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Impact of extreme rainfall shocks on the educational performance of vulnerable urban students: evidence from Brazil

Francisca Letícia Ferreira de Lima
Pós Graduação em Economia – CAEN, Federal University of Ceará, Fortaleza, Brazil
Rafael Barros Barbosa
Federal University of Ceará, Fortaleza, Brazil, and
Alesandra Benevides and Fernando Daniel de Oliveira Mayorga
Sobral Campus, Federal University of Ceará, Fortaleza, Brazil

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Abstract

Purpose – This paper examines the impact of extreme rainfall shocks on the performance in test scores of students living near at-risk urban areas in Brazil.

Design/methodology/approach – To identify the causal effect, we consider the exogenous variation of rainfall at the municipal level conditioned on the distance from the school to risk areas and the rainfall intensity in the school months.

Findings – The results suggest that extreme precipitation shocks, defined as a shock of at least three months of high-intensity rainfall, have an adverse impact on both math and language performance. Through a heterogeneous effects analysis, we find that the impact varies by student gender, with girls being more affected. In addition, among students who study near at-risk areas, those with better previous school performance and higher socioeconomic status are more negatively affected.

Originality/value – Our results suggest that extreme weather events can increase the differences in human capital accumulation between the population living near risk areas and those living more distant from these areas.

Keywords Extreme rainfall shocks, Risk areas, Educational performance

Paper type Research paper

1. Introduction

According to recent evidence from climate change literature, the expected number and magnitude of extreme weather events tend to increase in the coming years (IPCC, 2022). In urban areas, vulnerability to such events is geographically delineated by risk areas for natural disasters, i.e. regions of the cities where the occurrence of climatic shocks tends to produce more social damage. Nowadays, approximately 1.47 billion people, 19% of the world's population, live in those areas (WB, 2020). Although there is a considerable amount of literature documenting the social costs of extreme climate episodes [1], there is little evidence of their educational costs. In urban areas, weather shocks are less related to economic losses than in rural areas, where such events reduce agricultural productivity, affecting local

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economic opportunities. Despite the expected lower impact on educational outcomes in urban areas, students living near at-risk areas may be more exposed to climate shocks, potentially affecting human capital accumulation. If climate shocks negatively affect students living in at-risk areas, but not in other areas, this could partly explain why there is greater income inequality in urban areas (Glaeser, Resseger, & Tobio, 2009; Baum-Snow & Pavan, 2013; Baum-Snow, Freedman, & Pavan, 2018).

This paper aims to understand the impact of extreme precipitation shocks on students' performance living near risk areas in Brazil. According to the Brazilian government, there are approximately 2.47 million families (9.8 million individuals) living in such risk areas, mainly in highly urbanized cities (IBGE, 2018). Dwelling location near risk areas follows a process similar to slum formation and is more intensive in developing countries, such as Brazil (Cavalcanti, Da Mata, & Santos, 2019; Alves, 2021; Marx, Stoker, & Suri, 2013). Since central regions of cities become more expensive, individuals who seek to benefit from agglomeration effects (Combes, Duranton, & Gobillon, 2019; Bryan, Glaeser, & Tsivanidis, 2020; Duranton & Puga, 2004), but cannot afford housing in central areas, have no choice but to live in sub-housing conditions, such as slums or areas subject to climate hazards.

In this paper, we use a georeferenced database of risk areas in 826 municipalities in Brazil. The data are made available by the National Center for Natural Disaster Monitoring and Alert (*Centro Nacional de Monitoramento e Alerta de Desastres Naturais - CEMADEM*), an official Brazilian government agency that collects and monitors data on natural disasters. We linked the georeferenced risk areas to approximately 45 thousand georeferenced schools that participated in the National Educational Assessment (*Sistema de Avaliação da Educação Básica [SAEB]*) from 2007 to 2015 [2]. SAEB measures students' proficiency in mathematics and languages in the 5th and 9th grades (11 school years) of primary education and the 3rd grade of high school. However, we focus our analysis on the 9th grade because this is a critical period for Brazilian public school students. The 9th grade represents the transition from middle school to high school (first year of high school) and is the period with the highest dropout rate during the whole school cycle.

We measure students' vulnerability to climate shock using the distance from the school to risk areas. Since transportation is costly for students, especially in developing countries, enrollment in a specific school has a strong geographic element. Then, we posit that students who attend schools near risk areas are likely to be more vulnerable to extreme weather events.

To derive the causal impact of an extreme weather event on vulnerable students, we use a difference-in-difference empirical strategy. We define the precipitation shock as a variable that depends on three key factors: student vulnerability, measured by the distance from the student's school to the risk area; the duration of the shock, defined by the number of school months [3] in which students are exposed to a rainfall shock, and the intensity, measured by the standard deviations of rainfall in a given year in a given municipality relative to the historical average rainfall in that municipality. The literature on the impact of natural disasters points out that these three elements are determinants in measuring the effect of climate shocks (Chen, Mueller, Jia, & Tseng, 2017; Guiteras, Jina, & Mobarak, 2015; Krichene *et al.*, 2021). In addition, this is a straightforward and a flexible way of measuring precipitation shocks because we can easily compute such shocks at different values for the key factors, which enables us to better characterize the effect on educational outcomes and perform robustness checks.

We report four main results. First, comparing only vulnerable students whose school is at least 200 m from a risk area, the occurrence of an extreme precipitation shock negatively affects performance in math and language. We refer to extreme shocks as precipitation whose intensity is greater than 1.5σ relative to the average historical precipitation [4]. The effect size represents a reduction in test scores close to 0.05σ in math and 0.03σ in language, which corresponds to a small effect size relative to other educational interventions (Kraft, 2020).

Second, by using variations in the three key factors that compose the precipitation shock variable, we document that the magnitude of the impact changes according to shock intensity, duration of the event and the degree of student exposure. Furthermore, low-intensity shocks (intensity 1.0σ relative to the historical precipitation) have small and no significant effects on performance, and very extreme events (intensity 2.0σ relative to the historical precipitation) have a large effect on student performance. To examine these findings in more detail, we focus the rest of the analysis on extreme precipitation shocks (intensity 1.5σ relative to the historical precipitation).

Third, we find relevant heterogeneous effects. Girls are much more affected by extreme weather shocks than boys, suggesting that these types of shocks have a gender effect. In addition, students with better prior educational attainment and higher socioeconomic status (SES) are also more sensitive to extreme shocks. All results are valid for a battery of robustness checks.

This paper contributes to two main areas. First, recent literature investigates the effect of rainfall shocks on student outcomes in rural areas. In these areas, rainfall shocks represent an exogenous variation in the economic context (Zimmermann, 2020; Shah & Steinberg, 2017). However, this interpretation is misleading in urban areas because of the reduced importance of the agricultural sector in urban areas. Thus, this paper contributes to the literature that studies the impact of extreme climate shocks on urban areas (Gu, 2019; Sarmiento & Miller, 2006; Kumar, 2021; Gallagher, 2014). In these areas, vulnerability to climate shocks is much more related to the proximity of risk areas. Second, this paper contributes to measuring the social costs of climate change. There is extensive literature documenting the costs of climate change, such as Barrage, 2020; Diffenbaugh and Burke (2019) and Carleton and Hsiang (2016). We contribute to show that climate change shocks, especially to vulnerable individuals, have a large impact on the accumulation of human capital.

In addition to this introduction, this work is divided into three sections. The next section discusses the backgrounds, the data and the econometric strategy. The next section reports the main results, and section four discusses the concluding remarks.

2. Data and empirical strategy

2.1 Data

2.1.1 Educational data. The data on education come from the SAEB (*Sistema Nacional de Avaliação da Educação Básica*), a nationwide standardized exam conducted by INEP [5] every two years since 2007 for all 5th and 9th graders in public schools that have at least 20 students enrolled in that particular grade level. This is a low-stakes assessment administered by the federal government to assess the progress of students' cognitive abilities across the country. It uses Item Response Theory (ITR), which allows comparability of test scores over time. It has no direct implications for student progress in school, student grades, teacher promotion or removal. Students are not informed about their individual performance on this assessment. SAEB data were collected from 2007, 2009, 2011, 2013 and 2015 to measure student performance, focusing on students enrolled in 9th grade of primary education. To facilitate the interpretation of the estimates, we standardized student test scores according to the individual-level distribution of test scores for students in municipalities that did not experience a precipitation shock.

In addition, INEP applies, along with SAEB, a set of surveys among students, teachers and principals. We extract from this survey information on student socioeconomic backgrounds, such as gender, mother's education, age and racial status. INEP also provides the addresses of all public elementary schools in Brazil. We use these addresses to georeference the schools [6].

2.1.2 Risk areas data. The location of risk areas is provided by CEMADEN (*Centro Nacional de Monitoramento e Alerta de Desastres Naturais*). These data inform the location of risk areas in 826 Brazilian municipalities. Risk areas are defined as areas within municipalities that are vulnerable to the occurrence of natural phenomena or situations that cause accidents. Such areas are delimited based on the occurrence of indications and evidence of earth movements observed on site, such as cracks in the soil, landslide steps, leaning trees, landslide scars and flood marks, among others.

The regions that present a high risk are grouped and represented by polygons in the geographic space. The polygons were created by the federal agency IBGE (*Instituto Brasileiro de Geografia e Estatística*) [7] to characterize the risk areas according to the socioeconomic information of the residents. This information has been used to subsidize public policies in those areas whose population is more vulnerable. We extracted only the georeferenced data from these polygons.

In the online appendix [8], we compare the socioeconomic characteristics of municipalities with documented risk areas by CEMADEM and municipalities that are not in the sample. The municipalities in the sample are more urban and have a higher number of poor, as measured by the proportion of poor and the proportion of individuals with an income 1/4 of the minimum wage. They also have a higher per capita income and lower illiteracy rates. Indeed, the municipalities in the sample represent more populated municipalities in Brazil, nearly 47% of the Brazilian population.

Figure 1 shows the location where CEMADEN has identified risk areas. Note that the risk areas are concentrated in coastal municipalities, which also gather the largest share of the Brazilian population.

We relate Brazilian public schools to polygons of risk areas. Thus, we can measure the distance from each school to each risk area in the 826 municipalities. Our final sample contains approximately 15,506 elementary schools, serving approximately 864,000 9th-grade students each year, representing 36% of the total Brazilian students in that grade.

2.1.3 Other data. We supplement our core risk area and education data with municipal characteristics from IBGE. We use this source to gather information on municipal population, municipal income, inequality across municipalities and municipal Human Development Index (HDI). We use this information to address potential prior differences between municipalities.

2.2 Empirical strategy

2.2.1 Measuring extreme precipitation shock. The effect of precipitation shocks on social and economic outcomes depends on three factors: the intensity of rainfall, the duration of such an event and the degree of vulnerability of individuals exposed to the shock. We define precipitation shock in municipality m in state e in school year t, T_{met}, as follows:

$$T_{met} = 1 \; if \; \mathbb{1}\{d_{sm} < B\} \times \mathbb{1}\{shock_{mt} \geq n\} \tag{1}$$

Where, $shock_{mt}$ refers to the number of monthly precipitation shocks in the municipality m in the school year t and $\mathbb{1}\{shock_{mt} \geq n\}$ is an indicator function that assigns the value 1 to municipalities that were exposed to at least n precipitation shocks in the same school year. The term $\mathbb{1}\{d_{sm} < B\}$ is an indicator function that assigns the value 1 to schools located at a distance (d_{sm}) of B meters from the border of a risk area. The parameter n indicates the number of occurrences of precipitation shocks in schools near risk areas. We assume that $n \geq 3$, implying the variable T_{met} is equal to 1 if occurs at least three precipitation shocks during the school year and the student's school is located within B meters of some risk area. This parameter n allows us to measure the duration of precipitation events in the months that the students are at school. Assuming $n \geq 3$ also allows us to control rainfall events that may

Note(s): Figure shows the location of risk areas in Brazil
Source(s): Own elaboration

Figure 1. Location of risk areas in Brazil

occur sporadically in just one or two months. In addition, natural disasters caused by excessive rainfall are strongly associated with the accumulation of water on the surface that occurs just in longer periods of exposure.

In our main specification, we assume B = 200 m (218,723 yards). Therefore, treated students are enrolled in schools within 200 m of a risk area in municipalities that were exposed to at least three precipitation shocks during the school year. In turn, students in the control group are enrolled in schools more than 200 m away from a risk area and those never exposed to a precipitation shock.

We consider that students who attend school near a risk area are more likely to live near risk areas as well. This assumption is suitable for some reasons. First, in general, students enrolled in Brazilian public schools are poor [9]. For poor students the cost of attending a school far from their residence is not negligible, implying that they likely are also highly exposed to precipitation shocks. Second, there is a large literature documenting that the distance of student residence to school is an important factor of school choice (Carneiro, Das, & Reis, 2022). Approximately 200,000 students per year studying in a school within 200 m of a risk area in the 826 Brazilian municipalities considered in the analysis. This represents approximately $\frac{1}{4}$ of the students in these municipalities.

Since there is no appropriate criterion for defining exposure to risk areas by distance from the student's school in the presentation of the results, we change the value of the parameter B for the distances: $B = 500$ and $B = 800$ m. This variation prevents the conclusions of this article from being considered arbitrary and associated with a specific parameterization.

We define the occurrence of a rainfall shock in municipality m in the school year t as follows:

$$shock_{mt} = \mathbb{1}\{precip_{mjt} > k\sigma_{mj}\} \tag{2}$$

where, $precip_{mjt}$ is the amount of precipitation in municipality m in the school year t in month j. In general, the SAEB exam is applied in the months of October and November, then j refers to January through September. In turn, σ_{mj} is the standard deviation of the historical mean rainfall in municipality m in month j. The historical average was calculated from the last 30 years in each municipality (1976–2006). Finally, k is a parameter that measures the intensity of the precipitation. In presenting the results, we varied the parameter k by $k = 1, 1.5, 2$. Thus, $k = 1$ implies that the shock variable measures the incidence of a rainfall shock for which the intensity was greater than one standard deviation above the historical average.

This definition of extreme precipitation shock has the advantage of being very flexible, allowing a more complete characterization of the impact of precipitation shocks on student performance. That is, it is possible to vary different parameters associated with the precipitation shock and thereby understand in more detail how such shocks affect student performances.

2.2.2 Econometric specification. This paper aims to identify the causal effect of extreme precipitation shocks on the 9th-grade performance of vulnerable students, i.e. those who attend schools near risk areas. We assume that these students have a high probability of living near risk areas as well [10]. The control group are those who live within 1,000 m of the border of a risk area and students who live near risk areas (within 200 m of their border) but were not affected by the precipitation shock.

We estimate the following econometric specification:

$$Y_{ismet} = \beta_0 + \gamma T_{met} + \beta' X_{ismt} + \theta_s + \delta_{et} + \varepsilon_{ismet} \tag{3}$$

This kind of specification is known as the ring method. The ring method is motivated by the fact that since the treated and control units are all very close in spatial location, then shocks over time should be common across units in the neighborhood (Butts, 2022). The variable of interest (Y_{ismet}) is the performance, in math or language, of 9th graders of student i in school s in municipality m in state e in year t. T_{met} represents the rainfall shock in municipality m in state e in school year t. X_{ismt} is a vector of student characteristics, such as gender (girls), racial status (black and brown), student age and mother's education [11]. θ_s represents school fixed effects that absorb idiosyncratic factors related to school characteristics, such as number of students, quality of teachers, etc. Note that this fixed effect also absorbs factors related to school location, such as socioeconomic conditions, violence, urban amenities around the school, etc. The inclusion of school fixed effects allows us to obtain the relevant counterfactual for a school's nearly to risk areas: a school of the same type which may or may not be affected by an extreme precipitation shock. At last, δ_{et} represents the year-fixed effect interacted with the state, which aims to absorb time-varying factors across the states, such as state educational policies, economic activity, etc. The parameter of interest is γ which measures the occurrence of an extreme precipitation shock on student performance.

Our main identification assumption is that precipitation shock is exogenous to student performance when controlled by the student factors, school and state-by-year fixed effects, and considering that the treated and control schools are all very close in spatial location, that is:

$$\mathbb{E}[Y_{ismet}|X_{ismt},\theta_s,\delta_{et},T_{met}] = \mathbb{E}[Y_{ismet}|X_{ismt},\theta_s,\delta_{et}] \tag{4}$$

The main threat to the identification is if the students predict the occurrence of the extreme weather event and migrate to a different school. This may affect their performance and is correlated with unobservable factors. However, this is a very difficult possibility. First, we test in the robustness section that the precipitation shock does not change significantly the class size of the treated school in comparison with the control schools. This suggests that students do not migrate to a different school in response to a precipitation shock, implying that students do not predict the occurrences of precipitation shocks. Second, predicting the occurrence of extreme weather events is hard even for experts, thus is not expected that students, or their parents, predicted adequately the occurrence of such events.

3. Results

3.1 Main results

In this section, we present the main results. Table 1 reports the treatment effect of an extreme precipitation shock on the performance of students studying close (less than 200 m) to a risk area. To analyze the sensitivity of the estimates, we vary the specifications of the econometric model. In column 1, only school and year-fixed effects are added. In column 2, we add some controls at the student level, such as gender (female as a reference), self-reported racial status (black and brown as a reference), the student's age and the education of the student's mother or father. In column 3, time-varying state fixed effects are included. This specification, in column 3, represents our preferred model. Finally, in columns 4 and 5, the same specification

	(1) k = 1.5	(2) k = 1.5	(3) k = 1.5	(4) k = 1.0	(5) k = 2.0
Panel A: math					
Treatment	−0.0663***	−0.0915***	−0.0559**	0.0218	−0.130*
	(0.0147)	(0.0119)	(0.0225)	(0.0218)	(0.0751)
Obs	10,35,266	967,338	967,338	967,338	967,338
R-2	0.076	0.112	0.113	0.113	0.113
School fixed effect	Y	Y	Y	Y	Y
Year-fixed effect	Y	Y	N	N	N
Student control	N	Y	Y	Y	Y
State-year fixed effect	N	N	Y	Y	Y
Panel B: language					
Treatment	−0.0688***	−0.0947***	−0.0396*	0.0138	−0.113*
	(0.012)	(0.0119)	(0.0218)	(0.0236)	(0.0613)
Obs	10,35,266	967,338	967,338	967,338	967,338
R-2	0.068	0.127	0.128	0.128	0.128
School fixed effect	Y	Y	Y	Y	Y
Year-fixed effect	Y	Y	N	N	N
Student control	N	Y	Y	Y	Y
State-year fixed effect	N	N	Y	Y	Y

Note(s): Table 1 shows the estimates of the impact of a precipitation shock in the performance of students in math and language. Significance: ***1, **5 and *10%. Standard errors clustering at municipality level. Own elaboration

Table 1. Effect of extreme precipitation shock on the performance of the students at-risk areas

from column 3 is replicated, with the only difference being the intensity of the shocks, set to 1 ($k = 1$) and 2 ($k = 2$) standard deviations of precipitation above the municipality's historical average. Since Brazil has large population differences in its municipalities, we weighted the estimates by the municipality's population size. In addition, the standard errors are estimated by clustering at the municipality level, following recommendations from Abadie, Athey, Imbens, and Wooldridge (2017).

Panel A presents the estimates for 9th-grade math performance. The occurrence of an extreme rainfall shock reduces mathematics performance by 0.055σ (column 3). In turn, performance in language, presented in panel B, indicates that an extreme precipitation shock negatively impacts by 0.04σ (column 3). Modifications in the econometric specification do not affect the findings, marginally changing the effect size. The estimates are sensitive to the introduction of time-varying state fixed effects, suggesting that local state actions may contribute to moderating the impact of extreme precipitation on student performance in math and language.

Putting the estimates in perspective, we also calculated the effect of an extreme precipitation shock in terms of months of effective learning. The impact of an extreme precipitation shock corresponds to a loss of 1.48 and 2 months of effective learning during the school year for language and mathematics, respectively [12]. This implies that approximately 20% of the school year is lost due to extreme precipitation shocks.

The estimates suggest that extreme rainfall events affect learning. Literature focused on rural areas, rainfall shocks may increase student dropout rates (Shah & Steinberg, 2017; Baez, De la Fuente, & Santos, 2010; Ferreira & Schady, 2009). Due to the composition change in schools, these studies do not identify the effect on learning adequately. In the robustness tests, we show that our estimates do not affect the class composition. Then, our results suggest that the rainfall shock causes a learning loss and not a school attendance reduction. This result provides evidence that a different type of policy mitigation is required, focusing on learning recovery.

Given the trends of climate change and the resulting increase in the occurrence and intensification of weather events, students from municipalities affected by extreme precipitation shocks tend to widen the gap in terms of skill accumulation compared to students from municipalities that are less affected and also in comparison with students from municipalities that live further away from risk areas.

Columns 4 and 5 show that the intensity of the shock matters for the size of the average effect. Precipitation shocks of low magnitudes, such as 1 standard deviation above the average precipitation (column 4), have no significant effects on student performance. On the other hand, if a high-intensity shock is considered, such as 2 standard deviations above average rainfall (column 5), the negative impact on performance is significant and has a high impact, -0.13σ and -0.11σ in mathematics and language, respectively.

Considering the main specification, the magnitude of the impact is small, according to Kraft (2020)'s classification. Kraft (2020) classifies effect sizes according to a meta-analysis containing 750 Randomized Control Trials (RCTs) for developed countries. However, some additional aspects are important. First, the effect size depends on the magnitude of the extreme event. In Table 1, the very extreme events, $k = 2$, have a medium effect size according to Kraft's classification. Second, the size of the effect can be sensitive to the stage of education. We focused only on 9th-grade students. Thirdly, although small, the frequency of events during the school year can increase the size of the impact.

Given this variation according to the intensity of the precipitation shock, we will focus specifically on the results for $k = 1.5$. Table 2 presents the results by varying the minimum distance of schools from risk areas. As the minimum distance between schools and risk areas increases, the less likely the student is to live near such a risk area, and the impact of an

	(1) $B = 200$ m	(2) $B = 500$ m	(3) $B = 800$ m
Panel A: math			
Treatment	−0.0559**	−0.0391**	−0.0124
	(0.0225)	(0.0164)	(0.0170)
Observations	967,338	1,827,887	2,658,716
R-2	0.128	0.131	0.121
School fixed effect	Y	Y	Y
Year-fixed effect	N	N	N
Student controls	Y	Y	Y
State-by-year fixed effect	Y	Y	Y
Panel B: language			
Treatment	−0.0396*	−0.0307**	−0.00403
	(0.0218)	(0.0138)	(0.0131)
Observations	967,338	1,827,887	2,658,716
R-2	0.128	0.131	0.136
School fixed effect	Y	Y	Y
Year-fixed effect	N	N	N
Student controls	Y	Y	Y
State-by-year fixed effect	Y	Y	Y

Note(s): Table 2 presents the results of estimation of the impact of a precipitation shock on student performance in language and math considering different distances from schools to risk areas. Significance: ***1, **5 and *10%, estimated standard errors clustering at the county level. Own elaboration

Table 2.
Effect of extreme precipitation shock on the performance of vulnerable students – different distances from risk areas

extreme precipitation shock is expected to decrease. Column 1 replicates the results of the preferred specification from Table 1 (column 3). Columns 2 and 3 present the same specification, considering $B = 500$ and $B = 800$ m as the minimum distance of schools from risk areas, respectively.

The results suggest that the inclusion of schools more distant from risk areas reduces the effect of the precipitation shock on student performance. The further away a school is from a risky area, the less likely the student is to live near such an area, and therefore, the less the impact of precipitation shocks in urban areas tends to be. Thus, the occurrence of such shocks generates differences in terms of human capital accumulation between (affected and not affected by precipitation shocks) and within municipalities (schools near or far from a risk area) that have risk areas. This evidence may contribute to intra-municipal wage differences, partly explaining the higher income inequality in more urban municipalities (Wheeler, 2004; Glaeser *et al.*, 2009; Ahlfeldt & Pietrostefani, 2019). Since individuals living near risk areas are adversely affected by precipitation shocks, the difference in human accumulation among those living farther away from risk areas increases, potentially resulting in differences in lifetime earnings.

A further important aspect of the magnitude of the effect of weather events is duration. Specifically, in the case of precipitation shocks, the duration of the event is critical because the highest costs arising from these types of weather phenomena occur through the accumulation of water in the soil. Zhang, Li, Ma, Song, and Song (2018) and Islam and Ahsanuzzaman (2020) show that, especially in the case of rainfall disasters, such as floods, the duration of the event is directly related to the size of the impact on health and education. In other words, shocks that occur in just one month may not necessarily cause damage because the soil can absorb some of the rainwater. However, the occurrence of other subsequent shocks will be more difficult to absorb because the soil will be soaked due to the previous shocks.

Figure 2 presents the estimation of the preferred model varying the amount of extreme precipitation shocks that students are exposed to ($n = 1, 2, 3$ and 4) [13]. It was limited to the occurrence of a maximum of four shocks during the school year because the number of shocks above four is quite rare and, thus, the estimation of the standard errors is hindered.

The results suggest that occasional extreme shocks, $n = 1$ or 2, are not sufficient to affect student performance. However, as more shocks occur, $n = 3$ and 4, not only does the effect of the extreme precipitation shock become relevant, but it also becomes more intense. Students living near risk areas who are affected by four extreme precipitation shocks during the school year reduce their performance in language and math by 0.09σ and 0.13σ, respectively. This implies a loss of approximately 3.3 and 4.8 months of effective learning in language and math, respectively. Thamtanajit (2020) found a similar learning loss effect in Thailand as a result of severe flooding that occurred in 2011.

Moreover, this result is in line with the empirical finding in other contexts that precipitation shocks in risk areas become relevant when there is difficulty in rainwater runoff (Zhang *et al.*, 2018). In the case of education performance, this effect increases according to the occurrence of more than three shocks during the school year.

3.2 Robustness

Different robustness tests were performed to check the reliability and sensitivity of the results.

3.2.1 Placebo. To verify whether the results are driven by previous trends in the outcome variables, we conducted a placebo test. As the SAEB exam is conducted biannually (2007, 2009, 2011, 2013, 2015), we use the same econometric specification, considering shocks in periods when there was no SAEB (2008, 2010, 2012, 2014, 2016). That is, we test whether a precipitation shock that occurs after the SAEB affects student performance in previous years.

The results are presented in Supplemental Material (Appendix 1). It is observed that extreme precipitation shocks in the future (one year after the SAEB) do not affect students' performance in the previous year. This rules out the possibility that the findings are driven by previous trends between treated and untreated students.

3.2.2 Change in class composition. Extreme precipitation shocks can also affect average student performance by changing the composition of students in the school. For example, if the precipitation shock causes a higher dropout of high-achieving students, then the effect of the shock is not due to learning difficulty but rather to potential composition change, i.e. a higher proportion of students with low prior performance.

To check whether there is a composition change as a result of precipitation shocks, we estimate a school-level model similar to the main specification. As outcome variables, we use

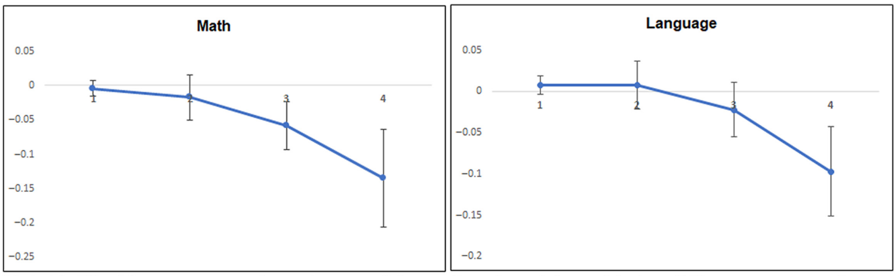

Figure 2.
Intensity of the effect of more precipitation shocks

Note(s): The Figure presents the estimates of the preferred model considering different amounts of extreme precipitation shocks. Significance: *** 1%, ** 5%, and *10%, estimated standard error clustering at the county level
Source(s): Own elaboration

the dropout rate, the reprobation rate and the number of students per classroom in the 9th grade of elementary school. We expected that the occurrence of a precipitation shock would not modify the composition of the classroom.

The results, reported in Supplemental Material (Appendix 2), show that extreme precipitation shocks of at least three months in schools near risk areas do not significantly impact any of the dropout rates, the reprobation rate and the class size. That is, there is no evidence that the class composition changes because of the occurrence of extreme precipitation shocks. Therefore, the main estimated effect is explained only by direct learning loss and not by the classroom composition change.

This result is interesting because it is different from that observed in rural areas. In rural areas, where extreme rainfall events increase the productivity of the agricultural sector, it implies a reduction in student attendance (Shah & Steinberg, 2017; Baez *et al.*, 2010; Ferreira & Schady, 2009). In our case, we identified that extreme rainfall shocks more directly affect students' learning in urban areas.

3.2.3 Additional specifications. We test alternative specifications. First, we analyze the results for the same specification as Equation 3, excluding from the sample the 10% largest and the 10% smallest municipalities. Since Brazil is a country with a high difference in terms of population among its municipalities, our goal is to verify whether the results are dependent on the municipalities *outliers*. The results are similar in terms of magnitude; however, for language, the estimates become non-significant, suggesting that there is a dependence of the variance estimated for language on the *outliers* municipalities.

In turn, the same estimation of Equation 3 was performed without weighting by the population size of the municipalities. The results are quite similar in terms of magnitude and significance.

Finally, the validity of the difference-in-difference strategy requires that the trends in the outcome variables be similar. The presence of nonlinearities in the outcome variables can invalidate the interpretation of this type of empirical strategy. In general, such nonlinearities arise as a result of idiosyncratic interactions with local characteristics. To minimize such a possibility, the main model was re-estimated considering the inclusion of four local variables that interacted with t years. The objective of this exercise is to capture potential time-varying pre-trends that may affect the results.

The variables considered are related to student performance on standardized tests. They are Income inequality (Gini index), the proportion of poor, per capita income, municipal HDI and the proportion of elderly people [14]. The estimated results are similar to the main results, suggesting that there are no nonlinearities arising from pre-trends. The estimates of these additional exercises are reported in the appendix.

3.3 Heterogeneous effects

Extreme precipitation shocks may differently affect the performance of specific groups of students. To check this possibility, we conducted a heterogeneous effect analysis. We considered four student characteristics that could potentially moderate the impact of the extreme precipitation shock. The first category is student gender. There is broad evidence that girls are affected by economic and natural shocks (Neumayer & Plümper, 2007; Enarson, Fothergill, & Peek, 2018). The second characteristic refers to educational quality. The goal is to find out whether the effect of the precipitation shock is greater on students who report that they have already failed a school year or dropped out of school. The quality of the student may mitigate the effect of precipitation shock on performance.

Finally, it was verified whether the precipitation shock has a differential effect on students with different SESs. It is difficult to measure the SES of students with our data because precipitation shocks can also affect the socioeconomic characteristics of students. Then, utilizing self-reported variables of family assets may be "bad control." Therefore, an alternative measure that is less sensitive to precipitation shocks consists of using the SES of students and the relationship between family size in the household and the number of bedrooms. Both family size and number of bedrooms are less affected by extreme precipitation shocks [15]. Thus, we posit that the lower the ratio between family size and the number of rooms in the residence, the higher the SES of the students is expected to be. In other words, a family of high SES is one that has a large number of bedrooms for its members. To facilitate the interpretation of the results, an indicator variable was created that receives a value of 1 if the ratio is less than 2 (high SES) and zero otherwise. Thus, if there is a negative interaction effect between the socioeconomic measure and the occurrence of precipitation shocks, it implies that students from higher socioeconomic families are more negatively affected than students from lower socioeconomic families.

To estimate the heterogeneous effects of each of these variables, henceforth, $factor_{ismet}$ is interacted with the variable T_{met}. Then the equation to be estimated is defined by:

$$Y_{ismet} = \beta_0 + \gamma T_{met} + \alpha T_{met} \times factor_{ismet} + \beta_1 factor_{ismet} + \beta' X_{ismt} + \theta_s + \delta_{et} + \varepsilon_{ismet} \quad (5)$$

where, α captures the differential effect of the specific student characteristic i ($factor_{ismet}$) when affected by an extreme precipitation shock (T_{met}) relative to the control group.

Table 3 presents the results by considering the preferred specification. [16] Panel A presents the results for math and B for language. The results suggest that girls are more sensitive to such extreme precipitation shocks than boys. This result confirms a large body of

Table 3.
Heterogeneous effect

	(1)	(2)	(3)	(4)
Panel A: math				
Treatment	0.00599	−0.104***	−0.0626***	−0.0423*
	(0.0255)	(0.0231)	(0.0216)	(0.0241)
Treatment × Girl	−0.115***			
	(0,0253)			
Treatment × Reproved		0.121***		
		(0.0297)		
Treatment × Dropout			0.152***	
			(0.0523)	
Treatment × SES				−0.0288***
				(0.0103)
Panel B: language				
Treatment	0.0406	−0.0900***	−0.0557***	−0.00878
	(0.0253)	(0.0226)	(0.0214)	(0.0236)
Treatment × Girl	−0.149***			
	(0.0247)			
Treatment × Reproved		0.127***		
		(0.0317)		
Treatment × Dropout			0.248***	
			(0.0591)	
Treatment × SES				−0.0648***
				(0.0107)
School fixed effect	Y	Y	Y	Y
Year-fixed effect	N	N	N	N
Student controls	Y	Y	Y	Y
State-by-year fixed effect	Y	Y	Y	Y

Note(s): Table 3 presents the heterogeneous results from estimation of the impact of a precipitation shock on student performance in Portuguese and mathematics. Significance: ***1, **5 and *10%, estimated standard errors clustering at the county level. Own elaboration literature indicating much greater sensitivity on the part of girls. Björkman-Nyqvist (2013) found that rainfall shocks also have a more prevalent effect on girls than boys. This evidence is related to how parents' values of child labor differ across sexes as a consequence of income shock. In addition, the heterogeneous effect on girls does not depend on the type of natural disaster or the educational level. Di Pietro (2018) found that the L'Aquila earthquake in Italy reduced the learning gains in girls more than in boys for undergraduate students.

On the other hand, students with worse prior performance are less affected by the precipitation shock than other students, given that the differential effect of having already reproved or having dropped out of school before the 9th grade of elementary school is positive and significant. This means that precipitation shocks tend to impact students with high prior performance more strongly.

Finally, having a low (high) SES reduces or increases the effect of extreme precipitation shocks on students. The impact of the interaction between students with higher SES and the precipitation shock is negative, suggesting that such students are more negatively affected. Chetty, Friedman, and Rockoff (2014) examining the effects of teachers on students with different SESs, concluded that the effect of teacher quality is greater for students with high SES. This evidence is explained by the high sensitivity of high SES to changes in school quality. This result is referred to by other studies, such as Jackson, Porter, Easton, and Kiguel (2020), Lockwood and McCaffrey (2009). We interpret our results in a similar way: extreme rainfall shocks can affect school quality by reducing students' learning activities and, consequently, have a greater effect on students with high SES. In summary, girls, students with high prior performance and relatively higher SES are the most affected by extreme precipitation shocks.

4. Conclusion

The present paper revealed that an extreme rainfall shock adversely affects the performance in language and math in 9th grade of students most vulnerable to weather events, i.e. those who study near risk areas. This effect varies according to the intensity and duration of the shock. The robustness tests suggest that the extreme precipitation shock does not significantly alter class composition, indicating that the effect of the extreme precipitation shock is directly associated with learning loss.

Furthermore, it was found that such shocks have a strong differential impact by gender, by students' previously accumulated skills and by the SES of students' families. Girls, students with high prior educational skills and students with higher SES are more strongly negatively affected.

In addition to the identification strategy and the robustness test, a limitation of our empirical design is the target of the effect of extreme rainfall shocks on the school-level, not directly on students. In our empirical strategy, due to data restrictions, we focused on students who attend schools near risky areas. However, not all of these students may be equally exposed to extreme weather shocks. This suggests that, with identification at the individual level, the impact of extreme events may be greater.

Thus, this paper shows that extreme rainfall shocks generate social costs not only related to infrastructure loss but also to human capital accumulation. Due to the quasi-exogenous occurrence of these events, an increase in the difference in human capital accumulation is expected among individuals not affected by such shocks or who are at an adequate distance from risk areas. An important implication of this result is the expected increase in within-municipality inequality caused by the loss of human capital by individuals living near the risk area.

Many policies can be implemented to mitigate the effects of extreme rainfall events on education. However, standard policies to reduce the effect of extreme weather events, as reliable information to monitor risks and vulnerabilities, may not work to minimize the impact on learning. Since the impacts of rainfall shocks are more prevalent among higher-ability students, one potential policy is to develop programs that support learning after such shocks, such as flexible safety nets or programs focused on learning recovery. These policies should focus on schools close to areas of vulnerability.

Future research should focus on identifying policies that help mitigate the effects of extreme rainfall events on human capital accumulation. In addition, another strand could focus on measuring the potential channels of climate shocks on students living near risk zones. Both aspects would help to design public policies focused on adapting this population to climate change.

Notes

1. See for example: (Deschênes & Greenstone, 2007; Burke, Hsiang, & Miguel, 2015; Dell, Jones, & Olken, 2012).
2. SAEB is conducted biannually, so the student variables are available for the years 2007, 2009, 2011, 2013 and 2015.
3. The SAEB is usually held in October or November of odd years. Therefore, we consider the months of January through September of each year as school months.
4. We calculate the average historical precipitation using the last 30 years of precipitation (1976–2006) of each month and municipality.
5. *Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira*.
6. To access the address of all public elementary schools in Brazil, we use the following link: http://idebescola.inep.gov.br/ideb/consulta-publica.
7. IBGE is a national agency responsible to document and analyze geographic and economic data in Brazil.
8. Appendix available upon request to the authors.
9. In Brazil, approximately 74% of the family of public students participate in *Bolsa Família* program, a cash-transfer program focus on poor (INEP).
10. There is a large literature documenting that distance from residence to schools is an important factor in school choice, especially in developing countries (Carneiro *et al.*, 2022).
11. We measured maternal education by a categorical variable, as follows: 1 indicates "Never attended or did not complete 4th grade," 2 indicates "Completed 4th grade but did not complete 8th grade," 3 indicates "Completed 8th grade but did not complete high school," 4 indicates that "Completed high school but did not complete college," 5 indicates the mother who completed college, and 6 indicates the mother who completed a degree.
12. According to dos Santos, Berlingeri, and de Braga Castilho (2017) during the school year (10 months), the student raises approximately 0.27σ in terms of proficiency. Thus, such effective months of learning were calculated as follows: $\frac{10\times\widehat{\gamma}}{0.27}$, where: $\widehat{\gamma}$ is the estimated effect reported in column 3 of Table 1.
13. The estimated econometric model was: $Y_{ismet} = \beta_0 + \sum_{j=1}^{4}\gamma_j \times P_{mt} + \beta' X_{ismt} + \theta_s + \delta_{et} + \varepsilon_{ismet}$, where: P_{mt} is quantity of precipitation shocks occurring in the municipality m in the school year t.
14. A higher proportion of elderly people may affect the demand for municipal resources, from education to health.
15. Extreme precipitation shocks can cause the deaths of members of the student's family and also reduce the number of rooms. However, these events that cause such changes are much rarer and geographically localized.

16. This specification includes school-level fixed effects, time-varying county fixed effects, and control for students. The model is weighted by county population size and standard errors are estimated by clustering at the county level.

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Appendix

The supplementary material for this article can be found online.

Corresponding author

Francisca Letícia Ferreira de Lima can be contacted at: leticialima@caen.ufc.br