Teacher Compensation and Structural Inequality: Evidence from Centralized Teacher School Choice in Peru[†]

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Abstract

This paper studies how increasing teacher compensation at hard-to-staff schools can reduce structural inequality in the access to high-quality teachers. Using rich administrative data from Perú, we document dramatic inequities in schooling inputs and teacher quality to which students have access. Using a regression discontinuity design, we show that a 25% increase in teacher pay at less desirable public schools attracts better quality applicants and improves subsequent student test scores. To quantify how teachers trade-off local amenities and compensation, we estimate a model of teacher school choice using detailed job posting and application data from the country-wide centralized teacher assignment system. We use the model to decompose the factors that drive teachers' labor supply and to approximate the cost-effectiveness of alternative policies. The results suggest that targeted pay increases can help reduce spatial inequalities in the access to quality education. Our results also indicate that current pay in less desirable regions is woefully insufficient to compensate teachers for the lack of school and community amenities. Model estimates suggest that a more cost-effective policy to attract better quality teachers in these less desirable regions is to invest in other schooling infrastructure and invest in training new teachers from these locations.

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JEL Codes: J31, J45, I21, C93, O15.

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1 Introduction

Children born in poorer and more rural communities face significant disadvantages in their ability to invest in their human capital. Some of these disadvantages are the product of the inequities from the past. Current policies can also reinforce inequality that is structural by providing unequal access to public school funding, investment in infrastructure and quality of instruction. This can create a feedback loop where poor education hampers local economic growth which makes it more difficult to adequately fund the local public-school system. This paper studies how teacher compensation for public school teaching jobs can contribute to reducing the structural inequality in education in Peru.

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 are less appealing, which therefore attract low-quality applicants or none at all. In the education sector, this can translate into large and persistent differences in teacher quality across communities in locations with varying levels of amenities valued by teachers.[1] In this paper we argue that given teacher preferences for community and school amenities, rigid teacher compensation profiles contribute to the structural inequities faced by children born in poorer rural regions of Peru. We also show evidence that reforming teacher pay to compensate for a lack of local amenities can help to reduce structural inequality.

We begin by documenting that a child will receive strikingly different school inputs depending upon where she is born. As in many countries, an important challenge in Peru is to provide access to quality education in rural areas. When compared to urban schools, students in rural schools are taught by teachers with lower competency scores, and are less likely to have access to libraries, doctors, and sewage. It is then not surprising to find that these students have lower academic achievement as measured by standardized test scores, persistence and college attendance. This only reinforces the original conditions of inequality.

One factor that generates the difference in teacher quality is that, historically, vacancies in rural schools have been both harder to fill or staffed with relatively lower-quality applicants. In this paper, we show causal evidence that compensation plays a direct role in the observed sorting of teaching talent and the outcomes of students. To establish a causal link between the wages offered at a specific job posting, we leverage a policy change to teacher compensation that raised public-sector teacher salaries by about 25% at 50,000 teaching positions in over 17,000

[1]This is particularly worrying given the recent evidence that teacher quality at all levels has long-term consequences on adult labor market outcomes (Chetty et al. 2014b).

rural schools spread across Perú. The policy, implemented in January 2014, first introduced wage bonuses ranging from S/. 70 to S/.200 to schools located far from the providence capital and with low locality population counts. Arbitrary cutoff rules for policy eligibility generate local quasi-experimental variation in wages across schools. This change in wage structure occurred in the context of a centralized mechanism that assigned teachers to schools based on teacher preferences and teacher performance on standardized competency tests. Specifically, in 2015, the Ministry of Education introduced bi-annual centralized recruitment drives using a centralized system to allocate contract (fixed-term) teachers (*docentes contratados*) and permanent teachers (*docentes nombrado*) across the entire country. This system is unique in that it provides data on job openings and job applications and a known structure regarding how assignments are resolved; these features are not typically observed in most labor markets. These two institutional details present a unique setting in which to study teachers' preferences, and to analyze their sorting patterns across schools/locations with different wage levels.

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 0.7 standard deviations higher in the competency test when compared to teachers who chose a position in lower paying but otherwise similar schools. Teachers in higher paying schools are also more effective – their students perform significantly better in national standardized achievement tests three years after the policy change. We find large and positive impacts on student outcomes at schools that had multiple open vacancies in the previous recruitment drive. In contrast, schools without vacancies experienced small and statistically insignificant effects on student achievement. These two pieces of evidence suggest that it is the inflow of new high-quality teachers that improves student outcomes.

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, a finding that 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 observed policy impact that we measure in Peru may be explained by the pairing of flexible teacher contracts with a transparent, meritocratic assignment mechanism.

These results suggest that targeted pay increases can help reduce spatial inequalities in the access to quality education. However, many factors could contribute to the lower desirability of a location such as the lower levels of school infrastructure and the overall scarcity of services, public goods and local amenities. Therefore, wage policies that adequately compensate for the lack of amenities in rural areas could induce higher-quality teachers to fill positions in less desirable locations. In order to reform teacher pay, policymakers need to know how teachers of different ability levels trade-off pecuniary and non-pecuniary aspects of different job vacancies. If policymakers know the elasticities, they can compute the fiscal costs of counterfactual policies that raise teacher pay in order to raise the quality of teachers in poor rural areas.

To quantify how teachers trade-off compensation and other amenities, we estimate a discrete choice model of the decision of potential teachers to apply for vacant positions in both rural and urban areas. This model allows us to better understand 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 this wage 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. We validate our estimated wage elasticity by replicating the observed changes in teachers' scores at the population cutoff that determines eligibility for the wage policy.

We use the model to evaluate the fiscal cost of using wage bonuses to equalize the playing field between children who attend urban and rural schools. Counterfactual experiments suggest that wage bonuses may be an effective policy to make the distribution of teachers more equitable for children attending urban schools versus schools 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. As a result, it is fiscally expensive to use wage-based policies to equalize the playing field. A less expensive policy option to improve teacher quality in rural areas may be to target teacher training programs and school infrastructure investments in remote, less desirable locations.

These results contribute 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, teacher compensation is low relative to other college graduates and at baseline it is difficult to staff 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 to increase teacher compensation. Several global policy think tanks have recommended for years to increase teacher pay in low-income countries as a way to attract talent towards 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. Furthermore, 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 does the level of compensation matter, but variation within job postings also affects teacher sorting. 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.

We also 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.

2 Data

In this paper, we use several 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. The data includes administrative panel data on all schools, students and teachers and covers the five year period between 2015 and 2019. We also leverage the centralized system that coordinates the match between all teaching job vacancies and teacher ranked job applications and final assignments. Data on the teacher payroll also allows for the tracking at the microlevel the changes to compensation that arise from recent policy changes.

We describe each source of data in more detail in what follows.

The first is the data source stems from the governments *centralized teacher job application and assingment system*. These data include all the vacancies posted at every public school in the country. It also includes teacher job applications to up to five jobs. These are ranked and provided to the centralized system. The data covers the assignment processes that took place in the October 2015 and 2017. These datasets also include information on the teacher evaluations for every applicant in the centralized test, the chosen UGEL, and field of expertise. The data also includes the assignment process for short term contract teachers.

A second administrative data source is the governments *teacher occupation and payroll system (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.)

A third source of information is the administrative school census dataset that includes *school inputs and characteristics* such as: 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.

A fourth data source is administrative records on *student academic 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).[2]

3 Context and Institutions

3.1 Inequality of Education Inputs and Outputs

Perú's colonial history has had persistent effects on current institutions, governance, public good provision and welfare (Dell (2010), Artiles (2020)). The country spans a vast and varied geography made up of mountainous, jungle and coastal regions, with a population composed of

[2]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.

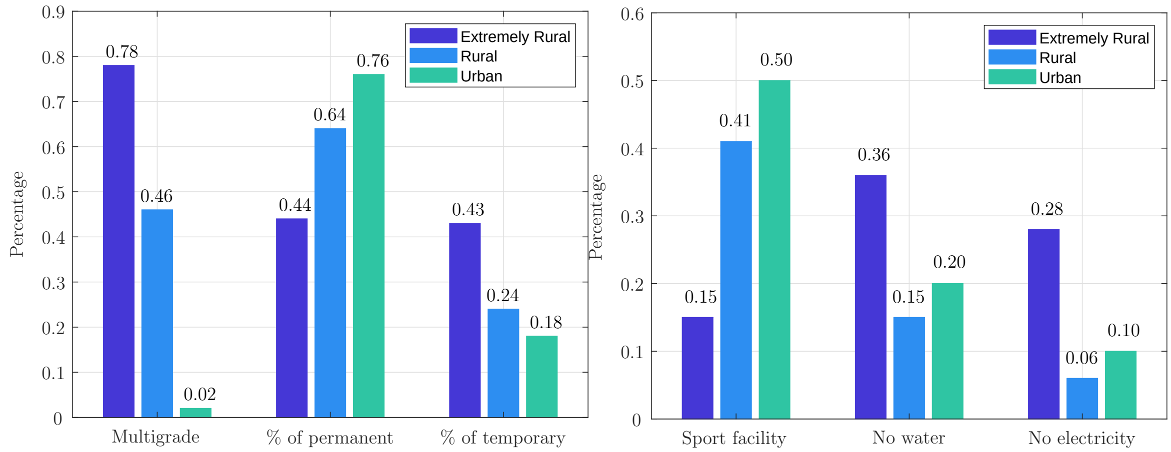
a diverse set of ethnic, cultural, linguistic groups who have lived for centuries under extractive systems of governance as a colony of the Spanish empire (Acemoglu et al. (2001)). Colonial policies often targeted the highlands and jungle regions where persistnent poverty is currently concentrated. For this reason, colonial policies is the main contributor to current structural inequalities.

Policy makers face staggering differences across urban and more rural communities in their economic development and the access to public services like education. Peruvian public primary schools educate 74% of the student population. In rural areas, where public schools are generally the only option to access educational services, more than 6,000 schools served 98% of school aged children in 2015. Students who attend rural schools score on average 50 points lower on both Math and Spanish exams relative to students in urbans schools, are more likely to attend schools serviced by only one teacher, and attend schools with fewer amenities.

Over the last decade, the government has undergone several efforts to help promote educational attainment in poorer rural areas, such as the implementating a large scale conditional cash transfer program, investmenting in school infrastructure projects, and improving access to drinking water and sewage, etc. However, there still exists large differences in the access to education inputs such as school infrastructure and the quality of the teaching staff.

We now show that educational inputs vary across schools by level of rurality based on population and distance to the regional capital as defined by the Ministry of Education (MINEDU). Figure I shows some examples of the stark contrast between schools in rural and urban areas: schools in extremely rural areas are much less likely to have running water, electricity and are unlikely to have any sort of sporting facility. Instruction at rural schools is carried out by teachers who are much less likely to have regular permanent contracts and instead are more likely to have only short term contract teachers or who are less likely to be certified. Table V shows this pattern holds across other indicators for school inputs.

Figure I: School Infrastructure and Teaching Staff by Rurality



a) School characteristics **b) Infrastructure**

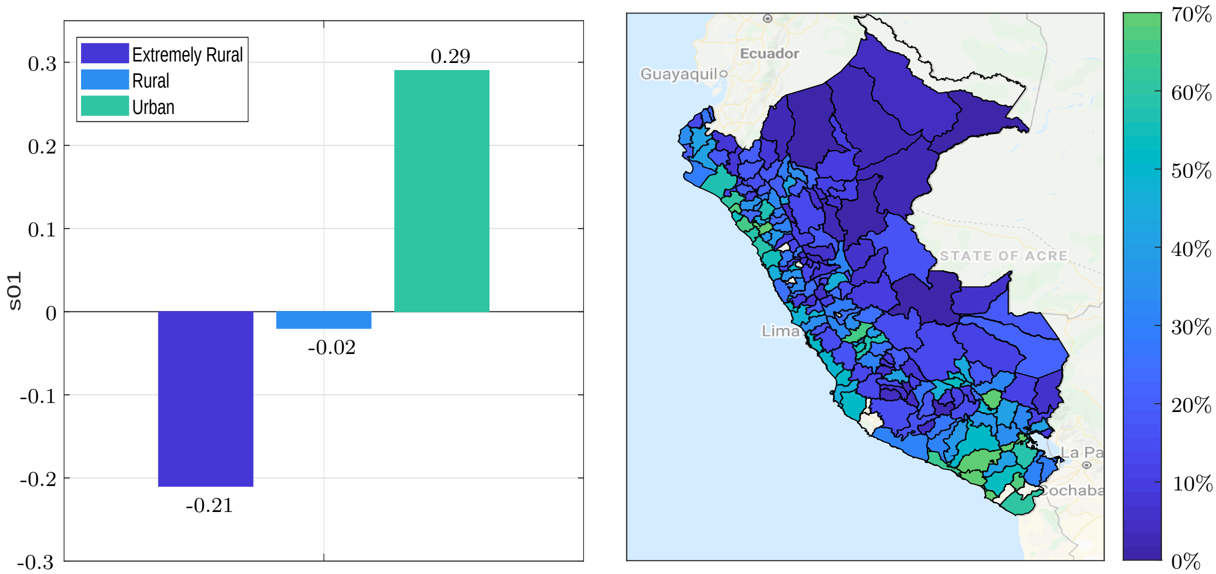
Notes: These figures show different summary statistics about schools by level of rurality. School infrastructure is shown in the right panel and the type of teachers at the schools in the left panel. *Extreme Rural* schools are shown in purple, other *Moderatly Rural* schools in blue, and *Urban* schools in green.

Teacher quality has been shown to be an important input into the education production function in the US; recent research in developing countries has confirmed this finding.[3] Recent evidence also shows that teacher subject competency test scores are correlated with teacher value added and more broadly teacher quality[4]. For this reason, it is especially concerning that rural schools that have lower performance and worse initial conditions also have teachers with much lower evaluations on the government teacher compentency tests. Figure XI shows that on average, teachers at rural schools score 0.2σ below the average while urban teachers score 0.3σ above the average. The map of Peru shown in the right panel of Figure XI shows the inequality in access to well evaluated teachers varies geographically.

[3] See evidence from the US by Chetty et al. (2014a), evidence from Ecuador by Araujo et al. (2016), Pakistan by Bau and Das (2020) and Uganda by Buhl-Wiggers et al. (2017).

[4] See Bold et al. (2017) for a review and see Gregorio et al. (2019), Gallegos et al. (2019) for evidence from Chile.

Figure II: Teacher Competency Evaluation by Geography



a) Average Teacher Evaluation by Rurality **b) % Teachers with Evaluation Top 25%**

NOTES: This figure shows average teacher evaluatation scores by level of rurality in the left panel. The right panel shows the map of Peru highlighting geographic variation in teacher evaluatation scores. Costal areas are richer and more urban and can be seen to have a larger share of teachers with evaluations in the top quartile.

3.2 Wages, Contracts and Sorting of Public School Teachers in Peru

To better understand the reasons behind the striking inequality in teacher quality across different areas of Peru, we now describe the institutions surrounding the labor market for the nearly 180,000 public school teachers in Perú.

3.2.1 Short and Long Term Teaching Jobs

Teachers are hired under two distinct types of contracts. Permanent teachers (*docentes nombrados*) work in conditions similar to tenured teachers in other countries: they are civil servants with permanent contracts, and in practice, the chances of dismissal are close to zero. Teachers can also be hired by the central administration to work at a specific school for the academic year in a short term teacher contract (*docentes contratados*). These are meant to be one year contracts but have the option of being renewed for one additional year. Both permanent and short term teaching contracts require teachers 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.

3.2.2 Public School Teaching Job Compensation

As in many 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 2020). Teachers' wages depend on (i) whether they are permanent or contract teachers, (ii) their seniority, and (iii) the location where they work. In addition to fixed wages, some teachers receive additional bonuses for taking specific responsibilities, for example deputy principals, or for teaching in special education or bilingual schools. In 2015, contract teachers received a 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 approximately S/ 1,500 and reaching S/ 3,000.

As in most of Latin America, public school teachers' compensations in Perú are low relative to other professionals: 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). 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 **?**).

3.2.3 Teaching Vacancies and Teacher Job Applications

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 generated concerns about a 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. Teachers recruited through the 2015 and 2017 drives started teaching in the 2016 and 2018 academic years (March-December), respectively. At the end of the 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.

The process consists of two main rounds. In the first round, all vacancies for permanent teachers in different fields and specializations are reported to the centralized system. Interested applicants must be certified and take a standardized teacher evaluation. This test includes competency 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 to participate in this first round and could apply for a permanent position. Applicants then choose a political region (UGEL), their field of expertise and, within that subset of job vacancies, they must select and rank up to five available positions.

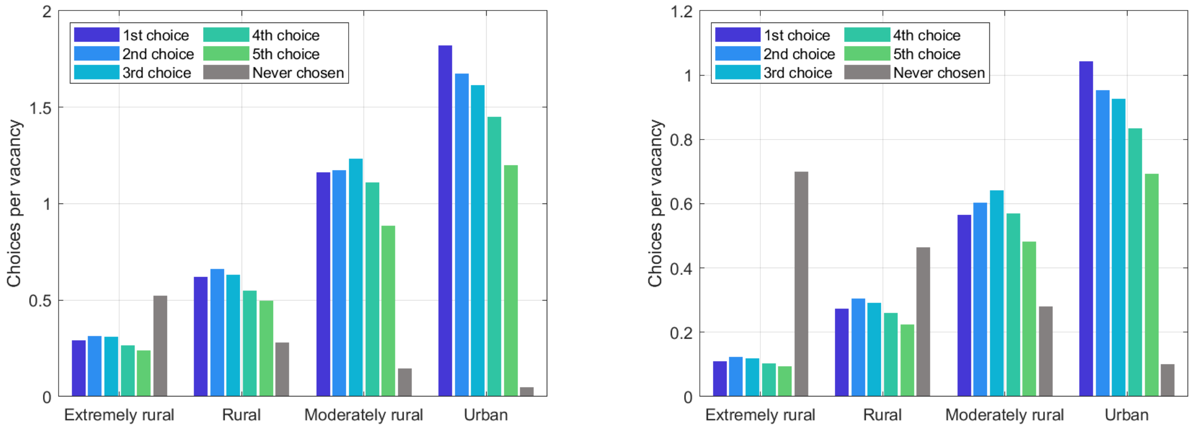
The school is sent the application files of up to 20 of the highest scoring teachers among those teachers who ranked an available position within that school. The school evaluates the short-list and scores the applicants based on an in-class demonstration, their experience, and an interview. At the end of the process, the grade in the centralized test and the decentralized evaluation are added, and positions are allocated to the highest scoring teacher who ranked each position. There were 19,500 and 37,000 vacancies for permanent teachers in 2015 and 2017, respectively.

In a second phase, all short term job vacancies are provided to the platform, in addition to any permanent positions that remain unfilled in the first process. In contrast to the assignment of permanent teaching contracts, short term teaching positions are designed to be matched quickly by eliminating the schools' (subjective) participation in the screening process. Instead, schools' preferences are taken to be a strict ranking of the teacher evaluation competency score. Applicants again choose a region (UGEL) and field. They then are sequentially allowed to choose from the available vacancies in that region according to their teacher evaluation score.[5] 56,000 short term teaching positions were available in 2015, while 73,000 were available in 2017.

Figure III shows the data on applications to vacancies divided by rurality. While each vacancy posted at schools in urban areas has many applicants, vacancies posted in rural areas have less than one application in expectation. If we further condition on applications from teachers that have an above median teacher evaluation, we see that 70% of all vacancies have not one application while this is true for less than 5% of vacancies posted at urban schools.

[5] For example, the highest scoring teacher within each UGEL/Field gets 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 now makes her choice, and so on until either all teaching positions are filled or all teachers are allocated to a position.

Figure III: Job Applications by School Rurality



a. Applications for Teachers (Any) *b.* Applications for Teachers (Above Median)

Notes: These figures show teacher applications for permanent job openings public schools by level of rurality. Application rates for teachers with below median evaluations are shown in the left panel while the right panel shows the application rates for teachers with above median evaluations.

Consistent with the application data presented in Figure III, the recruiting process leads to only 35% of job vacancies for permanent positions to be filled in extremely rural schools. At the same time, close to 80% of these positions were filled when the vacancies were at urban public schools. This is the result of the lack of applications to positions in rural areas, especially when it comes to teachers with higher evaluations and overall qualifications.

During the next process where teachers are ranked by their teacher evaluation and given the option to choose among remaining short term job openings, approximately 88% of the remaining positions in rural areas were finally filled. The remaining 10% of positions are filled in an ad-hoc manner in a decentralized secondary market. The remaining vacancies and other short term openings are then made available to teachers that have not yet found a job.

We conclude that the significant inequality in the access to qualified teachers is driven mostly by teacher job application behavior. The microdata on job postings and teacher ranked applications show that most of the applications are concentrated at positions in urban areas, and the system is hard pressed to staff the roughly 17,000 small rural public schools scattered all over the poorest parts of the country. While most of these vacancies are eventually filled using short term contracts, the teachers that eventually take these jobs are those who were not able to find other jobs and were overall significantly less qualified.

3.3 Policy Changes to Compensation in Rural Locations

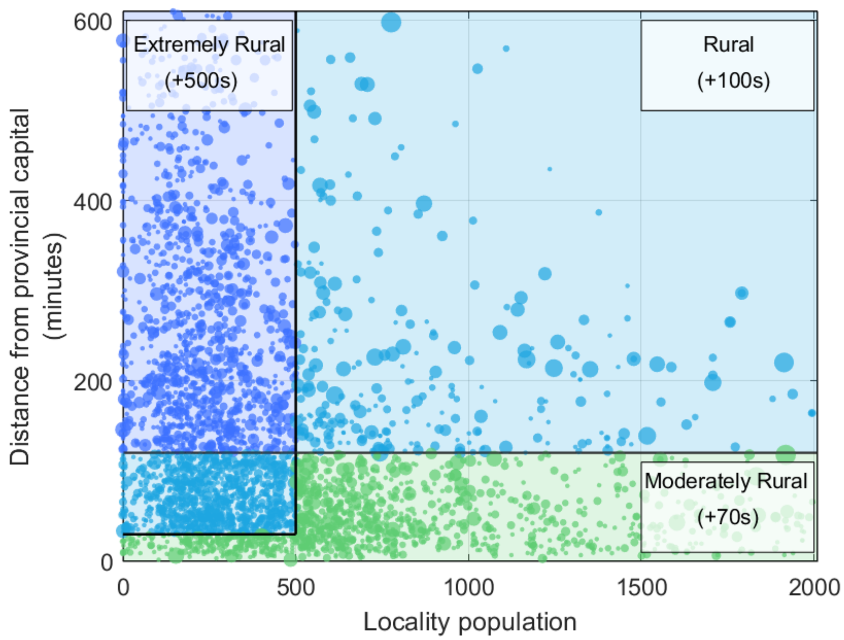
Teachers in poor rural areas face numerous challenges: scarcity of basic school inputs, lack of services, lack of public goods, few local amenities, and being far from friends and family. Thus the large gap between teachers preferences and the staffing requirements of the state documented above could be due to the fact compensation mostly ignores local and school amenities associated with the job. Unlike private labor markets, supply and demand do not determine equilibrium compensation so that if wage setting policies do not adequately compensate for the lack of amenities, those jobs will be less attractive. Consequently, vacancies in rural schools will be either more difficult to fill or will yield less competitive applicants, both outcomes that are consistent with the job application and assignment data presented above.

These considerations motivated the government to introduce a new policy significantly increasing wages at positions in rural schools. Wage bonuses were based on two pre-established criteria that categorized schools into three groups: *Extremely Rural*, *Rural* and *Moderately Rural*. These groups are defined as a function of the population of the local community and the location's proximity to the provincial capital.[6] *Extremely Rural* schools 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 of *Rural* is reserved for either: (a) schools in localities with less than 500 inhabitants and which are located between 30 and 120 minutes from the province capital, or (b) schools in localities with 500-2,000 inhabitants that are farther than 120 minutes from the province capital. The final set of *Moderately Rural* schools are either: (a) schools in localities with 500-2,000 people that are closer than 120 minutes, or (b) schools in localities with less than 500 inhabitants that 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 *Extremely Rural* , *Rural*, and *Moderately Rural* schools with wage bonuses of S/.200, S/.100, and S/.70, respectively. In August 2015, the bonus for teachers in *Extremely Rural* was increased to S/.500, and wage bonuses were extended to contract teachers as well. 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 *Extremely Rural* schools is fairly generous, as it represents 30-40% of the earnings of contract teachers and 20-30% of the earnings of permanent teachers. Figure IV 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.

[6]The population of the locality where the school is located is measured by population counts in the latest available census and the time it takes to travel from the locality to the province capital is measured on the basis of GPS coordinates taken by an inspector after taking into account usual modes of transport and types of roads available each year.

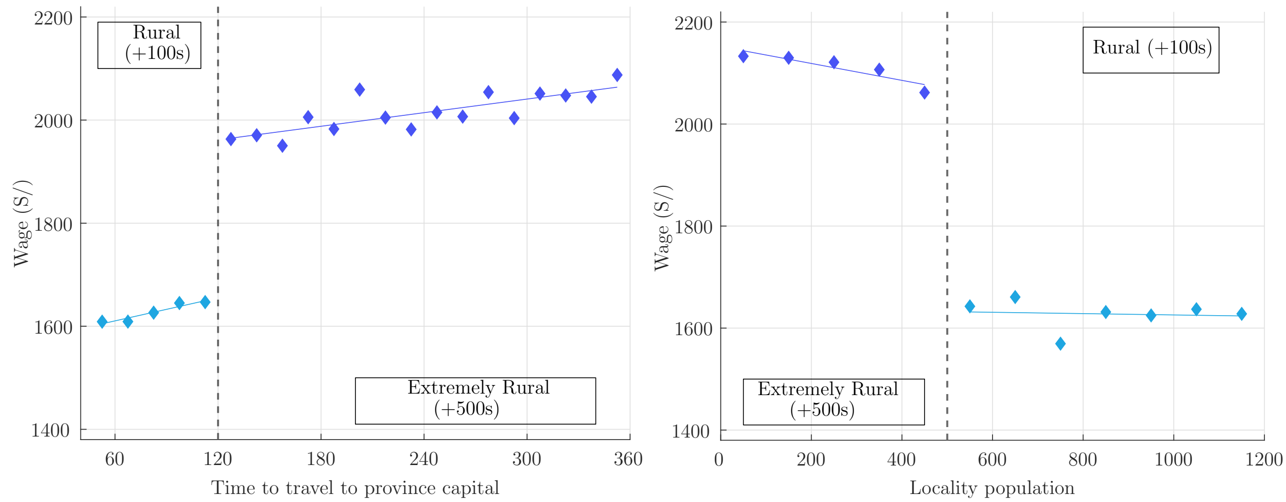
Figure IV: Spatial Distribution of Rural Schools



Notes. This figure shows the spatial distribution of rural primary schools along the two dimensions that determine the assignment of the wage bonus. *Extremely Rural* schools are the purple dots, *Rural* are light blue and *Moderately Rural* schools are green. The size of the dots reflects the cumulative number of open vacancies in each school over the recruitment drive.

Using administrative payroll data for teachers, we can verify the assignment rules lead to significant changes in compensation when schools pass the threshold from one category to another. Figure V shows empirically how teacher compensation varies depending on the travel distance from the school to the province capital (left panel), and on the number of inhabitants in the locality (right panel). The Figure is drawn based on teachers payroll data (contract teachers) for December 2015. As can be seen, teacher wages exhibit a large discrete jump when crossing from the left the 120 minutes threshold, and from the right the 500 inhabitants threshold (i.e. the two criteria used to identify *Extremely Rural* 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 S./400 (S./430) difference in the wage bonus between *Extremely Rural* and *Rural* schools.

Figure V: Wages of Teaching Jobs by Distance to Province Capital and Population



Time-to-travel **Population**

Notes. This figure shows how average teacher wages for short term contracts vary based on the travel time from the province capital (left) and number of locality inhabitants (right) for December 2015. Each marker indicates the average wage within each bin, defined following the IMSE-optimal evenly spaced method by Cattaneo (2017). The solid lines represent the predicted wages from linear regressions estimated separately for observations to the left and to the right of the cutoff. Wages are expressed in Peruvian Soles.

4 Policy Effects of the Increase in Compensation

4.1 Identification and Estimation

Higher wages offered at positions in rural locations could attract more teachers of higher-quality, which could in turn reduce the inequality in educational opportunities. For example, Dal Bo et al. (2013) show evidence from Mexico that increases in compensation for administrative positions in the public sector lead to a larger pool of applicants, a higher quality of hired employees and improved outcomes. In addition to the recruiting effects, additional compensation could increase the quality of instruction by affecting the productivity of the teachers already employed by these schools.

However, there are two potential reasons why raising compensation may not lead to improved educational opportunities for students in poorer rural areas. First, additional compensation might not change application behavior. If teacher preferences over schools is not driven by compensation, increasing pay would not induce higher quality teachers to rank positions in rural areas. Even though teachers may value compensation, the lack of demand for these rural jobs may be explained by other frictions such as limited information about these options so that just increasing wages would also not be effective.

A second potential limitation is that selection based on teacher evaluations or the schools discretionary ranking of teachers, do not lead to teachers that affect student learning. In this case, increasing the number and quality of applicants as measured by their average teacher evaluation scores would not produce the desired improvements in student outcomes. Under this scenario, results will not produce better results even if increased wages does indeed move high scoring teachers to apply for these job vacancies.

In summary, for a wage-reform policy to improve access to educational opportunities in poorer rural areas, three conditions must hold. First, compensation must have a causal and large enough effect on teacher job application behavior to generate changes to teacher sorting. Second, the increase in demand for vacancies must lead to an increase in measured teacher quality through the selection system. Third, that the increase in measured teacher quality has a causal and sufficiently large effect on student achievement.

To test these hypothesis, we use the assignment rules of the wage bonus policy to develop a regression discontinuity design (RDD) framework to identify the causal effects of unconditional wage increases on (i) the demand for teaching positions across the job postings made available through the assignment mechanism described in Section 4.2, (ii) the selection of teachers resulting from the filled vacancies, and (iii) student standardized test scores. Our main estimating equation is as follows:

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

where y_{jt} is an outcome variable for 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 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_{jt} is clustered at the level of assignment of the wage bonus, that is a school-year pair.

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 XIII, where we display the empirical densities based on local-quadratic density estimators with the corresponding confidence intervals for each of the assignment variables in each of the two years of the assignment mechanism. The population threshold is based on census data, and as such it is difficult to manipulate. The left-hand side panels show that indeed, there are no significant discontinuities at the 500-inhabitants threshold for either of the years of interest. The panels at the right hand side of Figure XIII shows the empirical densities of observations around the time-to-travel distance threshold. Instead, there is a significantly larger mass of schools that fall just into the *Extremely Rural* category for the assignment mechanism that took place in 2018. The formal manipulation tests (McCrary 2008) confirm these visual patterns.[7] 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). We get a similar result when limiting the sample to schools that had an open position for permanent teachers or for contract teachers during the two years of the centralized recruitment mechanism, which are displayed in columns 2 and 3, respectively, of Appendix Table B.1. We therefore only rely on the source of variation in teacher wages provided by the population threshold for our main estimation. Given continuity of potential outcomes around the population cutoff, the following reduced-form equation identifies an Intention-To-Treat (ITT) effect of the policy:

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

where, as before, $g(\cdot)$ is a flexible polynomial in the distance from the population cutoff and u_{jt} is an error term clustered at the school-year 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).

On average, 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 con-

[7] 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 2.39 (p-value=0.017) in 2018 and 1.15 (p-value=0.25) in 2016. T-stats are lower in size and they are not statistically significant for the population discontinuities, taking the value of -1.24 (p-value=0.22) in 2016 and of -0.24 (p-value=0.81) in 2018.

siderations motivate the use of a fuzzy regression discontinuity (FRD) approach, whereby an indicator function for crossing from above the 500 population threshold, $\mathbf{1}(pop_{jt} < pop_c)$, can be used as a valid instrument for the schools being in the *Extremely Rural* category.

Alternatively, we could use a sharp RD limiting the sample to schools located above the time-to-travel threshold. We don't pursue this empirical strategy for two important reasons. First, restricting the sample to schools located above the time-to-travel threshold would imply conditioning on a variable that is partially manipulated (see Figure XIII in the Appendix). Second, such sample restriction would also imply leaving out a large portion of schools, and in particular those that cross the threshold along the diagonal of Figure IV, i.e. from *Moderately Rural* to *Extremely Rural*, thereby missing relevant variation of wage bonuses in the data.

4.2 Compensation and the Demand for Teaching Positions

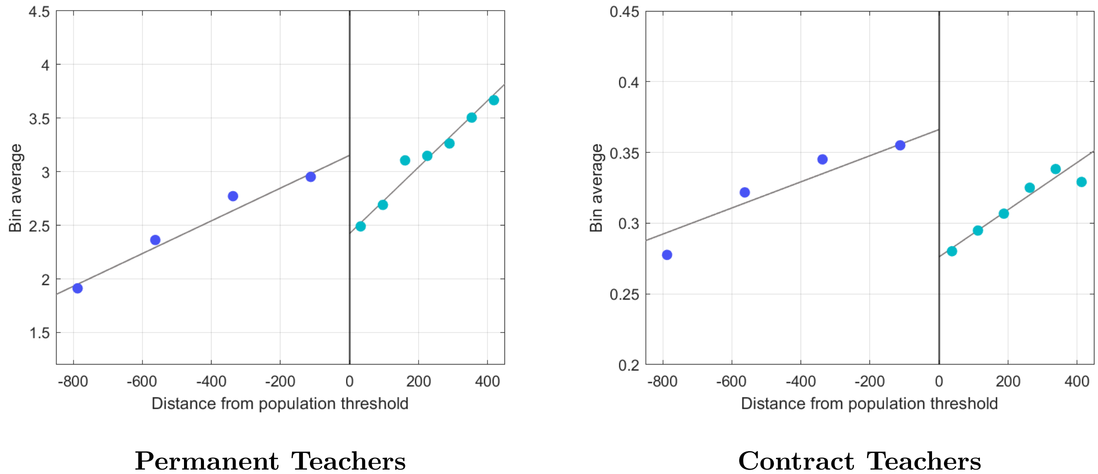
As shown in Figure V, the average contract teacher in a school located in an *Extremely Rural* place earns S/ 380 more than those in a school in a locality that is just above the 500 inhabitants threshold, which on average represents an increase in the unconditional wage of 23%. This wage increase makes teaching 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 Tables I and XIII. 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).

We start by documenting some graphical evidence on the demand for teaching positions. Figure VI displays the relationship between the rank of assigned teachers in schools in localities of different population size.[8] The panel on the left shows the effect of increased wages for permanent teaching positions, whereas the panel on the right shows this effect for temporary (contract) teaching positions. Away from the population threshold, the relationship is positive. That is, the more rural the locality in which the school is located the lower the demand for teaching positions. There is a sizable downward jump in the rank of teachers at the population threshold, which indicates that increased wages effectively increase the demand for both types of teaching positions leading to higher competition and potentially improving the quality of new teachers.

Tables I-II reports the RD estimates of the effect of increased wages for a broader set of teachers' outcomes, where again we consider separately the permanent and temporary teaching positions due to the different nature of the assignment mechanisms (see Section 3.2). Column (1) of Table I shows that rural schools with wage bonuses are more likely to be included in

[8]Given that there is a different number of total applicants in each UGEL×field, we normalize the ranking for contract teachers so that it takes values from zero to one, with one indicating the last teacher who applied in the UGEL×field.

Figure VI: Applications to Vacancies



Notes. This figure shows the relationship between the rank of an assigned teacher to a given school and the locality's population count. In both panels, we see that crossing the population eligibility threshold reduces the rank of the assigned teacher, suggesting that higher wages increases demand for teaching positions. In the right panel, we normalize the ranking for contract teachers, with 1 indicating the last teacher who applied for a position within the UGEL×field.

the applicants' ranked-order lists by 31 percentage points, out of an average share of filled vacancies of 81% in rural schools without wage bonuses. In column (2), we consider the rank of the applicants in the assigned schools and find that wage incentives move assigned applicants up the rank by 1.76 positions out of a scale from 1 to 6, where 6 indicates that the position remained unfilled.

Column (1) of Table II shows that the number of vacancies assigned to contract teachers do not significantly change due to the wage increases in *Extremely Rural* schools. The average vacancy is filled by the applicant in the 35^{th} percentile in the UGEL×field. As shown in Column (2), just below the population threshold teaching positions are filled by candidates who rank 10 percentage points higher. The average vacancy in a school classified as *Extremely Rural* because it is just below the population threshold 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.[9]

[9] 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 II is not significant, there may be concerns that the density of observations for these regressions is not continuous at the threshold. Appendix Figure XV 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.

Table I: Monetary Incentives and Selection, Permanent Teachers

	(1) School chosen	(2) Rank	(3) Vacancy filled	(4) Score (std)
Pop < 500 hab. (ITT)	0.177***	-0.938**	0.024	0.037
	(0.065)	(0.371)	(0.074)	(0.076)
Wage Bonus (LATE)	0.307***	-1.764***	0.043	0.090
	(0.110)	(0.602)	(0.132)	(0.182)
Mean dep. var. (LHS)	0.810	2.537	0.379	1.605
BW	156.129	179.883	158.037	166.103
Observations (BW)	1269	1469	1707	768
Observations	5266	5266	6584	2696

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 II: Monetary Incentives and Selection, Contract Teachers

	All Vacancies	Filled Vacancies		
	(1) Vacancy filled	(2) Rank	(3) Score (std.)	(4) > 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. (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

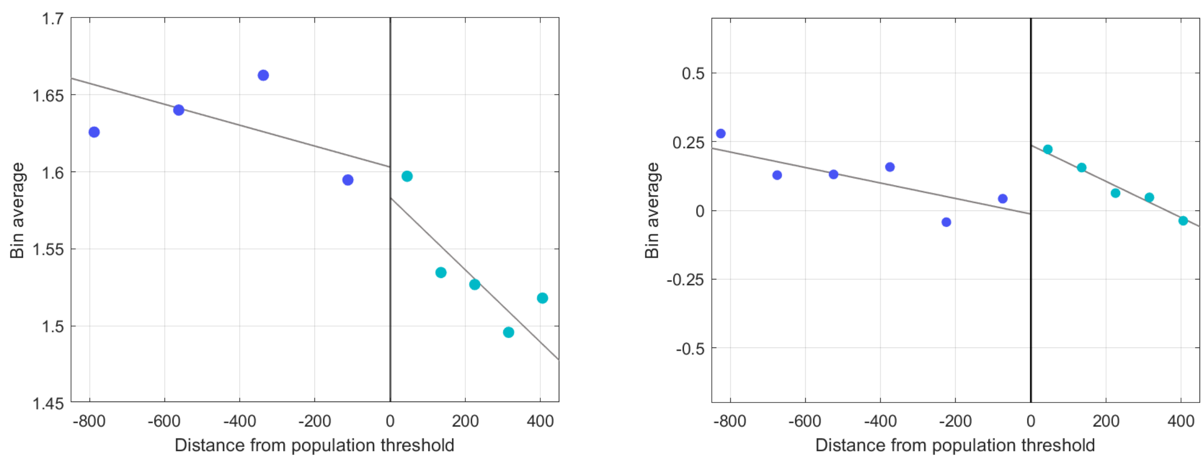
Notes. This table reports the effect of crossing the population threshold (ITT) and the effect of the wage bonus (LATE) on the probability that a vacancy is filled by a certified teacher (Column 1) and on different measures of teacher quality (Columns 2-4). These are the relative ranking in which the vacancy is filled – normalized so that it takes value from zero to one – (Column 2), the standardized score in the centralized test (Column 3), and an indicator for the test score being above the median score (Column 4). In Column 1, the sample includes all the teaching positions open in rural schools in the 2015 or 2017 recruitment drive, while only the positions filled by certified teachers in Columns 2-4. Each cell reports the bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014). Regressions are defined within a mean-square error optimal bandwidth (BW), reported at the bottom part of the table. The table also reports the mean of the dependent variable computed within the intervals $(0, +BW)$ (right-hand-side of the cutoff) and $(-BW, 0]$ (left-hand-side of the cutoff). SE are clustered at the school×year level. *** p< 0.01, ** p<0.05, and *p<0.10.

4.3 Compensation and Recruitment of Talent

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

Graphical evidence reported in the left panel of Figure VII shows that the quality of permanent teachers, as measured by their evaluation score, assigned through the assignment mechanism do not systematically change at the population threshold for the wage bonus policy. Instead there is a sizable upward jump in the quality of assigned contract teachers. 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.

Figure VII: Recruited Teacher Quality



Permanent teachers **Contract teachers**

Notes. This figure shows how teacher quality, as measure by the standardized teacher evaluation score, changes at the population eligibility threshold for the wage bonus. As can be seen, there is no meaningful difference in the quality of *permanent* teachers (left panel), while there is a sizable increase in the quality of *contract* teachers at the eligibility threshold (right panel).

The evidence reported in Columns (3)-(4) of Table I confirm that wage bonuses don't systematically alter the assignment of permanent teachers into school vacancies. There are no significant effects on the probability that a given vacancy is filled through the assignment process or on the score of the assigned teachers. We interpret these results as evidence that supply-side responses (i.e. school committees that acted independently in selecting applicants for vacant positions) may have neutralized the demand-side effects triggered by increased wages.

Columns (3) of Table II shows the regression results corresponding to the graphical evidence reported in the right panel of Figure VII. Teachers who select into a *Extremely Rural* schools have a score in the evaluation test that is 0.65σ higher. Importantly, this is not a marginal increase in quality, as we show in the column (4) of Table II: newly recruited teachers are 46 percentage points more likely to be in the top half of the distribution.

In Table XIV we study whether higher wages systematically attract contract 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.

Table III: Teachers' Characteristics

	(1) Female	(2) Age	(3) Novice Teacher	(4) Experience 1-3 yrs	(5) Experience > 3 yrs
Pop < 500 hab. (ITT)	0.056	-0.387	0.043	0.028	-0.089
	(0.048)	(0.623)	(0.030)	(0.049)	(0.059)
Wage Bonus (LATE)	0.107	-0.743	0.082	0.052	-0.169
	(0.093)	(1.204)	(0.057)	(0.094)	(0.113)
Mean dep. var.	0.600	37.725	0.111	0.374	0.427
BW	168.168	191.041	150.749	154.896	114.873
Schools (BW)	1362	1552	1203	1243	890
Observations (BW)	3080	3530	2801	2892	2129

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

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 **??** – and its companion Table B.7 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 **??** 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.

4.4 Wage Bonuses and Student Achievement

In this last 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 schools that had a chance of attracting a new (contract or permanent) teacher through an open vacancy in the 2015 and/or 2017 centralized recruitment drives. We then compare the standardized test scores (average of Math score and Spanish score) of students in the 4^{th} grade in 2018, between children in *Extremely Rural* schools and those in *Rural* and *Moderately Rural* schools.

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 IV. 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 IV 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 and/or 2017 recruitment drives. For these schools, the wage bonus does not significantly affect student achievement. The estimated RD effects are very small and statistically insignificant.[10]

In Column (2) of Table IV we alternatively consider the sub-set of schools that had an open vacancy for permanent teachers in the 2015 and/or 2017 recruitment drives. In this sample, the effects of the policy on 2018 standardized tests are again very small in magnitude and they are imprecisely estimated. This is consistent with the results discussed above and reported in Table I (see Columns 3-4), whereby in spite of increased demand the final effect on assignment

[10] 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).

of the wage bonuses for permanent teachers were not significant.

In Column (3) of Table IV we focus on those schools with an open vacancy for a contract teacher either in the 2015 and/or 2017 recruitment drives. Consistently with the substantial increase in teacher quality as a result of the wage bonus policy (see Table II and Figure VII), the estimated LATE of the wage bonus is large and statistically significant, with effect sizes of 0.64σ. Figure VIII displays graphically the ITT effect reported in Column of Table IV. As it was the case for teacher scores (see Figure VII), 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.

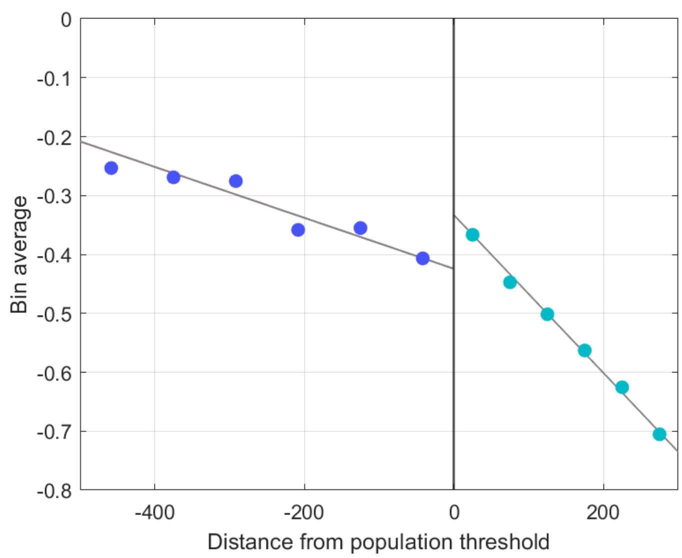
Table IV: Student Outcomes (2018)

	(1) No vacancy	(2) Permanent teacher	(3) Contract teacher
Pop < 500 hab. (ITT)	0.020	-0.009	0.296**
	(0.145)	(0.219)	(0.140)
Wage Bonus (LATE)	0.071	-0.032	0.644*
	(0.532)	(0.727)	(0.333)
Mean dep. var. (LHS)	-0.435	-0.347	-0.460
BW	116.841	161.746	124.925
Schools (BW)	544	308	806
Observations (BW)	6050	3655	11549

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

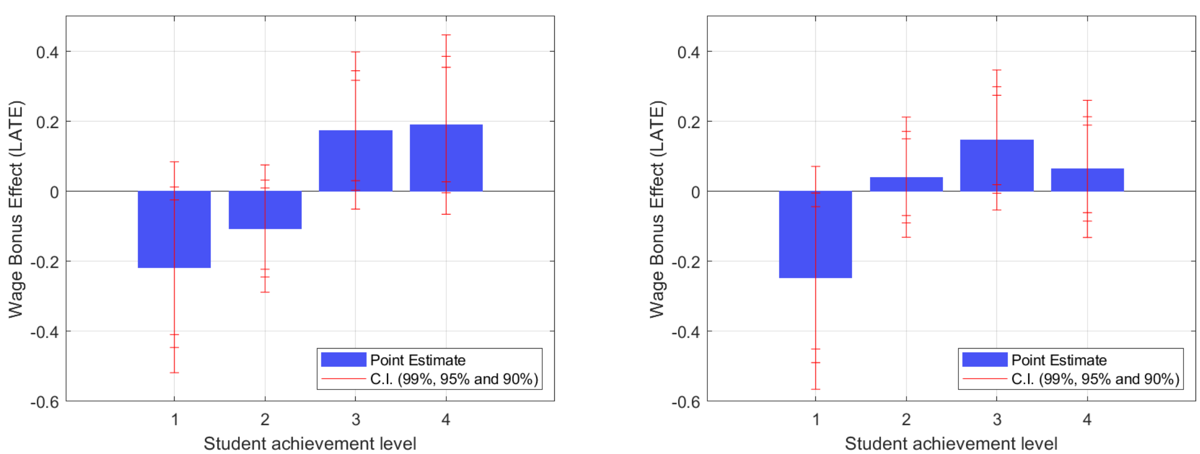
The Ministry of Education classifies students into four categories according to their responses in these standardized achievement tests. The lowest category correspond to students who have below basic knowledge (*Previo al inicio*), and the top category corresponding to outstanding students (*Satisfactorio*). Figure IX 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 (see also Table XII in the Appendix for the RD coefficients). 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.

Figure VIII: ITT Effects on Students' Standardized Test Scores (2018)



Notes. This figure displays the ITT effect of crossing the population eligibility threshold on student outcomes, focusing on schools with an open vacancy for *contract* teachers in either the 2015 and/or 2017 recruiting cycles (Column (3) of Table IV).

Figure IX: LATE Effects on Students' Achievement Level (2018)



a. Math | *b.* Spanish

Notes. This figure displays the LATE effects and the confidence intervals corresponding to our main specification using as dependent variables indicators for student achievement bins. Students are classified into four categories based on their performance in a standardized test – student achievement level 1 corresponds to students who have below basic knowledge while category 4 corresponds to outstanding students. Treatment reduces the number of category 1 students by about 25% in both reading and math, and increases the number of category 3 and 4 students.

5 A Model of Teacher School Choice

The evidence reported in the previous section documents causal evidence that higher wages increase the number of teachers interested in working at those positions, which in turn leads to an increase in the average quality of newly recruited teachers and subsequent improvements in students' academic achievement. This shows that it is possible to undo the staggering inequality of access to quality teachers by paying more for teaching jobs in places that are less desirable.

In this section, we quantify the way teachers trade off school and local communities amenities with the compensation offered to better understand teacher preferences. Using the unique data on teachers revealed preferences we estimate a model of teacher school choice. This empircal model allows us to better understand the labor supply of teachers and the reasons why the current situation is so unequal. We use the estimated preference parameters to evaluate alternative policy scenarios. In particular we use the model estimates to evaluate what a policy that provide equal opportunities for students across geographic locations. We use the model to benchmark the cost-effectiveness of the wage-bonus policy currently implemented with respect to alternative wage incentive schemes and other policies that improve other school inputs.

In order to decide which school characteristics enter into a teacher's utility function, we ran a survey that asked applicants to rank the most important characteristics for schools they choose to teach at. The results of that survey are shown in Table B.10. Forty-four percent of teachers rank "being close to home" as the most important characteristic. The two most often cited characteristics are prestige and cultural reasons. But as can be seen, there is clear heterogeneity in the characteristics that are most important to teachers. Moreover, teachers who score in the top quartile of the teacher evaluation test rank characteristics differently. More specifically, they appear to have stronger preferences for schools closer to home. Other characteristics that also drive decision-making for some teachers include: quality of school infrastructure, quality of students, and safety. These survey results inform the empirical model that we specify below.

5.1 An Empirical Model of Teachers School Choice

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

$$u_{ij} = \beta_i x_j + \alpha_i w_j + \lambda_i d_{ij} + \epsilon_{ij} \tag{3}$$

where 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 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 4.3. 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.

5.2 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 3, 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).[11] We thus maximize the following log-likelihood function:

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

where Ω_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

[11] 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.

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.

5.3 Model 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.

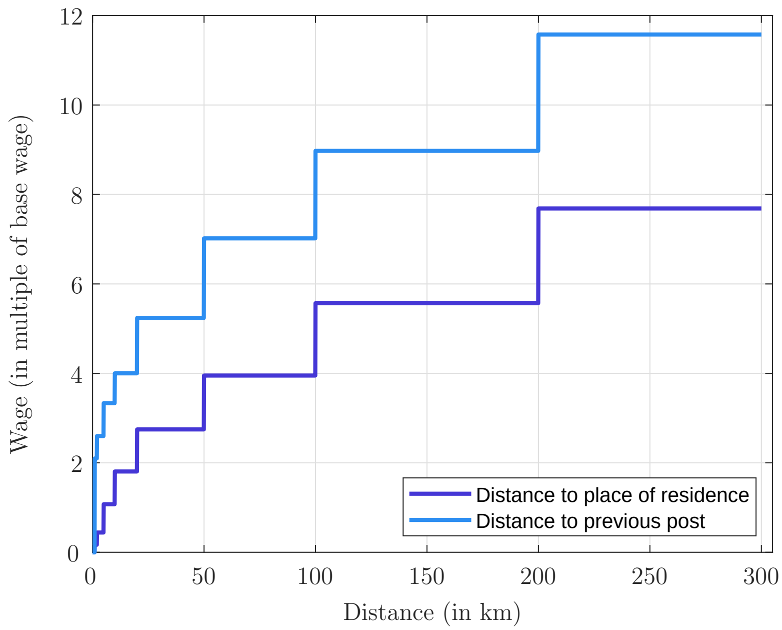
Table XVIII shows how the average estimated preference parameters across teachers vary across model specifications that include an increasing set of observed school and locality characteristics. The bare-bone model displayed in Column (1) shows that teachers seem to prefer relatively more populated places and schools situated in localities that are close to large cities. As discussed in Sections 3 and displayed in Figure **??** 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 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 4.[12] 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

[12]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 XVIII) changes from positive to negative from Column (2) to Column (3).

moving costs are key in explaining teachers' preferences over schools. Figure X 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 **??**, 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.

Figure X: 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).

Table XIX and XX document how the model estimates of column (5) of Table XVIII 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 XIX). 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 XIX). 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 XX 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 contrast to the estimates of Table XIX, 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 XX.

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 4. 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 XXI shows the result of this exercise: the baseline model depicted in Column (5) of Table XVIII 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.

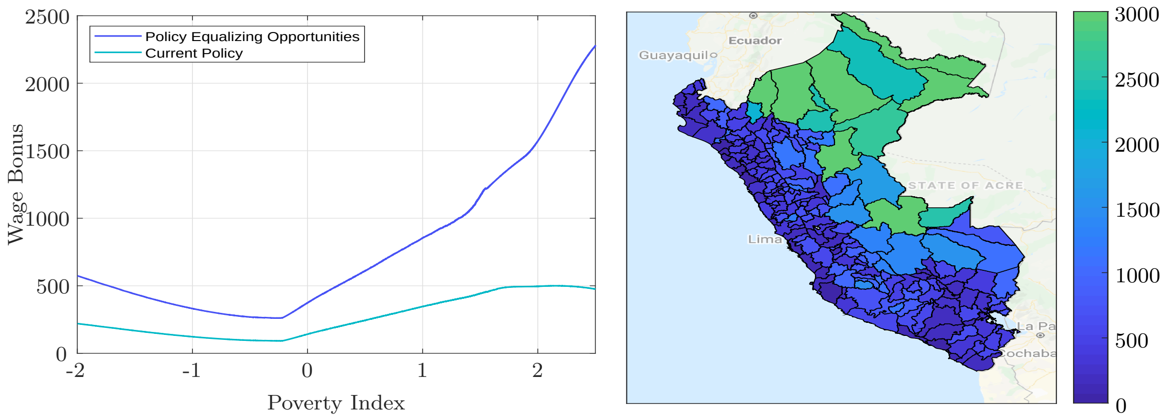
5.4 Policy Experiments

We consider a flexible, pooled model that incorporates all the sources of preference heterogeneity shown in Tables XIX and XX. 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.[13]

The left panel of Figure XVII 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 XVII 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 **??** 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 XVIII 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).

[13]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.

Figure XI: Wage



a) Wage Schedule That Equalizes Access **b) Equalizing Access Wages by Region**

Table B.10 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 X) a promising alternative may by investing in local teaching quality. We thus simulate such a policy by 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%.

6 Conclusion

This paper studies how increasing teacher compensation at hard-to-staff schools can reduce structural inequality in the access to high-quality teachers. Using rich administrative data from Perú, we document dramatic inequities in schooling inputs and teacher quality to which students have access. This is particularly worrying given the evidence that teacher quality has long term consequences on adult labor market outcomes (Chetty et al. 2014b) and can thus perpetuate the initial inequality students face.

We study how teacher compensation can contribute to reducing the inequality in educational opportunities offered to students from poorer rural locations in Peru. The Peruvian education context is uniquely well suited to study this question for three reasons. First, the government implementated a policy that generated arbitrary cutoff rules for wage increases 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 use the data and policy variation to conduct two sets of empirical excersizes. The first is to show causal evidence that increasing teacher pay has both recruitment and productivity effects. Specifically 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.

The second empirical contribution is to quantify the way teachers trade off wages and local school and community amenities leveraging the rich data on applications and job postings from the centralized assignment system. 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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Appendix

Table V: School Inputs and Outputs

	Extremely rural schools		Rural schools		Urban schools	
	Mean	Sd	Mean	Sd	Mean	Sd
Teaching Staff						
Teacher score in 2016 test (std)	-0.21	0.87	-0.02	0.88	0.29	0.83
Teachers with permanent contract (%)	0.44	0.34	0.64	0.25	0.76	0.17
Teachers with temporary contract (%)	0.43	0.35	0.24	0.23	0.18	0.17
Infrastructure						
No water	0.36	0.48	0.15	0.36	0.20	0.42
No electricity	0.28	0.45	0.06	0.23	0.10	0.32
Sport facility	0.15	0.36	0.41	0.49	0.50	0.53
Community Characteristics						
Sewage in town/village	0.23	0.42	0.49	0.50	0.40	0.52
Doctor in town/village	0.39	0.49	0.66	0.47	0.50	0.53
Library in town/village	0.01	0.10	0.05	0.22	0.20	0.42
School Size						
Single-teacher school	0.12	0.32	0.02	0.15	0.01	0.07
Multigrade school	0.78	0.41	0.46	0.50	0.02	0.14
Number of students	57	35.63	100	76.09	397	265.58
Number of teachers	3.19	1.89	6.25	3.87	19.19	11.57
Number of schools	1773		3130		3367	

Notes:

Table VI: School Vacancies Filled in Each Round

	Extremely rural schools		Rural Schools		Urban Schools	
	Mean	Sd	Mean	Sd	Mean	Sd
Ratio vacancies/existing positions	0.58	0.31	0.34	0.24	0.17	0.20
N. of permanent teacher vacancies	1.13	0.87	0.86	1.02	0.95	1.28
% filled	0.35	0.46	0.56	0.48	0.78	0.38
N. of contract teacher vacancies	1.17	0.99	1.30	1.34	1.85	1.94
% filled within the first assignment round	0.88	0.30	0.87	0.31	0.81	0.35
% filled (all rounds)	0.91	0.27	0.91	0.27	0.87	0.30

Notes.

Table VII: Teaching Job Applicant Characteristics

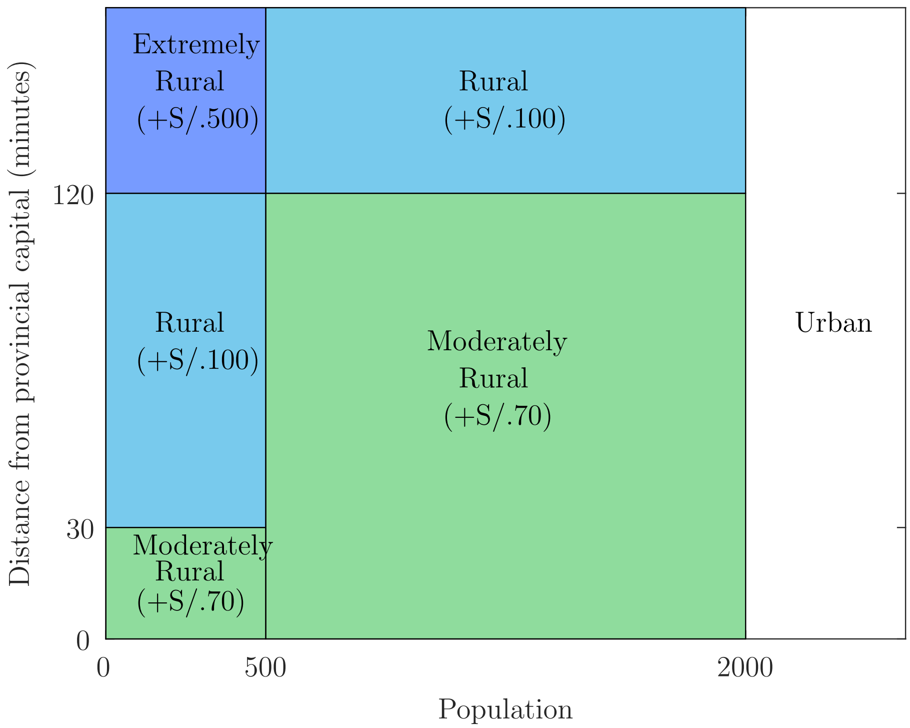
	Extremely rural schools		Rural schools		Urban schools	
	Mean	Sd	Mean	Sd	Mean	Sd
Age	38.30	7.13	37.45	6.57	37.80	6.59
Female	0.49	0.50	0.62	0.49	0.81	0.39
Experience (0-6 years)	3.41	1.78	3.34	1.90	2.93	1.99
Novice teacher	0.07	0.26	0.12	0.32	0.18	0.39
Permanent teachers score (std)	1.36	0.43	1.51	0.46	1.68	0.47
Contract teachers score (std)	-0.06	0.83	0.30	0.90	0.94	0.94
Number of applicants	3217		5399		8921	

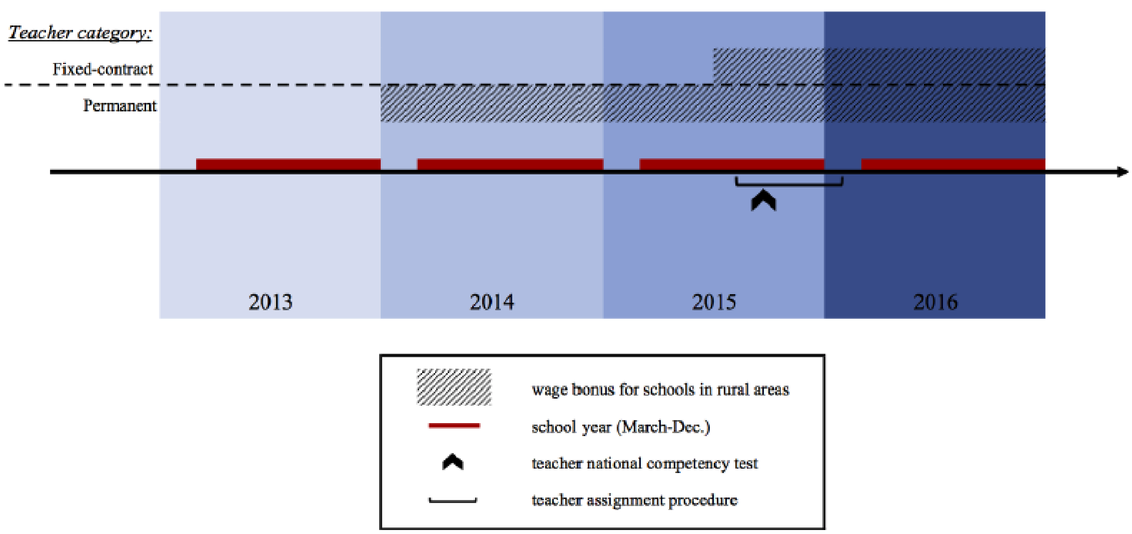
Notes.

	Extremely rural schools	Rural schools	Moderately rural schools	Urban schools
Preferences per vacancy:				
1st option	0.318	0.737	1.364	2.299
	(0.757)	(1.642)	(2.219)	(4.074)
2nd option	0.348	0.798	1.401	2.132
	(0.824)	(1.654)	(2.221)	(3.523)
3rd option	0.342	0.754	1.479	2.118
	(0.826)	(1.525)	(2.459)	(3.391)
4th option	0.300	0.676	1.341	1.906
	(0.769)	(1.344)	(2.222)	(2.984)
5th option	0.270	0.611	1.106	1.601
	(0.730)	(1.246)	(1.934)	(2.592)
Any preference	1.577	3.576	6.691	10.05
	(3.018)	(6.212)	(9.739)	(14.74)
No preferences received	0.522	0.278	0.143	0.0460
	(0.500)	(0.448)	(0.350)	(0.210)

NOTES. This table shows the number of applications that ranked each vacancy in 1st,2nd, 3rd, 4th, 5th place. The last two rows show the applications in any rank at all or vacancies that did not get no applications at all. Here we see that vacancies at extremely rural schools recieved no applications at all over 50% of the time. SE clustered at the school level. *** p< 0.01, ** p<0.05, and *p<0.10

Figure XII: Wage Bonus Categories in Rural Areas





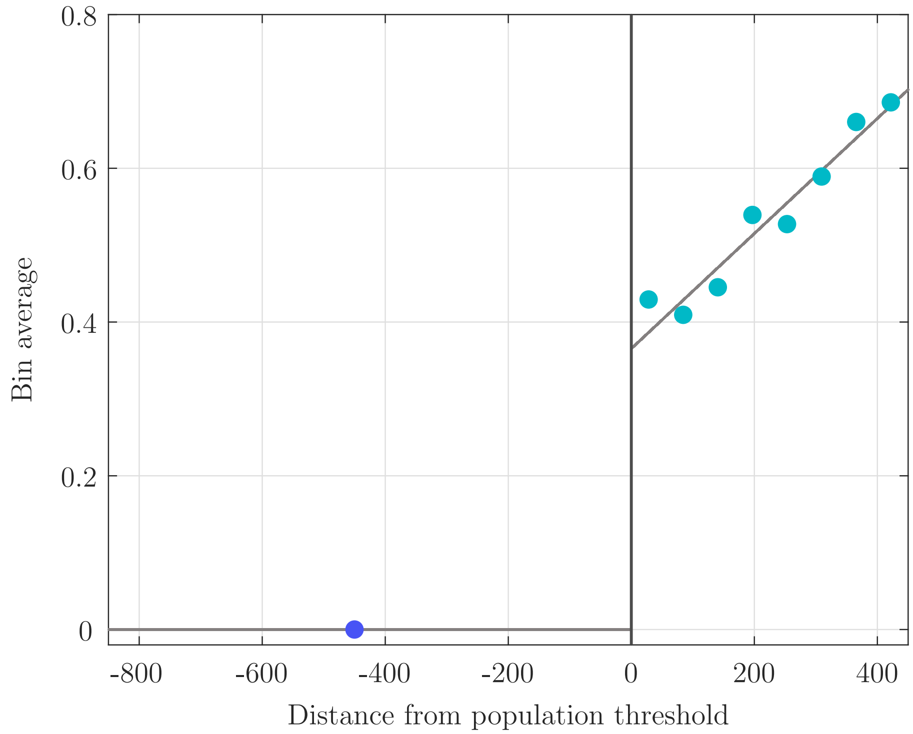
Notes.The top panel of this figure shows the rural categories used to classify schools and their associated wage bonuses as a function of travel time to the province capital and population counts. Teachers in *Rural 1* schools receive the highest wage bonuses, followed by *Rural 2* and *Rural 3* teachers. The bottom panel shows the timeline of the policy implementation.

Table VIII: Monetary Incentives and the Selection of Permanent teachers

	(1) Average pref.	(2) School chosen	(3) Vacancy assigned	(4) Teacher Score (std)
Pop < 500 hab. (ITT)	-15.770***	0.177***	0.024	0.037
	(5.468)	(0.065)	(0.074)	(0.076)
Wage Bonus (LATE)	-27.498***	0.307***	0.043	0.090
	(9.450)	(0.110)	(0.132)	(0.182)
Mean dep. var. (RHS)	15.164	0.846	0.425	1.574
Mean dep. var. (LHS)	18.992	0.810	0.379	1.605
BW	146.135	156.129	158.037	166.103
Observations (BW)	1173	1269	1707	768
Observations	5266	5266	6584	2696

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

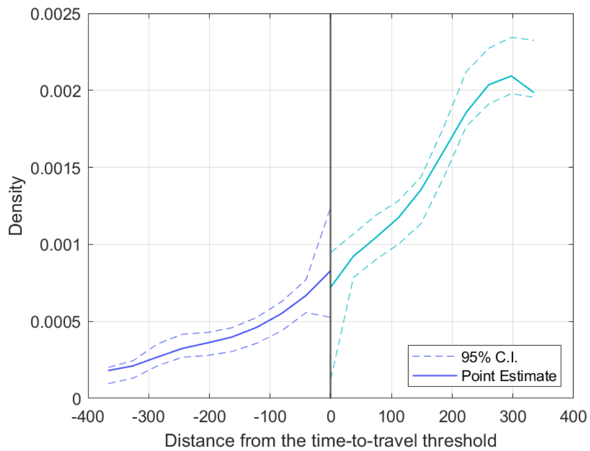
Figure XIV: Prob(Rural 1)



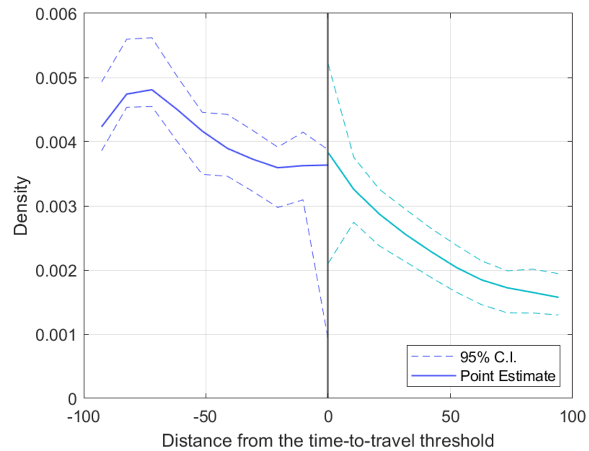
Population

Notes. This figure shows the first-stage impact of crossing the population eligibility threshold on being classified as *Rural 1*. Negative numbers indicate by how much localities exceeded the population the threshold for being classified as *Rural 1*.

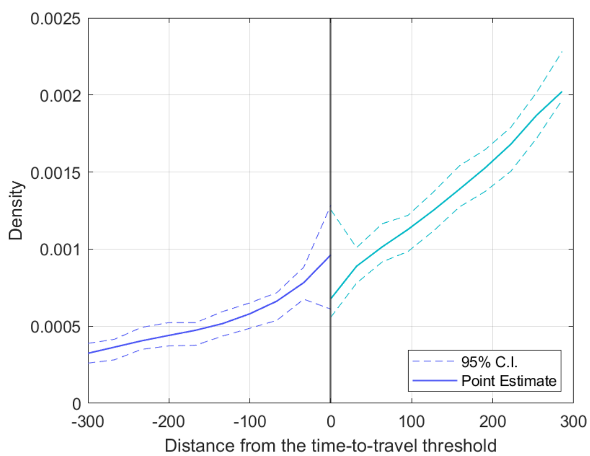
Figure XIII: Density Test



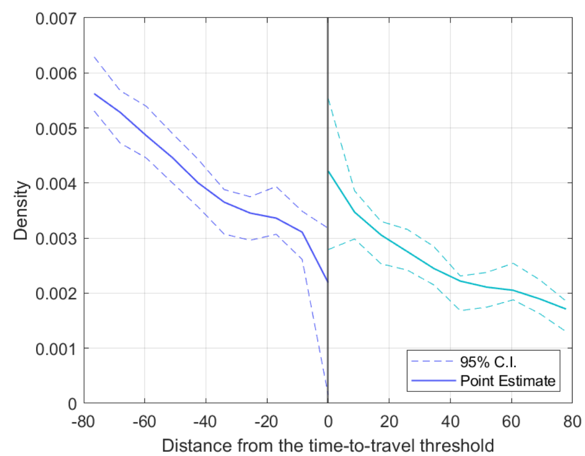
Population 2016



Distance 2016



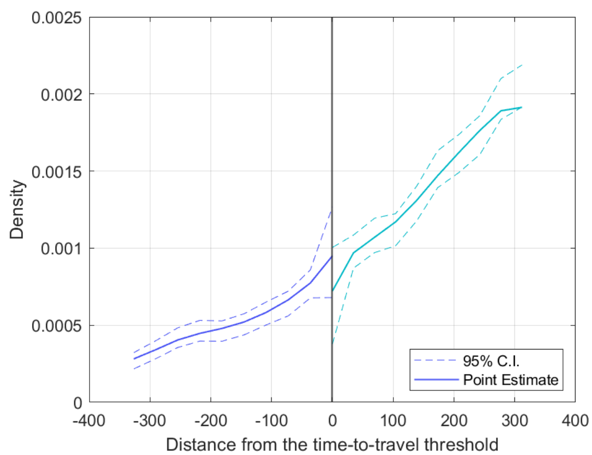
Population 2018



Distance 2018

Notes. P-values: .30 (population), .01 (distance).

Figure XV: Density Test – Schools for Filled Vacancies



b. Spanish

Table IX: Covariate Smoothness around the Population Cutoff

	(1)		(2)		(3)	
	All schools		Permanent teacher vacancy		Contract teacher vacancy	
Village amenities						
Electricity	0.035	(0.023)	0.042*	(0.023)	0.068	(0.043)
Drinkg water	0.004	(0.043)	0.042	(0.097)	-0.018	(0.065)
Sewage	0.034	(0.056)	-0.061	(0.108)	0.063	(0.081)
Water tank	-0.038	(0.049)	-0.103	(0.101)	-0.078	(0.078)
Medical clinic	0.082	(0.058)	-0.002	(0.085)	0.035	(0.070)
Meal center	0.029	(0.045)	0.095	(0.102)	0.102	(0.078)
Community phone	0.029	(0.027)	0.020	(0.062)	0.017	(0.042)
Internet access point	-0.026	(0.036)	0.009	(0.086)	0.008	(0.048)
Bank	-0.007	(0.016)	-0.041	(0.026)	-0.011	(0.029)
Public library	-0.013	(0.015)	-0.056*	(0.030)	-0.029	(0.025)
Police	0.001	(0.040)	0.022	(0.076)	-0.009	(0.069)
School amenities						
Science lab	-0.006	(0.035)	0.009	(0.066)	0.010	(0.044)
Library	-0.120*	(0.066)	0.072	(0.107)	-0.031	(0.092)
At least a personal computer	-0.030	(0.044)	0.094	(0.083)	0.043	(0.055)
Internet access	-0.054	(0.056)	-0.050	(0.115)	-0.087	(0.087)
Electricity	0.039	(0.027)	0.069	(0.058)	0.098*	(0.052)
Drinking water	-0.008	(0.036)	-0.056	(0.078)	0.019	(0.055)
Sewage	-0.047	(0.046)	-0.073	(0.092)	-0.022	(0.079)
Reading room	-0.042	(0.034)	0.009	(0.050)	-0.010	(0.047)
Sport pitch	0.017	(0.057)	0.362***	(0.112)	0.047	(0.077)
Courtyard	0.001	(0.055)	0.088	(0.098)	-0.093	(0.082)
Gym	0.004	(0.018)	0.038	(0.036)	0.009	(0.014)
Stadium	-0.014	(0.012)	-0.023	(0.025)	-0.011	(0.019)
Auditorium	-0.015	(0.040)	-0.031	(0.057)	-0.016	(0.049)
Administrative office	0.024	(0.053)	0.138	(0.107)	0.064	(0.080)
Pool	-0.050	(0.033)	-0.060	(0.043)	-0.014	(0.048)
Courtyard	-0.048**	(0.021)	-0.100**	(0.041)	-0.051*	(0.031)
Resting room	0.012	(0.033)	-0.004	(0.064)	0.093*	(0.052)
Breastfeeding room	-0.072	(0.051)	0.094	(0.091)	-0.044	(0.075)
Courtyard	0.011	(0.018)	0.002	(0.021)	-0.013	(0.025)
Dining hall	-0.028	(0.046)	-0.038	(0.095)	-0.027	(0.079)
Cafeteria	-0.049	(0.035)	0.066	(0.080)	-0.021	(0.055)
Kitchen	-0.021	(0.053)	0.018	(0.107)	-0.067	(0.071)
Teachers accomodations	-0.005	(0.020)	0.009	(0.048)	-0.012	(0.030)

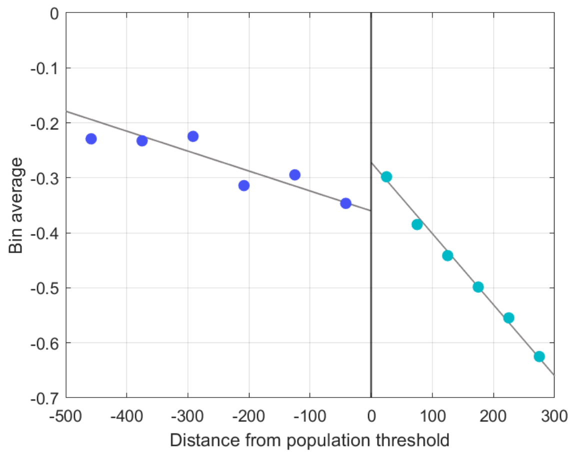
NOTES. Robust SE in parentheses. *** p< 0.01, ** p<0.05, and *p<0.10

Table X: Probability of Recruitment by Population Bins of the School of Origin

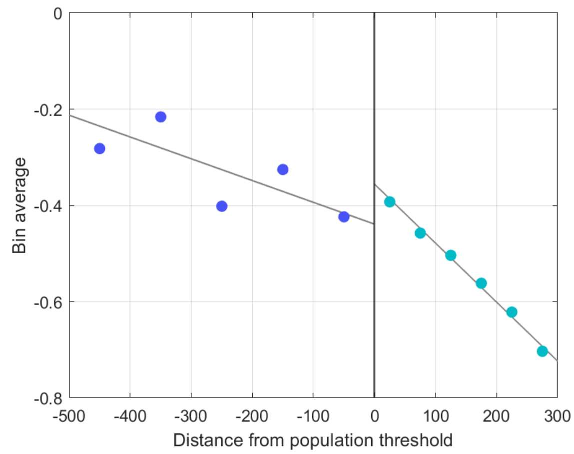
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	0-99	100-199	200-299	300-399	400-499	500-599	600-699	700-799	800-899	900-999	1000-2000	Urban	New entrant	Same school
Pop < 500 hab. (ITT)	-0.023	-0.012	0.031	0.038	0.003	0.003	-0.019	-0.014	-0.002	0.016**	-0.002	-0.058	0.040	0.015
	(0.019)	(0.033)	(0.030)	(0.024)	(0.019)	(0.020)	(0.017)	(0.013)	(0.008)	(0.008)	(0.018)	(0.036)	(0.039)	(0.036)
Wage Bonus (LATE)	-0.045	-0.024	0.058	0.072	0.006	0.006	-0.037	-0.027	-0.003	0.031**	-0.004	-0.109	0.075	0.029
	(0.037)	(0.063)	(0.058)	(0.045)	(0.036)	(0.038)	(0.032)	(0.026)	(0.015)	(0.015)	(0.035)	(0.069)	(0.074)	(0.070)
Mean dep. var.	0.062	0.106	0.097	0.060	0.045	0.037	0.022	0.018	0.010	0.012	0.037	0.125	0.193	0.172
BW	222.298	113.757	123.762	140.070	167.523	167.129	150.965	192.007	150.549	167.450	146.266	134.828	127.907	170.864
Schools (BW)	1861	882	961	1112	1358	1358	1203	1561	1203	1358	1156	1059	1002	1377
Observations (BW)	4256	2128	2299	2622	3138	3138	2817	3622	2817	3138	2708	2512	2388	3177
Schools	4647	4647	4647	4647	4647	4647	4647	4647	4647	4647	4647	4647	4647	4647
Observations	10323	10323	10323	10323	10323	10323	10323	10323	10323	10323	10323	10323	10323	10323

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

Figure XVI: ITT Effects on Student Test Scores (2018), by subject



a. Math



b. Spanish

Table XI: Student test scores, by year

	(1) Pooled	(2) 2016	(3) 2018
Pop < 500 hab. (ITT)	0.208*	0.169	0.253*
	(0.111)	(0.194)	(0.139)
Wage Bonus (LATE)	0.413*	0.286	0.558*
	(0.240)	(0.361)	(0.331)
Mean dep. var.	-0.474	-0.499	-0.449
BW	148.064	160.496	136.043
Schools (BW)	987	471	779
Observations (BW)	18963	7308	11131

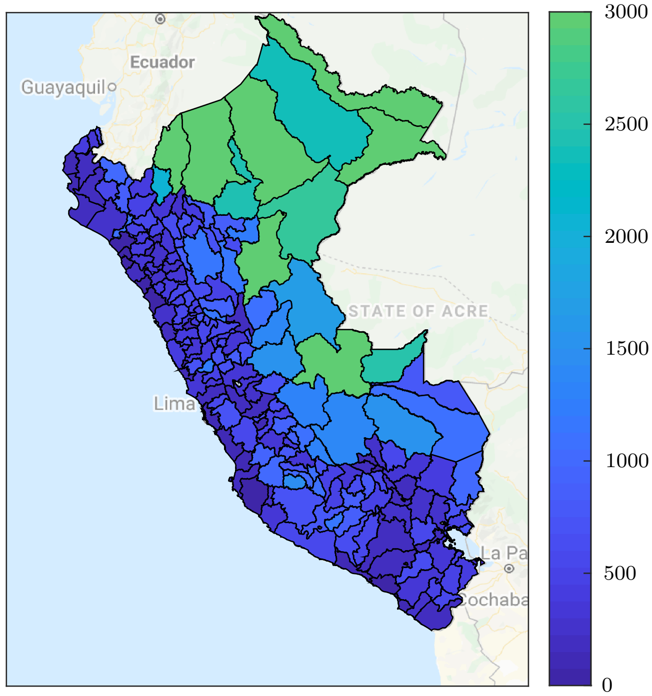
NOTES. All outcomes are standardized. SE clustered at the school level. *** p< 0.01, ** p<0.05, and *p<0.10. The sample includes students in schools with a contract teacher vacancy in the test year.

Table XII: Student Outcomes (2018), by Subject

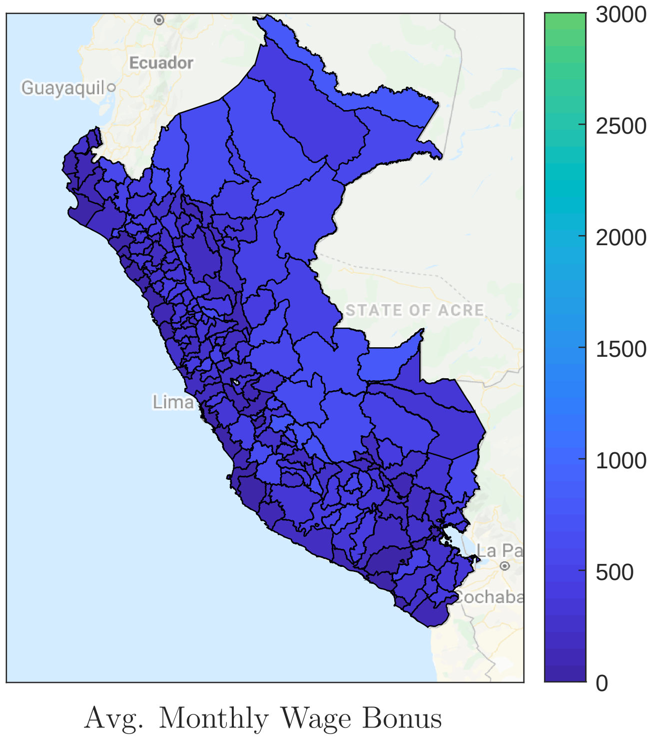
	Score (std)	Achievement level			
Panel A: Math					
	(1)	(2) Level 0	(3) Level 1	(4) Level 2	(5) Level 3
Pop < 500 hab. (ITT)	0.352**	-0.099**	-0.048	0.078**	0.095**
	(0.141)	(0.049)	(0.031)	(0.036)	(0.044)
Wage Bonus (LATE)	0.756**	-0.219*	-0.107	0.175**	0.200**
	(0.338)	(0.118)	(0.071)	(0.088)	(0.101)
Mean dep. var. (LHS)	-0.408	0.199	0.278	0.357	0.184
BW	116.751	136.362	139.004	167.459	106.024
Schools (BW)	747	889	909	1126	694
Observations (BW)	10750	12601	12872	15862	10068
Panel B: Spanish					
	Score (std)	Achievement level			
	(1)	(2) Level 0	(3) Level 1	(4) Level 2	(5) Level 3
Pop < 500 hab. (ITT)	0.207	-0.111**	0.018	0.065**	0.031
	(0.127)	(0.051)	(0.030)	(0.031)	(0.034)
Wage Bonus (LATE)	0.458	-0.247**	0.041	0.147*	0.068
	(0.299)	(0.124)	(0.066)	(0.078)	(0.077)
Mean dep. var. (LHS)	-0.462	0.232	0.339	0.252	0.181
BW	135.725	145.870	161.750	152.373	134.587
Schools (BW)	879	944	1085	1009	870
Observations (BW)	12468	13320	15345	14210	12361

NOTES. All outcomes are standardized. SE clustered at the school level. *** p< 0.01, ** p<0.05, and *p<0.10. The sample includes students in schools with a contract teacher vacancy in 2015 and/or 2017.

Figure XVII: Distribution of Wage Bonuses Under Counterfactual Policy



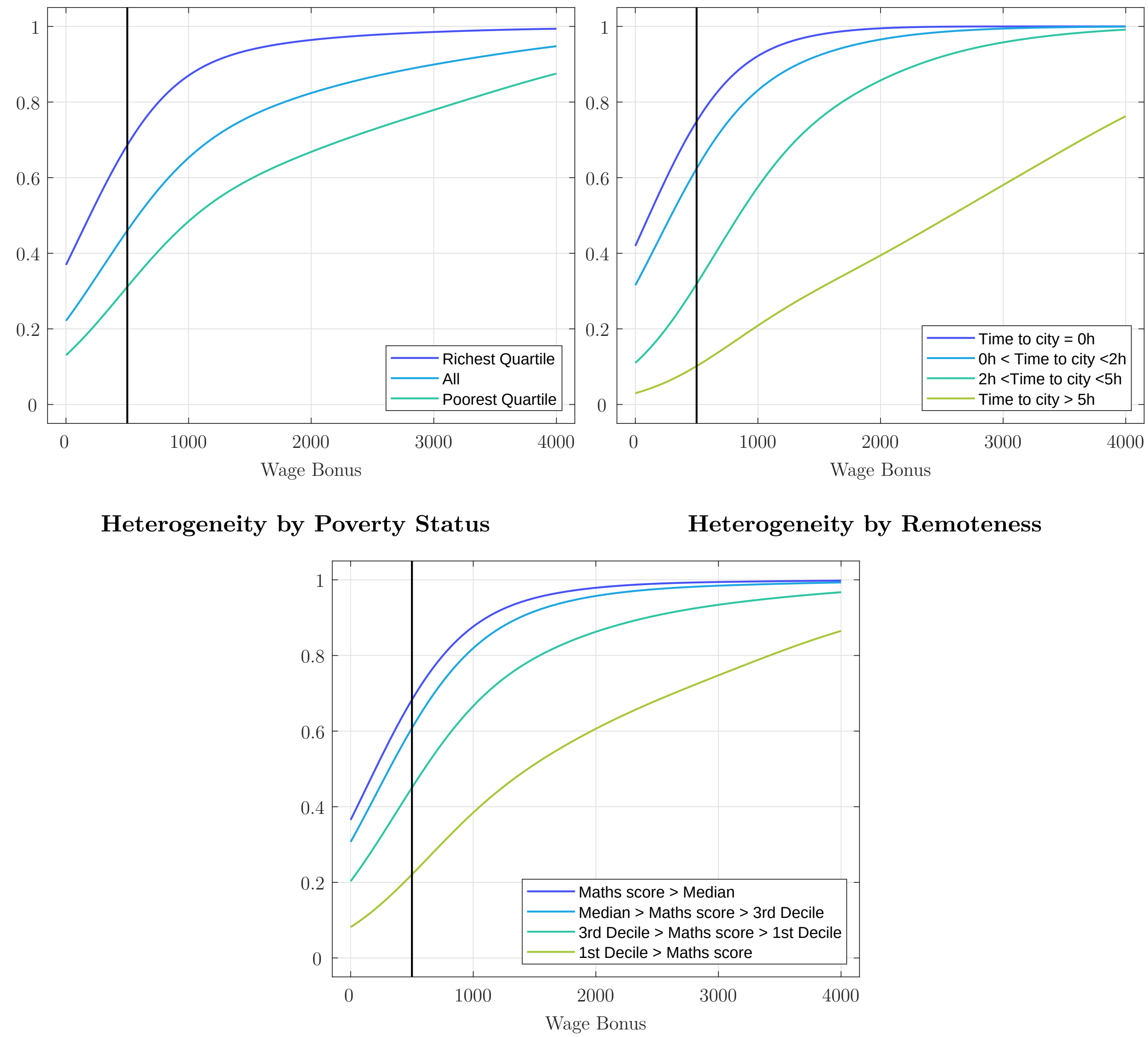
Policy Equalizing Teacher Quality



Current Policy

Notes. The first 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 second panel maps the monthly wage bonuses offered by the current policy averaged at the province level.

Figure XVIII: Cumulative Distribution of Counterfactual Wage Bonuses



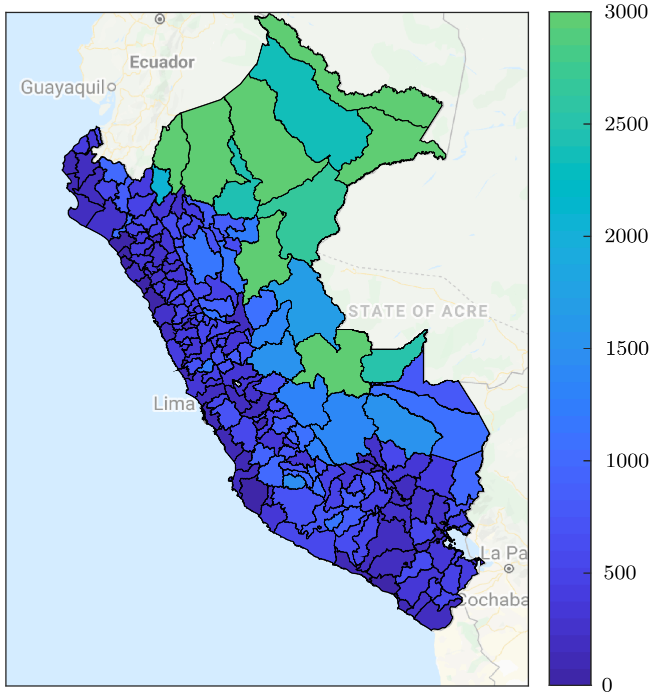
Heterogeneity by Poverty Status

Heterogeneity by Remoteness

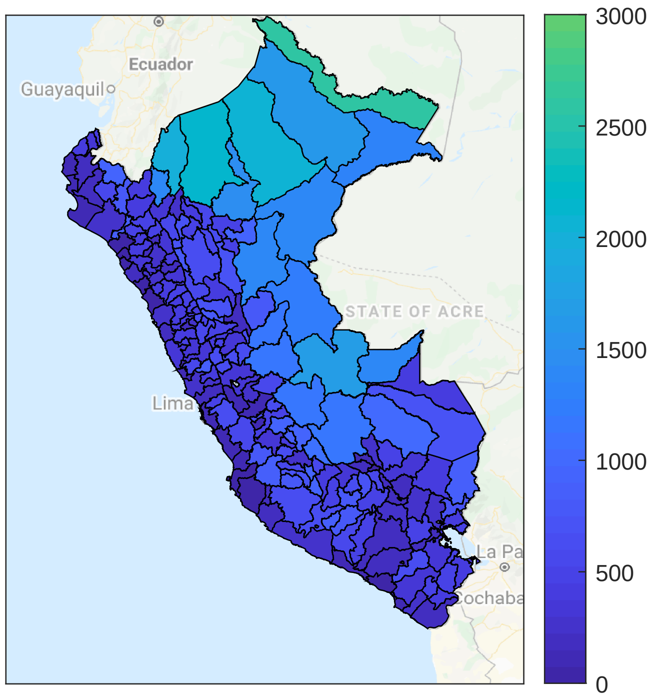
Heterogeneity by Students' Math Achievement

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 XIX: Increasing the Supply of Skilled Teachers in Remote Areas



Wage Incentives Only



Avg. Monthly Wage Bonus

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.

Table XIII: 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. This table reports the effect of crossing the population threshold (ITT) and the effect of the wage bonus (LATE) on the probability that a vacancy is filled by a certified teacher (Column 1) and on different measures of teacher quality (Columns 2-4). These are the relative ranking in which the vacancy is filled – normalized so that it takes value from zero to one – (Column 2), the standardized score in the centralized test (Column 3), and an indicator for the test score being above the median score (Column 4). In Column 1, the sample includes all the teaching positions open in rural schools in the 2015 or 2017 recruitment drive, while only the positions filled by certified teachers in Columns 2-4. Each cell reports the bias-corrected regression-discontinuity estimates obtained using the robust estimator proposed in Calonico et al. (2014). Regressions are defined within a mean-square error optimal bandwidth (BW), reported at the bottom part of the table. The table also reports the mean of the dependent variable computed within the intervals $(0, +BW)$ (right-hand-side of the cutoff) and $(-BW, 0]$ (left-hand-side of the cutoff). SE are clustered at the school×year level. *** p< 0.01, ** p<0.05, and *p<0.10.

Table XIV: 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 XV: 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 XVI: 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 XVII: 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 XVIII: 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 XIX: 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 XX: Preference Estimates – Heterogeneity by Age and Experience

	(1) Age $<$ 30	(2) 30 $\leq$ Age $<$ 40	(3) Age $\geq$ 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 XXI: Model Fit – Change in Teachers' Score at Population Cutoff

	Data	Predicted		
		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 XVIII). 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 XXII: Alternative Policy Counterfactuals

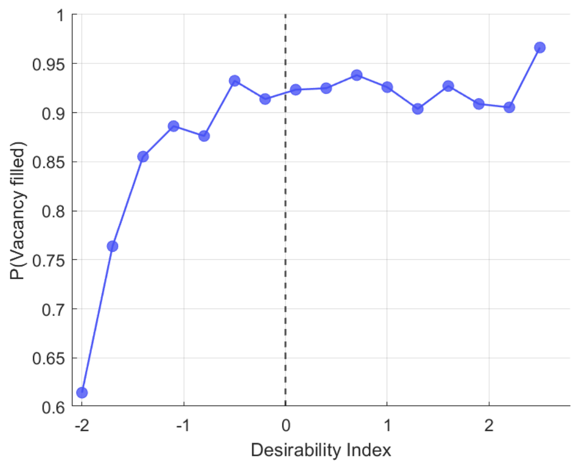
	Total Wage Bill per Month		Net Present Value	% of Total Cost
	2015	2017		
Policy 1: Wage Bonus Only				
Cost of Current policy (benchmark)	3.53	4.66	2,264.97	35.93
Cost of Equalizing teacher quality	12.33	13.30	6,303.71	100
Policy 2: Equalizing Structural Inequalities				
Infrastructure	0.26	0.21	127.88	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.

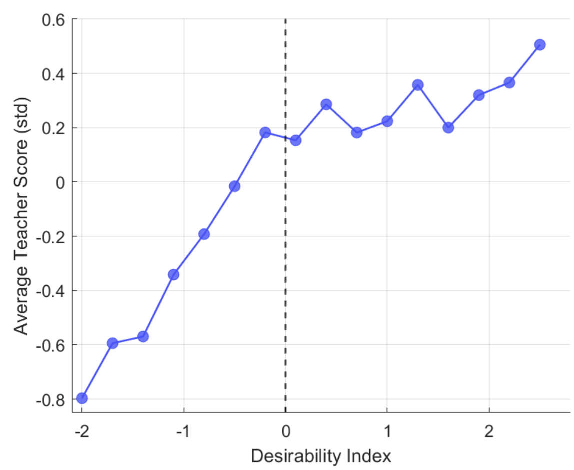
Appendix

A Additional Figures

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

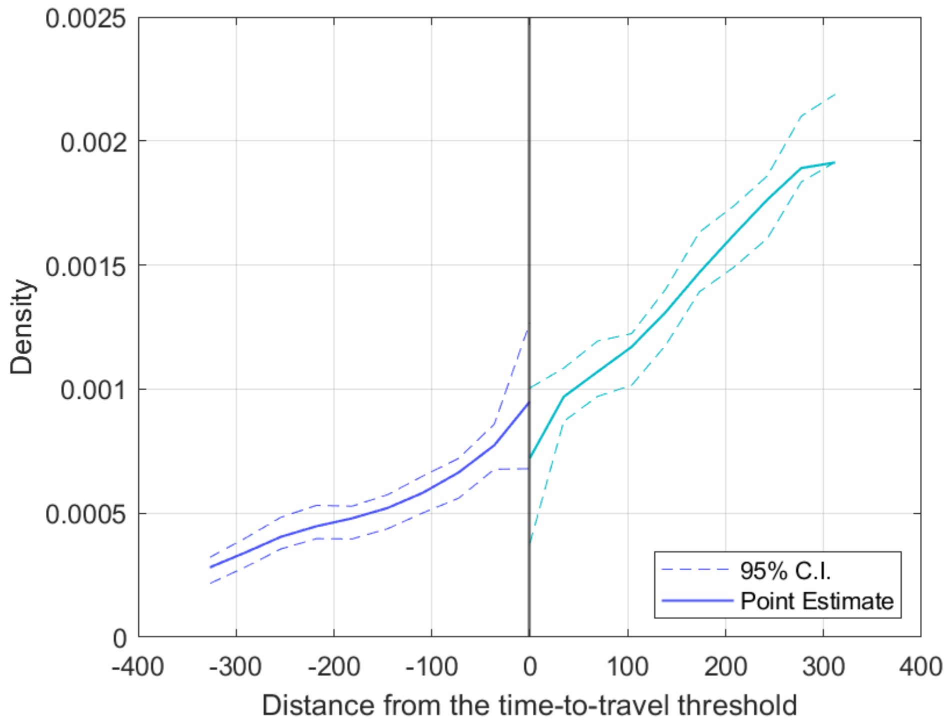


Vacancy Filled by a Certified Teacher



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) Vacancy	(2) N. of vacancies	(3) Vacancy 2016	(4) Vacancy 2018	(5) 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) Number of Teachers	(2) Share of contract teachers	(3) 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) Vacancy filled	(2) Rank	(3) Score (std.)	(4) > 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) Vacancy filled	(2) Rank	(3) Score (std.)	(4) > 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: Monetary Incentives and the Selection of Permanent teachers

	(1) Average pref.	(2) School chosen	(3) Vacancy assigned	(4) Teacher Score (std)
Pop < 500 hab. (ITT)	-15.770***	0.177***	0.024	0.037
	(5.468)	(0.065)	(0.074)	(0.076)
Wage Bonus (LATE)	-27.498***	0.307***	0.043	0.090
	(9.450)	(0.110)	(0.132)	(0.182)
Mean dep. var. (RHS)	15.164	0.846	0.425	1.574
Mean dep. var. (LHS)	18.992	0.810	0.379	1.605
BW	146.135	156.129	158.037	166.103
Observations (BW)	1173	1269	1707	768
Observations	5266	5266	6584	2696

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

Table B.7: 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.8: 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.9: 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

Table B.10: Survey: Preferences

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

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