Natural Disasters and the Urban-Rural Gap in Human Capital: Evidence from an Unusual Rainfall Shock

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Abstract

Significant disparities in the accumulation of human capital exist between urban and rural areas in developing countries. Selective migration seems to explain part of this gap, but it is not its only determinant. In this paper, I provide evidence that natural disasters also explain why students in rural areas obtain lower academic achievement compared to those in urban areas. I use data on the census of Colombian schools, and employ a difference-in-differences strategy that leverages variation from an unusual rainfall shock that affected more than two million people in urban and rural Colombia. The results suggest that unusual rainfall disruptions increase school dropout and failure rates, and decrease learning of remaining students at least during a decade. The effects are focused on students enrolled in rural schools, leaving those in urban schools mostly unaffected. I explore several mechanisms and rule out that the effects are driven by selective migration or a loss on educational resources. I find evidence that the rainfall shock increased poverty and production, suggesting that rural students are more likely to drop out due to smaller returns to education on the agricultural sector.

Keywords: Natural disasters, human capital, education, urban-rural gap, Colombia.

JEL classifications: I24, I25, R11.

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1 Introduction

Significant disparities in the accumulation of human capital exist between urban and rural areas in developing countries. Students in rural areas of Latin America, for instance, are 25 percent less likely to successfully graduate from secondary education, and their test scores indicate a deficit of more than a full year of schooling by the age of 15 (Bassi et al., 2015). These substantial discrepancies can be partially attributed to the migration of individuals with higher skill levels to urban centers. However, if this selective migration was the only determinant of the urban-rural gap, then we will expect that rural-to-urban migrants do not experience any wages gains. This seems to not be the case as individuals who migrate from rural to urban areas typically obtain income gains, suggesting that the mere process of efficient sorting cannot exclusively account for the persistence of the urban-rural gap (Lagakos, 2020). Therefore, it is yet not fully clear why the urban-rural gap in human capital exists and persists among almost every developing economy.

In this paper, I suggest a complementary hypothesis by analysing if natural disasters explain the existence of the urban-rural gap in human capital. I exploit exogenous variation on exposition to an unusual heavy rainfall disruption in Colombia to estimate the differential effects of natural disasters on educational outcomes between urban and rural areas. Colombia is a tropical country ranked as one of the rainiest countries in the world. In 2010, drastic variations in the sea temperature created a strong and unpredictable transition between the tropical cycles of *El Niño* and *La Niña*. This transition originated an unusual episode of heavy rains that flooded 47 percent of the Colombian territory, both in rural and urban areas. Due to the severity of the rains, the president at the time declared the situation as a national emergency in order to provide assistance to the more than two million people affected by the rains.

I employ detailed data on the census of all Colombian schools to compute dropout, failure, and approval rates at the school level. I combine these data with administrative test score measures from the Colombian high school exit exams. To compute the effect of the shock, I construct exposure measures by combining information on the location of the victims with information on the area per municipality that is declared as in potential risk of flooding. The combination of these two measures captures the potential severity of the rain disruption at the municipality level.

The results suggest that heavy rain disruptions negatively affect educational outcomes, and the detrimental effects are systematically focused on students enrolled in rural schools. Rain disruptions *increased* school dropout rates in rural schools in 20 percent and failure rates in 29 percent. Obviously, this implied that approval rates decreased because the share of students who approve a grade depends on the share of those who fail or drop out. Learning among the remaining rural students also decreased in around 0.04 standard deviations.

The situation among urban schools was the opposite. School dropout and failure rates among them *decreased* in 14 and 26 percent, respectively, translating into a 4 percent increase on approval rates. In addition, test score measures of the remaining students decreased in around 0.1 standard deviations, although this effect is not statistically different from zero. In general, these results imply that heavy rain disruptions decrease educational outcomes, but the effect is mainly driven by rural students leaving urban relatively unaffected.

Multiple potential mechanisms could explain why natural disasters affect disproportionately students in rural areas. I explore if selective sorting, a loss in educational resources, or an increase in poverty can explain the differential effects between urban and rural areas. I do not find evidence that the heavy rains induced migration nor decreased educational resources.

I do find suggestive evidence that the rains increased, jointly, poverty and economic activity. I estimate the effects of the rain disruption on an index of multidimensional poverty and on two measures of economic activity: night-time luminosity; and agricultural production. The results indicate that both poverty and economic activity increased after the rains, but poverty increased marginally more in urban areas and production increased marginally more in rural ones. These two effects are consistent with evidence suggesting that the returns to education are lower in agricultural sectors (Herrendorf and Schoellman, 2018), and imply that the rainfall shock could have increased labor supply in rural areas, and thereby increase agricultural production and school dropout. The situation is different for students in urban schools where the returns to schooling are higher among non-agriculture sectors, so the rainfall shock should not drive them out of school.

This paper contributes to three different strands of literature. First, it contributes to the literature addressing the existence of the urban-rural gap. Economic development has been traditionally linked with the sorting process of individuals from rural to urban centers. Strong evidence suggests that more educated individuals locate in urban centers and less educated ones in rural areas (Gollin et al., 2014; Young, 2013; Herrendorf and Schoellman, 2018). This sorting explains why the rural-urban gap exists, but there is mixed evidence about how much it is able to explain.

On the one side, some studies suggest that including individual fixed effects drives the urban-rural gap to zero, implying that sorting fully explains the gap because the returns to migration are nearly zero (Hamory et al., 2020; Alvarez, 2020). On the other side, some other studies suggest that individual sorting only accounts for a small part of the urban-rural gap. Lagakos et al. (2020), for instance, show that including individual fixed effects decreases the gap substantially but not entirely. The authors rationalize this claim by suggesting that observational studies with non-experimental data confound the urban premium and the individual benefits of migrants.

Experimental and quasi-experimental evidence seem to be in line with the claim that selective migration does not completely explain the urban-rural gap. For instance, Bryan et al. (2014) and Akram et al. (2017) gave random incentives to temporary migrants in Bangladesh and found consistent increases in consumption and earnings. Moreover, Sarvimäki et al. (2022) study the exogenous forced migration of Finish after the second world war, and find consistent income increases among rural migrants. This evidence is in line with the findings of Gollin et al. (2014) who show that the urban-rural gap remains when accounting for hours worked and human capital, and with Imbert and Papp (2020) who find that Indian migrants decide to earn 35 percent less rather than migrating because of the non-monetary cost of migration.[1]

The results in this paper contribute to this debate by showing that the urban-rural gap can be partially explained by the differential effects of natural disasters. These natural phenomena are increasingly more common, raising concerns about their effects on inequality between rural and urban populations.

Second, this paper contributes to the literature on the effects of natural disasters. This broad literature provides causal estimates of the effects of natural disasters on migration, economic growth, and labor markets, among others.[2] Earlier work has also related natural disasters to the accumulation of human capital. For instance, Sacerdote (2012) shows how hurricanes negatively affect students' academic performance, and Opper et al. (2023) provide evidence on how natural disasters decrease learning using the universe of Presidential Disaster Declarations in the United States. In a related paper, Özek (2023) estimates the indirect effects of natural disasters on educational outcomes by analysing the spillover effects of migrants induced by hurricane Maria on educational outcomes of natives. I contribute to this literature by showing how natural disasters not only decrease academic outcomes of students, but how these negative effects translate into inequality across urban and rural students.

Third, this paper contributes to the literature on equality of opportunity. A growing literature on the topic has highlighted how place of birth determines lifetime trajectories (Alesina et al., 2021; Chetty et al., 2014, 2016; Chetty and Hendren, 2018; Deutscher, 2020). In a paper close to this, van Maarseveen (2020) shows how individuals born in cities have a comparative advantage in human capital production compared to those born in rural areas, thereby explaining the differential learning trajectories between students in urban and rural areas. This paper contributes to this literature by posing evidence on how the place of residence determines the magnitude of the effects of natural disasters, potentially affecting lifetime future trajectories differently between students in urban and rural schools.

The rest of the paper is organized as follows. Section 2 describes the Colombian setting and provides details about the heavy rain crisis faced during 2010 and 2011. Section 3 describes the data used. Section 4 details the empirical strategy of the paper. Section 5 provides the main results of the effects of heavy rain disruptions on student outcomes. Section 6 provides some suggestive evidence about potential mechanisms and on how low returns to education in the agricultural sector can explain the results. Finally, Section 7 concludes.

[1] A very complete description of this debate can be found in Lagakos (2020).

[2] For effects on migration see, for instance: Deryugina et al. (2018); Boustan et al. (2012); Baez et al. (2017); and Boustan et al. (2020). For the effects on economic growth see, for instance: Strobl (2011). For the effects on labor markets see, for instance: McIntosh (2008); Belasen and Polachek (2008); and Groen et al. (2020). A big bulk of papers in this literature also focuses on the inter-generational effects of in-utero exposure to natural disasters. For this see, for instance: Maccini and Yang (2009); Fuller (2014); Caruso and Miller (2015) ; and Caruso (2017). Dell et al. (2014) provide a detailed review of the relationship between weather and multiple several outcomes including aggregate output, agriculture, labor productivity, health, energy, political stability, and conflict.

2 Background

2.1 Education System in Colombia

The Colombian education system is divided into preschool, five years of primary, four of lower secondary, and two of upper secondary school education. Around 80 percent of schools are public and 70 percent are located in rural areas.[3] Secondary school graduation rates have remarkably increased in the last decades, reaching around 60 percent by 2010 (Bassi et al., 2015). Quality of education is low and the country constantly ranks among the last positions in the different editions of the PISA exams.

Students who wish to graduate from secondary school education take a standardized exam that evaluates their knowledge in different subjects. The exam is known as *Saber 11* (formerly, ICFES exam). During our period of study, students were consistently evaluated in reading, mathematics, natural sciences (i.e., physics, chemistry, and biology), social sciences, and English proficiency. The exam is mandatory for graduation and results are used for admission into tertiary education.

2.2 The Human Capital Urban-Rural Gap in Colombia

Education in Colombia is very unequal between rural and urban areas. During the last decades, secondary school graduation rates in Colombia grew considerably, but the gap between urban and rural areas remained constant in remarkably high levels. In fact, Colombia is one of the countries in Latin America with the largest urban-rural gap in secondary school graduation (Bassi et al., 2015).

Using Colombian household survey data, I document the evolution of secondary school graduation rates in urban and rural areas between 2008 and 2018 in Figure 1a. Graduation rates increased from 20 to 30 percent in rural areas and from 60 to 70 percent in urban ones. Students in rural areas are three times less likely to graduate from secondary education. A steady 40 percent gap has constantly existed during the last decade, and it does not show any sign of closing, despite the generalized progress.

Student learning is also disproportionately different between urban and rural areas. Figure 1b, uses the secondary school exit exam to plot the evolution of standardized test scores among students in urban and rural schools. The difference in learning between urban and rural areas has been constantly increasing during the last two decades. On average, students in urban schools score 0.4 standard deviations above students in rural schools, and this gap increased from 0.3 in the year 2000 to 0.5 standard deviations between in 2020.

2.3 The 2010-2011 Unusual Rainfall Disruption

Colombia is a tropical country located on the equator with coastal access to the Atlantic and the Pacific oceans. Its geography and location induces constant rains in some areas of the country, ranking Colombia as one of the rainiest countries on earth. In 2020, the average volume of precipitation in Colombia was of 3,240 mm, implying

[3]There are around 53,000 schools in the country.

that Colombia was the rainiest country on earth for that specific year.[4]

The Colombian western access to the Pacific ocean makes the country vulnerable to climate variation in the tropical Pacific. The interaction between unexpected temperature oscillations of the tropical Pacific ocean and the atmosphere creates what is often referred to as *El Niño Southern Oscillation* cycle. Temperature variation in the high sea surface induces drastic climate changes that gives birth to *El Niño* (dry season) and *La Niña* (rainy season); two opposing phenomena that can unexpectedly affect the severity of tropical weather in countries like Colombia (Philander, 1989, 1985). The duration and intensity of each cycle (i.e., *El Niño* or *La Niña*) exhibit significant differences and are unpredictable as they are induced by anomalies in the sea temperature. *El Niño* tends to have a shorter duration, whereas *La Niña* can be more persistent and last through around a year (Okumura and Deser, 2010). Each *La Niña* event is different and its impact depends on its intensity and the interaction it might have with other phenomena (CEPAL, 2012). These events occur relatively randomly and do not take place every year.

During the second half of 2010 and the first of 2011, an unusual *La Niña* cycle induced an unexpected rainy season that disrupted several areas of the country by flooding around 47 percent of the territory.[5] During 2010, there was a drastic transition between *El Niño* and *La Niña* causing heavy climate oscillations that resulted in atypical rainfall in some areas of the country. It was considered as the strongest *La Niña* event since 1949. *La Niña* –jointly with deforestation and construction of villages in potentially risky areas– dramatically increased the flood risk by rising the volume of rivers and water bodies. By May 2011, 2,219 emergencies where reported: 57 percent for floods; 35.1 percent for landslides; and the rest for avalanches and windstorms (CEPAL, 2012).

Figure 2 presents the average precipitation per month from 1994 to 2016, for cycles from June to May. Panel 2a presents monthly averages before 2010 and Panel 2b after 2011. The period from June 2010 to May 2011 was the heaviest rainy season in the two analysed decades. On average, monthly rainfall increased 34 percent compared to previous years. This increase varied from a five percent increase in January 2011 to a 69 percent increase in December 2010.

The unusual heavy rainfall strongly affected different areas of the country by flooding territories and creating landslides. The president at the time declared the situation as a national disaster, and stipulated an economic and ecological emergency under the Decree 4579 of 2010. The law implemented a strategic plan to deal with the emergency. As part of the plan, it was necessary to identify the people who had been affected. Therefore, a census of victims was implemented in all the national territory, revealing that more than two million people (of around 560,000 households) were affected by the rains.

[4]Data is publicly available by the world bank at: https://data.worldbank.org/indicator/AG.LND.PRCP.MM.

[5]This estimate was computed by the DANE. The analysis is available at https://www.dane.gov.co/files/noticias/Reunidos_presentacion_final_areas.pdf.

3 Data

I combine data from three different sources to estimate the effect of natural disasters on educational outcomes. First, I employ the nationwide census of schools in Colombia from 2005 to 2019 (officially named the C-600 form). These data are gathered by the Colombian statistical institution (DANE, in Spanish) and collects information about all the schools in the country. Every year, school directors fill up a form that collects information about students, teachers, staff, and school facilities. The information is gathered at the school level and includes details about the school location, including the municipality, if the school is public or private, and if it is located in an urban or rural area. Importantly, the data include the number of students who approved, failed, dropped-out or transferred in a given academic year. With these measures is possible to construct school-level rates of dropout, approval, failure, and transfer by computing the ratio of students who dropped out, approved, failed, or transferred with respect to the total number who were enrolled at the beginning of the academic year.

Second, I employ test score data from the high school exit exam (officially named *Saber 11*) from 2000 to 2018. These data include test score measures of all the students who were about to graduate upper secondary school. The exam is taken twice per year, and is a requisite for graduation. Students are tested in multiple areas including reading, math, social sciences, natural sciences, and a foreign language. I compute the average of these to have an aggregated test score measure, and build school level measures by averaging the test scores standardized with respect to the test edition's mean and standard deviation.

Finally, I gather information about municipalities affected by the heavy rain emergency from the Colombian statistical institution.[6] I identify affected municipalities by using information gathered from the census of victims that is published online. The information identifies the municipalities that were affected, but there is no measure of the severity of the shock.

Therefore, I combine this information with data on the potential severity of the emergency per municipality. To face the crisis, public officials analysed satellite images of the Colombian territory and identified areas that could be subject to unusual floods during the *La Niña* disruption.[7] These measures computed the area per municipality that was in risk of flooding, in addition to the areas that are usually flooded during any given year. Thus, the computed measures capture the additional severity of the current crisis, recording valuable information on the potential severity of the disruption at the municipality level given certain pre-established geographic conditions.

A total of 755 municipalities (68 percent, out of 1,122) were identified as affected by the rain disruptions during 2010 and 2011, and the average municipality had around

[6] The data is public and can be accessed in: https://www.dane.gov.co/index.php/estadisticas-por-tema/ambientales/reunidos.

[7] The areas were identified using the morphological systems of the Colombian territory gathered in 2010 (IDEAM, 2010) by identifying the areas that receive sediments enough to constitute a risk for a given population or the use of the territory.

18 thousand hectares of potentially affected area. This implies that around 11 percent of the average municipality's area was under risk of flooding. Some municipalities, however, had no areas under risk of flooding whereas others had up to 100 percent.[8] I describe the percentage area under risk of flooding in Figure 3a and depict the affected municipalities in Figure 3b. We observe large heterogeneity across municipalities, which constitutes the identifying variation of the empirical strategy detailed in Section 4.

4 Empirical Strategy

I leverage the variation induced by the unusual heavy rain episode to estimate the effect of natural disasters on educational outcomes. Formally, I estimate a dynamic event study specification as follows:

$$y_{smt} = \sum_{t \neq 2009} \alpha_t \left(D_m \mu_t \right) + \delta X_{st} + \mu_m + \mu_t + \varepsilon_{smt}, \tag{1}$$

where y_{smt} corresponds to a given outcome for school s, in municipality m, and in year t.[9] The variable D_m is the product of two variables:

$$D_m = A_m \times T_m,$$

where A_m corresponds to the percentage of the municipality's area that is considered under threat of unusual flooding and T_m is binary and takes the value of one if there was at least one victim reported in the municipality and zero otherwise. I interact D_m with year dummies, μ_t, to estimate the dynamic effects, and use 2009 as the baseline year. Combining these measures quantifies the level of affection per municipality that was caused by the heavy rain disruption.

The vector X_{st} includes school-level characteristics such as a binary variable for whether the school is public, a dummy for whether the school is in a rural area (this variable is dropped in the cases where the estimations are performed separately for urban or rural schools), and a set of dummy variables that capture whether the school offers pre-school, primary, lower-secondary, or upper-secondary level education. The baseline specification includes municipality and year fixed effects to control for unobserved characteristics at the municipality level. A second, more saturated specification includes school level fixed effects that control for time-unvarying school characteristics. Standard errors are conservative and clustered always at the municipality level.

The parameters of interest are the α_ts that capture the dynamic effects of the heavy rain disruption in a given year t. This event study specification allows me to test for the nonexistence of pre-trends on the treatment assignment under the null hypothesis that the α_t parameters are equal to zero before 2009. Furthermore, the roll-out of the treatment was not staggered so the specification is free of any confounding issues regarding negative weights.

[8] Appendix Table 1 provides descriptive statistics of the analysed data.

[9] Some of the estimations in the paper are done at the municipality level, in which case the subscript s can be dropped.

Specification (1) does not allow me to formally test if the effect of heavy rain disruption differs between rural and urban schools. I formally test the null hypothesis of equality of effects by estimating the following equation:

$$y_{smt} = \beta\left(D_m \times Post_t\right) + \gamma\left(D_m \times Post_t \times R_s\right) + \delta X_{st} + \mu_{ms} + \mu_{ts} + \varepsilon_{smt}. \quad (2)$$

As opposed to specification (1), the specification in (2) includes the triple interaction between treatment intensity, D_m, with $Post_t$, a dummy that takes the value of one if the observations is after 2009, and R_s, a dummy variable for whether or not the school is in a rural area. I include municipality (μ_{ms}) and year (μ_{ts}) fixed effects interacted with the dummy for whether the school is in a rural area in order to capture the differential effect between urban and rural schools. The parameter β captures the effect of unusual heavy rain disruption on urban schools, whereas the parameter γ captures the differential effects between urban and rural schools. The sum of $\beta + \gamma$ captures the overall effect on rural schools.[10]

Many of the outcomes in this paper are either counts or rates, implying that I have to deal with zeroes in them. Traditional methods estimate these as log-linearized models using ordinary least squares, but this may lead to biased estimates of the true semi-elasticities in the presence of heteroskedasticity (Silva and Tenreyro, 2006). Therefore, I employ Poisson regression when the outcome is either a count or a rate to properly account for zeroes in the log-linear model. I employ ordinary least squares when the outcome corresponds to standardized test score measures, which are continuous and can take negative values.

5 Results

I begin by estimating Equation 1 using dropout, failure, and approval rates as outcomes. I additionally present the results splitting between schools in urban and rural areas to depict the opposing trajectories. The results are presented in Figure 4. Panel 4a shows that unusual rain disruption increases the overall share of students who drop out of school in around 20 percent. The effect is transitory and lasts for around five years after the episode. These negative estimates are entirely driven by students in rural schools (as shown by Figure 4b), where heavy rain disruption increases school dropout for the first five years after the episode. The situation is very different among urban schools where school dropout is not affected in the short term but decreases six years after the disruption.

The effect of rain disruptions goes beyond school dropout by also affecting students who remain enrolled in school, and this effect is again disproportionately larger for students in rural schools. Figure 4c shows that failure rates increased (also in around 20 percent) after the episode, and this effect is again driven by rural schools, as Figure 4d suggests. A similar situation happens with the share of students who approve a given grade. Overall, there are not precisely estimated effects on approval rates (as shown in Figure 4e), but there are positive effects among students in urban schools and somewhat negative for students in rural ones (as shown in Figure 4f).

[10] I additionally present event study estimates separately for urban and rural schools to provide evidence of the non-existence of pre-trends by heterogeneous groups.

However, these effects on approval rates are expected for both urban and rural schools as the share of students who approve a grade depends on the share of students who drop out or fail.

These previous estimates do not provide formal tests of the differential effects of unusual rain disruption on educational outcomes between schools in urban and rural areas. I therefore estimate Equation 2, and present the results in Table 1. I provide point estimates for urban schools (β), rural schools ($\beta + \gamma$), and the difference between these two (γ). The effects are significantly different between urban and rural areas across all the three different outcomes. After a heavy rain disruption, students in rural schools, compared to urban ones, are 40 percent more likely to drop out of school, 70 percent more likely to fail the grade, and thereby five percent less likely to approve the school year.[11]

Unusual rain disruption also affects learning among those students who remain enrolled in school. Figure 5a depicts the point estimates of Equation 1 using student test score measures in the high school exit exam as outcomes. Figure 5b splits the same estimation by students enrolled in urban and rural schools. I observe an overall persistent decrease in test scores of around 0.15 standard deviations. The point estimates are negative for schools in both urban and rural areas, but they are significantly larger among students in rural schools. In fact, I cannot reject the null hypothesis of no effect among urban schools.

I also provide formal tests comparing the effects on test scores between students in urban and rural schools in Table 2. The effect is more than twice larger for students in rural schools (-0.1 standard deviations) compared to students in urban ones (-0.043 standard deviations), and this difference is statistically significant. Moreover, the negative effects are always larger in magnitude for rural schools across the multiple sub-tests (i.e. math, reading, natural sciences, social sciences and English), although I cannot fully reject that the effects are equal in every single test.

6 Mechanisms

Several explanations can be posed to understand why natural disasters affect human capital differently between urban and rural areas. I hereby provide evidence for three potential mechanisms that can explain this fact: selective migration; loss of educational resources; and increases in poverty.

6.1 Selective Migration

Natural disasters can induce people to migrate, especially from rural to urban areas. In fact, the results in this paper can be fully explained if the heavy rain disruption was so strong that it induced the best students to migrate from affected to non-affected areas, and, specifically, from rural affected areas to urban non-affected ones. If this is

[11] Recall that the point estimates in Table 1 are estimated using a Poisson regression, so the marginal effects are computed using the exponential function.

the case, educational outcomes should drop in the affected areas and increase in non-affected ones.

Regrettably, I am unable to directly test this due to the unavailability of student-level information regarding their place of residence before and after the disruption. Nonetheless, leveraging the school census data, I can examine the number of students who transferred schools within a given year. This avenue allows me to explore whether the rain-induced disruption led to student mobility between schools, and whether these effects were different between urban and rural areas. I proceed to estimate Equation 1 using the proportion of students transferring at the school level, and showcase the findings in Figure 6, where the overall results are displayed in Panel 6a and the breakdown between urban and rural schools is presented in Panel 6b. The analysis does not reveal any discernible effects of heavy rain disruption on overall school transfer rates, implying an absence of significant student movement induced by these disruptions.

This lack of effect also persists when separating by urban and rural schools. Although transfer rates post-disruption exhibit a marginal increase among rural schools and a slight decrease among urban ones, statistical analysis does not provide sufficient grounds to conclude that either effect significantly deviates from zero. Nor can it be established that these effects diverge meaningfully from each other. Formal evidence in support of this is provided in Appendix Table 2, where I employ Equation 2 to formally assess the potential differential impact on urban and rural schools. Notably, the point estimates fail to exhibit statistically significant differences, thereby suggesting that school transfers (linked to migration) may not adequately account for the principal findings pertaining to school dropout, school failure, and learning outcomes.

I provide a second piece of evidence that validates this result by estimating the main specifications but dropping urban schools in cities that usually host migrants (i.e. urban schools located in state capital cities or in municipalities with a population above 600,000). These estimations account by the fact that the best students could have probably migrated to urban areas in bigger cities, thereby driving the effects. The results are displayed in Table 3, and show very similar point estimates compared to the main results across all the outcomes analysed.

Finally, if selective migration was indeed the explanation, we should expect population to increase in unaffected areas compared to affected ones. I formally test this claim by estimating the effect of heavy rain disruption on municipalities' population. Unfortunately, Colombia only has measures of population by municipality per decade gathered using population censuses. For this reason, I employ the censuses gathered in 2005 and 2018 and estimate a difference-in-differences specification with municipality and year fixed effects with only two periods. Table 4 displays the results. I do not observe any statistically significant increase in population between affected and unaffected municipalities, nor for rural nor urban areas. Furthermore, I do not observe statistical differences between the effects in rural and urban areas in column (4).

All together, these results suggest that the heavy rain disruptions did not induce any selective migration. Therefore, the main results seem to not be driven by sorting (i.e. the best students migrated from rural to urban areas).

6.2 Loss of Education Resources

Natural disasters can also affect educational resources differently between schools in urban and rural areas, and thereby affect students' educational outcomes. Even though I cannot observe resource losses at the student level, I still provide two pieces of evidence against this claim. First, I examine if the number and the type of teachers change due to the heavy rain disruption. I estimate Equation 1 at the school level using number of teachers as outcome and present the results in Figure 7. I provide overall estimates in Figure 7a and independent estimations for urban and rural schools in Figure 7b. I do not observe any effect on the overall number of teachers, and I cannot reject that the effect is different between urban and rural schools.[12] Furthermore, I analyse if the composition of teachers changed after the disruption by using the share of teachers with tertiary education at the school level as outcome, and present the results in Figure 8. I do not observe any overall effect and, again, I cannot reject that the point estimates are different between urban and rural schools.[13]

Second, I analyse if there are school closures after the disruption by estimating the effects on the number of reported schools in the school census data. I collapse the data at the municipality level and estimate Equation 1 using the number of schools per municipality as outcome. The results are presented in Figure 9. Panel 9a shows that the overall number of schools per municipality does not change after the weather shock. I then split the results using number of urban and rural schools per municipality (Panel 9b) and do not find any significant effect. Furthermore, the null of difference in point estimates between urban and rural schools cannot be rejected.[14]

6.3 Poverty and Economic Conditions

One remaining mechanism behind these results relates educational outcomes with an increase in poverty that induces students to drop out of school and into the labor force —or into household chores. If this is the case, then it is expected that school dropout rates increase and student learning decreases because less time could be devoted to schooling. Unfortunately, I am not able to directly test if children labor force participation changed due to data limitations, but I can indirectly test this claim by analysing if there was an increase in poverty and a change in economic activity.

Increase in Poverty:– The heavy rains drove households into poverty in both urban and rural areas. To verify this, I estimate a difference-in-differences specification with two periods using as outcome a multidimensional poverty index.[15] The specification is

[12] The p-value for the difference in effects of urban and rural schools in Equation 2, γ, using number of teachers as outcomes is 0.208.

[13] The p-value for the different in effects is 0.605 when using the share of teachers with tertiary education as outcome.

[14] The p-value for difference in effects is 0.244 when using number of schools per municipality as outcome.

[15] Colombia does not count with yearly nationwide measures of poverty at the municipality level. The only available poverty measures that spam all the Colombian municipalities are computed using the nationwide censuses of 2005 and 2018.

estimated at the municipality level and includes municipality and year fixed effects.[16] Table 5 presents the overall results in column (1), results for urban areas in column (2), results for rural areas in column (3), and the test for equality between urban and rural areas in column (4). As expected, the heavy rains induced people into poverty across all the Colombian municipalities. This effect was larger in urban areas, where it increased around 25 percent. Among rural areas, the increase was significantly smaller and equal to around six percent.

Decrease in Economic Activity:– Colombia does not have direct measures of economic activity at the municipality level. However, a good proxy for economic activity, especially in developing countries, is night-time luminosity (Henderson et al., 2012). These measures seem to behave particularly well for Colombia, constituting a valuable measure of economic activity (Pérez-Sindín et al., 2021). I employ the data by the the U.S. Air Force Defense Meteorological Satellite Program gathered through satellites that take multiple night-time lights measures every night. Specifically, I use the data build by Li et al. (2020) (and available in Li et al. (2022)) to compute a municipality measure of night-time luminosity. The results are plotted in Figure 10. Panel 10a presents overall results at the municipality level and Panel 10b splits for urban and rural areas within the municipalities. The outcome corresponds to the logarithm of the area-weighted night-time light measure at the municipality and year level.

The heavy rains had no negative effect on night-time light. On the contrary, more affected areas increased night-time lights by around 20 percent, indicating that economic activity might have not been really affected. Furthermore, the effect on night-time luminosity is driven by rural areas, whereas urban remain relatively unaffected.[17]

I validate this result by estimating Equation 1 using agricultural production at the municipality level as outcome.[18] I plot the results in Figure 11. Panel 11a shows the results on planted area, Panel 11b on harvested area, and Panel 11c on total production of agricultural goods (measured in tons). The heavy rains seem to have induced people to plant and harvest more hectares. This translated into a final increase of production, which is in line with the positive effect found on night-time luminosity.

Reconciling the Effects:- These results indicate that poverty and production increased jointly after the rains. Poverty increased marginally more in urban areas, whereas production increased marginally more in rural ones. These two effects are consistent with the fact that returns to education are lower in agriculture (Herrendorf and Schoellman, 2018), implying that the rainfall shock could have increased labor supply in rural areas and thereby increase agricultural production and school dropout. For urban households, on the contrary, it might be more profitable to keep children in school as returns to education might be higher in sectors outside of agriculture.

[16] This same specification is used in Table 4 but using population as the outcome.

[17] I estimate Equation 2 using night-time lights as outcome to test if the effect is different between rural and urban areas. I reject the null of equality of effects with a $p - value = 0.000$.

[18] These data is gathered using the "Evaluaciones Agropecuarias Municipales", in Spanish, gathered by the Colombian Ministry of Agriculture. I employ the data between 2007 to 2019, which include records of production for multiple agricultural products at the municipality level. The outcomes are computed summing up across products within municipalities.

These results pose suggestive evidence on why natural disasters affect more educational outcomes in rural areas. High returns to education should be enough to keep students enrolled in schools after an adverse income shock like a natural disaster. However, returns to education in agriculture are low compared to returns other sectors that are more prominent in urban centers. As a consequence, it is expected that, in the presence of low returns to education in agriculture, a natural disaster drives rural children out of school, decrease its learning, and does not strongly affect urban students whose returns to stay enrolled in school are higher.

7 Conclusions

The urban-rural gap in human capital exists across almost all developing countries. This gap is partially explained by selective sorting of more skilled individuals into urban centers and less skilled individuals into rural ones. However, this is not the only determinant of the existence of the urban-rural gap (Lagakos, 2020).

In this paper, I explore if natural disasters can complement this hypothesis in order to explain the nature of the urban-rural gap. Natural disasters strongly affect individuals and are sufficiently broad to affect at the same time urban and rural areas. Using an episode of unusual heavy rains disruptions in Colombia, I leverage municipality-level variation to estimate the effect of natural disasters on educational outcomes. During 2010-2011, an unusual *La Niña* episode unexpectedly affected 41 percent of the Colombian territory affecting more than two million people in around 560,000 households. I estimate a difference-in-differences specification using this exogenous variation.

The results suggest that heavy rain disruptions increase school dropout and failure rates, and thereby decrease approval rates. These effects are entirely driven by students in rural schools, whereas students in urban ones remain relatively unaffected. Furthermore, the rain disruption decreases student learning among the remaining students in rural schools and does not affect significantly students in urban ones.

I test if selective migration, losses in educational resources, or poverty are the drivers of these effects. I do not find evidence that the heavy rains caused selective migration from rural to urban areas nor a loss of educational resources. The heavy rains did increase poverty and economic activity. Poverty was mainly increased in urban areas, whereas economic activity thrived in rural ones. These effects are consistent with low returns to education in the agricultural sector (Herrendorf and Schoellman, 2018), which suggests that rural students could have dropped out of school after the disruption to join labor markets and thereby increase economic activity in agriculture. The returns to education for urban students, on the contrary, are enough to allow them to stay enrolled in school.

The results of the paper show that the urban-rural gap in human capital can be also explained by natural disasters that, jointly with lower returns to education in the agricultural sector, induce students in rural areas to drop out of school and learn less. The paper only poses suggestive, and not-conclusive, evidence about the link of the returns to education in agriculture and the existence of the urban-rural gap. Future work linking these two could be helpful to understand why the urban-rural gap in human capital exists and how should it be addressed by policy-makers. This topic gains constant relevance in the current world where natural disasters seem to happen more often, and the urban rural gap in human capital constantly expands.

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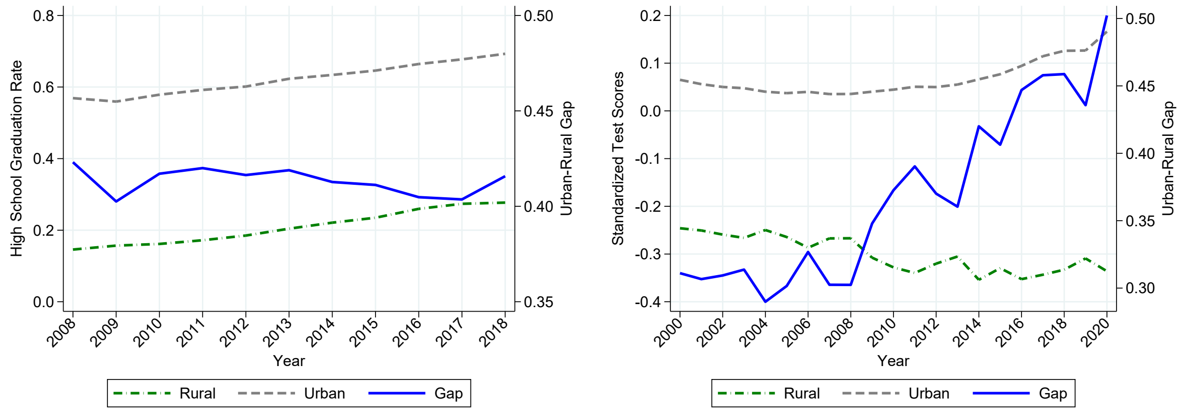
Figure 1: Urban-Rural Gap in Colombian Education

(a) Secondary School Graduation Rates

(b) Scores in High School Exit Exam

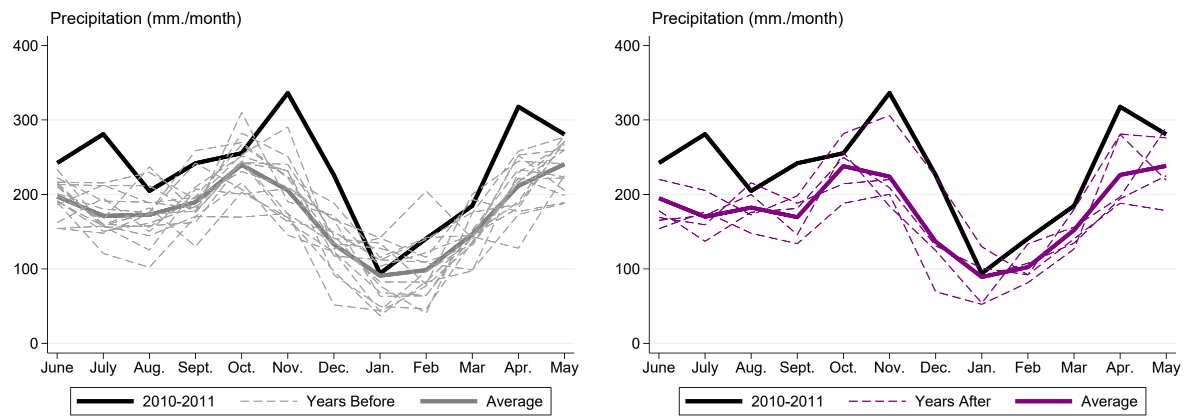


Notes: Panel 1a uses the Colombian household survey to plot the share of individuals between 23 and 60 who have at least completed secondary school education and live in rural and urban areas. Panel 1b plots standardized average test scores in the Colombian high school exit exam of students enrolled in rural and urban schools. The gap in blue is defined as the urban minus the rural value.

Figure 2: Unusual Rainfall 2010-2011

(a) Before 2010-2011

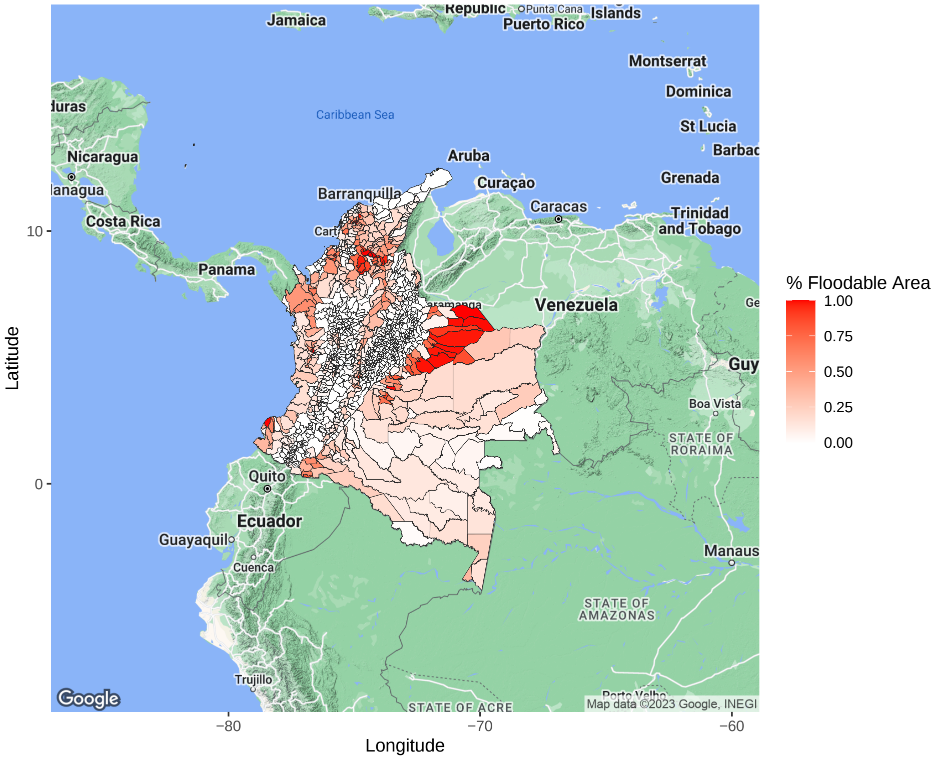
(b) After 2010-2011



Notes. Data on average monthly precipitation – defined as millimeters per month – was provided by IDEAM. It include the years 1994 to 2016.

Figure 3: Areas affected by the Unusual Heavy Rain Disruption

(a) Areas Under Risk of Flooding



(b) Affected Municipalities

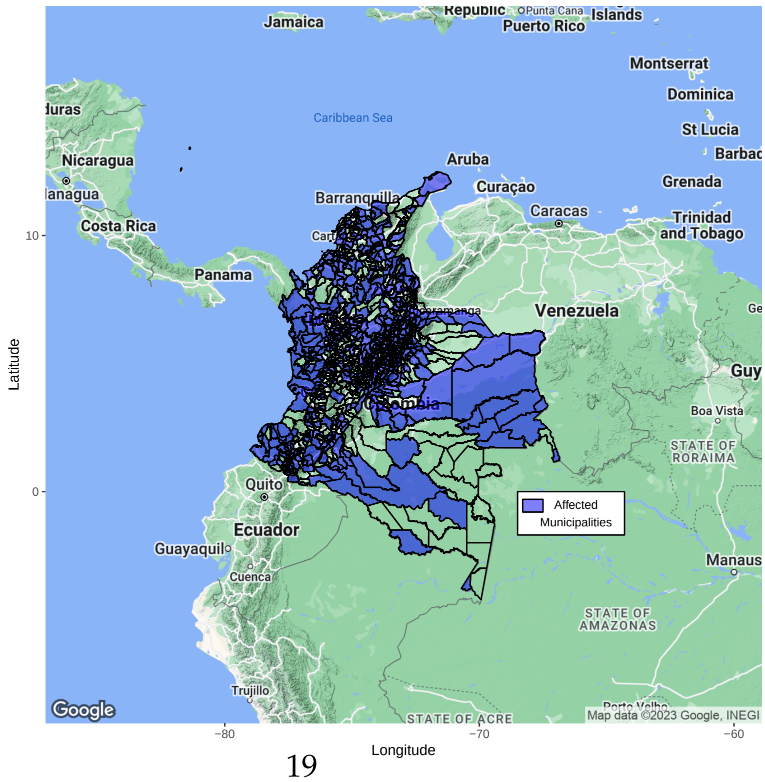
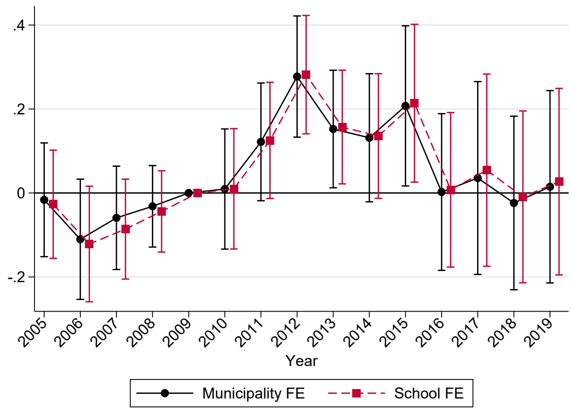
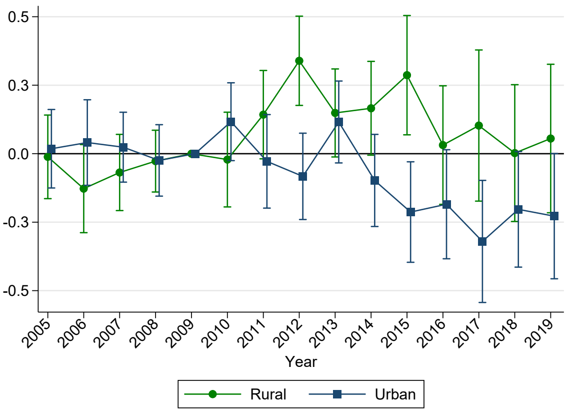


Figure 4: Effects of Unusual Rain Disruption on Students Situation

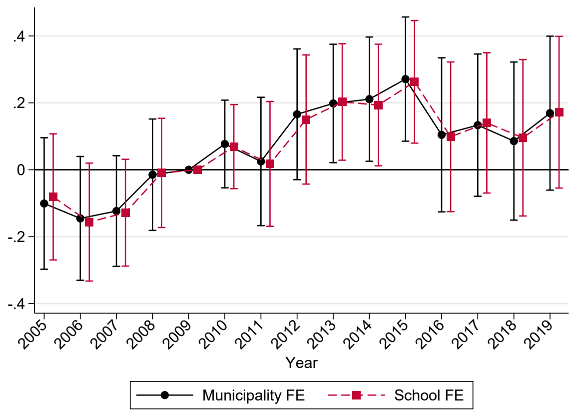
(a) Dropout Rate



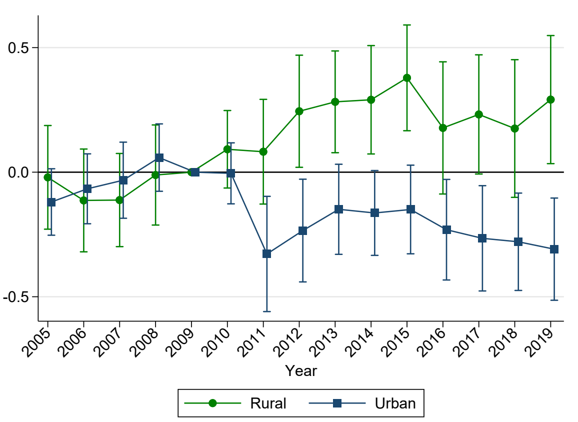
(b) Dropout Rate by Urban and Rural Schools



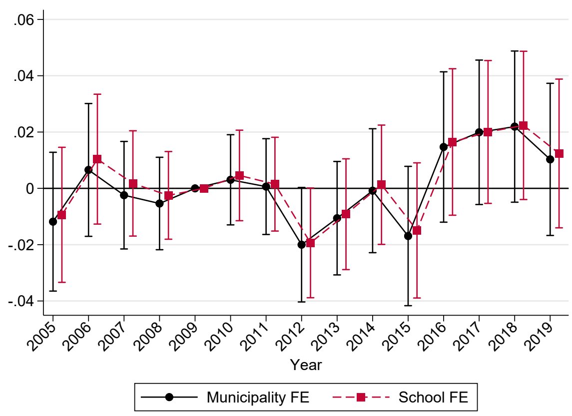
(c) Failure Rate



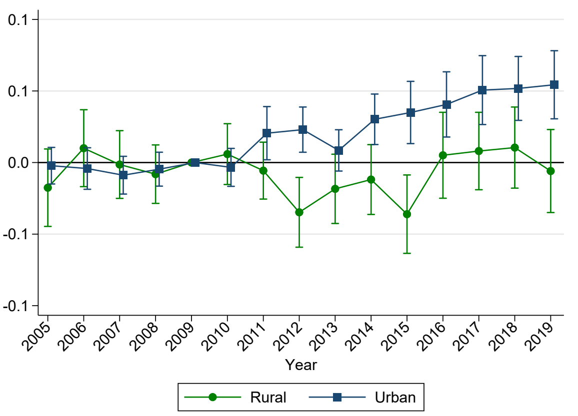
(d) Failure Rate by Urban and Rural Schools



(e) Approval Rate



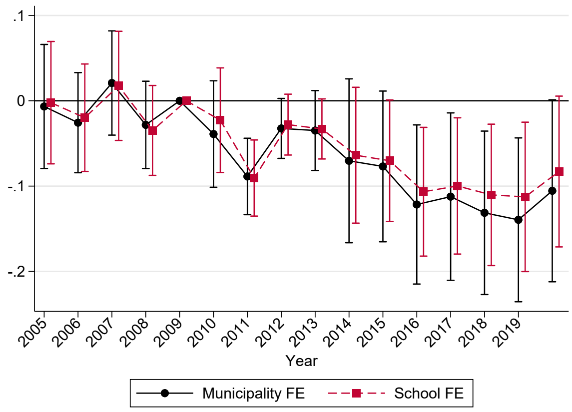
(f) Approval Rate by Urban and Rural Schools



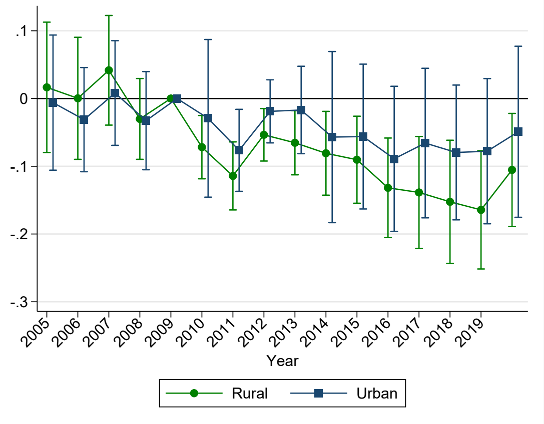
Notes. These figures present estimates of Equation 1 at the school level. The outcomes correspond to dropout, failure, and approval rates. All the models are estimated using a Poisson regression. Left panels include all schools in the country ($N = 758,495$). The black line depicts a specification including municipality fixed effects, whereas the red line depicts a specification including school fixed effects. Right panels present estimates separately by urban ($N = 227,340$) and rural schools ($N = 531,155$), estimated including municipality fixed effects. All the estimations include year fixed effects and standard errors clustered at the municipality level. 95 percent confidence intervals are displayed.

Figure 5: Effect of Unusual Rain Disruption on Test Scores of Remaining Students

(a) Overall



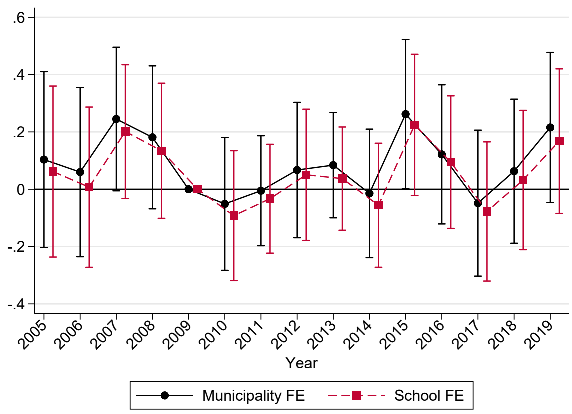
(b) Between Urban and Rural Schools



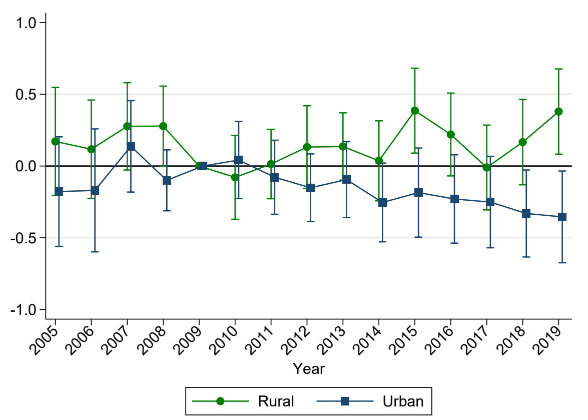
Notes. These figures present estimates of Equation 1 at the school level. The outcome corresponds to the school average of the standardized test scores with respect to each edition's mean and standard deviation. This test score is computed as the average across the different exams. Models are estimated using ordinary least squares. The left panel includes all schools in the country (N = 136, 161). The black line depicts a specification including municipality fixed effects, whereas the red line depicts a specification including school fixed effects. The right panel presents estimates separately by urban (N = 90, 301) and rural schools (N = 45, 854), estimated including municipality fixed effects. All the estimations include year fixed effects and standard errors clustered at the municipality level. 95 percent confidence intervals are displayed.

Figure 6: Effects of Unusual Rain Disruption on School Transfer Rates

(a) Overall



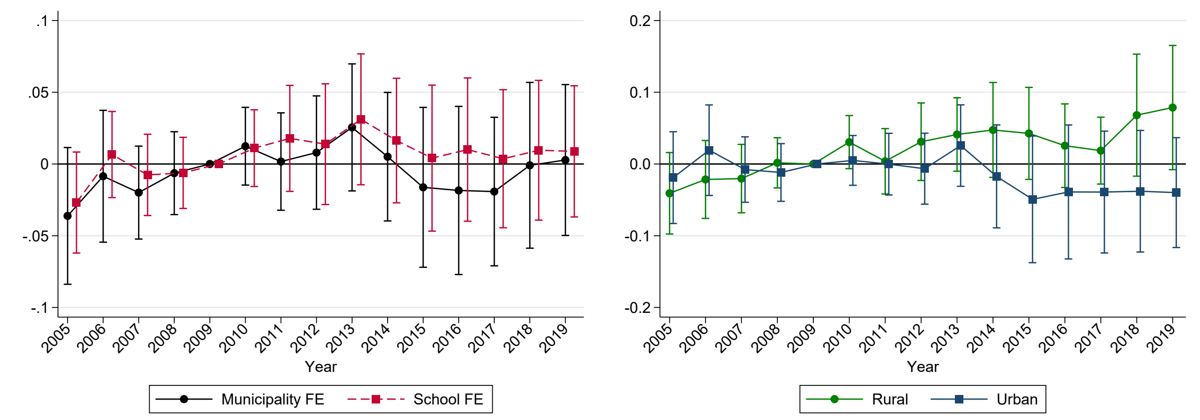
(b) Between Urban and Rural Schools



Notes. These figures present estimates of Equation 1 at the school level. The outcome corresponds the share of students who transfer to another school. All models are estimated using a Poisson regression. The left panel includes all schools in the country (N = 758, 495). The black line depicts a specification including municipality fixed effects, whereas the red line depicts a specification including school fixed effects. The right panel presents estimates separately by urban (N = 227, 340) and rural schools (N = 531, 155), estimated including municipality fixed effects. All the estimations include year fixed effects and standard errors clustered at the municipality level. 95 percent confidence intervals are displayed.

Figure 7: Effects of Unusual Rain Disruption on Number of Teachers

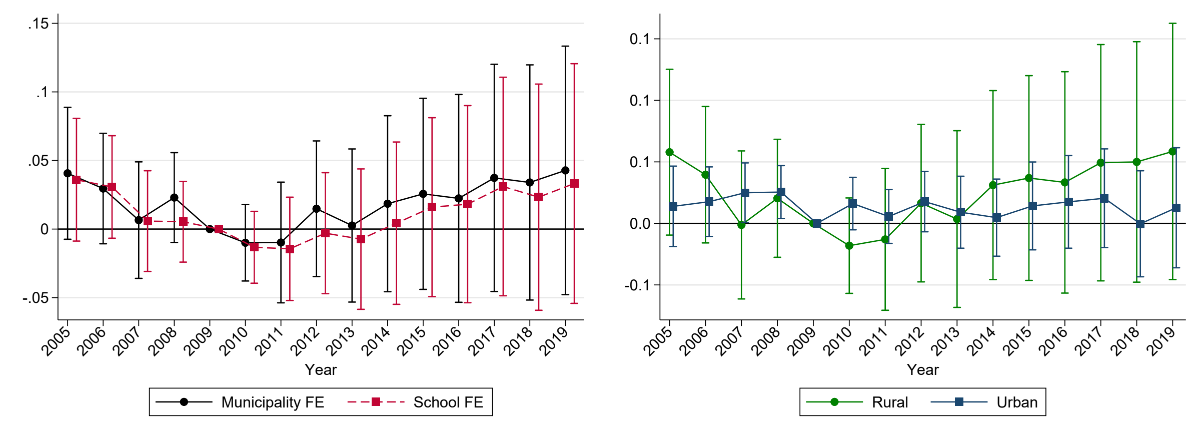
(a) Overall (b) Between Urban and Rural Schools



Notes. These figures present estimates of Equation 1 at the school level. The outcome corresponds to the number of teachers per school. All models are estimated using a Poisson regression. The left panel includes all schools in the country ($N = 751,599$). The black line depicts a specification including municipality fixed effects, whereas the red line depicts a specification including school fixed effects. The right panel presents estimates separately by urban ($N = 227,050$) and rural schools ($N = 524,549$), estimated including municipality fixed effects. All the estimations include year fixed effects and standard errors clustered at the municipality level. 95 percent confidence intervals are displayed.

Figure 8: Effects of Unusual Rain Disruption on Share Teachers with Tertiary Education

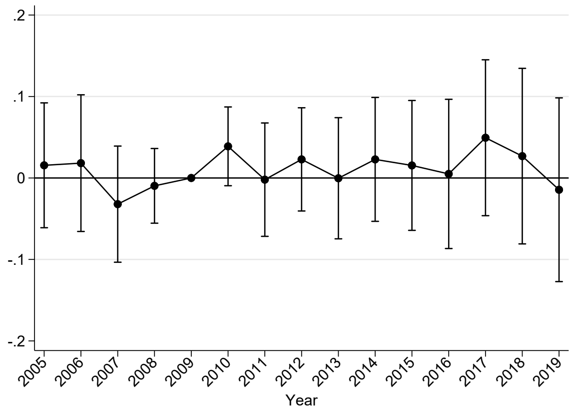
(a) Overall (b) Between Urban and Rural Schools



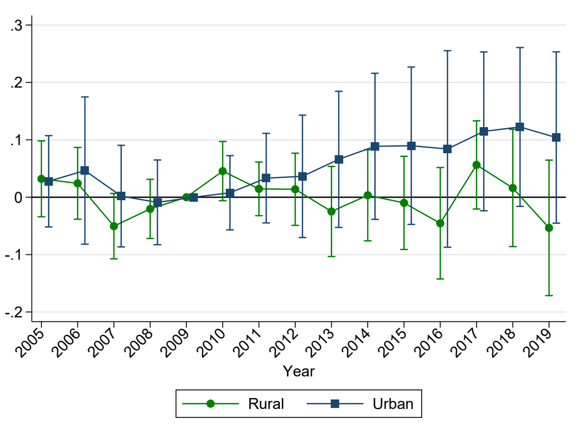
Notes. These figures present estimates of Equation 1 at the school level. The outcome corresponds to the share of teachers with tertiary education. All models are estimated using a Poisson regression. The left panel includes all schools in the country ($N = 751,522$). The black line depicts a specification including municipality fixed effects, whereas the red line depicts a specification including school fixed effects. The right panel presents estimates separately by urban ($N = 227,042$) and rural schools ($N = 524,480$), estimated including municipality fixed effects. All the estimations include year fixed effects and standard errors clustered at the municipality level. 95 percent confidence intervals are displayed.

Figure 9: Effects of Unusual Rain Disruption on Reported Number of Schools per Municipality

(a) Overall



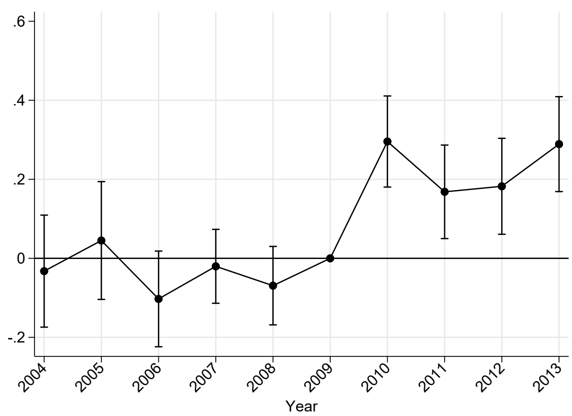
(b) Between Urban and Rural Schools



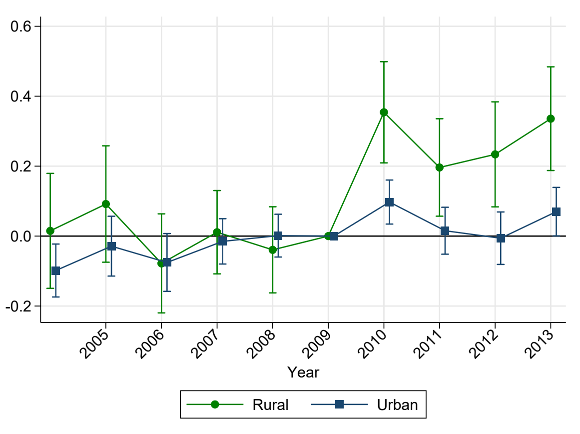
Notes. These figures present estimates of Equation 1 at the municipality level. The outcome corresponds to the number of schools per municipality. All models are estimated using a Poisson regression. The left panel includes all municipalities ($N = 16,758$). The black line depicts a specification including municipality fixed effects. The right panel presents estimates separately using as outcome the number of urban ($N = 13,894$) and rural schools ($N = 16,682$) per municipality and including municipality fixed effects. All the estimations include year fixed effects and standard errors clustered at the municipality level. 95 percent confidence intervals are displayed.

Figure 10: Effects of Unusual Rain Disruption on Night-Time Luminosity

(a) Overall



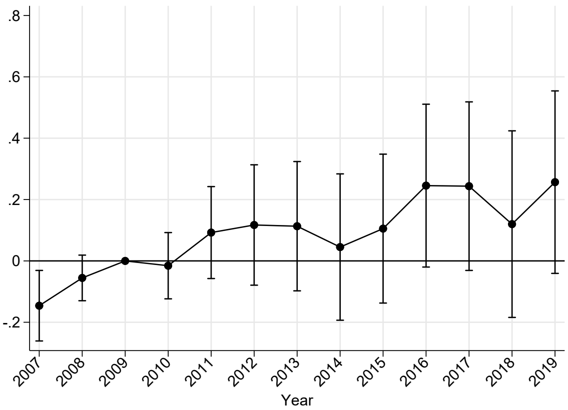
(b) Between Urban and Rural Schools



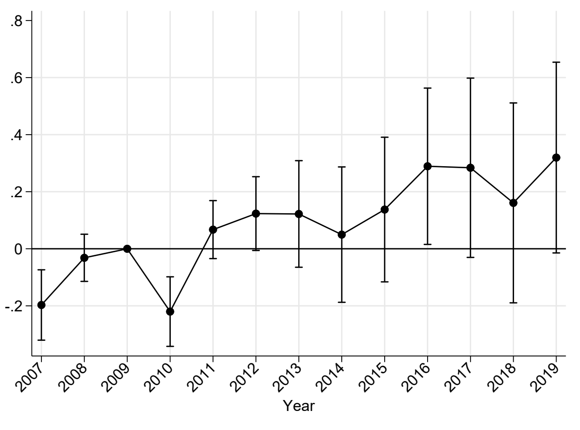
Notes. These figures present estimates of Equation 1 at the municipality level. The outcome corresponds to the log of the area-weighted average of night-time lights at the municipality level from the Defense Meteorological Satellite Program gathered from Li et al. (2022). It includes data from satellites F16 and F18, and the spatial resolution is of 30 arc-seconds. The left panel includes all municipalities ($N = 10,602$). The right panel presents estimates separately by urban ($N = 10,409$) and rural areas ($N = 10,602$) per municipality. All the estimations include year and municipality fixed effects, and standard errors clustered at the municipality level. 95 percent confidence intervals are displayed.

Figure 11: Effects of Unusual Rain Disruption on Agricultural Production

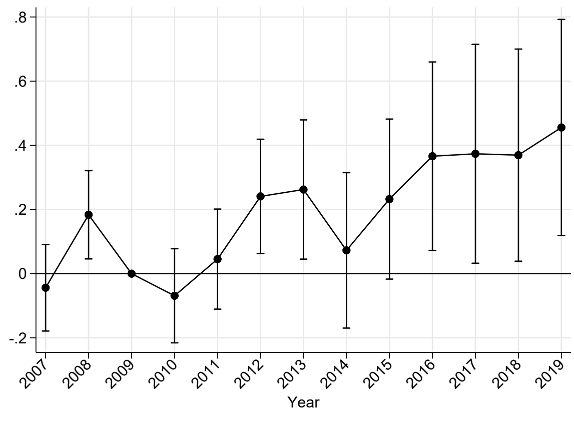
(a) Planted Area



(b) Harvested Area



(c) Production (Tons)



Notes. These figures present estimates of Equation 1 at the municipality level. Estimations performed using Poisson regression. The outcomes correspond to number of planted hectares in Panel 11a, the number of harvested hectares in Panel 11b, and to the volume of agricultural production (measured in tons) in Panel 11c. All the estimations include year and municipality fixed effects, and standard errors clustered at the municipality level. 95 percent confidence intervals are displayed.

Table 1: Differential Effects on Students' Situation by Urban-Rural Schools

	Dropout Rate		Approval Rate		Failure Rate	
	(1)	(2)	(3)	(4)	(5)	(6)
Affected*Post (β)	0.157***	-0.143**	0.004	0.041***	0.210**	-0.256***
	(0.053)	(0.060)	(0.013)	(0.009)	(0.097)	(0.082)
Affected*Post*Rural (γ)		0.346***		-0.049***		0.541***
		(0.077)		(0.013)		(0.113)
Rural ($\beta + \gamma$)		0.204		-0.008		0.285
p-value		0.000		0.457		0.004
Observations	758,495	758,454	758,495	758,490	758,495	758,425
Mean Dep. Var.	0.0527		0.856		0.0542	
School Controls	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
Municip.-By-Rural FE		Yes		Yes		Yes
Year-By-Rural FE		Yes		Yes		Yes

Note: This table presents the results of the estimation of Equation 1 in a static fashion in odd columns and the estimation of Equation 2 in even columns. The outcomes correspond to dropout, approval, and failure rates. Every rate is computed as the ratio of the number of students in each situation divided by the total number of students. Estimations performed using Poisson regression. Estimations in odd columns include school controls, municipality fixed effects, and year fixed effects. Estimations in even columns include school controls, municipality-by-rural fixed effects, year-by-rural fixed effects. School controls include a dummy for whether or not the school is public, and a set of dummy variables capturing if the school offers pre-, primary-, secondary-, or middle-scool level education. Standard errors are clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1.

Table 2: Effects on Test Scores of Remaining Students

	Average Score		Math		Reading		Natural Sciences		Social Sciences		English	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Affected*Post (β)	-0.077*	-0.043	-0.226***	-0.197***	-0.065	-0.033	-0.169***	-0.126**	-0.059*	-0.024	-0.095**	-0.071
	(0.041)	(0.040)	(0.062)	(0.066)	(0.051)	(0.050)	(0.049)	(0.052)	(0.036)	(0.033)	(0.041)	(0.044)
Affected*Post*Rural (γ)		-0.057**		-0.034		-0.031		-0.076**		-0.051*		-0.030
		(0.026)		(0.041)		(0.032)		(0.037)		(0.029)		(0.029)
Rural ($\beta + \gamma$)		-0.100		-0.232		-0.064		-0.202		-0.075		-0.102
p-value		0.013		0.000		0.131		0.000		0.044		0.005
Observations	136,161	136,158	136,161	136,158	136,161	136,158	136,161	136,158	136,161	136,158	136,159	136,156
Municipality FE	Yes		Yes		Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		Yes		Yes		Yes	
Municip.-By-Rural FE		Yes		Yes		Yes		Yes		Yes		Yes
Year-By-Rural FE		Yes		Yes		Yes		Yes		Yes		Yes

Note: This table presents the results of the estimation of Equation 1 in a static fashion in odd columns and the estimation of Equation 2 in even columns. The outcomes correspond to standardized test score measures computed at the school level. Estimations performed using ordinary least squares. Specifications in odd columns include municipality and year fixed effects. Specifications in even columns include municipality-by-rural and year-by-rural fixed effects. Standard errors are clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Effects after Dropping Urban Schools in Migrant Destinations

	Dropout Rate		Approval Rate		Failure Rate		Av. Test Scores	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Affected*Post (β)	0.181***	-0.101*	-0.006	0.033***	0.257***	-0.217***	-0.065*	-0.036
	(0.051)	(0.056)	(0.010)	(0.006)	(0.089)	(0.062)	(0.039)	(0.040)
Affected*Post*Rural (γ)		0.307***		-0.042***		0.496***		-0.064**
		(0.073)		(0.012)		(0.099)		(0.029)
Rural ($\beta + \gamma$)		0.206		-0.009		0.279		-0.100
p-value		0.000		0.452		0.004		0.013
Observations	683,698	683,657	683,698	683,693	683,698	683,628	106,305	106,302
Mean Dep. Var.	0.0556		0.849		0.0564		-0.148	
School Controls	Yes	Yes	Yes	Yes	Yes	Yes		
Municipality FE	Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		Yes	
Municip.-By-Rural FE		Yes		Yes		Yes		Yes
Year-By-Rural FE		Yes		Yes		Yes		Yes

Note: This table presents the results of the estimation of Equation 1 in a static fashion in odd columns and the estimation of Equation 2 in even columns. The outcomes correspond to dropout, approval, and failure rates as outcomes. Urban schools that are in state capital cities or in municipalities with population above 600,000 are dropped. Estimations performed using Poisson regression. Every rate is computed as the ratio of the number of students in each situation divided by the total number of students. Estimations in odd columns include school controls, municipality fixed effects, and year fixed effects. The specifications in even columns municipality-by-rural fixed effects, year-by-rural fixed effects. School controls include a dummy for whether or not the school is public, and a set of dummy variables capturing if the school offers pre-, primary-, secondary-, or middle-scool level education. Standard errors are clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Effects on Municipalities' Population

	Overall (1)	Urban (2)	Rural (3)	Difference (4)
Affected*Post (β)	0.038	0.044	0.054	0.044
	(0.037)	(0.049)	(0.055)	(0.049)
Affected*Post*Rural (γ)				0.010
				(0.075)
Rural ($\beta + \gamma$)				0.0545
p-value				0.326
Observations	2,226	2,196	2,226	4,422
Municipality FE	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	
Mean Dep. Var.	38294	29765	8930	
School Controls				Yes
Municip.-By-Rural FE				Yes
Year-By-Rural FE				Yes

Note: This table presents in columns 1-3 the results of the estimation of Equation 1 with two periods using the municipalities' population as outcome. Column 4 displays the result of estimating Equation 2. Estimations are performed using Poisson regression at the municipality level and include information for 2005 and 2018. Municipality and year fixed effects are included in the first three columns. Municipality-by-rural and year-by-rural fixed effects are included in column (4). Standard errors are clustered at the municipality level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 5: Effects on Multidimensional Poverty Index

	Overall (1)	Urban (2)	Rural (3)	Difference (4)
Affected*Post (β)	0.081*** (0.026)	0.252*** (0.029)	0.060** (0.027)	0.252*** (0.029)
Affected*Post*Rural (γ)				-0.192*** (0.026)
Rural ($\beta + \gamma$)				0.0597
p-value				0.0257
Observations	2,222	2,190	2,186	4,376
Municipality FE	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	
Mean Dep. Var.	55.46	40.77	64.98	
School Controls				Yes
Municip.-By-Rural FE				Yes
Year-By-Rural FE				Yes

Note: This table presents in columns 1-3 the results of the estimation of Equation 1 with two perios using the index of the share of people in multidimensoinal poverty as outcome. Column 4 displays the result of estimating Equation 2. School controls include a dummy for whether or not the school is public, and a set of dummy variables capturing if the school offers pre-, primary-, secondary-, or middle-scool level education. Estimations are performed using Poisson regression at the municipality level and include information for 2005 and 2018. Municipality and year fixed effects are included in the first three columns. Municipality-by-rural and year-by-rural fixed effects are included in column (4). Standard errors are clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix: Additional Figures and Tables

Appendix Table 1: Descriptive Statistics

	Obs. (1)	Mean (2)	Stand. Dev. (3)	Median (4)	Max. (5)	Min. (6)
A) Municipality Shock						
Affected	1,122	0.67	0.47	1.00	1.00	0.00
Area Under Risk of Flooding (%)	1,122	0.11	0.22	0.00	1.00	0.00
Interaction	1,122	0.09	0.21	0.00	1.00	0.00
B) Census of Schools						
Rural School (%)	758,495	0.70	0.46	1.00	1.00	0.00
Public School (%)	758,495	0.83	0.38	1.00	1.00	0.00
Pre-School (%)	758,495	0.90	0.30	1.00	1.00	0.00
Primary School (%)	758,495	0.94	0.25	1.00	1.00	0.00
Lower-Secondary School (%)	758,495	0.29	0.45	0.00	1.00	0.00
Upper-Secondary School (%)	758,495	0.27	0.45	0.00	1.00	0.00
Dropout Rate (%)	758,495	0.05	0.08	0.02	1.00	0.00
Approval Rate (%)	758,495	0.86	0.14	0.88	1.00	0.00
Failure Rate (%)	758,495	0.05	0.08	0.03	1.00	0.00
Transfer Rate (%)	758,495	0.04	0.07	0.00	1.00	0.00
Number of Students	758,495	196.00	369.74	50.00	8925.00	1.00
Number of Teachers	751,599	8.48	14.55	2.00	978.00	0.00
Teachers with tertiary education (%)	751,522	0.73	0.38	1.00	1.00	0.00
c) Test Score Measures						
Average Score (σ)	136,161	-0.06	0.68	-0.19	5.07	-3.27
Math Score (σ)	136,161	-0.06	0.57	-0.14	6.82	-2.54
Reading Score (σ)	136,161	-0.06	0.57	-0.12	3.21	-3.92
Nat. Sciences Score (σ)	136,161	-0.05	0.59	-0.14	4.73	-3.09
Soc. Sciences Score (σ)	136,161	-0.05	0.55	-0.12	3.40	-2.84
English Score (σ)	136,159	-0.04	0.70	-0.22	5.18	-5.59

Appendix Table 2: Effects on Share of Students who Transfer School

	(1)	(2)	(3)	(4)
Affected*Post (β)	0.002	-0.190	0.005	-0.172
	(0.084)	(0.132)	(0.079)	(0.124)
Affected*Post*Rural (γ)		0.240		0.219
		(0.155)		(0.146)
Rural ($\beta + \gamma$)		0.049		0.047
p-value		0.600		0.599
Observations	758,495	758,328	679,077	679,077
Mean Dep. Var.	0.0373		0.0373	
School Controls	Yes	Yes		Yes
Municipality FE	Yes			
Year FE	Yes		Yes	
Municip.-By-Rural FE		Yes		
Year-By-Rural FE		Yes		Yes
School-By-Rural FE				Yes
School FE			Yes	

Note: This table presents the results of the estimation of Equation 1 in a static fashion in odd columns and the estimation of Equation 2 in even columns. The outcome corresponds to the share of students who transfer school. Estimations performed using Poisson regression. Specifications in odd columns include municipality and year fixed effects. Specifications in even columns include municipality-by-rural and year-by-rural fixed effects. School controls include a dummy for whether or not the school is public, and a set of dummy variables capturing if the school offers pre-, primary-, secondary-, or middle-scool level education. Standard errors are clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1.