Teacher Compensation and Structural Inequality:

Evidence from Centralized Teacher School Choice in Perú

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Online Appendices – Not for Publication

Contents

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A Descriptive Evidence

Table A.1: School and Locality Characteristics

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

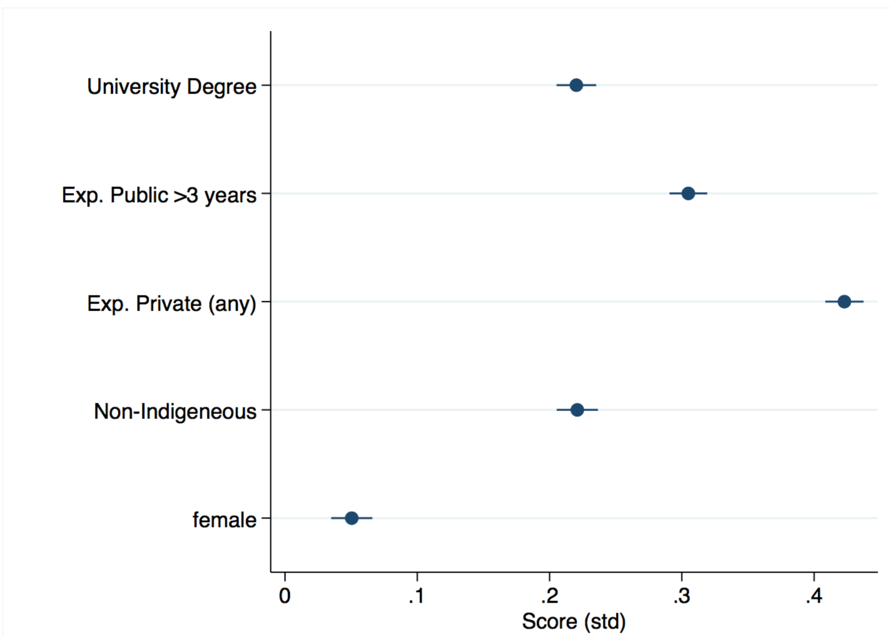
Notes. This table reports the summary statistics for the universe of rural and urban primary schools in Peru over the period 2016-2018. The first panel describes the baseline characteristics of each type of school (size, bilingual spanish/indigenous language curriculum) for the year 2016, and the teaching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

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

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

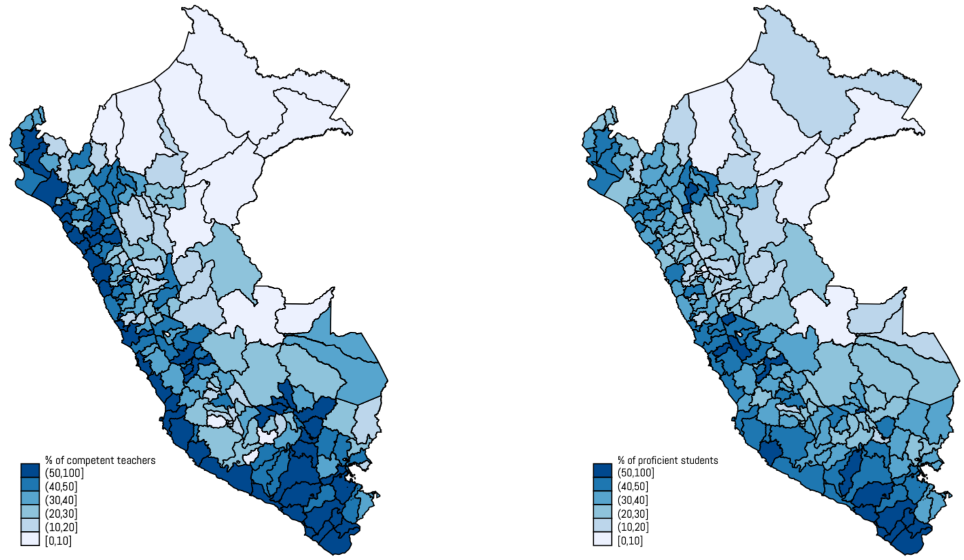
NOTES. This table displays the share of the 5,553 survey respondents that chose the corresponding answers to Question A. The first three columns show which answer they chose and how they ranked them (by order of importance) while column 4 shows the share of respondents that listed the corresponding choice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

Figure A.1: Determinants of Teacher Competency



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

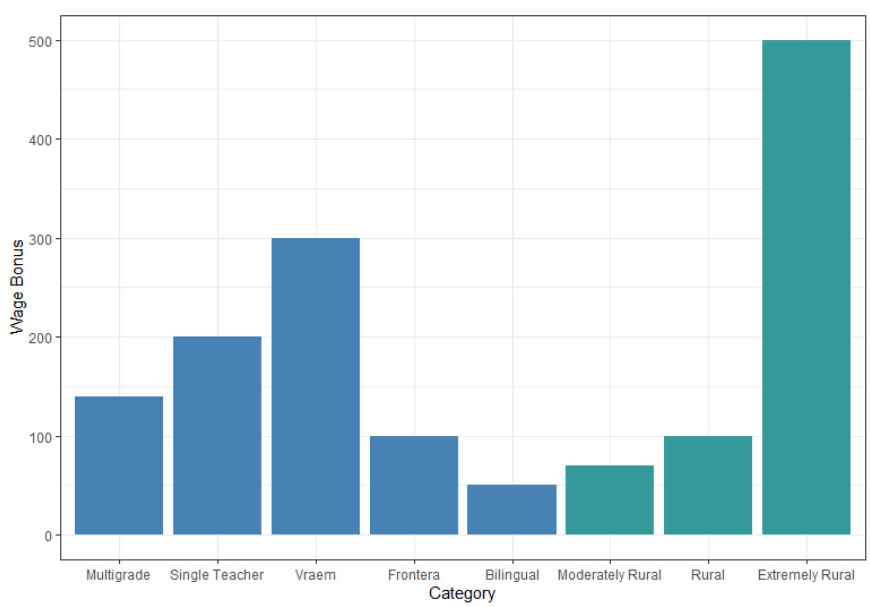
Figure A.2: Geographic Distribution of Teacher Competency and Student Achievement



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

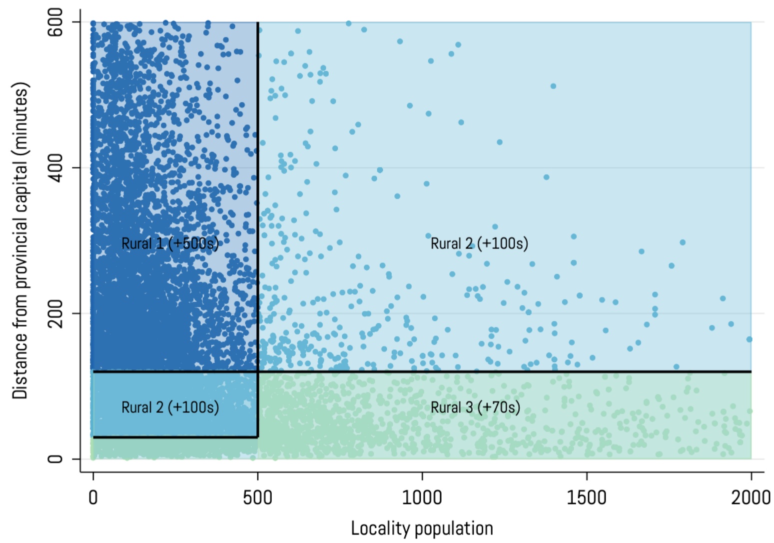
Notes: This figure depicts the geographical variation in the share of competent teachers (panel A) and the share of proficient students (panel B) within each province of Peru. Proficient students are defined as those who attain a proficient (*Satisfactorio*) achievement level in Math and/or Spanish.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

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

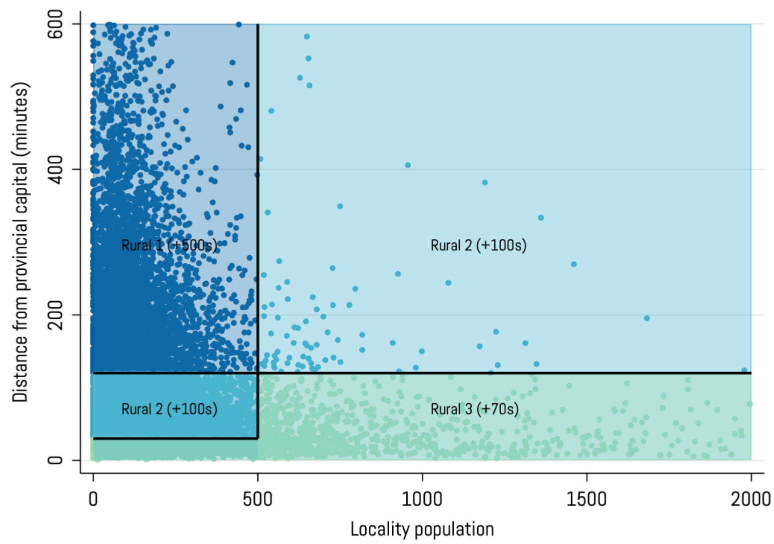


Notes. This figure shows the monetary amount in Peruvian Soles for the different wage bonuses implemented by the Government as of December 2015. Vraem correspond to schools located in the Valle de los Rios Apurimac, Ene y Mantaro which is extremely poor and under the control of drug cartels. Frontera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

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



a) Schools with Vacancies in 2015-2017

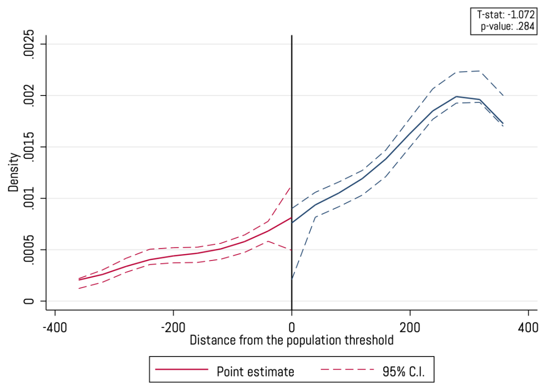


b) Schools without Vacancies in 2015-2017

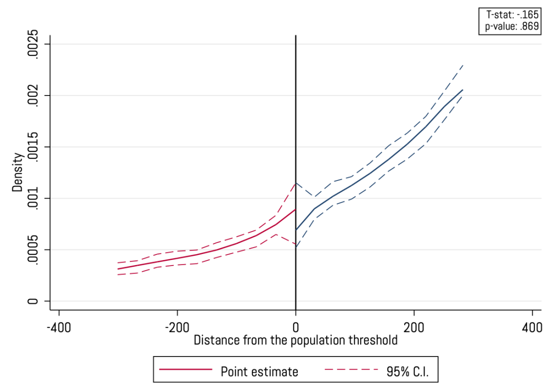
NOTES: This figure shows the spatial distribution of rural primary schools along the two dimensions that determine the assignment of the wage bonus. *Extremely Rural* schools are the purple dots, *Rural* are light blue and *Moderately Rural* schools are green.

B RD Evidence

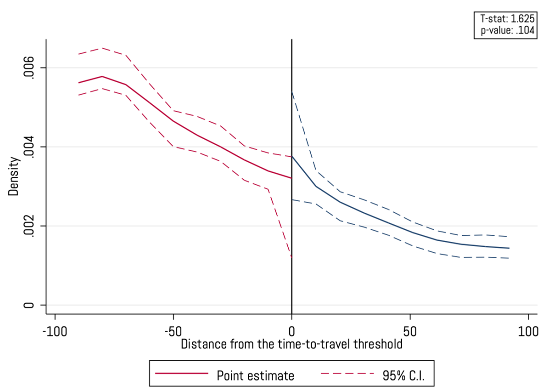
Figure B.1: Manipulation charts



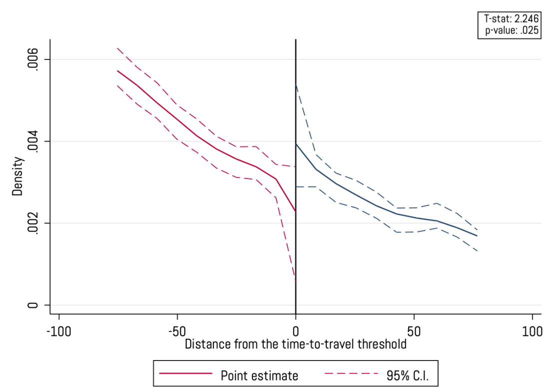
a. Population (2015)



b. Population (2017)



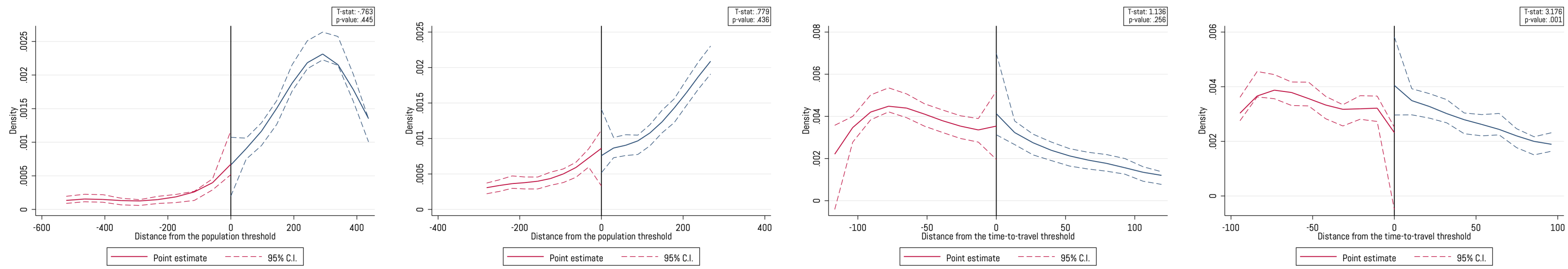
c. Time-to-travel (2015)



d. Time-to-travel (2017)

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

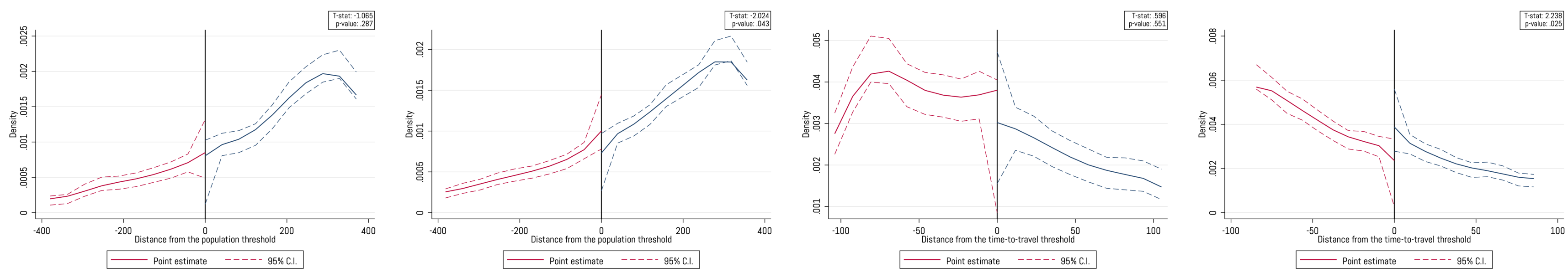
Figure B.2: Manipulation Charts - Schools with a Vacancy for Permanent Teachers



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

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

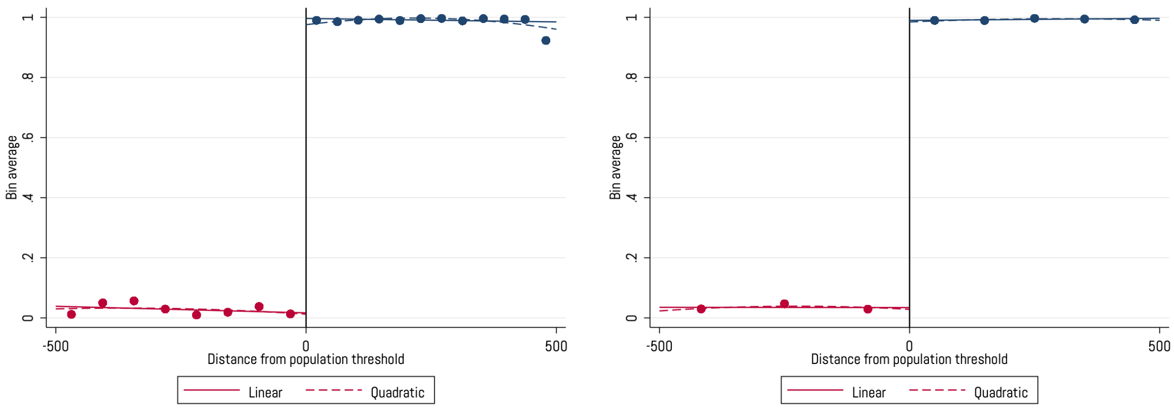
Figure B.3: Manipulation Charts - Schools with a Vacancy for Contract Teachers



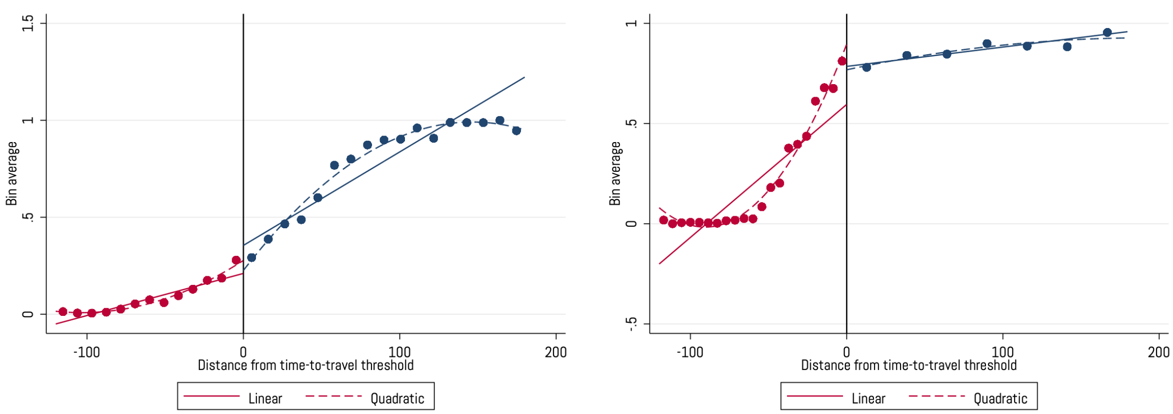
a. Population (2015) *b.* Population (2017) *a.* Time-to-travel (2015) *b.* Time-to-travel (2017)

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

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



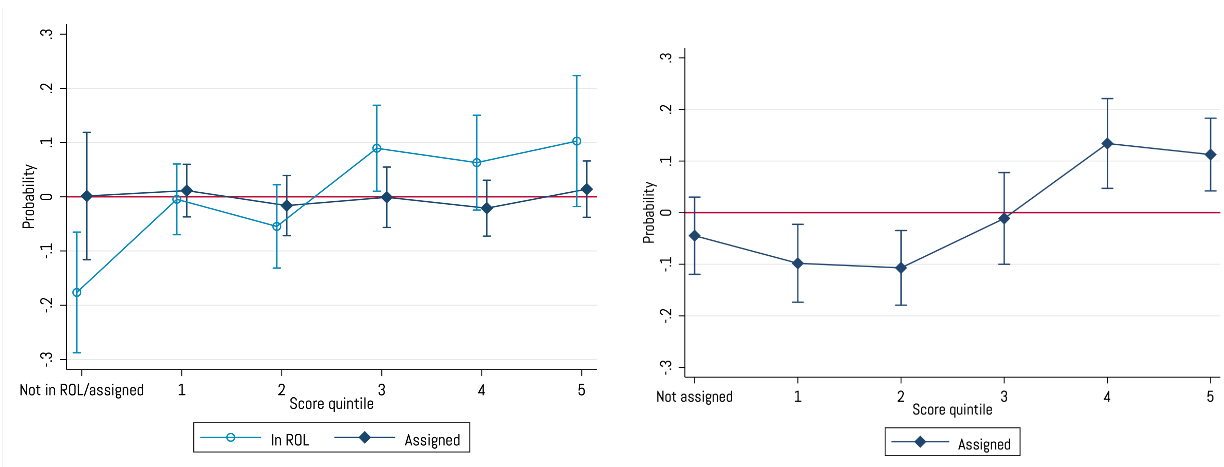
a. Treatment 2017; RV: population 2015 *b.* Treatment 2015; RV: population 2017



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

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

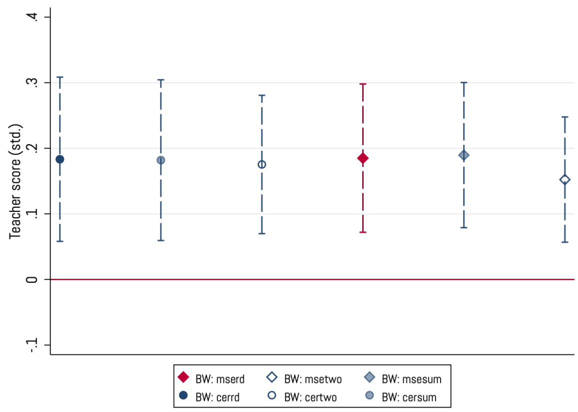
Figure B.5: Wage Bonuses and the Selection of Quality Teachers



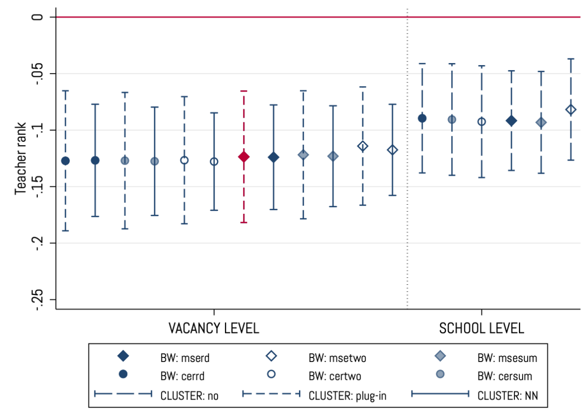
a. Permanent teacher *b.* Contract teacher

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

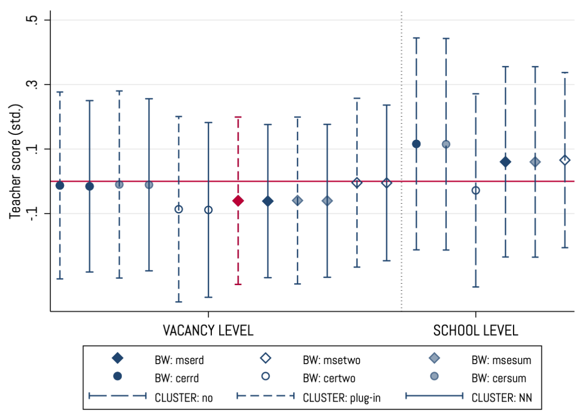
Figure B.6: Robustness to Alternative RD Specifications – Preferences and Sorting



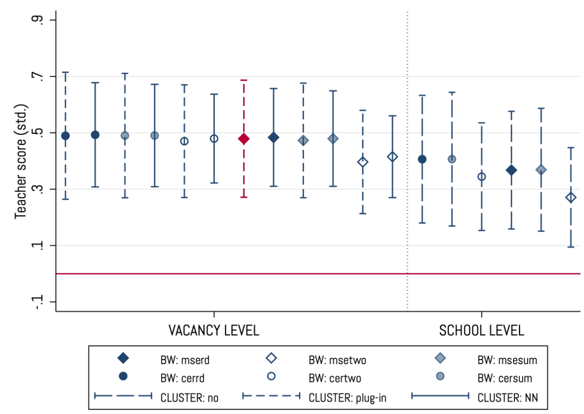
a. In ROL, Permanent teachers



b. Teacher rank, Contract teachers



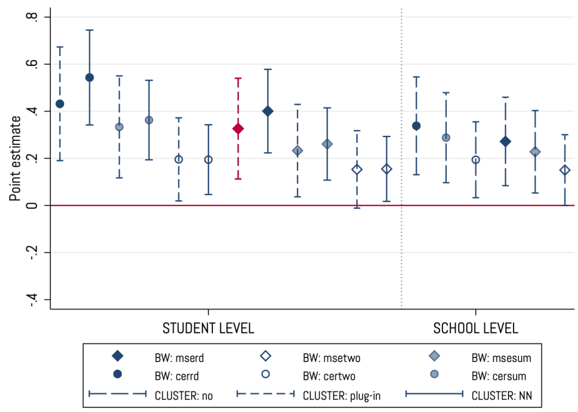
c. Teacher score, Permanent teachers



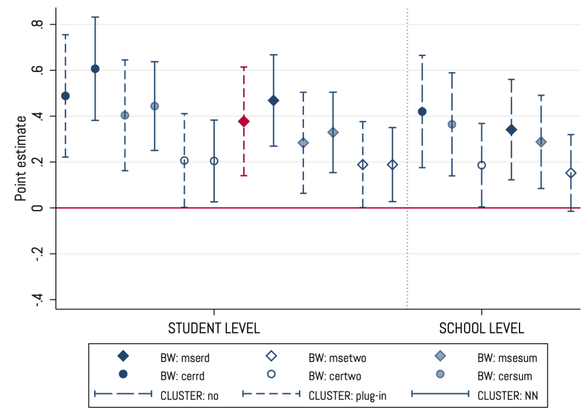
d. Teacher score, Contract teachers

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

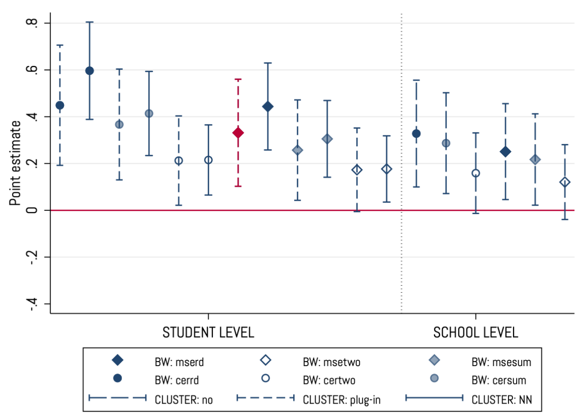
Figure B.7: Robustness to Alternative RD Specifications – Student Achievement



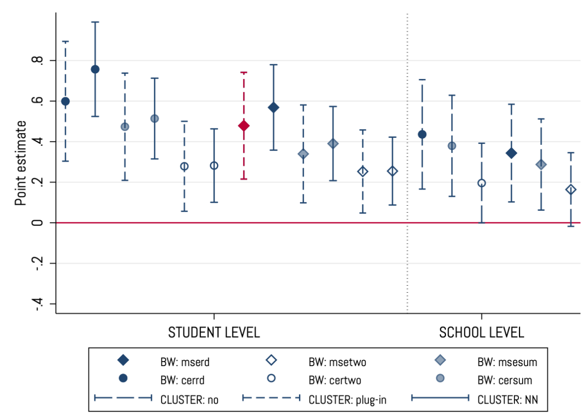
a. Spanish scores, Any vacancy



b. Math scores, Any vacancy



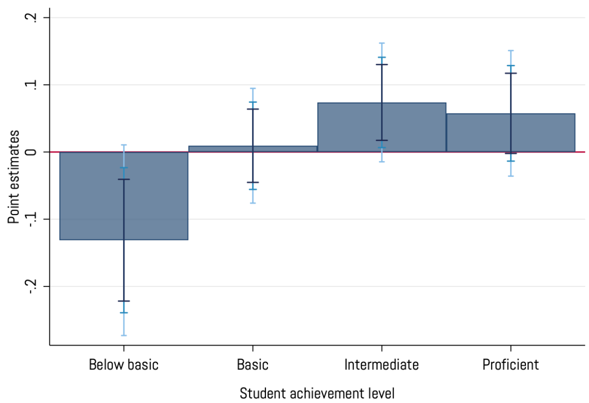
c. Spanish scores, Short-Term vacancy



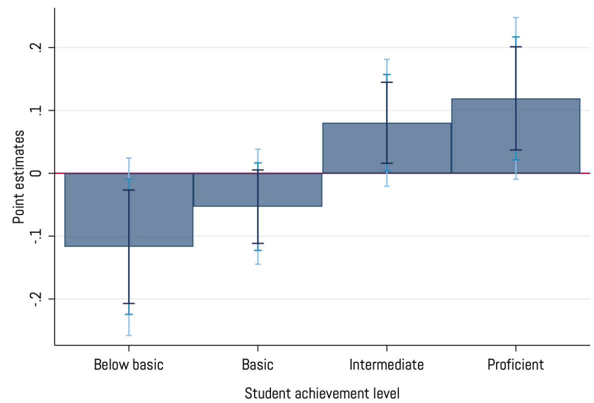
d. Math scores, Short-Term vacancy

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

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



a. Spanish



b. Math

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

Table B.1: Wage increases around the population cutoff

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

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

Table B.2: Covariate Smoothness around the Population Cutoff

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Table B.8: Monetary Incentives and Teaching Staff Composition

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

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

Table B.9: Monetary Incentives and Teachers' Retention

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

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

C Evidence from the Model of Teacher Sorting

Table C.1: Preference Estimates

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

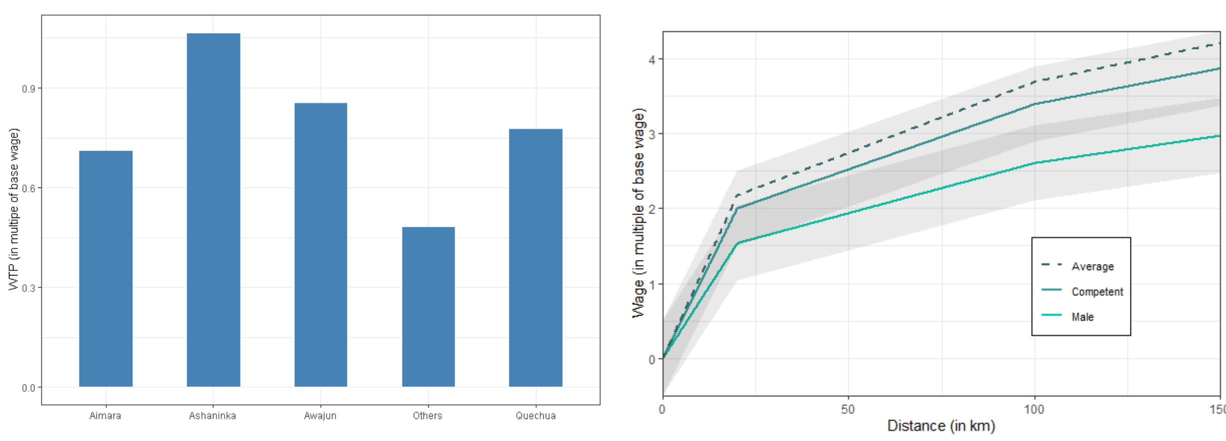
NOTES. This table displays estimates and standard errors (in parentheses) of the parameters of the model described in Equation 2. Panel A shows the estimated coefficients associated to a selected set of schools/locality characteristics while Panel B shows estimated preferences for geographical proximty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

Table C.2: Counterfactuals: Increase in Local Supply

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

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

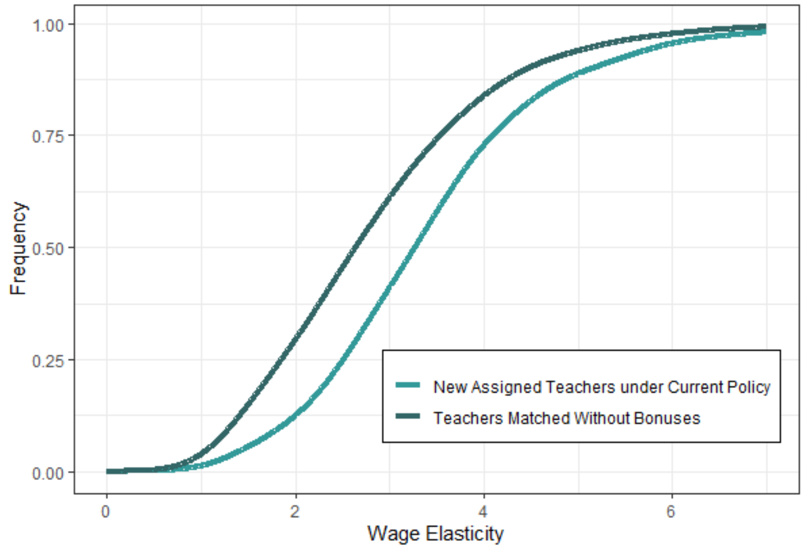
Figure C.1: Match Effects



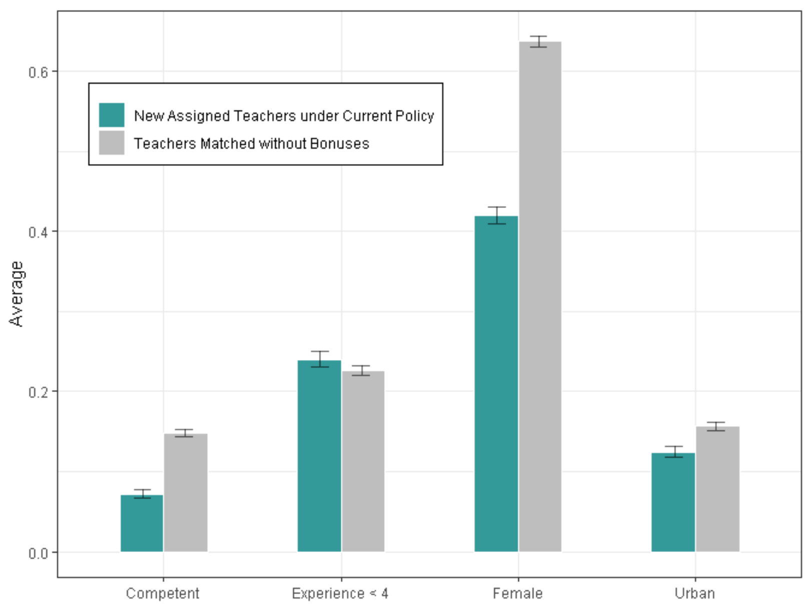
a) Ethnolinguistic Match **b) Disutility of Distance**

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

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



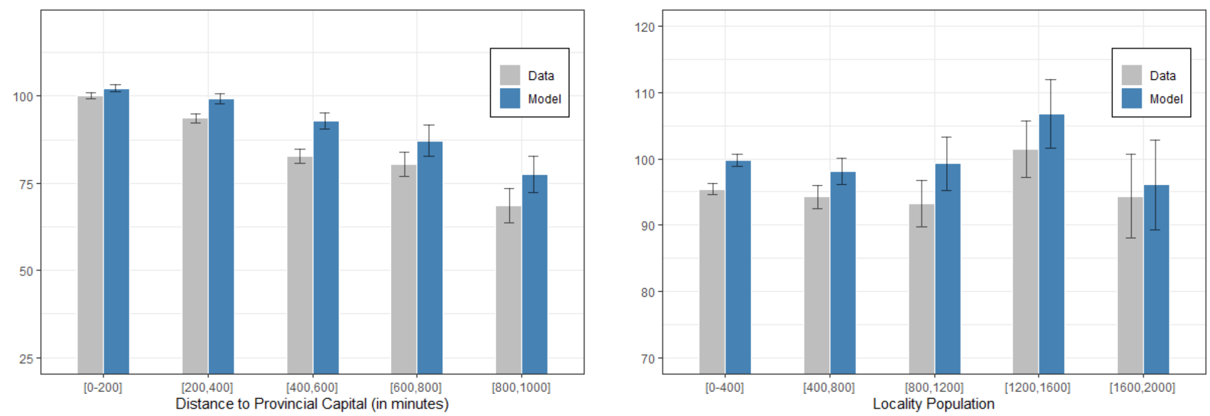
a) CDF of Wage Elasticities



b) Teacher Characteristics

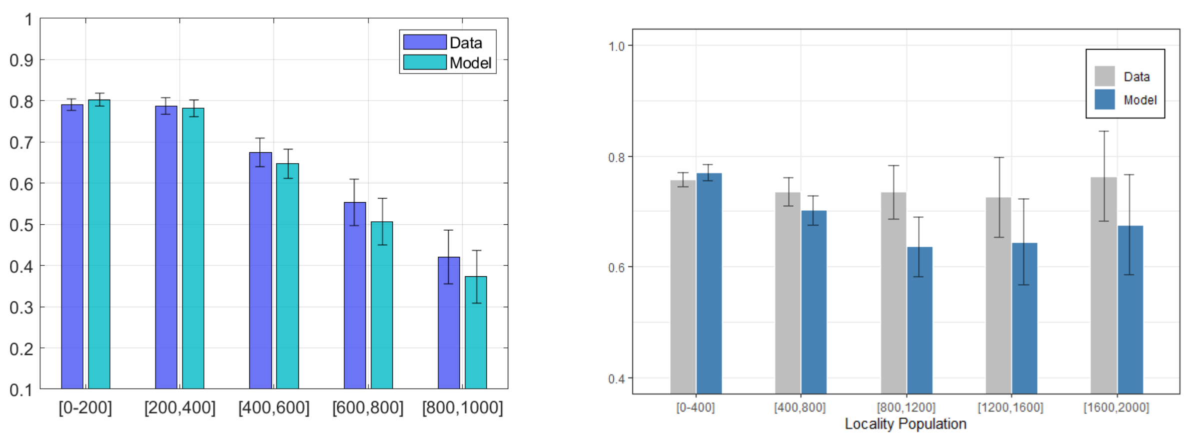
Notes. Panel A of this Figure plots the CDF of the wage elasticity for the assigned teachers in the counterfactual scenario where all wage bonuses would be removed along with the distribution of the wage elasticity of the new teachers that chose to be matched rather than the outside option under the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

Figure C.3: Model Fit: Teacher Score



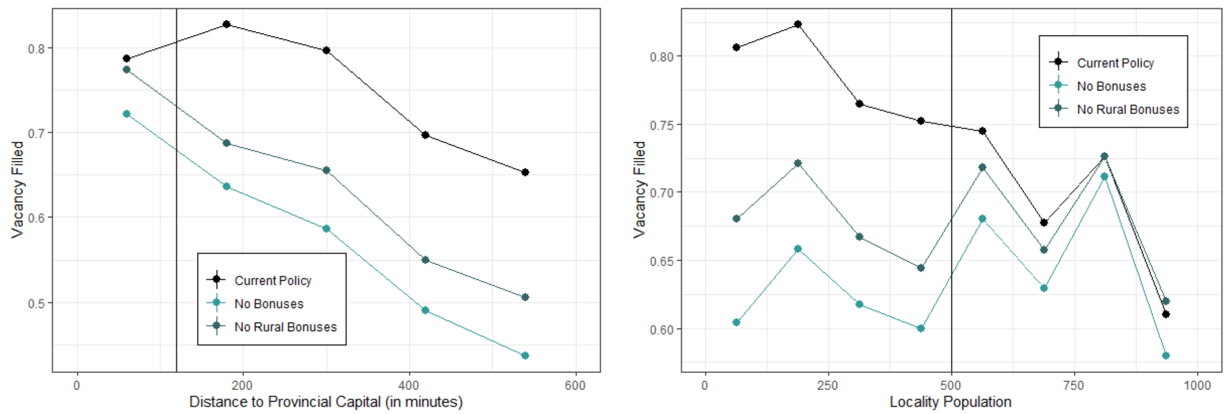
Notes. This figure uses simulated assignment data which is generated by running the serial dictatorship algorithm using predicting utilities computed from the estimates from Table 3 as well as a randomly drawn set of taste shocks ϵ_{ij}. It then compares the average score of teachers assigned to vacancies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

Figure C.4: Model Fit: Vacancy Filled



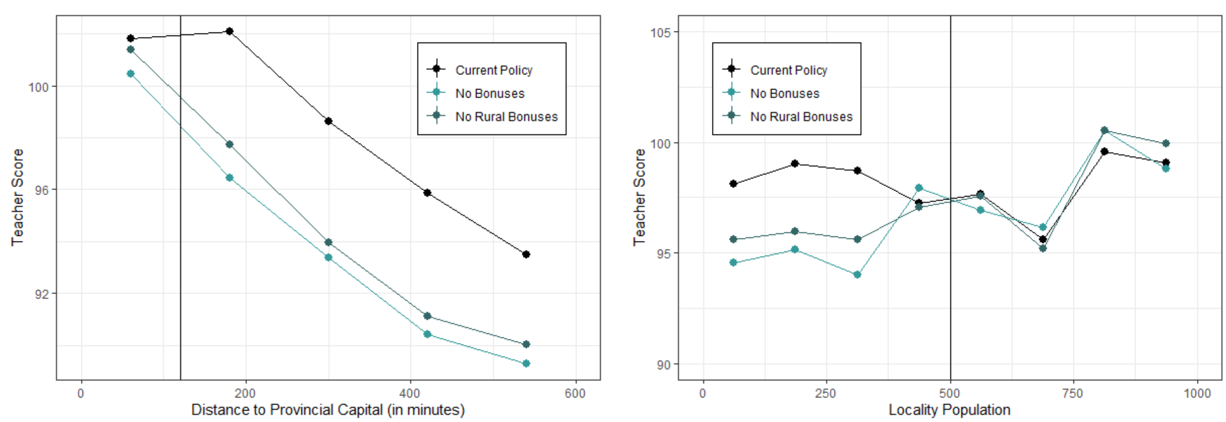
Notes. This figure uses simulated assignment data which is generated by running the serial dictatorship algorithm using predicting utilities computed from the estimates from Table 3 as well as a randomly drawn set of taste shocks ϵ_{ij}. It then compares the share of vacancies filled observed in the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

Figure C.5: Global Policy Evaluation: Vacancy Filled



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

Figure C.6: Global Policy Evaluation: Teacher Score



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

D Matching with contracts: Theory

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

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

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

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

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

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

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

Sketch of Proof:

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

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

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

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

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

score above $\bar{s}$.

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

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

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

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

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

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

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