Geographic Isolation and Learning in Rural Schools

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Geographic Isolation and Learning in Rural Schools[*]

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Abstract

Rural schools are usually behind in terms of learning, and part of this could be related to geographical isolation. We explore this hypothesis, assessing the causal effect of distance between rural schools and local governments on learning in Colombia. We use spatial discontinuous regression models based on detailed administrative records from the education system and granular geographic information. Results indicate that distance to towns and Secretary of Education has significant negative effects on students' standardized test scores. We evaluated alternative mechanisms, finding that the effect of distance is partly explained by differences in critical educational inputs, such as teachers' education attainment and contract stability. Finally, we assess the mediating role of a program providing monetary incentives to teachers and principals in remote areas.

JEL Classification: R12, I21, I24, H75, R10.
Key words: Geographic isolation, education, rural, Colombia.

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Aislamiento Geográfico y Aprendizaje en las Escuelas Rurales*

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Resumen

Las escuelas rurales están generalmente rezagadas en términos de aprendizaje y parte de esto puede estar relacionado con el aislamiento geográfico. Este documento explora esta hipótesis, evaluando el efecto causal de la distancia entre las escuelas rurales y los gobiernos locales en el aprendizaje. Empleamos modelos de regresión discontinua espaciales a partir de registros administrativos detallados e información geográfica granular del sistema educativo. Los resultados indican que tanto la distancia a las cabeceras municipales como aquella a las Secretarías de Educación tiene efectos negativos y significativos sobre los puntajes en las pruebas estandarizadas de los alumnos. Estudiamos diferentes mecanismos, encontrando que el efecto de la distancia se explica en parte por diferencias importantes en insumos educativos, como la formación de los docentes y los nombramientos permanentes. Finalmente, estudiamos en que medida el programa de incentivos monetarios para escuelas en zonas de difícil acceso media estos resultados.

Classificación JEL: R12, I21, I24, H75, R10.
Palabras clave: Aislamiento geográfico, educación, rural, Colombia.

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1. Introduction

Learning gaps between urban and rural schools are common across countries (Young, 1998; Bedi & Marshall, 1999; Blackwell & McLaughlin, 1999; Roscigno & Crowley, 2001; Urquiola y Vegas, 2005; Woßmann, 2010). Colombia is no exception; public school students in urban areas consistently score higher than their rural peers. From third grade, gaps close to 0.04 standard deviations in language arts, and from fifth grade, 0.1 standard deviations in math. The differences tend to increase as one advances through the school cycle.

Multiple factors explain the urban-rural gap in learning. First, there are often differences in families' socioeconomic characteristics. Rural households tend to have less educated parents, which has negative effects on student learning (Hannahway & Talbert, 1993; Young, 1998). Second, rural students also face higher opportunity costs to education, particularly in agricultural and mining activities, which increases absenteeism and dropouts and affect learning (Jensen & Nielsen, 1997; Kim & Zepeda, 2004; Buonomo, 2011; Holgado et al., 2014; Bonilla-Mejía, 2020). Third, students in low-density areas have less options. Schools systems are smaller, less competitive, and have fewer resources, resulting in significant gaps in school inputs, and particularly in teacher's quality (Gibbons & Silva, 2008; Duarte, Bos & Moreno, 2010; Hanushek, 2011, 2014; García et al., 2014; Bonilla et al., 2018).

Literature has also shown that some of the disadvantages of the rural population are related to geographic isolation. Proximity to cities offers productive advantages associated with better access to labor markets, educational institutions, and information sources (Porter, 2000; Sassen, 2001; Shukla, 2010; Krishna & Bajpai, 2011). Some of these benefits are related to better administrative capacity and a higher provision of public goods (Tlebere et al., 2007; Kopczewska, 2013; Michalopoulos & Papaioannou, 2013; Krishna & Schober, 2014). Consistently, numerous studies have found a negative correlation between the distance to the closest city (or the nearest secondary school) and school performance (Cresswell & Underwood, 2004; Bradley, 2007; Mitra, Dangwal & Thadani, 2008; Panizzon, 2015; Odell, 2017).

This document provides causal evidence of the effect of geographical isolation on learning in rural schools in Colombia. Specifically, we use spatial regression discontinuity methods to estimate the effect of distance between schools and local governments on students' standardized test scores. The main idea is to compare schools that are very similar in terms of geographic and socioeconomic characteristics but differ in the distance to local governments. We focus on two administrative levels that, given the country's decentralization scheme, are primarily responsible for the provision of public education: municipal governments and State governments, in charge of the Secretaries of Education (SED) in small, non-certified municipalities. Since most rural schools offer only primary grades, our analysis focuses on this level.

We use rich administrative records from the educational system in Colombia, which includes school coordinates, standardized test scores, and multiple measures of school inputs from the universe of public schools in the country. We also collect high-resolution geographic information on altitude, roughness, soil quality, night light density in the vicinity of each school, and demographic and socioeconomic characteristics of the municipalities. The distance between schools and local governments is computed using the Google Maps API. Given the heterogeneity in topography and road conditions, our main specifications use travel time to measure distance.

Our main results indicate that an increase in the distance between rural schools and local governments significantly decreases primary school learning. An additional traveling hour to towns reduces the average score by approximately 0.34 standard deviations, equivalent to a 51.4% change compared to the control group average. The estimated effects are similar in math and language. The distance to the Secretary of Education has an estimated effect of -0.245 standard deviations, equivalent to a 43.6% reduction. In this case, the estimated effect is considerably larger for language. These results are robust to alternative distance measurements, school samples, model specifications, and treatment assignments. Overall, we find that geographic isolation is partly responsible for the learning gaps in rural areas.

We explore different mechanisms through which geographic isolation can affect learning. First, we rule out significant differences in geographical and socioeconomic characteristics between schools. We then assess the role of school inputs. Results show that schools located closer to local governments have, on average, more teachers with permanent contracts. Distance to SED also affects the share of teachers with college and post-graduate degrees. In contrast, there are no detectable differences in student-teacher ratio and teachers' academic skills. When we include inputs as controls in the main regressions, the estimated effect of distance to towns are smaller in magnitude and significance, which indicates that inputs are mediating the impact on learning. This is not the case for distance to SEDs, where the effects of distance on students' test scores remain similar.

In our last set of results, we explore the mediating role of a government program providing monetary incentives to attract and retain teachers and principals in difficult access areas. Such programs have had positive effects on the recruiting of qualified teachers in remote areas in Gambia (Pugatch & Schroeder, 2014). We include this classification as an explanatory variable, finding similar estimated coefficients, which indicates that this program is not attenuating the effect of isolation. Moreover, our main estimates are mostly driven by schools in difficult access areas. Therefore, distance is only relevant when schools are located in remote areas. This is consistent with previous evidence suggesting that this program has been limited in the Colombian context (Saavedra & Forero, 2018). This may reflect that the monetary incentives are the same for all schools in difficult access areas, independently of the distance to local authorities.

This study contributes to the abundant literature on urban-rural gaps in education (Young, 1998; Bedi & Marshall, 1999; Blackwell & McLaughlin, 1999; Roscigno & Crowley, 2001; Lee y McIntire, 2001; Urquiola y Vegas, 2005; Williams, 2005; Woßmann, 2010; Ramos et al., 2012; Duarte, Bos & Moreno, 2010). Previous studies have shown a negative correlation between distance to cities and educational performance (Cresswell & Underwood, 2004; Bradley, 2007; Mitra, Dangwal & Thadani, 2008; Panizzon, 2015; Odell, 2017). This is, to the best of our knowledge, the first paper to provide causal evidence that geographical isolation affects learning in rural schools. Our findings also indicate educational inputs, such as contract stability and teachers' educational attainment, are mediating these effects. These results are in line with Asher, Nagpal, and Novosad (2018), who find that the distance to administrative centers significantly affects the provision of public goods in rural areas.

Our results also contribute to the literature on decentralization. Administrative and fiscal decentralization schemes, which transfer responsibilities to local governments, aim to bring public administration closer to citizens by improving efficiency in public service delivery and monitoring (Crook & Manor, 1998; Manor, 1999; Blair, 2000; Bardhan and Mookherjee, 2002, 2005, 2006; Faguet & Sánchez, 2008; Freinkman & Plenakanov, 2009; Falch & Fischer, 2012; Campante & Do, 2014; Krishna & Schober, 2014). The success of decentralization depends on local governments' administrative capacity and on monitoring by the central government and citizens. While in some countries decentralization has significantly improved the delivery of public services, in other countries, this has not been the case (Fiske, 1996; King & Ozler, 1998; Faguet & Sánchez, 2008; Bardhan & Mookherjee, 2002; Zhang, 2006; Galiani, Gertler & Schargrodsky, 2008; Gutiérrez, 2010; Garay, 2010; Bonilla & Galvis, 2012; Sánchez & Pachón, 2013; Brutti, 2020). Our results indicate that both the distance to the municipal and the State governments have important effects on education quality. This finding not only highlights the importance of each level of administration in a decentralization scheme, but also provides useful elements for the design of better incentives to attract and retain high-quality teachers and principals in the most remote areas of the country.

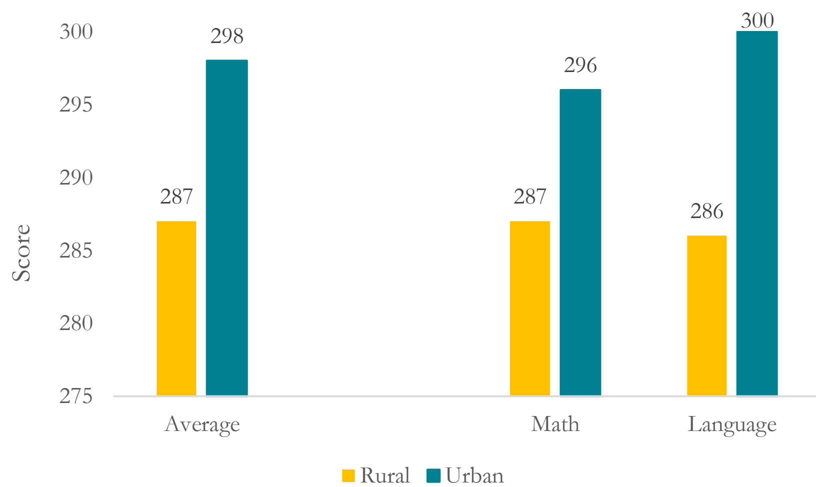
The remaining of the article is organized in five sections. The second section presents a summary of the context of the rural education sector. The third section describes the data used and the variables constructed; the fourth section presents the methodology used and the results associated with the validation of assumptions. The fifth section presents the results, including robustness exercises and mechanisms, and the last section concludes.

2. Rural education in Colombia

While Colombia experienced an accelerated urbanization process over the past few decades, most of its municipalities remain small. According to the 2018 Population Census, of the 1,122 municipalities, only 4 (Bogotá, Medellín, Cali, and Barranquilla) have more than 1 million inhabitants, and 134 have a population of more than 50,000. Of the remaining municipalities, 736 have a population of less than 20,000. Moreover, 22.2% of the country's population still lives in rural areas. Given the geographic isolation, approximately 65% of the country's public schools are located in rural areas. These are relatively small schools, offering mainly primary education.[1]

Gaps between urban and rural schools are particularly evident in Colombia. While individuals over 15 have on average six years of schooling in rural areas, those in urban areas have 9.6 (Bautista & González, 2018). There are also considerable differences in learning. The different Saber tests show that students from public urban schools score consistently higher than their peers in rural schools, both in math and language (Figures 1). These differences between rural and urban schools reflect large gaps in school inputs. In particular, there are significant differences in teacher education. Of the 330,625 teachers and school directors assigned to public schools, 34% work in rural schools. On average, they have lower levels of education and lower Saber 11 test scores than their urban peers. Teachers in rural areas are also considerably less likely to have a permanent contract. Both teachers' quality and the work stability are significantly correlated with student performance (Bonilla et al., 2018).

Figure 1. Urban-rural gap average scores of public schools on Saber 3 and 5 tests (2014-2017)



Source: own calculations based on Icfes Saber 3 and 5 tests.
Note: The average Saber 3 and 5 score is reported on a scale of 100 to 500 points. In order to be able to compare the results over time, the average of the scale for the Saber 3, 5, and 9 tests is defined at 300 points and the standard deviation at 80 points. The differences in deviations between urban and rural areas, from left to right, are: 0.15, 0.11 and 0.18.

[1] Of the 57,190 public schools in the country, 36,922 are rural. Of these, 4,678 offer 11th grade (12.6%); 7,115 9th grade (19.1%); 35,385 5th grade (95.2%) and 35,705 3rd grade (96.1%). While the average rural schools have 63 students, in urban areas, schools have on average 632 students.

To bring the State closer to the most remote areas, the Colombian government has deepened political and administrative decentralization over the last decades, implementing the popular vote election of local authorities and handing over multiple responsibilities to municipal and State governments. In the education sector, decentralization was materialized in the Political Constitution of 1991 and the Law 715 of 2001, which established that the provision of education would be mainly in charge of the Secretaries of Education (SED). SEDs depend on municipal governments when they are over 100,000 inhabitants, and State governments for smaller, non-certified municipalities.[2] There are currently 96 SEDs, of which 32 are run by State governments and 64 by municipal governments. SEDs administer most of the sector's resources, planning and providing the service at the preschool, primary, secondary, and middle school level. This includes managing personnel and resources and designing and implementing quality improvement plans.

The education sector is mostly financed by the National Government through the General Participation System, which transfers resources to SEDs based on the number of students registered each year. The National Government is also responsible for establishing the technical, curricular, and pedagogical standards and conducting the evaluations through the Colombian Institute for Educational Evaluation (Icfes). In small, non-certified municipalities, municipal governments co-administer some of the resources allocated for maintenance and quality improvement and may participate with local taxes to finance these investments. Municipal governments also have discretion over temporary teachers' assignment and collecting information, and monitor spending for the SED and Ministry of Education.

Decentralization in the educational sector has considerably increased school enrollment, with larger effects in municipalities with more fiscal capacity (Faguet & Sánchez, 2008; Cortés, 2010, Sánchez & Pachón, 2013). The impact on learning also varies according to the administrative capacity of the municipalities. While municipal control of education provision improves student test scores in well-managed municipalities, it decreases them in those with insufficient administrative capacity (Brutti, 2020). Resource allocation choices partly explain these differences. In fact, wealthier municipal governments invest more in education, which translates into better school inputs and higher test scores (Bonilla & Galvis, 2012).

In addition to the decentralization process, the national government has different programs to close urban-rural gaps in education. One of them is the Rural Education Project, co-financed by the World Bank, which uses supply-side subsidies to reduce educational inequalities in the rural sector. The program designs and implements flexible educational

[2] Municipalities under 100,000 inhabitants that prove to have the administrative and fiscal capacity may be certified by the Ministry of Education to run the education system. There are currently 5 of them.

models with materials and methodologies more suited to diverse populations or in conditions of vulnerability, replacing traditional models designed for students in urban areas. One of the most common flexible education models in the country is Escuela Nueva (new school), which adapts the curriculum to multi-grade classrooms in remote, rural areas. Evidence indicates that these flexible models have successfully decreased dropout rates and improved learning in rural areas (Rodríguez, Sánchez y Armenta, 2007).

The Ministry of Education also provides a monetary incentive to attract and retain teachers and principals in difficult access areas since 2010. Schools are located in difficult access areas if they meet at least one of the following: i. staff requires the regular use of two or more means of transport to travel to the closest town; ii. no roads allow for motorized traffic for most of the school year; iii. the provision of public transport by land, river, or sea has a single daily frequency. The monetary incentive is equivalent to 15% of the basic salary and currently benefits nearly 60% of the teachers working in rural areas. While similar programs have had positive effects in other countries (Pugatch & Schroeder, 2014), the impact remains limited in Colombia (Saavedra and Forero, 2018).

3. Data and empirical strategy

3.1. Data

We study the relationship between the geographical isolation of rural schools and school performance. To do this, we use three primary sources of information: i. School census (C600) from the National Department of Statistics (DANE), which include school-level information on enrollment and teachers, and the coordinates of approximately 12,000 rural schools; ii) Test scores from the Colombian Institute for the Evaluation of Education (Icfes); iii) Administrative records from the Ministry of Education (Resolution 166), with individual data from teachers allowing us to measure their educational background. Considering that fewer than 20% of rural schools offer secondary and middle school grades, our analysis focuses on primary schools. The steps used to build the estimation datasets are briefly described below.

The first step is to calculate the distance between rural schools and local governments. We retrieve town coordinates, where municipal governments are located, from the official DANE cartography. We then use the Google Maps API to compute the travel time and road distance between each school and the respective municipal and State governments. The travel time measure is particularly relevant in this context, given the mountainous topography and the heterogeneous quality of tertiary roads.[3] We also compute the distance between each school

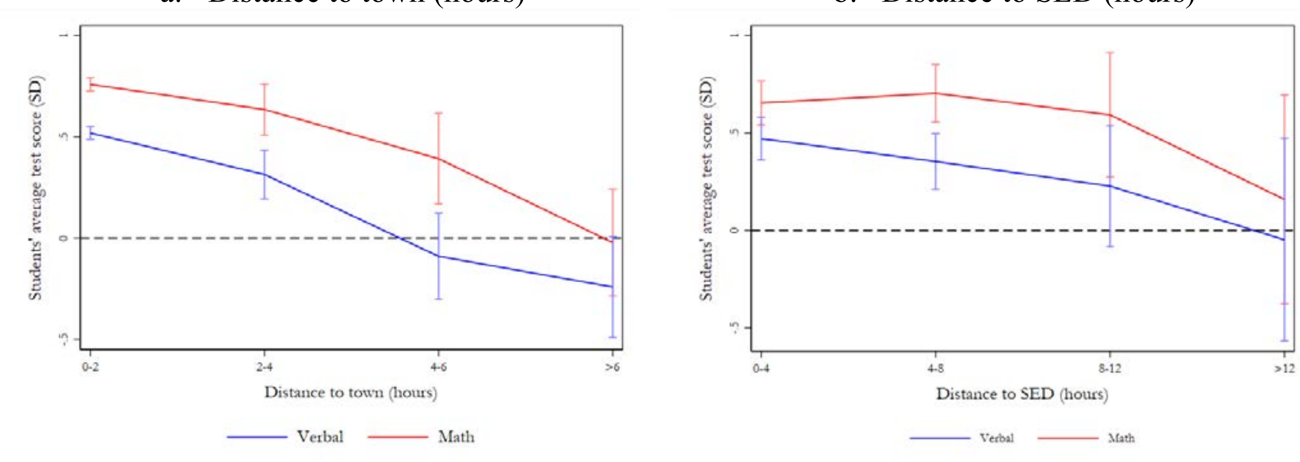
[3] The Google Maps API fails to compute the travel time of road distance for some schools. In these cases, distances are estimated with a linear model that includes the linear distance schools and towns or SEDS, and controls for municipal fixed effects.

and the nearest city over 50,000 inhabitants, which we include as a control variable reflecting the distance to larger cities. In addition to this, we compute the linear (Euclidean) distance between each school and the nearest municipal and State border segment.

We measure learning with the 2017 average mathematics and language score of Saber 3 and 5, administered in third and fifth grade, respectively. Scores are standardized with mean 0 and standard deviation 1. Figure 2 shows that test scores are negatively related to the distance to the respective town and SED. Our estimates will confirm that this is partly explain by geographic isolation.

Figure 2. Distance and school performance in primary school – Saber 3 and 5

a. Distance to town (hours) b. Distance to SED (hours)



Source: own calculations based on Icfes Saber 3 and 5 tests.
Note: 95% confidence intervals. Math and language scores are standardized with mean 0 and a standard deviation 1.

We study the potential mechanisms using detailed information on school inputs, and particularly teachers. We collect data from the Ministry of Education's administrative records to measure the student to teacher ratio of each school, the average educational attainment of teachers, and the share of teachers with a permanent position in each school. Additionally, we measure teachers' academic ability by retrieving the test scores they obtained at the national exit exam (Saber 11).[4] We use the Ministry of Education administrative records to identify schools located in difficult access areas. A school is classified in difficult access area if at least half of the staff benefits from the monetary incentive.

[4] We observe individual exit exam (Saber 11) test scores between 1990 and 2016. We were able to match 47% of the 318,655 teachers in the sample with their test scores.

We further characterize schools with geographical and socioeconomic characteristics. Geography measures include terrain altitude and roughness, calculated with the Digital Elevation Model (Danielson & Gesch, 2011) and soil nutrient availability from the harmonized soil quality mapping from the Food and Agriculture Organization of the United Nations (FAO) (Fischer et al., 2008). We use night lights' intensity as a proxy of local economic development, using information from the National Oceanic and Atmospheric Administration (NOAA). Specifically, we measure the 2013-night lights intensity in the 1 km^2 pixel where each school is located. We also use municipal characteristics provided by DANE and the National Planning Department (DNP as per its Spanish acronym). These include municipal population, the Multidimensional Poverty Index of the rural areas in each municipality, and the municipal investment in education in 2017.[5]

3.2. Empirical strategy

The main challenge in estimating the effect of the distance between schools and local governments is that there are numerous unobservable characteristics of schools and their environment that may be simultaneously related to geographic isolation and learning outcomes. To address this potential source of endogeneity, we estimate spatial regression discontinuity models, in the spirit of Asher, Nagpal, and Novosad (2018), allowing to identify the effect of distance from other potential mechanisms. Specifically, we compare schools from different municipalities that are relatively close to each other, and similar in terms of geographical and socioeconomic characteristics, but differ in the distance to local governments. In our main specification, we focus on rural schools located within 10km of the closest municipal border. We balance the sample by dropping the borders in which more than 90% of the schools are located on one side of it.

Table 1 presents the descriptive statistics for three samples of schools. The first one includes all rural schools within 10 km of the nearest balanced municipal border. The second one excludes cities and certified municipalities, which are in control of the education sector. The third one further restricts the sample to schools located in difficult access areas. As expected, schools in the second and third samples tend to be farther away from local governments and have lower night light intensity and higher poverty rates, reflecting lower population density and less economic activity. Schools in the second and third sample also have fewer students per teacher. However, there are no significant differences in terms of teacher school attainment or academic abilities or students' test scores.

Following Asher, Nagpal, and Novosad (2018), we classify schools as treaded or control based on the average travel time to local governments. Specifically, we compute the average

[5] We use high-resolution imagery from the DMSP-OLS program. This measure has been widely used in literature as an indicator of population density and economic development (Henderson, Storeygard & Weil, 2012; Michalopoulos & Papaioannou, 2013, 2014).

travel distance for all schools within 10km of each side of the border. Schools on the border side with the smallest average distance are classified as treated, and those on the other side are classified as control. Figure 3 illustrates this step with an example, in which we classify schools located near the border between two municipalities, Rioblanco and Chaparral, based on the travel time to towns. Schools within 10km of the border are represented with thick dots, and towns are represented with stars. In this example, rural schools from Rioblanco are on average closer to their town, and therefore we classify them as treated. Schools from Chaparral are classified as control.

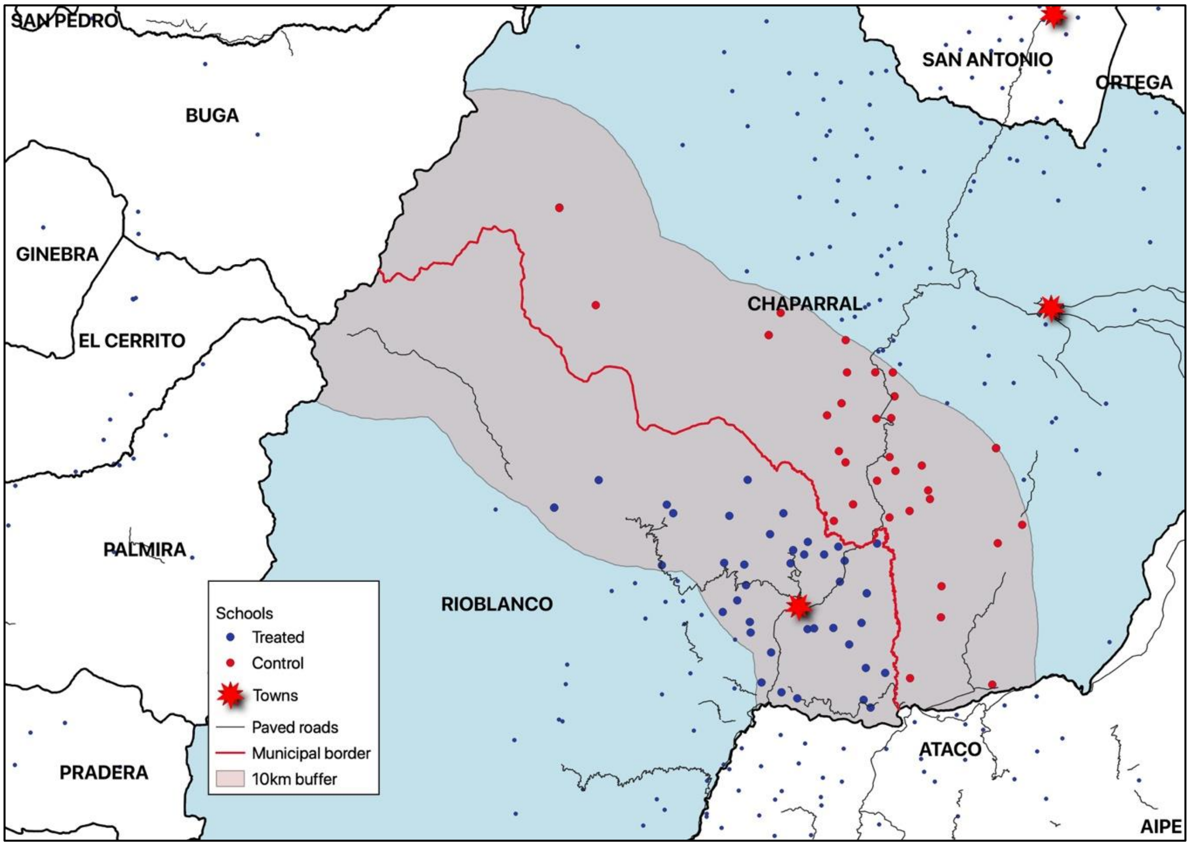
Table 1. Descriptive statistics

	All municipalities			Small (non-certified) municipalities			Small (non-certified) municipalities and difficult access area schools		
	N	mean	sd	N	mean	sd	N	mean	sd
Distance measures									
Distance to Town (Hours)	15,511	0.87	1.35	14,014	0.88	1.41	10,361	0.94	1.41
Distance to SED (Hours)	15,511	3.01	2.24	14,014	3.24	2.23	10,361	3.4	2.26
Distance to closer border	15,511	2.77	2.18	14,014	2.73	2.16	10,361	2.79	2.19
Geographic characteristics									
Altitude	15,459	1,227.44	858.68	13,970	1,251.13	850.72	10,324	1,236.00	862.41
Roughness	15,459	190.53	175.38	13,970	196.6	176.63	10,324	199.21	180.99
Nightlight intensity	15,454	5.32	9.31	13,967	4.25	7.16	10,322	3.18	5.5
Distance to town >50.000	15,511	34.36	23.25	14,014	36.37	23.25	10,361	37.8	23.34
Municipal characteristics									
Population	15,511	53,867	163,206	14,014	24,064	17,296	10,361	23,802	17,387
Rural Poverty	15,509	81.97	11.63	14,012	82.83	10.67	10,360	84.02	9.68
Local Investment in Education	15,511	791,085	3,470,000	14,014	49,293	124,645	10,361	53,874	131,301
School inputs									
Student/teacher ratio	15,056	15.45	11.09	13,623	14.97	10.51	10,150	14.43	10.35
Permanent position	15,511	0.78	0.38	14,014	0.79	0.37	10,361	0.78	0.38
Professional or more	15,511	0.76	0.38	14,014	0.76	0.38	10,361	0.75	0.39
Postgrad degree	15,511	0.31	0.41	14,014	0.31	0.41	10,361	0.29	0.41
Teacher's Language score	10,450	-0.14	0.83	9,321	-0.15	0.83	6,892	-0.17	0.84
Teacher's math score	10,999	-0.23	0.77	9,828	-0.23	0.77	7,283	-0.24	0.79
Student learning									
Average	13,645	0.6	1.63	12,334	0.64	1.65	9,160	0.65	1.68
Language	13,653	0.46	1.62	12,342	0.5	1.64	9,168	0.49	1.67
Math	13,648	0.69	1.71	12,337	0.74	1.73	9,162	0.75	1.76

Source: own calculations.

Note: The distance from rural schools to towns and SEDs is a measured in hours. The linear distance to the nearest border is measures in kilometers. Teachers and students' test scores are standardized, with mean 0 and variance 1.

Figure 3. Example of treatment assignment



Source: own calculations.

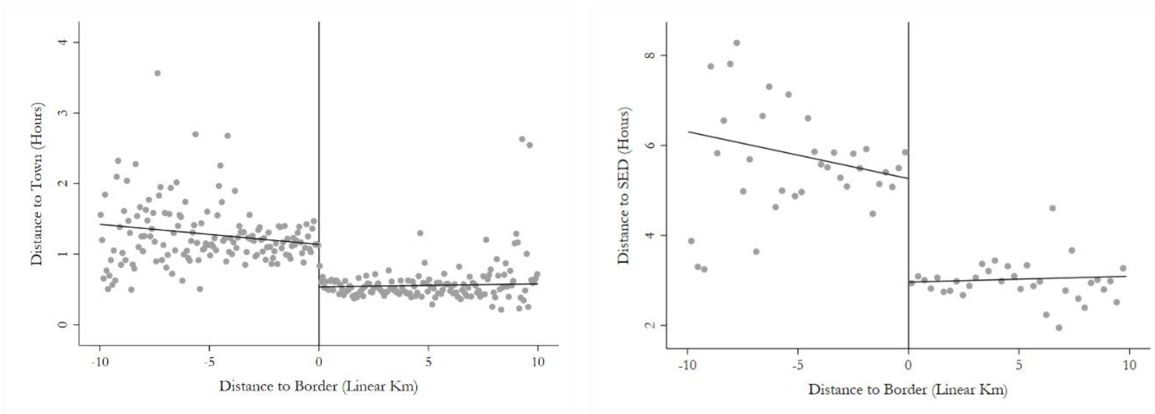
Note: The line and the red area represent the border between two municipalities, Rioblanco and Chaparral, and a 10km strip around this border. Schools within the red area are represented by thick dots, and those outside are represented by smaller dots. Towns, where municipal governments are located, are represented with a star. Given the average distance between schools and towns, schools from Rioblanco are classified as treated (blue), and those from Chaparral as control (red).

We estimate the causal effect of geographical isolation on school performance and other measures of educational quality using the Calonico, Cattaneo, and Titiunik (2014) fuzzy regression discontinuity model, where the running variable is the linear distance between schools and the municipal border, with positive values for treatment schools and negative for control. The instrumented variable is the travel time between schools and the respective towns or SED. The Calonico, Cattaneo, and Titiunik (2014) model selects the optimal bandwidth and estimates the effect using a non-parametric regression with local polynomials and triangular weights. Our main specification excludes large cities and certified municipalities. We account for observable characteristics by controlling for altitude, terrain roughness, soil quality, night-lights intensity, and distance to the nearest municipality of more than 50,000 people. Our main specification also includes border fixed effects, accounting for observable and non-observable characteristics of both the municipalities and the borders. Errors are clustered at the border level.

As expected, treated schools tend to be closer to local governments. Figure 4 presents the discontinuity in the travel time to both town and SED. The X-axis represents the linear distance to the border, with positive values for the treated schools and negative values for the control schools. The Y-axis represents the travel time to local government. As expected, we observe a sharp discontinuity in travel time to local governments around the municipal border. The sharp regression discontinuity estimates of the first stage presented in Table A1. The differences between treated and control schools are negative and significant in all specifications. While the estimated difference in travel time to the municipalities is 0.606 hours, in the case of the SED, it is 2.44 hours. Columns 3 to 6 of Table A1 estimate the first stage using the linear distance and in kilometers of road to the respective town and SED. Results are also negative and statistically significant.

Figure 4. Discontinuity in the distance to town and SED

a. Distance to town b. Distance to SED



Note: Figures are obtained using the *rdplot* command with uniformly generated partitions, with a uniform kernel and a polynomial of order 1.

The model has two main assumptions. The first one is the continuity of the density of the *running* variable around the cut-off point. As shown in Figure A1 of the Appendix, we observe no such discontinuities, and the McCrary (2008) test confirms that there is no evidence of discontinuity in density. The second assumption is the local continuity of baseline covariates, which require no significant differences in the schools' observable characteristics between treated and control groups. We test this assumption using the Canay and Kamat (2018) in Appendix Table A2. For both towns and SEDs, the differences between treated and control schools are small and statistically insignificant for all variables, indicating that the variables are continuous around the cut-off point and that schools are, in general, comparable. The join tests confirm these findings, with p-values of 0.64 for towns and 0.88 for SED. We include municipal control variables in Table A3, finding similar results. While the sample is overall balanced, our main specification includes school-level covariates to account for observable differences and increase the estimates precision.

4. Results

4.1. Main results

Our main results indicate that students from schools located near towns and SEDs tend to learn more. Table 2 presents the estimated effects of distance to local governments on test scores. Estimates are consistently negative and statistically significant in most cases. An additional travel hour to town reduces average and math scores by -0.344 standard deviations. When compared to the control group mean, this is equivalent to a reduction between 45.2% and 51.4%. The coefficient for language tests is similar in magnitude but smaller in significance. In the case of SEDs, the effect of an additional traveling hour is -0.245 on the average score and -0.333 for language. This is equivalent to a change between 43.6% and 81.2%. In this case, the effect on math is considerably smaller in magnitude and significance.

Table 2. Effect of geographical isolation on primary school performance

	Test Scores					
	Town			SED		
	Average	Language	Math	Average	Language	Math
	(1)	(2)	(3)	(4)	(5)	(6)
Distance	-0.344*	-0.331	-0.344*	-0.245**	-0.333***	-0.137
	(0.199)	(0.202)	(0.206)	(0.114)	(0.122)	(0.103)
Optimal Bandwidth (km)	2.006	1.842	2.128	2.841	2.561	3.573
Control group Mean (y)	0.669	0.518	0.76	0.561	0.41	0.698
Eff. Observations	5,326	4,970	5,591	892	840	1,017

Notes: * is significant at 10%, ** at 5% and *** at 1%. Test scores are standardized with mean 0 and standard deviation 1. The distances to the towns and SED are measured in hours, while the distance to the nearest border is measured in km. All regressions control for altitude, terrain roughness, intensity of night light, distance to nearest city with a population of 50,000 or more, and include border fixed effects. Estimates use triangular kernels, polynomials of order 1, optimal bandwidths based on Calonico, Cattaneo, and Titiunik (2014), and robust bias corrected inference.

We estimated the reduced-form model in Appendix Table A4, assessing the directed effect of treatment on test scores. Results are consistent with the fuzzy models, with consistently higher test scores in treated schools. While the effects of distance to town are comparable in magnitude to those of the main specification, their significance levels are slightly smaller (10.3%).

These results are robust to alternative model specifications. In Panels A and B of Appendix Table A5, we measure the distance to local governments in linear and road kilometers. The estimated coefficients are generally similar in magnitude. However, in the case of road kilometers, they are slightly less significant. In Appendix Table A6, we use different sets of control variables and fixed effects. Panel A has no controls or fixed effects. Panel B and C include border and municipality fixed effects, respectively. Panels D to F have no fixed effects, but control for school and municipality characteristics. Overall, results are similar across specifications. In Appendix Table A7, we include rural schools from certified municipalities. While estimates remain overall negative, they are lower in magnitude and significance. This is particularly true for distance to town, where the coefficients are no longer statistically significant. These results may reflect that cities and certified municipalities, with control over the educational sector, have better performing rural schools, even in remote areas, making distance a less relevant factor.

We measured the sensitivity of the results to bandwidth selection, estimating the main specification with fixed bandwidths in Figure A2 of the Appendix. Each point represents an estimated coefficient, with arbitrary bandwidths ranging from 1 to 10km, in 500m increments. As can be seen, the coefficients are relatively stable around the optimal bandwidth. Finally, we test the sensitivity to the sample of schools used to define treated and control groups. Our main specification is based on the average distance of schools located within 10km of the border. In Table A8, we restrict the sample to schools located within 5 and 15km of the border, respectively. Results are overall similar.

4.2. Mechanisms

We explore alternative mechanisms through which the distance between rural schools and local governments can affect learning. The first thing to note is that we found no significant differences in geographical and socioeconomic characteristics between treated and control schools (Appendix Tables A2 and A3). Moreover, the results are generally robust to including different control variables and fixed effects (Table A6). Therefore, while there could be some differences in household characteristics that we are not able to observe, there are reasons to believe that these factors are not the main drivers of our results.

We evaluated the role of school supplies in Table 4, focusing on the teacher characteristics previously identified as good predictors of student performance. These include the students to teacher ratio, the share of teachers with a permanent contract, and the average educational attainment, and their academic abilities, measured with their exit exam (Saber 11) test scores. Results indicate that distance does have a significant impact on some of these inputs. A one-hour increase in travel time to town and SED reduce the share of teachers with a permanent contract by 7.6 pp and 4 pp., respectively. The distance to SED also affects educational attainment, with negative and significant effects on university (4.6 pp.) and post-graduate degrees (4.4 pp.). In contrast, we find no significant differences in students to teacher ratio, which implies that isolation does not affect the capacity of local governments to hire enough teachers. There are also no differences in their exit exam test scores, indicating that there is no greater selection in terms of academic skills.

Table 4. Effect of geographical isolation on educational inputs

	Student-teacher ratio	**Professional or more**	**Postgrad degree**	**Teacher's language score**	**Teacher's math score**	**Permanent position**
	(1)	(2)	(3)	(4)	(5)	(6)
				***A*- Town**		
Distance (hours)	0.582	0.050	0.003	-0.018	0.144	-0.076**
	(1.064)	(0.050)	(0.045)	(0.098)	(0.118)	(0.036)
Optimal Bandwidth (km)	2.188	1.768	2.174	3.068	1.957	3.185
Control group Mean (y)	14.594	0.759	0.308	-0.126	-0.212	0.787
Eff. Observations	6,253	5,384	6,387	5,422	4,059	8,442
				B- SED		
Distance (hours)	-0.107	-0.046**	-0.044*	-0.005	0.073	-0.040*
	(0.696)	(0.021)	(0.024)	(0.068)	(0.065)	(0.023)
Optimal Bandwidth (km)	4.424	3.329	3.402	3.121	2.167	3.825
Control group Mean (y)	15.619	0.704	0.251	-0.145	-0.302	0.741
Eff. Observations	1,287	1,122	1,134	722	595	1,218

Notes: * is significant at 10%, ** at 5% and *** at 1%. Distances to towns (Panel A) and SEDs (Panel B) are measured in hours, while the distance to the nearest border is measured in km. All regressions control for altitude, terrain roughness, intensity of night light, distance to nearest city with a population of 50,000 or more, and include border fixed effects. Estimates use triangular kernels, polynomials of order 1, optimal bandwidths based on Calonico, Cattaneo, and Titiunik (2014), and robust bias corrected inference.

To further assess the role of educational inputs, we estimate the effect of distance on students' test scores, including them as control variables in Table 5. The estimated effect of distance to town is considerably smaller in magnitude and significance than the baseline model. This indicates that school inputs are responsible for at least part of the student learning gap that is attributed to distance. This is not the case for distance to SEDs. Even though there are considerable differences in school inputs, the effects of distance on students' test scores are similar when controlling for inputs. This suggests that there are other factors explaining the effect of distance to SED on learning.

Table 5. Effect of geographical isolation on school performance

(control by educational inputs)

	Standardized Score					
	Town			SED		
	Average	Language	Math	Average	Language	Math
	(1)	(2)	(3)	(4)	(5)	(6)
Distance	-0.208	-0.104	-0.279	-0.259**	-0.340**	-0.126
	(0.214)	(0.230)	(0.212)	(0.128)	(0.139)	(0.122)
Optimal Bandwidth (km)	2.27	2.017	2.511	2.927	2.440	3.698
Control group Mean (y)	0.566	0.428	0.648	0.446	0.307	0.556
Eff. Observations	3,823	3,457	4,140	594	535	686

Notes: * is significant at 10%, ** at 5% and *** at 1%. Test scores are standardized with mean 0 and standard deviation 1. Distances to towns and SEDs are measured in hours, while the distance to the nearest border is measured in km. All regressions control for altitude, terrain roughness, intensity of night light, distance to nearest city with a population of 50,000 or more, and include border fixed effects. Estimates use triangular kernels, polynomials of order 1, optimal bandwidths based on Calonico, Cattaneo, and Titiunik (2014), and robust bias corrected inference.

4.3. Monetary incentives program for difficult access areas

Finally, we assess the role of the monetary incentives program for teachers and principals in difficult access areas. We do not pretend to identify the causal effect of this programs, as in Pugatch & Schroeder (2014). In fact, the eligibility criteria do not allow us to do so; there are no sharp distance cutoffs, and information regarding road availability and means of transportation is insufficient. Instead, we assess whether this program could be mediating the effect of distance presented in the previous sections. We first include a dummy variable that takes value one if schools are classified as difficult access area and zero otherwise. As can be seen in Panel A of Table 6, results are similar in magnitude and significance, suggesting that this program is not attenuating the negative effects of distance on learning. In Panels B and C of Table 6, we restricted the sample to schools classified or not as difficult access areas. The estimated effects are only significant for schools in difficult access areas, which indicates that distance is only relevant for rural schools located in remote areas.

These findings are consistent with previous evidence suggesting that the program has been limited in the Colombian context (Saavedra & Forero, 2018). On one hand, most of the negative effects of distance on learning are driven by schools located in difficult access areas, benefiting from the program. Moreover, the program fails to attenuate the effect of distance on learning outcomes. This may reflect that the monetary incentives are the same for all schools in difficult access areas, independently of the distance to local authorities. The Government could consider providing larger incentives for schools located farther away for local authorities. This may improve the impact of the program and attenuate the negative effects of distance.

Table 6. The mediating role of the difficult access areas program

	Test Scores					
	Town			**SED**		
	Average	Language	Math	Average	Language	Math
	(1)	(2)	(3)	(4)	(5)	(6)
	A- Difficult access area as control					
Distance	-0.340*	-0.33	-0.338	-0.255**	-0.345***	-0.142
	(0.199)	(0.202)	(0.206)	(0.118)	(0.128)	(0.107)
Optimal Bandwidth (km)	2.009	1.841	2.129	2.760	2.425	3.388
Control group Mean (y)	0.669	0.518	0.761	0.563	0.419	0.682
Eff. Observations	5,329	4,969	5,592	873	810	989
	B- Only schools in difficult access area					
Distance	-0.678**	-0.691**	-0.652**	-0.172*	-0.192*	-0.146
	(0.276)	(0.289)	(0.274)	(0.098)	(0.113)	(0.122)
Optimal Bandwidth (km)	2.035	1.892	2.172	4.351	3.571	3.526
Control group Mean (y)	0.722	0.557	0.835	0.721	0.480	0.768
Eff. Observations	3,421	3,235	3,605	679	595	591
	C- Only schools not in difficult access area					
Distance (hours)	0.173	0.215	0.007	-0.255	-0.386	-0.044
	(0.482)	(0.433)	(0.523)	0.331	0.295	0.367
Optimal Bandwidth (km)	2.295	2.662	2.188	2.829	2.985	2.742
Control group Mean (y)	0.75	0.647	0.8	0.835	0.706	0.944
Eff. Observations	1,159	1,285	1,122	192	201	188

Notes: * is significant at 10%, ** at 5% and *** at 1%. Test scores are standardized with mean 0 and standard deviation 1. Distances to towns and SEDs are measured in hours, while the distance to the nearest border is measured in km. All regressions control for altitude, terrain roughness, intensity of night light, distance to nearest city with a population of 50,000 or more, and include border fixed effects. Estimates use triangular kernels, polynomials of order 1, optimal bandwidths based on Calonico, Cattaneo, and Titiunik (2014), and robust bias corrected inference.

5. Conclusions

We study the causal effect of geographical isolation and, more specifically, the distance between rural schools and local governments on learning. We use detailed administrative records and granular geographic information from Colombia. The identification strategy is based on spatial regression discontinuity models allowing to disentangling the effect of geographic isolation from other potential mechanisms. Our main results indicate that both the distance to town and SED have significant negative effects on primary school test scores. An additional travel hour to town reduces the average score by approximately 0.34 standard deviations (51.4%). In the case of SEDs, the estimated effect of an additional hour of travel is -0.245 standard deviations (43.6%). These results highlight the complementary role of the two local government levels that are responsible for the education sector in the country's decentralization scheme.

We study alternative mechanisms through which distance to local governments can affect learning. First, there is no evidence of differences in the school environment's geographic and socioeconomic characteristics, and results are robust to the inclusion of these variables as controls. We study alternative mechanisms through which distance to local governments can affect learning. First, there is no evidence of differences in the school environment's geographic and socioeconomic characteristics, and results are robust to the inclusion of these variables as controls. Second, we evaluate the role of monetary incentives for teachers and principals in difficult access areas. We find similar results when we include this variable as a control, indicating that this policy is no mediating the effect of distance on learning. However, the effects are driven by schools classified as difficult access area, which indicates that distance is only relevant for schools located in remote areas.

Finally, we evaluate the mediating role of a program providing monetary incentives for teachers and principals in difficult access areas. We find similar results when we include this variable as a control, indicating that this policy is not attenuating the effect of distance on learning. However, the effects are driven by schools classified as difficult access area, which indicates that distance is only relevant for schools located in remote areas. This is consistent with previous studies suggesting that the program has been limited in Colombia (Saavedra & Forero, 2018). In light of our results, it is reasonable to believe that providing larger incentives for schools located farther away from local authorities may improve the impact of the program and attenuate the negative effects of distance.

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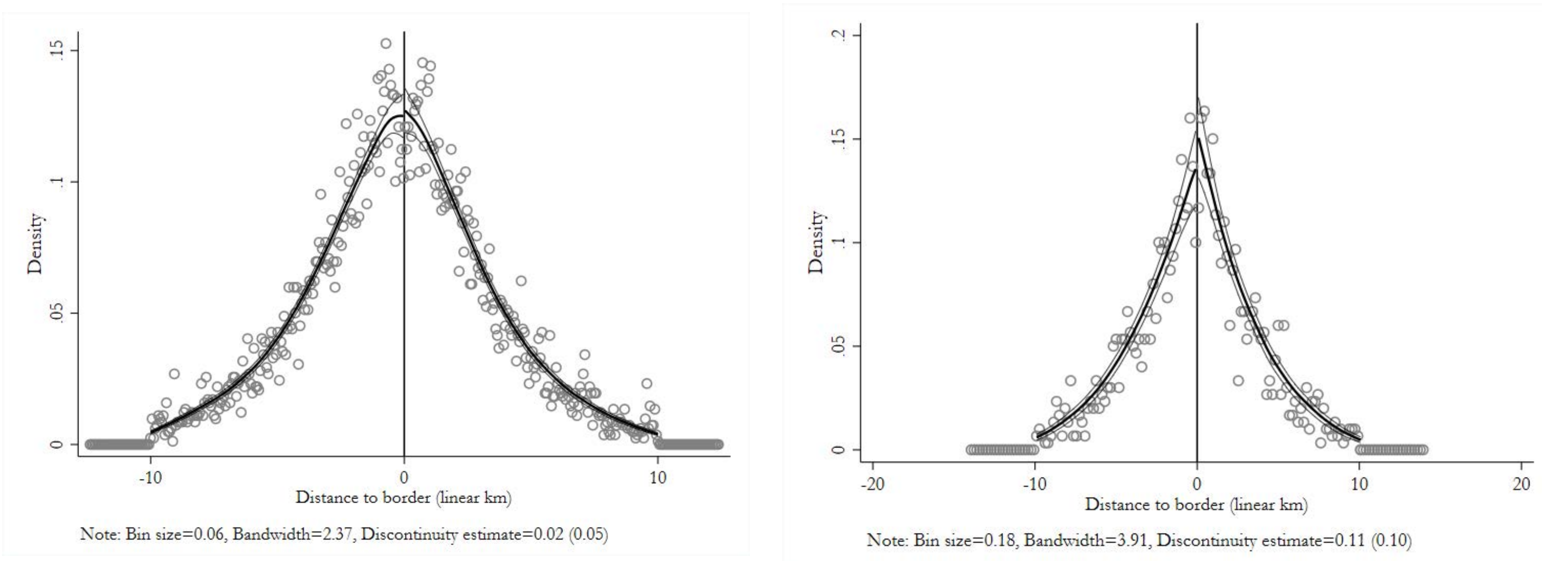
Online Appendix

Figure A1. Treatment manipulation test

a. Distance to town

b. Distance to SED

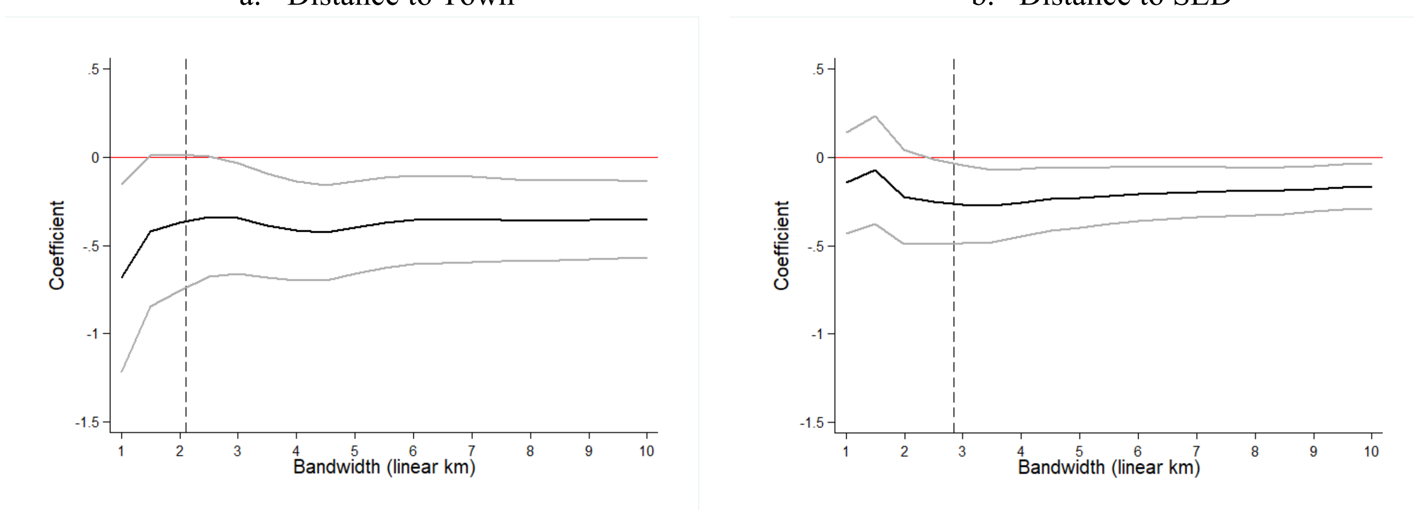


Notes: The bandwidth and the bin size are based on McCrary (2008).

Figure A2. Effect of geographical isolation on average test score: different bandwidths

a. Distance to Town

b. Distance to SED



Notes: 90% confidence intervals. Coefficients are measured in standard deviations. The vertical dotted line is to the optimal bandwidth that minimizes the mean square error for the distance to town as well as the distance to the SED. All regressions control for altitude, terrain roughness, intensity of night light, distance to nearest city with a population of 50,000 or more, and include border fixed effects. Estimates use triangular kernels, polynomials of order 1, and robust bias corrected inference.

Table A1. Discontinuity in the distance to the respective municipal governments and SEDs

	Distance (hours)		Distance (linear)		Distance (km)	
	Town	SED	Town	SED	Town	SED
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.606***	-2.440***	-5.878***	-69.098***	-15.584***	-104.329***
	(0.091)	(0.485)	(1.103)	(11.309)	(2.885)	(22.736)
Optimal Bandwidth (km)	3.303	2.616	1.991	2.321	2.733	2.599
Control group Mean (y)	1.164	5.405	12.581	139.986	32.338	228.830
Eff. Observations	8,643	971	7,946	1,122	7,628	966

Notes: * is significant at 10%, ** at 5% and *** at 1%. Distances to towns and SEDs are measured in hours, linear kilometers, and kilometers of road. All regressions control for altitude, terrain roughness, intensity of night light, distance to nearest city with a population of 50,000 or more, and include border fixed effects. Estimates use triangular kernels, polynomials of order 1, optimal bandwidths based on Calonico, Cattaneo, and Titiunik (2014), and robust bias corrected inference.

Table A2. Test of balance in the characteristics of the schools

	P-value	Number of obs		Eff. Number of obs		Fixed q	Number of perms
		Left	Right	Left	Right		
				A- Distance to Town			
Altitude	0.517	6,772	7,112	327	327	327	999
Roughness	0.275	6,773	7,112	328	328	328	999
Night-lights	0.721	6,773	7,110	330	330	330	999
Distance to city > 50.000	0.552	6,802	7,134	314	314	314	999
Joint test	0.646	6,770	7,110	313	313	313	999
				B- Distance to SED			
Altitude	0.891	855	975	78	78	78	999
Roughness	0.542	855	975	78	78	78	999
Night-lights	0.121	855	974	79	79	79	999
Distance to city > 50.000	0.741	856	982	72	72	72	999
Joint test	0.882	855	974	72	72	72	999

Notes: * is significant at 10%, ** at 5% and *** at 1%.
Note: The distances to towns and SEDs are measured in hours. We report the p-value of the Canay and Kamat (2018) join test.

Table A3. Test of balance in the characteristics of the schools and municipalities

	P-value	Number of obs		Eff. Number of obs		Fixed q	Number of perms
		Left	Right	Left	Right		
				A- Distance to Town			
Altitude	0.517	6,772	7,112	327	327	327	999
Roughness	0.275	6,773	7,112	328	328	328	999
Night-lights	0.721	6,773	7,110	330	330	330	999
Distance to city > 50.000	0.552	6,802	7,134	314	314	314	999
Population	0.611	6,802	7,134	331	331	331	999
Rural poverty	0.445	6,802	7,130	330	330	330	999
Investment in Education	0.601	6,802	7,134	330	330	330	999
Joint test	0.874	6,770	7,106	312	312	312	999
				B- Distance to SED			
Altitude	0.891	855	975	78	78	78	999
Roughness	0.542	855	975	78	78	78	999
Night-lights	0.121	855	974	79	79	79	999
Distance to city > 50.000	0.741	856	982	72	72	72	999
Population	0.291	856	982	79	79	79	999
Rural poverty	0.817	854	980	78	78	78	999
Investment in Education	0.218	856	982	79	79	79	999
Joint test	0.834	853	972	72	72	72	999

Notes: * is significant at 10%, ** at 5% and *** at 1%.
Note: The distances to towns and SEDs are measured in hours. We report the p-value of the Canay and Kamat (2018) join test.

Table A4. Effect of geographical isolation on school performance: reduced form

	Test Scores					
	Town			**SED**		
	Average	Language	Math	Average	Language	Math
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.191	0.188	0.193	0.710***	0.992***	0.372
	(0.117)	(0.117)	(0.121)	(0.275)	(0.294)	(0.263)
Optimal Bandwidth (km)	1.983	1.942	2.08	1.968	1.635	2.871
Control group Mean (y)	0.672	0.526	0.763	0.553	0.387	0.673
Eff. Observations	5,274	5,191	5,484	691	602	903

Notes: * is significant at 10%, ** at 5% and *** at 1%. Test scores are standardized with mean 0 and standard deviation 1. All regressions control for altitude, terrain roughness, intensity of night light, distance to nearest city with a population of 50,000 or more, and include border fixed effects. Estimates use triangular kernels, polynomials of order 1, optimal bandwidths based on Calonico, Cattaneo, and Titiunik (2014), and robust bias corrected inference.

Table A5. Effects of distance on school performance: alternative distance measures

	Test Scores					
	Town			**SED**		
	Average	Language	Math	Average	Language	Math
	(1)	(2)	(3)	(4)	(5)	(6)
	A- Linear distance					
Distance	-0.027	-0.034**	-0.018	-0.006*	-0.009**	-0.003
	(0.017)	(0.017)	(0.017)	(0.003)	(0.004)	(0.003)
Optimal Bandwidth (km)	1.863	1.921	1.911	2.184	2.096	2.706
Control group Mean (y)	0.778	0.617	0.877	0.498	0.307	0.629
Eff. Observations	6,678	6,848	6,810	932	901	1,082
	B- Road distance in km					
Distance	-0.010	-0.012	-0.008	-0.006**	-0.009***	-0.004
	(0.008)	(0.008)	(0.008)	(0.003)	(0.003)	(0.003)
Optimal Bandwidth (km)	2.01	1.81	2.204	2.192	1.957	2.558
Control group Mean (y)	0.698	0.536	0.804	0.559	0.405	0.667
Eff. Observations	5,330	4,896	5,738	750	690	839

Notes: * is significant at 10%, ** at 5% and *** at 1%. Test scores are standardized with mean 0 and standard deviation 1. Distances to town and SEDs are measured in hours, while the distance to the nearest border is measured in km. All regressions control for altitude, terrain roughness, intensity of night light, distance to nearest city with a population of 50,000 or more, and include border fixed effects. Estimates use triangular kernels, polynomials of order 1, optimal bandwidths based on Calonico, Cattaneo, and Titiunik (2014), and robust bias corrected inference.

Table A6. Effects of distance on school performance: different controls and fixed effects (continues)

	Test Scores					
	Town			**SED**		
	Average	Language	Math	Average	Language	Math
	(1)	(2)	(3)	(4)	(5)	(6)
	A- No controls					
Distance	-0.364*	-0.366*	-0.35	-0.264**	-0.345***	-0.167
	(0.207)	(0.209)	(0.215)	(0.114)	(0.118)	(0.116)
Optimal Bandwidth (km)	1.941	1.823	1.998	2.638	2.449	2.798
Control group Mean (y)	0.667	0.514	0.759	0.567	0.431	0.663
Eff. Observations	5,180	4,925	5,307	844	819	883
	B- Only Border fixed effects					
Distance	-0.369*	-0.363*	-0.354*	-0.273**	-0.353***	-0.175
	(0.206)	(0.209)	(0.214)	(0.114)	(0.120)	(0.114)
Optimal Bandwidth (km)	2.013	1.875	2.06	2.664	2.463	2.841
Control group Mean (y)	0.668	0.523	0.758	0.567	0.423	0.662
Eff. Observations	5,339	5,066	5,432	852	824	893
	C- Only Municipality fixed effects					
Distance	-0.335*	-0.328	-0.320	-0.278**	-0.384***	-0.156
	(0.202)	(0.203)	(0.211)	(0.130)	(0.141)	(0.126)
Optimal Bandwidth (km)	2.030	1.901	2.059	2.693	2.467	2.930
Control group Mean (y)	0.667	0.523	0.758	0.570	0.426	0.670
Eff. Observations	5,369	5,110	5,431	857	823	908
	D- No fixed effects, school characteristics controls					
Distance	-0.344*	-0.334*	-0.348*	-0.210**	-0.300***	-0.130
	(0.199)	(0.202)	(0.206)	(0.102)	(0.111)	(0.098)
Optimal Bandwidth (km)	1.966	1.79	2.119	3.234	2.831	3.671
Control group Mean (y)	0.67	0.514	0.762	0.561	0.409	0.701
Eff. Observations	5,240	4,854	5,562	960	890	1,037

Table A6. Effects of distance on school performance: different controls and fixed effects

	Test Scores					
	Town			**SED**		
	Average	Language	Math	Average	Language	Math
	(1)	(2)	(3)	(4)	(5)	(6)
	E- No fixed effects, municipal characteristics controls					
Distance	-0.349*	-0.328	-0.348*	-0.249**	-0.348***	-0.145
	(0.200)	(0.204)	(0.207)	(0.120)	(0.127)	(0.122)
Optimal Bandwidth (km)	2.186	2.063	2.247	2.933	2.719	3.058
Control group Mean (y)	0.679	0.526	0.771	0.572	0.419	0.643
Eff. Observations	5,697	5,441	5,827	907	865	935
	F- No fixed effects, school and municipal characteristics controls					
Distance	-0.342*	-0.322	-0.342*	-0.218**	-0.325***	-0.135
	(0.196)	(0.197)	(0.204)	(0.109)	(0.122)	(0.107)
Optimal Bandwidth (km)	2.111	2.014	2.157	3.176	2.734	3.382
Control group Mean (y)	0.674	0.527	0.763	0.554	0.411	0.685
Eff. Observations	5,541	5,344	5,647	952	871	988

Notes: * is significant at 10%, ** at 5% and *** at 1%. Test scores are standardized with mean 0 and standard deviation 1. Estimates use triangular kernels, polynomials of order 1, optimal bandwidths based on Calonico, Cattaneo, and Titiunik (2014), and robust bias corrected inference.

Table A7. Effect of geographic isolation on school performance: including certified municipalities

	Test Scores					
	Town			**SED**		
	Average	Language	Math	Average	Language	Math
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.131	-0.121	-0.161	-0.183*	-0.272**	-0.083
	(0.190)	(0.190)	(0.197)	(0.106)	(0.110)	(0.105)
Optimal Bandwidth (km)	1.830	1.779	1.950	2.127	2.091	2.324
Control group Mean (y)	0.584	0.453	0.688	0.434	0.306	0.554
Eff. Observations	5,853	5,727	6,171	1,751	1,730	1,866

Notes: * is significant at 10%, ** at 5% and *** at 1%. Test scores are standardized with mean 0 and standard deviation 1. Distances to towns and SEDs are measured in hours, while the distance to the nearest border is measured in km. All regressions control for altitude, terrain roughness, intensity of night light, distance to nearest city with a population of 50,000 or more, and include border fixed effects. Estimates use triangular kernels, polynomials of order 1, optimal bandwidths based on Calonico, Cattaneo, and Titiunik (2014), and robust bias corrected inference.

Table A8. Effects of distance on school performance: different treatment definitions

	Test Scores					
	Town			**SED**		
	Average	Language	Math	Average	Language	Math
	(1)	(2)	(3)	(4)	(5)	(6)
	A- Treatment with schools 5km or less from the border					
Distance	-0.355*	-0.372*	-0.328	-0.283*	-0.400**	-0.122
	(0.203)	(0.198)	(0.213)	(0.171)	(0.180)	(0.172)
Optimal Bandwidth (km)	1.71	1.825	1.692	1.468	1.506	1.326
Control group Mean (y)	0.629	0.5	0.717	0.515	0.397	0.541
Eff. Observations	4,636	4,899	4,585	554	569	507
	B- Treatment with schools 15 km or less from the border					
Distance	-0.427**	-0.412**	-0.420**	-0.216**	-0.308***	-0.127
	(0.185)	(0.186)	(0.190)	(0.106)	(0.116)	(0.101)
Optimal Bandwidth (km)	2.421	2.323	2.529	3.231	2.867	3.702
Control group Mean (y)	0.673	0.524	0.759	0.554	0.423	0.685
Eff. Observations	6,191	6,012	6,414	961	903	1,044

Notes: * is significant at 10%, ** at 5% and *** at 1%. Test scores are standardized with mean 0 and standard deviation 1. Panel A classifies treatment and control based on schools within 5km of the border, while Panel B classifies them with those within 15km. Distances to towns and SEDs are measured in hours, while the distance to the nearest border is measured in km. All regressions control for altitude, terrain roughness, intensity of night light, distance to nearest city with a population of 50,000 or more, and include border fixed effects. Estimates use triangular kernels, polynomials of order 1, optimal bandwidths based on Calonico, Cattaneo, and Titiunik (2014), and robust bias corrected inference.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