in Section 3. Provided that only wages change at the population cutoff, the estimated size of the jump in teacher scores may be used for model validation. We thus simulate teachers' choices using the estimated preference parameters, replicate the RD analysis on simulated data, and compare the resulting estimates across models and data. Table 10 shows the result of this exercise: the baseline model depicted in Column (5) of Table 7 seems to predict at least 70% of the ITT effect in teacher scores that we observe in the data. When we move to a more flexible model that incorporates heterogeneous preferences (column 3) the predicted change in teacher scores increase to roughly 75% of the estimated coefficient. The fit improves to 80% when we restrict the simulated data to the sub-sample of teachers that are assigned into schools located within the RD bandwidth.

4.4 Policy Experiments

We consider a flexible, pooled model that incorporates all the sources of preference heterogeneity shown in Tables 8 and 9. The resulting estimated preference parameters are used to predict the counterfactual wage bonus that would be sufficient to attract one teacher who is above the median of the score distribution in each teaching vacancy made available through the 2015 and 2017 centralized recruitment drives. To do so, we compute for each vacancy that was filled with a teacher below the median of the score distribution the implied wage distribution that would make any above-median teachers indifferent between their current match and the match with the school associated to that vacancy. We then take the minimum of this distribution for each school, which allows us to compute the resulting average wage bonus across vacancies at the province level.[21]

The left panel of Figure 13 shows the geographic distribution of the wage incentives that would eliminate the observed regional inequality in teachers' quality. In order to put the resulting magnitudes in perspective, the right panel of Figure 13 depicts as benchmark the wage bonuses under the status quo implementation of the policy. While it is clear that the current policy is progressively targeting more disadvantaged locations, the magnitude of the monetary incentives in place seems to fall short in driving the extent of teachers sorting by quality across space. Figure 14 further illustrates this point by showing a high correlation between the counterfactual wage bonuses and poverty across provinces (upper panels). The bottom panel of the figure depicts the same correlation at the locality level under both the status quo and the counterfactual scenarios. While there is a mildly positive correlation between wages and poverty in the current policy, it becomes much steeper after the mean level of the poverty index with the counterfactual policy. Finally, Figure 15 shows the CDF of the implied minimum wage bonus across school and locality characteristics, where the status quo bonus is indicated with a vertical (red) bar. For instance, under the current policy 80% of the teaching vacancies are filled with relatively high-quality teachers in schools that are located in provincial capitals, whereas it would take a wage bonus that is eight times larger than the status quo bonus in order to accomplish the same objective in localities that are 5 hours away or more from provincial capitals (upper-left panel). Similarly, 60% of the vacancies are filled with relatively high-quality teachers under the current policy in schools that are above-median in the distribution of students' test score in mathematics, whereas it would take a wage bonus 6 times larger to do so in schools at the bottom decile of math scores (lower panel).

Table 11 provides a breakdown of both the total monthly wage bill implied by the policy equalizing teaching quality, which is three times higher than the current policy, under alternative policy levers that may partly contribute to achieve the same objective in terms of the distribution of teaching quality. We first investigate what would be the effect of removing all the observed structural inequalities between localities. This would only allow to save about 20% on the total wage bill of the policy that would attract an above median teacher in every school. Given how much distance matters in teachers choices (see Figure 12) a promising alternative may by investing in local teaching quality. We thus simulate such a policy by

[21] This exercise has two drawbacks. First, we don't take into account that the policy under study may alter the equilibrium cutoffs, which would in turn affect the choice sets of teachers. Indeed, we might attract an above median teacher from a school that would in the end be left with a lower-quality teacher. Second, by taking the minimum of the wage bonus distribution for each vacancy we might end up considering the same teacher more than once. If this was the case, the resulting total wage bill would be a lower bound of the actual cost of the policy. Notice though that even when using this restrictive criterion, 3,792 of the 8,581 selected teachers are different individuals.

artificially setting all distances to zero between an above median teacher and all schools from the same province. This would reduce the total wage bill of the policy by 30%.

5 Conclusion

This paper studies the recruitment and productivity effects of a policy that raised public sector teacher salaries in rural Perú significantly. The Peruvian education context is quite unique for three reasons. First, the implementation of the policy has generated arbitrary cutoff rules for school eligibility that allow for a credible empirical strategy built around a crisp regression discontinuity design. Second, the entire public school system organizes teacher job postings, teacher job applications and final assignments in a centralized way, providing rich data on the entire process through which a teacher is assigned to a particular post. This system also provides an internally consistent measure of teacher quality that is specific to the job. Third, the large presence of contract teachers that are assigned to temporary teaching positions creates built-in flexibility in the teacher labor market, which in turn can generate large sorting responses to wage incentives within a relatively short time span.

We find that unconditional wage increases are successful in effectively attract and retain talent to public schools. These higher wages also cause significantly higher retention rates when combined with transparent, merit-based assignment rules for contract teachers. We are further able to look at the productivity effects of these newly recruited workers, and document that students in high wage schools perform better in standardized tests. The observed increase in productivity is highly correlated with the increase in average teacher talent across schools. In fact, the policy effect on student outcomes is entirely driven by students in schools that had multiple openings during the period when the policy was in place, while it is estimated to be a tight zero in schools where no new openings were available.

In order to better understand the extent to which wage increases may be an effective policy tool to re-allocate high-quality teachers within the public sector, we estimate a model of teachers' sorting by leveraging the rich data on the centralized assignment. The model estimates nicely replicate the reduced-form findings and they reveal a strong dis-utility effect of distance from teachers' residence to the school, which is much larger in magnitude than the estimated wage elasticity. Counterfactual changes in the wage bonus aimed at reducing the extent of cross-regional inequality in the quality of teachers are predicted to be very large, and they should be probably accompanied by complementary policy interventions in order to accomplish the stated objectives in a more cost-effective way.

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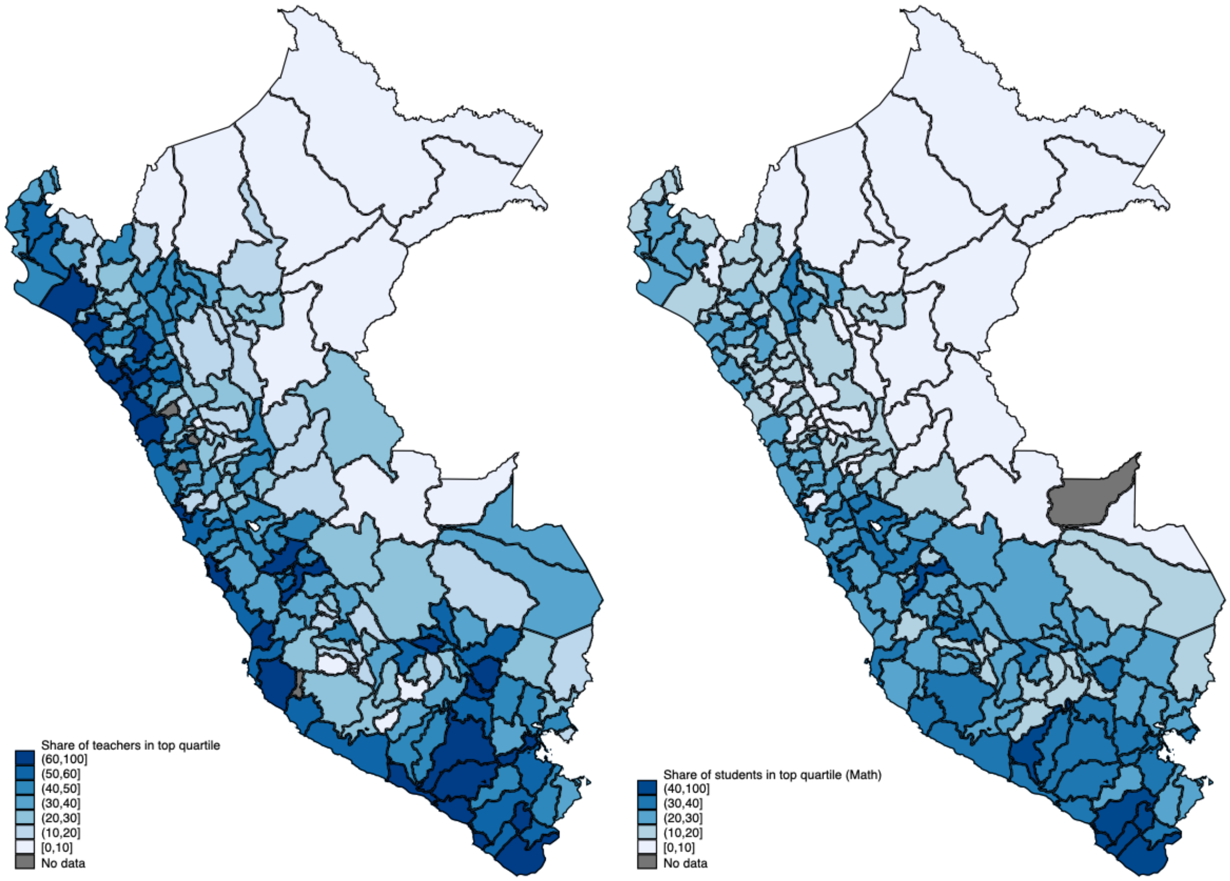
Figures

Figure 1: Distribution of School Inputs (Left) and Output (Right)



Teachers' Evaluation Scores **Students' Test Scores (math)**

Figure 2: Wage Bonus in Rural Areas

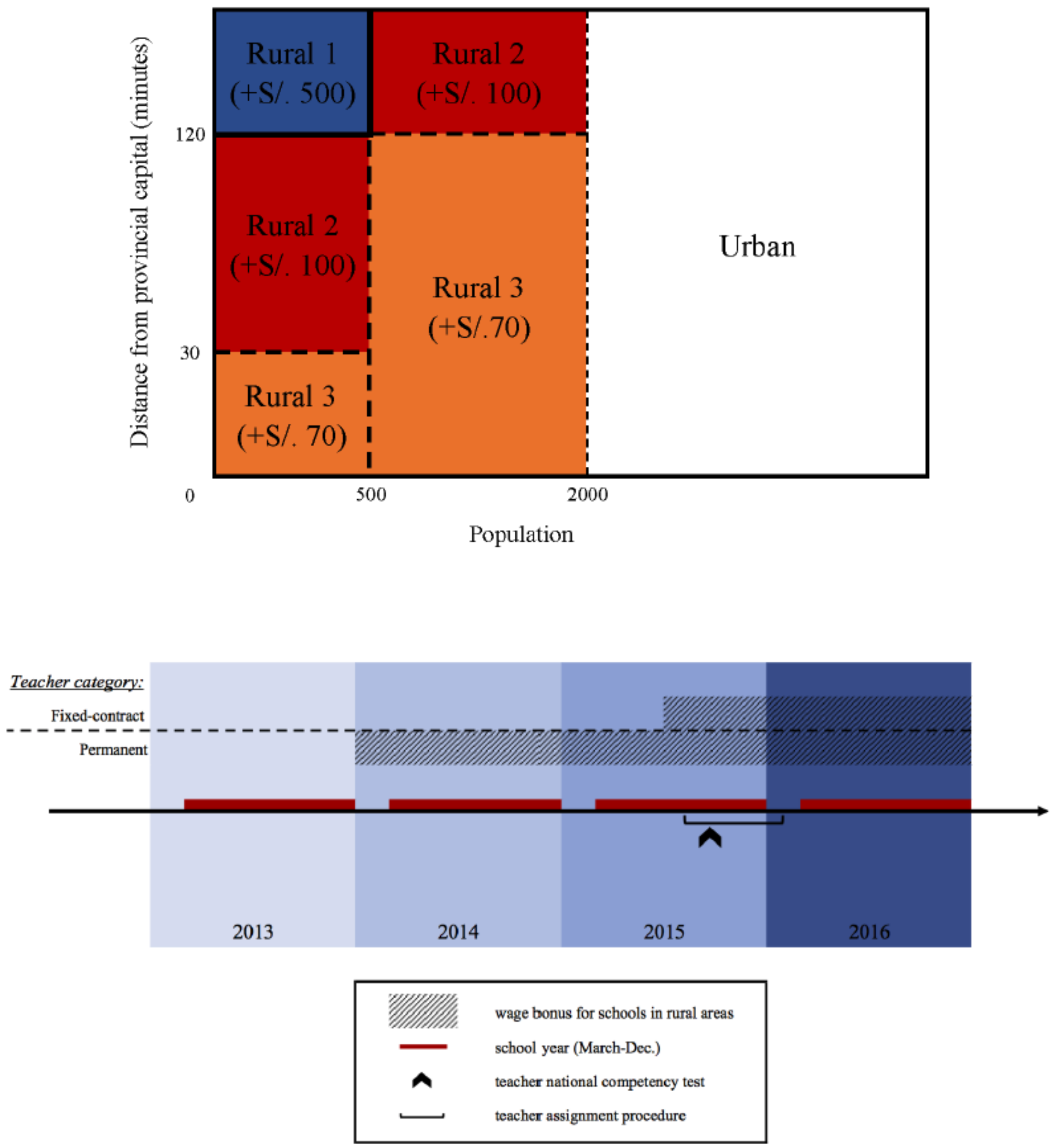
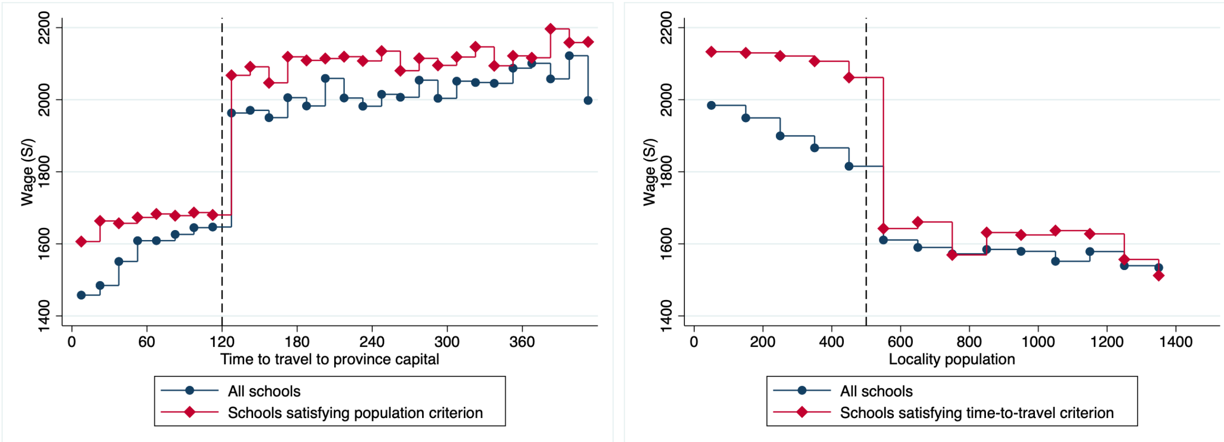


Figure 3: Teacher Wages by Distance from Province Capital and Locality Population



Time-to-travel **Population**

Figure 4: Spatial Distribution of Schools

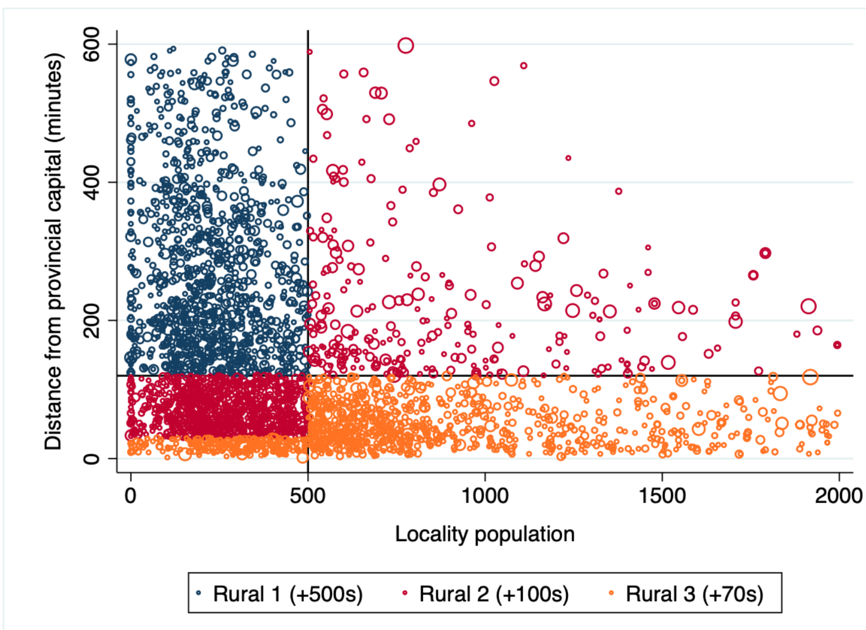


Figure 5: Correlation between Teacher Scores and Student Test Scores

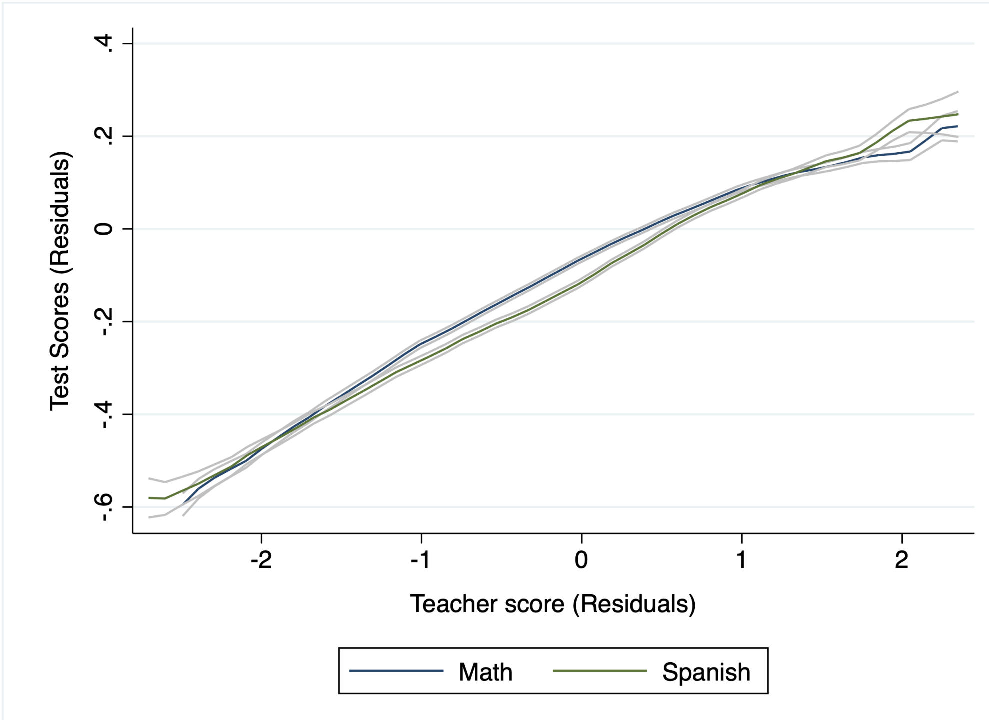
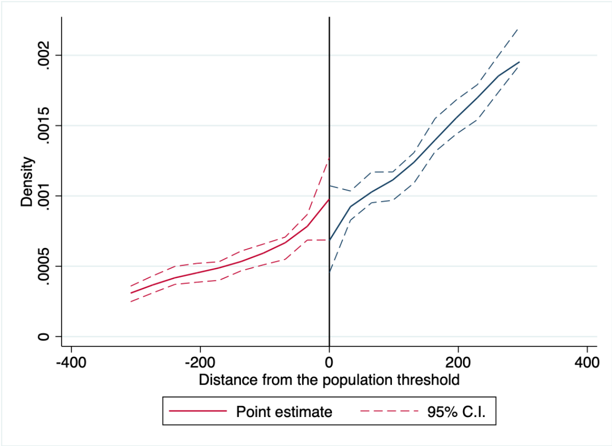
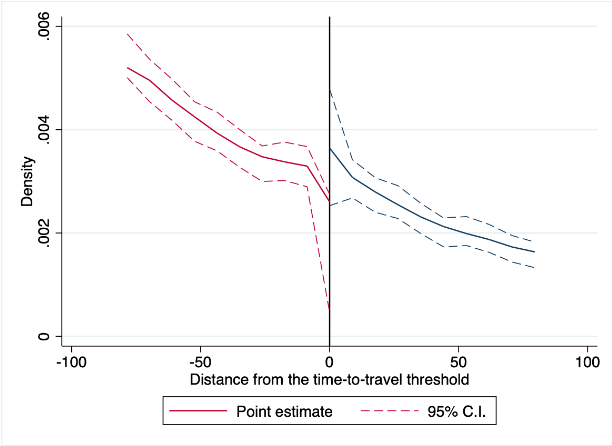


Figure 6: Density Test



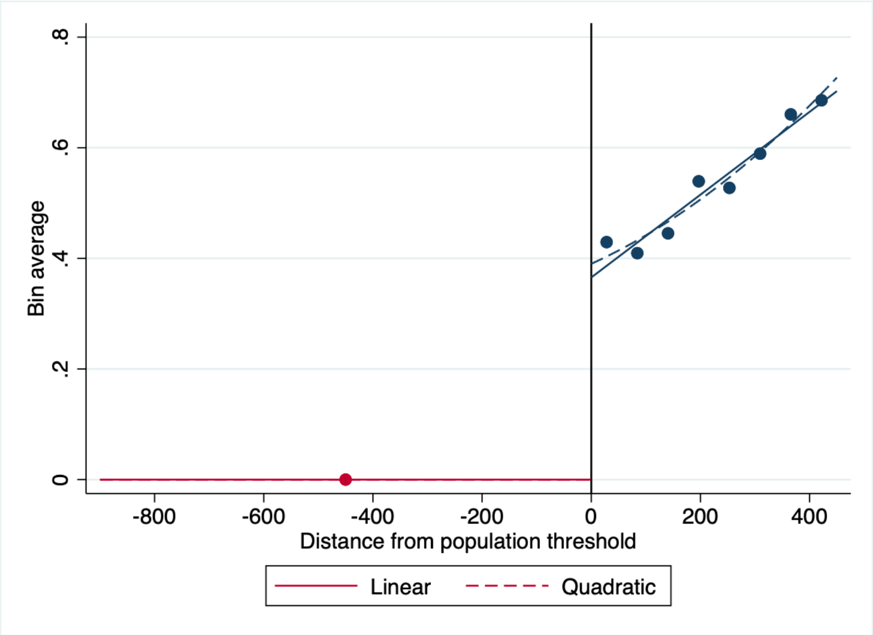
Population



Distance

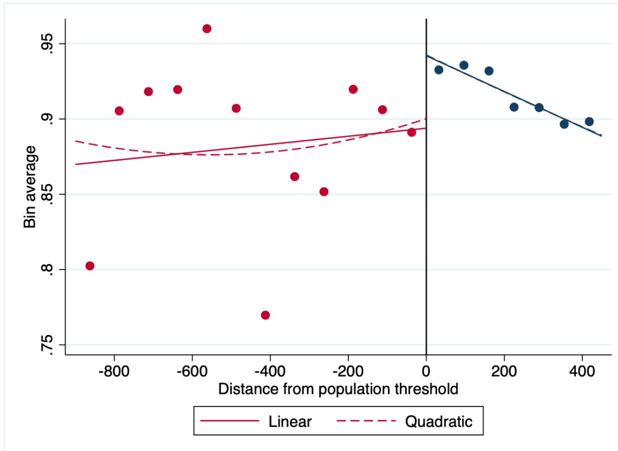
Notes. .

Figure 7: Prob(Rural 1)

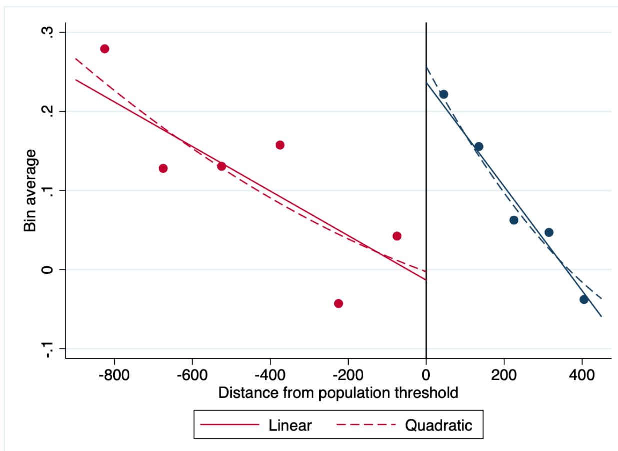


Population

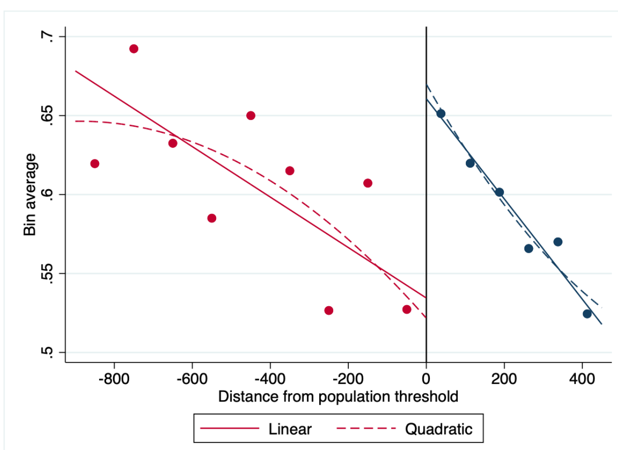
Figure 8: Monetary Incentives and Teacher Selection



Vacancy filled by a certified teacher

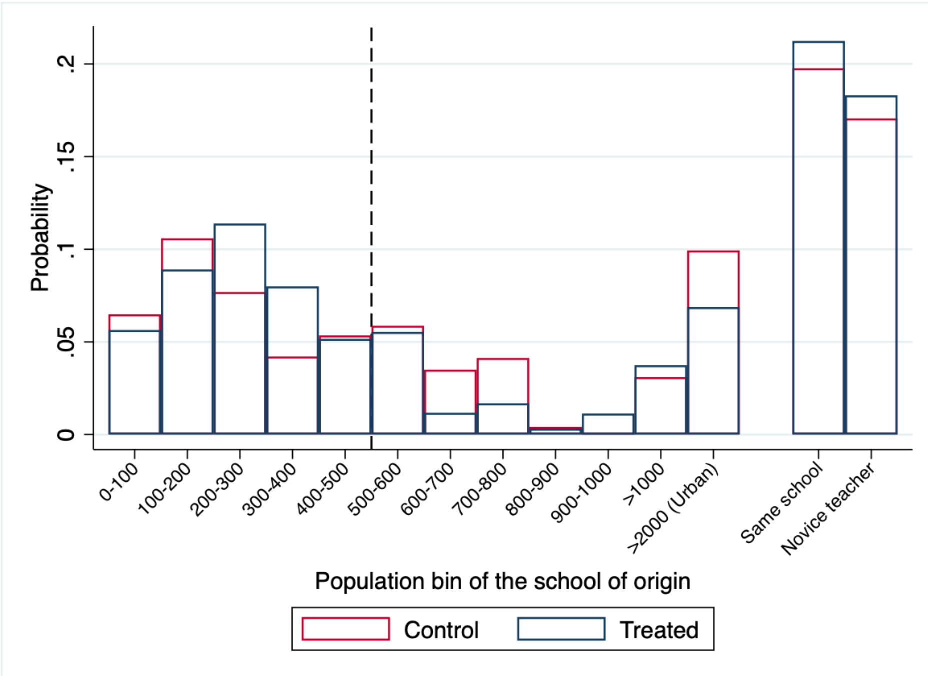


Teacher score (std)

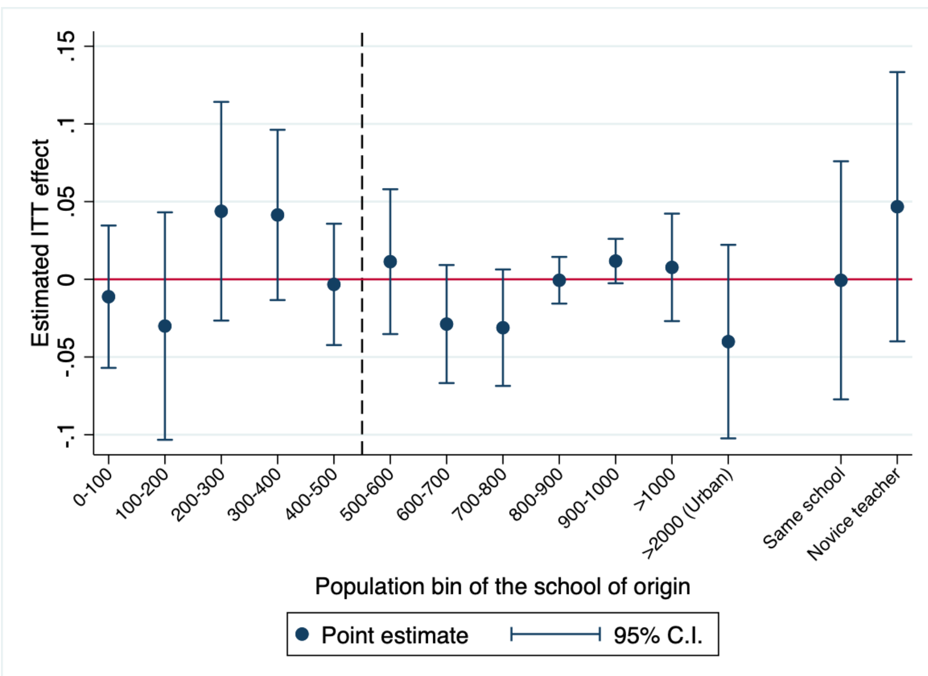


Teacher score above median

Figure 9: Probability of Recruitment by Population Bins of the School of Origin



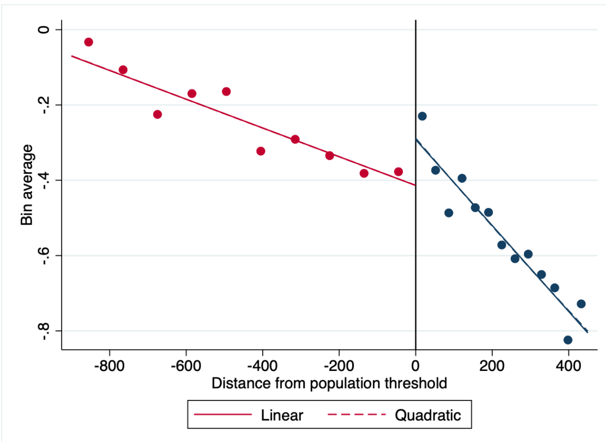
Probability



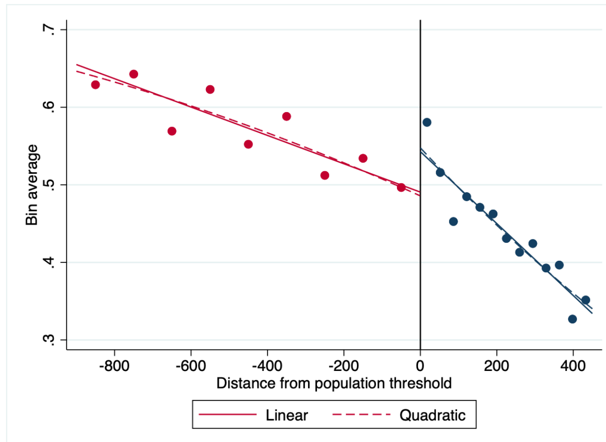
ITT Estimates

Figure 10: ITT Effects on Student Outcomes (2018)

Math

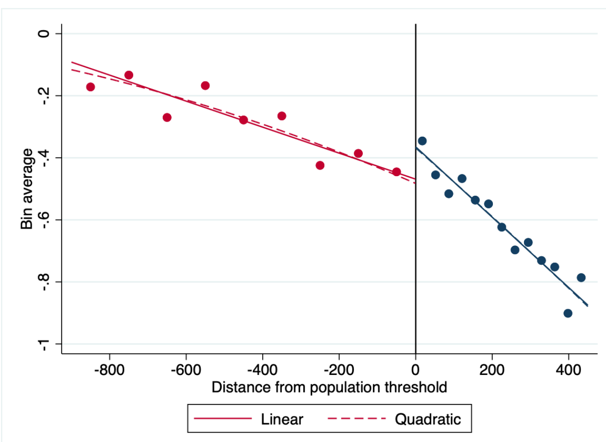


Standardized score

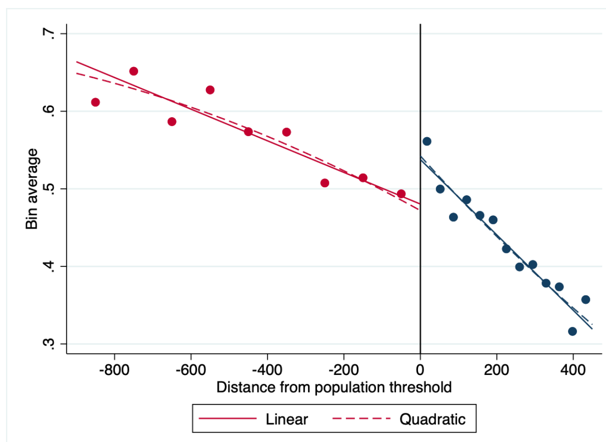


Score above median

Spanish



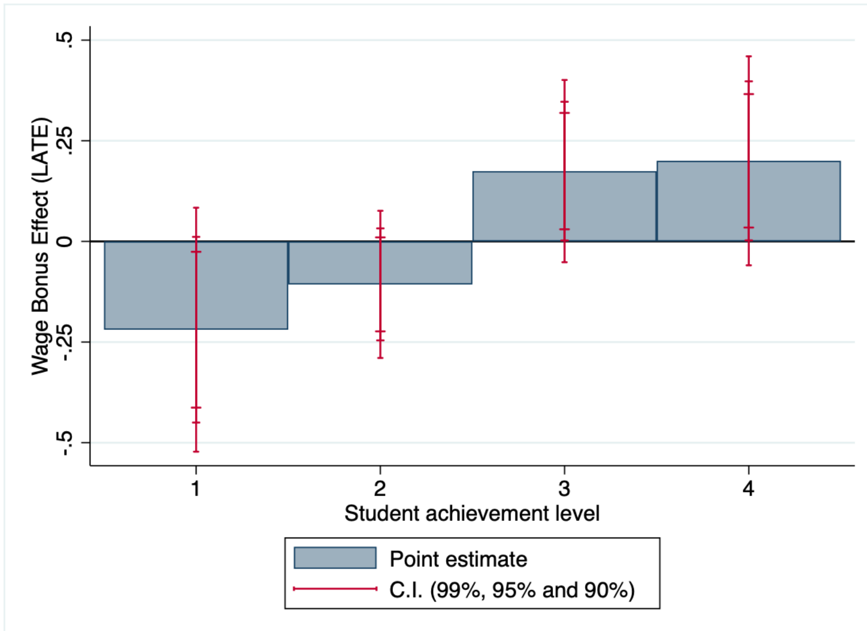
Standardized score



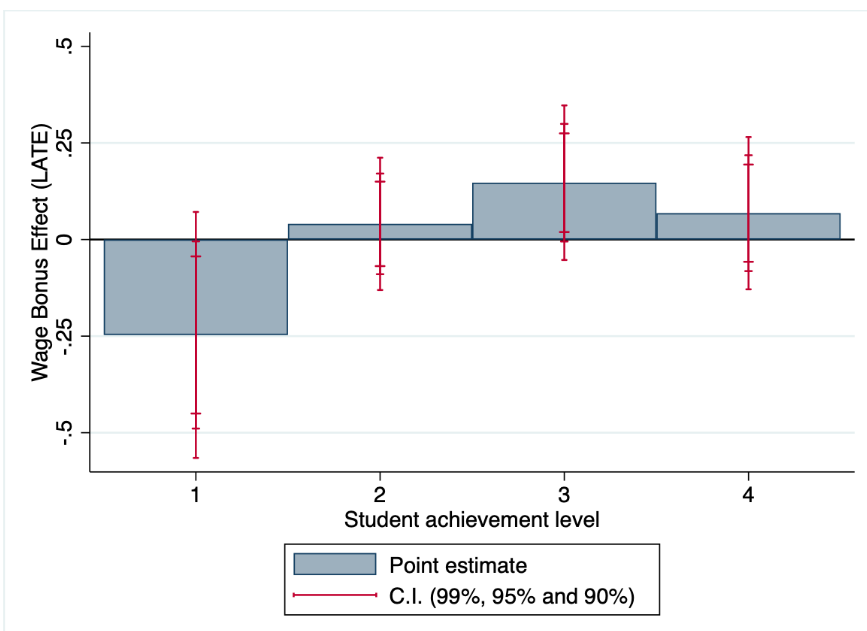
Score above median

NOTES. Schools with vacancies in 2016 and/or 2018.

Figure 11: Monetary Incentives Effects on Students' Achievement Level

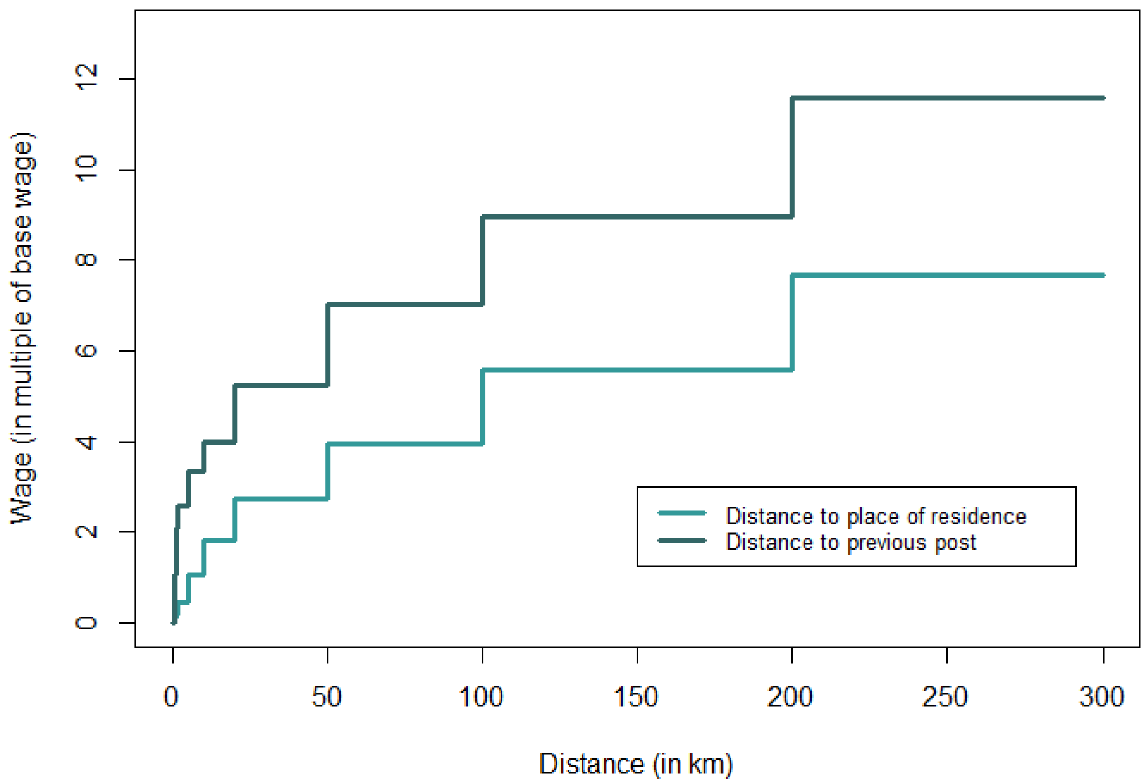


Math



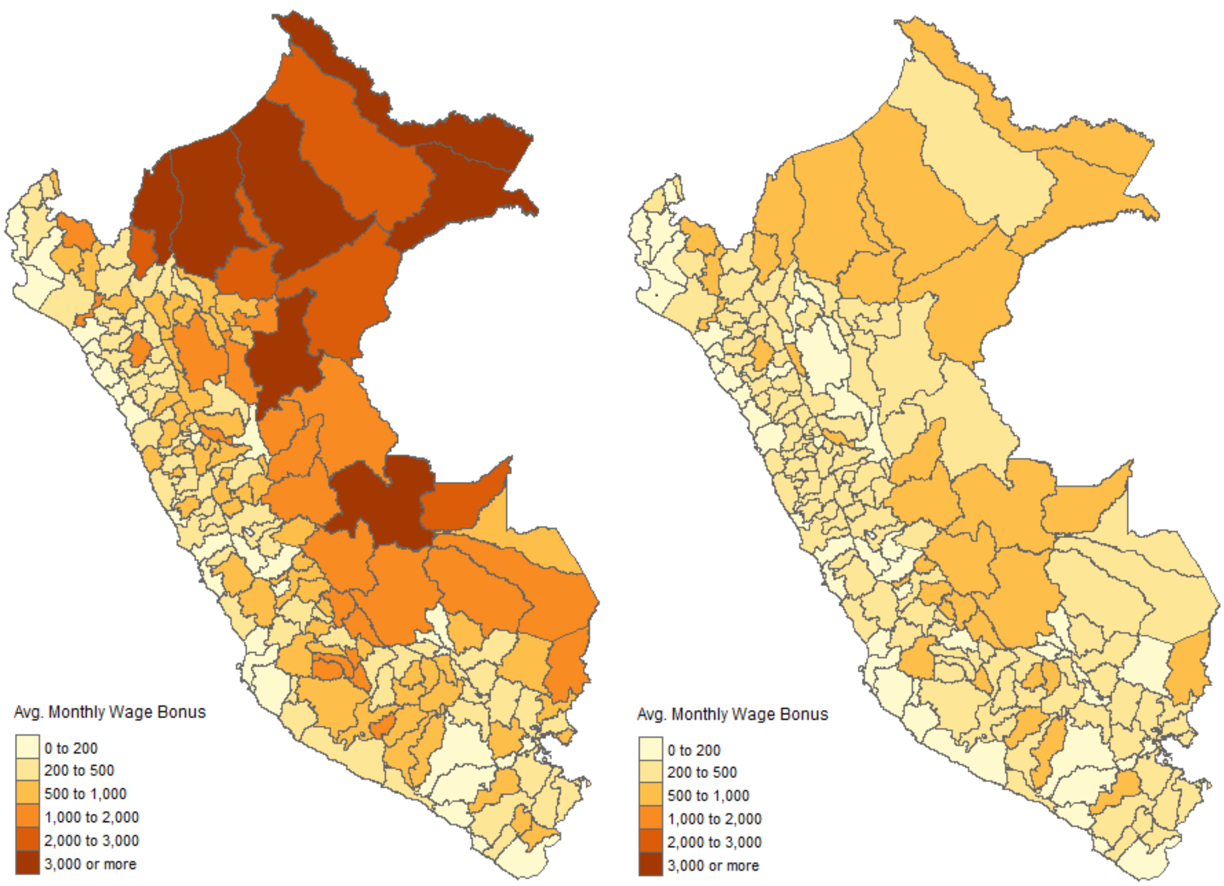
Spanish

Figure 12: Monetary Equivalent of the Estimated Cost of Moving



Notes. This figure draws the indifference curves of teachers on the wage-distance axis using the two definitions of distance (from the municipality of origin or from the previous job). Distance is measured in km and wages are measured in multiples of the base wage (which is 1555 soles).

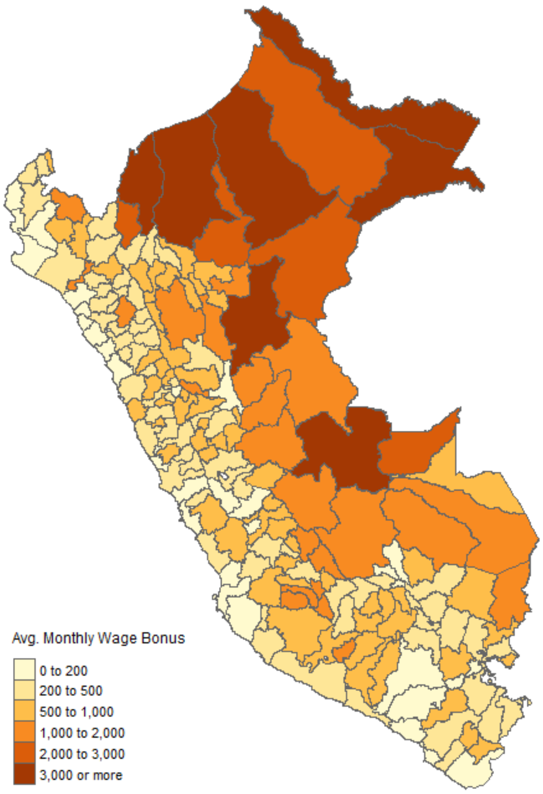
Figure 13: Distribution of Wage Bonuses Under Counterfactual Policy



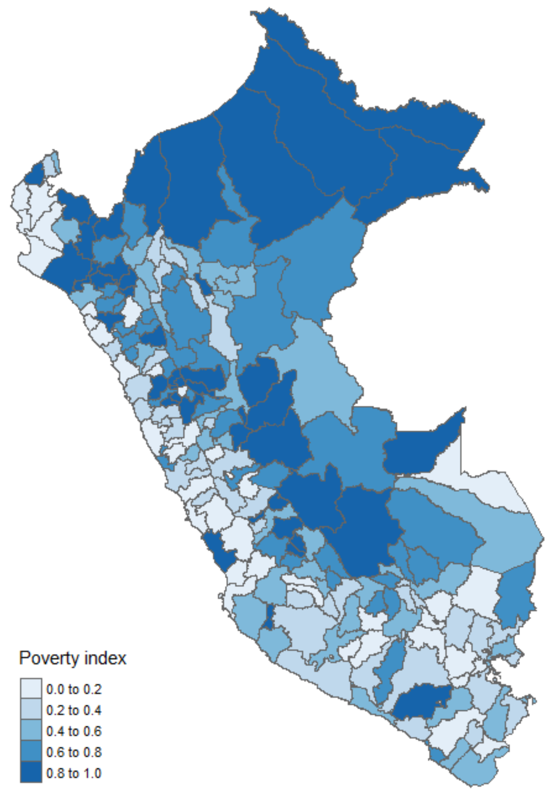
Policy Equalizing Teacher Quality **Current Policy**

Notes. The left panel shows the monthly wage bonuses (in soles) needed to fill every vacancy in the 2015 and the 2017 concurso with an above median teacher averaged at the province level. The right panel maps the monthly wage bonuses offered by the current policy averaged at the province level.

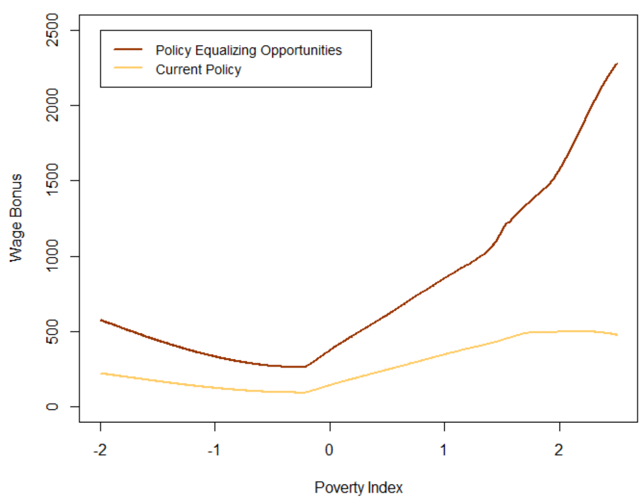
Figure 14: Wage Bonus Policy and Poverty Distribution



Policy Equalizing Opportunities

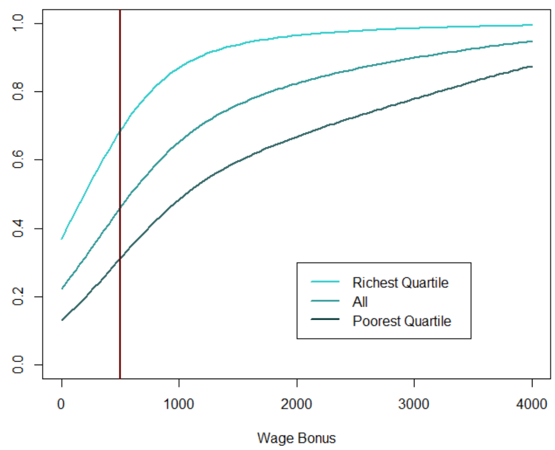


Poverty Distribution

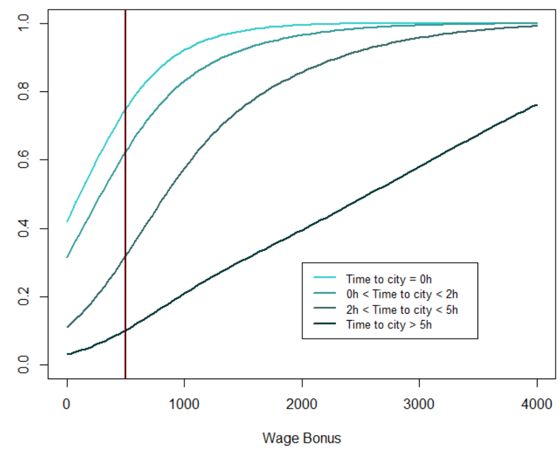


Notes. The left panel maps the monthly wage bonuses (in soles) needed to fill every vacancy in the 2015 and the 2017 concurso with an above median teacher averaged at the province level. The right panel maps the poverty quantiles of the municipalities in which each school is located averaged at the province level. The bottom panel plots a smoothed scatter plot with poverty on the x axis and the wage bonus needed to attract an above median teacher on the y-axis for both the policy equalizing teaching quality and the current policy in place in Peru.

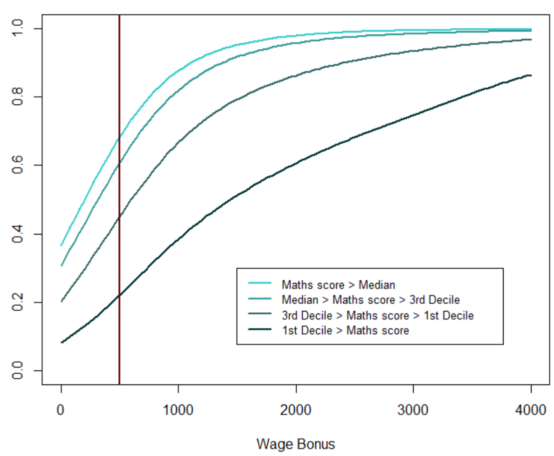
Figure 15: Cumulative Distribution of Counterfactual Wage Bonuses



Heterogeneity by Poverty Status



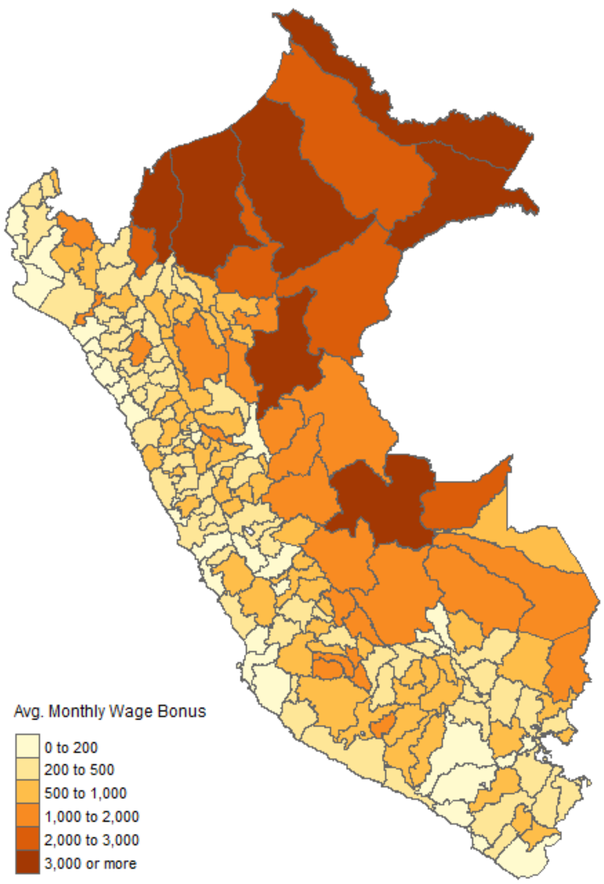
Heterogeneity by Remoteness



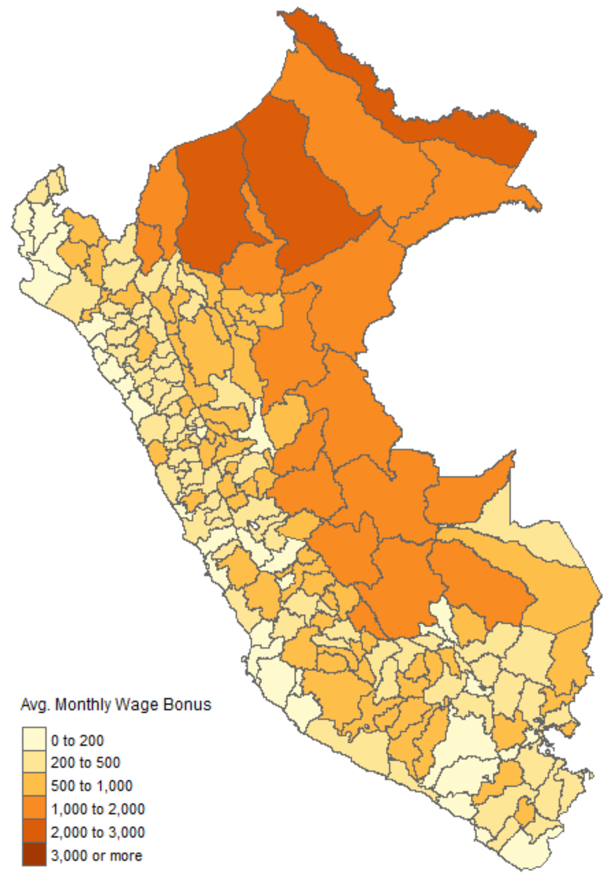
Heterogeneity by Students' Math Achievement

Notes. The left panel plots the cdf of the counterfactual wage bonuses depending on the poverty index of the municipality in which the school is located. The right panel looks at the heterogeneity with respect to the time (in hours) it takes to travel from the school to the largest city of the province. The bottom panel looks at the heterogeneity with respect to the score students achieved at the ECE maths test.

Figure 16: Increasing the Supply of Skilled Teachers in Remote Areas



Wage Incentives Only



Wage Incentives + Investment in Local Training

Notes. The figures compare the distribution of monthly wage bonuses between a policy which only uses wage incentives and a policy which combines investment in local teachers training and wage incentives.

Tables

Table 1: Summary Statistics

Panel A: School characteristics	Rural 1 Schools		Other Rural Schools		Urban Schools	
	Mean	Sd	Mean	Sd	Mean	Sd
Wage (with bonuses)	2194.59	148.10	1775.14	177.11	1574.82	85.13
Single-teacher school	0.11	0.32	0.02	0.13	0.00	0.06
Multigrade school	0.77	0.42	0.41	0.49	0.02	0.14
Number of students	57.82	36.56	105.81	78.94	405.79	269.14
Number of teachers	3.23	1.95	6.59	3.94	19.56	11.78
% of permanent teachers	0.41	0.33	0.63	0.25	0.75	0.17
% of contract teachers	0.46	0.35	0.26	0.23	0.18	0.17
Sport facility	0.15	0.36	0.43	0.49	0.50	0.53
No water	0.40	0.49	0.14	0.35	0.12	0.35
No electricity	0.30	0.46	0.05	0.22	0.12	0.35
Test score (Math)	513.54	102.86	557.44	88.41	564.22	73.06
Test score (Spanish)	517.30	73.00	554.52	61.16	561.78	45.13
Sewage in town/village	0.21	0.41	0.51	0.50	0.50	0.53
Doctor in town/village	0.38	0.49	0.70	0.46	0.50	0.53
Library in town/village	0.01	0.10	0.06	0.23	0.25	0.46
Number of schools	1376		2475		3005	

Panel B: Teachers' dynamics (2016-2018)	Rural 1 Schools		Other Rural Schools		Urban Schools	
	Mean	Sd	Mean	Sd	Mean	Sd
N. of vacancies	1.53	0.86	1.69	1.29	2.23	1.93
Ratio vacancies/existing positions	0.57	0.31	0.32	0.23	0.16	0.19
% of vacancies filled in first round	0.88	0.30	0.87	0.31	0.81	0.35
% of vacancies filled (all rounds)	0.91	0.27	0.91	0.27	0.87	0.30

Panel C: Applicants' characteristics	Rural 1 Schools		Other Rural Schools		Urban Schools	
	Mean	Sd	Mean	Sd	Mean	Sd
Age	39.27	7.40	38.03	6.86	38.29	6.82
Female	0.48	0.50	0.61	0.49	0.81	0.39
Experience (0-6 years)	3.29	1.80	3.21	1.92	2.87	2.00
Novice teacher	0.08	0.27	0.13	0.33	0.19	0.39
Score (std)	-0.12	0.78	0.21	0.84	0.81	0.88
Took both tests	0.72	0.45	0.77	0.42	0.70	0.46
Number of applicants	2822		4826		7766	

NOTES.

Table 2: Monetary Incentives and Teacher Selection

	All Vacancies	Filled Vacancies		
	(1)	(2)	(3)	(4)
	Vacancy filled	Rank	Score (std.)	> median
Pop < 500 hab. (ITT)	0.050	-0.108***	0.352***	0.258***
	(0.043)	(0.034)	(0.100)	(0.067)
Wage Bonus (LATE)	0.089	-0.194***	0.646***	0.465***
	(0.078)	(0.065)	(0.197)	(0.135)
Mean dep. var. (RHS)	0.922	0.314	0.124	0.602
Mean dep. var. (LHS)	0.900	0.352	0.047	0.559
BW	155.244	157.240	197.506	148.050
Schools (BW)	1050	1013	1295	945
Observations (BW)	2385	2232	2804	2095

Notes. SE clustered at the school level. *** p< 0.01, ** p<0.05, and *p<0.10.

Table 3: Teacher Selection – Other Teachers' Characteristics

	(1)	(2)	(3)	(4)	(5)
	Female	Age	Novice Teacher	Exp. 1-3 yrs	Exp. > 3 yrs
Pop < 500 hab. (ITT)	0.058	-1.179	0.035	0.051	-0.089*
	(0.057)	(0.815)	(0.036)	(0.047)	(0.052)
Wage Bonus (LATE)	0.104	-2.100	0.063	0.094	-0.161*
	(0.103)	(1.508)	(0.065)	(0.086)	(0.095)
Mean dep. var.	0.586	38.209	0.127	0.402	0.394
BW	153.486	139.088	138.281	215.374	165.468
Schools (BW)	983	877	872	1428	1071
Observations (BW)	2149	1915	1937	3058	2332

Notes. SE clustered at the school level. *** p< 0.01, ** p<0.05, and *p<0.10.

Table 4: Teacher Selection – Heterogeneity by School/Locality Amenities

	Low Desirability		High Desirability	
	(1)	(2)	(3)	(4)
	Vacancy filled	Score (std.)	Vacancy filled	Score (std.)
Pop < 500 hab. (ITT)	0.298**	0.184	-0.045	0.459***
	(0.127)	(0.284)	(0.047)	(0.120)
Wage Bonus (LATE)	0.431**	0.253	-0.081	0.836***
	(0.170)	(0.391)	(0.087)	(0.249)
Mean dep. var. (RHS)	0.902	-0.206	0.912	0.411
Mean dep. var. (LHS)	0.740	-0.329	0.897	0.122
BW	141.113	164.689	144.810	138.581
Schools (BW)	226	263	714	648
Observations (BW)	622	649	1533	1387

Notes. SE clustered at the school level. *** p< 0.01, ** p<0.05, and *p<0.10.

Table 5: Student Outcomes

	Pooled		2016		2018	
	(1)	(2)	(3)	(4)	(5)	(6)
	Spanish	Math	Spanish	Math	Spanish	Math
Pop < 500 hab. (ITT)	0.180*	0.229**	0.166	0.145	0.209	0.282**
	(0.099)	(0.116)	(0.176)	(0.194)	(0.130)	(0.140)
Wage Bonus (LATE)	0.363*	0.443*	0.275	0.252	0.462	0.616*
	(0.217)	(0.243)	(0.328)	(0.361)	(0.308)	(0.331)
Mean dep. var.	-0.488	-0.390	-0.498	-0.456	-0.458	-0.380
BW	155.697	134.629	158.360	167.333	135.873	129.341
Schools (BW)	1041	880	464	495	770	735
Observations (BW)	19882	17095	7202	7593	11013	10593

Notes. All outcomes are standardized. Only schools with vacancies. SE clustered at the school level. *** p< 0.01, ** p<0.05, and *p<0.10

Table 6: Student Outcomes – Short and Long Term Effects

Panel A: Math			
	(1)	(2)	(3)
	No vacancy	Vacancy 2016 or 2018	Vacancy 2016 and 2018
Pop < 500 hab. (ITT)	-0.009	0.096	0.464**
	(0.144)	(0.134)	(0.224)
Wage Bonus (LATE)	-0.034	0.305	0.642*
	(0.526)	(0.438)	(0.341)
Mean dep. var.	-0.384	-0.318	-0.528
BW	118.536	200.978	121.804
Schools (BW)	560	901	272
Observations (BW)	6221	11982	4327
Panel B: Spanish			
	(1)	(2)	(3)
	No vacancy	Vacancy 2016 or 2018	Vacancy 2016 and 2018
Pop < 500 hab. (ITT)	0.048	-0.037	0.425**
	(0.135)	(0.124)	(0.190)
Wage Bonus (LATE)	0.171	-0.115	0.590**
	(0.500)	(0.386)	(0.298)
Mean dep. var.	-0.442	-0.381	-0.599
BW	116.289	207.427	123.426
Schools (BW)	544	933	275
Observations (BW)	6050	12461	4362

NOTES. All outcomes are standardized. SE clustered at the school level. *** p< 0.01, ** p<0.05, and *p<0.10

Table 7: Preference Estimates

	(1)	(2)	(3)	(4)	(5)
log(Pop)	0.0833***	0.0371***	-0.0666***	-0.342***	-0.287***
	(0.00263)	(0.00346)	(0.00445)	(0.00554)	(0.00648)
Time to Closest City	-0.0672***	-0.0486***	-0.0416***	0.0228***	0.0148***
	(0.00201)	(0.00202)	(0.00216)	(0.00211)	(0.00280)
Wage		-0.822***	0.162***	0.688***	0.560***
		(0.0410)	(0.0453)	(0.0482)	(0.0533)
Size School			0.363***	0.459***	0.393***
			(0.0105)	(0.0110)	(0.0119)
Bilingual School			-0.159***	-0.370***	-0.473***
			(0.0198)	(0.0238)	(0.0272)
Poverty Score			-0.0358***	-0.138***	-0.0922***
			(0.00687)	(0.00737)	(0.00819)
Infrastructure Index			0.282***	0.141***	0.0774***
			(0.0118)	(0.0134)	(0.0146)
Distance from place of residence					
1km < Dist < 2km				-0.294***	-0.146**
				(0.0412)	(0.0456)
2km < Dist < 5km				-0.623***	-0.385***
				(0.0355)	(0.0406)
5km < Dist < 10km				-1.311***	-0.936***
				(0.0360)	(0.0412)
10km < Dist < 20km				-2.104***	-1.573***
				(0.0357)	(0.0412)
20km < Dist < 50km				-3.230***	-2.392***
				(0.0339)	(0.0404)
50km < Dist < 100km				-4.582***	-3.441***
				(0.0358)	(0.0441)
100km < Dist < 200km				-6.225***	-4.849***
				(0.0378)	(0.0481)
200km < Dist < 500km				-8.319***	-6.694***
				(0.0445)	(0.0567)
Dist > 500km				-10.34***	-8.808***
				(0.0640)	(0.0848)
Distance from previous job post					
1km < Dist < 2km					-1.827***
					(0.0529)
2km < Dist < 5km					-2.263***
					(0.0370)
5km < Dist < 10km					-2.903***
					(0.0349)
10km < Dist < 20km					-3.484***
					(0.0327)
20km < Dist < 50km					-4.562***
					(0.0317)
50km < Dist < 100km					-6.112***
					(0.0399)
100km < Dist < 200km					-7.815***
					(0.0572)
200km < Dist < 500km					-10.08***
					(0.0979)
Dist > 500km					-12.64***
					(0.206)

Notes. Standard errors in parenthesis. *** $p < 0.001$, ** $p < 0.01$, and * $p < 0.05$. This table displays the estimates of the model for teachers' preferences described in Section 4.1. We use the 8,190 teachers assigned in 2015 along with the 10,569 teachers assigned in 2017 and consider the two samples as independent cross sections. We construct the feasible choice sets by first determining the score of the lowest ranked applicant in each school (which we will call cutoffs). If the school hasn't filled all vacancies it is feasible by definition, if the school is full, it is feasible only if the teacher has a score above the cutoff. We then estimate this discrete choice model with personalized choice sets by maximum likelihood. Across both years, the feasible choice sets contain 5,672 schools on average.

Table 8: Preference Estimates – Heterogeneity by Gender and Population of City of Origin

	(1) All	(2) Female	(3) Male	(4) Rural	(5) Semi Rural	(6) Semi Urban	(7) Urban
log(Pop)	-0.287***	-0.290***	-0.310***	-0.219***	-0.241***	-0.282***	-0.228***
	(0.00648)	(0.00775)	(0.0120)	(0.0159)	(0.0142)	(0.0128)	(0.0133)
Time to Closest City	0.0148***	0.0157***	0.0125**	0.00522	0.0312***	0.0217***	-0.00458
	(0.00280)	(0.00408)	(0.00386)	(0.00537)	(0.00489)	(0.00526)	(0.00835)
Wage	0.560***	0.102	1.059***	0.810***	0.503***	0.294**	0.610***
	(0.0533)	(0.0727)	(0.0800)	(0.0951)	(0.103)	(0.105)	(0.141)
Size School	0.393***	0.398***	0.383***	0.383***	0.399***	0.439***	0.366***
	(0.0119)	(0.0147)	(0.0203)	(0.0250)	(0.0242)	(0.0230)	(0.0243)
Bilingual School	-0.473***	-0.488***	-0.469***	-0.265***	-0.586***	-0.561***	-0.804***
	(0.0272)	(0.0372)	(0.0406)	(0.0476)	(0.0520)	(0.0517)	(0.0886)
Poverty Score	-0.0922***	-0.114***	-0.0649***	-0.0164	-0.0497**	-0.0964***	-0.152***
	(0.00819)	(0.0103)	(0.0139)	(0.0162)	(0.0159)	(0.0158)	(0.0188)
Infrastructure Score	0.0774***	0.127***	0.0291	0.0594*	0.0810**	0.0975***	-0.0473
	(0.0146)	(0.0200)	(0.0216)	(0.0261)	(0.0278)	(0.0292)	(0.0364)
Distance from place of residence							
1km < Dist < 2km	-0.146**	-0.148**	-0.253*	-0.138	-0.147	-0.300***	-0.157
	(0.0456)	(0.0514)	(0.102)	(0.135)	(0.112)	(0.0816)	(0.0819)
2km < Dist < 5km	-0.385***	-0.425***	-0.320***	-0.382***	-0.418***	-0.475***	-0.511***
	(0.0406)	(0.0468)	(0.0825)	(0.0944)	(0.0965)	(0.0774)	(0.0781)
5km < Dist < 10km	-0.936***	-1.002***	-0.794***	-1.105***	-0.595***	-1.152***	-1.088***
	(0.0412)	(0.0482)	(0.0801)	(0.0883)	(0.0811)	(0.0876)	(0.0827)
10km < Dist < 20km	-1.573***	-1.671***	-1.380***	-1.911***	-1.042***	-1.330***	-1.950***
	(0.0412)	(0.0493)	(0.0772)	(0.0866)	(0.0726)	(0.0929)	(0.0888)
20km < Dist < 50km	-2.392***	-2.459***	-2.250***	-3.009***	-2.080***	-1.888***	-2.429***
	(0.0404)	(0.0490)	(0.0748)	(0.0858)	(0.0696)	(0.0826)	(0.0955)
50km < Dist < 100km	-3.441***	-3.462***	-3.330***	-4.270***	-3.373***	-2.722***	-3.131***
	(0.0441)	(0.0542)	(0.0795)	(0.0927)	(0.0774)	(0.0856)	(0.116)
100km < Dist < 200km	-4.849***	-4.910***	-4.664***	-5.631***	-4.986***	-4.228***	-4.317***
	(0.0481)	(0.0592)	(0.0857)	(0.101)	(0.0873)	(0.0933)	(0.116)
200km < Dist < 500km	-6.694***	-6.810***	-6.397***	-7.409***	-6.817***	-6.118***	-6.251***
	(0.0567)	(0.0713)	(0.0973)	(0.116)	(0.108)	(0.107)	(0.136)
Dist > 500km	-8.808***	-8.772***	-8.725***	-9.837***	-9.398***	-8.542***	-7.500***
	(0.0848)	(0.105)	(0.145)	(0.186)	(0.201)	(0.168)	(0.157)
Distance from previous job post							
1km < Dist < 2km	-1.827***	-1.950***	-1.494***	-1.310***	-1.455***	-1.997***	-2.246***
	(0.0529)	(0.0614)	(0.104)	(0.133)	(0.133)	(0.0997)	(0.0816)
2km < Dist < 5km	-2.263***	-2.424***	-1.894***	-1.728***	-1.719***	-2.289***	-2.906***
	(0.0370)	(0.0447)	(0.0655)	(0.0775)	(0.0860)	(0.0747)	(0.0609)
5km < Dist < 10km	-2.903***	-3.035***	-2.603***	-2.291***	-2.413***	-2.842***	-3.742***
	(0.0349)	(0.0430)	(0.0596)	(0.0676)	(0.0740)	(0.0731)	(0.0643)
10km < Dist < 20km	-3.484***	-3.583***	-3.247***	-2.977***	-2.949***	-3.269***	-4.469***
	(0.0327)	(0.0411)	(0.0544)	(0.0638)	(0.0657)	(0.0661)	(0.0677)
20km < Dist < 50km	-4.562***	-4.631***	-4.355***	-4.067***	-3.969***	-4.481***	-5.519***
	(0.0317)	(0.0405)	(0.0517)	(0.0627)	(0.0618)	(0.0619)	(0.0731)
50km < Dist < 100km	-6.112***	-6.249***	-5.814***	-5.575***	-5.346***	-5.994***	-7.389***
	(0.0399)	(0.0528)	(0.0621)	(0.0798)	(0.0758)	(0.0728)	(0.108)
100km < Dist < 200km	-7.815***	-8.054***	-7.402***	-7.232***	-6.858***	-7.997***	-8.793***
	(0.0572)	(0.0784)	(0.0846)	(0.113)	(0.105)	(0.113)	(0.136)
200km < Dist < 500km	-10.08***	-10.20***	-9.749***	-9.063***	-8.984***	-9.618***	-12.39***
	(0.0979)	(0.130)	(0.150)	(0.182)	(0.206)	(0.155)	(0.280)
Dist > 500km	-12.64***	-13.02***	-11.88***	-11.17***	-11.68***	-13.37***	-13.19***
	(0.206)	(0.287)	(0.298)	(0.417)	(0.421)	(0.513)	(0.361)

NOTES. Standard errors in parenthesis. *** $p < 0.001$, ** $p < 0.01$, and * $p < 0.05$. This table displays the estimates of the model for teachers' preferences described in Section 4.1 for selected subsets of teachers to learn about preference heterogeneity. We use the 8,190 teachers assigned in 2015 along with the 10,569 teachers assigned in 2017 and consider the two samples as independent cross sections. We construct the feasible choice sets by first determining the score of the lowest ranked applicant in each school (which we will call cutoffs). If the school hasn't filled all vacancies it is feasible by definition, if the school is full, it is feasible only if the teacher has a score above the cutoff. We then estimate this discrete choice model with personalized choice sets by maximum likelihood. Across both years, the feasible choice sets contain 5,672 schools on average.

Table 9: Preference Estimates – Heterogeneity by Age and Experience

	(1) Age < 30	(2) 30 ≤ Age < 40	(3) Age ≥ 40	(4) New Entrant	(5) Experience > 0
log(Pop)	-0.275***	-0.287***	-0.302***	-0.359***	-0.281***
	(0.0164)	(0.00836)	(0.0131)	(0.0167)	(0.00707)
Time to Closest City	0.00376	0.0130***	0.0185***	0.0136	0.0136***
	(0.00876)	(0.00374)	(0.00502)	(0.00817)	(0.00301)
Wage	0.593***	0.599***	0.463***	-0.0657	0.620***
	(0.146)	(0.0690)	(0.103)	(0.174)	(0.0563)
Size School	0.457***	0.419***	0.292***	0.489***	0.378***
	(0.0316)	(0.0154)	(0.0234)	(0.0352)	(0.0126)
Bilingual School	-0.645***	-0.475***	-0.383***	-0.636***	-0.447***
	(0.0747)	(0.0353)	(0.0528)	(0.0837)	(0.0290)
Poverty Score	-0.141***	-0.101***	-0.0517**	-0.229***	-0.0788***
	(0.0214)	(0.0106)	(0.0164)	(0.0235)	(0.00877)
Infrastructure Score	0.137***	0.0767***	0.0641*	0.0625	0.0823***
	(0.0408)	(0.0189)	(0.0281)	(0.0485)	(0.0154)
Distance from place of residence					
1km < Dist < 2km	-0.227	-0.182**	-0.00339	-0.527***	-0.103*
	(0.116)	(0.0583)	(0.0944)	(0.125)	(0.0488)
2km < Dist < 5km	-0.388***	-0.395***	-0.354***	-0.857***	-0.329***
	(0.100)	(0.0516)	(0.0865)	(0.107)	(0.0437)
5km < Dist < 10km	-1.132***	-0.918***	-0.851***	-1.669***	-0.841***
	(0.105)	(0.0525)	(0.0865)	(0.111)	(0.0443)
10km < Dist < 20km	-1.841***	-1.584***	-1.384***	-2.509***	-1.448***
	(0.105)	(0.0526)	(0.0862)	(0.115)	(0.0443)
20km < Dist < 50km	-2.720***	-2.389***	-2.202***	-3.304***	-2.254***
	(0.102)	(0.0512)	(0.0866)	(0.105)	(0.0437)
50km < Dist < 100km	-3.745***	-3.463***	-3.186***	-4.505***	-3.247***
	(0.109)	(0.0562)	(0.0940)	(0.111)	(0.0480)
100km < Dist < 200km	-5.258***	-4.835***	-4.607***	-6.064***	-4.576***
	(0.120)	(0.0614)	(0.102)	(0.115)	(0.0529)
200km < Dist < 500km	-6.936***	-6.720***	-6.438***	-8.108***	-6.312***
	(0.136)	(0.0734)	(0.118)	(0.133)	(0.0628)
Dist > 500km	-9.170***	-8.761***	-8.623***	-9.940***	-8.437***
	(0.208)	(0.109)	(0.179)	(0.177)	(0.0964)
Distance from previous job post					
1km < Dist < 2km	-1.844***	-1.779***	-1.926***		-1.819***
	(0.150)	(0.0674)	(0.104)		(0.0528)
2km < Dist < 5km	-2.194***	-2.229***	-2.372***		-2.260***
	(0.105)	(0.0478)	(0.0702)		(0.0369)
5km < Dist < 10km	-2.836***	-2.842***	-3.082***		-2.903***
	(0.0990)	(0.0449)	(0.0669)		(0.0348)
10km < Dist < 20km	-3.434***	-3.409***	-3.693***		-3.489***
	(0.0937)	(0.0421)	(0.0628)		(0.0326)
20km < Dist < 50km	-4.568***	-4.508***	-4.696***		-4.566***
	(0.0910)	(0.0406)	(0.0613)		(0.0315)
50km < Dist < 100km	-5.947***	-6.073***	-6.281***		-6.106***
	(0.110)	(0.0514)	(0.0773)		(0.0396)
100km < Dist < 200km	-7.723***	-7.760***	-7.951***		-7.774***
	(0.163)	(0.0744)	(0.106)		(0.0566)
200km < Dist < 500km	-9.525***	-10.11***	-10.26***		-9.937***
	(0.236)	(0.133)	(0.184)		(0.0964)
Dist > 500km	-12.15***	-12.67***	-12.74***		-12.41***
	(0.510)	(0.272)	(0.406)		(0.206)

Notes. Standard errors in parenthesis. *** $p < 0.001$, ** $p < 0.01$, and * $p < 0.05$. This table displays the estimates of the model for teachers' preferences described in Section 4.1 for selected subsets of teachers to learn about preference heterogeneity. We use the 8,190 teachers assigned in 2015 along with the 10,569 teachers assigned in 2017 and consider the two samples as independent cross sections. We construct the feasible choice sets by first determining the score of the lowest ranked applicant in each school (which we will call cutoffs). If the school hasn't filled all vacancies it is feasible by definition, if the school is full, it is feasible only if the teacher has a score above the cutoff. We then estimate this discrete choice model with personalized choice sets by maximum likelihood. Across both years, the feasible choice sets contain 5,672 schools on average.

Table 10: Model Fit – Change in Teachers' Score at Population Cutoff

		Predicted		
	Data	Base model	Flexible model	Within RD bandwidth
Pop $<$ 500 hab.	0.369***	0.260***	0.278***	0.287***
	(0.062)	(0.061)	(0.062)	(0.063)

Notes. SE clustered at the school level. *** $p < 0.001$, ** $p < 0.01$, and * $p < 0.05$. To assess model fit, we predict indirect utilities for each teacher and simulate the match using the serial dictatorship algorithm. We then recompute the jump in teachers' test scores at the population cutoff and compare it with the estimated jump observed in the data. Column (1) shows the jump estimated from the data. Column (2) gives the simulated jump when using the estimates of the base model (see Column (5) of Table 7). Column (3) shows the simulated jump when using the estimates of a more flexible model with preference heterogeneity. Finally, Column (5) gives us the simulated jump when using estimates from the model restricted to teachers matched to schools located within the bandwidth of the RD (between 300 and 700 hab.).

Table 11: Alternative Policy Counterfactuals

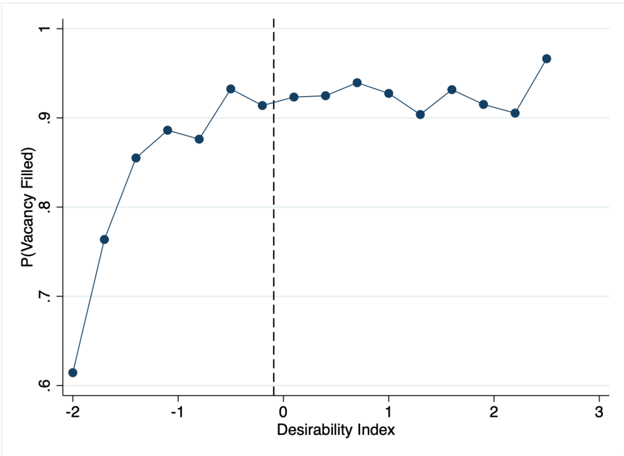
	Total Wage Bill per Month		Net Present Value	% of Total Cost
	2015	2017		
Policy 1: Wage Bonus Only				
Cost of Current policy (benchmark)	3.53	4.66	2,264.97	35.93
Cost of Equalizing teacher quality	12.33	13.30	6,303.71	100
Policy 2: Equalizing Structural Inequalities				
Infrastructure	0.26	0.21	127.88	2.03
Time to travel	1.07	0.01	356.43	5.65
Size school	0.36	0.82	481.92	7.65
Poverty index	0.01	-0.01	23.65	0.37
Village Population	0.01	0.12	-121.59	-1.93
Bilingual Schools	0.78	0.25	295.61	4.69
Adjusted Cost of Equalizing teacher quality	9.75	11.90	5,139.81	81.54
Policy 3: Increasing Local Supply of High-quality Teachers				
Adjusted Cost of Equalizing teacher quality	7.16	10.72	4,377.67	69.45

Notes. The table displays the total cost per month (in millions of soles) of attracting an above median teacher in each vacancy for each year (column 1 and 2). It also shows the net present value of each policy on a duration of 20 years using a discount factor of 2% (column 3). The top panel shows this cost when wage incentives are the only policy instrument available. In the second panel of the table we remove inequalities in schools/locality characteristics one by one and recompute the wage bonuses needed to equalize opportunities. In the bottom panel we simulate local increases of teaching quality by setting the distance to zero between an above median teacher and all schools within the same province. We then recompute and display the wage bonuses needed to equalize opportunities.

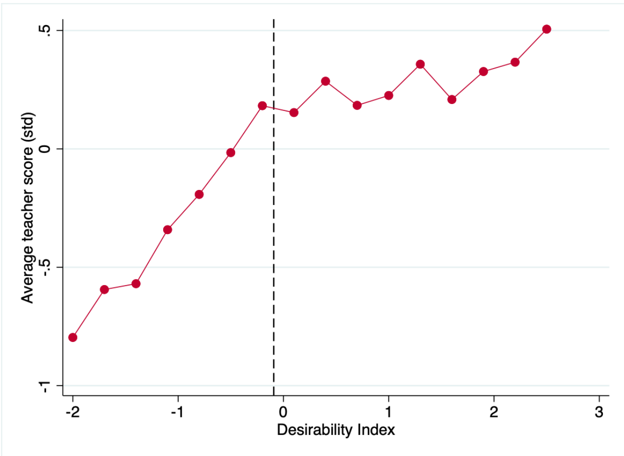
Appendix

A Additional Figures

Figure A.1: Correlation Between the Amenity Index and Teacher Recruitment

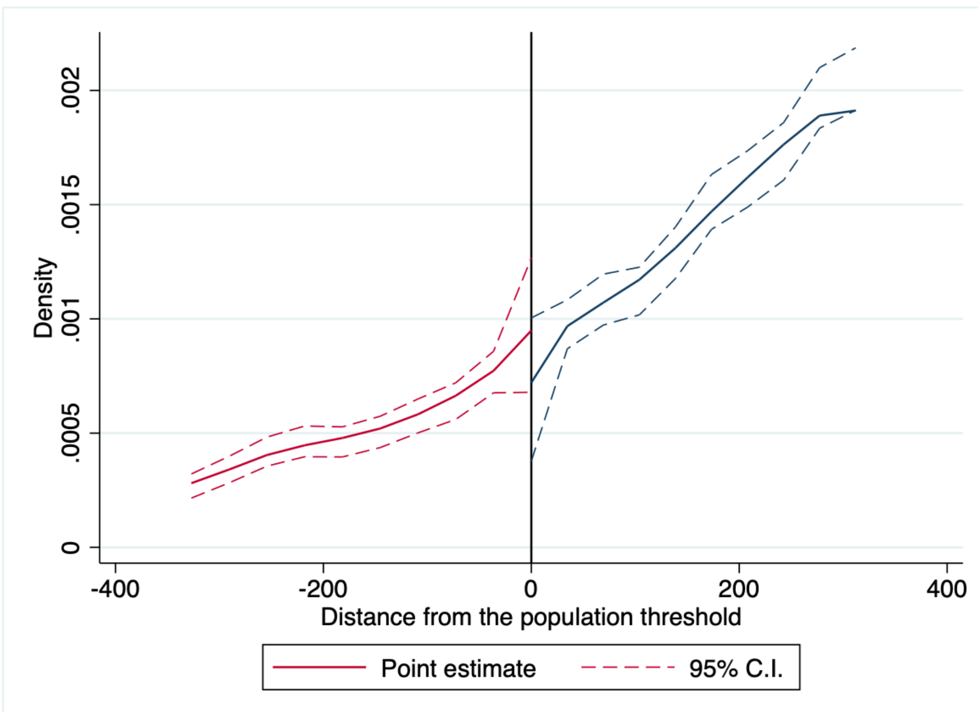


Vacancy Filled by a Certified Teacher



Teacher Scores (std)

Figure A.2: Density Test - Vacancies Filled by Certified Teachers



B Additional Tables

Table B.1: Covariate smoothness

				2016				2018			
		(1)		(2)		(3)		(4)		(5)	
	Mean	All schools		W/vacancies		W/vacancy filled		W/vacancies		W/vacancy filled	
Village amenities											
Electricity	0.91	0.035	(0.023)	0.100	(0.068)	-0.002	(0.051)	0.058	(0.042)	0.047	(0.042)
Drinkg water	0.68	0.004	(0.043)	0.180	(0.114)	0.100	(0.114)	-0.006	(0.069)	-0.009	(0.077)
Sewage	0.37	0.034	(0.056)	0.147	(0.114)	0.096	(0.110)	0.039	(0.086)	-0.005	(0.090)
Water tank	0.24	-0.038	(0.049)	-0.103	(0.111)	-0.072	(0.110)	-0.026	(0.078)	-0.047	(0.080)
Medical clinic	0.51	0.082	(0.058)	0.017	(0.126)	-0.062	(0.122)	0.042	(0.072)	0.015	(0.068)
Meal center	0.22	0.029	(0.045)	0.150	(0.098)	0.156	(0.102)	0.085	(0.079)	0.091	(0.084)
Community phone	0.06	0.029	(0.027)	-0.052	(0.047)	-0.010	(0.042)	0.033	(0.043)	0.032	(0.046)
Internet access point	0.12	-0.026	(0.036)	-0.035	(0.081)	-0.039	(0.078)	0.011	(0.058)	0.021	(0.059)
Bank	0.03	-0.007	(0.016)	-0.064	(0.046)	-0.056	(0.048)	-0.004	(0.033)	-0.005	(0.035)
Public library	0.03	-0.013	(0.015)	-0.085*	(0.050)	-0.055	(0.049)	-0.004	(0.023)	-0.006	(0.025)
Police	0.14	0.001	(0.040)	0.008	(0.105)	-0.014	(0.105)	-0.027	(0.075)	-0.049	(0.077)
School amenities											
Science lab	0.07	-0.006	(0.035)	-0.040	(0.081)	-0.060	(0.088)	0.003	(0.047)	-0.011	(0.051)
Library	0.29	-0.120*	(0.066)	-0.195	(0.147)	-0.276*	(0.153)	-0.058	(0.094)	-0.068	(0.093)
At least a personal computer	0.73	-0.030	(0.044)	0.191**	(0.095)	0.060	(0.090)	0.033	(0.051)	0.019	(0.052)
Internet access	0.31	-0.054	(0.056)	-0.261*	(0.138)	-0.264*	(0.142)	-0.069	(0.086)	-0.064	(0.091)
Electricity	0.87	0.039	(0.027)	0.166*	(0.091)	0.052	(0.081)	0.090*	(0.051)	0.083	(0.052)
Drinking water	0.78	-0.008	(0.036)	0.214**	(0.107)	0.109	(0.105)	0.027	(0.058)	0.017	(0.059)
Sewage	0.60	-0.047	(0.046)	0.021	(0.103)	-0.014	(0.109)	-0.005	(0.085)	-0.028	(0.090)
Reading room	0.07	-0.042	(0.034)	-0.016	(0.052)	-0.043	(0.054)	-0.023	(0.044)	-0.036	(0.050)
Sport pitch	0.30	0.017	(0.057)	-0.038	(0.112)	-0.040	(0.116)	0.060	(0.082)	0.023	(0.083)
Courtyard	0.47	0.001	(0.055)	-0.092	(0.123)	-0.120	(0.128)	-0.090	(0.080)	-0.156*	(0.088)
Gym	0.02	0.004	(0.018)	0.012	(0.017)	0.006	(0.017)	0.007	(0.013)	0.008	(0.015)
Stadium	0.01	-0.014	(0.012)	-0.000	(0.000)	-0.000	(0.001)	-0.005	(0.019)	-0.008	(0.021)
Auditorium	0.11	-0.015	(0.040)	-0.030	(0.081)	-0.054	(0.090)	-0.020	(0.054)	-0.032	(0.056)
Administrative office	0.64	0.024	(0.053)	0.012	(0.119)	-0.045	(0.134)	0.085	(0.086)	0.074	(0.089)
Pool	0.06	-0.050	(0.033)	-0.017	(0.056)	-0.030	(0.057)	-0.012	(0.054)	-0.008	(0.054)
Courtyard	0.03	-0.048**	(0.021)	-0.058	(0.050)	-0.065	(0.055)	-0.066*	(0.040)	-0.079*	(0.042)
Resting room	0.09	0.012	(0.033)	0.004	(0.064)	0.009	(0.073)	0.110**	(0.055)	0.112*	(0.059)
Breastfeeding room	0.19	-0.072	(0.051)	-0.124	(0.102)	-0.141	(0.109)	-0.045	(0.075)	-0.066	(0.074)
Courtyard	0.02	0.011	(0.018)	0.022	(0.027)	0.022	(0.029)	-0.014	(0.026)	-0.015	(0.030)
Dining hall	0.32	-0.028	(0.046)	-0.061	(0.107)	-0.086	(0.109)	-0.017	(0.089)	-0.059	(0.095)
Cafeteria	0.07	-0.049	(0.035)	0.024	(0.076)	0.027	(0.080)	-0.043	(0.050)	-0.056	(0.057)
Kitchen	0.46	-0.021	(0.053)	-0.080	(0.106)	-0.126	(0.111)	-0.066	(0.079)	-0.122	(0.083)
Teachers accomodations	0.07	-0.005	(0.020)	0.070*	(0.038)	0.067*	(0.037)	-0.028	(0.030)	-0.028	(0.031)

NOTES. Robust SE in parentheses. *** p< 0.01, ** p<0.05, and *p<0.10

Table B.2: Probability of open vacancy

	Pooled		2016	2018	
	(1)	(2)	(3)	(4)	(5)
	Vacancy	N. of vacancies	Vacancy 2016	Vacancy 2018	Vacancy 2016&2018
Pop < 500 hab. (ITT)	-0.012	-0.099	0.005	-0.033	-0.030
	(0.037)	(0.113)	(0.041)	(0.045)	(0.045)
Mean dep. var.	0.304	0.523	0.215	0.386	0.156
BW	234.112	183.267	216.799	253.075	155.136
Observations (BW)	7241	5316	3271	4009	2205

NOTES. SE clustered at the school level. *** p< 0.01, ** p<0.05, and *p<0.10

Table B.3: Teacher Composition Changes

	(1)	(2)	(3)
	Number of Teachers	Share of contract teachers	Teacher-student ratio
Pop < 500 hab. (ITT)	-0.399	-0.003	-0.164
	(0.313)	(0.026)	(0.188)
Mean dep. var.	5.739	0.335	2.691
BW	140.900	215.684	138.969
Observations (BW)	1229	1989	1190

NOTES. SE clustered at the school level. *** p< 0.01, ** p<0.05, and *p<0.10

Table B.4: Monetary Incentives and Teacher Selection (2016)

	All Vacancies	Filled Vacancies		
	(1)	(2)	(3)	(4)
	Vacancy filled	Rank	Score (std.)	> median
Pop < 500 hab. (ITT)	-0.038	-0.113**	0.513***	0.307***
	(0.086)	(0.054)	(0.180)	(0.104)
Wage Bonus (LATE)	-0.060	-0.190**	0.807***	0.493***
	(0.138)	(0.094)	(0.310)	(0.178)
Mean dep. var. (RHS)	0.847	0.354	-0.104	0.501
Mean dep. var. (LHS)	0.815	0.384	-0.182	0.458
BW	161.119	213.108	164.837	170.931
Schools (BW)	506	635	473	486
Observations (BW)	838	1004	763	779

NOTES. SE clustered at the school level. *** p< 0.01, ** p<0.05, and *p<0.10.

Table B.5: Monetary Incentives and Teacher Selection (2018)

	All Vacancies	Filled Vacancies		
	(1)	(2)	(3)	(4)
	Vacancy filled	Rank	Score (std.)	> median
Pop < 500 hab. (ITT)	0.052	-0.116***	0.297**	0.216***
	(0.056)	(0.040)	(0.137)	(0.075)
Wage Bonus (LATE)	0.101	-0.225***	0.576**	0.418***
	(0.109)	(0.087)	(0.286)	(0.159)
Mean dep. var. (RHS)	0.911	0.296	0.253	0.655
Mean dep. var. (LHS)	0.886	0.338	0.151	0.598
BW	161.498	151.490	178.855	207.538
Schools (BW)	950	842	994	1192
Observations (BW)	1655	1434	1667	1971

NOTES. SE clustered at the school level. *** p< 0.01, ** p<0.05, and *p<0.10.

Table B.6: Probability of Recruitment by Population Bins of the School of Origin

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	0-99	100-199	200-299	300-399	400-499	500-599	600-699	700-799	800-899	900-999	1000-2000	Urban	New entrant	Same school
Pop $<$ 500 hab. (ITT)	-0.011	-0.030	0.044	0.041	-0.003	0.011	-0.029	-0.031	-0.001	0.012	0.008	-0.040	0.047	-0.001
	(0.023)	(0.037)	(0.036)	(0.028)	(0.020)	(0.024)	(0.019)	(0.019)	(0.008)	(0.007)	(0.018)	(0.032)	(0.044)	(0.039)
Wage Bonus (LATE)	-0.021	-0.053	0.077	0.073	-0.006	0.020	-0.051	-0.055	-0.001	0.021	0.014	-0.071	0.082	-0.001
	(0.043)	(0.067)	(0.064)	(0.050)	(0.037)	(0.043)	(0.035)	(0.034)	(0.014)	(0.013)	(0.032)	(0.057)	(0.079)	(0.071)
Mean dep. var.	0.069	0.105	0.107	0.060	0.048	0.037	0.024	0.021	0.011	0.011	0.034	0.087	0.198	0.189
BW	210.568	121.370	134.121	126.244	236.136	159.993	152.068	132.439	206.669	193.866	176.727	137.073	120.566	193.941
Schools (BW)	1393	756	843	791	1594	1026	976	836	1354	1269	1133	866	750	1269
Observations (BW)	3003	1709	1886	1787	3430	2251	2162	1873	2921	2755	2455	1935	1696	2755

NOTES. SE clustered at the school level. *** $p<0.01$, ** $p<0.05$, and *$p<0.10$.

Table B.7: Student Outcomes (Math 2018) - By Student Achievement Level

	(1) Level 0	(2) Level 1	(3) Level 2	(4) Level 3
Pop < 500 hab. (ITT)	-0.099**	-0.048	0.078**	0.095**
	(0.049)	(0.031)	(0.036)	(0.044)
Wage Bonus (LATE)	-0.219*	-0.107	0.175**	0.200**
	(0.118)	(0.071)	(0.088)	(0.101)
Mean dep. var.	0.190	0.276	0.361	0.182
BW	136.362	139.004	167.459	106.024
Schools (BW)	889	909	1126	694
Observations (BW)	12601	12872	15862	10068

NOTES. SE clustered at the school level. *** p< 0.01, ** p<0.05, and *p<0.10

Table B.8: Student Outcomes (Spanish 2018) - By Student Achievement Level

	(1) Level 0	(2) Level 1	(3) Level 2	(4) Level 3
Pop < 500 hab. (ITT)	-0.111**	0.018	0.065**	0.031
	(0.051)	(0.030)	(0.031)	(0.034)
Wage Bonus (LATE)	-0.247**	0.041	0.147*	0.068
	(0.124)	(0.066)	(0.078)	(0.077)
Mean dep. var.	0.226	0.343	0.259	0.176
BW	145.870	161.750	152.373	134.587
Schools (BW)	944	1085	1009	870
Observations (BW)	13320	15345	14210	12361

NOTES. SE clustered at the school level. *** p< 0.01, ** p<0.05, and *p<0.10