Teacher Wages and Academic Achievement*

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Abstract

This paper studies the effects of a large unconditional increase in the salary of public-sector teachers in Peru. Population-based rules that determine the level of teacher compensation generate locally exogenous discrete changes in wage posting across rural locations. School vacancies offering 25 percent higher wages attract better teachers, as measured by standardized evaluation tests that are used to determine priorities in national recruitment drives. Students in primary schools offering higher wages have better performance on standardized test scores, with effect sizes of 0.6 of a standard deviation in math and 0.5 of a standard deviation in Spanish three years after the salary increase. These results are entirely driven by schools that had multiple open vacancies over time, suggesting that the re-allocation of contract (and hence mobile) teachers is the main mechanism at work. Overall, our results suggest that unconditional pay increases targeted at less desirable locations can help reduce spatial inequalities in the quality of public good provision.

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1 Introduction

The level and structure of public sector compensation play a key role in the ability of governments to attract, retain and motivate high-quality employees. However, contracts in the public sector typically offer flat wage profiles based on seniority, which are unable to compensate workers for positions-specific amenities or changing labor market conditions. This issue is particularly important for the provision of services in jobs or locations where work conditions can be less attractive and therefore, they end up attracting low quality applicants. In the education sector, this translates into a persistent inequality in teacher quality between regions. This is particularly worrying given the evidence that teacher quality at all levels has long term consequences on adult labor market outcomes (Araujo et al. 2016, Chetty et al. 2014). In spite of how potentially important this aspect of teacher compensation could be, the evidence on the effectiveness of these policies or the mechanisms through which they may operate is scarce.

In this paper, we study the recruitment, retainment, and productivity effects of a policy that raised public sector teacher salaries by 25% at 50,0000 teaching positions in over 17,000 rural schools spread across Peru. Arbitrary cutoff rules for school eligibility tied to population counts generate local quasi-experimental variation in wages across schools. Estimating the effects of wage increases on the selection of workers is notoriously difficult, as this does not only require information on those who are recruited, but also to either observe the full applicant pool or worker's choices and their choice set. The fact that in 2015 the Ministry of Education established a centralized recruitment mechanism presents a unique opportunity to observe teachers' choices, and analyze their sorting patterns across schools with different wage levels. Importantly, it also provides us with a reliable and standardized measure of competence by means of the scores in the teacher evaluations that are used to determine priorities in the assignment system

Evidence from the centralized matching system shows that teachers who took a position at a rural school with higher wages score higher by 0.5 of a standard deviation in the competency test when compared to teachers who choose a position in lower paying rural schools. We rule out that the observed changes in teacher quality are associated with changes in socio-demographic characteristics of the applicants. Also, we did not detect any meaningful demand-side response to the wage incentives, such as school-level changes in vacancy creation, that can explain the estimated effects on teacher quality. Higher wages also increase school retention rates: temporary teachers whose contracts are due are more likely to reapply for the same position when the policy is in place. Importantly, this result does not hold when the assignment process of teachers did not follow strict merit-based priority rules, suggesting the role of potential complementarities between the matching mechanism in place and wage incentives for retaining higher-quality teachers in less desirable locations.

Teachers in higher paying schools are also more productive, as their students perform significantly better in national standardized achievement tests three years after the policy change. These effects on student outcomes are very large in magnitude and they are even larger in schools that had an open vacancy in the previous recruitment drive, suggesting a link with the sorting pattern by teacher quality mentioned above. In fact, we show that the treatment effects on achievement are very small and not different from zero for schools that had no vacancies throughout the period while they are entirely concentrated among schools that had multiple vacancies and hence that were more likely to experience a prolonged inflow of new (higher-quality) teachers.

These results contribute to the recent and rapidly growing literature on the personnel economics of the state (see Finan et al. (2017) for a review). In particular, Dal Bo et al. (2013) show that increased compensation for public sector positions in Mexico lead to a larger pool of applicants, and a higher quality of hired employees. Deserranno (2016) finds that higher financial incentives attract more applicants and increase the probability of filling a vacancy, while crowding out pro-socially motivated agents. We contribute to this literature by showing evidence that is broadly consistent with these findings. In addition, the presence of a direct link between teachers and their students allow us to provide the first evidence in the literature of the effects of monetary incentives on the quality of public good provision through a selection channel.

We also add to the literature on teacher compensation and teacher productivity, showing that relative pay differences can have significant effects on the re-allocation of talent across jobs. In the Peruvian context, teachers compensation is low relative to other college graduates and at baseline there are issues with staffing rural positions with talented teachers. Increasing salaries in this setting is found to generate positive productivity effects through improved ability to recruit and retain relatively more talented teachers. The evidence presented in this paper shows that this mechanism can have important productivity effects. Existing evidence on "pay for performance" or "efficiency wages" has been mixed at best Muralidharan and Sundararaman (2011), Fryer (2013).[1] The evidence presented here suggests that there is no meaningful direct effect of wages on productivity of individual teachers already hired in the system. This is consistent with a recent and related paper studying a large unconditional salary increase in Indonesia by de Ree et al. (2017), where 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

[1] See evidence on teacher pay incentives in Latin American in Barrera-Osorio and Raju (2017).

the context studied in de Ree et al. (2017), 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 large turnover where the selection margin can play an important role in improving the quality of teachers and student outcomes within a relatively short time pan. As found in other settings, Duflo et al. (2015) the local institutions determining how teachers are evaluated and assigned could be an important necessary condition for increased wages to lead to a meritocratic sorting of talent. The fact the Peruvian system allows for some teacher jobs to be flexible, paired with the fact the assignments are done in a transparent, meritocratic way may play an important role in explaining the observed policy effect.

More generally, our results are relevant for the design and the evaluation of policies that aim at increasing teacher compensation. Several global policy think tanks have recommended for years to increasing teacher pay in low-income countries as a way to attract talents toward the education sector (McKinsey 2010, UNICEF 2011, UNESCO 2014). Prior evidence seems to suggest a positive relationship between teacher earnings and school productivity in the long-run Card and Krueger (1992a,b). However, de Ree et al. (2017) note that while increasing teacher compensation can improve the overall talent pool through the extensive margin eventually, it may take a long time to see the effects and it will be very costly during the transition if higher earnings do not translate into higher productivity for current teachers as well. This paper addresses a different aspect of teachers' incentives schemes, focusing on the way these policies should also take into account the effects on relative teacher wages across teaching jobs. We show this can have significant effects on the re-allocation of teacher quality across schools, with crucial implications for the distribution of productivity across schools.

In the next section, we provide the background on the institutional setting under study. Section 3 presents the datasets we use in the empirical analysis, which is explained in Section 4. Section 5 discusses our main findings, and we conclude with a brief discussion and policy implications in Section 6.

2 Institutional Setting

2.1 The Labor Market for Teachers in Peru

Teachers in public schools are hired under two types of contracts. Permanent teachers (*docentes nombrados*) work in very similar conditions as in other countries around the world and are civil servants with permanent contracts. On the other hand, certified teachers can also be hired for a fixed period of time, who usually have an explicit one year commitment to teach at a particular school (*docentes contratados*). A third type of teacher worth distinguishing are non-certified teachers, who can be hired to fill-in when no other certified teachers are found (be they permanent or temporary). Contract teachers are payed a flat rate of S/.1,550 (approximately, 460$) in primary school and S/.1,244 in secondary, whereas the wages of permanent teachers increase with experience starting at S/.1,451 and reaching S./2,902 in primary while in secondary they range from S./1,348 to S./2,695. Contract teachers represent a significant portion of the population of rural public school teachers, which provides the system with built-in flexibility and generates large turnover for any given cohort of exposed students. In the year 2015, 41% of the total number of teachers in public schools in rural areas had a one year contract.

Up until 2015, the recruitment of teachers was done in a decentralized fashion, whereby the central government allocated the number of open positions for permanent and contract teachers and each of the 25 regional education authorities was in charge of the recruitment process. While this scheme was supposed to reward merit, little supervision of the process and wide institutional heterogeneity rose concerns about corruption and political patronage in the hiring of public school teachers. In an effort to make the process more efficient and transparent, the Education Ministry introduced nation-wide, centralized recruitment drives, where teacher job postings and teacher job applications were processed on a single platform. The first national recruitment drive took place in the Fall of 2015, when 202,000 teachers applied for one of the 16,000 positions available. The application process includes a standardized teacher evaluation, where all applicants took a knowledge test on their specific field of expertise, eg. primary education, secondary math, secondary history and social sciences, etc. Those who pass the minimum required grade were deemed eligible for a permanent position, and went through to participate in a two-sided matching system which includes an in-school evaluation.[2] Temporary teaching positions were filled using a one sided matching

[2] In this matching process, teachers choose a region and their field of expertise, and are allowed to list in order of preference up to five of the available positions. Based on the rank in the centralized test, schools receive a list of up to twenty teachers, who move through to a decentralized evaluation. In this second phase, they are scored based on an in-class demonstration, their experience, and an interview. At the end of the process, the grade in the centralized test and the decentralized evaluation are added, and the position is

mechanism. Teachers within a region×field were ranked according to their scores in the standardized test, and the highest scoring teachers got to choose first among the available positions. Once a position is chosen by the leading applicant, it is assigned and eliminated from the list of available options. The next highest scoring teacher makes a choice, and so on until either all positions are filled or all teachers are allocated to a position. Teaching vacancies that are not taken through this mechanism are filled by uncertified teachers.

2.2 Wage Bonuses in Rural Locations

In 2015, the Peruvian education system employed about 180,000 teachers in roughly 110,000 public schools. Staffing the 17,000 small rural public schools scattered all over the Country with competently trained teachers is a challenge. Figure 1 depicts in one geographic map of Peru the proportion of certified teachers who score in the upper quartile in each district in the national evaluation tests of 2015 and 2017, and present it side by side with a similar map showing the proportion of students scoring in the upper quantile of their district in the national standardized test in 2018. These maps are a mirror image of each other, showing that the poor provision of schooling inputs is a major factor in reproducing historical inequalities between regions in Peru. In addition, while most of the open vacancies in urban areas were filled by certified teachers through the matching mechanism, only half of the permanent positions and two thirds of the temporary positions were filled by certified teachers in rural areas. To the extent that we observe the scores in the evaluation tests only for certified teachers, Figure 1 is a lower bound for the extent of regional inequality in teachers' quality.

Many factors may be playing a part in determining the lack of quality teachers being recruited in rural areas. Rural schools have lower levels of infrastructure and other teaching inputs. Teachers in rural areas face a number of challenges, from language barriers to simply being isolated from friends and family. However, in addition to these difficulties it is natural to think that inadequate compensation is also a factor. Like many other countries in Latin America, the wage schedules of public sector teachers are such that they earn significantly less than other college graduates (Mizala and Ñopo 2016).[3] If wage setting policies do not adequately compensate for the lack of amenities in rural areas, those jobs will be less attractive and as a consequence vacancies in rural schools will be harder to fill.

These considerations motivated the government to significantly improve the compensation of teaching positions in rural areas. A new classification of schools was used to allocate

allocated to the highest scoring teacher who choses that position.

[3]This stands in contrast with institutional settings in other developing countries in South East Asia such as India, Pakistan and Indonesia where public teachers tend to earn relatively more relative to other comparable professionals. See de Ree et al. (2017) for references.

wage bonuses according to two criteria: the population of the locality where the school is located (measured by official population counts in the latest census) and the time it takes to travel from that locality to the province capital (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). The most rural schools (henceforth, *Rural 1*) were those located in localities with less than 500 inhabitants, and for which it takes more than 120 minutes to reach the province capital. The second category *(Rural 2*) is reserved for those schools in localities with less than 500 inhabitants and for which it takes between 30 and 120 minutes to reach the province capital, or those in localities with 500-2,000 inhabitants and that are located farther than 120 minutes. The final set of rural schools (*Rural 3*) are those in localities with 500-2,000 people and that are located closer than 120 minutes, or those with less than 500 inhabitants and that are less than 30 minutes away from the capital. All other schools are classified as Urban.

The policy was first implemented in January 2014 providing permanent teachers in *Rural 1*, *2*, and *3* schools with wage bonuses of S/.200, S/.100, and S/.70, respectively. In August 2015, the bonus for *Rural 1* was increased to S/.500, and all the wage bonuses received by permanent teachers were extended to contract teachers.[4] The bonus for *Rural 1* is fairly generous, as it represents 30-40% of the earnings of contract teachers and 20-30% of the earnings of permanent teachers. Figure 2 displays the rural categories and the associated wage bonuses as a function of population and time-to-travel as well as the timeline of the implementation of the policy.

3 Data and Descriptive Statistics

3.1 Administrative Records

The empirical analysis in this paper uses a large array of administrative datasets, mostly obtained from the Ministry of Education of Peru, which are linked through unique identifiers at either the teaching position-level or the school-level.

Teacher employment records. An official dataset that links the universe of public-sector teaching positions and teachers. It further allows identifying the type of contract (permanent or temporary, number of hours, etc.), as well as the school where the teacher is located (but not the grade). This information is available for every year since 2012, for the months of March, August and December.

[4]Note that these changes were introduced in the middle of the school year and thus can't induce sorting of teachers.

Teachers' nation-wide recruitment drives. For the two centralized processes that took place in the Fall of 2015 and in the Fall of 2017, we have the applicants' scores obtained in the centralized test, the list of all the positions available for permanent and contract teachers as well as the locality-level values of the population and time-to-travel criteria used in each year to assign the wage bonuses.

School Characteristics. The school census provides information on the infrastructure available in each school: number of pupils, libraries, computers, classrooms, sport facilities, access to basic services (electricity, sewage, water source), staff (teachers by status, administrative staff), etc. This information is reported yearly by school principals.

Student outcomes. The *Evaluación Censal de Estudiantes*, (ECE) is a national standardized test administered every year at selected grades by the Ministry of Education to all public and private schools throughout the country. 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).

3.2 Sample Description

We exclude from the sample urban schools, since the Urban/Rural population threshold of 2,000 inhabitants (see Figure 2) is partly associated with the targeting schemes of other policies. We focus the analysis on primary schools with at least one open vacancy in any of the two national-wide recruitment drives. As we lack in our dataset detailed information on the grade and subject taught by each teacher, this sample allows us to better characterize the impact of new teachers on student outcomes to the extent that students in primary school are usually taught by only one teacher per grade. The final sample for the empirical analysis is thus comprised of 12,747 teaching positions over the two recruitment drives in 5,336 schools, which represent 30% of the teaching positions in rural areas and 62% of the rural public primary schools in Peru in 2018.

Figure 3 depicts a scatter plot for the primary schools in our sample along the two variables that determine the assignment of the rural wage bonus, where the size of the dots reflects the cumulative number of open vacancies in each school over the two recruitment drives. The figure shows that there is a large mass of data around both thresholds for *Rural 1* schools, with relatively more mass concentrated below the population threshold. At any given value of time-to-travel from the province capital, *Rural 1* schools are less likely to have more than one open vacancy when compared to *Rural 2* schools situated in more populated localities.

Panel A of Table 1 reports means and standard deviations of school characteristics measured in 2015, separately for the schools satisfying or not satisfying the criteria for the allocation of the *Rural 1* wage bonus. Consistently with the policy, teachers' wages are on average 25% higher in *Rural 1* schools when compared to less rural schools. *Rural 1* schools serve a smaller population of students, they have less teachers (albeit a higher share of contract teachers), and they are more likely to lack access to basic infrastructures, such as electricity or water. Academic performance – as measured by standardized test scores in 2015 – tend to be worse in more rural schools.

Some basic facts about the within-school dynamics of teachers measured during the period 2016-2018 are reported in Panel B of Table 1. There is a large degree of teacher turnover that is particularly pronounced in more rural areas. More than half of the teachers move out from a *Rural 1* school after one year on average, with most of the effect being driven by movements of contract teachers. *Rural 1* schools open on average slightly more than one vacant position per year, which gets filled half of the times by a certified teacher.

Finally, Panel C of Table 1 reports descriptive statistics for socio-demographic characteristics of both permanent and contract teachers participating in at least one of the two centralized recruitment drives and who got hired in the schools in our sample. When compared to applicants who got a position in less rural schools, applicants who ended up in *Rural 1* schools are more likely to be male, they are a half a year older and they have slightly more experience teaching in the public sector. Importantly, applicants who ended up in *Rural 1* schools perform 0.2 of a standard deviation worse in the admission test.

4 Empirical Strategy

4.1 Multi-score Sharp RD

We use the assignment rules of the rural wage bonus in a regression discontinuity (RD) design framework. Figure 4 shows the unconditional effects of crossing from above the population and crossing from below the time-to-travel thresholds on the probability that schools are *Rural 1*. The regression equation that pools together these two sources of variation in a multivariate sharp RD design is the following:

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

where y_{ijt} is the outcome variable for teacher or student i in school j in time t. The treatment is defined by $Rural1$, an indicator variable equals to one if the locality in which school j is situated has less than 500 inhabitants ($pop_{jt} < pop_c$) and is located more than 120 minutes away from the province capital ($time_{jt} > time_c$). The parameter of interest is

β_1, which captures a weighted average of the effects of crossing the population threshold, the time-to-travel threshold, and both thresholds simultaneously. We further include higher-order polynomials of the two running variables, and the interaction between them in order to flexibly control for any direct influence of these characteristics on the outcomes of interest. The term δ_t is a time dummy, and the error term ϵ_{ijt} is clustered at the school level.

The usual identification assumption for consistent estimation of the treatment effect parameter β_1 in the RD framework is a local continuity assumption – i.e. potential outcomes with and without the wage bonus are not different around both the population and the time-to-travel cutoffs.

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 potential violation of the continuity assumption. To check this, Figure 5 displays the empirical densities based on local-quadratic density estimators with the corresponding confidence intervals for each of the assignment variables. This graphical evidence shows that schools are probably sorting endogenously across the time-to-travel threshold in the second year (2017) of the centralized recruitment process whereas there seems to be no strategic manipulation of the population assignment variable in both years. The formal manipulation test (McCrary 2008) seems indeed to confirm these visual patterns.[5]

4.2 Fuzzy RD

Overall, the evidence reported above seems consistent with the view that in this setting schools were in part able to strategically sort around the time-to-travel eligibility cutoffs while they were less able to do so for the population eligibility cutoffs. To further corroborate this claim, Table 2 reports RD estimates of the empirical specification in Equation (1) for the population discontinuity using the available pre-determined (2015) school characteristics as dependent variables (see Panel A of Table 1). Point estimates for the treatment effect coefficient β_1 are very small and not statistically different from zero.

These considerations motivate the use of a standard Fuzzy RD approach, whereby an indicator function for crossing from above the population threshold, $\mathbf{1}(pop_{jt} < pop_c)$, can be used as a valid instrument for the schools being in the *Rural 1* category. Given continuity of potential outcomes around the population cutoff, the following reduced-form equation identifies an Intent-To-Treat (ITT) effect of the policy:

[5]The estimated (robust) T-statistic for the null hypothesis of no difference in height between the two interpolating kernel density estimators for the time-to-travel discontinuity is 2.08 (p-value=0.037) in 2017 and 1.39 (p-value=1.16) in 2015. T-stats are much lower in size and are not statistically significant for the population discontinuities: 0.37 in 2015 and 0.49 in 2017.

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

where, as before, $g(\cdot)$ is a flexible polynomial in the distance from the population cutoff and u_{ijt} is an error term clustered at the school-level. The γ parameter opportunely scaled by the compliance effect of crossing from above the population threshold (see the top chart of Figure 4) defines a Local-Average-Treatment-Effect (LATE) of the policy (Hahn et al. 2001).

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.

5 Estimation Results

5.1 The Effect of Wage Bonuses on Teachers

Table 3 reports our main regression discontinuity estimates of the effects of the wage bonus on teacher quality. We display the estimated ITT and LATE parameters associated to the γ_1 coefficient in Equation (2), separately by the school-calendar years following each wave of centralized recruitment (2016 and 2018). Columns (1), (3) and (5) show that teachers who took a position at a school with higher wages score 0.5-0.6 of a standard deviation higher in the centralized test when compared to teachers who choose a position in lower paying rural schools. Consistent with this result, Columns (2), (4) and (6) show that the probability that teaching positions are chosen by teachers with above-median scores increases by 40-50 percentage points in *Rural 1* positions when compared to other rural positions. These are very large effects, as they are about twice as large as the difference between the sample averages of teacher scores in *Rural 1* schools and other Rural schools (see Panel C of Table 1). To put these magnitudes in perspective, Figure 6 displays the relationship between the distance to the population cutoff for the locality in which the school is situated and local averages of teacher score (top chart) or the share of teachers with above-median score (bottom chart). The cumulated erosion in teacher quality associated with a decrease in locality population by 500 inhabitants at both sides of the cutoff is about as large as the discrete increase in quality at the cutoff.

We perform a series of robustness checks for this result. We first explore whether the observed large increase in teacher quality in response to the wage bonuses is also associated with simultaneous changes in other teacher characteristics. As shown in Table A.1 in the Appendix, teachers who choose to go to schools that offer higher wages are not different along basic demographics, such as age and gender, or the extent of previous experience in the public sector. If anything, they are slightly younger (by one year) although that effect is not statistically different from zero.

We next consider whether or not the estimated effects reported in Table 3 may be driven by demand-side responses to the wage incentives. Table A.3 in Appendix shows that both the number of yearly open vacancies and its cumulated stock over time does not seem to systematically differ between *Rural 1* schools and other rural schools. Relatedly, Table A.2 shows no differences across schools above and below the population cutoff in the total number of teachers, in the relative share of contract teachers, and in the student/teacher ratios.

One last concern with our regression discontinuity estimates is that they may be driven either by an increase in the quality of teachers that decide to go to high paying schools or by a drop in the quality of teachers who choose to go to low paying positions that are close enough to the population cutoff. Table A.4 in the Appendix shows that in fact the bulk of newly recruited teachers in *Rural 1* schools seems to be coming from locations with population below 500 inhabitants, rather than above 500 inhabitants. This evidence suggests that the observed increase in teacher quality is not the result of a zero-sum game between schools located across the population cutoff.

As discussed above (see Panel B of Table 1), there is a high degree of mobility in the labor market for teachers in rural areas that is mainly driven by the large presence of contract teachers. In Table 4, we finally evaluate whether and how the introduction of the wage bonus in *Rural 1* schools alters these movements. We compute retention rates at the school-level both between-year (December-March) and within-year (March-December) year. We do so using the teacher roster for the school-calendar following the centralized assignment procedures (2016 and 2018) and for the school-calendar year in between (2017) in which recruitment practices were more erratic and decentralized. Columns (1), (3) and (5) show that teachers in *Rural 1* schools are equally likely to stay within the school year when compared to teachers in other rural schools. This result is not too surprising given the fact that more than 90 percent of teachers don't move within the year anyway. Columns (2) and (6) show that higher wages generate higher retention rates between school years, and particularly so in the year 2018. Teachers earning a higher wage due to the *Rural 1* wage bonus are almost 20 percentage points more likely to remain in that same school in the next academic cycle. This is a very large effect given the fact that the average baseline retention probability across school-calendar years is only 8 percent. This result does not hold in the year 2017 in which the assignment process of teachers did not follow strict merit-based priority rules (Column 4),[6] suggesting the role of potential complementarities between

[6]The baseline retention probability between the school years 2016-2017 is higher when compared to the years in which the centralized assignment mechanism was in place (30 percent, see Column 4 of Table 4).

the matching mechanism and wage incentives for retaining higher-quality teachers in less desirable locations.

5.2 The Effect of Wage Bonuses on Student Achievement

We proceed by discussing the effects of the policy discontinuity induced by the *Rural 1* wage bonus on student achievement, as measured by standardized test scores in the fourth grade for mathematics and language. Table 5 reports the estimated treatment effect parameters by school-calendar year associated to the γ_1 coefficient of Equation (2). Treatment effects are very small and quite noisy for all primary schools during the first school-year after the centralized recruitment (Columns 1 and 3). These estimates substantially increase in magnitudes for schools that had an open vacancy in the assignment system, although they remain not significantly different from zero (Columns 2 and 4). There is a large and statistically significant effect of the policy on student outcomes during the school-year following the second round of the centralized assignment mechanism. Columns (5) and (7) show that test scores of children studying in schools that offer higher wages to all of their teachers are between 0.5 and 0.6 standard deviation higher. This effect seems to be driven by relative changes in the two tails of the ability distribution.[7]

The effects of the policy are more pronounced in schools that had an open vacancy in the previous recruitment drive (Columns 6 and 8), suggesting a link with the resulting changes in the allocation of teachers across teaching positions documented in the previous section. Figure 7 corroborates visually this pattern of heterogeneity in the estimates reported in Table 5 by displaying the relationship between the distance to the population cutoff for the locality in which the school is situated and local averages of math score (left charts) or Spanish score (right charts). As it was the case for teacher scores (see Figure 6), there is a clear negative relationship indicating that student scores monotonically deteriorates as the size of the locality gets smaller. Crossing the population threshold seems to clearly shift up that relationship, with more visible jumps at the cutoff among schools with open vacancies in the previous recruitment drive.

To further explore the possibility that the sorting patterns of teachers by quality may be partly explaining the observed changes in student outcomes, Tables 6 and 7 report treatment effects for alternative sub-samples of schools according to their differential exposure over time to newly recruited teachers through the assignment mechanisms. The first Columns of each

This is consistent with the presence of more erratic and decentralized recruitment practices in that year.

[7] Tables A.5 and A.6 in the Appendix show that the policy is associated with a decrease in the share of students in the bottom quartile of the score distribution and an increase in the share of students in the top quartile.

Table show that treatment effects are very small and not different from zero for schools that had no open vacancies. This result echos the zero effect of unconditional wage increases on teacher effort documented elsewhere (de Ree et al. 2017). The same null results hold for schools that had only one vacancy in one of the two recruitment drives (Columns 2 and 3 in Tables 6 and 7), which is consistent with the small short-run effects of the policy on test scores for the year 2016 reported in Columns (1)-(4) of Table 5. When compared to the effects reported in Columns (6) and (8) of Table 5, the estimated coefficients of the wage policy roughly double in magnitude for both outcomes among the sub-set of schools that had multiple vacancies and hence they were more likely to experience a prolonged inflow of new (higher-quality) teachers throughout the period (Columns 4 of Tables 6 and 7).

Taken together, these different pieces of evidence seem to suggest that most of the effect of the policy on student achievement is driven by the re-allocation process of teachers induced by the wage bonuses.

6 Conclusion

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

We find that unconditional wage increases are successful in effectively mobilize talent to remote, hard-to-staff 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. These findings suggest that wage increases are an effective policy tool to re-allocate talent within the public sector, which in turn leads to an improvement in the provision of public goods.

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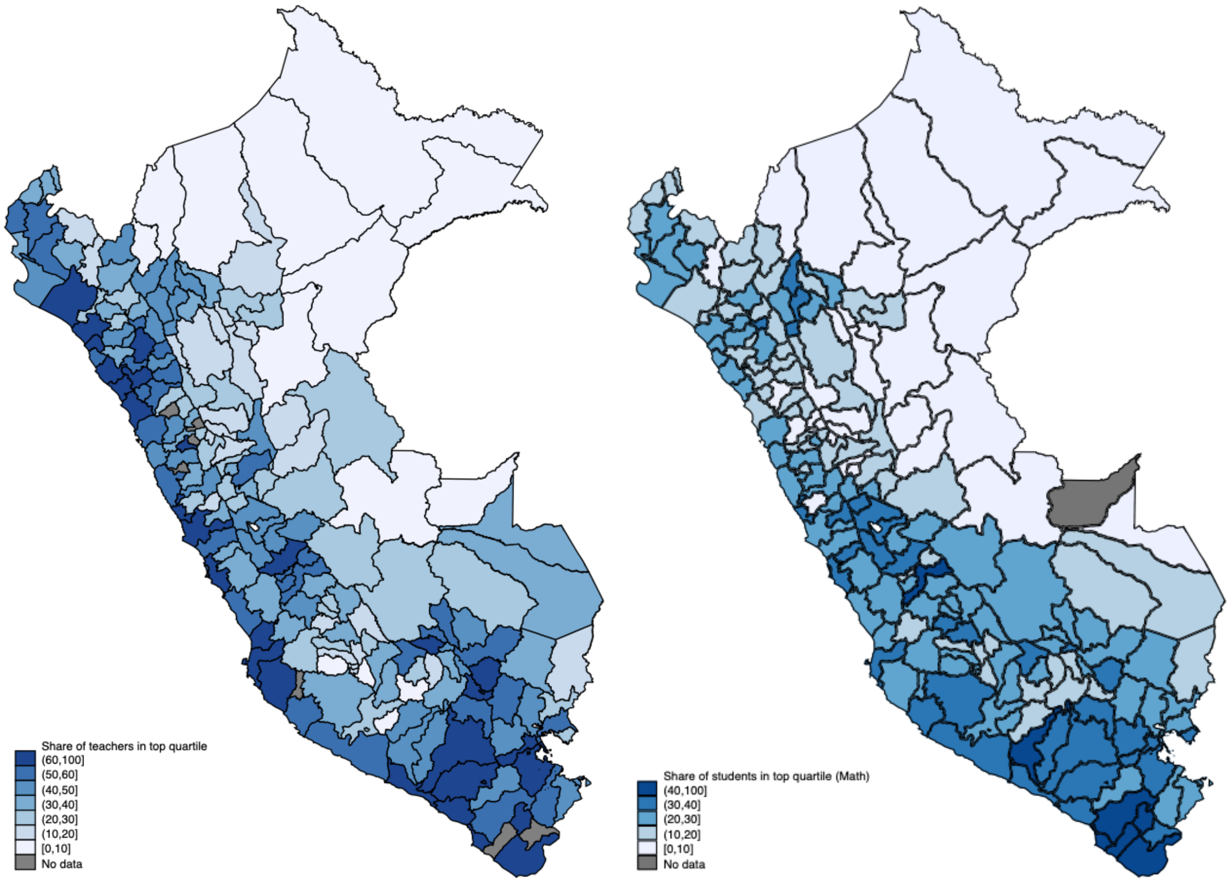
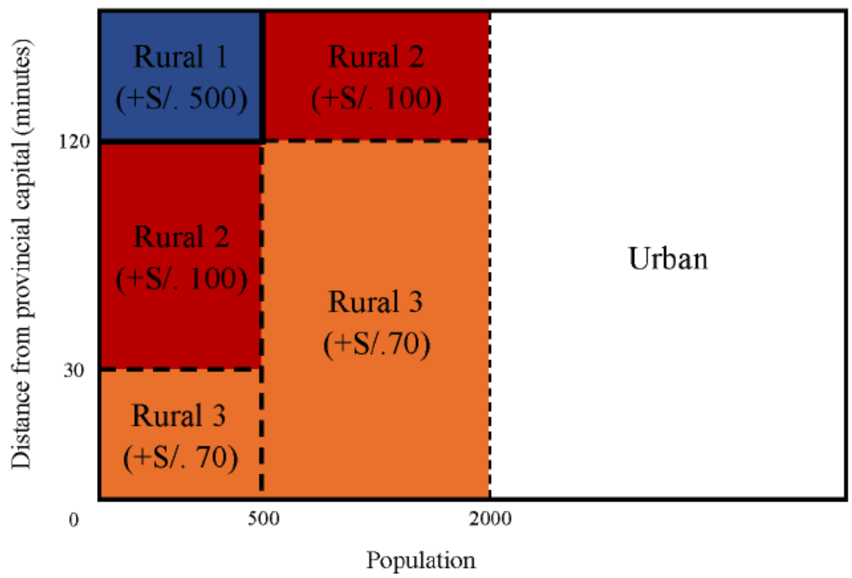
Figures

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



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

Figure 2: Wage Bonus in Rural Areas



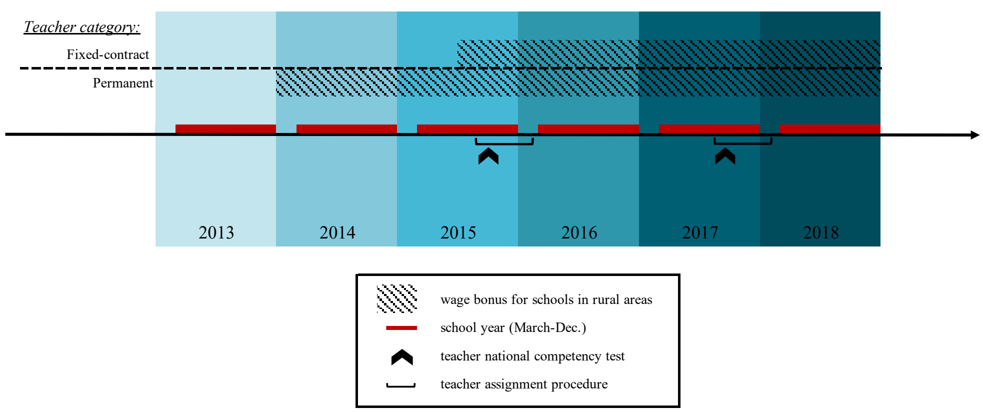


Figure 3: Spatial Distribution of Schools

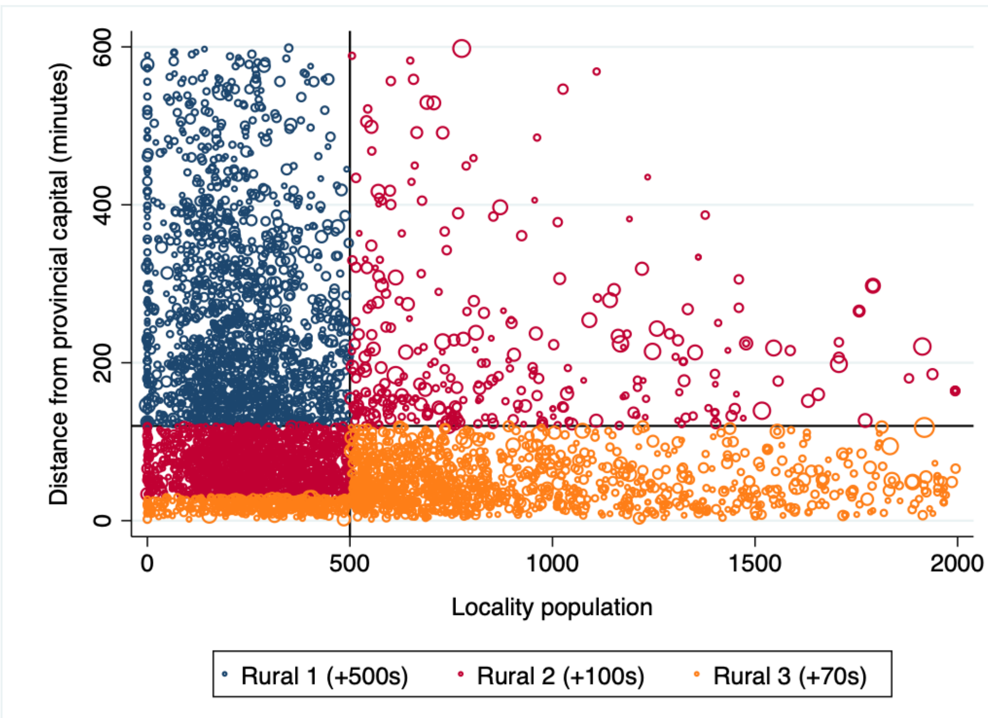
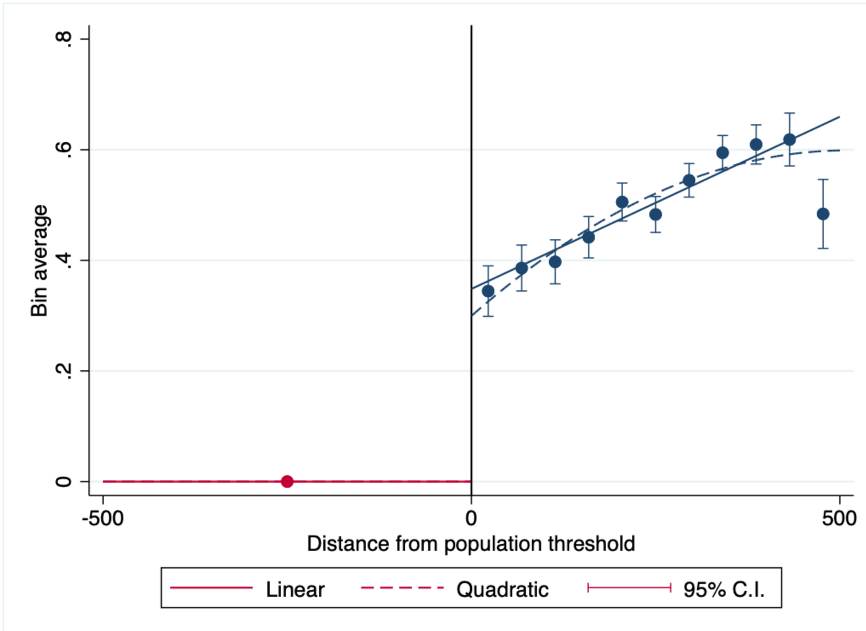
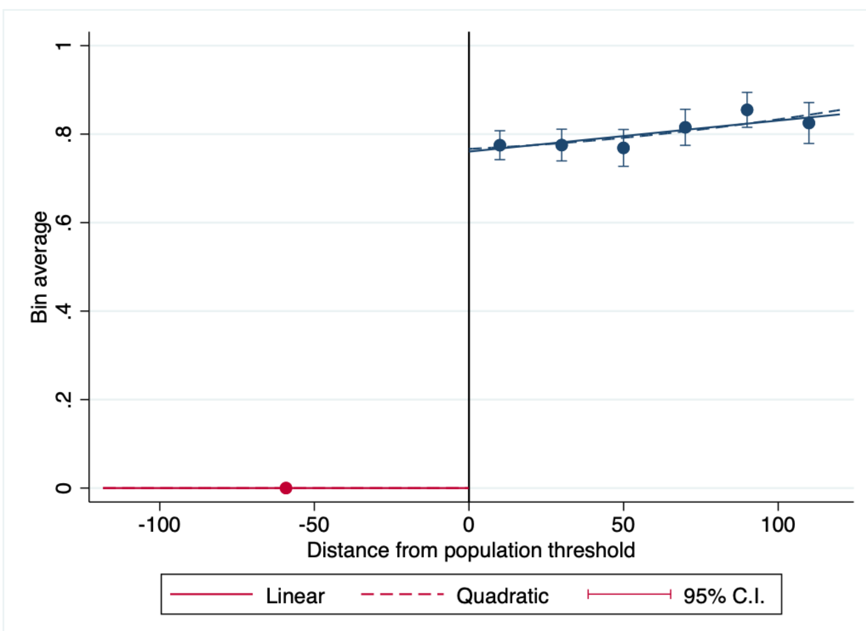


Figure 4: Prob(Rural 1)

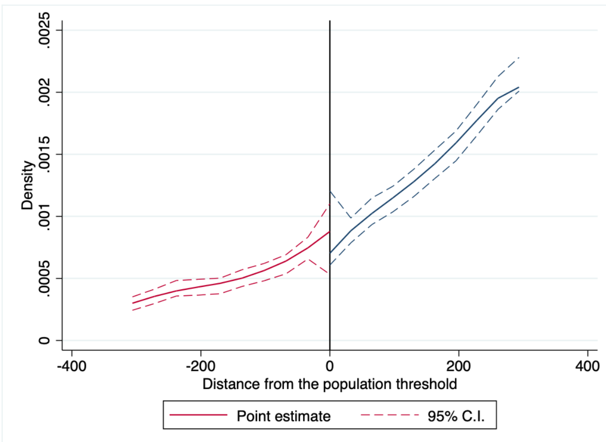


Population

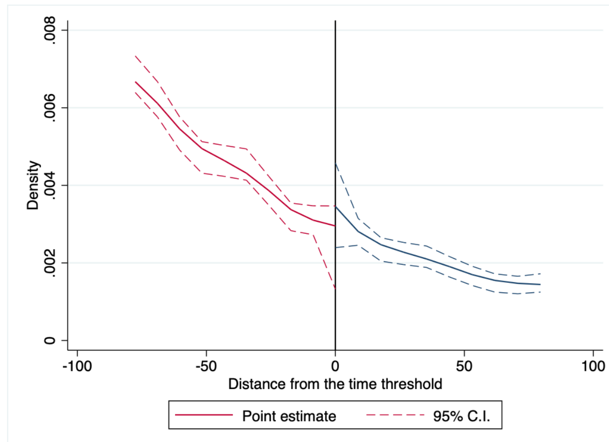


Time

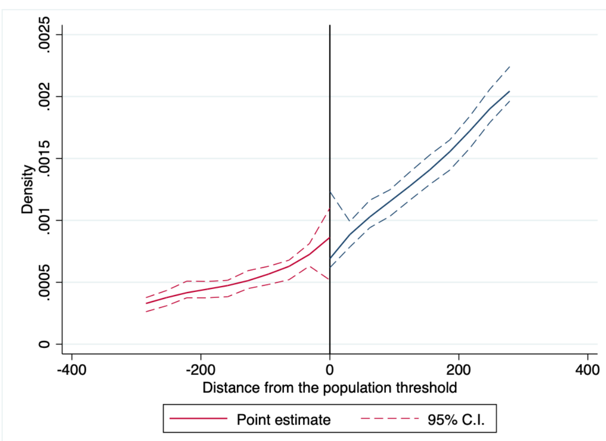
Figure 5: Density Test



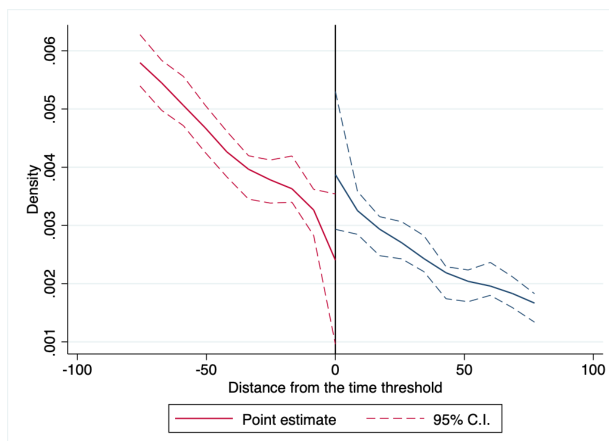
Population (2016)



Distance (2016)

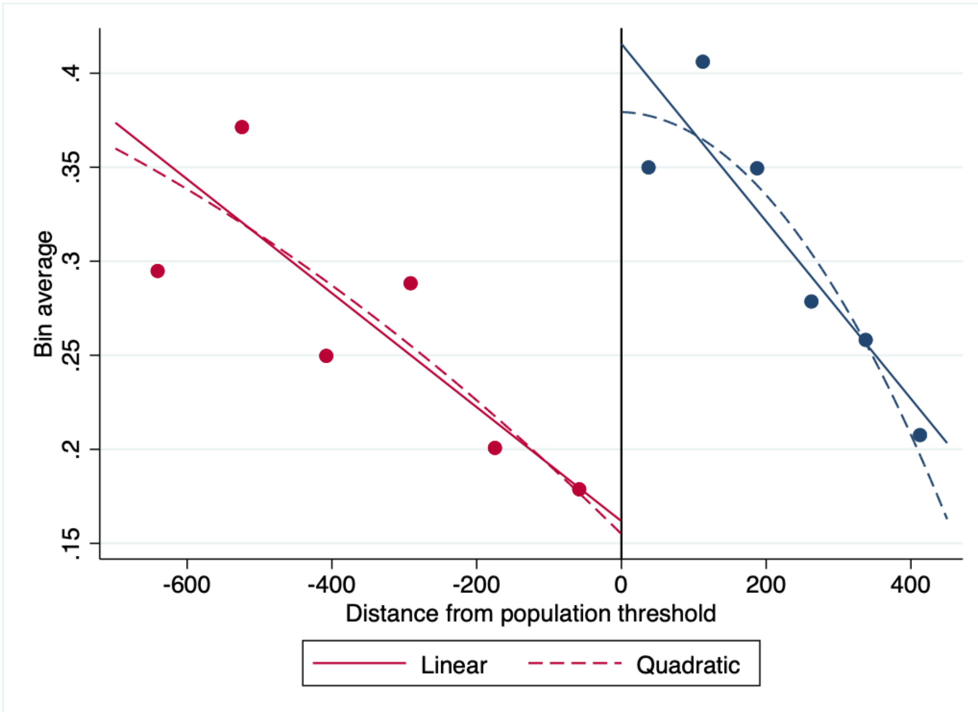


Population (2018)

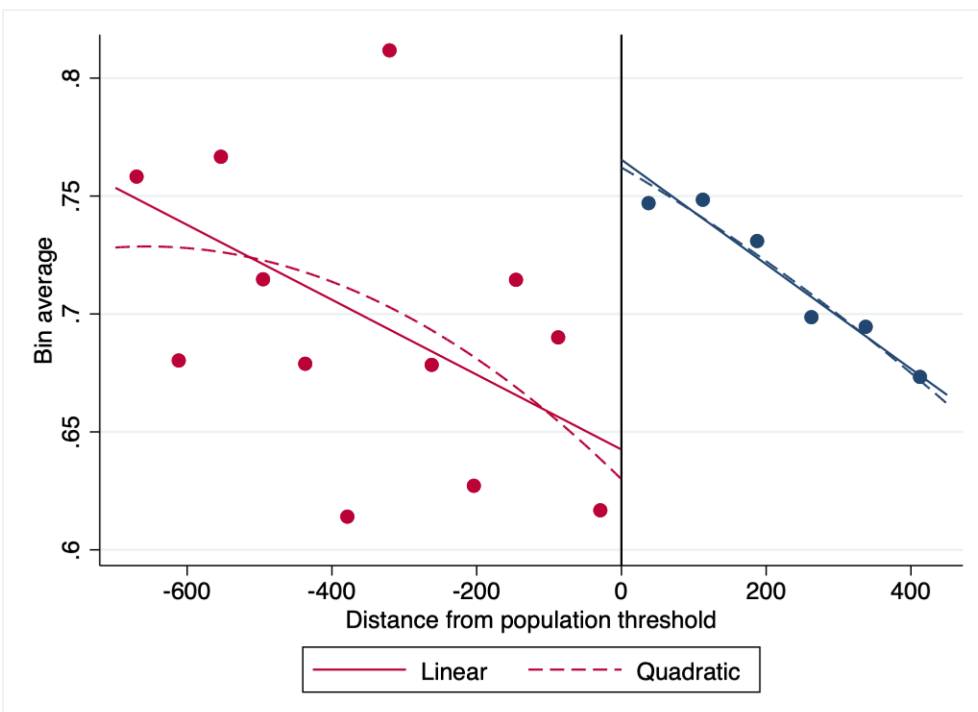


Distance (2018)

Figure 6: ITT Effects on Teacher Quality (Pooled 2016-2018)



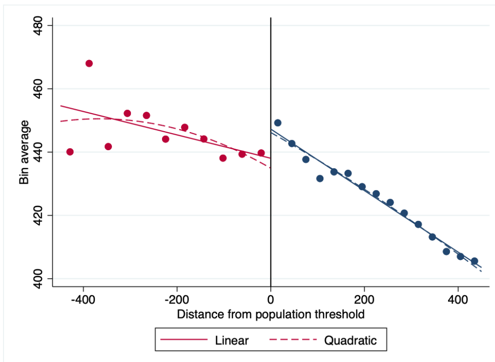
Teacher score (std)

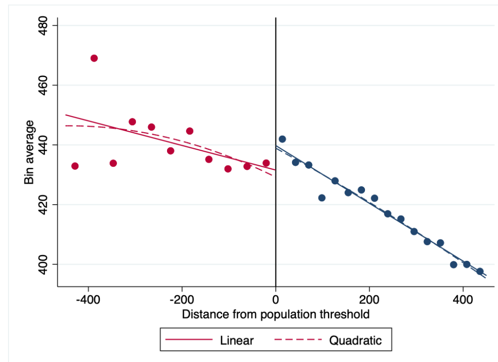


Teacher score above median

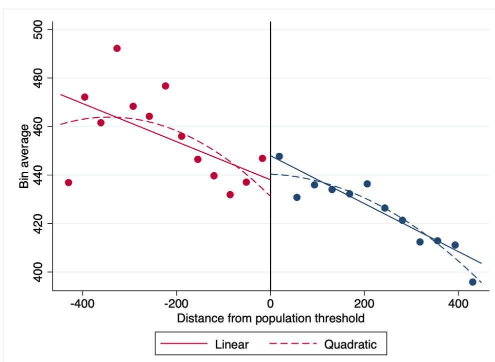
Figure 7: ITT Effects on Student Outcomes (2018)

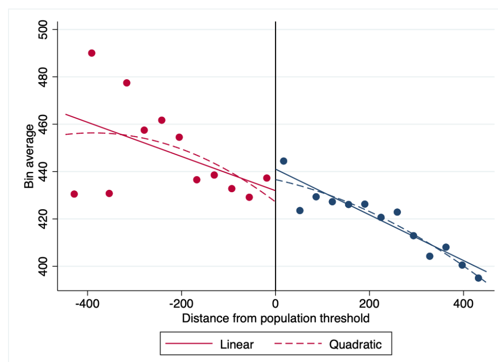
All schools



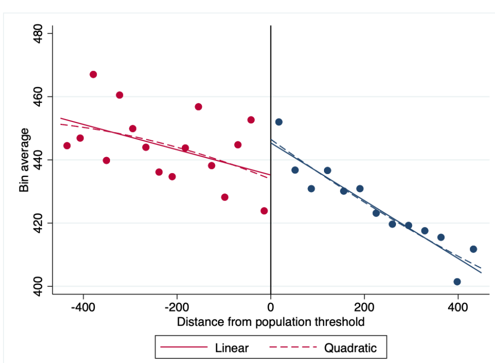


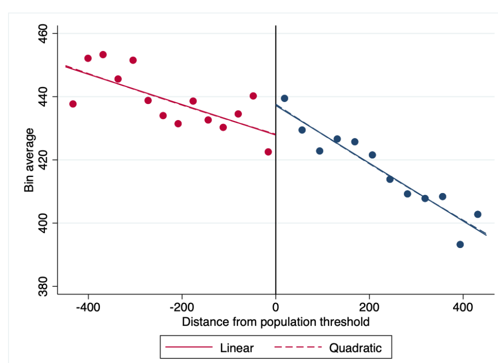
Schools without vacancies in 2017





School with Vacancies in 2017





Test score in Math **Test score in Spanish**

Tables

Table 1: Summary Statistics

Panel A: School characteristics (2015)	Rural 1 Schools		Other Rural Schools	
	Mean	Sd	Mean	Sd
Wage (with bonuses)	2198.66	134.91	1752.55	138.30
Single-teacher school	0.09	0.29	0.01	0.12
Multigrade school	0.77	0.42	0.44	0.50
Number of students	56.33	32.35	100.24	75.48
Number of teachers	3.23	1.79	6.18	3.78
Teachers with permanent contract (%)	0.45	0.33	0.65	0.25
Teachers with temporary contract (%)	0.43	0.34	0.24	0.23
Sport facility	0.10	0.30	0.32	0.47
No water	0.71	0.45	0.56	0.50
No electricity	0.33	0.47	0.07	0.26
% chairs in good conditions	0.58	0.39	0.53	0.38
Chairs per student	1.04	0.62	1.15	0.66
Test score (Spanish)	522.03	71.03	553.27	61.22
Test score (Math)	519.60	100.36	555.33	88.76
Sewage in town/village	0.16	0.37	0.40	0.49
Doctor in town/village	0.39	0.49	0.64	0.48
Library in town/village	0.01	0.07	0.05	0.22
Number of schools	1805		3491	
Panel B: Teachers' dynamics (2016-2018)	Rural 1 Schools		Other Rural Schools	
	Mean	Sd	Mean	Sd
Yearly turnover	0.54	0.35	0.31	0.27
- *permanent contract*	0.16	0.32	0.09	0.21
- *temporary contract*	0.88	0.29	0.88	0.30
N. of vacancies	1.21	1.05	1.21	1.37
- *permanent contract*	0.81	0.91	0.50	0.89
- *temporary contract*	0.94	1.02	0.96	1.26
% of vacancies filled	0.52	0.47	0.48	0.46
- *permanent contract*	0.35	0.46	0.55	0.48
- *temporary contract*	0.69	0.45	0.62	0.46
Panel C: Applicants' characteristics (2016-2018)	Rural 1 Schools		Other Rural Schools	
	Mean	Sd	Mean	Sd
Age	37.13	6.24	36.67	5.98
Female	0.50	0.50	0.63	0.48
Experience (0-6 years)	3.17	1.76	3.04	1.86
Novice teacher	0.09	0.28	0.13	0.34
Score (std)	0.26	0.94	0.46	0.92
Took both tests	0.77	0.42	0.80	0.40
Number of applicants	4752		9076	

Notes.

Table 2: Covariate balance

	School characteristics						Village facilities	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Stud./Teach.	% contract t.	No electricity	Chairs per st.	Spanish score	Math score	Doctor	Library
ITT (pop. 2015)	-0.871	-0.000	-0.006	-0.080	8.265	14.956	0.042	0.008
	(0.861)	(0.031)	(0.044)	(0.096)	(7.747)	(11.443)	(0.067)	(0.018)
Mean dep. var.	16.498	0.255	0.101	1.109	550.921	554.102	0.663	0.031
Std. dev. dep. var.	5.860	0.232	0.301	0.622	61.429	91.379	0.473	0.175
BW	155.301	149.837	133.128	153.073	199.149	204.637	154.979	156.005
Observations (BW)	1418	1354	1162	1363	1732	1774	1318	1336
Observations	5290	5291	5142	5146	4669	4669	4945	4941
ITT (pop. 2017)	-0.829	-0.002	0.008	-0.068	2.121	6.597	0.068	0.004
	(0.859)	(0.030)	(0.042)	(0.095)	(8.301)	(11.537)	(0.069)	(0.019)
Mean dep. var.	16.454	0.256	0.100	1.105	550.666	554.614	0.657	0.028
Std. dev. dep. var.	5.973	0.231	0.301	0.616	60.542	91.079	0.475	0.166
BW	158.424	149.955	138.978	157.720	167.512	194.870	145.790	148.945
Observations (BW)	1429	1339	1195	1382	1428	1678	1205	1240
Observations	5211	5212	5067	5070	4593	4593	4871	4867

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

Table 3: Teacher Quality

	2016		2018		Pooled	
	(1)	(2)	(3)	(4)	(5)	(6)
	Score	> median	Score	> median	Score	> median
ITT	8.656*	0.232***	7.156**	0.190***	7.657**	0.182***
	(5.076)	(0.084)	(3.429)	(0.066)	(3.494)	(0.058)
LATE	18.535	0.485**	14.356**	0.379***	15.837**	0.382***
	(11.426)	(0.194)	(7.234)	(0.141)	(7.577)	(0.130)
Mean dep. var.	107.647	0.709	115.998	0.765	112.409	0.736
Std. dev. dep. var	28.663	0.455	25.626	0.424	27.320	0.441
BW	150.060	125.491	229.462	208.343	184.840	195.864
Schools (BW)	995	808	1779	1595	1684	1815
Observations (BW)	1781	1469	3232	2911	4726	5083
Schools	3860	3860	4238	4238	5282	5282
Observations	6572	6572	7491	7491	14063	14063

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

Table 4: Teacher Retention

	2016		2017		2018	
	(1)	(2)	(3)	(4)	(5)	(6)
	Within-year	Between-years	Within-year	Between-years	Within-year	Between-years
ITT	-0.012	0.011	0.023	-0.032	0.020	0.094**
	(0.040)	(0.029)	(0.035)	(0.062)	(0.022)	(0.041)
LATE	-0.027	0.024	0.047	-0.063	0.040	0.190**
	(0.089)	(0.061)	(0.072)	(0.124)	(0.045)	(0.088)
Mean dep. var.	0.914	0.055	0.931	0.296	0.944	0.083
BW	159.326	167.414	152.846	147.199	216.053	117.651
Schools (BW)	1062	1124	1165	1117	1660	859
Observations (BW)	1886	1659	2252	1958	3025	1454
Schools	3858	3858	4458	4458	4235	4235
Observations	6571	5418	8186	7255	7489	6758

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

Table 5: Student Outcomes

	Spanish (2016)		Math (2016)		Spanish (2018)		Math (2018)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	With vacancy	All	With vacancy	All	With vacancy	All	With vacancy
ITT	0.257	17.834	-4.051	17.433	15.173*	23.164**	19.387**	33.094***
	(6.438)	(11.261)	(7.545)	(12.946)	(8.640)	(11.472)	(9.293)	(12.731)
LATE	0.988	45.055	-15.428	44.918	43.671*	61.055*	55.724**	86.866**
	(24.611)	(31.148)	(28.789)	(35.639)	(26.109)	(32.142)	(28.196)	(36.405)
Mean dep. var.	428.929	430.393	429.409	429.342	432.921	430.908	439.613	437.980
Std. dev. dep. var.	85.607	88.400	93.859	95.641	91.579	91.700	93.530	94.820
BW	210.403	184.718	222.182	192.278	123.722	119.299	120.821	110.380
Schools (BW)	2898	963	3113	1025	1678	874	1642	811
Observations (BW)	37068	14012	39358	14791	21887	12597	21414	11755
Schools	7330	2928	7330	2928	8607	4289	8607	4289
Observations	96199	44305	96172	44294	103554	59758	103527	59746

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

Table 6: Student Outcomes (Spanish 2018)

	(1)	(2)	(3)	(4)
	No vacancy	Vacancy in 2016 only	Vacancy in 2018 only	Vacancy in 2016&2018
ITT	1.048	8.303	-2.807	46.861***
	(14.135)	(23.666)	(12.650)	(15.616)
LATE	3.337	22.262	-13.640	83.592**
	(47.324)	(77.677)	(55.113)	(33.894)
Mean dep. var.	432.432	440.608	431.439	428.360
Std. dev. dep. var.	89.716	93.124	87.368	95.068
BW	112.937	159.373	197.099	110.715
Schools (BW)	474	240	689	399
Observations (BW)	5458	3030	9054	6393
Schools	2542	882	1754	1984
Observations	26478	11528	23622	32348

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

Table 7: Student Outcomes (Math 2018)

	(1)	(2)	(3)	(4)
	No vacancy	Vacancy in 2016 only	Vacancy in 2018 only	Vacancy in 2016&2018
ITT	-4.336	6.215	4.841	63.179***
	(15.343)	(26.856)	(12.994)	(18.570)
LATE	-14.121	16.521	22.124	112.322***
	(51.078)	(83.943)	(56.095)	(40.969)
Mean dep. var.	438.287	448.288	437.870	438.052
Std. dev. dep. var.	91.422	93.402	89.821	97.992
BW	114.683	132.224	203.357	99.992
Schools (BW)	481	195	713	365
Observations (BW)	5520	2533	9292	5916
Schools	2542	882	1754	1984
Observations	26470	11525	23613	32347

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

Appendix

A Additional Tables

Table A.1: Teacher Characteristics

	(1) Age	(2) Female	(3) Experience	(4) New entrant
ITT	-0.607	0.034	-0.094	0.011
	(0.603)	(0.047)	(0.151)	(0.029)
LATE	-1.213	0.069	-0.195	0.023
	(1.238)	(0.097)	(0.315)	(0.059)
Mean dep. var.	36.800	0.615	3.055	0.123
Std. dev. dep. var.	6.106	0.487	1.834	0.328
BW	128.961	162.012	182.816	170.463
Schools (BW)	1156	1488	1666	1558
Observations (BW)	3221	4135	4645	4360
Schools	5276	5276	5276	5276
Observations	13754	13830	14024	14024

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

Table A.2: Teacher Compositional Changes

	(1) N. of total positions	(2) N. of teachers	(3) % temporary teachers	(4) Student/Teacher ratio
ITT	0.177	0.146	-0.025	-0.067
	(0.313)	(0.312)	(0.028)	(0.127)
LATE	0.519	0.430	-0.073	-0.195
	(0.925)	(0.920)	(0.086)	(0.376)
Mean dep. var.	5.882	5.825	0.286	2.482
Std. dev. dep. var.	2.861	2.837	0.257	1.027
BW	166.048	166.660	204.415	152.319
Observations (BW)	3100	3100	3837	2719
Observations	10721	10721	10718	10061

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

Table A.3: Probability of open vacancy

	All schools				No vacancy in 2016	Vacancy in 2016
	(1) Vacancy (2016)	(2) Vacancy (2018)	(3) Total Nb. of vacancies	(4) Vacancy in 2016&2018	(5) Vacancy (2018)	(6) Vacancy (2018)
ITT	0.020	0.036	-0.059	0.007	0.055	-0.005
	(0.053)	(0.052)	(0.233)	(0.045)	(0.068)	(0.075)
Mean dep. var.	0.382	0.519	1.579	0.258	0.420	0.696
Std. dev. dep. var.	0.486	0.500	1.991	0.437	0.494	0.460
BW	178.385	197.720	204.396	217.505	179.313	196.878
Observations (BW)	2553	2896	3009	3265	1587	1090
Observations	8475	8475	8475	8475	5236	3239

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

Table A.4: Probability of Recruitment by Population Bins of the School of Origin

	(1) 0-99	(2) 100-199	(3) 200-299	(4) 300-399	(5) 400-499	(6) 500-599	(7) 600-699	(8) 700-799	(9) 800-899	(10) 900-999	(11) 1000-2000	(12) Urban	(13) New entrant	(14) Same school
ITT	-0.018	-0.023	-0.003	0.039**	-0.017	0.008	-0.021	-0.011	-0.002	0.008	-0.030*	-0.023	0.033	0.026
	(0.020)	(0.032)	(0.021)	(0.019)	(0.015)	(0.018)	(0.016)	(0.012)	(0.007)	(0.006)	(0.018)	(0.032)	(0.038)	(0.029)
LATE	-0.038	-0.047	-0.005	0.079**	-0.035	0.016	-0.042	-0.021	-0.004	0.017	-0.059	-0.046	0.067	0.053
	(0.043)	(0.066)	(0.044)	(0.040)	(0.032)	(0.037)	(0.031)	(0.024)	(0.014)	(0.012)	(0.036)	(0.064)	(0.079)	(0.060)
Mean dep. var.	0.065	0.108	0.101	0.060	0.048	0.040	0.025	0.018	0.011	0.012	0.039	0.124	0.210	0.144
BW	205.295	104.610	175.508	112.583	215.304	139.940	122.451	142.858	196.057	206.287	122.411	126.275	143.499	180.878
Schools (BW)	1907	933	1599	998	2028	1264	1090	1289	1819	1916	1090	1130	1294	1644
Observations (BW)	5321	2697	4490	2879	5602	3569	3095	3634	5092	5336	3095	3202	3648	4605
Schools	5282	5282	5282	5282	5282	5282	5282	5282	5282	5282	5282	5282	5282	5282
Observations	14063	14063	14063	14063	14063	14063	14063	14063	14063	14063	14063	14063	14063	14063

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

Table A.5: Student Outcomes (Spanish 2018) - By Quartiles of the Score

	(1) Level 0	(2) Level 1	(3) Level 2	(4) Level 3
ITT	-0.226***	0.043	0.053	0.105***
	(0.068)	(0.036)	(0.035)	(0.041)
LATE	-0.402***	0.081	0.100	0.189**
	(0.150)	(0.068)	(0.072)	(0.086)
Mean dep. var.	0.247	0.337	0.255	0.173
Std. dev. dep. var.	0.431	0.473	0.436	0.378
BW	110.445	175.178	207.200	115.463
Schools (BW)	399	626	765	417
Observations (BW)	6393	9839	11802	6671
Schools	1984	1984	1984	1984
Observations	32348	32348	32348	32348

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

Table A.6: Student Outcomes (Math 2018) - By Quartiles of the Score

	(1) Level 0	(2) Level 1	(3) Level 2	(4) Level 3
ITT	-0.141**	-0.052	0.074*	0.199***
	(0.067)	(0.035)	(0.044)	(0.059)
LATE	-0.252*	-0.099	0.140	0.355***
	(0.136)	(0.070)	(0.090)	(0.127)
Mean dep. var.	0.206	0.272	0.347	0.190
Std. dev. dep. var.	0.405	0.445	0.476	0.393
BW	123.803	182.116	192.041	94.498
Schools (BW)	442	657	706	339
Observations (BW)	6993	10261	10944	5428
Schools	1984	1984	1984	1984
Observations	32347	32347	32347	32347

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