Flooding the Brains: Natural Disasters, Student Outcomes, and the Urban-Rural Gap in Human Capital

Juan Muñoz-Morales *

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Abstract

This study provides evidence that natural disasters negatively affect student outcomes, potentially explaining the lower academic achievement of students in rural areas compared to their urban counterparts in developing countries. Using data from the Colombian school census, I estimate a difference-in-differences strategy that exploits variation from an unusual rainfall shock affecting over two million people in both urban and rural Colombia. The results show that these disruptions increase school dropout rates and reduce learning outcomes for at least a decade. The effects are concentrated in rural schools, while students in urban schools remain unaffected. I explore several mechanisms and rule out the possibility that the effects are driven by selective migration or a loss of educational resources. Instead, I find evidence that the rainfall shock exacerbated poverty, pushing poorer rural children into unemployment and longer work hours.

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

JEL classifications: I24, I25, R11.

*IESEG School of Management, Univ. Lille, CNRS, UMR 9221- LEM-Lille Économie Management, F-59000 Lille, France (j.munoz@ieseg.fr). I want to thank two anonymous referees for their remarkable contributions. I additionally thank seminar participants at LACEA-LAMES 2024.

1 Introduction

Natural disasters have been very prevalent in recent years, prompted in part by the surge in climatic variability (Banholzer et al., 2014). Episodes of increased temperature, precipitation, and/or windstorms have all increased, raising concerns about their economic impacts due to rising global temperatures (NOAA, 2024). Natural disasters have been documented to affect populations worldwide in many economic margins.[1] However, evidence on the effects of weather shocks on schooling outcomes remains scarce, especially for developing countries where the incentives to remain in school differ from those in more developed economies.

When focusing on developing countries, the effects of natural disasters on schooling outcomes could be expected to differ significantly between rural and urban students. Incentives to remain in school can vary greatly between these two groups since the returns to education in agricultural activities are remarkably lower (Herrendorf and Schoellman, 2018). Therefore, significant disparities in the accumulation of human capital between urban and rural areas have been documented. Students in rural areas of Latin America, for instance, are 25 percent less likely to graduate successfully 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). Even though the urban-rural gap in human capital exists in almost every developing economy, it is not fully clear how it emerges and why it persists (Lagakos, 2020), and no evidence exists about its connection to increasing weather variability.

In this paper, I analyze how natural disasters affect the educational outcomes of

[1] 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). For the effects on migration, see, for instance: Deryugina et al. (2018); Boustan et al. (2012); Baez et al. (2017); and Boustan et al. (2020). A large body of literature also focuses on the intergenerational 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) provides a detailed review of the relationship between weather and various outcomes, including aggregate output, agriculture, labor productivity, health, energy, political stability, and conflict.

urban and rural students by studying an unusual heavy rainfall episode that took place in Colombia, a developing country, during 2010. Colombia is a tropical country ranked as one of the rainiest countries in the world. In 2010, drastic variations in sea temperature created a strong and unpredictable transition between the tropical cycles of *El Niño* and *La Niña*. This transition caused an unusual episode of heavy rains that flooded a significant portion of the Colombian territory, affecting both rural and urban areas. Due to the severity of the rains, the president at the time declared the situation a national emergency to provide assistance to more than two million people (i.e., between 4-5 percent of the country's population) affected by the rains.

I exploit municipality-level variation induced by this unusual rain episode to implement a difference-in-differences design that examines the causal effect of heavy rainfall on schooling outcomes. By combining multiple data sources, I construct a school-level panel that tracks dropout, failure, approval, and transfer rates of students in Colombian rural and urban schools, and complement it with test score information at the time of secondary school graduation. To build the shock, I combine information on precipitation at the municipality level with predicted flooding computed by the Colombian government to address the crisis in 2011. By combining these two data points, I develop an exposure measure that captures the orthogonal component from long-term rainfall by extracting the variation in rainfall that is uncorrelated with predicted flooding. This measure is also unrelated to pre-existing characteristics of Colombian municipalities, allowing me to estimate the effect of the rains on schooling outcomes. Identification of the shock requires that the evolution of affected and unaffected areas evolved in parallel in the absence of the shock. I provide evidence in support of the validity of the study design.

The results suggest that heavy rain disruptions negatively affect educational outcomes, and the detrimental effects are systematically focused on students enrolled in rural schools. A one standard deviation increase in unusual rainfall *increases* overall school dropout in two to three percent, but this point estimate remarkably increases to almost eight percent when focused on rural schools. This effect is permanent for almost a decade, which is consistent with previous evidence on the persistence of the effects of natural disasters on human capital (Andrabi et al., 2023). Students in urban schools remain unaffected; no sizable effect is detected among them.

The estimated effects are concentrated on younger students enrolled in primary schools. I do not observe precise effects on failure rates, although they show opposite trajectories, with negative point estimates for rural schools and positive ones for urban schools. Learning, captured through test scores at the moment of high school graduation and among remaining rural students, additionally decreased six years after the shock, consistent with the effect being concentrated on younger students at the time of the shock who took the high school exit exam several years later at the time of graduation. Overall, these results imply that heavy rain disruptions *increase* school drop out and *decrease* learning, and the effect is focused on rural students, leaving urban students unaffected. These point estimates translate into very sizable losses for Colombian rural youth population in terms of life-time income.

Multiple potential mechanisms could explain why natural disasters affect student outcomes and why the effects are concentrated among students living in rural areas. I explore whether selective sorting, a loss in educational resources, or an increase in poverty leading to labor market responses can explain the estimated results. I do not find evidence that the heavy rains induced migration or decreased educational resources, but I do find suggestive evidence that the rains increased poverty and induced children into unemployment and longer working hours. I employ household surveys to estimate the effects of the rain disruption on poverty measures and find that the weather shock significantly increased extreme poverty in both rural and urban areas. Additionally, I identify an increase in the likelihood of being unemployed and the number of working hours among children living in rural areas. These effects are concentrated among children living in poorer households, consistent with the increase in extreme poverty induced by the shock. I do not find any effect on economic activity after the shock, as measured by nighttime luminosity and agricultural production. The effects on poverty and labor market outcomes are consistent with evidence suggesting that returns to education in the developing world are lower in the agricultural sector (Herrendorf and Schoellman, 2018), implying that increases in child labor supply could be a reaction to increased poverty after natural disasters among rural children. Similar results have been found in alternative contexts in which children trade off the accumulation of human capital for child labor (Bau et al., 2020).

This paper contributes to two broad strands of literature. First, it contributes to the literature on the effects of natural disasters, especially those of heavy rainfalls. This broad literature provides causal estimates of the effects of natural disasters on migration, economic growth, and labor markets, among others (Strobl, 2011; McIntosh, 2008; Belasen and Polachek, 2008; Groen et al., 2020; Deryugina et al., 2018; Boustan et al., 2012; Baez et al., 2017; Boustan et al., 2020; Maccini and Yang, 2009; Fuller, 2014; Caruso and Miller, 2015; Caruso, 2017; Dell et al., 2014). Earlier work has also related unusual rainfalls to the accumulation of human capital, focusing mostly on the effects in the United States. For instance, Sacerdote (2012) shows how hurricanes Katrina and Rita negatively affect students' academic performance, and Opper et al. (2023) provides 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 analyzing the spillover effects of migrants induced by Hurricane Maria on the educational outcomes of natives. Some other work has focused on analyzing the effects in the developing world showing that natural disasters can additionally have inter-generational effects in human capital accumulation (Caruso, 2017). Nonetheless, evidence from developing economies about the human capital effects of weather shocks remains still scarce.

I contribute to this literature by filling this gap and showing that the negative effects of natural disasters on schooling outcomes extend to various settings in the developing world, with these effects being particularly pronounced among rural students. Additionally, this paper leverages data that allows for the identification of long-term effects in low-income countries, an aspect that has not been addressed in previous studies. Natural disasters are becoming increasingly common, raising concerns about their effects on inequality between rural and urban populations in developing countries.

Second, this paper contributes to the literature addressing the existence of the urban-rural gap in human capital. Economic development has traditionally been 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). However, if this selective migration was the only determinant of the urban-rural gap, then we would expect that rural-to-urban migrants do not experience any wage gains. This does not seem to 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).

There is mixed evidence about how much individual sorting can explain the rural-urban gap in human capital. On 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 by suggesting that observational studies with non-experimental data confound the urban premium and the individual benefits of migrants.

Experimental and quasi-experimental evidence seems to support the claim that selective migration does not completely explain the urban-rural gap. 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 Finns after the Second World War and find significant income increases among rural migrants. This evidence is consistent with the findings of Gollin et al. (2014), who show that the urban-rural gap persists 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.[2] Finally, in a related paper, 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.

I contribute to this literature by providing a complementary hypothesis. Differential responses to natural disasters can explain the existence and persistence of the urban-rural gap in human capital. My results suggest that an urban-rural gap in educational outcomes emerges after an episode of exposure to unusual heavy rains, and these effects persist for almost a decade after the shock. These results complement the debate on the rural-urban gap in human capital by highlighting the connection between weather variability and schooling outcomes.

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.

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

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. Section 7 concludes.

2 Background

2.1 Education System in Colombia

The Colombian education system is divided into 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 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

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

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 that it 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

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

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 in Colombia. A drastic transition between *El Niño* and *La Niña* caused 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 areas of the country, flooding around

8 percent of the Colombian territory: 1.5 percent corresponded to bodies of water; 2.5 percent to periodically flooded areas; and the remaining 4 percent (i.e., 1,642,108 hectares) were excess areas that were not traditionally flooded. This translated into 5 percent of urban and 3.5 percent of rural areas excessively flooded (CEPAL, 2012). A total of 755 municipalities (68 percent, out of 1,122) were affected by the rain disruptions.

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: 1) identify the people who had been affected; and 2) track areas that were under potential risk of flooding. 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, 65 percent of which corresponded to people residing in rural areas and the rest in urban ones.

Areas under Risk of Flood:- In addition, public officials analyzed satellite images of the Colombian territory and identified areas that could be subject to unusual floods during the *La Niña* disruption. These areas were identified using the morphological systems of the Colombian territory gathered in 2010 (IDEAM, 2010). Territories that receive sediments enough to constitute a risk for a given population were declared as areas under risk of flooding.[5] 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.

[5]For every municipality, the officials declared a percentage of its territory that was under risk of unusual flooding. I name these percentages as A_m^{2010} in the empirical strategy section.

3 Data

I combine four main data 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 2005 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.

Third, I employ the information produced by the government in 2011 about predicted flooding per municipality.[6] These measures estimate the municipality's area that was under risk of flooding –in addition to the areas that are usually flooded–

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

based on certain pre-established geographic conditions. The average municipality had around 18 thousand hectares of potentially affected area, implying that around 12 percent of the its area was under risk of flooding. Some municipalities, however, had no risk areas whereas others had up to 100 percent.

Fourth, I use precipitation data from the Colombian Institute of Hydrology, Meteorology and Environmental Studies (known as IDEAM, in Spanish). These correspond to data captured by almost 2,500 weather stations around the country that monitor temperature and rain. Combining information on the different stations, I compute municipality level measures of rainfall for 832 municipalities (out of a total of 1,101) from 1994 to 2015. I primarily use information on 2010 for the empirical strategy, but I employ additional years to compute descriptive measures (see, for instance, Figure 2).

I present a summary of the estimating data set in Appendix Table 1. Panel A describes precipitation and areas under risk of flooding, panel B focuses on outcomes at the school level, and panel C focuses on test score data, which include the subgroup of schools that had students taking the high-school exit exam for a given year (i.e., those in upper-secondary level).

4 Empirical Strategy

I leverage variation induced by the unusual heavy rain episode to estimate the effect of natural disasters on educational outcomes. To isolate the exogenous variation of the rains, I compute a weather shock equivalent to the standardized residuals of a regression between the rainfall in municipality m in 2010 and a measure corresponding to the share of the municipality's area that is considered under risk of unusual flooding. Formally, the weather shock, w_m^{2010}, corresponds to the predicted residuals of the linear regression:

$$R_m^{2010} = \gamma A_m^{2010} + w_m^{2010}, \tag{1}$$

where R_m^{2010} stands for the total precipitation in municipality m in 2010, and A_m^{2010} is the percentage of area under risk of flooding. The residuals are then standardized with respect to its standard deviation.

Intuitively, the residual measure of unusual rainfall estimates in Equation (1) captures the variation in rainfall from long-term patterns that is orthogonal to pre-existing characteristics in a given municipality. Predicted flooding, A_m^{2010}, is a measure estimated by experts, quantifying the share of a municipality's area that was at risk of flooding, given the morphological structure of its territories. This measure serves as a strong predictor of long-term, *usual* rainfall in a given territory. The residual measure, w_m^{2010}, therefore, captures the *unusual* severity of the weather shock in the 2010-2011 episode, conditional on the municipality's characteristics. [7]

Exploiting this cross-sectional variation, I then estimate a dynamic event study specification as follows:

$$y_{smdt} = \sum_{t \neq 2009} \alpha_t \left(w_m^{2010} \times \mu_t \right) + \delta X_{smdt} + \mu_m + \mu_{st} + \mu_{dt} + \varepsilon_{smdt}, \tag{2}$$

where y_{smdt} corresponds to a given outcome for school s, in municipality m, in state d, and in year t.[8] I interact w_m^{2010} with year dummies, μ_t, to estimate the dynamic effects, and use 2009 as the baseline year.[9] The vector X_{smdt} includes school-level character-

[7]Alternatively, I provide two additional measures for the weather shock as robustness checks. First, I use the residuals, w_m^{94-09}, from a regression of precipitation in 2010 on the average precipitation between 1994-2009, $R_m^{2010} = \gamma \bar{R}_m^{94-09} + w_m^{94-09}$. Second, I use the residuals, $\hat{w}_m^{94-09}$, from a regression of precipitation in 2010 on both predicted flooding *and* average precipitation between 1994-2009, $R_m^{2010} = \gamma A_m^{2010} + \delta \bar{R}_m^{94-09} + \hat{w}_m^{94-09}$. Using any of these measures yields similar results.

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

[9]Static estimations of Equation (2) interact w_m^{2010} with a dummy that takes the value of one after 2010.

istics such as a binary variable 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 primary, lower-secondary, or upper-secondary level education. The baseline specification includes municipality fixed effects (μ_m) to control for time-invariant characteristics at the municipality level, year-by-rural fixed effects (μ_{st}) to control for differential trends between rural and urban schools, and state-specific trends (μ_{dt}) to account for differential time variation across states. A second, more saturated specification includes school level fixed effects that control for time-unvarying school characteristics. Standard errors are conservative and always clustered 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.

Specification (2) 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:

$$y_{smdt} = \beta \left(w_m^{2010} \times Post_t \right) + \gamma \left(w_m^{2010} \times Post_t \times R_s \right) + \delta X_{smdt} + \mu_{sm} + \mu_{st} + \mu_{sdt} + \varepsilon_{smt}. \tag{3}$$

As opposed to specification (2), the specification in (3) includes the triple interaction between treatment intensity, w_m^{2010}, 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_{sm}) and state-specific trends (μ_{sdt}) 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 (Chen and Roth, 2024; 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

5.1 Validity

The validity of the identification strategy can be tested by regressing the weather shock, w_m^{2010}, on values of the outcomes during the years prior to the shock. Exogeneity implies that the shock is uncorrelated with these measures in its absence (i.e., during a counter-factual period), which can be assumed to take place before the unusual rainfall disruption. I present the results of such estimation in Figure 4, where I plot the p-values of separate regressions that vary by the dependent variable that is presented on the y-axis.[11] Even though the shock is measured at the cross-sectional level, I mimic the main estimation by including year fixed effects, state-specific trends, and regressing the outcome in first differences to account for heterogeneity between

[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.

[11] The full results of the estimations are presented in Appendix Table 2.

municipalities.[12] I do not observe that the shock predicts any of the outcomes, posing strong evidence about the exogeneity of the measure and the validity of the research design.

5.2 The Effects of Natural Disasters on Schooling Outcomes

Figure 5 presents the results of estimating Equation (2) using dropout, failure, and approval rates as outcomes. I additionally present the results splitting between schools in urban and rural areas. Unusual rain disruption has a positive and persistent effect on school dropout, creating a gap between rural and urban schools. Panel 5a shows that a one standard deviation increase in unusual rainfall increases school dropout in between two to three percent, and the effect is persistent in time. These estimates are entirely driven by students in rural schools (as shown by Figure 5b), where a one standard deviation increase in rainfall raises school dropout in almost eight percent and the effect persists for almost a decade. The situation is very different among urban schools where school dropout is not affected at any point in time, depicting very different trajectories between schools in urban and rural areas.

These opposing trajectories can be also found when analysing effects on approval and failure rates, although the effects are remarkably more imprecise. Figure 5c does not show any significant effect on approval rates when pooling the estimation, but, as shown in Figure 5d, this null effect is driven by a decrease in approval rates among students in rural schools that compensates an increase among urban ones. A similar situation happens with the share of students who fail the grade. There are not significant overall effects (as shown in Figure 5e), but there are some opposing trajectories that contrast between students in urban and rural schools.

These estimates do not provide formal tests of the differential effects of unusual

[12] This estimation can be also understood as a way of testing for differential trends in the outcomes, which are also implicitly tested in the event study estimates in Equation (2.)

rain disruption on educational outcomes between schools in urban and rural areas. I therefore estimate Equation (3), 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 for school dropout, but the differences in failure and approval rates are substantially smaller and imprecise, although the effects among rural and urban schools have different signs consistent with the dynamic effects in Figure 5. Overall, these results imply that the unusual rain disruption creates a gap between the outcomes of students in urban and rural schools by strongly inducing students in rural schools to drop out.[13]

Effects by Student Age:- These effects on school dropout are mostly concentrated on younger students. I provide evidence consistent with this claim in Table 2, where I present the effects of unusual rainfall by school level.[14] The increase in school dropout is focused on students who attend primary school, whereas no precise effects effect is detected on older students.

Effects on Learning:- Unusual rain disruption also affects learning among those students who remain enrolled in school, creating again a gap between rural and urban areas. Figure 6 depicts the point estimates of Equation (2) using student test score measures in the high school exit exam as outcome. No overall effect is observed (as shown by panel 6a), but a gap between students in urban and rural schools starts to emerge around seven years after the weather shock (as shown by panel 6b). These results are consistent with the fact that younger students seem to be the most affected, implying that the negative effects on learning are observed some years later at their moment of graduation. I also provide formal tests comparing the effects on test scores between students in urban and rural schools in Table 3. I observe significant differ-

[13] I provide results using the two alternative definitions of the weather shock in Appendix Table 3. The results remain fairly unchanged, except that using the alternative definitions imply a significant difference between urban and rural areas in terms of approval rate.

[14] Appendix Figure 1 presents the dynamic effects providing tests for the absence of differential trends.

ences when focusing on the overall score, and this seems to be primarily driven by reading scores.

Altogether, these results suggest that unusual rainfall increases school dropout rates, with the effect being particularly pronounced among primary school students in rural areas. No such effects are observed for students in urban schools, indicating the emergence of a schooling gap between urban and rural students. These negative impacts appear to persist, translating into a decrease in learning outcomes several years after the shock. This is consistent with the observation that younger students are more severely affected, as evidenced by their lower test scores at the time of graduation.

Additionally, these estimates suggest significant long-term income losses for the affected youth. Descriptive statistics suggest that graduating from secondary school in rural Colombia in 2010 led to an average income increase of approximately $50 USD, which, on an annual basis, was equivalent to twice the monthly minimum wage.[15] This implies a lifetime income loss of about 16 percent for those earning the minimum wage, which represents a substantial reduction in total lifetime earnings. Furthermore, with approximately 3 million students enrolled in Colombian public schools in 2010, if 5 percent of them dropped out before completing secondary school, the total yearly income loss would amount to around 90 million USD, per cohort.

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.

[15] Comparing the income of rural workers with only primary education to those who completed secondary school reveals a difference of 100,000 COP, or roughly $50 USD at an exchange rate of 2,000 COP per USD. At the time, the minimum wage was 567,000 COP.

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 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.[16] 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 (2) using the proportion of students transferring at the school level, and showcase the findings in Figure 7, where the overall results are displayed in Panel 7a and the breakdown between urban and rural schools is presented in Panel 7b. 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. 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 4, where I employ Equation (3) to formally assess the potential differential impact on urban and rural schools. Notably, the point estimates fail to exhibit statistically

[16]The official definition of students who transfer corresponds to: "Students who withdraw from the school to continue their studies in other school, municipality, country, or the private sector. Although they are no longer part of the school, they are still part of the education system."

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 effect on urban and rural population. If selective migration was indeed the explanation, we should expect population to decrease in affected areas compared to unaffected 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. Point estimates in this estimation have to be interpreted with caution as I am not able to test for the parallel trend assumption and because the two data points are far away from the 2010 shock. Appendix Table 5 displays the results. I do not observe effects on urban population, nor decreases in rural population among affected municipalities. In fact, for rural areas I observe the contrary, implying an increase in affected areas, which is inconsistent with selective migration as a mechanism.

These two pieces of evidence suggest that the heavy rain disruptions did not induce any selective migration. 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 results against this claim. First, I examine if the number and the type of teachers change due to the heavy rain disruption. I estimate Equation (2) and (3) at the school level using number of teachers as outcome and present the results in columns (1) and (2) of Appendix Table 6.[17] There is a small reduction in the number of teachers during the first years after the shock, which is expected, but I cannot reject that the point estimates are different between urban and rural schools. 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 columns (3) and (4) of Appendix Table 6. I do not observe any overall effect and, again, I cannot reject that the point estimates are different between urban and rural schools.

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 (2) using the number of schools per municipality as outcome. The results are presented in columns (5) and (6) of Appendix Table 6. The overall number of schools per municipality does not change after the weather shock, nor the effects vary between urban and rural schools.

These two results suggest that the weather shock did not strongly alter educational resources. There is no evidence to think that the policy reaction in terms of resources was different between school in urban and rural areas, despite the government's interest to face the crisis.

6.3 Poverty and Labor Markets

One remaining mechanism relates educational outcomes with increases in poverty that induce students to drop out of school and into the labor force. 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. I employ Colombian household surveys to test for this, and find evidence that unusual rainfall increases extreme poverty and induces rural kids in poor households into the labor force –especially into unem-

[17] I provide dynamic estimates for all the outcomes in Appendix Figure 2.

ployment. These effects, however, have to be interpreted with caution because of data limitations with the Colombian household surveys.[18] Economic activity and agricultural productivity seem to not be affected by the shock.

Increase in Poverty:– The heavy rains seem drive households into extreme poverty in both urban and rural areas. I estimate a modified version of Equations (2) and (3) using as outcomes the share of people in poverty and extreme poverty at the municipality level.[19] The results are presented in Table 4.[20] The heavy rains had a strong effect in the share of people in extreme poverty (as shown in Panel A), but did not affect the share of people living in poverty (as suggested by Panel B). The effect was similar in both urban and rural areas, significantly increasing the likelihood of falling into extreme poverty for students who were enrolled in school.

Labor Market Responses:– Increases in extreme poverty create incentives for children to join labor markets and, thereby, decrease schooling outcomes. Reactions to adverse shocks can be different for children living in rural and urban areas, since both labor markets behave differently. I test for this by employing again Colombian household surveys and testing for potential responses on children labor market outcomes. I estimate Equation (2) at the individual level, restricting the sample to kids between 10 and 18 years old, and use a dummy for unemployment, a dummy for employment (extensive margin), and the log of total labor hours (intensive margin) as outcomes.[21] The results are presented in Table 5, where I present results for all children and for those living in rural and urban areas separately.[22]

[18] I use the 2007 to 2018 rounds of the survey. Unfortunately, the survey does not cover all Colombian municipalities, but it constitutes the most detailed labor market survey surveying around 240,000 rural and urban households annually. A sub-sample of individuals in around 350 municipalities (out of 1,101) is included every year.

[19] I define poor as individuals with monthly household income per member smaller than 5.5 USD, and extremely poor as those below the 2.15 USD threshold.

[20] Appendix Figure 3 presents dynamic estimations, suggesting evidence of the non-existence of differential trends in the period prior to the shock.

[21] These specifications include municipality and month-by-rural fixed effects, and control for gender, age, age squared, parents education, and household size.

[22] I additionally present dynamic estimations in Appendix Figure 4 to test for pre-existing trends in the outcomes.

Unusual rainfall significantly increases the likelihood of a children being unemployed in rural areas but not in urban ones. Columns (1) to (3) of Table 5 show significant effects on the probability of being unemployed, that are all concentrated among kids in rural households. The magnitude of the point estimates also increases when focusing on poorer, rural kids, consistent with the evidence showing an increase in extreme poverty.

I then analyse if there are extensive (i.e., probability of being employed) or intensive (i.e., number of hours worked) margin responses in employment due to the unusual rainfalls. Columns (5) to (8) of Table 5 show the results using a dummy for employment as outcome, whereas columns (9) to (12) use the log of hours worked as dependent variable. There are no significant responses in the extensive margin, but there is a significant effect on the number of hours worked, which is concentrated among poor and very poor households. The point estimates among poorer kids are larger for those living in rural areas, as opposed to those in urban ones, but I cannot reject that the effects are statistically equal.

Altogether, these results suggest that the weather shock pushed kids in rural areas into unemployment and into working additional hours. The effect is monotonic with poverty, suggesting that it was particularly focused on kids living in poorer households. These results are fairly consistent with the evidence showing an increase of extreme poverty, posing a promising explanation for the decrease in schooling outcomes.

Effects in Economic Activity:– Lastly, I test if unusual rainfall decreases economic activity. Colombia does not have direct measures of economic activity at the municipality level, but night-time luminosity is a good proxy for economic activity, especially in developing countries (Henderson et al., 2012).[23]. I employ data by the the U.S. Air

[23] These measures seem to behave particularly well for Colombia, constituting a valuable measure of economic activity (Pérez-Sindín et al., 2021)

Force Defense Meteorological Satellite Program gathered through satellites that take multiple night-time lights measures every night.[24] I complement these results by estimating Equation (2) using agricultural production at the municipality level as outcome.[25] The results are plotted in Appendix Figures 5 and 6. The heavy rains had no effect neither on night-time light nor in agricultural production, suggesting that there was not an effect on overall economic activity or productivity.

These results pose suggestive evidence on why natural disasters affect more educational outcomes in rural areas. The weather shock increases poverty in both rural and urban areas, but poorer children in rural areas are more likely to join labor markets either by looking for a job (i.e., unemployed) or by increasing the time allocated to labor hours. Both results are consistent and suggest that children compensate for the lack of household resources by increasing labor supply, and this type of reaction is more concentrated among students in rural areas, where returns to education are lower (Herrendorf and Schoellman, 2018). Similar results have been found in alternative contexts in which children trade off the accumulation of human capital with child labor (Bau et al., 2020)

6.4 Health Vectors

An additional, yet unexplored, mechanism involves the effects of natural disasters on human capital accumulation through health-related factors. Previous studies have identified a causal link between natural disasters and the health of affected populations (Caruso, 2017; Maccini and Yang, 2009). These effects may be particularly pronounced among vulnerable populations with limited access to healthcare resources. As such, rural populations in developing countries could experience significant harm

[24] 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.

[25] 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.

from natural disasters, with consequences for future human capital accumulation. While analyzing these health-related mechanisms is beyond the scope of the current paper, it represents an important avenue for future research.

7 Conclusions

Natural disasters caused by heavy rainfall have been more prevalent in recent years, affecting a rising number of individuals worldwide (Dell et al., 2014). Recent evidence has shown that hurricanes, unusual rains, and natural disasters, in general, have detrimental effects on human capital accumulation, mostly in the United States (Özek, 2023; Opper et al., 2023; Sacerdote, 2012). Some other work has focused on analysing the effects in the developing world showing that natural disasters can additionally have inter-generational effects in human capital accumulation (Caruso, 2017).

This literature, however, has not yet addressed the heterogeneity in the effect of natural disasters between students in rural and urban areas. Rural students face differential incentives when deciding whether to school or not, and this makes them vulnerable when facing the social costs of a natural disaster. In addition, 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, but this is not its only determinant (Lagakos, 2020).

In this paper, I explore if natural disasters affect educational outcomes, and, at the same time, if it can complement the literature to explain the nature of the urban-rural gap. Natural disasters can affect urban and rural areas alike, but the effects of them on human capital accumulation may vary depending on the incentives to pursue additional education. 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 a large portion of the Colombian territory affecting more than two million people (around 560,000 households) in urban and rural areas. I estimate a difference-in-differences specification using this exogenous variation, and provide evidence about the validity of the research design.

The results suggest that heavy rain disruptions increase school dropout in a persistent fashion, and had long lasting effects in student learning. These effects are entirely driven by younger students in rural schools, whereas students in urban ones remain unaffected. This evidence is consistent with the persistent effects of natural disasters found elsewhere Andrabi et al. (2023). I then test if selective migration, losses in educational resources, or poverty leading to labor market responses 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 induced children into unemployment and into working additional hours. 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 labor supply to compensate for the increases in poverty. These results pose additional evidence of the tradeoff faced by students in the developing world between child labor and schooling (Bau et al., 2020) and imply very sizable losses in terms of life-time income for the affected youth.

The results of the paper show that heavy rainfall can have detrimental effects on student outcomes in the developing world, and it can be a driver of the existence of the urban-rural gap in human capital. Furthermore, these effects can persist during many years having long-lasting negative consequences for the economy. Jointly with lower returns to education in the agricultural sector, natural disasters can 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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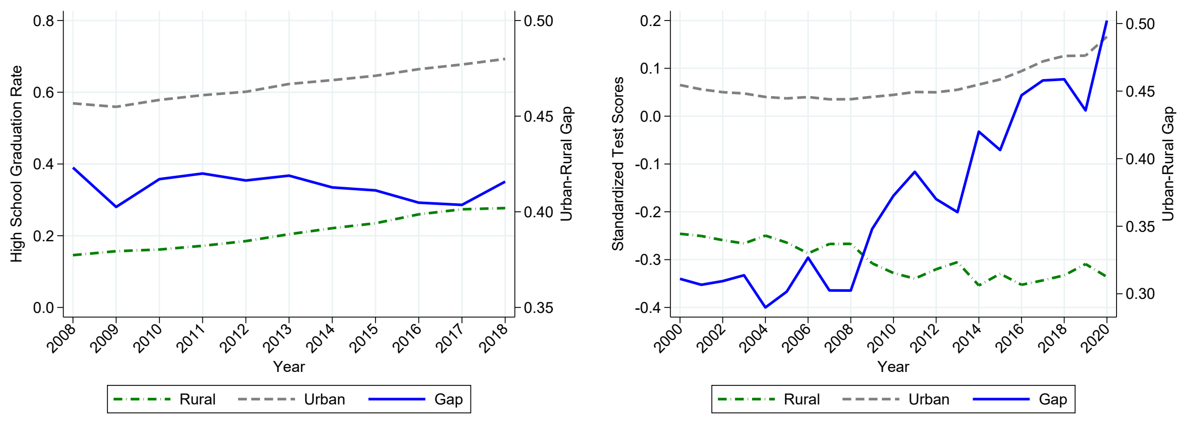
Figure 1: Urban-Rural Gap in Colombian Education

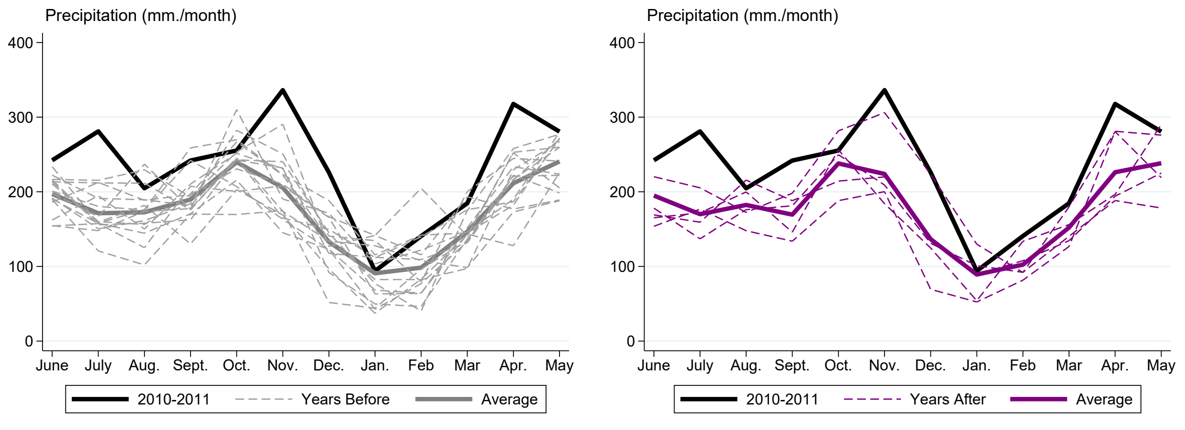
(a) Secondary School Graduation Rates (b) Scores in High School Exit Exam



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

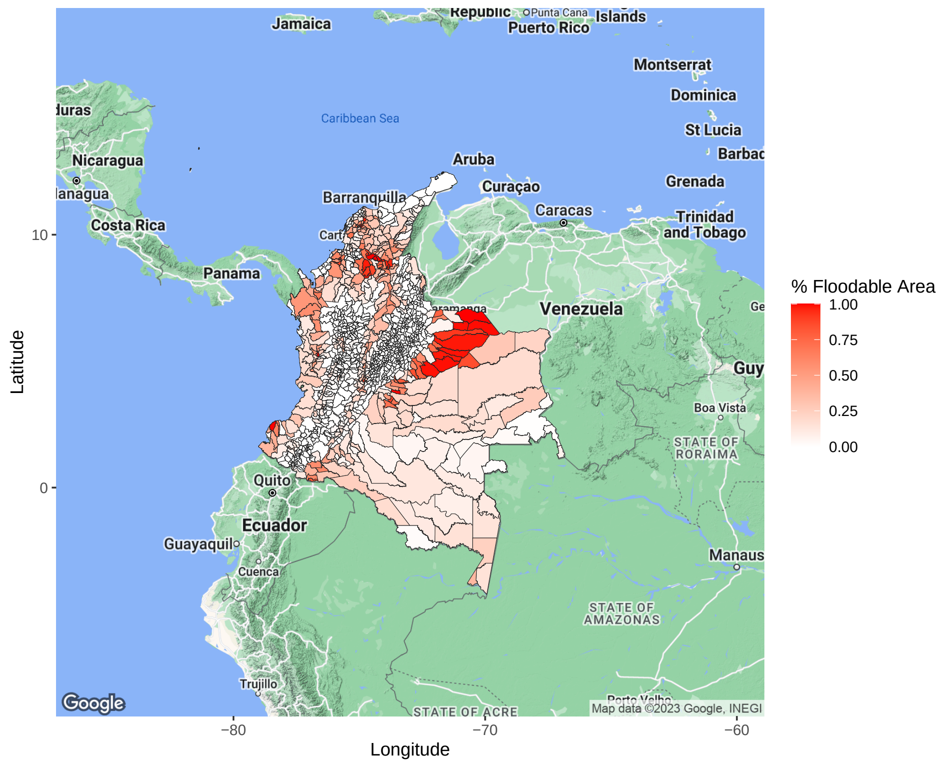
(a) Before 2010-2011 (b) After 2010-2011



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 (A_m^{2010})



(b) Affected Municipalities

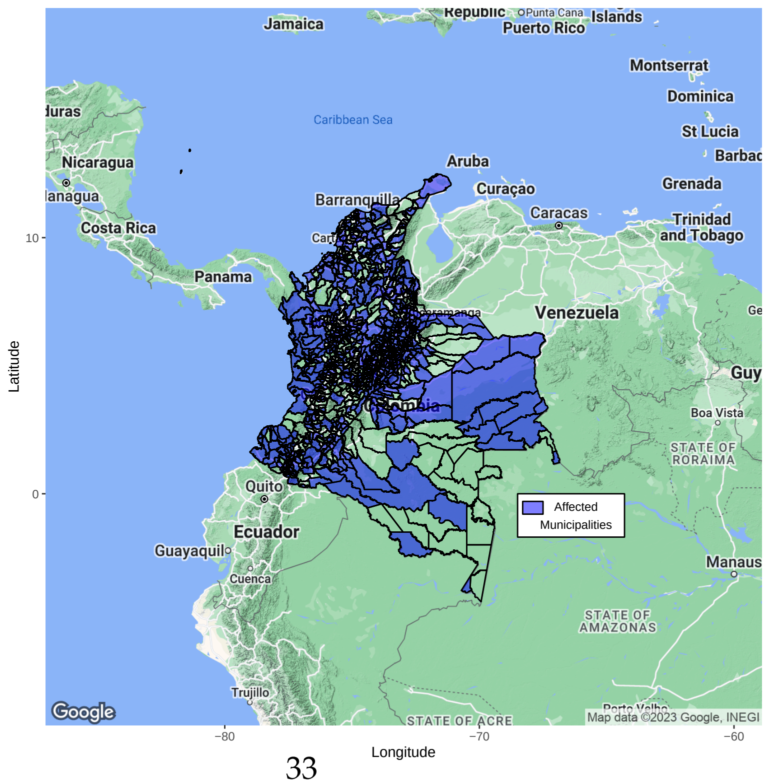
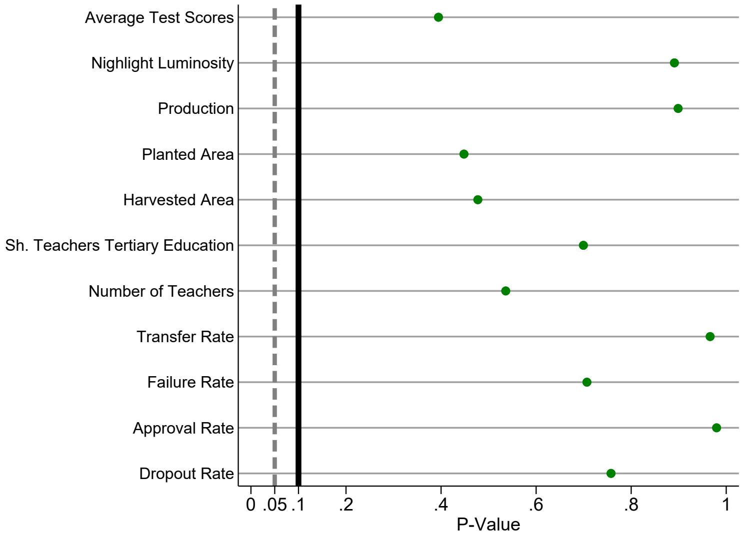


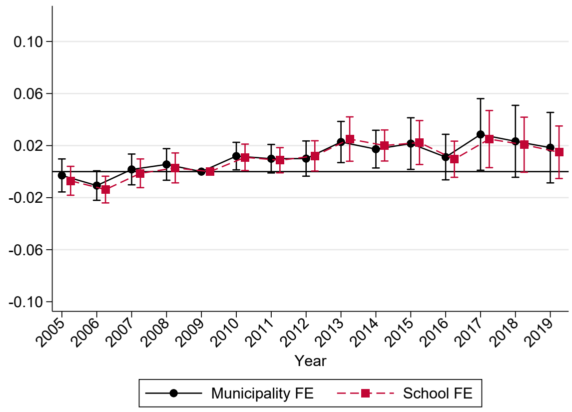
Figure 4: Balance of the Weather Shock



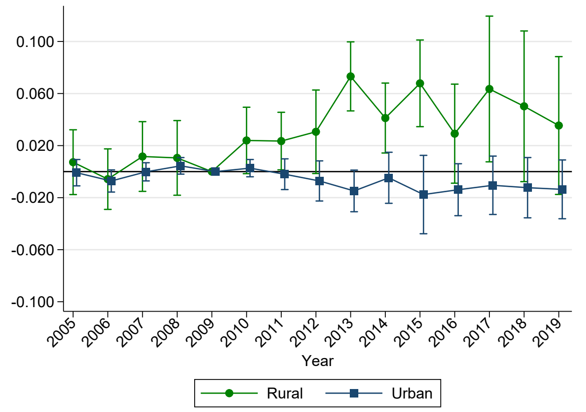
Notes. This figure presents the p-values of the coefficient in a regression between the variable in the y-axis and the measure of unusual rainfall, which is computed as the residuals of the regression between rainfall and predicted flooding. All the outcomes displayed in the y-axis are measured before 2010. The models are estimated in first differences, and include year fixed effects and state-specific trends. Standard errors are clustered at the municipality level.

Figure 5: Effects of Unusual Rain Disruption on Schooling Outcomes

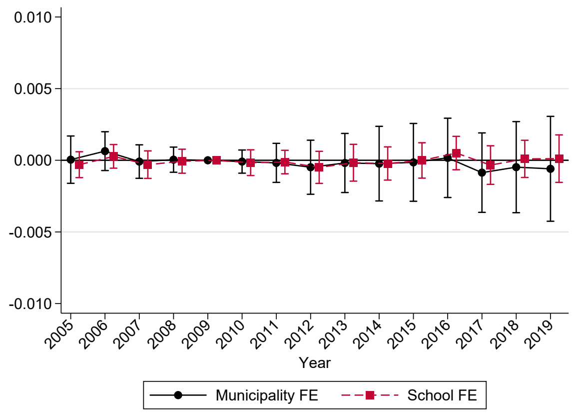
(a) Dropout Rate



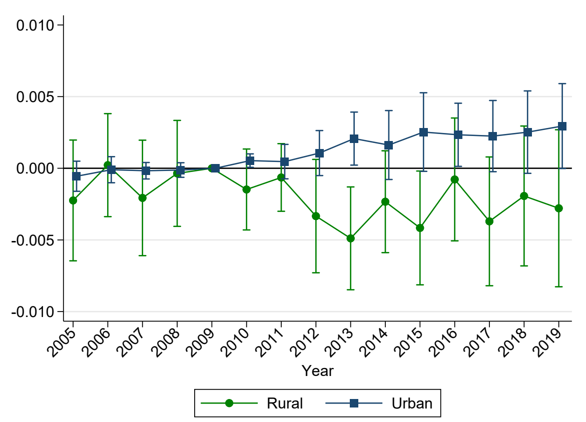
(b) Dropout Rate by Urban and Rural Schools



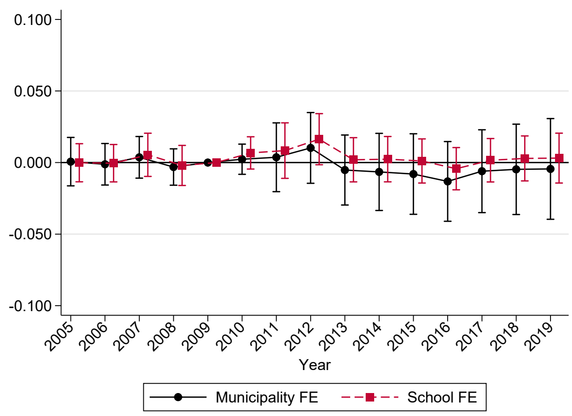
(c) Approval Rate



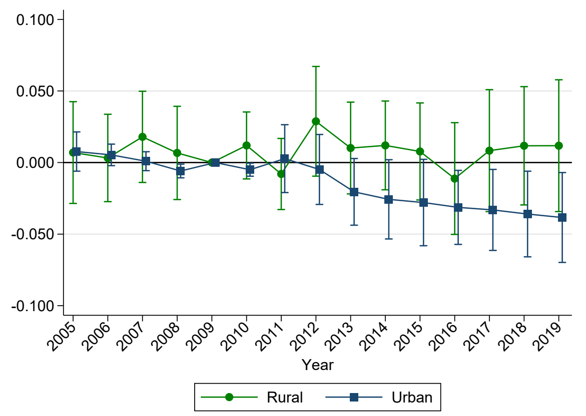
(d) Approval Rate by Urban and Rural Schools



(e) Failure Rate



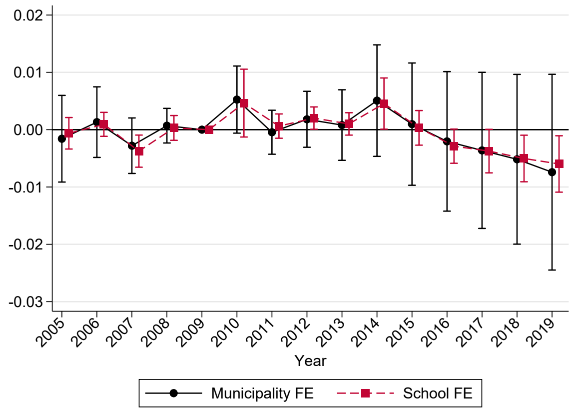
(f) Failure Rate by Urban and Rural Schools



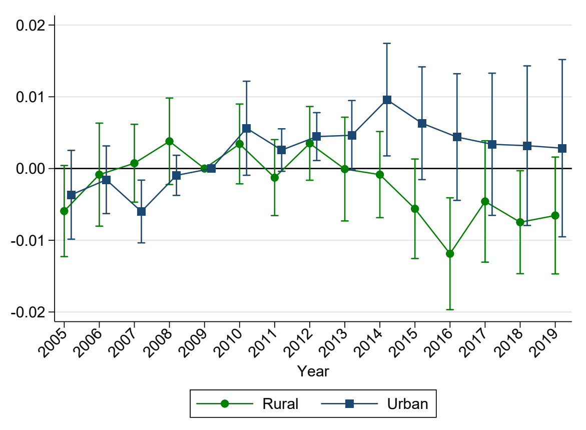
Notes. These figures present estimates of Equation (2) at the school level. The outcomes correspond to dropout, failure, and approval rates. All the models are estimated using a Poisson regression. Left panels include all schools (N = 653,101). The black line depicts a specification including municipality fixed effects, whereas the red line depicts a specification including school fixed effects. Right panels present estimates separately by urban ($N = 209,611$) and rural schools ($N = 443,490$), estimated including municipality fixed effects. All the estimations include rural-by-year fixed effects, dummies for the type of school, and state-specific trends. Standard errors clustered at the municipality level. 95 percent confidence intervals are displayed.

Figure 6: Effect of Unusual Rain Disruption on Test Scores of Remaining Students at the Moment of Graduation

(a) Overall



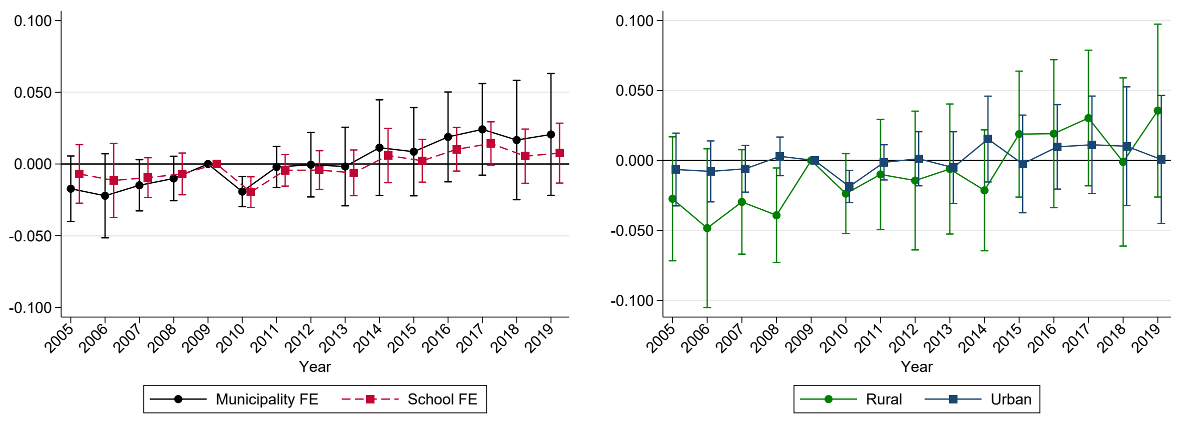
(b) Between Urban and Rural Schools



Notes. These figures present estimates of Equation (2) 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 ($N = 108,511$). 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 ($N = 71,038$) and rural schools ($N = 37,463$), estimated including school fixed effects. All the estimations include rural-by-year fixed effects, dummies for the type of school, and state-specific trends. Standard errors clustered at the municipality level. 95 percent confidence intervals are displayed.

Figure 7: Effects of Unusual Rain Disruption on School Transfer Rates

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



Notes. These figures present estimates of Equation (2) 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 ($N = 653,101$). 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 ($N = 209,611$) and rural schools ($N = 443,490$)), estimated including municipality fixed effects. All the estimations include rural-by-year fixed effects, dummies for the type of school, and state-specific trends. 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)
Weather*Post (β)	0.014**	-0.009	-0.000	0.001	-0.001	-0.006
	(0.006)	(0.009)	(0.001)	(0.001)	(0.014)	(0.019)
Weather*Post*Rural (γ)		0.046***		-0.003		0.008
		(0.018)		(0.002)		(0.022)
Rural ($\beta + \gamma$)		0.038		-0.002		0.002
p-value		0.001		0.332		0.918
Observations	653,101	653,061	653,101	653,097	653,101	653,053
Mean Dep. Var.	0.0527		0.856		0.0542	
School Controls	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes		Yes		Yes	
State Trends	Yes		Yes		Yes	
Year-By-Rural FE	Yes	Yes	Yes	Yes	Yes	Yes
Municip.-By-Rural FE		Yes		Yes		Yes
State-By-Rural Trends		Yes		Yes		Yes

Note: This table presents the results of the estimation of Equation (2) in a static fashion in odd columns and the estimation of Equation (3) 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 municipality fixed effects, year-by-rural fixed effects, and state-specific trends. Specifications in even columns include municipality-by-rural fixed effects, year-by-rural fixed effects, and state-by-rural trends. All specifications include a set of dummy variables capturing if the school offers primary-, secondary-, or middle-scool level education as school controls. Standard errors are clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1.

Table 2: Effects on Dropout Rates by Education Level

	Primary		Lower Secondary		Upper Secondary	
	(1)	(2)	(3)	(4)	(5)	(6)
Weather*Post (β)	0.019***	-0.007	-0.003	-0.010	-0.007	-0.008
	(0.007)	(0.008)	(0.004)	(0.008)	(0.006)	(0.009)
Weather*Post*Rural (γ)		0.049***		0.020		0.001
		(0.017)		(0.014)		(0.017)
Rural ($\beta + \gamma$)		0.042		0.010		-0.007
p-value		0.000		0.231		0.561
Observations	592,655	592,563	162,075	162,037	118,243	118,199
Mean Dep. Var.	0.0509		0.0533		0.0340	
School Controls	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes		Yes		Yes	
State Trends	Yes		Yes		Yes	
Year-By-Rural FE	Yes	Yes	Yes	Yes	Yes	Yes
Municip.-By-Rural FE		Yes		Yes		Yes
State-By-Rural Trends		Yes		Yes		Yes

Note: This table presents the results of the estimation of Equation (2) in a static fashion in odd columns and the estimation of Equation (3) in even columns. The outcomes correspond to dropout rates during primary, lower secondary secondary, and upper secondary school. Every rate is computed as the ratio of the number of students who dropout in each education level divided by the total number of students who were registered in that level. Estimations performed using Poisson regression. Estimations in odd columns include municipality fixed effects, year-by-rural fixed effects, and state-specific trends. Specifications in even columns include municipality-by-rural fixed effects, year-by-rural fixed effects, and state-by-rural trends. Standard errors are clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Effect of Unusual Rain Disruption on Test Scores of Remaining Students at the Moment of Graduation

	Average Score		Math		Reading		Natural Sciences		Social Sciences		English	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Weather*Post (β)	-0.000	0.004***	0.001	0.003**	0.006**	0.013***	0.002	0.004	0.001	0.002	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)
Weather*Post*Rural (γ)		-0.008***		-0.002		-0.013***		-0.004		-0.003		-0.002
		(0.003)		(0.003)		(0.003)		(0.003)		(0.003)		(0.002)
Rural ($\beta + \gamma$)		-0.004		0.001		0.001		0.000		-0.001		-0.001
p-value		0.131		0.846		0.827		0.861		0.878		0.870
Observations	108,501	108,501	108,501	108,501	108,501	108,501	108,501	108,501	108,501	108,501	108,501	108,501
School FE	Yes		Yes		Yes		Yes		Yes		Yes	
State Trends	Yes		Yes		Yes		Yes		Yes		Yes	
Year-By-Rural FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School-By-Rural FE		Yes		Yes		Yes		Yes		Yes		Yes
State-By-Rural Trends		Yes		Yes		Yes		Yes		Yes		Yes

Note: This table presents the results of the estimation of Equation (2) in a static fashion in odd columns and the estimation of Equation (3) 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 school fixed effects, state-specific trends, and year-by-rural fixed effects. Specifications in even columns include school-by-rural fixed effects, year-by-rural fixed effects, and state-by-rural trends. Standard errors are clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Effects of Unusual Rainfall on Poverty

	Overall (1)	Urban (2)	Rural (3)	Difference (4)
A) Extreme Poverty				
Weather*Post (β)	3.094***	2.734***	2.101**	2.734***
	(0.824)	(1.003)	(0.907)	(1.003)
Weather*Post*Rural (γ)				-0.633
				(1.021)
Rural ($\beta + \gamma$)				2.101
p-value				0.0205
B) Poverty				
Weather*Post (β)	0.433	0.129	-0.080	0.129
	(0.382)	(0.506)	(0.892)	(0.506)
Weather*Post*Rural (γ)				-0.209
				(0.784)
Rural ($\beta + \gamma$)				-0.0804
p-value				0.928
Observations	7,363	7,077	7,253	14,330
Municipality FE	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	
Mean Dep. Var.	0.805	0.735	0.885	
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 (2) at the municipality level using the share of people in extreme poverty (panel A) and poverty (panel B) as outcomes. Poverty is defined as having a daily household income per member below 5.5 USD, whereas extreme poverty is defined as below 2.15 USD. Column 4 displays the result of estimating Equation (3) at the municipality level. Estimations are performed using Poisson regression at the municipality level. 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 of Unusual Rainfall on Children Labor Market Outcomes

	Unemployed				*Employed*				*log(Labor Hours)*			
	Overall	Urban	Rural	Difference	Overall	Urban	Rural	Difference	Overall	Urban	Rural	Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A) Overall												
Weather*Post (β)	0.030	0.026	0.147***	0.027	-0.010	-0.006	-0.169	-0.006	0.691	0.748	-0.498	0.747
	(0.029)	(0.031)	(0.043)	(0.031)	(0.125)	(0.127)	(0.216)	(0.127)	(0.461)	(0.502)	(0.667)	(0.510)
Weather*Post*Rural (γ)				0.128**				-0.182				-1.161
				(0.053)				(0.234)				(0.871)
Rural				0.155				-0.188				-0.414
P-value				0.000420				0.365				0.526
Observations	2,326,813	2,087,322	239,491	2,326,813	2,326,813	2,087,322	239,491	2,326,813	157,994	128,921	29,056	157,977
B) Poor												
Weather*Post (β)	0.024	0.019	0.184***	0.019	-0.041	-0.042	-0.039	-0.042	1.189*	1.158*	1.914**	1.165*
	(0.038)	(0.041)	(0.055)	(0.041)	(0.110)	(0.112)	(0.297)	(0.112)	(0.653)	(0.695)	(0.935)	(0.700)
Weather*Post*Rural (γ)				0.170**				-0.054				0.798
				(0.071)				(0.291)				(1.289)
Rural				0.189				-0.0964				1.964
P-value				0.000685				0.736				0.0387
Observations	1,249,917	1,130,886	119,030	1,249,916	1,249,917	1,130,886	119,030	1,249,916	71,900	59,801	12,058	71,859
C) Extremely Poor												
Weather*Post (β)	0.012	0.007	0.178**	0.007	-0.029	-0.029	-0.144	-0.028	1.680*	1.654	2.608*	1.654
	(0.040)	(0.043)	(0.080)	(0.043)	(0.097)	(0.096)	(0.456)	(0.096)	(0.989)	(1.076)	(1.513)	(1.081)
Weather*Post*Rural (γ)				0.176*				-0.152				0.978
				(0.094)				(0.432)				(1.947)
Rural				0.183				-0.179				2.632
P-value				0.0243				0.685				0.0819
Observations	597,249	540,534	56,710	597,244	597,249	540,534	56,710	597,244	29,151	24,097	4,987	29,084
Municipality FE	Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes	
Month-by-year FE	Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes	
Rural-by-Month-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality-by-rural FE				Yes				Yes				Yes

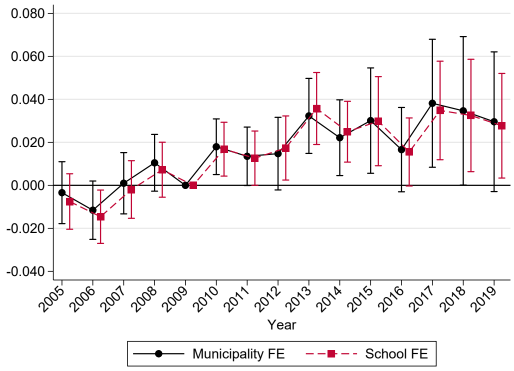
Note: This table presents the results of an estimation at the individual level in a sample of children between five and 18 years of age. The estimations are performed using the Colombian household survey data from 2007 to 2018 which is gathered at the monthly level. The outcomes correspond to dummy variables taking the value of one if the individual is unemployed, employed, and log of hours worked. Models are estimated using a linear probability model. Columns (1)-(3), (5)-(7), and (9)-(11) include municipality fixed effects, month-by-rural fixed effects, and control for gender, age, age squared, parents' education, and household size. Columns (4), (8), and (12) interact the weather shock and the fixed effects by a dummy variable taking the value of one if the individual lives in a rural area. Standard errors clustered at the municipality level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix: Additional Figures and Tables

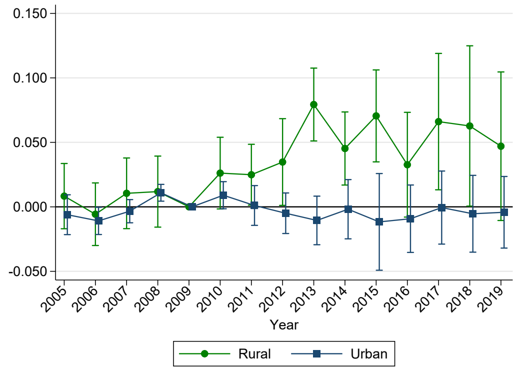
A Figures

Appendix Figure 1: Effects of Unusual Rain Disruption on Dropout Rates by Type of School

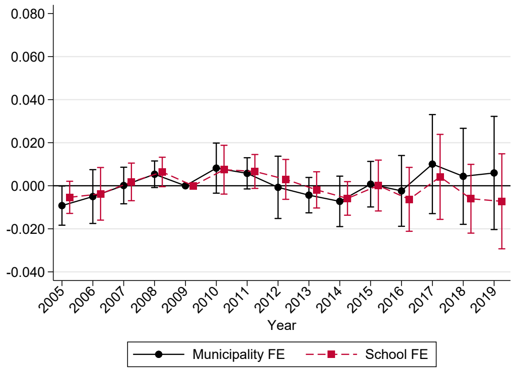
(a) Primary School



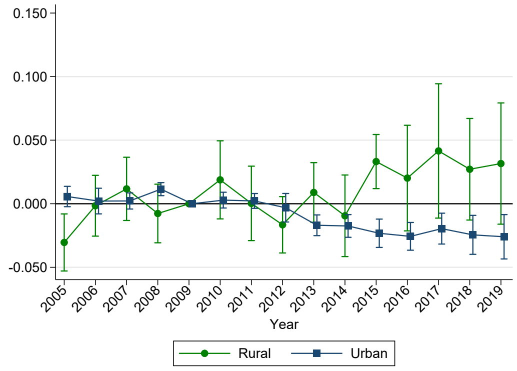
(b) Primary School (Urban VS Rural)



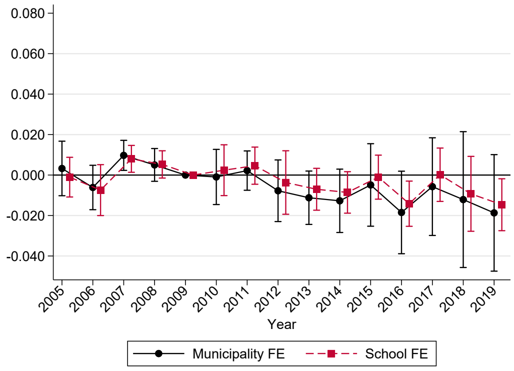
(c) Lower-Secondary School



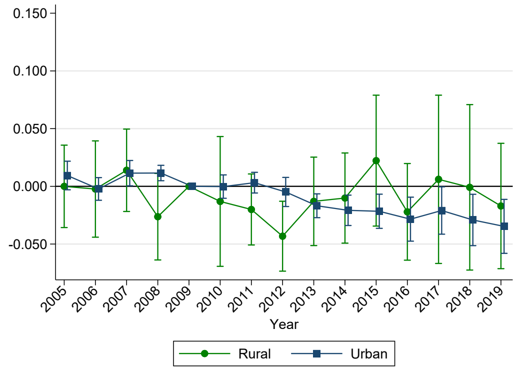
(d) Lower Secondary School (Urban VS Rural)



(e) Upper Secondary School



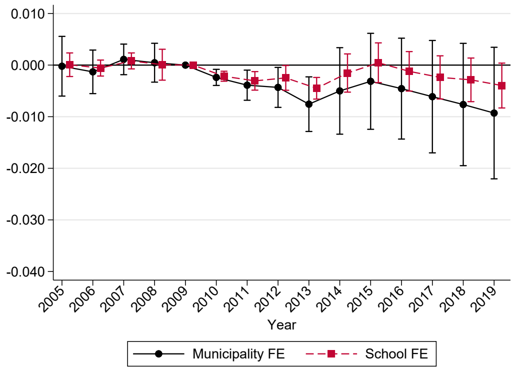
(f) Upper Secondary School (Urban VS Rural)



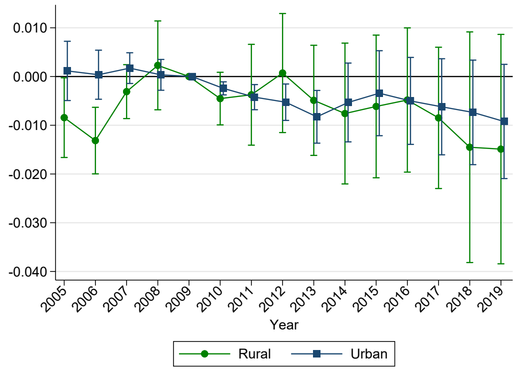
Notes. These figures present estimates of Equation 2 at the school level. The outcome corresponds to the dropout rate in different school levels. All the models are estimated using a Poisson regression. Left panels include all schools. The black line depicts a specification including municipality fixed effects, whereas the red line depicts a specification including school fixed effects. Right panels present estimates separately by urban and rural schools, estimated including municipality fixed effects. All the estimations include rural-by-year fixed effects and state-specific trends. Standard errors clustered at the municipality level. 95 percent confidence intervals are displayed.

Appendix Figure 2: Effects of Unusual Rain Disruption on School Resources

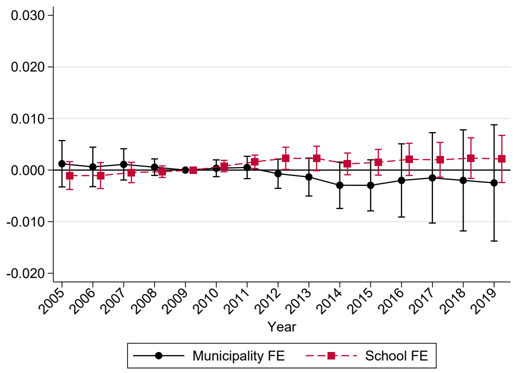
(a) Number of Teachers (Overall)



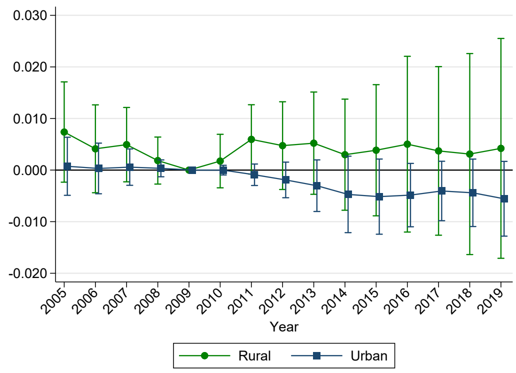
(b) Number of Teachers (Urban VS Rural)



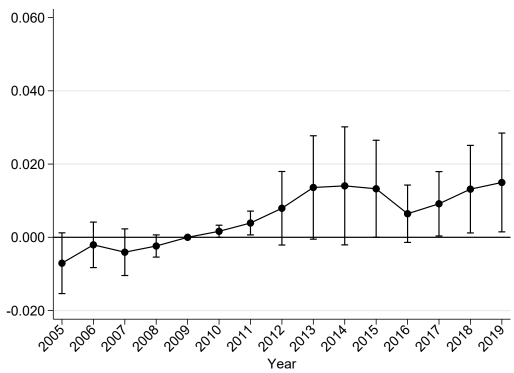
(c) Share Teachers with Tertiary Education (Overall)



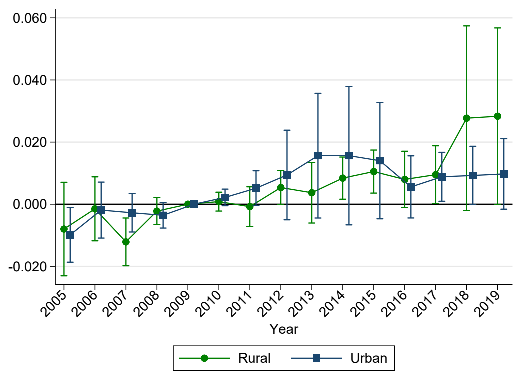
(d) Share Teachers with Tertiary Education (Urban VS Rural)



(e) Number of Schools per Municipality (Overall)



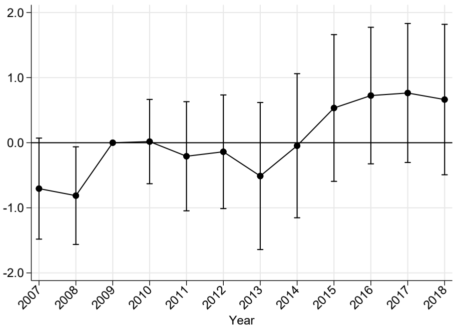
(f) Number of Schools per Municipality (Urban VS Rural)



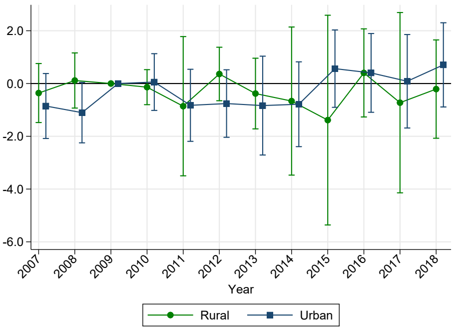
Notes. These figures present estimates of Equation (2) at the school level (panels 2a, 2b, 2c, and 2d) and municipality levels (panels 2e and 2f). The outcomes correspond to the number of teachers per school, the share of teachers with tertiary education, and number of schools per municipality. All models are estimated using a Poisson regression. Left panels include overall estimations, whereas right panels present estimates separately by urban and rural schools, estimated including municipality fixed effects. The first four estimations include school/municipality fixed effects, year-by-rural fixed effects, state-specific trends, and dummies for the type of school. The last two estimations include municipality and year fixed effects, and state-specific trends. Standard errors clustered at the municipality level. 95 percent confidence intervals are displayed.

Appendix Figure 3: Effects of Unusual Rain Disruption on Poverty

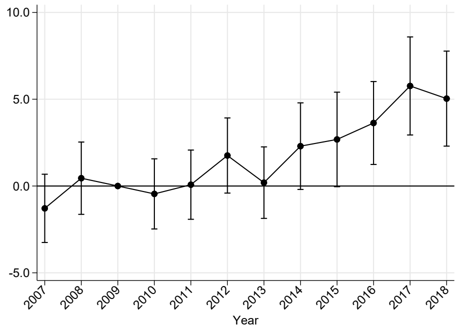
(a) Poverty (Overall)



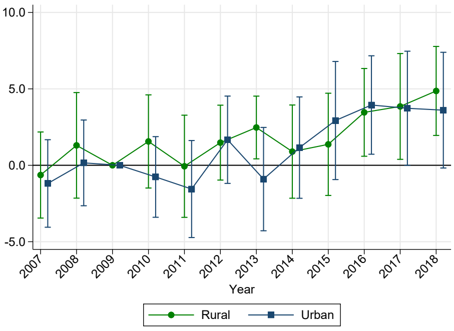
(b) Poverty (Urban VS Rural)



(c) Extreme Poverty (Overall)



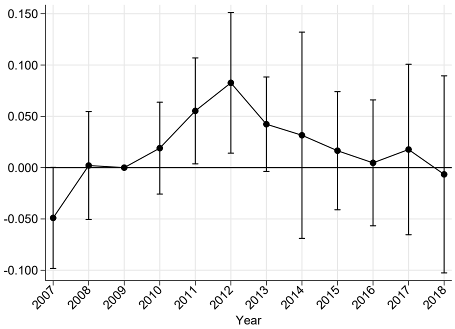
(d) Extreme Poverty (Urban VS Rural)



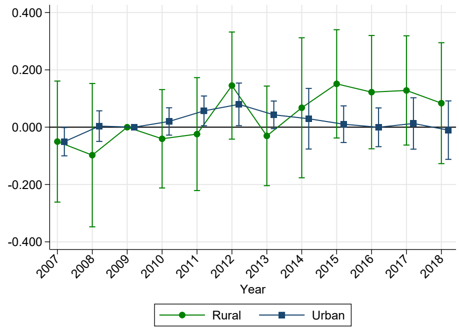
Notes. These figures present estimates of Equation (2) at the municipality level using the share of people in poverty (panels 3a and 3b) and extreme poverty (panels 3c and 3d) as outcomes. All the models are estimated using a Poisson regression. Left panels pool across all municipalities ($N = 7,363$). The black line depicts a specification including municipality and year fixed effects. Right panels present estimates separately by urban ($N = 7,077$) and rural schools ($N = 7,253$), estimated including municipality and year fixed effects. Standard errors clustered at the municipality level. 95 percent confidence intervals are displayed.

Appendix Figure 4: Effects of Unusual Rain Disruption on Labor Market Outcomes

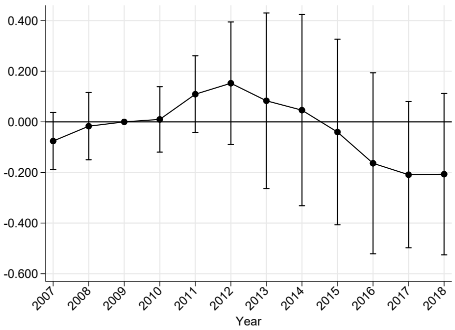
(a) Unemployed



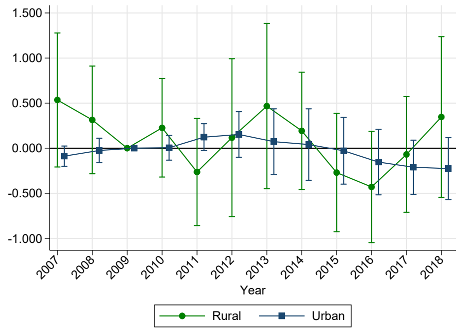
(b) Unemployed by Urban and Rural



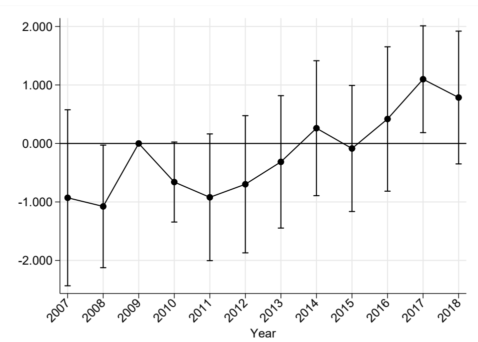
(c) Employed



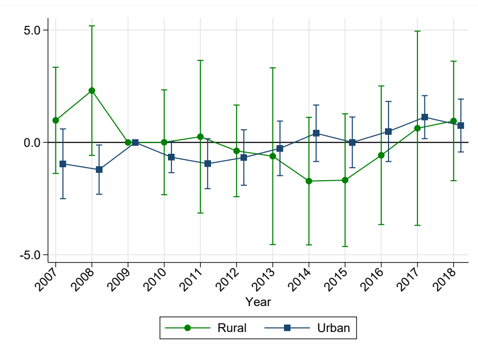
(d) Employed by Urban and Rural



(e) Log(Hours Worked)



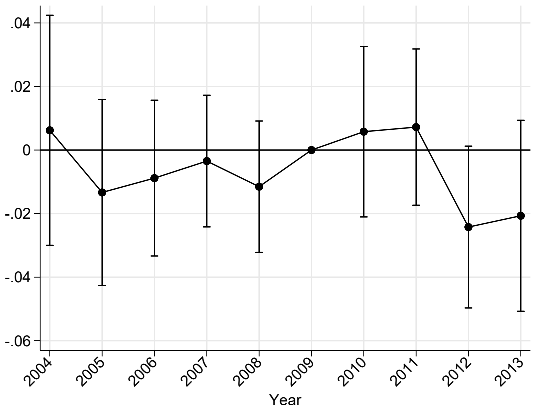
(f) Log(Hours Worked) by Urban and Rural



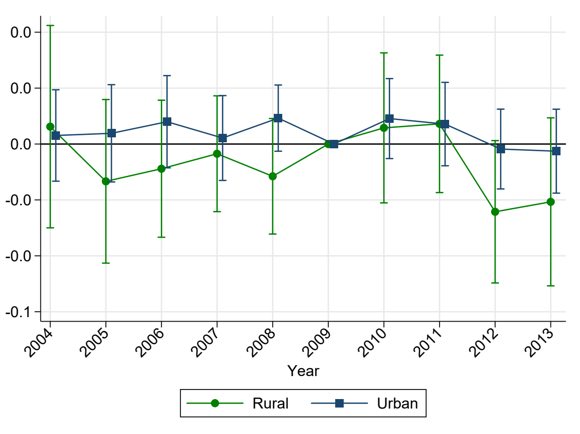
Notes. These figures present estimates at the individual level in a sample of children between five and 18 years of age. The estimations are performed using the Colombian household survey data from 2007 to 2018 which is gathered at the monthly level. The outcomes correspond to dummy variables taking the value of one if the individual is unemployed, if she is employed, and log of hours worked. Left panels include all individuals, whereas right panels present estimates separately by those living in urban and rural schools. All specifications include municipality and month-by-rural fixed effects, and control for gender, age, age squared, parents education, and household size. Standard errors clustered at the municipality level. 95 percent confidence intervals are displayed.

Appendix Figure 5: Effects of Unusual Rain Disruption on Night-Time Luminosity

(a) Overall



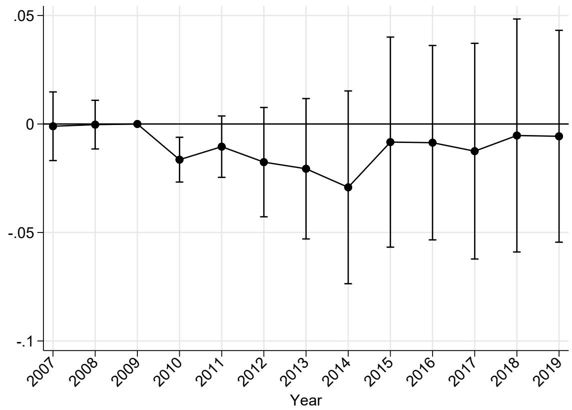
(b) Between Urban and Rural Schools



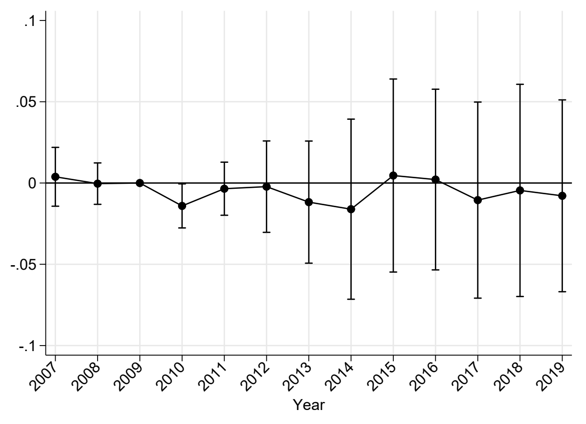
Notes. These figures present estimates of Equation 2 at the municipality level. The outcome corresponds to the log of the area-weighted average of night-time lights at the municipality level from the Defense Meteorological Satellite Program gathered from Li et al. (2022). It includes data from satellites 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.

Appendix Figure 6: Effects of Unusual Rain Disruption on Agricultural Production

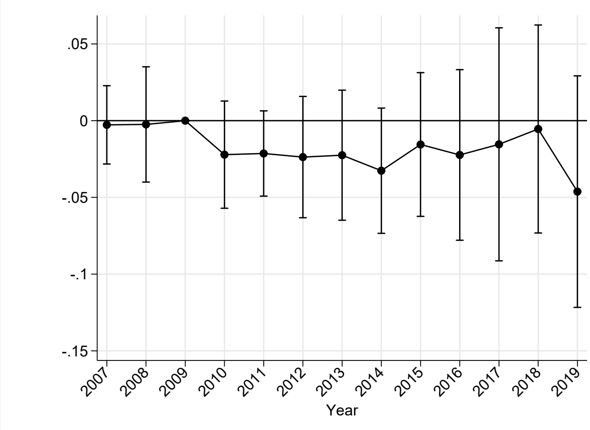
(a) Planted Area



(b) Harvested Area



(c) Production (Tons)



Notes. These figures present estimates of Equation (2) at the municipality level. Estimations performed using Poisson regression. The outcomes correspond to number of planted hectares in Panel 6a, the number of harvested hectares in Panel 6b, and to the volume of agricultural production (measured in tons) in Panel 6c. All the estimations include year and municipality fixed effects, and standard errors clustered at the municipality level. 95 percent confidence intervals are displayed.

B Tables

Appendix Table 1: Descriptive Statistics

	Obs. (1)	Mean (2)	Stand. Dev. (3)	Median (4)	Max. (5)	Min. (6)
A) Municipality Shock						
Precipitation	832	5930.43	6426.89	3902.10	70251.30	45.40
Area Under Risk of Flooding (%)	832	0.12	0.23	0.00	1.00	0.00
Standardized Residuals (w_m^{2010})	832	0.00	1.00	-0.29	10.15	-1.29
B) Census of Schools						
Rural School (%)	653,101	0.68	0.47	1.00	1.00	0.00
Public School (%)	653,101	0.82	0.39	1.00	1.00	0.00
Pre-School (%)	653,101	0.90	0.30	1.00	1.00	0.00
Primary School (%)	653,101	0.93	0.25	1.00	1.00	0.00
Lower-Secondary School (%)	653,101	0.30	0.46	0.00	1.00	0.00
Upper-Secondary School (%)	653,101	0.28	0.45	0.00	1.00	0.00
Dropout Rate (%)	653,101	0.05	0.08	0.02	1.00	0.00
Approval Rate (%)	653,101	0.86	0.14	0.89	1.00	0.00
Failure Rate (%)	653,101	0.05	0.08	0.03	1.00	0.00
Transfer Rate (%)	653,101	0.04	0.07	0.00	1.00	0.00
Number of Students	653,101	205.49	382.49	53.00	8925.00	1.00
Number of Teachers	647,271	8.89	15.05	3.00	978.00	0.00
Teachers with tertiary education (%)	647,204	0.73	0.38	1.00	1.00	0.00
c) Test Score Measures						
Average Score (σ)	108,501	-0.00	0.73	-0.14	5.07	-2.76
Math Score (σ)	108,501	-0.02	0.60	-0.10	6.82	-2.49
Reading Score (σ)	108,501	-0.02	0.60	-0.08	4.48	-2.79
Nat. Sciences Score (σ)	108,501	0.00	0.62	-0.09	4.73	-3.06
Soc. Sciences Score (σ)	108,501	-0.01	0.57	-0.07	3.40	-2.84
English Score (σ)	108,501	0.02	0.76	-0.18	5.18	-5.59

Appendix Table 2: Balance of the Weather Shock

	Dropout Rate (1)	Approval Rate (2)	Failure Rate (3)	Transfer Rate (4)	Number of Teachers (5)	Sh. Teachers Tert. Education (6)	Harvested Area (7)	Planted Area (8)	Agricultural Production (9)	Nighlight Luminosity (10)	Average Test Scores (11)
Weather Shock	0.007	0.001	-0.009	0.001	0.139	-0.031	0.532	0.462	-0.106	0.056	-0.174
	(0.024)	(0.039)	(0.024)	(0.016)	(0.225)	(0.080)	(0.748)	(0.609)	(0.833)	(0.405)	(0.204)
Observations	3,319	3,319	3,319	3,319	3,319	3,319	1,626	1,626	1,626	3,117	3,158
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Specific Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the results of estimating a linear regression of the weather shock on outcomes measured before 2010. The outcome is estimated in first differences, and includes year fixed effects, and state-specific trends. Standard errors are clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 3: Robustness of the Effect to Alternative Definitions of the Weather Shock

	Dropout Rate		Approval Rate		Failure Rate	
	(1)	(2)	(3)	(4)	(5)	(6)
A) Controlling by Rain in Previous Years						
Weather*Post (β)	0.013**	-0.006	-0.001	0.001	0.010	-0.002
	(0.006)	(0.008)	(0.001)	(0.001)	(0.013)	(0.016)
Weather*Post*Rural (γ)		0.040**		-0.005**		0.024
		(0.018)		(0.002)		(0.020)
Rural ($\beta + \gamma$)		0.034		-0.004		0.022
p-value		0.006		0.043		0.214
B) Controlling by Predicted Flooding and Rain in Previous Years						
Weather*Post (β)	0.012**	-0.006	-0.001	0.001	0.010	-0.002
	(0.006)	(0.008)	(0.001)	(0.001)	(0.013)	(0.016)
Weather*Post*Rural (γ)		0.040**		-0.005**		0.023
		(0.018)		(0.002)		(0.020)
Rural ($\beta + \gamma$)		0.034		-0.004		0.021
p-value		0.007		0.044		0.231
Observations	652,497	652,458	652,497	652,494	652,497	652,450
Mean Dep. Var.	0.0527		0.856		0.0542	
School Controls	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes		Yes		Yes	
State Trends	Yes		Yes		Yes	
Year-By-Rural FE	Yes	Yes	Yes	Yes	Yes	Yes
Municip.-By-Rural FE		Yes		Yes		Yes
State-By-Rural Trends		Yes		Yes		Yes

Note: This table presents the results of the estimation of Equation (2) in a static fashion in odd columns and the estimation of Equation (3) in even columns. Panel A defines the weather shock as the residuals of the regression of rainfall in 2010 on rainfall from 1994-2009. Panel B defines the weather shock as the residuals of a regression of rainfall in 2010 on rainfall from 1994-2009 and predicted flooding. 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 municipality fixed effects, year-by-rural fixed effects, and state-specific trends. Specifications in even columns include municipality-by-rural fixed effects, year-by-rural fixed effects, and state-by-rural trends. All specifications include a set of dummy variables capturing if the school offers primary-, secondary-, or middle-scool level education as school controls. Standard errors are clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 4: Effects on Share of Students who Transfer School

	(1)	(2)
Weather*Post (β)	0.016	0.008
	(0.012)	(0.010)
Weather*Post*Rural (γ)		0.021
		(0.013)
Rural ($\beta + \gamma$)		0.029
p-value		0.109
Observations	653,101	653,011
Mean Dep. Var.	0.0373	
School Controls	Yes	Yes
Municipality FE	Yes	
State Trends	Yes	
Year-By-Rural FE	Yes	Yes
Municip.-By-Rural FE		Yes
State-By-Rural Trends		Yes

Note: This table presents the results of the estimation of Equation (2() in a static fashion in columns (1) and the estimation of Equation (3) in column (2). The outcome corresponds to the share of students who transfer school. Estimations performed using Poisson regression. The specification in column (1) includes municipality fixed effects, year-by-rural fixed effects, and state-specific trends. The specification in column (2) includes municipality-by-rural fixed effects, year-by-rural fixed effects, and state-by-rural trends. All specifications include a set of dummy variables capturing if the school offers pre-, primary-, secondary-, or middle-scool level education as school controls. Standard errors are clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 5: Effects on Municipalities' Population

	Overall (1)	Urban (2)	Rural (3)	Difference (4)
Weather*Post (β)	-0.001	-0.005	0.043***	-0.005
	(0.002)	(0.003)	(0.010)	(0.003)
Affected*Post*Rural (γ)				0.048***
				(0.011)
Rural ($\beta + \gamma$)				0.043
p-value				0.000
Observations	1,662	1,644	1,662	3,306
Municipality FE	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	
Mean Dep. Var.	46417	36704	10110	
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 (2() with two periods using the municipalities' population as outcome. Column 4 displays the result of estimating Equation (3). 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 Table 6: No Differential Effects on School Resources by Urban and Rural Schools

	Number of Teachers		Teachers with Tertiary Educ. (%)		Schools in Municipality	
	(1)	(2)	(3)	(4)	(5)	(6)
Weather*Post (β)	-0.003	-0.004*	-0.001	-0.002	0.010	0.010
	(0.002)	(0.002)	(0.002)	(0.003)	(0.007)	(0.008)
Weather*Post*Rural (γ)		0.002		0.004		0.006
		(0.004)		(0.008)		(0.006)
Rural ($\beta + \gamma$)		-0.002		0.001		0.016
p-value		0.699		0.814		0.002
Observations	647,271	647,267	647,204	647,198	12,460	23,113
Mean Dep. Var.	8.479		0.728		45.26	
School Controls	Yes	Yes	Yes	Yes		
Municipality FE	Yes		Yes		Yes	
State Trends	Yes		Yes		Yes	
Year-By-Rural FE	Yes	Yes	Yes	Yes		Yes
Municip.-By-Rural FE		Yes		Yes		Yes
State-By-Rural Trends		Yes		Yes		Yes
Year FE					Yes	

Note: This table presents the results of the estimation of Equation (2) in a static fashion in odd columns and the estimation of Equation (3) in even columns. The outcomes correspond to the number of teachers per school, the share with tertiary education, and the total number of schools per municipality. Estimations performed using Poisson regression. Estimates in columns (1) to (4) are estimated at the school level, whereas estimates in column (5) are performed at the municipality level, and those in column (6) at the municipality-by-rural level. Estimations in columns (1) and (3) include school controls, municipality fixed effects, year-by-rural fixed effects, and state specific trends. Estimations in columns (2) and (4) include school controls, municipality-by-rural fixed effects,, year-by-rural fixed effects, and state-by-rural trends. Point estimates in column (5) include municipality and year fixed effects, and state-specific trends. Estimates in column (6) include municipality-by-rural fixed effects, year-by-rural fixed effects, and state-by-rural trends. School controls include 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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.