After the storm: the effects of natural disasters on cognitive skill's formation.

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Abstract

In this paper, I explore the impact of natural disasters on education. For this purpose, I bring together unique data on the exposure to several natural disasters and cognitive skills observed at the school levels. Applying one of the most recent events study methodologies, I evaluate if the experience of more severe climate disasters reduces student performance in standardized cognitive tests. Moreover, using detailed information from the Colombian Ministry of Education, I also explore the effect of natural disasters on dropout, absenteeism, and grade retention rates. In line with prior literature on the consequences of natural disasters on education, I find that natural disasters negatively affect students' cognitive skills. They reduce the standardized test scores, increase the share of students at the insufficient level and increase it on the advanced and satisfactory levels. Moreover, they raise the dropout and absenteeism rates. In that sense, my conclusions highlight the importance of the strategies to promote the academic recovery of victims of natural disasters.

Keywords: Natural disasters; Climate change; Cognitive skills, Dropout; Absenteeism; Human development, Education quality; Negative shocks; Event studies.

JEL codes: I25; J13; O15; Q54.

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1 Introduction

Between 2005 and 2014, natural disasters affected 196 million people, claimed nearly 100,000 lives, and caused more than US $159 billion in direct losses worldwide (IPCC, 2021). These direct losses occasioned by disasters are the immediate consequences of the physical phenomenon and are often classified into market losses and intangible losses. Additionally, disasters can produce indirect losses caused by their secondary effects, not by the physical hazard itself. Such costs usually span more extended periods, larger spatial units, or different economic sectors than the initial event (World Bank, 2014).

Consequently, the indirect effects of disasters are harder to measure and often can be overlooked. This bias has led the valuations of natural disasters to ignore their impacts on critical aspects, such as increases in poverty and reductions in human capital (McDermott, 2012). Therefore, it is essential to make better assessments of damages caused by disasters that account for their higher-order consequences (World Bank, 2014).

One of these higher-order consequences is affectation on human development. Literature has clearly established that early and young-life events can affect adulthood outcomes. Foremost, early childhood is a critical stage where future fundamental abilities and health trajectories are tempered by the environment's characteristics (Heckman, 2006). Besides, young people in their teens experience physical and psychological changes, primarily determined by social and cultural factors, that can anticipate threats to adult health and well-being (Richter, 2006).

Thus, given that natural disasters are *"a serious disruption of the functioning of a community or a society at any scale due to hazardous events interacting with conditions of exposure, vulnerability, and capacity, leading to one or more of the following: human, material, economic and environmental losses, and impacts*" (United Nations Office for Disaster Risk Reduction, 2022), it is not surprising that they have particularly negative consequences over children and adolescents.

Therefore, understanding the effects of external shocks associated with climate change on human capital formation is a significant step in estimating the indirect costs of disasters and generating adequate responses. This effort is necessary given that a disaster's welfare impact can't be measured only by the physical characteristics of the event or by its direct implications on lost lives and assets (Hallegatte, 2014).

Under this framework, I analyze the effects of natural disasters on students' cognitive skills development in rural areas of Colombia and test the hypothesis that greater exposure to natural disasters is associated with lower scores on standardized tests. My theory is grounded on evidence of the adverse effects of natural disasters on human capital accumulation and on evidence of children's and adolescents' vulnerability to external circumstances. Natural disasters may decrease income levels, undermine the normal functioning of public services, such as schools, displace the population, and increase the prevalence of physical and mental diseases. Literature has demonstrated that certain demographic groups, such as children and the elderly, are particularly vulnerable to these detrimental effects (Dell et al., 2014).

For that purpose, I develop a model of event studies using a novel source of information: the Unique Register of Victims (RUD), which characterizes the affectations of natural disasters on the Colombian population. Empirically, I construct a measure of exposure to natural disasters for nearly 40,000 of the existing rural schools in the Country. Second, I build a detailed panel dataset at the school level containing information for every school from three aspects: i) the student's level of cognitive skills measured in standardized academic tests and academic trajectory indicators such as dropout, absenteeism, and grade retention; ii) the teacher's education level and the students-teacher ratio; and iii) students' socioeconomic aspects such as the nutrition level, the number of students who work, their perspectives about economic conditions, the highest level of studies attained by students' mothers, and the number of members per household.

Then, I use one of the latest econometric methods developed by Dechaisemartin & D'hautfeuille (2022a) to find the causal effect of schools' exposure to a natural disaster. Essentially, I exploit the geographic space and time variations of the disasters that occurred in Colombia between 2016 and 2019 to estimate their causal impact on students' academic performance. Under this method, I recover the causal effect of natural disasters by comparing schools already impacted by natural disasters (treated) with schools that have not yet been affected by natural disasters but that will later be affected by them (not yet treated).

This approach allows me to contribute to the economic literature in four ways. First, I employ the Unique Register of victims[1] (RUD), which is the only official report of natural disasters in Colombia. It contains 10,864 observations representing households affected by 542 disasters between 2016 and 2019. This dataset allows me to build a refined measure of the disasters for two main reasons. First, I can observe the location of the disasters and assign them to a village or a neighborhood. This assignment implies that I can exploit greater levels of

[1] Registro único de damnificados in Spanish

geographical variation than other papers in the literature that use more aggregated measures of disasters, such as precipitation stations (Brando and Santos, 2015) or municipality reports of disasters (Alamir and Heidelk, 2020) have made. Second, as every observation on it corresponds to the claims of households who face difficulties in coping with the disasters and claim resources from the National Government, it grasps socioeconomic affectations, and not only geological aspects. The latter distinction is crucial because disasters of the same geological magnitude can have very different welfare effects depending on the ability of the affected economy to cope, recover and reconstruct itself (World Bank, 2014).

Second, I expand the focus of previous studies by comparing how the harmful effects of natural disasters vary according to their affected populations' ages. In particular, I observe the impacts of disasters on students' academic performance in the 3rd, 5th, 9th and 11th grades. Therefore, I explore the differential impacts of disasters on students who range from 8 up to 18 years old. Most of the existing literature has studied exposure to disasters at early stages such as gestation or the first five years of age (Brando & Santos, 2015; Duque et al., 2014; Adhvaryu et al., 2018). Although this period is critical for developing skills and physical conditions (Heckman, 2006), during childhood and adolescence, individuals interact with the environment to shape pathways to adulthood and are also sensitive to external circumstances (Richter, 2006). Besides, most children under age five have not begun their studies, and they lack the support that schools can have to mitigate the adverse effects of disasters on learning. For example, Andrabi et al., (2021) have found that educated mothers could minimize the learning losses of children who suffered the Pakistan earthquake. In that sense, it is interesting to assess whether the effects of disasters on school-aged children differ from what the literature has found for younger children.

Third, I use one of the latest estimation methods to construct an appropriate counterfactual that correctly estimates the causal effect of natural disasters on standardized tests. To the best of my knowledge, all existing papers that assess the impact of multiple natural disasters on education-related outcomes use linear regressions with period and group fixed effects. However, it has recently been shown that these regressions produce misleading estimates in the presence of heterogeneous treatment effects (de Chaisemartin and D'hautfoeuille, 2022b). This would be the case if, for example, the natural disaster's effect is different between groups or over time. Therefore, my paper contributes to the literature by revisiting a fairly studied question using more robust methods to validate previous findings.

Finally, I explore potential mechanisms that could mediate the relation between natural disasters and skills development. In particular, by combining multiple sources of information on the quality of education and economic status, I estimate the effects of natural disasters on income and academic quality. By doing so, I advance the existing knowledge on natural disasters in Colombia and produce input for public policies that mitigate and prevent its harmful effects. Given the budgetary constraints that governments face in the aftermath of a disaster, identifying the critical factors of catastrophes that could exacerbate the damages to human capital is essential to prioritize the allocation of resources (World Bank, 2014).

My results show that natural disasters affect cognitive skills. Experiencing a natural disaster causes a percentual reduction (with respect to the baseline average) in the share of students in the advanced level by up to 12% and in the percentage of students with at least a satisfactory level by up to 5%. Also, they reduce standardized test scores by 0.07 standard deviations, equivalent to 10% of the baseline average. Similarly, they provoke an increase in the share of students with an insufficient level of 14%.

In addition to the affectation on the cognitive skills level, the negative shock of a natural disaster increases absenteeism rates by nearly 4% of the baseline average. These adverse effects are more substantial on students with lower socioeconomic levels or limited academic supply access.

2 Context

The period and the Colombian context of the study are especially relevant for three reasons. First, climate change is causing an increase in the prevalence of disasters, coupled with the escalating potential for catastrophic loss. Also, weather shocks are becoming less predictable in terms of intensities and durations (IPCC, 2021). With these threats, it is time to prepare for what appears to be the inevitability of more extreme weather events (Zebiak et al., 2015).

Second, Colombia is characterized by its geological, hydrological, and climatic diversity, factors that increase its natural disaster risk (Banco Mundial Colombia, 2012). Moreover, due to demographic growth and migration forces, the exposed population to high and medium risk doubled between 1970 and 2010.

During this same period, the Country experienced more than 28,000 natural disasters that affected nearly 27,5 million people (Banco Mundial Colombia, 2012). Future perspectives are also discouraging. According to estimations from the World Bank (2012), by 2050, 34%

of the Colombian territory will experience extreme variation in annual rain levels (-30% to 30%), and sea level could rise by 50cm, making vulnerable to floodings 55% of the Caribbean Coast population and 41% in the Pacific coast. Moreover, 14% of national GDP would be affected by climate change-related factors, touching the income of 3.5 million people.

The ability of households to minimize welfare losses caused by such disasters and recover quickly from them is called economic resilience (Hallegatte, 2014). Although it also depends on social protection factors and access to insurance, it is directly related to a household's vulnerability. This means that families with worse conditions in terms of capital ownership, income, access to public services, and exposure to natural hazards will endure greater welfare losses. Therefore, natural disasters are regressive, implying they fall more heavily on the poor than the rich (Skoufias et al., 2011).

Accordingly, Sánchez and Calderon (2015) show that in Colombia, municipalities with greater levels of poverty have higher odds of suffering intensive affectation by disasters. Moreover, families with children face higher risks of poverty because of the extra costs of children and because of the effect on parents' working hours (World Bank, 2020). In that sense, the mechanisms outlined in the next section could operate more heavily over vulnerable households with children, leading them to underprioritize education and have worse results on standardized academic tests and more significant dropout and grade retention rates. Consequently, natural disasters seem to constitute a poverty trap that undermines the formation of cognitive skills essential for economic success. This problematic situation highlights the importance of rethinking the strategies to promote the economic resilience of its victims.

Regardless of the considerable threats that natural disasters represent in Colombia, their effects have not been fully understood. The rainfall shocks caused by *La niña* have been the only natural disaster investigated. Results show that the experience of extreme precipitation in utero increases the probability of dropping out of school and reduces scores on standardized academic tests (Duque et al., 2018). Furthermore, kids exposed to similar unfavorable conditions during their first years have an increased risk of socio-emotional problems and lower cognitive test results (Brando and Santos, 2015).

Despite these efforts, there remains a knowledge gap on the impacts of natural disasters in Colombia, particularly regarding their effects on human capital formation. All the studies developed in the Country evaluate one single disaster rather than a set of disasters, so their findings may not be truly representative (Belasen and Polachek, 2008). Moreover, none of them has considered the consequences of natural disasters on critical indicators of the skill acquisition process such as dropout, absenteeism, and grade retention rates. Also, they are focused on children under age five. My generalized approach is better since it considers many kinds of disasters, multiple treatment groups, and unexplored outcomes.

3 Conceptual framework

Adverse weather shocks and natural disasters are one of the more common sources of disadvantage faced by households in developing countries. These events challenge human development and are likely to exacerbate poverty's incidence, severity, and persistence in low-income populations (World Bank, 2010).

It has been established that adverse shocks heavily affect children in several aspects of their development, such as physical and mental health, socioemotional skills development, and learning. Childhood is a crucial stage where environments play a pivotal role in determining cognitive and noncognitive abilities essential for future economic success (Heckman, 2006). Therefore, conditions faced in childhood can determine various later-life outcomes such as crime, health, education, occupation, and social engagement (Cunha and Heckman, 2007; Almond and Currie, 2011). Moreover, attempting to correct in adulthood for earlier experienced disadvantages may be economically inefficient (Heckman et al., 2014).

Similarly, adolescence is a critical period that links childhood and adulthood and is marked by profound physical, emotional, and social transitions through which individuals achieve several development milestones. External circumstances experienced during these years affect the opportunities and support structures available to adolescents to develop their cognitive and socioemotional competencies needed to perform in labor markets, family dynamics, and mental health (UNICEF, 2018).

In this paper, I aim to quantify the impact of natural disasters on children and adolescent students' scores on standardized academic tests in Colombia. Standardized tests are a means to assess students' attainment of basic skills, such as literacy and mathematics. They are designed externally and aim to create consistent conditions, questions, and scoring procedures across schools (Wang et al., 2006). In that sense, their results allow estimating if students are meeting national minimum standards and checking the performance against goals. Therefore, standardized tests are an evaluation of a country's education system that measure levels of human capital accumulation and allow to take remedial actions if needed

(OECD, 2011).

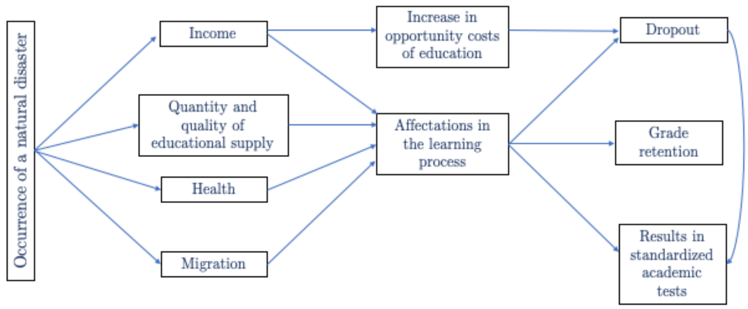
Literature has widely studied the effects of natural disasters on academic performance. In a comparative study of four countries, Nguyen and Pham (2018) find that children who experience droughts, frosts, and hailstorms have lower scores in mathematical tests by nearly 9.3 percent of the mean score. Using a 17 years panel over 13 Caribbean countries, Spencer et al. (2016) find that there are negative effects of hurricanes of 0.05 sd in Biology, Chemistry, and Physics standardized tests. This type of adverse effects can persist even in the presence of remediation efforts. For example, Andrabi et al. (2021) show that the earthquake from 2005 in Pakistan significantly reduced scores on academic tests for children whose mothers hadn't completed primary school, even after receiving substantial aid compensation.

Similar studies have also found unfavorable effects of natural disasters on other critical outcomes for skills development. For example, the tropical storm Stan in El Salvador reduced school enrollment (Baez et al., 2010), seasonal floods in Ethiopia, India, and Vietnam decreased the completed grades of children aged 12 to 15 years (Nguyen and Pham, 2018), and the rainfalls from Hurricane Mitch reduced school retention and progression rates in Nicaragua.

3.1 Mechanisms

As figure 1 shows, the are four direct mechanisms through which natural disasters can affect skills development: income, changes in both the quality and the quantity of educational supply, changes in health conditions of the students and their caregivers, and migration.

Figure 1: Conceptual framework e￿ects of natural disasters on education



Notes: This figure summarizes the four main mechanisms through which natural disasters might affect education.

Natural disasters can be understood as negative capital shocks that reduce economic output and per capita income. They undermine a firm's productivity (Leiter et al., 2009), reduce the economic activity in some economic sectors, such as mining or tourism (Hsang, 2013), and increase unemployment in climate-sensitive activities (Ahsanuzzamana and Islam, 2020). In the short term, these a￿ectations translate into reductions in households' incomes and livelihoods.

In settings where school costs are relatively high or where families can draw upon the labor of their children to mitigate the income shortfall, income variability undermines children's school enrollment and dedication (Jacoby and Skoufias, 1997). For instance, Baez and Santos (2007) find that children in households most a￿ected by the 2001 earthquakes in El Salvador were almost three times more likely to work after the shock than their una￿ected peers.

Households can also absorb these shocks by making equivalent reductions in expenditures, mainly in the categories of human capital investment (Anttila-Hughes and Hsiang, 2013) and nutrition (Ahsanuzzaman and Islam, 2020). In that sense, when facing income reductions, households provide students with less economic resources key for the learning process, which reduces their average cognitive ability (Björkman-Nyqvist, 2013).

Another one of the direct consequences of natural disasters is the destruction of education infrastructures, such as schools' facilities and roads of access, causing a decrease in the availability of educational facilities (Vansoncellos, 1997). For instance, in Colombia, the floods of 2010 and 2011 damaged 2,295 schools, and its reparation costs were equivalent to

81% of the annual investment budget of the National Ministry of Education and to 3.8% of all the education budget (BID and CEPAL, 2012)

Disasters can also generate reductions in instruction time due to the necessity to use schools as community shelters or to their partial closure for reparation, which prevents them from operating as classrooms (Brookings, 2018). Moreover, teachers and students can be displaced in the aftermath of a disaster, increasing the pressure on resources such as the available teachers or the school's budget (Bonanno et al., 2010). All these factors reduce teachers' productivity in the classroom and worsen the learning environment, which reduces the acquisition of skills (Spencer, 2016).

Natural disasters can also affect students' traits, such as mental and physical health, which are crucial for developing skills. Children in areas affected by disasters have worse measures of physical wellness, such as birth weight, weight gain per month, and weight for height (Brando and Santos, 2015), and are less likely to visit the doctor (Baez et al., 2010). These children also are at higher risk of having mental health problems since disasters are traumatic events that can cause psychological harm by the stressful and frightening experience during the event, but also through the harm to the social environment of the children (Kousky, 2014). In that sense, literature estimates a prevalence of PTSD of nearly 30% among direct victims of disasters, which accentuates to 43 % for children (Kar, 2009; Goldman and Galea, 2013). There is evidence that children of adults with mental health disorders face developmental issues and fare worse in school (Caruso and Miller, 2015) and that a positive relationship exists between mental health and academic achievement (Agnafors, 2021).

In response to the lower incomes, health damages, and assets losses that natural disasters cause, households can use migration as an adaptation strategy. The International Organization for Migration (2009) defines environmental migrants as persons who, "*for compelling reasons of sudden or progressive change in the environment that adversely affects their lives or living conditions, are obliged to leave their habitual homes either temporarily or permanently*".

This kind of forced migration negatively affects education. Migrant children face unique difficulties such as interrupted or limited schooling, psychological stress, and changes in their physical and social environments that undermine their learning process (OECD, 2018).

Estimating the magnitude of all these mechanisms is a problematic empirical task because they are interrelated and do not independently affect education. In this paper, I aim to empirically approach the effect of natural disasters on variables that serve as proxies for these mechanisms. Moreover, in addition to the results in standardized academic tests, I also consider disasters' e□ects on three outcomes related to skill formation: grade retention, absenteeism and dropout rates. As figure 1 shows, these outcomes are also interrelated. For example, dropout rates can have an impact on test results since they change the composition of the sample of evaluated students.

Inside the conceptual framework that studies the e□ects of natural disasters on education, it is indispensable to pay attention to attrition, given that ambiguous selection biases could be at play. For example, more educated and healthy individuals might migrate to cope with the shock (Mbaye et al., 2017). Similarly, the most vulnerable households could take children out of school in an attempt to smooth the income shocks caused by the disasters (Baez et al., 2010). Essentially, all these influences make students in areas a□ected by disasters less likely to present the standardized academic tests. Therefore, as Angrist et al. (2004) have demonstrated, direct comparisons of test scores between treated and untreated schools are subject to selection bias.

Disentangling these changes in sample composition is a challenging task since it is di□cult to track individuals over time, and there is no detailed data on the shocks and events that shape their lives. In that sense, I do not have any available data of individuals who experience natural disasters and do not present the standardized tests. Nevertheless, I explore two potential sources of selection bias by employing the mother's education level as a proxy variable for changes in sample composition due to migration and by using the dropout indicators of each school. Moreover, in section 7 I describe a robustness exercise that could address this problem.

4 Data sources and descriptive statistics

4.1 Natural disasters

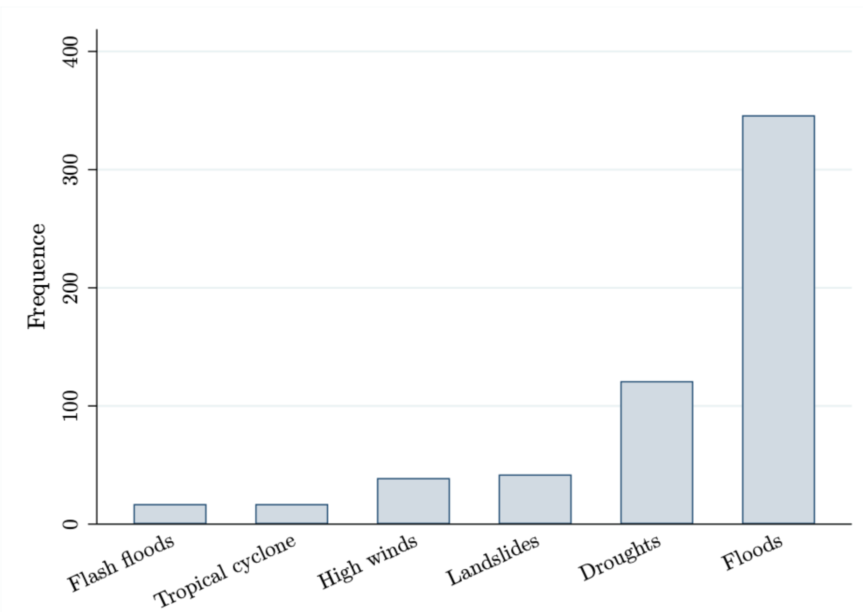
I Identify the occurrence and magnitude of disasters using the Unique Register of Victims[2] (RUD), managed by the National Unit for Disasters and Risk Management[3] (UNGRD). This register, created in 2013, is the only o□cial source of information that identifies and characterizes the population a□ected by natural or unintended anthropogenic disasters in Colombia. Every observation on it represents a household that, as a direct consequence of such events, either had a partial or total loss in assets, agricultural activities, or the loss or

[2] *Registro Único de Damnificados* in Spanish.
[3] *Unidad Nacional para la Gestión del Riesgo de Desastres* in spanish.

the death of a household member. Since the RUD database contains personal information subject to data protection laws, it is private and is only shared with governmental entities that justify its use. However, I requested access to its anonymized information by filling out a petition through the Right to Information Act.

Hence, I recovered information from 704 disasters that occurred between 2016 and 2019 in Colombia. I find that the most common type of disaster is floods; they represent 60% of the total number of disasters. Other types of disasters also present in the Country were droughts (21%), storms (7.3%), and hurricanes (4.2%). Figure 2 shows the total frequency of these disasters.

Figure 2: Disasters's frequence by type (2016-2019)



Notes: This figure plots the total frequence for each type of disaster occurred between 2016 and 2019.

Colombia has 1103 municipalities divided into urban and rural areas. Rural areas represent more than 99% of the National territory (IGAC, 2015) and are characterized by sparse buildings and numerous agricultural exploitations. Generally, their addresses are not defined by a street nomenclature but through a division of villages[4]. Precisely, Colombia has 32,377 villages whose average area is 3,560 hectares.

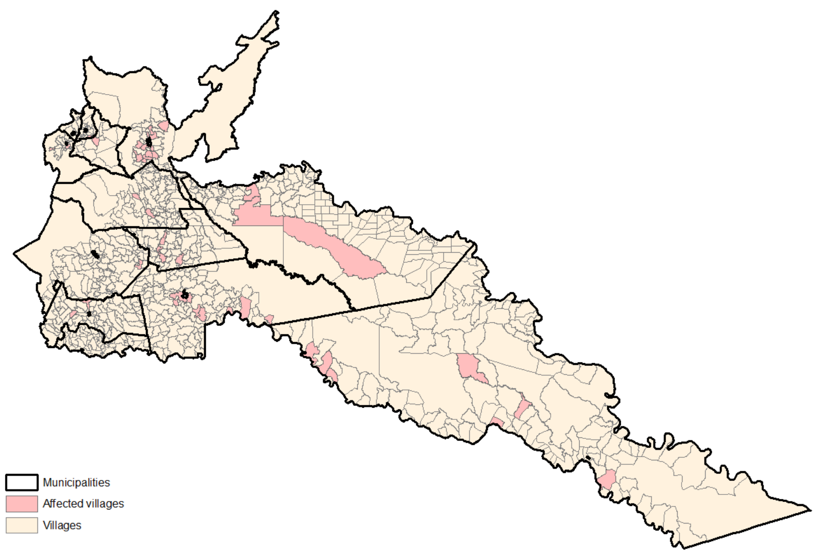
RUD records focus on rural areas and have lower coverage of disasters that occur inside the urban permiter of municipalities. Accordingly, most registers of the affected households' addresses only includes the village's name. Although this information doesn't allow me to

[4] *Vereda* in Spanish.

geocode the addresses and obtain their coordinates, the village's polygons are a very granular unit.

For example, figure 3 shows that in the department of Putumayo, there are 13 municipalities composed of 872 villages, of which 92 reported one natural disaster in the RUD. While each municipality in Putumayo has an area of 1900 km2, its smaller villages have an average area of 3,12 km2. Besides, the urban zones without villages represent a minuscule proportion of the department.

Figure 3: Example affected villages in Putumayo (2016-2019)



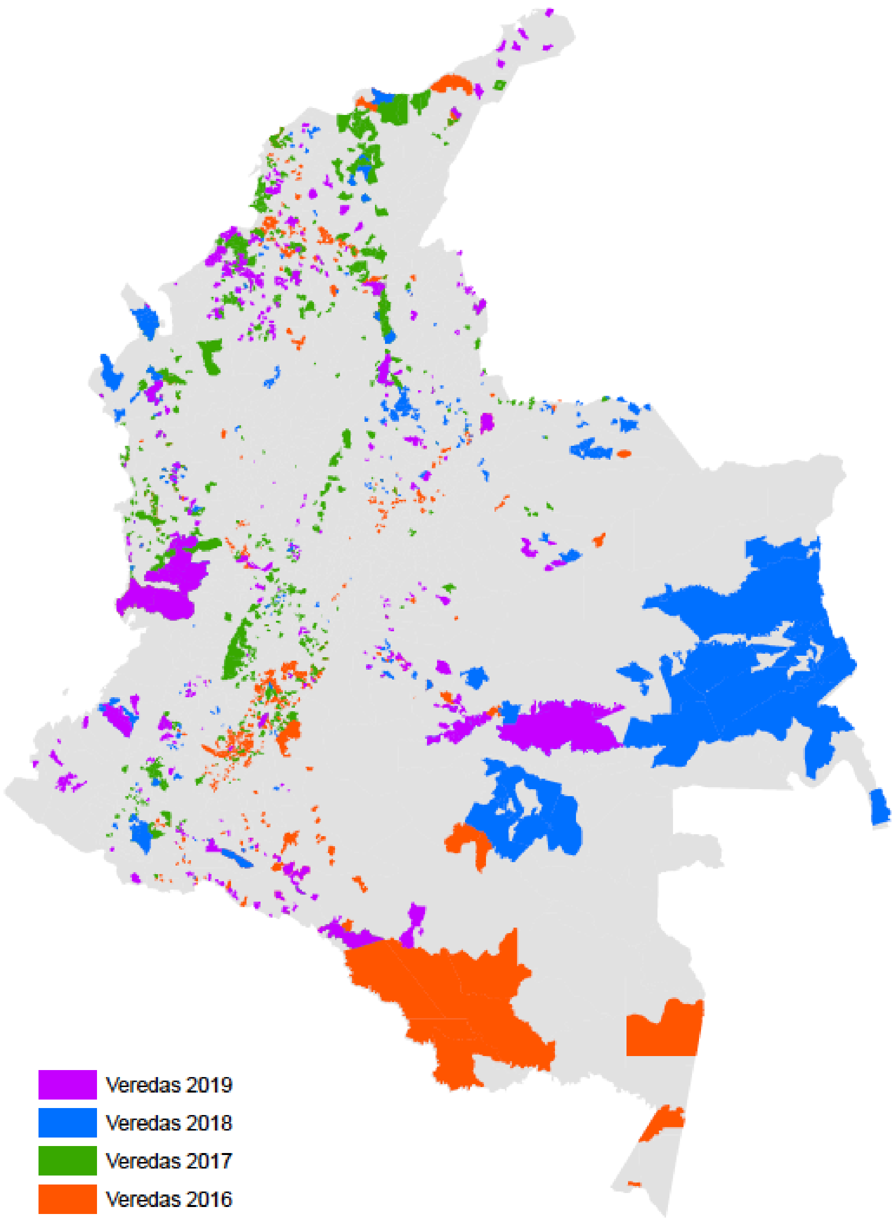
Notes: This figure plots the municipalities and villages polygons from the Putumayo department. It highlights the villages where at least one natural disaster was reported between 2016 and 2019. Black zones inside municipalities represent urban areas uncovered by villages.

Between 2016 and 2019, 428 municipalities of Colombia and 3049 villages suffered at least one disaster. Figure 4 plots the yearly cohorts of affected villages to show the temporal and spatial variation of natural disasters across villages. However, it is important to remark that 3.5% of villages experience two disasters in different years, and 1.2% experience three.

In this paper, I will restrict the analysis to villages with exactly one affectation between 2016 and 2019. I impose this condition because places that experience a natural disaster could be better prepared to face the consequences of the subsequent natural disasters. Therefore, the effects of the second and third disasters might not be comparable to those of the first disaster. It would be interesting to estimate such differential impacts to assess households' adaptability to natural disasters. However, villages with multiple disasters only represent 4.7% of the sample, which doesn't provide enough statistical power to do such estimations.

Also, I will define that a disaster is only active for one year and then turns off but can have dynamic effects over other periods. I make this choice because natural disasters are temporary shocks that partially improve with time due to the reconstruction and adaptation measures. However, they can still maintain medium and long-term effects.

Figure 4: Affected villages per year (2016-2019)



Notes: This figure plots the first year of affectation for each village.

Panel A from table 1 shows the summary statistics for all the 704 events of natural disasters that occurred between 2016 and 2019. On average, a disaster affects 1370 persons, damages

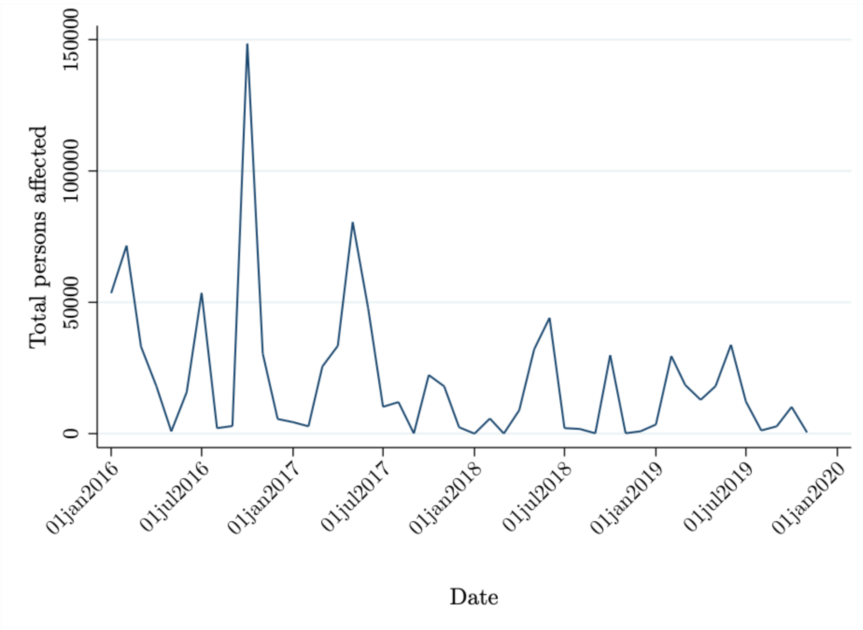
335 dwellings and 2988 hectares of crops, and kills 179,700 livestock animals on average. Panel B from table 1 disaggregates these affectations across all the 3049 affected villages. On average, in each affected village, a disaster affects 233 people (109 women, 124 men, 172 adults, and 61 minors), damages 505 hectares of crops, and kills 30,700 livestock animals.

Table 1: Disaster's affectations

Panel A: affectations at the event level				
(n = 704)	Mean	SD	Min	Max
Dwellings	335	722	0	7,451
Affected persons	1,370	2,587	1	27,489
Lost hectares	2,988	27,385	0	666,087
Animals (hundreds)	1,797	32,828	0	854,893
Plants (hundreds)	57	1,201	0	31,834
Panel B: affectations at the village level				
(n = 3049)	Mean	SD	Min	Max
Dwellings	3	7	0	147
Affected persons	233	1,162	1	27,489
Lost hectares	505	11,083	0	650,982
Animals (hundreds)	307	13,572	0	854,893
Plants (hundreds)	10	495	0	31,734

Figure 5 shows that disasters behave cyclically and have peaks in the first semester of the year. Changes in precipitations driven by El Niño Southern Oscillation strongly influence these temporal variations in affectations (Banco Mundial Colombia, 2012).

Figure 5: A□ected people by disasters (montlhy)



Notes: This figure plots a montlhy time series of the number of affected people by disasters.

The RUD dataset constitutes a novel rich source of information for two reasons. First, it characterizes the disasters at the village level, which, as shown in figure 3, is a very detailed geographic unit. Most of the existing papers in the economic literature on natural disasters have obtained information at less granular levels. For example, they have used large polygons such as municipalities (Alamir and Heidel, 2020; Duque et al., 2019) or 0.25 laittude and longitude grids (Björkman-Nyqvist, 2013).

The e□ort to obtain data at this very granular level is valuable because defining treatment status over larger polygons, such as municipalities, implies assuming the same level of a□ectation for all the locations within the polygons. While in fact, disasters may only have local e□ects. In that sense, the results of the estimations that use more aggregated measures of treatments represent an intent to treat (ITT) e□ect and correspond to a lower bound of the authentic average treatment e□ect (ATE). By increasing the detail level of my treatment measure, my methodology will reduce the gap between the real ATE and the estimated coe□cients.

Second, all the registers in the RUD database represent households in municipalities that faced di□culties coping with the e□ects of natural disasters and needed to request aid from the National Government. Therefore, they capture those disasters that had the largest a□ectations on populations. This approach is crucial in measuring disasters since, as I mentioned in the conceptual framework, their impact depends not only on their physical characteristics but also on the economic resilience of the affected population.

Moreover, as described in table 1, the RUD dataset contains detailed information on the impact of the disaster, such as the age and gender of every member of the affected household and the number of crops, livestock, and other assets affected. Although in this paper I do not use this information as a source of treatment variation, it has the potential to characterize the magnitude of the disasters measured by its affectations on the population rather than by only its physical characteristics, as most other sources of information have made.

I only exploit the variations in time and space in the occurrence of natural disasters. I can use this binary approach because all the disasters from the RUD correspond to comparable events that exceeded the capacity of the local governments to respond. However, this implies that I am aggregating disasters from different magnitudes into a single category. Therefore, my results should only be interpreted as the average effect of being exposed to a natural disaster.

4.2 Schools

In Colombia, the National Administrative Department of Statistics (DANE) performs a yearly census of all the public and private schools that offer preschool, primary, middle, and high school services. Using these reports, I construct a panel that characterizes the educational supply in the Country.

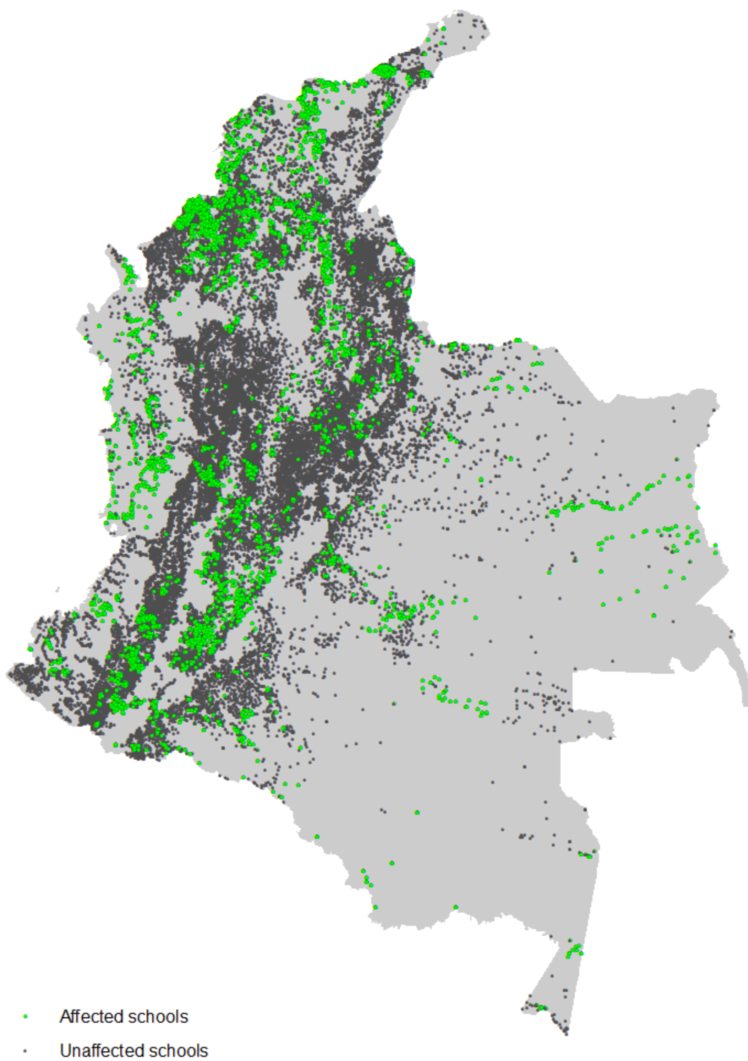
First, I select a subsample of schools in rural areas that operate during weekdays and offer primary, middle, and high school services. These restrictions allow me to focus on schools with three key characteristics: i) schools with suitable measures of the occurrence of disasters, given that the data from RUD doesn't have enough coverage of urban areas; ii) schools focused on child and adolescent education, given that schools with night and weekend schedules are typically targeted to adult education; and iii) schools where levels of skills can be estimated using the ICFES tests, given that they are not applied to preschool children.

The DANE dataset has the exact address of every school in Colombia. I use this information to geocode them and obtain their exact coordinates. I also recover key characteristics from each school, such as the number of teachers and other staff members, the teacher's level of studies, and the number of students.

I can compare the censuses between years to detect if schools change their academic quality. Unfortunately, data on partial school closures is not available. Therefore, to explore the extent of educational supply changes, I examine the effect of disasters on the student-teacher ratio and teachers' level of studies.

Using the exact coordinates, I find 4942 schools located inside a village where at least one natural disaster was reported in the RUD. Figure 6 shows the spatial distribution of this group.

Figure 6: Rural schools in Colombia

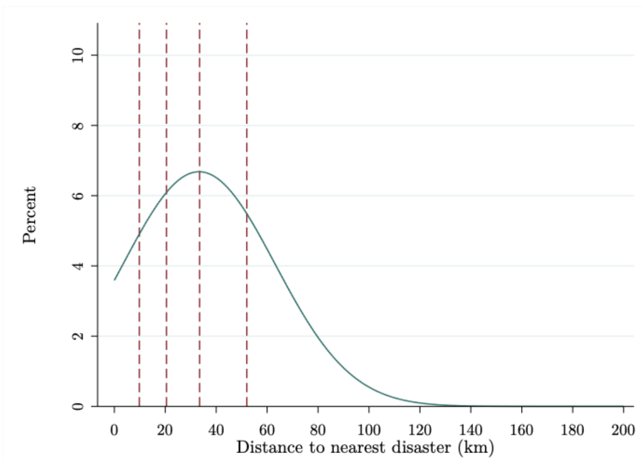


Notes: Green dots represent the location of every rural school that was located inside a village where one disaster occurred between 2016 and 2019. Black dots represent the location of all the other rural schools in the Country.

One limitation of this dataset is that it doesn't have information about the student's residency addresses. In cosequence, I can only observe the natural disasters around a student's school. Nevertheless, some of the mechanisms I have outlined in section 3, such as income and health changes, could also operate if the disasters occur in the vicinity of students' households. However, I can use the coordinates of every school to compute its distance to the nearest affected village every year. As example from figure 8 shows, I can define distance buffers to explore multiple treatment measures.

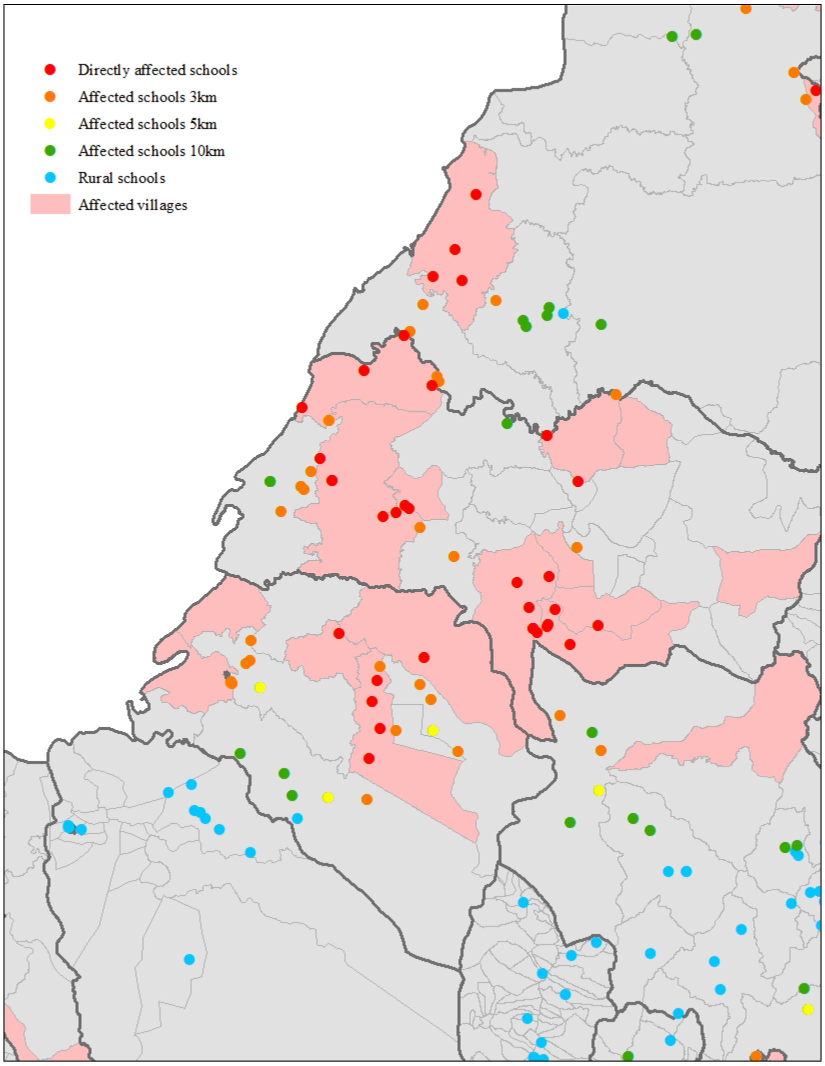
Therefore, my estimations can also account for geographical spillovers. Such effects would be present if, for example, the impacts of natural disasters extended over the village's boundaries. This scenario is plausible given that students from seemingly unaffected schools can travel to their households and receive the harmful effects of natural disasters. Figure 7 shows the distribution of the distance to the nearest affected village for all the rural schools in Colombia.

Figure 7: Distribution of school's distance to disasters



Notes: This graph plots the distribution of the distance in kilometers to affected villages for all the rural schools in Colombia. Red dashed lines signal the five quantiles of the distribution.

Figure 8: Distance to nearest disaster



Notes: This map classifies a subset of rural schools into distance buffers with respect to natural disasters. Blue dots represent rural schools more than 10km away from a village where a natural disaster occurred.

Tables 2-6 summarize the characteristics of the 4942 directly affected schools (A) located inside a village where a disaster occurred and of the other 38,015 rural schools (N-A). Directly affected schools represent 13% of all the rural schools in Colombia, and on average, they have worse learning conditions. In this section, I use the unaffected rural schools as a reference point to compare the characteristics of the directly affected schools. However, in the causal estimations from section 5, I will use the affected schools that had not yet been affected to build a counterfactual group.

Affected schools have more students and teachers than unaffected rural schools. On average, they have 61 primary school students, 142 middle school students, and 54 high school students. Therefore, similarly to all the rural Colombian schools, the affected schools are more oriented to lower levels of studies. Moreover, almost half of its teachers have only completed undergrad studies.

Table 2: Rural school's charactheristics (2016-2019)

	N-A (SD)	A (SD)	Difference (SE)
Total students	79.431	103.884	-24.452
	(150.186)	(160.202)	(1.341)
Total teachers	3.274	4.462	-1.188
	(5.875)	(6.778)	(0.041)
Primary-school students	45.989	61.301	-15.312
	(77.082)	(81.426)	(0.714)
Middle-school students	122.914	142.934	-20.020
	(120.437)	(116.445)	(2.118)
High-school students	49.118	54.965	-5.846
	(43.060)	(40.462)	(0.864)
Students-teacher ratio	14.865	15.865	-1.000
	(6.889)	(6.544)	(0.061)
% teachers with grad studies	24.939	21.203	3.735
	(40.046)	(36.568)	(0.272)
% teachers with undergrad studies	46.633	50.011	-3.378
	(45.304)	(43.943)	(0.309)
% teachers with technical studies	20.300	18.447	1.852
	(37.172)	(34.696)	(0.253)
Observations	186,348	24,070	210,418

4.3 Cognitive skills

The term ¨skills¨ comprehends all the modifiable competencies, attitudes, and beliefs across an individual's development that give him capacities to act (Heckman, 2014). The literature has divided this broad set of skills into socio-emotional and cognitive skills (Guerra et al., 2014). Cognitive skills are the intelligence or mental abilities to solve abstract problems. They are composed of lower-order basic skills that are foundational skills or elementary academic knowledge such as literacy or numeracy, and higher-order advanced skills that involve complex thinking such as critical thinking or problem-solving (Brunello et al., 2011).

To estimate the student's level of cognitive skills, I first use data from the Saber tests made by the Colombian Institute for Evaluation of Education (ICFES) between 2014 and 2017 to students from the 3rd, 5th, and 9th grades. These exams were performed yearly in Colombia to students between 8 and 16 years old to assess their abilities in math and Spanish, and report at the school level the percentage of students who attain a certain level (insufficient, minimum, satisfactory, and advanced).

Additionally, I use the data from the tests made by ICFES to students in 11th grade (the last year of high school education in Colombia) between 2014 and 2019. This data source reports a score based on answers to closed questions in math, social and natural sciences, reading, and English. In order to guarantee the comparability of these results between years and to facilitate the interpretation of the estimated coefficients, I standardize all the scores for every year and grade.

Finally, for every test, I recover its exact date using the Ministry of Education minutes that rule the ICFES procedures. This allows me to observe the relative time between the test and natural disaster dates.

Tables 3 and 4 summarize the students's results in the standardized tests. In affected schools, 3rd-grade students distribute equally among the four levels. However, in grades 5th and 9th, the average proportion of students in advanced levels decreases significantly. For example, in 9th grade, the proportion of students that do not attain at least a satisfactory level is 81%, while in 5th and 3rd grade, it is 70% and 50%. This fact shows that there is a lower quality in upper levels among the treated schools.

Overall the performance of affected schools is lower than that of unaffected schools. Across all grades, they have a higher share of students in the insufficient level and a lower share of students in the satisfactory and advanced levels. Similarly, for the Saber 11th test, the affected schools'scores stand 0.24 sd below the unaffected schools even though both groups underperform compared to the national mean.

Table 3: Percentage of students per level in rural schools (2014-2017)

	Saber 3rd			Saber 5th			Saber 9th		
	N-A (SD)	A (SD)	Difference (SE)	N-A (SD)	A (SD)	Difference (SE)	N-A (SD)	A (SD)	Difference (SE)
Insufficient	17.922	22.649	-4.727	27.866	34.043	-6.176	25.351	30.808	-5.457
	(26.321)	(28.379)	(0.312)	(29.002)	(30.163)	(0.355)	(21.431)	(22.317)	(0.564)
Minimum	28.116	28.763	-0.648	35.599	35.467	0.132	51.341	51.153	0.187
	(28.168)	(26.243)	(0.329)	(26.852)	(24.858)	(0.324)	(18.709)	(17.448)	(0.485)
Satistactory	27.089	25.393	1.697	23.440	20.042	3.398	20.944	16.653	4.292
	(28.148)	(26.179)	(0.328)	(25.801)	(23.511)	(0.311)	(18.725)	(15.986)	(0.481)
Advanced	26.317	22.625	3.692	12.592	9.957	2.634	2.011	1.081	0.930
	(34.059)	(31.787)	(0.397)	(24.068)	(21.190)	(0.289)	(6.703)	(3.446)	(0.166)
Observations	61,317	8,199	69,516	59,066	7,620	66,686	10,582	1,695	12,277

Table 4: Standardized Saber 11th score in rural schools (2014-2019)

	N-A (SD)	A (SD)	Difference (SE)
Standardized score	-0.421	-0.665	0.245
	(0.870)	(0.752)	(0.018)
Observations	16,819	2,737	19,556

4.4 Academic trajectory

I also use the Sistema Integrado de Matrícula (SIMAT) database, a yearly census of all students. This database has the academic trajectory from 2012 to 2019 of every student that was at least once matriculated in the educative system. Therefore, by following students over the years and across all the legal schools in Colombia, it allows to establish four possible academic statuses for every student in a given year:

- Intra-annual absence: student is registered in April from period t, but not in December from period t
- Inter-annual absence: student is registered in period t, but not in period $t + 1$
- Drop-out: student is registered in period t, but neither in period $t + 1$ or period $t + 2$
- Grade retention: in period t student is registered in grade g, and in period $t+1$ student is also registered in grade g

This dataset constitutes a very detailed measure of students's academic situation given that it allows to track their enrollment across multiple shcools, and not only captures the absence from a particular school, but from all the schools.

Table 5 summarizes these characteristics for students from the rural schools. For the affected schools the average inter-annual absence rate (6.9%) is larger than the intra-annual rate (3.17%) and the dropout rate (5.25%). Moreover, the grade retention rate (14%) is relatively high. These indicators are slightly larger in affected schools than in unaffected schools.

Table 5: Academic trajectory in affected schools

	N-A	A	Difference
	(SD)	(SD)	(SE)
Intra-annual absence	3.126	3.171	-0.044
	(6.511)	(7.029)	(0.046)
Inter-annual absence	6.381	6.904	-0.524
	(9.223)	(9.646)	(0.065)
Dropout	4.714	5.254	-0.540
	(7.578)	(8.044)	(0.059)
Grade retention	12.179	14.080	-1.901
	(12.181)	(12.611)	(0.086)
Observations	176,603	22,641	199,244

4.5 Student's chractheristics

Finally, I use the ICFES database of the 11th-grade tests from 2014 to 2019 to obtain more information about the student's characteristics. Therefore, for more than 50,000 students, I build the following variables: if he is working; whether he perceives that their household's economic situation worsened last year; if he eats meat, fish, or egg at least three times per week; the number of people living at the student's house; and whether his mother has attained a level of studies higher than highschool. Using this information, I can observe the average changes in the level of characteristics for each school. Unfortunately, this information is only available for 11th-grade students.

Results from table 6 show that students from the affected schools face disadvantageous socioeconomic conditions. On average, 12% of them feel that their socioeconomic situation worsened last year, 38% of them work, only 48% of them eat meat, fish, or egg more than three times per week, and nearly 15% of these student's mothers did not complete high school studies. However, their situation is not much worse than that of the students from unaffected schools. For example, they have lower work participation and better-educated mothers.

Table 6: Student's socioeconomic status in rural schools

	Mean control (SD)	Mean treated (SD)	Difference (SE)
Worse economic situation (%)	10.250	11.866	-1.616
	(9.941)	(10.175)	(0.277)
Works (%)	40.300	38.420	1.880
	(27.015)	(25.671)	(0.657)
Eats meat-egg +3 times/week (%)	54.306	48.609	5.697
	(22.123)	(19.225)	(0.604)
Mother completed highschool(%)	83.538	85.027	-1.488
	(19.568)	(14.755)	(0.464)
Total persons at home	4.894	5.184	-0.289
	(0.826)	(0.797)	(0.020)
Observations	11,913	1,936	13,849

5 Methodology

The most popular method to estimate the effect of multiple natural disasters is to compare groups experiencing different evolutions of treatment exposure over time using the so-called TWFE regressions. All of the papers I have cited in the conceptual framework that study the effects of multiple natural disasters use this method.

However, recent research (Goodman Bacon, 2021) shows that TWFE estimators' unbiasedness depends on the assumption that treatment effects should be constant between groups and over time. This latter assumption is unlikely to hold in most empirical designs where the TWFE regressions have been used (De Chaisemartin and D'hautfoueille, 2022b) as this implies, for example, assuming that there are no dynamic treatment effects. Considering these pitfalls, a growing body of literature has proposed alternative estimators robust to heterogeneous effects.

I visited these methods seeking to choose a methodology that could unbiasedly estimate the treatment effects considering two particular traits of my experimental design: first, the exposure to natural disasters can decrease over time and change more than once; this implies that the schools' treatment is not staggered. Second, natural disasters can have effects several years after they occur, implying that school treatment may have dynamic effects. Therefore, I chose the estimators proposed by de Chaisemartin and D'Haultfoeuille (2022a), which are robust to heterogeneous and dynamic treatment effects in non-staggered adoptions.

This methodology proposes a generalization of the event-study design by defining the event as the period where a group's treatment changes for the first time. In that sense, I use a panel of schools, indexed by *g*, that are exposed to disasters at different time periods, indexed by *t*. D_{gt} is a binary variable that represents the treatment status of school g in period t. Then, this variable takes the value of one in the period in which the disaster is active for school g.

The results I will present in the next section follow an initial definition of schools' treatment taht depends on the direct effects of being inside a village where a disaster occurred and the indirect effect of being near a natural disaster. Therefore, I define that a school is treated if it experienced a natural disaster inside its village or if it was located less than 9.8km away from a village where a natural disaster occurred in a on a one-year window before the Saber tests[5].

D_{gt}, group g's period *t* treatment, may have instantaneous effects on Y_{gt}, but also dynamic effects over group g's period *t*+ℓ outcome $Y_{g,t+\ell}$. This allows the possibility that the school's outcome at time t may be affected by the dynamic effects of their past disasters.

Under this framework, I estimate the following equation:

$$Y_{gt} = \alpha_g + \lambda_t + \delta_g D_{gt} + \epsilon_{gt} \tag{5.1}$$

Where Y_{gt} is the outcome of school g in period t. To estimate the effect on cognitive skills, I define Y_{gt} as the percentage of students from school g who are at a certain performance level (insufficient, more than satisfactory, and advanced) in year t for students in 3rd 5th and 9th grade, and as the standardized score in the saber test for the 11th-grade students. I include school (α_g) and period (λ_t) fixed effects. The estimation is weighted by the inverse of the number of students per school. Moreover, all the standard errors are estimated using 200 bootstrap replications clustered at the municipality level.

Under this setting $\delta_{g\ell} = E(Y_{g,F_g+\ell} - Y_{g,F_g+\ell}(D_{g,1}, ..., D_{g,1}))$ is the expected difference between

[5]As observed in figure 7 this number corresponds to the first quintile from the distribution of the distance of schools to natural disasters

school g's actual outcome at $F_g + \ell$ [6] and the counterfactual status quo outcome it would have obtained if its treatment had remained unchanged from his period one to $F_g + \ell$. Essentially, to estimate δ_{gl} this methodology compares the outcome evolution of treated and not yet treated schools by comparing the 1 to $F_g + l$ outcome evolution between school g, and schools whose treatment has not changed yet at $F_g + l$ and with the same treatment as g at period one.

The latter approach allows me to conduct a cost analysis comparing the school's actual outcomes to the counterfactual scenario where every school would have been unaffected by disasters.

De Chaisemartin D'hautfoeuille (2022a) argue that the unbiasedness of the estimators relies on the following main assumptions:

1. **No anticipation:** For all g for all $d \in \{0,1\}^T, Y_{gt}(d) = Y_{gt}(d_1, ..., d_t)$. This assumption means that a school's current outcome does not depend on her future treatments.
2. **Independent groups:** The vectors $((Y_{g,t}(0))_{1 \leq t}, D_g)$ are mutually independent. This assumption requires that different schools' potential outcomes and treatments be independent
3. **Strong exogeneneity:** $E(Y_{g,t}(0) - Y_{g,t-1}(0)|D_g) = E(Y_{g,t}(0) - Y_{g,t-1}(0))$. This assumption is met when other shocks affecting school g's never treated outcome are mean independent of school $g's$ treatments.
4. **Parallel trends for never treated outcomes:** $\forall t \geq 2, E(Y_{g,t}(0) - Y_{g,t-1}(0))$ does not vary across g. This assumption is a generalization of the standard parallel trends assumption to allow for dynamic effects and requires that the expectation of the never-treated outcome follows the same evolution over time for both treatment and control groups.

De Chaisemartin and D'Haultfoeuille (2022a) propose placebo estimators for assumptions 1 and 4 that compare the outcome trends of schools that switch their treatment and schools that do not change the treatment before the switchers switch. To support assumption 2, the literature suggests clustering standard errors at the municipality level (Bertrand et al. 2004). Finally, assumption 3 is plausible since it is improbable that a school gets a natural disaster because it experienced a particular shock. This assumption would not be valid in cases such as when a group gets treated because it experiences adverse shocks, the so-called Ashenfelter's dip.

[6] F_g denotes the first period at which group g gets treated.

It is also necessary to consider that some schools may have already been treated before 2016, the first period in the RUD, and see their later outcomes affected. This is the so-called initial conditions problem. However, I cannot estimate these dynamic effects, as treatment status is not observed for periods before 2016. Therefore, I will need to make the strong assumption that all the shools were untreated before 2016.

Traditional DiD models are applied to settings where the treatment hits units at the same time. Essentially, it involves a treated group, an untreated group for comparison, and a single treatment rollout period. However, this is not the most common situation in studies analyzing multiple shocks that assign units to treatment at different moments. For such instances, the econometricians developed the TWFE models, such as the one described in equation 5.1. Unfortunately, the traditional OLS estimation of these models produces biased estimators (Goodman-Bacon, 2021). Therefore, some researchers (Callaway and Sant'anna, 2020; Borusyak, 2021; De Chaisemartin and D'Haultfoeuille, 2022a) developed new solutions to estimate the causal effect unbiasedly.

Essentially, the model from equation 5.1 is the same as traditional TWFE model. However, I use the novel estimation methodology proposed by De Chaisemarin and D'haultfoeuille (2022a), which allows the existence of dynamic treatment effects and non-staggered adoption. This approach produces estimators with the same economic interpretation and relies on the same assumptions tan traditional DiD and TWFE models, but avoids the unlikely hypothesis of homogeneous treatment effects.

6 Results

6.1 Assumptions validity

As I mentionned, De chaisemartin and D'hautfoeuille (2022a) propose placebo estimators for assumptions 1 and 4. Like the estimators described in the previous section, they compare the outcome evolution of any treated school to that of schools untreated from period one to $F_g + \ell$ to assess if school g and schools not yet treated are on paralell trends. The number of periods over which the paralell trends has to hold for the estimator $\delta_{g,\ell}$ to be unbiased is $\ell + 1$.

Given that for the 3rd, 5th, and 9th-grade test results, I will only estimate the static effects ($\ell = 0$), I only need to validate the assumption for one period and compare the outcome evolution between F_{g-1} and F_{g-2}. Besides, for the saber 11th dynamic estimators to be unbiased for two periods ($\ell = 2$), assumptions 1 and 4 need to hold for three periods.

Table 7 shows the results of the estimated placebo coefficients. None of them is statistically signicant even at the 90% confidence level. Therefore, I can not reject the null hypothesis that the placebos are zero. This lends credibility to the parallel trends assumption, at least over a few years.

Table 7: Placebo estimators of treatment effects

	Coefficient	**SE**	**LB 90% CI**	**UB 90% CI**
Placebo t=-1 advanced level	-0.00	0.01	-0.01	0.01
Placebo t=-1 insufficient level	0.00	0.01	-0.01	0.01
Placebo t=-1 at least satisfactory level	0.00	0.01	-0.01	0.01
Placebo t=-3 Saber 11th score	-0.07	0.04	-0.15	0.02
Placebo t=-2 Saber 11th score	0.00	0.03	-0.06	0.07
Placebo t=-1 Saber 11th score	0.02	0.02	-0.03	0.06

6.2 Primary outcomes

Having proved that the primary assumption needed for the methodology is valid, I estimate equation 5.1 to quantify the effects of natural disasters on standardized academic test results for the four grades of my analysis. As I have described in section 4, the temporal availability of the saber tests varies between the 3rd, 5th, and 9th-grade students and 11th-grade students. Therefore, as for the first group of students I only have two periods of data after the first occurrence of natural disasters, I can only compute the static treatment effect. However, as for 11th-grade students I have data available for four years after the first occurrence of natural disasters, I can calculate its dynamic treatment effects

Figures 9-11 show the static effects of natural disasters on the distribution of students across the three levels of academic performance. Similar to the previous findings from the literature, my results prove that natural disasters negatively affect education.

Overall, natural disasters reduce the share of students at the advanced level by 1.3 percentage points and at more than satisfactory level by 1.2 percentage points. In comparison, they increase the share of students at an insufficient level by 0.6 percentage points. Although these results are statistically insignificant at the aggregated level, they become significant when examined separately across the 3rd, 5th, and 9th-grade students. Moreover, they confirm the hypothesis proposed in the conceptual framework, such as that the early ages are more sensitive to adverse shocks (Heckman, 2006).

As a consequence of natural disasters, 3rd-grade students' share in the insufficient level increases by 2.6 percentage points, which is equivalent to 15% of the baseline share of all rural schools. Moreover, the share of 3rd-grade students in advanced and more than satisfactory levels decreases by 1.49 and 3.3 percentage points, respectively. These effects represent nearly 6% of the rural school's average share of students on these levels.

Older students from the 5th grades have lower affectations. Natural disasters increase the share of 5th-grade students in the insufficient level by 1.5 percentage points, representing 5% of the average baseline share in rural schools. Moreover, they reduce the share of students at the more than satisfactory level by 1.4 percentage points.

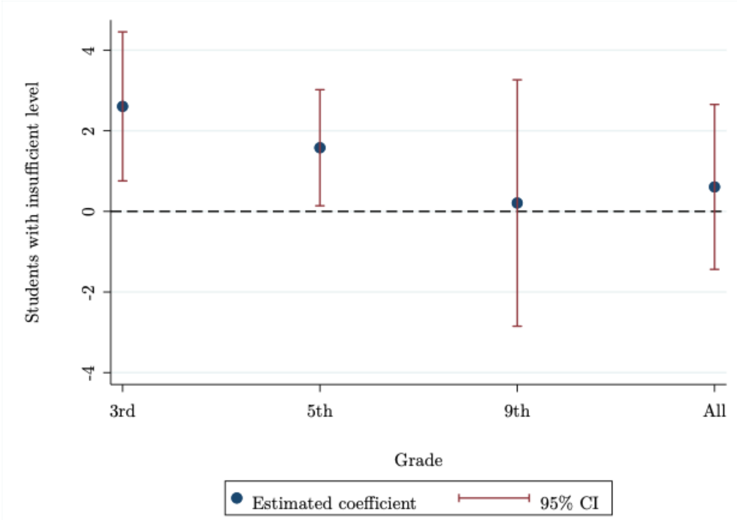
Conversely, natural disasters do not have affectations on 9th-grade students. However, there is a marginally statistically significant effect increase in the share of students in the advanced level of 0.59 percentage points. This result is economically counterintuitive and statistically insignificant at the 99% confidence level. Still, it cautions about a possible sample selection bias in the estimation.

The results of the 11th-grade students are measured differently since ICFES reports a continuous average score for every school and not the distribution across performance levels). This implies that the Saber 3rd, 5th, and 9th tests are not directly comparable to the Saber11th test. However, findings derived from the Saber 11th test also show evidence of natural disasters' harmful effects on academic performance.

Figure 12 shows that natural disasters reduce the standardized Saber 11th score by 0.071 standard deviations, equivalent to 10% of the average baseline national mean. To better explain the affectations of natural disasters, figure 12 also shows the dynamic effects of the treatment that span over later years. It shows that the adverse affectations of natural disasters increase one year after the event and reach up to -0.18 standard deviations but disappear two years later. This result suggests that the worse consequences of disasters don't come immediately in the aftermath, but require some small amount of time to consolidate.

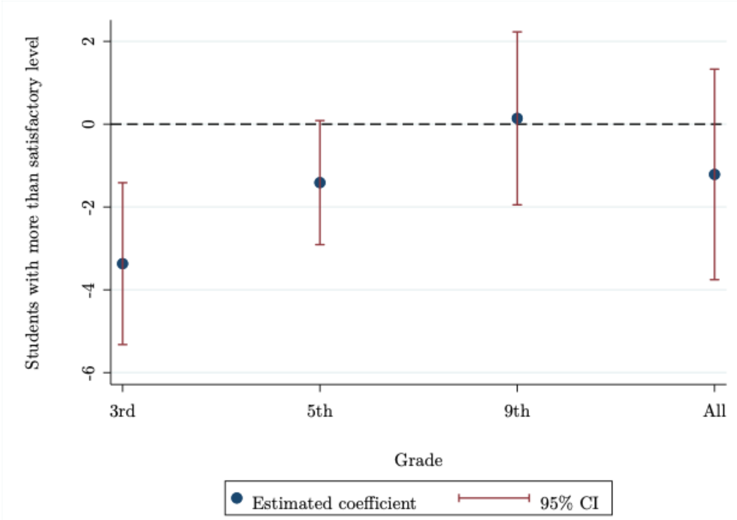
Finally, the magnitude of my results is similar to what other authors have found. For example, Spencer et al. (2016) demonstrate that natural disasters in the Caribbean negatively affected results on standardized academic tests by 0.05sd.

Figure 9: Students with insu□cient level on Saber 3rd 5th, and 9th tests.



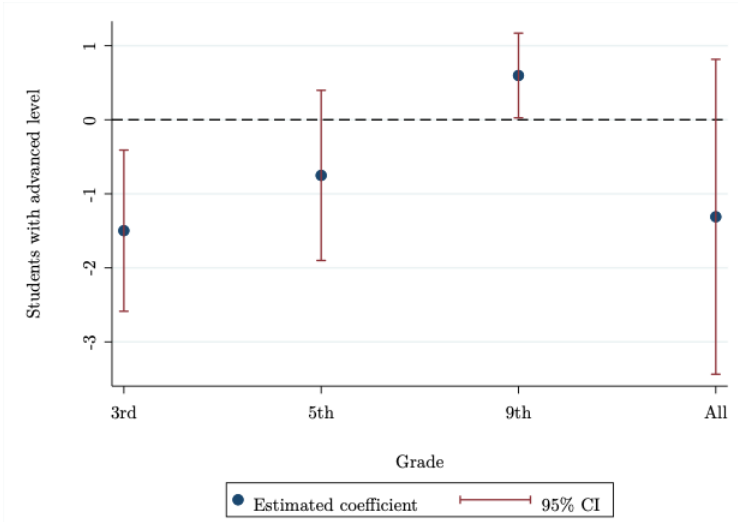
Notes: This graph plots the estimated change in the number of students at the insufficient level.

Figure 10: Students with more than satisfactory level on Saber 3rd 5th, and 9th tests.



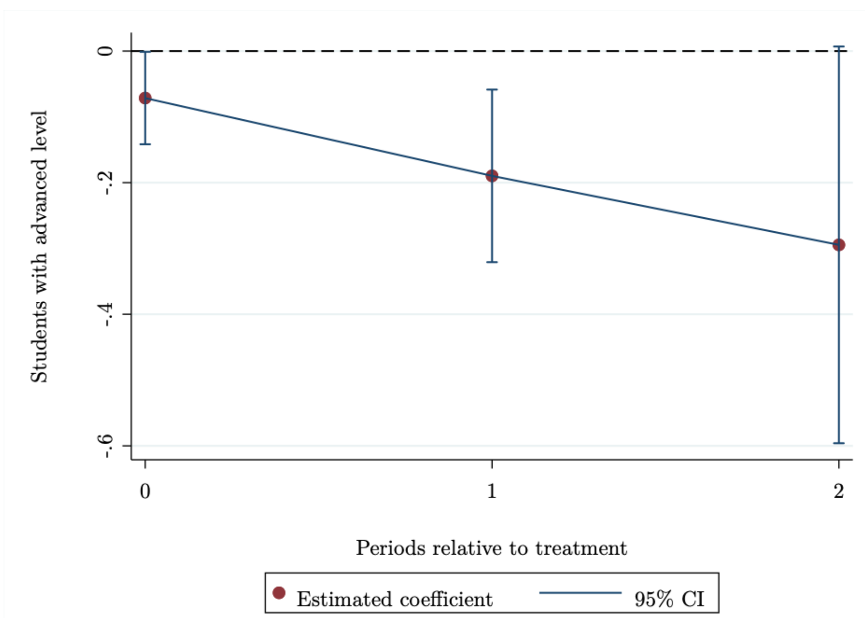
Notes: This graph plots the estimated change in the number of students at levels higher than satisfactory.

Figure 11: Students with advanced level on Saber 3rd 5th, and 9th tests.



Notes: This graph plots the estimated change in the number of students at the insufficient level.

Figure 12: Dynamic eects standardized Saber 11th score



Notes: This graph plots the estimated change in the standardized Saber 11th score. Blue lines represent the confidence interval at the 95% level.

6.3 Secondary otucomes

As I proposed in the conceptual framework, natural disasters can aect other outcomes directly related to education. Therefore, I estimate the equation 5.1 defining as the dependent variable the intra-annual and inter-annual absence rates, the dropout rate, and the grade retention rate.

Results from table 8 show that natural disasters do not increase the grade retention rate. The estimated coe cient of grade retention rates is small and statistically unsigni cant. However, in line with previous literature, natural disasters increase intra-annual absence, inter-annual absence, and dropout rates by 0.19, 0.14, and 0.09 percentage points. Although statistically significant, these results are economcally small, the intra and inter-annual absence rate changes represent 6% and 2% of all the rural schools baseline mean and the dropout change only represents 0.2% of it.

Table 8: E ects on academic trajectory outcomes.

	Treatment e ect (SE)
Inter-annual absence	0.195**
	(0.083)
Intra-annual absence	0.142**
	(0.064)
Dropout	0.09*
	(0.048)
Grade retention	0.013
	(0.069)

*** p<0.01, ** p<0.05, * p<0.1.

6.4 Heterogeneous effects

I can analyze the heterogeneous treatment e ects using the same specification and estimation of equation 5.1 and restricting the sample to population's specific characteristics of interest. Given that I did not consider urban schools on my analysis and that public schools represent more than 95% of the sample, I can only explore variations across the socioeconomic levels of schools. To do so, I use the Saber 11th results that report the two following socioeconomic levels for my sample of treated schools:

- **Level 1:** Students' households lack essential appliances (such as washing machines or computers) and consume low amounts of protein and milk. Moreover, students' parents have low educative levels and work in low-skilled tasks.
- **Level 2:** A higher share of students' households have essential appliances and consume moderate amounts of protein and milk. Moreover, students' mothers have completed

high-school studies.

Results from table 9 show that the negative effect is only present among the schools with socioeconomic level 1. Moreover, it is nearly 1.4 times the average effect among all the affected schools. This finding proves that natural disasters fall more heavily on vulnerable populations, as outlined in the conceptual framework.

Unfortunately, the socioeconomic shool's classification is unavailable for the 3rd, 5th, and 9th tests. Therefore, I can only estimate the heterogeneous socioeconomic effects for 11th grade test results.

Table 9: Heterogeneous effects on Saber 11th scores

	Treatment effect	
	Level 1	Level 2
Standardized score	-0.108***	0.019
	(0.037)	(0.026)

*** p<0.01, ** p<0.05, * p<0.1.

I also analyze the heterogeneous effects of natural disasters on dropout, absenteeism, and grade retention rates according to the school's supply of academic levels. Specifically, I consider the following six categories of schools.

- **1st-5th:** schools that only offer primary grades.
- **6th-9th:** schools that only offer middle grades.
- **10th-11th:** schools that only offer high grades.
- **1st-11th:** schools that offer all grades.
- **1st-9th:** schools that do not offer high grades.
- **6th-11th:** schools that do not offer primary grades.

Results from table 10 show that the effects of natural disasters on academic trajectory vary according to academic level's availability at school. For example, the inter-annual absence and dropout rates are higher among schools that offer 6th to 9th grades but do not offer higher grades. These results show that students in schools with limited academic options have greater threats of leaving or interrupting their studies when facing a negative shock, such as natural disasters.

Table 10: Heterogeneous e⬚ects on academic trajectory outcomes.

	Treatment e⬚ect					
	1st-5th	6th-9th	10th-11th	1st-11th	1st-9th	6th-11th
Inter-annual absence	0.253***	2.943*	-1.050	0.238*	1.701***	-0.034
	(0.102)	(1.650)	(3.876)	(0.137)	(0.280)	(0.126)
Intra-annual absence	0.117	0.210	-0.472	0.246***	0.383	0.071
	(0.093)	(1.122)	(0.783)	(0.101)	(0.321)	(0.143)
Dropout	0.126***	2.318***	0.970	0.194	1.191***	-0.219
	(0.055)	(1.042)	(5.128)	(0.128)	(0.133)	(0.128)
Grade retention	-0.013	-0.178	4.534**	-0.053	0.776*	-0.115
	(0.090)	(1.892)	(2.299)	(0.136)	(0.437)	(0.250)

*** p<0.01, ** p<0.05, * p<0.1.

6.5 Mechanisms

I explore the e⬚ect of natural disasters on variables that proxy socioeconomic characteristics that could shape the educative process. First, for the students in 11th grade, I estimate the impact on five variables that indicate their socieoconimic conditions and, as table 11 shows, I do not find any statistically significant e⬚ect. Although I cannot estimate these a⬚ectations on the rest of the students because the data is unavailable, I infer that given that all the students go to the same school, they must have comparable socioeconomic levels. Therefore, they should follow a similar trend after the disaster as the 11th-grade students.

The variable of the study level from the students' mothers is a good indicator of the e⬚ects of disasters on migration patterns. This outcome cannot be a⬚ected by disasters since it takes more than a year to change, and it is unlikely that mothers decide to study as a response to natural disasters. However, it would change if certain groups of individuals (for example, the less educated) moved away from disaster zones, causing a recomposition of the evaluated students sample. Therefore, my results indicate that there is no evidence of changes in the composition of the socioeconomic characteristics of evaluated students.

Table 11: Effect of natural disasters on socioeconomic indicators

	Treatment effect
Total persons at home	0.042
	(0.032)
Mother completed highschool (%)	-0.145
	(0.783)
Eats meat-egg +3 times/week (%)	-0.771
	(1.464)
Worse economic situation (%)	0.952
	(0.955)
Works (%)	-0.967
	(1.168)

*** p<0.01, ** p<0.05, * p<0.1.

The quality and quantity of academic supply is another strain of mechanisms through which natural disasters could negatively impact education. I do not have data on the temporal school closures or access constraints students face. Still, I have data on indicators of academic quality, such as the student-teacher ratio and the teacher's level of studies.

Results from table 12 indicate that there are no statistically significant effects of natural disasters on these outcomes. However, analyzing its magnitude and economic significance, it seems that teachers from the highest and lowest academic level (postgraduate and technical studies) remained in positions after the disaster, while medium-level teachers changed their schools. I hypothesize that this result could be due to different mobility patterns across economic levels where the most favored teachers are not so severely affected by disasters, and the most vulnerable teachers do not have the means to do so. Finally, there is also a slight decrease in the student-teacher rate, which could be because, as signaled in table 8 natural disasters cause higher intra-annual and dropout rates.

Table 12: Effect of natural disasters on academic quality indicators

	Treatment effect
Teachers with complete postgraduate studies(%)	0.163
	(0.581)
Teachers with complete undergraduate studies(%)	-1.728***
	(0.658)
Teachers with complete technical studies(%)	0.572
	(0.499)
Students-teacher ratio	-0.290
	(0.144)

*** p<0.01, ** p<0.05, * p<0.1.

7 Robustnesss

I run two robustness exercises in this section to validate my previous findings. First, I examine if the results from section 6.2 are robust to changing the size of the buffers I draw around villages affected by natural disasters, which delimit the area where I study these effects shocks. Second, I use untreated schools as the comparison group instead of only the not-yet-treated schools. Finally, I describe the correction proposed by Angrist et al. (2006) as a means to correct a potential selection bias.

7.1 Changing buffer sizes

In all my previous specifications, I have defined that natural disasters affect schools in a village where a natural disaster occurred or inside a buffer defined 9.8km around its boundaries. This limit corresponds to the top 20% distances between affected villages' boundaries and school locations.

In table 13 I test whether my results hold when changing the buffer sizes. In particular, I make one estimation defining the treatment only inside affected villages and four other estimations using the top 5, 10, 25, and 50 percentiles of the distance distribution.

In general, the magnitude of the coefficients decreases as the distance parameter increases. Moreover, the pattern of natural disasters reducing the share of students in the upper-performance level while increasing it on the insufficient level persists.

7.2 Untreated schools

Taking into account that my main specification uses the not yet treated units as a comparison group, as the second robustness exercise, I estimate equation 5.1 using the rural schools that never experienced a disaster as the counterfactual group. Table 14 shows that some of the results lose their statistical significance when changing the comparison group. However, the magnitude and direction of the coefficients still holds. On average, natural disasters reduce the share of students in the advanced level by 0.72 percentage points and in the more than satisfactory level by 1.2 percentage points, while increasing it in the insufficient level by 0.65 percentage points.

7.3 Sample selection bias correction

As I had previously described, students in affected areas are less likely to present academic tests. However, it was unclear whether the attrition concentrates on students with better or worse intellectual characteristics. The fragile socioeconomic students (with worse cognitive skills) could have lower chances of presenting the saber tests in the affected schools because they leave the academic system in the aftermath of disasters. In contrast, the more privileged students (with better cognitive skills) could also have lower chances of presenting the saber tests in the affected schools because they migrate to better places to mitigate the effects of natural disasters.

My results indicate that there are no changes in the socioeconomic composition of the sampled students. However, my previous results from table 8 point out that there is a statistically significant effect on dropout rates. These two findings suggest that the more vulnerable students might leave schools after the disasters. This implies that the estimates of the effects on standardized tests from section 6.2 could suffer from a positive bias and provide only an upper bound on the likely impact of disasters on school achievement.

Under this framework, I could implement the correction proposed by Angrist et al. (2006). This technique has also been adopted by similar papers seeking to mitigate selection bias in standardized academic tests (Collante et al., 2022).

For that purpose, I would use a censored model that determines an artificial threshold that corresponds to the score of a specific percentile of the distribution and then assigns that score to students who did not present the test or whose scores were below that threshold. This imputation assumes that students who did not present the test would have obtained a score below the artificial threshold and that the treatment effect is monotonous. In my specific case, this would mean assuming that the impact of natural disasters is never positive. Under the normality assumption, this methodology yields consistent estimations of the treatment effects on all student's test results.

However, all the test scores data I employ is available at the school level, and I can't observe the number of students who did not present the test. Therefore, I described the Angrist correction technique to propose it as a pending robustness test that I could implement if I obtained data on the number of students enrolled in a school but did not present the Saber test.

7.4 Other approaches

My paper still leaves an open space to improve the investigation of natural disaster effects. I identify three main limitations of my study and propose possible solutions to them.

First, in this paper I considered a binary treatment. Yet, the richness of the RUD data allows to exploit variation in the magnitude of the disaster, measured by its affectation on the population. So, an alternative strategy would have been defining a continuous or categorical treatment. However, this methodology presents two problems. On the one side, asset losses are endogenous to population characteristics and are measured using different units that are not easily aggregable and can suffer from self-report bias. Consequently, there is an empirical challenge to define a proper measure of disaster's affectations. Moreover, due to the newness of the event-study methodology I follow, estimations methods for a continuous treatment have not yet been developed (de Chaise Martin and D'hautfoeuille, 2022b).

The second limitation of my analysis is that it is based on self-reported information from victims. The available data can be easily completed with non-self-reported criteria of the intensity of the shock, such as rainfall stations or satellite-based imagery. However, as mentioned in the conceptual framework, the effects of natural disasters depend not only on their physical affectations but also on multiple factors that determine socioeconomic resilience. For example, reports of high-level precipitations might not always be an adequate indicator of a natural disaster's effects since some households might be able to cope with them.

Finally, throughout this study, I have focused on affectations in students' school surroundings since I cannot observe affectations on students' households or detect if they were reported in the RUD as victims of natural disasters. Even if I had this information, I couldn't link it to academic results since they are anonymized. With higher data availability, another approach would have been exploiting variations in household affectation to natural disasters. For example, one could compare students of the same households affected and unaffected by natural disasters before taking the standardized tests.

8 Conclusions and policy recommendations

In this work, I analyzed if natural disasters affect human capital formation focusing on the test performance and academic trajectory of populations studying in rural areas of Colombia. For that purpose, I built a novel database with detailed information about the magnitude and occurrence of natural disasters. Moreover, I used data from the results in standardized academic tests, the student's trajectory across the educative system, the educational supply, and the students' socioeconomic conditions.

My investigation constitutes an advancement in the knowledge frontier about natural disasters' consequences becasue I considered outcomes on which natural disasters had not been previously analyzed in Colombia, such as absenteeism and dropout. Moreover, I studied the heterogeneity of effects according to students' age. Finally, I built a refined measure of exposure to natural disasters and incorporated novel econometric techniques to estimate natural disasters' effects robustly.

This research process led me to three main conclusions: First, natural disasters compromise the acquisition of cognitive skills. Second, at a methodological level, geographic-detailed data and estimations that account for heterogeneous treatment effects provide a more precise picture of the impacts of natural disasters. Third, there is a need for more elaborate information systems, as there remain many shortcomings in understanding the effects of natural disasters on communities from the lack of appropriate data regarding its impact on outcomes such as partial school closures, infrastructure dammage, income reductions, or migration.

My investigation represents an essential input for policymakers because it allows them to make better-informed decisions in disaster management that account for its higher order affectations. In that sense, I propose three policy recommendations deriving from my findings.

It is well established that the loss of cognitive skills and academic achievement negatively influences long-term economic success and quality of life (IADB, 2022). My results proved that there is a significant negative impact of natural disasters that falls more heavily on economically vulnerable students. This fact implies that climate-related adverse shocks represent a poverty trap that contributes to the persistence of poverty through human capital reductions. Therefore, the educative sector must mitigate the affectations of natural disasters on academic skills by implementing ex-ante, simultaneous, and ex-post measures. In that sense, it is recommendable that schools: i) make contingency plans to guarantee education continuity; ii) minimize school closures to what is strictly necessary to avoid life threats; and iii) monitor students in the aftermath of disasters to detect learning losses and remediate them.

Second, in a context of profound inequality, such as the Colombian, education is a tool that guarantees unfavoured students a better future. My results have shown that students who face a disaster are at greater risk of dropping out of school, especially if they attend schools that do not offer upper education grades. Therefore, it is necessary to deploy a multi-sectoral strategy involving schools, local governments, students, and their parents to avoid decoupling students from the educative system. This strategy could include identifying early alerts of dropouts, providing economic incentives to prevent pupils' work, and actively seeking absent students.

Finally, my paper speaks to policymakers planning the educative infrastructure in Colombia. In 2021 the National Government declared the importance of increasing and improving the school facilities in rural areas and destinated COP 540,000 million for that purpose (DNP, 2021). Therefore, such efforts must account for natural disasters' vulnerability to define where the schools will be built and how resilient they are to adverse climatic events. Similarly, an assessment of the susceptibility of existing schools to these threats should also be made. Finally, it is essential that the educative supply is prepared to absorb the effects of negative shocks and protects the students' learning process.

9 Annexes

Table 13: Robustness to changes in treatment definiton

	0km	P5	P10	P25	P50
Saber 3rd					
Advanced	-1.399*	-3.076	-1.048**	-1.490**	-0.091
	(2.268)	(2.050)	(1.317)	(2.332)	(0.898)
Insufficient	-0.273	1.500***	1.656***	1.313**	0.896
	(2.133)	(1.822)	(1.127)	(2.419)	(0.946)
More than satisfactory	-2.272	-4.056*	-2.036***	-2.016**	-0.818
	(2.435)	(2.163)	(1.456)	(2.737)	(1.033)
Saber 5th					
Advanced	-1.233	-0.042	-0.946	-0.710	1.015**
	(1.018)	(0.878)	(0.663)	(1.478)	(0.509)
Insufficient	1.121	2.784**	2.780**	1.824*	0.315
	(1.741)	(1.215)	(0.955)	(2.259)	(0.796)
More than satisfactory	-3.623*	-2.514*	-1.361*	-1.814*	1.330
	(2.031)	(1.488)	(1.101)	(2.456)	(0.805)
Saber 9th					
Advanced	-0.238	-0.213	0.355	0.241*	0.768*
	(0.360)	(0.405)	(0.357)	(0.479)	(0.316)
Insufficient	-1.314	-0.475	0.694	-0.628	-0.328
	(1.924)	(1.741)	(1.870)	(2.262)	(1.030)
More than satisfactory	-1.695	-0.096	-0.227	1.868	2.224**
	(1.907)	(1.699)	(1.331)	(1.914)	(1.056)
Saber 3rd-5th-9th					
Advanced	-0.722	-0.999	-0.722	-0.045	0.867*
	(0.890)	(0.690)	(0.618)	(1.395)	(0.469)
Insufficient	-0.524	0.810	0.652	0.467	0.040
	(1.107)	(0.936)	(0.747)	(1.450)	(0.527)
More than satisfactory	-1.634	-1.815*	-1.206	-0.840	0.917
	(1.180)	(0.935)	(0.807)	(1.843)	(0.655)
Saber 11th					
Standardized score	0.012	-0.022	-0.074**	-0.056**	-0.002
	(0.048)	(0.059)	(0.048)	(0.035)	(0.039)

*** p<0.01, ** p<0.05, * p<0.1.

Table 14: Control group: never treated schools

	3rd, 5th, 9th	3rd	5th	9th
Insufficient level				
	0.652	1.607	1.572*	0.183
	(0.505)	(1.248)	(0.630)	(1.013)
More than satisfactory level				
	-1.206**	-1.764**	-1.395**	-0.772
	(0.635))	(1.234)	(0.735)	(0.947)
Advanced level				
	-0.722	-1.082	-1.455**	0.399
	(0.635)	(1.067)	(0.640)	(0.320)

*** p<0.01, ** p<0.05, * p<0.1.

Table 15: Estimations traditional TWFE model

	3rd, 5th, 9th	3rd	5th	9th
Insufficient level				
	-0.709**	-0.879*	-0.226	-1.244
	(0.346)	(0.489)	(0.530)	(0.810)
More than satisfactory level				
	0.901**	1.419**	-0.00534	0.637
	(0.449)	(0.685)	(0.615)	(0.824)
Advanced level				
	0.417	0.558	0.0403	-0.334
	(0.371)	(0.616)	(0.451)	(0.300)

*** p<0.01, ** p<0.05, * p<0.1.

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