Pontifícia Universidade Católica do Rio de Janeiro

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Essays in Climate and Development Economics

Tese de Doutorado

Thesis presented to the Programa de Pós–graduação em Economia of PUC-Rio in partial fulfillment of the requirements for the degree of Doutor em Economia.

Advisor: Prof. Juliano Assunção

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Abstract

Martins, Julia Soihet; Assunção, Juliano (Advisor). **Essays in Climate and Development Economics**. Rio de Janeiro, 2024. 82p. Tese de doutorado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

In the Brazilian empirical context, this thesis investigates the impact of extreme weather events on three key dimensions of development: health, gender-based violence, and education, focusing on how climate change exacerbates existing inequalities by disproportionately affecting vulnerable populations. The first chapter examines the relationship between heat and mortality, showing that while heat-related mortality among non-elderly individuals is primarily caused by cardio-respiratory diseases, for the elderly, the risk of death extends across a wider range of health conditions. Additionally, the findings indicate that heat-related deaths occur within a short time span, highlighting the need for rapid healthcare responses during heat waves. The second chapter explores the effects of drought on intimate partner violence (IPV), comparing rural and urban areas. The results reveal that long-term droughts significantly increase IPV rates in rural municipalities, where economic losses resulting from water scarcity are substantial. In contrast, prolonged droughts in urban areas have minor economic impacts and do not affect IPV rates. The third chapter investigates the short-term impact of extreme rainfall on student achievement in Southern Brazil. The findings show that short, intense rainfall episodes reduce student test scores on a national standardized exams, with disadvantaged groups—such as non-white students, those from lower socioeconomic backgrounds, and students with previous poor achievement—being the most affected.

Keywords

Economic Development   Environment and Development   Climate Change   Health and Inequality   Education and Inequality

Resumo

Martins, Julia Soihet; Assunção, Juliano. **Ensaios em Economia do Clima e Desenvolvimento**. Rio de Janeiro, 2024. 82p. Tese de Doutorado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

No contexto emírico do Brasil, esta tese investiga o impacto de eventos climáticos extremos em três aspectos chave do desenvolvimento: saúde, violência de gênero e educação, focando em como as mudanças climáticas agravam as desigualdades existentes ao afetar desproporcionalmente populações mais vulneráveis. No primeiro capítulo, examina-se a relação entre calor e mortalidade. A análise revela que, enquanto as mortes relacionadas ao calor entre os não idosos são causadas, sobretudo, por doenças cardiorrespiratórias, o risco de morte entre os idosos aumenta para um grupo mais amplo de doenças. Além disso, os resultados indicam que as mortes induzidas pelo calor extremo ocorrem em um intervalo curto de tempo, evidenciando a necessidade de respostas rápidas por parte do sistema de saúde durante ondas de calor. O segundo capítulo explora os efeitos de secas sobre a violência doméstica, comparando áreas urbanas e rurais. Os resultados mostram que as secas de long prazo aumentam significativamente as taxas de violência doméstica em municípios rurais, onde as perdas econômicas provenientes da escassez de água são mais expressivas. Em contraste, em municípios urbanos, onde as secas têm impactos econômicos menores, secas prolongadas não estão associadas a um aumento da violência doméstica. O terceiro capítulo investiga os impactos de curto prazo de chuvas intensas no performance escolar no Sul do Brasil. Os resultados sugerem que episódios curtos de chuvas intensas reduzem as notas dos alunos em uma exame nacional padronizado, com os grupos mais vulneráveis—estudantes não-brancos, de origem socioeconômica mais baixa e com pior desempenho escolar prévio—sendo os mais afetados.

Palavras-Chave

Desigualdade   Meio Ambiente e Desenvolvimento   Mudanças Climáticas   Saúde e Desigualdade   Educação e Desigualdade

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1 Introduction

Climate change is increasing the frequency and intensity of extreme weather events, such as extremely high temperature days, intense rainfall episodes, and droughts (IPCC, 2021b). This scenario is expected to worsen with further global warming. Extreme events are no longer isolated incidents, but are becoming recurring occurrences that will increasingly shape development outcomes. While the impacts of climate change are widespread, they are not equally distributed. Vulnerable populations—both across and within countries—face the most severe consequences due to their limited capacity to cope and adapt.

This thesis combines individual-level data with high-resolution weather data to explore how extreme weather events affect three key dimensions of development: health, gender-based violence, and education. Brazil, with its vast geographical and climatic diversity, as well as significant socio-economic inequalities, offers a unique setting for studying the impacts of extreme weather on development. In this empirical context, we use panel-data techniques to assess the causal impact of extreme weather on development outcomes. As highlighted by Dell *et al.* (2014), focusing on changes in weather realizations over time within a given spatial area helps to credibly identify (i) the channels linking weather and the economy, (ii) heterogeneous treatment effects across different areas, and (iii) nonlinear effects of weather.

The first chapter examines the relationship between heat and mortality, which has been extensively documented in high-income countries but less explored in developing countries like Brazil. Using mortality data disaggregated by cause of death and age, we confirm previous findings that heat-induced mortality is significantly higher among the elderly compared to the overall population. Our contribution to the literature lies in revealing an additional layer of vulnerability: while heat-related mortality among non-elderly individuals is primarily linked to cardio-respiratory diseases, for the elderly, it is associated with increased mortality across a broader range of health conditions. Moreover, we find that heat-related deaths occur within a short time span, suggesting that heat increases mortality by directly impacting health, rather than through indirect economic channels, which have been shown to be important in other developing countries. These findings highlight the need for the health system to be prepared to respond quickly to heat waves.

The second chapter explores the effects of drought on intimate partner violence (IPV), comparing rural and urban municipalities. Using IPV compulsory notification data from official health sources, our estimation shows that droughts significantly increase IPV rates in rural municipalities, particularly as droughts become more severe and prolonged. In rural areas, substantial declines in both agricultural production and local economic activity are also observed. In contrast, prolonged droughts show no effects on IPV or agricultural production in urban municipalities and have only minor impacts on the local economy. Based on theoretical models, we argue that in rural areas, income loss leads to heightened stress, exacerbates household tensions, and reduces women's bargain power within the household, ultimately contributing to an increase in IPV prevalence. In urban municipalities, where income sources are more diversified, the economic consequences of droughts are less severe, resulting in a weaker association between droughts and IPV. This chapter contributes to the literature by being one of the first to explore the role of drought duration in IPV dynamics and to emphasize the differing effects between rural and urban areas.

The third chapter investigates the impact of short-term, high-intensity rainfall episodes on student achievement in Southern Brazil. We observe a decline in students performance on a national standardized exam, with the effects increasing as the intensity and frequency precipitation rise. These effects are more pronounced among non-white students, those from lower socioeconomic backgrounds, and students with lower prior achievement. In this sense, they contribute to aggravate educations inequities. We contribute to the literature on the impacts of natural disasters on educational outcomes by examining the direct impact of rainfall—an event that typically causes less damage than major disasters (such as hurricanes, earthquakes, and widespread flooding) but occurs more frequently. Our empirical approach also contrasts with previous studies that generally define extreme shocks as deviations in accumulated precipitation over longer periods (e.g., months or years) from long-term averages.

Together, these chapters offer important insights into how climate change exacerbates existing inequalities in several dimensions of development. In terms of public policy implications, they underscore the need for mitigation strategies with a special focus on these groups.

2
Heat and Mortality: Evidence from a Tropical Developing Country

2.1
Introduction

Emissions of greenhouse gases from human activities have contributed to approximately 1.1°C of warming since 1850, with projections indicating a further increase of 1.5°C over the next 20 years (IPCC, 2021a). One of the most severe consequences of global warming is the threat it poses to human health. In high-income countries, there is robust evidence linking extreme heat to excess mortality, increased emergency room visits, and higher hospital admissions (e.g., Deschênes & Greenstone (2011); Masiero *et al.* (2022); Gould *et al.* (2024)). Although evidence from developing countries is growing, it remains more limited. Nevertheless, the effects are likely to be even greater due to warmer climates, weaker healthcare systems, and reduced adaptive capacities (Burgess *et al.*, 2017; Cohen & Dechezleprêtre, 2022).

In this study, we examine the relationship between heat exposure and mortality in Brazil, a tropical developing country. While existing evidence points to a positive association between high temperatures and mortality in the country, it primarily comes from epidemiological studies focused on one or a few municipalities (e.g., Fátima *et al.* (2020); de Moraes *et al.* (2022); Silveira *et al.* (2023a,b)). Our research expands on these findings by providing national-level evidence.

Our analysis leverages a large mortality dataset comprising 11,903,803 official death records from 5,555 Brazilian municipalities, covering the years 2010 to 2019—a period marked by an upward trend in extreme temperatures. This dataset includes detailed information about the deceased, such as age, municipality of residence, date, and cause of death. By merging death records with municipal population data, we construct a panel of mortality rates disaggregated by age groups and causes of death. This panel is then combined with monthly indicators of temperature extremes derived from daily gridded weather data.

Our primary focus is on absolute indicators of temperature extremes—the number of days in a month with temperatures exceeding a certain threshold. But we also consider relative indicators, defined as the number of days with maximum temperature surpassing the 95th percentile of the municipality-specific historical distribution of daily maximum temperatures. This method accounts for the possibility of adaptation, as evidence from developed countries suggests that heat-related mortality tends to be lower in areas with consistently higher temperatures. (Deschênes & Greenstone, 2011; Barreca *et al.*, 2015).

The estimation of heat effects on mortality relies on a municipality-by-month panel of mortality rates and temperature extreme indicators. The use of monthly data at the local level allows for the inclusion of a large set of fixed effects: year-month, municipality-year, and municipality-month. These fixed effects control for various confounding factors related to both mortality and temperature. By including these fixed effects, we mitigate concerns of omitted variable bias and ensure that the identification of the heat effects relies on within-municipality temporal variations in temperature extremes. This setup provides a robust framework for isolating the causal impact of heat on mortality.

Our findings indicate that heat is strongly associated with higher mortality rates. In our benchmark specification, each day in a month with temperatures above 35° C increases the mortality rate by 0.19 deaths per 100,000 inhabitants, equivalent to 0.42% of the monthly average rate. For the elderly (adults aged 65 years and older), the coefficient is ten times larger, indicating 1.9 additional deaths per 100,000 inhabitants per month.

Our study builds on the existing literature examining the health risks of global warming. Consistent with previous research, our findings confirm that the elderly individuals are especially vulnerable to extreme heat (Benmarhnia *et al.*, 2015; Heal & Park, 2016; Yu *et al.*, 2019). We provide additional evidence by showing that extreme temperatures not only have a greater impact on the elderly, but also affect them by a wider range of diseases. For non-elderly individuals, extreme heat is primarily associated with an increased mortality due to circulatory and respiratory diseases, whereas for the elderly, the risk extends across most causes of death. In particular, temperatures exceeding 40°C increase mortality across all disease groups. Additionally, by including lagged values of temperature extremes indicators, we find no evidence of delayed or persistent impacts. This suggests that heat-related mortality is primarily driven by immediate deterioration in health conditions rather than by indirect channels such as income losses. Furthermore, we show that heat is not simply anticipating the deaths of ill individuals that would have occurred shortly afterward, as the contemporary effect of heat is stronger than the lagged effects.

Our paper also has important implications for public policy in Brazil. Not only are extreme temperatures are becoming more frequent, but the population is aging. Between 2010 and 2022, the number of people 65 years and older increased by 57.4% (IBGE, 2002). Even if heat-related deaths represent only a small fraction of total deaths, they could impose significant costs on the public health system. Data from the Health Ministry indicate that the average cost of hospitalization for circulatory disease, the leading cause of heat-related deaths, is R$1,280.00 (approximately 220 US dollars). Our findings underscore the need for effective heat health action plans and mitigation policies that consider the vulnerabilities of the population. Moreover, because heat-related deaths are likely to occur within a short period of time, rapid interventions during emergency situations, such as heat waves, are crucial.

The rest of the paper is structured as follows: Section 2.2 reviews the literature on the relationship between heat, mortality, and mitigation policies. Section 2.3 describes the sources of mortality and weather data and presents descriptive statistics. Section 2.4 outlines the empirical strategy. Section 2.5 presents and discusses the main results, including heterogeneous analyses by age and cause of death. Finally, Section 2.6 concludes.

2.2 Literature Review: Heat, Mortality and Adaption

The most direct mechanism linking extreme temperatures to mortality is the deterioration of health. Heat exposure disrupts the body's ability to regulate internal temperature, triggering biological responses that increase the risk of cardiovascular, respiratory, cerebrovascular diseases (Mora *et al.*, 2017; Ebi *et al.*, 2021). The elderly and individuals with preexisting health conditions are particularly vulnerable, as these risks often compound (Heal & Park, 2016; Deschênes & Moretti, 2009).

The impact of high temperatures on mortality varies significantly depending on the season and location, with local average temperatures and the timing of heat events playing crucial roles. For instance, Barreca *et al.* (2015) finds that mortality rates are lower in U.S. states with more frequent extreme heat episodes. This could result from adaptation strategies such as the use of air conditioning, as well increased body's tolerance to heat (Deschenes, 2014). Consequently, many studies define heat extremes using relative measures, such as the top 1% of hottest days in a specific location.

However, adaptation has its limits. Prolonged exposure to wet-bulb temperatures exceeding 35°C overwhelms the body's ability to cool itself, leading to hyperthermia and severe health risks, even for well-adapted populations (Sherwood & Huber, 2010).[2.1] Additionally, people in socioeconomic disadvantage often have limited access to adaptation technologies like air conditioning, making them more susceptible to heat dangers. Therefore, while relative measures can be valuable in understanding adaptation, absolute thresholds are essential for addressing universal heat risks.

Beyond these direct health effects, heat can also affect mortality through indirect channels. Higher temperatures reduce agricultural output, water availability, and household income, particularly in poorer regions. Dell *et al.* (2012) shows that high temperatures significantly constrain economic growth in poor countries where the economy relies heavily on agriculture. In turn, reduced economic activity and lower agricultural production can lead to poorer health outcomes by depressing healthcare spending and contributing to malnutrition, ultimately raising mortality rates (Mahendran *et al.*, 2021). Similarly, Burgess *et al.* (2017) find that in rural India, hot days during the growing season reduce agricultural productivity and wages, indirectly increasing mortality by limiting income and access to resources.

Technologies can help mitigate the effects of extreme heat. Barreca *et al.* (2016) estimates that nearly 90% of the reduction in heat-related mortality in the U.S. from 1960 to 2004 can be attributed to the widespread use of air conditioning. In urban areas, green spaces also provide natural cooling. A recent study by Iungman *et al.* (2023) suggests that increasing tree cover in European cities by up to 30% could prevent one-third of premature deaths caused by urban heat islands during the summer. Additionally, improving access to healthcare and increasing public spending on heat mitigation strategies could reduce vulnerabilities to heat-related mortality (Cohen & Dechezleprêtre, 2022; Masiero *et al.*, 2022; Nguyen *et al.*, 2023).

This review underscores the importance of understanding how the impact of heat differs among population groups, such as the elderly. It also highlights the need to consider both relative and absolute measures of temperature extremes, especially in regions with limited adaptive capacity. Moreover, identifying the direct and indirect mechanisms through which heat affects mortality is essential for designing effective mitigation policies. This study addresses several of these aspects, providing a comprehensive perspective on the impact of heat in Brazil. Although adaptation strategies are beyond the scope of our analysis, they remain a topic for future research.

[2.1] Wet-bulb temperature combines heat and humidity, representing the point at which the human body can no longer cool itself through sweating.

2.3 Data

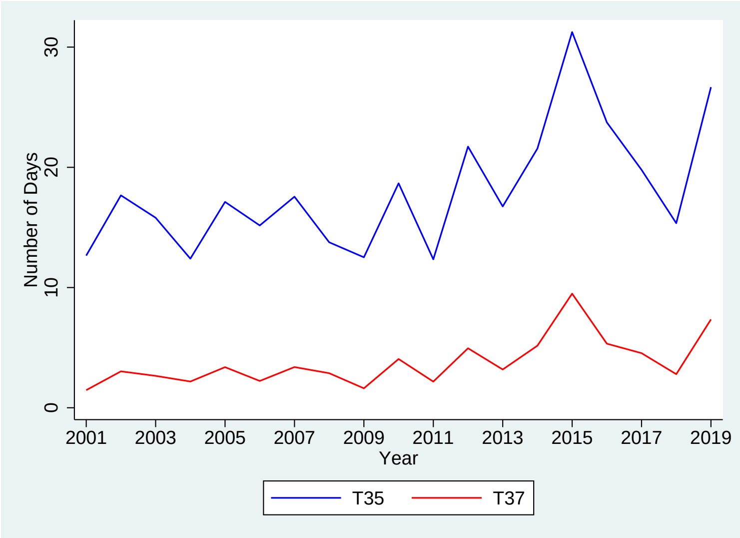
To understand the impacts of high temperatures on health, we construct a panel of municipalities with monthly observations on temperature and mortality rates for the period 2010 to 2019, covering 5,555 municipalities.

We rely on mortality microdata from the Brazilian National System of Mortality Records (*Sistema de Informações de Mortalidade - SIM/DATASUS*), managed by the Brazilian Ministry of Health. The microdata provide detailed information on each officially registered death in Brazil, including the date and basic cause of death, the deceased's municipality of residence, and age. The basic cause of death follows the criteria set by the International Classification of Diseases, 10^{th} Revision (ICD-10). We group basic causes of death into six categories based on ICD chapters: i) circulatory diseases, ii) respiratory diseases, iii) metabolic, nutritional, and endocrine disorders, iv) neoplasms (tumors), v) infectious and parasitic diseases, and vi) all other non-external causes. We exclude deaths from external causes from our sample. We aggregate death records by municipality of residence and month and year of death, and calculate monthly mortality rates (total deaths per 100,000 residents) for different age groups and causes of death.

Data on daily maximum temperature come from Brazilian Daily Weather Gridded Dataset (BR-DWGD) developed by Xavier *et al.* (2022). The current version provides daily weather data at a spatial resolution of 0.1 $\times$ 0.1 degrees. This dataset results from interpolating observational records from Brazilian weather stations. For each Brazilian municipality, we compute the daily maximum temperature as the average of grid-cell values that fall within the municipality's boundaries. We then calculate the number of days in each month with temperature exceeding 35, 37, and 40 degrees Celsius. Additionally, we compute the number of days in a month with temperatures above the 95^{th} percentile of the municipality-specific distribution of daily maximum temperatures, using the period of 2001-2019 as a reference. From the same weather dataset, we also obtain the monthly averages of daily precipitation and relative humidity for each municipality. Additional data sources include the population base, divided by gender and age group, from the Brazilian Ministry of Health.

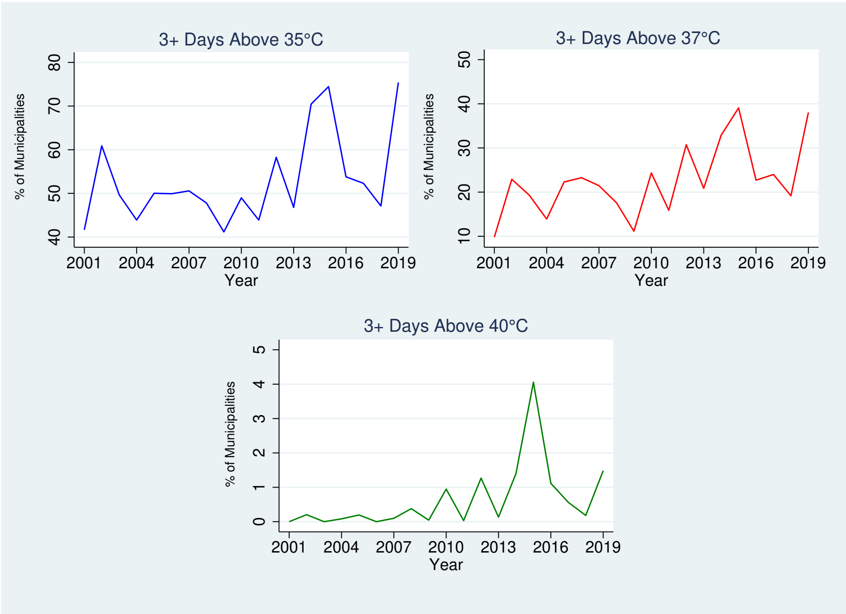
Figures 2.1 and 2.2 illustrate the evolution of population exposed to extreme temperatures in Brazil between 2001 and 2019. Figure 2.1 displays population-weighted number of days in a year with temperatures above 35°C and 37°C, showing an upward trend starting from 2010. Figure 2.2 presents the share of the municipalities experiencing three or more days in a year with temperatures exceeding 35°C, 37°C, and 40°C, weighted by municipality population. We observe that while the percentage of the population experiencing temperatures surpassing 40°C remains small throughout the period, it shows a noticeable upward trend.

Figura 2.1: Average Number of Days in a Year with Temperatures Above 35°C and 37°C



Notes: This figure shows the evolution of the average number of days in a year with temperature above 35 ° and 37° between 2001 and 2019. The source of temperature data is Xavier *et al.* (2022). Municipality averages have been weighted by total population in a municipality.

Figura 2.2: Share of Municipalities with 3 or more Days in a Year with Temperatures Above 35° and 37°C and 40°C



Notes: This figure shows the evolution of the average number of days in a year with temperature above 35 ° and 37° between 2001 and 2019. The source of temperature data is Xavier *et al.* (2022). Observations are weighted by municipality population of the relevant group between 2010 and 2019.

Table 2.1 presents the descriptive statistics of the municipality-by-month panel of mortality rates and weather indicators between 2010 and 2019. The summary statistics are reported separately for the entire population, as well as for the elderly and non-elderly. As expected, mortality rates are higher among the elderly for all conditions. Circulatory diseases emerge as the leading cause of death, followed by neoplasms and respiratory diseases. On average, there are 1.73 days per month with maximum temperatures above 35°C, 0.41 days with temperatures above 37°C, and 0.008 days exceeding 40°C. The standard deviations for the temperature indicators are large, indicating considerable variation across municipalities and over time.

Tabela 2.1: Descriptive Statistics

	All		**Non-Elderly (<65 y)**		**Elderly (≥65 y)**	
	mean	sd	mean	sd	mean	sd
Mortality Rate (per 100,000 pop)						
Digestive	2.60	2.77	1.39	2.07	15.96	21.89
Infectious	2.17	2.45	1.31	1.82	11.55	19.36
Neoplasm	8.47	5.56	4.02	3.55	57.31	42.63
Metabolic	3.14	3.42	1.04	1.86	26.19	32.38
Others	8.38	6.08	4.16	3.89	54.44	48.78
Circulatory	14.2	7.91	4.61	3.90	120.25	69.16
Respiratory	5.86	4.79	1.50	2.12	53.72	44.15
All Causes	44.8	16.5	18.0	8.18	339.43	117.75
Weather						
# T35	1.73	4.84	1.73	4.85	1.70	4.73
# T37	0.41	2.16	0.41	2.17	0.40	2.09
# T40	0.0079	0.15	0.0079	0.16	0.01	0.15
# Tp95	1.86	3.70	1.86	3.70	1.85	3.63
Heat Wave	0.24	0.43	0.24	0.43	0.25	0.43
Precipitation	3.95	3.41	3.95	3.42	3.86	3.31
Relative Humidity	73.8	8.87	73.8	8.88	73.53	8.72
Observations	666600		666600		666600	

Notes: This table presents descriptive statistics for mortality and weather conditions data in Brazilian municipalities from 2010 to 2019. Mortality data comes from SIM/DATASUS, and weather information is Xavier *et al.* (2022) gridded weather dataset. Descriptive statistics are shown for the entire population, as well as for non-elderly (<65 years) and elderly (65 years) populations, as defined by the Brazilian Health Ministry. # T35, # T37, and # T40 are the number of days in a month with maximum temperatures above 35°C, 37°C, and 40 °C, respectively. # Tp95 is the number of days in a month where temperatures exceed the 95$^{\text{th}}$ percentile of the daily maximum temperature distribution. Heat waves are defined as two or more consecutive days in a month with temperatures exceeding the 95$^{\text{th}}$ percentile. Observations are weighted by the municipality's average population of the group of interest over the 2010-2019 period.

2.4 Empirical Strategy

To identify the impacts of heat on mortality rates, we estimate the following linear regression:

$$M_{imt} = \alpha + \beta_1 T_{imt} + \beta_2 W_{imt} + \delta_{mt} + \gamma_{it} + \theta_{im} + \epsilon_{imt} \tag{2.1}$$

Where: The dependent variable, M_{imt}, represents the mortality rate in municipality i, during month m and year t. The variable of interest, T_{imt}, denotes the number of days in a month with temperatures above a specified threshold (we use 35, 37, and 40 degree Celsius). The vector W_{imt} includes daily average precipitation and relative humidity. δ_{mt} and γ_{it} are vectors of year-month and municipality-year fixed effects, respectively, while θ_{im} represents municipality-month fixed effects. ϵ_{imt} is the error term. We cluster the standard errors at the municipality level. Moreover, since municipalities differ in size and, therefore, in the number of people exposed to extreme temperatures, we weight the regressions by the average population in each municipality.

The year-month fixed effects account for time-specific shocks affecting all municipalities, such as macroeconomic conditions, national weather phenomena, aggregate mortality trends, and national health policies. The municipality-year fixed effects capture factors specific to each municipality that remain constant within a given year, such as local governance, demographic composition, and health infrastructure. The municipality-month fixed effects absorb local seasonality and ensure that variations in mortality arise from temperature deviations from typical weather conditions rather than expected seasonal fluctuations. Additionally, we include controls for precipitation and relative humidity, as these weather variables are often correlated and can influence mortality.

The coefficient of interest, β_1, captures the effect of each additional day in a month with maximum temperature above a specific limit on the mortality rate. Under the assumption that, conditional on fixed effects and weather controls, temperature is uncorrelated with any other determinants of mortality, β_1 estimates the causal effect of heat on mortality. The sample includes observations from 5,555 municipalities over ten years, across twelve months each year, resulting in the estimation of a large number of additional parameters. These parameters account for various unobserved confounding factors that could bias our estimation. Furthermore, we show that our main results remain robust as we incrementally add fixed effects to the model, suggesting that our findings are not driven by omitted variable bias.

Importantly, by using different temperature thresholds, this approach allows us to explore the non-linear effects of heat, as the impact on mortality can vary significantly with temperature intensity. Finally, as a robustness check, we cluster the standard errors at a more aggregated level—the microregion (557 in total)—to account for spatial and temporal correlations across observations within the same microregion.

2.5 Results

The results section is structured into four subsections. First, we present the effects of contemporary temperatures extremes on mortality, focusing on days with temperatures above 35°C, 37°C, and 40°C. Then, we explore how different age groups and causes of death are affected by high temperatures. Next, we analyze the effect of temperature extremes based on the local climate conditions, including heatwaves. Lastly, we investigate the dynamic effects of temperature on mortality.

2.5.1 Main Results

Table 2.2 summarizes the results of the benchmark model. We estimate regressions for the number of days in a month with temperatures above 35°C, 37°C, and 40°C as independent variables. Columns (1)-(5) compare the results from different specifications of equation 2.1 for each temperature threshold. In the first four columns, we cluster standard errors at the municipality level, and in the last one, we cluster them at the microregion level. In column (1), we control the regression for year-month and municipality fixed effects. In column (2), we add municipality-year fixed effects, and in column (3), we incorporate municipality-month fixed effects. Finally, column (4) reports the effects of the full specification, which also controls for daily average precipitation and relative humidity. Column (5) presents the exact same specification as column (4), but clustering standard errors at the microregion-level.

The estimated coefficients are positive and significant across all columns and for all temperature thresholds. In addition, the magnitude of the coefficients increases as the temperature threshold rises, indicating that more intense heat leads to greater effects on mortality rates. Notably, the coefficients for *T35* and *T37* are substantially larger when the models account for municipality-month fixed effects, suggesting that heat-related mortality increases significantly when temperatures exceed what is typically expected for a particular municipality in a given month.

In our preferred specification, displayed in column (4), we estimate that each additional day with a temperature above 35°C increases mortality rates by approximately 0.19 deaths per 100,000 people, or 0.42% of the average monthly rate.

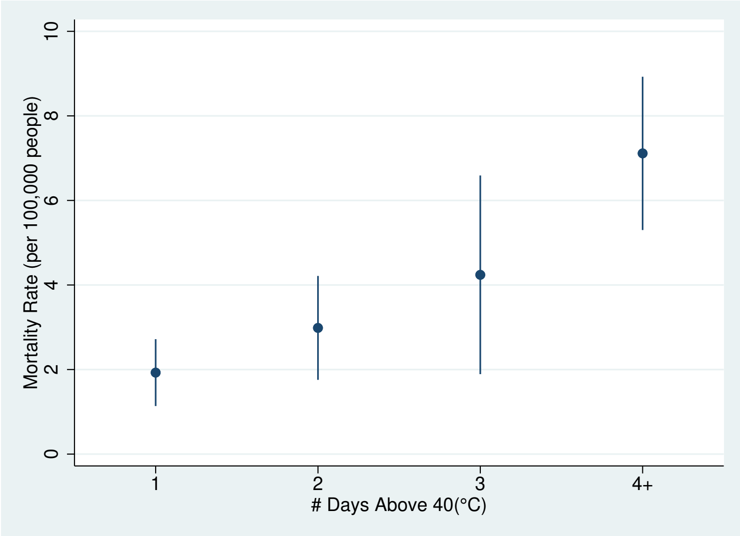
Tabela 2.2: The Effect of Heat on Mortality Rate

Dependent Variable: Mortality Rate (per 100,000 people)	(1)	(2)	(3)	(4)	(5)
#T35	0.0467***	0.0416***	0.1762***	0.1906***	0.1906***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
R^2 Adj.	0.4830	0.4888	0.4987	0.4987	0.4987
#T37	0.1713***	0.1628***	0.3164***	0.3166***	0.3166***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
R^2 Adj.	0.4833	0.4891	0.4986	0.4987	0.4987
#T40	1.3728***	1.4559***	1.4268***	1.3882***	1.3882***
	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)
R^2 Adj.	0.4831	0.4889	0.4983	0.4983	0.4983
Observations	666,600	666,600	666,600	666,600	666,600
Year-Month FE	Y	Y	Y	Y	Y
Municipality FE	Y	Y	Y	Y	Y
Municipality-Year FE	N	Y	Y	Y	Y
Municipality-Month FE	N	N	Y	Y	Y
Weather Controls	N	N	N	Y	Y
Microregion Cluster	N	N	N	N	Y

Notes: This table shows the effect of heat on mortality. The dependent variable is the mortality rate per 100,000 people. The independent variables of interest are the number of days in a month with maximum temperatures above 35°C, 37°C, and 40°C. Each column represents a different specification of equation 2.1. We estimate separate regressions for each temperature threshold. The weather controls are average daily and humidity values. Observations are weighted by the municipality's average population between 2010 to 2019. In columns (1)-(4) standard errors are clustered at the municipality level, and in Column (5) at the microregion level. Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Figure 2.3 illustrates the significant risks associated with days when temperatures exceed 40°C. It presents the results of estimating the same model specified in column (4) of Table 3.2, but categorizing the number of days in a month with temperatures above 40°C into 1, 2, 3, and 4 or more days, rather than treating it as a continuous variable. Although such extreme heat is very rare—occurring on average approximately 0.008 days per month in our sample—these events carry substantial risks. For example, a single day of exposure to temperatures above 40°C increases the mortality rate by about 2 deaths per 100,000 inhabitants compared to months without such days, which represents an increase of almost 5% above the monthly average. Experiencing four or more of these days in a month can lead to an increase of nearly 16% above the monthly average.

Figura 2.3: The Effect of Days Above 40° C on Mortality Rate



Note: This figure shows the estimation of the number of days exceeding 40 ° C on the mortality rate per 100,000 people. The results are based on the full specification of benchmark model, which includes year-month, municipality-year, and municipality-month fixed effects. The dots represent the point estimations, and the lines the 95% confidence intervals. Observations are weighted by the municipality's average population between 2010 to 2019. Standard errors clustered at the municipality level.

2.5.2 Heterogeneous Effects of Heat by Age and Cause of Death

As previously discussed, heat-related risks vary by age. For this reason, we estimate the benchmark models eparately for different age groups: 0-9 years, 10-29 years, 30-49 years, 50-64 years, and 65 years or older. The results, presented in Table 2.3, show that older adults are the most vulnerable to heat. For them, the coefficient for days with temperatures above 35°C is 1.9, which is ten times larger than the coefficient estimated for the entire population (0.19). During the 2010-2019 period, the average elderly population in Brazil was approximately 17 million people. They were exposed, on average, to 20 days per year with temperatures surpassing 35°C. Based on these estimates, we attribute approximately 6,300 deaths related to heat each year among the elderly.

Tabela 2.3: The Effect of Heat on Mortality by Age Group

	Dependent Variable: Mortality Rate (per 100,000 people)				
	0-9 Years	10-29 Years	30-49 Years	50-64 Years	65+ Years
	(1)	(2)	(3)	(4)	(5)
# T35	0.0176*	0.0015	0.0306***	0.1223***	1.9278***
	(0.009)	(0.004)	(0.008)	(0.03)	(0.1)
R^2 Adj	0.0225	-0.0025	0.0414	0.0974	0.1874
# T37	0.0298*	0.0120*	0.0525***	0.1798***	3.2320***
	(0.02)	(0.006)	(0.02)	(0.05)	(0.2)
R^2 Adj	0.0225	-0.0025	0.0414	0.0973	0.1873
# T40	0.1578	0.0950**	0.4010***	0.5995*	14.1742***
	(0.1)	(0.05)	(0.10)	(0.3)	(1.7)
R^2 Adj	0.0225	-0.0025	0.0414	0.0973	0.1866
Observations	666,600	666,600	666,600	666,600	666,600
Month-Year FE	Y	Y	Y	y	Y
Municipality-Year FE	Y	Y	Y	Y	Y
Municipality-Month FE	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y

Notes: This table show the effect of heat on mortality according to age. The dependent variables are the mortality rate per 100,000 inhabitants by population age group. The independent variables are number of days in a month with maximum temperatures above 35°C, 37°C, and 40°C, respectively. We estimate separate regressions for each temperature threshold. The weather controls are average daily precipitation and humidity. Observations are weighted by the municipality's average population for the relevant age group during the 2010-2019 period. Standard errors are clustered at the municipality level. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

To understand the different risks of death among the elderly, we examine the effects of high temperatures for different causes of death for non-elderly (<65 years) and elderly ($\geq$ 65 years) individuals. We present the results in Table 2.4, with each column corresponding to a different cause of death. The regressions indicate that for both elderly and non-elderly people, circulatory and respiratory diseases are the main causes of heat-related deaths. For the elderly, however, heat is associated with a higher risk of death across a broader range of causes. For instance, temperatures above 40°C increase mortality across all causes. Although such temperatures are rare, between 2010 and 2019 they exhibited an upward trend, which may signal even greater risks in the future.

Tabela 2.4: Effect of Heat on Mortality Rates by Cause for Non-Elderly and Elderly

	Dependent Variable: Mortality Rate (per 100,000 people)							
	All	Circulatory	Respiratory	Metabolic	Neoplasm	Infections	Digestive	Others
Panel A: Non-Elderly (<65y)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
# T35	0.0313***	0.0116***	0.0045***	0.0026**	-0.0005	0.0019	0.0009	0.0104***
	(0.005)	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
R^2 Adj	0.1917	0.1150	0.0471	0.0242	0.0944	0.0691	0.0122	0.0964
# T37	0.0524***	0.0161***	0.0106***	0.0069***	-0.0047	0.0026	-0.0010	0.0220***
	(0.01)	(0.004)	(0.002)	(0.002)	(0.004)	(0.003)	(0.002)	(0.004)
R^2 Adj	0.1917	0.1150	0.0471	0.0242	0.0944	0.0691	0.0122	0.0964
T40	0.2750***	0.1186***	0.0615***	0.0335	0.0469	-0.0098	-0.0246	0.0489
	(0.07)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
R^2 Adj	0.1917	0.1150	0.0471	0.0242	0.0944	0.0691	0.0122	0.0964
Panel B: Elderly (≥65y)								
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
#T35	1.9278***	0.6911***	0.3201***	0.2238***	0.0584*	0.0481***	0.0374**	0.5488***
	(0.1)	(0.06)	(0.03)	(0.03)	(0.03)	(0.01)	(0.02)	(0.04)
R^2 Adj	0.1866	0.1349	0.1358	0.1020	0.0796	0.0508	0.0046	0.2357
# T37	3.2320***	1.2888***	0.5536***	0.3686***	0.0811	0.1091***	0.0643**	0.7664***
	(0.2)	(0.10)	(0.06)	(0.04)	(0.06)	(0.02)	(0.03)	(0.08)
R^2 Adj	0.1866	0.1349	0.1358	0.1020	0.0796	0.0508	0.0046	0.2357
T40	14.1742***	4.0437***	2.6292***	1.5997***	1.6058***	0.9813***	0.4833**	2.8311***
	(1.7)	(0.9)	(0.6)	(0.4)	(0.5)	(0.3)	(0.2)	(0.5)
R^2 Adj	0.1866	0.1349	0.1358	0.1020	0.0796	0.0508	0.0046	0.2357
Observations	666,600	666,600	666,600	666,600	666,600	666,600	666,600	666,600
Year-Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Municipality-Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Municipality-Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y	Y	Y

Notes: This table presents the effect of heat on mortality rate by cause for non-elderly (Panel A) and elderly (Panel B). The dependent variables are the mortality rates per 100,000 people by causes for each population group. Independent variables of interest are the number of days in a month with maximum temperatures above 35°, 37°C, and 40°, respectively. We estimate separate regressions for each temperature threshold. The weather controls are average daily precipitation and humidity. Observations are weighted by the municipality's average population for the relevant population group. Standard errors are clustered at the municipality level. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

2.5.3 Alternative Heat Indicators

As an alternative approach, we use temperature extreme measures that account for the municipality-specific distribution of daily maximum temperatures. Specifically, we estimate the effects of days in a month that exceed the 95$^{\text{th}}$ percentile of this distribution on mortality rates. We also define a heatwave as a binary variable indicating the occurrence of two or more consecutive days in a month with temperatures above the 95$^{\text{th}}$ percentile. Table 2.5 summarizes the findings for the entire population (Panel A), non-elderly (Panel B), and elderly (Panel C). We present the results for overall mortality rates as well as for causes most sensitive to heat. Overall, the results show a pattern similar to those obtained using absolute temperature measures, with greater effects observed among individuals aged 65 and older, particularly for cardio-respiratory diseases.

In terms of magnitude, the coefficient of days with temperatures above the 95th percentile on overall mortality for the entire population is slightly smaller than that of days exceeding 35 degrees. Moreover, two days with temperatures above the 95th percentile are associated with an increase of 0.31 in mortality per 10,000 people, while two or more consecutive days (heat wave) result in an increase of 0.44. This suggests that consecutive days of extreme heat may have more severe effects, although they are less frequent.

Tabela 2.5: The Effect of Heat on Mortality: Alternative Heat Indicators

	Dependent Variable: Mortality Rate (per 100,000 people)			
	All	Circulatory	Respiratory	Metabolic
Panel A: All Sample				
	(1)	(2)	(3)	(4)
# Tp95	0.1574***	0.0517***	0.0248***	0.0174***
	(0.01)	(0.005)	(0.003)	(0.002)
R^2 adj.	0.5038	0.3085	0.2491	0.1454
Heat Wave	0.4373***	0.1352***	0.0646***	0.0441***
	(0.07)	(0.03)	(0.02)	(0.02)
R^2 adj.	0.5034	0.3083	0.2489	0.1453
Panel B: (<65 years)				
	(5)	(6)	(7)	(8)
# Tp95	0.0260***	0.0073***	0.0022	0.0020*
	(0.005)	(0.002)	(0.001)	(0.001)
R^2 adj.	0.2000	0.1240	0.0568	0.0342
Heat Wave	0.0485	-0.0059	0.0082	0.0116
	(0.03)	(0.02)	(0.010)	(0.008)
R^2 adj.	0.2000	0.1240	0.0568	0.0342
Panel C: (≥65 years)				
	(9)	(10)	(11)	(12)
# Tp95	1.6058***	0.5420***	0.2714***	0.1915***
	(0.1)	(0.05)	(0.03)	(0.02)
R^2 adj.	0.1955	0.1436	0.1446	0.1111
Heat Wave	4.3896***	1.6013***	0.6220***	0.3955**
	(0.7)	(0.3)	(0.2)	(0.2)
R^2 adj.	0.1948	0.1434	0.1444	0.1110
Observations	666,600	666,600	666,600	666,600
Year-Month FE	Y	Y	Y	Y
Municipality-Year FE	Y	Y	Y	Y
Municipality-Month FE	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y

Notes: This table shows the effect of relative heat measures on mortality for the entire population (Panel A), non-elderly (Panel B), and elderly (Panel C). The dependent variable is the mortality rate per 100,000 people. The independent variables of interest are the number of days with maximum temperatures above the 95th percentile of the municipality-specific distribution of daily maximum temperature and a heat wave indicator. The heat wave indicator is a dummy variable equal to 1 when at least two consecutive days exceeding the 95th percentile. The weather controls are average daily precipitation and humidity. Observations are weighted by the municipality's average population for the relevant population group between 2010 and 2019.. Standard errors are clustered at the municipality level. Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

2.5.4 Dynamic Effects of Heat on Mortality Rate

So far, we have assessed the contemporary effects of heat on monthly mortality rates. However, there is concern that elevated temperatures in the previous months could also influence mortality. A positive association between high temperatures observed in prior months and current mortality would suggest delayed or persistent effects of heat. Conversely, a negative association could indicate the presence of a displacement phenomenon (also known as harvest effects), which implies that extreme temperatures may simply anticipate the deaths of individuals whose health is already compromised and who would have died shortly afterward, even in the absence of the event (Deschênes & Moretti, 2009).

To explore the dynamic relationship between temperature exposure and mortality, we include 1-month and 2-month lagged values of extreme temperature days in the benchmark model. Table 2.6 presents the results. The positive association between lagged values of days above 35°C and 37°C and mortality suggests the presence of harvest effects. However, the coefficients for contemporary days of high temperature remain positive and larger than the lagged ones, indicating that the increase in mortality due to heat is primarily driven by the immediate impact of extreme temperatures, rather than solely by anticipatory deaths. Furthermore, the results suggest that heat-related deaths occur within a short time span, indicating that higher mortality is primarily due to immediate health deterioration.

Tabela 2.6: Dynamic Effect of Temperature on Mortality Rate

	Dependent Variable: Mortality Rate (per 100,000 people)		
	(1)	(2)	(3)
# T35	0.1913***		
	(0.01)		
# T35 (t-1)	-0.0604***		
	(0.008)		
# T35 (t-2)	0.0081		
	(0.009)		
# T37		0.3141***	
		(0.02)	
# T37 (t-1)		-0.0597***	
		(0.02)	
# T37 (t-2)		-0.0007	
		(0.01)	
# T40			1.3937***
			(0.2)
# T40 (t-1)			0.1237
			(0.1)
# T40 (t-2)			0.2718*
			(0.2)
Observations	655,490	655,490	655,490
R^2adj	0.5027	0.5026	0.5023
Month-Year FE	Y	Y	Y
Municipality-Year FE	Y	Y	Y
Municipality-Month FE	Y	Y	Y
Weather Controls	Y	Y	Y

Notes: This table studies the dynamic relationship between heat and mortality by including lagged values of temperature independent variables. The dependent variable is the mortality rate per 100,000 people. The independent variables of interest are the number of days in a month with maximum temperatures above 35°C, 37°C, and 40°C, respectively. Standard errors are clustered at the municipality level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2.6 Conclusion

In this paper, we examined the relationship between extreme temperatures and mortality in Brazil. Our empirical approach leverages high-frequency data, allowing us to control for a large list of fixed effects. This provides strong evidence that we are indeed capturing the causal impact of heat on mortality.

Our findings indicate a clear association between heat exposure and mortality. Each additional day with temperatures above 35°C increases the monthly mortality rate by 0.19 per 100,000 people, equivalent to 0.42% of the monthly average rate. When disaggregating deaths by cause, we observe that circulatory and respiratory diseases are the leading contributors to heat-related fatalities. Consistent with previous research, our results show that the elderly are significantly more vulnerable, with the estimated effect being ten times larger for this group compared to the one estimated for entire population. Based on these estimations, we project approximately 6,528 heat-related deaths per year among older adults between 2010 and 2019. Moreover, heat exposure is linked to a broader range of health conditions in the elderly than in younger individuals.

Temperatures exceeding 40°C are particularly dangerous, although they remain relatively rare. However, when examining temperature trends from 2001 to 2019, there is an upward trajectory, suggesting an increasing risk over time.

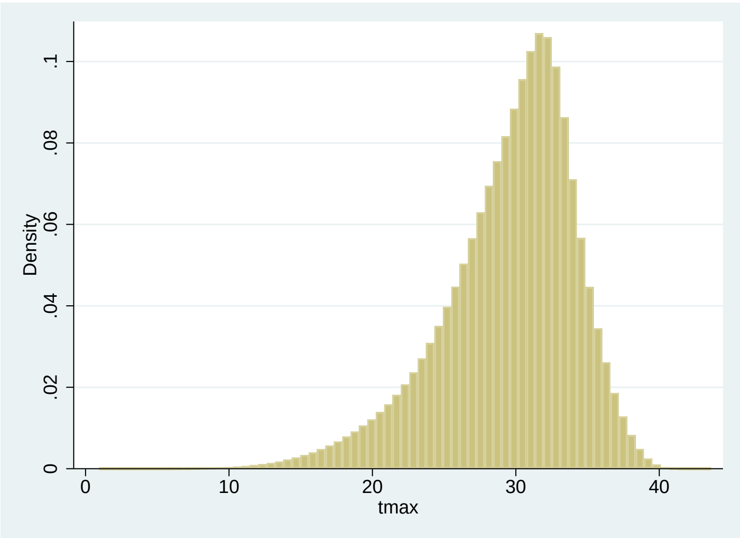
Our results are also robust when measuring heating through temperature anomalies, ie, unusual deviations in temperature from the municipality long-term temperature average. We also observe stronger short-term effects of heat on mortality, suggesting a direct mechanism through which heat worsens health conditions. This immediate impact of heat has important policy implications, emphasizing the need for well-coordinated health plans that facilitate rapid interventions during heat waves.

Our study provides valuable insights into the impact of heat in a tropical, developing country where research is more limited compared to developed nations. As the population ages and global warming intensifies, heat-related mortality is expected to rise, underscoring the urgent need for adaptation strategies. Given that individual-level adaptation to extreme heat is less common or often restricted to specific groups in countries with significant inequalities like Brazil, it is essential for policymakers to develop affordable adaptation measures. One potential solution could be the expansion of green spaces in urban areas, which can help mitigate heat exposure. Future research could further investigate the role of adaptation policies in Brazil to better understand their effectiveness in mitigating these increasing risks.

Appendix A

Daily Maximum Temperature Distribution

Figura A.1: Daily Maximum Temperature Distribution for Brazilian Municipalities



Notes: This figure shows the distribution of daily maximum temperatures across Brazilian municipalities between 2010 and 2019. Data is from Xavier *et al.* (2022).

3
Droughts, Economic Distress, and Intimate Partner Violence: Evidence from Brazil

3.1
Introduction

Droughts are among the most serious hazards to livestock and crops globally, affecting approximately 55 million people annually (WHO, 2024). While they pose significant threats to rural communities, their impacts vary across different population groups. In particular, drought effects are unlikely to be gender-neutral. Traditional gender roles, persistent labor market disparities, and unequal access to resources and productive assets make women more vulnerable to the adverse effects of droughts (Fruttero *et al.*, 2023; Bryan *et al.*, 2024). Building on the literature that examines the unequal gender impacts of droughts, this paper investigates the relationship between droughts and intimate partner violence (IPV) in Brazil, exploring differences between rural and non-rural municipalities.

The empirical analysis relies on a municipality-by-month panel dataset that combines IPV records with drought indicators, covering the period from 2011 to 2019. The IPV data come from the Brazilian Health Ministry and include information on all mandatory notifications of interpersonal violence. To construct the drought indicators, we calculate the Standardized Precipitation-Evapotranspiration Index (SPEI) for each municipality at different time scales using data from the Global SPEI Database. The SPEI is a widely accepted index used to monitor drought conditions, capturing deviations in the water balance (the difference between precipitation and evapotranspiration) from long-term averages. Positive SPEI values indicate wet conditions, while negative values indicate drought conditions.

The empirical strategy is based on a two-way fixed effects model, which explores within-municipality changes in IPV and drought conditions over time. Identification relies on the assumption that, after controlling for municipality and time fixed effects, droughts are exogenous events, allowing us to estimate their causal impact on IPV.

Using data from the 2010 Brazilian Population Census, we categorize municipalities as rural and urban. Specifically, urban municipalities are defined as those with less than 15% of the population residing in urban areas. We then conduct the analysis separately for rural and urban municipalities.

Our estimations indicate that droughts increase IPV rates in rural municipalities, with the effects intensifying with both the duration and severity of droughts. We find no significant association between a 1-month drought and IPV. Nevertheless, our estimates show that IPV rates are 2%, 3.6%, and 5.9% higher in municipalities exposed to 3-month, 6-month, and 12-month drought episodes, respectively. When distinguishing between moderate and severe drought episodes, we find that a moderate drought over the past 12 months is associated with a 4.3% increase in the IPV rate, while a severe drought corresponds to a 7% increase. In contrast, in urban municipalities, we find a positive association only between IPV and 1-month droughts, suggesting that droughts may have immediate effects on IPV in urban areas, but these impacts do not persist, unlike in rural areas.

To investigate our hypothesis that droughts increase IPV mainly through an economic channel, we obtain data on agricultural production and GDP by economic sector from IBGE. Since these data are only available at the annual frequency, we average monthly SPEI values to construct an annual panel linking weather, agriculture, and local economic activity. Our findings show that in rural municipalities prolonged droughts reduce agricultural production (in terms of planted area, harvested area, and production value) and negatively impact overall economic activity. The largest negative impact is seen in the agricultural sector, but the effects also spill over into the industrial sector. In urban municipalities, the results show no impact on agriculture and much smaller effects on economic activity. These findings suggest that the economic channel is a key driver: when the economic impacts of droughts are limited, IPV rates are less likely to be affected.

Our study contributes to the emerging literature on the gendered effects of droughts. Previous research has shown that during droughts, women are less likely to shift to non-farm income-generating activities, assume disproportionately greater household responsibilities, and may experience worse outcomes in terms of nutrition and health compared to men (Algur *et al.*, 2021; Afridi *et al.*, 2022; Hirvonen *et al.*, 2023). We add to this body of knowledge by specifically examining the impact of droughts on gender-based violence.

Most studies on the effects of drought shocks on IPV have focused on poorer countries in Africa, yielding mixed results—some find a positive association, while others report no significant effects (Cooper *et al.*, 2021). Few studies have examined this relationship in Latin America. A notable exception is Díaz & Saldarriaga (2022), who documented a 65% increase in physical IPV following droughts in the Peruvian Andes. Our study contributes to this literature in several important ways. First, we provide evidence from Brazil, a compelling case for study due to: (i) the persistence of IPV, with 30% of Brazilian women reporting experiences of domestic violence despite legal advancements to punish and prevent such violence; (ii) significant weather variability, with several regions experiencing severe droughts during the 2010s; and (iii) the central role of agriculture in the economy, accounting for nearly a quarter of the GDP (BRASIL, 2024).

Second, we advance the understanding of the relationship between droughts and IPV by empirically demonstrating that the impact of droughts on IPV intensifies with both their severity and duration. To the best of our knowledge, this is the first study to analyze how IPV responds to droughts of different duration. Third, by comparing rural and urban municipalities, we provide strong evidence that the economic channel is a key mechanism through which droughts influence IPV. Finally, we introduce a novel measure of IPV. Most studies rely on surveys or mortality data to construct IPV indicators. While mortality data capture only the most extreme case, survey-based indicators often suffer from under-reporting, as women may fear retaliation from their partners. Alternatively, we use compulsory IPV notifications from healthcare units. Under Brazilian law, healthcare professionals are required to report any suspected or confirmed cases of violence once a woman seeks care, meaning that notifications do not depend on the victim's willingness to report. Yet, our measure may still have limitations, as it could primarily capture only severe cases of IPV.

The rest of the paper is structured as follows. Section 3.2 provides a theoretical discussion of the relationship between drought, economic factors, and IPV. Section 3.3 describes the data sources, explains the construction of drought and IPV indicators, and shows descriptive statistics. Section 3.4 outlines the empirical strategy and identification hypothesis. Section 3.5 reports and discusses the main results and performs some robustness checks. Finally, Section 3.6 concludes.

3.2 Theoretical Framework

In this section, we review theoretical contributions from economics, sociology, and psychology that help establish a causal pathway between droughts, economic shocks, and IPV, along with empirical applications of theoretical models.

From an economic perspective, droughts can be seen as a proxy for a negative income shock, particularly for rural households. Farmer & Tiefenthaler (1997) develops a non-cooperative household bargaining model to explain the effects of economic factors (e.g., employment, income) on IPV. In this model, the relative bargaining power between the man (aggressor) and the woman (victim) determines the level of violence. The model assumes that man's satisfaction increases when he exercises violence (due to increased self-esteem, better control of the family's financial resources, etc.). The man maximizes his satisfaction, constrained by the woman staying in the relationship. The woman chooses to stay in an abusive relationship as long as her outside option (divorce) offers her less utility than staying. The utility from staying in the relationship comes from a shared household income. Gains (losses) in the woman's income increase (decrease) the utility of her outside option and her bargaining power, which means the level of violence she tolerates decreases (increases), thus effectively reducing (increasing) the violence when she chooses to stay in the relationship.

In the empirical literature, the bargaining model has been applied to show how improvements in a woman's income, the female/male wage ratio, or other forms of external support that increase the relative bargaining power of the woman can help prevent IPV. Aizer (2010) finds that more equal wages between genders lead to fewer female hospital visits in California. In Brazil, however, Bhalotra *et al.* (2021) demonstrate that both women's and men's job loss are associated with increases in domestic violence, which cannot be fully explained by bargaining models, as they predict opposite effects for male and female unemployment. Furthermore, several studies document that cash transfer programs can prevent IPV (Haushofer *et al.*, 2019; Roy *et al.*, 2019; Díaz & Saldarriaga, 2022). There's also evidence that asset ownership reduces IPV. Panda & Agarwal (2005) show that both land and home ownership are protective factors against IPV in India. Similarly, Oduro *et al.* (2015) estimate that a greater share of a woman's wealth in the couple's total wealth reduces the odds of emotional abuse in Ghana and lowers the risk of physical IPV in Ecuador.

Family stress models also offer a useful framework for understanding how economic hardship caused by water scarcity increases women's vulnerability to IPV. These models assume that economic hardship triggers a chain of stressors that put pressure on family relationships, reducing couple well-being and marital quality (Conger *et al.*, 1990; Voydanoff, 1990). For example, Kuhn *et al.* (2009) show that large wealth losses lead to increased feelings of depression and the use of antidepressant drugs. Browning & Heinesen (2012) demonstrate that job loss increases the risk of mortality, suicide, and suicide attempts, as well as death and hospitalization due to traffic accidents, alcohol-related diseases, and mental illness. This psychological distress, in turn, can deteriorate the quality of relationships and increase the risk of conflict within couples (Fox *et al.*, 2002; Arenas-Arroyo *et al.*, 2021).

Schneider *et al.* (2016) test the family stress model in the context of the Great Recession in the United States. They estimate that rapid increases in unemployment rates are associated with a rise in abusive behavior among men. Their research indicates that the effects of the recession are not fully captured by individual or household measures of job loss or material hardship. They conclude that economic crises lead to feelings of fear and insecurity, which likely contribute to abusive behavior.

These models illustrate how power imbalances within households, increased control over scarce resources, and psychological distress triggered by droughts create an enabling environment where IPV arises.

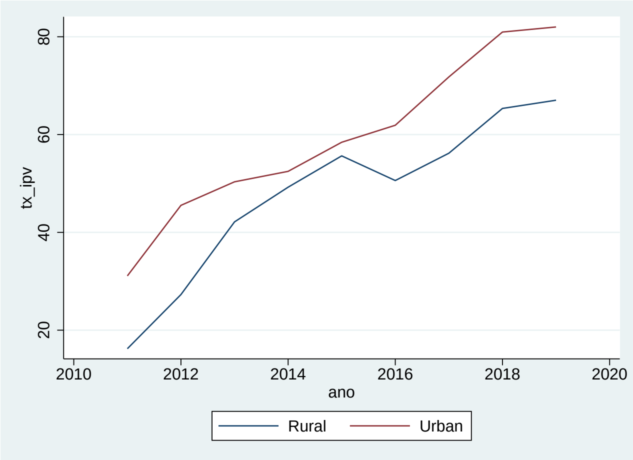
3.3 Data

In this section, we present the sources of data for IPV, weather, agriculture, and economic activity. We describe how we create the IPV indicators and drought measures. Next, we provide descriptive statistics for the sample and conduct some preliminary descriptive analyses.

3.3.1 IPV

The source of IPV data is the Notifiable Diseases Information System (*Sistema de Informação de Agravos de Notificação, SINAN/DATASUS*), managed by the Brazilian Ministry of Health. The SINAN is a system that reunites all notifications of diseases and health conditions that are part of the national list of compulsory notifications. The Brazilian Health Ministry is responsible for elaborating, updating, and publishing this list. Since 2011, interpersonal violence has been included in this list, obligating all healthcare units - public and private - to report any confirmed or suspected case. The attending medical personnel must fill out a form detailing victim's characteristics (such as age, race and material status), the relationship between the victim and the aggressor, the type of violence (sexual, physical, psychological) and the date and location of the aggression. We classify as IPV those cases in which the aggressor was the woman's husband, ex-husband, boyfriend, or ex-boyfriend.

Figura 3.1: IPV Rate Evolution



Notes: This figure shows the evolution of IPV rate between 2011 and 2019 in Brazilian rural and non-rural municipalities. Data is from the SINAN/DATASUS.

more severe cases of violence because not all IPV would lead the victim to seek health services.

The IPV measure is the rate of IPV notifications by 100,000 women. The annual female population is also from Brazilian Health Ministry. We assume that the female population remains constant over the months of the same year. We apply an inverse hyperbolic sine (i.h.s) transformation in the IPV rate to attenuate the effects of outliers. But, we show that the main results are robust to other IPV specifications.

Figure 3.1 illustrates the evolution of the rate of IPV notifications between 2011 and 2019 for rural and urban municipalities. It indicates a consistent upward trend in IPV rates in both rural and urban areas, with urban areas consistently showing higher IPV rates over time.

3.3.2 Weather

We obtained monthly series of the Standard Precipitation-Evapotranspiration Index (SPEI) from the Global SPEI database (SPEI-base). SPEIbase provides information about drought conditions at the global scale, with a spatial resolution of 0.5 degrees. The SPEI index is derived from monthly precipitation and potential evapotranspiration records from the Climatic Research Unit of the University of East Anglia and is available for time scales ranging from 1 to 48 months. For the purposes of this study, we collected SPEI series for the Brazilian territory at 1-month, 3-month, 6-month, and 12-month time scales. We then calculate the SPEI for each municipality as the weighted average of values within the municipality's boundaries.

The SPEI is an extension of the Standard Precipitation Index (SPI). Unlike the SPI, which defines drought based only on precipitation deficits, the SPEI also accounts for the effect of temperature in drought determination by incorporating evapotranspiration. Essentially, the SPEI represents the number of standard deviations by which the precipitation-evapotranspiration amount deviates from the long-term mean. Positive values indicate wet conditions, while negative values represent drought conditions. The period of accumulation of the precipitation-evapotranspiration amount corresponds to the SPEI time scale. Different time scales are useful for evaluating the duration of droughts. Short-term droughts (1 month) can indicate reduced soil moisture, while medium-term droughts (3–6 months) typically lead to crop failures and agricultural losses. Long-term droughts (12 months) are associated with reduced water availability in rivers, lakes, reservoirs, and groundwater. It is important to estimate and compare the effects of drought across different time scales, as they reflect different aspects of water scarcity, while recognizing that a short-term drought index may actually capture the effects of an ongoing, longer drought.

In this study, we classify drought episodes according to the criteria below:

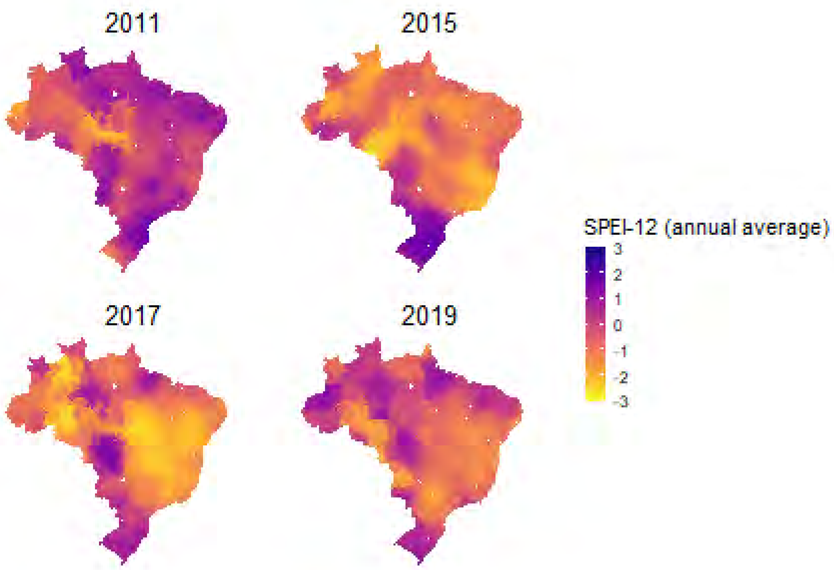
$$\text{Drought} = \begin{cases} 1 & \text{if SPEI} < -1 \\ 0 & \text{otherwise} \end{cases}$$

$$\text{Moderate Drought} = \begin{cases} 1 & \text{if } -1 < \text{SPEI} \leq -1.5 \\ 0 & \text{otherwise} \end{cases}$$

$$\text{Severe Drought} = \begin{cases} 1 & \text{if SPEI} < -1.5 \\ 0 & \text{otherwise} \end{cases}$$

Figure 3.2 illustrates the annual average SPEI-12 for Brazilian municipalities in 2011, 2015, 2017, and 2019. In 2011, most regions exhibit wet conditions (purple to blue areas), but by 2015, drought conditions (yellow to orange) have spread. The drought intensifies in 2017, especially in the eastern portion of the country. In 2019, there is some attenuation, although some parts continue to experience moderate droughts, particularly in central and southeastern Brazil.

Figura 3.2: Average SPEI-12



Notes: This figure illustrates the annual average SPEI-12 for the years of 2011, 2013 ,2017 and 2019. Data source is the Global SPEI database.

3.3.3 Other Data

We use additional data sources to gather information on municipal characteristics. From the 2010 Brazilian Census, conducted by the Brazilian Institute of Geography and Statistics (IBGE), we collect information on the rural and urban populations of each municipality. Additionally, we use IBGE's data series on municipal output by economic sector, along with data on crop production, including planted area, harvested area, and production value. For robustness checks, we use gridded weather data from Xavier *et al.* (2022) as an alternative source for constructing drought indices.

3.3.4 Sample Selection and Summary Statistics

We follow the criteria of Braga *et al.* (2016) to classify Brazilian municipalities into three categories based on the share of the rural population: predominantly urban (< 15%), intermediate rural (15%-50%), and predominantly rural (> 50%). Using the 2010 Brazilian territorial division, out of 5,565 municipalities, we successfully combine data on weather and IPV for 5,471 municipalities. Of these, 4,317 were classified as predominantly rural or intermediate rural, and 1,154 as urban. In this article, we refer to both intermediate rural and predominantly rural municipalities simply as rural. The data are organized into a municipality-by-month balanced panel for the 2011–2019 period, during which all necessary data were available.

Table 3.1 presents the descriptive statistics for rural and urban municipalities. The summary statistics indicate that the average IPV rate is higher in urban municipalities, with an average of 4.95 per 100,000 women, compared to 3.98 per 100,000 women in rural municipalities. However, since IPV rates are based on notifications, it may also reflect disparities in the availability of healthcare services. The large standard deviations in IPV rates suggest significant variation between municipalities and across time. Moreover, approximately 30% of rural municipalities and 26% of urban municipalities experienced drought conditions during the 2011–2019 period. There are also notable differences in economic indicators between rural and urban municipalities. In both contexts, per capita values suggest that the service and industry sectors contribute more to GDP than agriculture. However, agriculture remains significantly more important in rural municipalities, where per capita agricultural output is R$2520, nearly five times higher than the R$464.3 recorded in urban areas.

Tabela 3.1: Descriptive Statistics

	Rural Municipalities			**Urban Municipalities**		
	Mean (SD)	Min	Max	Mean (SD)	Min	Max
IPV Rate (per 100,000 women)	3.98	0	1105.0	4.95	0	1030.9
	(12.70)			(9.26)		
Drought						
SPEI (1-month)	-0.28	-6.92	5.76	-0.16	-5.00	6.19
	(1.12)			(1.12)		
SPEI (3-month)	-0.34	-4.79	3.41	-0.20	-4.79	3.16
	(1.09)			(1.10)		
SPEI (6-month)	-0.39	-3.90	3.47	-0.26	-3.50	3.41
	(1.07)			(1.06)		
SPEI (12-month)	-0.47	-3.66	3.34	-0.34	-3.66	3.26
	(1.07)			(1.08)		
Drought (1-month)	0.29	0	1	0.26	0	1
	(0.46)			(0.44)		
Drought (3-month)	0.30	0	1	0.26	0	1
	(0.46)			(0.44)		
Drought (6-month)	0.31	0	1	0.27	0	1
	(0.46)			(0.45)		
Drought (12-month)	0.35	0	1	0.31	0	1
	(0.48)			(0.46)		
Economic and Agriculture						
Agriculture (R$)	2520	14.2	1,07,030	464.3	0	42,412
	(4041)			(1344)		
Industry (R$)	3110	5.2	690,873	6222	74	250,325
	(11384)			(7808)		
Services (R$)	4700	443	130,857	15804	1052	149,752
	(4728)			(9854)		
Harvested Area (Ha)	15,853	0	702530	16965	0	1,205,669
	(42535)			(52648)		
Planted Area (Ha)	16194	0	704911	17061	0	1,205,669
	(42416)			(52786)		
Production Value per capita (R$)	2.7	0	234	0.64	0	85.0
	(7.2)			(2.4)		
Observations	466236			124632		

The data presents summary statistics of IPV, drought, and local economy for urban and rural municipalities in Brazil. Standard deviations are reported in parentheses. The IPV rate is the number of IPV notifications per 100,000 women. We classify IPV as any aggression against women committed by a husband, ex-husband, boyfriend, or ex-boyfriend. The IPV microdata come from the SINAN/DATASUS. Economic and agricultural data are from IBGE and are available only at the annual frequency. All monetary values are in Brazilian Reais (R$), adjusted to 2010 prices. The SPEI index are derived from the Global SPEI database.

3.4 Empirical Strategy

The estimation of the impact of drought on IPV is based on a two-way fixed effects model that includes both municipality and time fixed effects. The source of variation used in the identification strategy comes from within-municipality changes in IPV rates and drought conditions over time.

Formally, we estimate the following linear regression:

$$IPV_{it} = \alpha + \beta \text{Drought}_{it} + \theta i + \lambda_t + \epsilon_{it} \tag{3.1}$$

The outcome variable of interest, IPV_{it}, represents the inverse hyperbolic sine (IHS) transformation of the IPV notification rate per 100,000 women in municipality i at time t. The term $Drought_{it}$ measures drought conditions. θ_i denotes municipality fixed effects, λ_t represents time fixed effects, and ϵ_{it} is the random error term. Standard errors are clustered at the municipality level.

The time fixed effects control for common factors across all municipalities within a given month, year, or specific month-year combination. This includes macroeconomic conditions, nationwide weather phenomena, national gender policies, and seasonal factors that may influence IPV rates and drought severity. Municipality fixed effects, in turn, control for time-invariant characteristics that are unique to each municipality, such as cultural norms, long-term climate patterns, and environmental conditions. The regression is weighted by the average population of each municipality between 2011 and 2019, ensuring that larger municipalities have greater influence on the coefficient estimates. This weighted approach ensures that results are representative of the overall population, and reduces the risk that rare IPV events in small municipalities distort the analysis through disproportionately high IPV rates.

In equation 3.1, β is the coefficient of interest. Our key identifying assumption is that, conditional on municipality and time fixed effects, droughts are uncorrelated with any other determinants of IPV. If this assumption holds, β estimates the causal effects of droughts on IPV. The methodology we use to define drought conditions ensures that they reflect unusual dry conditions, making these events less predictable and less likely to be systematically correlated with other determinants of IPV. This feature helps minimize concerns about potential bias from omitted variables.

To examine the link between IPV and economic factors, we estimate the impacts of droughts on agricultural production and economic activity using a municipality-by-year panel, as economic and agricultural data are not available at a monthly frequency. Formally, we estimate the model below:

$$Y_{iy} = \kappa + \phi\overline{\text{Drought}}_{iy} + \delta i + \mu_y + \varepsilon_{iy} \tag{3.2}$$

In equation 3.2, i indexes the municipality and y the year. Y_{iy} represents an outcome variable related to either agriculture or economic activity. The term $\overline{\text{Drought}}_{iy}$ is the annual measure of drought conditions, derived from averaging monthly SPEI-12 values.

The terms δ_i and μ_y represent municipality fixed effects and year fixed effects, respectively. Year fixed effects capture annual trends common to all municipalities, but unlike the time fixed effects in equation 3.1, they do not account for seasonal variations.

3.5
Results

In this section, we present the results of the impact of droughts on IPV, agricultural production, and economic activity for rural and non-rural municipalities. We also perform robustness checks to validate the results.

3.5.1
IPV

In Table 3.2, we present the results of estimating equation 3.1 for rural (panel A) and urban (panel B) municipalities. Each column (1)–(4) and (5)–(8) corresponds to regressions using drought indices over 1, 3, 6, and 12-month accumulation periods. All specifications include both municipality and time fixed effects. We estimate the benchmark model using three drought specifications as independent variables: (i) SPEI directly, (ii) a binary indicator for drought occurrence, and (iii) binary indicators for moderate and severe droughts. This approach enables us to evaluate two important aspects of drought: duration and intensity.

In rural municipalities, the results show that short-term droughts (1 month) do not significantly affect IPV, whereas medium-term (3 and 6 months) and long-term (12 months) droughts lead to an increase in IPV incidence. Moreover, drought intensity also plays a significant role. In our preferred specification, displayed in column (4), long-term droughts increase the IPV rate by 5.8%. When distinguishing drought episodes by intensity, moderate droughts are associated with a 4.3% higher IPV rate, while severe droughts correspond to a 7.7% increase.

In urban municipalities, the estimations show only a weak association between drought and IPV. Specifically, the pattern differs from rural municipalities, with a negative and significant coefficient only for 1-month droughts.

This suggests that in urban areas, droughts have an immediate but transitory impact on IPV.

Tabela 3.2: Impact of Droughts on IPV

Dep Var: IPV Rate (IHS transformation)				
Panel A: Rural Municipalities				
	1-month	3-month	6-month	12-month
	(1)	(2)	(3)	(4)
SPEI	-0.0052**	-0.0065*	-0.0137***	-0.0247***
	(0.003)	(0.003)	(0.005)	(0.007)
R^2adj	0.0376	0.0376	0.0377	0.0378
Drought	0.0008	0.0209***	0.0355***	0.0582***
	(0.006)	(0.008)	(0.009)	(0.010)
R^2adj	0.0376	0.0376	0.0377	0.0378
Moderate Drought	-0.0093	0.0241***	0.0258***	0.0428***
	(0.008)	(0.009)	(0.009)	(0.010)
Severe Drought	0.0113	0.0175*	0.0463***	0.0765***
	(0.008)	(0.010)	(0.010)	(0.010)
R^2adj	0.0376	0.0376	0.0377	0.0380
Observations	466,236	466,236	466,236	466,236
Panel B: Urban Municipalities				
	(5)	(6)	(7)	(8)
SPEI	-0.0106**	-0.0091	-0.0070	-0.0032
	(0.005)	(0.007)	(0.010)	(0.010)
R^2adj	0.1612	0.1612	0.1611	0.1614
Drought	0.0288**	0.0085	0.0115	-0.0219
	(0.010)	(0.020)	(0.020)	(0.020)
R^2adj	0.1612	0.1612	0.1611	0.1614
Moderate Drought	0.0293*	0.0316	0.0468	0.0032
	(0.020)	(0.020)	(0.040)	(0.030)
Severe Drought	0.0282**	-0.0168	-0.0334	-0.0518
	(0.010)	(0.040)	(0.040)	(0.050)
R^2adj	0.1612	0.1612	0.1611	0.1614
Observations	124,632	124,632	124,632	124,632
Municipality FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y

Note: This table presents the results of the effects of droughts on IPV. The dependent variable is IHS transformation of the IPV notification rate per 100,000 women. Panel A reports the results for rural municipalities, and B for the Urban's. The SPEI (Standard Precipitation-Evapotranspiration Index) is used as the measure of drought. *Drought* is defined as SPEI < -1, *Moderate Drought*' as -1.5 < SPEI < -1, and *Severe Drought* as SPEI < -1.5. Standard errors are clustered at the municipality level. Significance values: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.5.2
Agriculture and Economic Outputs

To assess the agricultural and economic implications of drought, we estimate the model described in equation 3.2, with results presented in Table 3.3. Panel A displays the results for rural municipalities, while Panel B covers urban municipalities. All outcomes are expressed in the logarithmic scale, and all specifications include municipality and year fixed effects. Columns (1)–(3) and (7)–(9) report the impact of annual drought conditions. The agriculture outcomes we examine are planted area, harvested area, and production value of crops. In rural settings, we estimate significant declines in planted area, harvested area, and production value, with effects ranging between 6% and 13%. In addition, severe droughts are associated with even greater losses. For example, the coefficient for severe droughts on harvested area is more than three times larger than that for moderate droughts, representing a 20% loss. In urban settings, all coefficients are statistically insignificant, suggesting that drought conditions do not significantly affect agricultural outcomes in these areas.

Columns (4)–(6) and (11)–(12) of Table 3.3 focus on local economic activity, categorized by sector: agriculture, industry, and services. In rural municipalities, prolonged droughts reduce agricultural output by 4.8% and industrial output by 3%, while the service sector experiences a relatively minor reduction of less than 1%. These results are expected, as the agricultural sector is typically the most vulnerable to adverse weather conditions. However, the findings also indicate that prolonged droughts lead to broader economic losses across sectors. In urban municipalities, although there is some evidence of negative effects on economic activity, the estimated coefficients are consistently smaller than those for rural municipalities, suggesting that the economic impact of drought is less severe in urban areas.

While we do not directly assess the effects on employment, it is likely that droughts cause a sharp reduction in employment in rural areas. Albert *et al.* (2021) observes that droughts lead to a significant reduction in agricultural employment in Brazil, with workers that stay in affected regions partially reallocating to the manufacturing sector.

Tabela 3.3: Impact of Prolonged Droughts on Agriculture and Economic Outcomes

	Agriculture Outcomes			**GDP**		
	(1)	(2)	(3)	(4)	(5)	(6)
	Planted Area	Harvested Area	Production Value	Agriculture	Industry	Services
	Panel A: Rural Municipalities					
SPEI	0.0510***	0.0802***	0.0966***	0.0401***	0.0205***	0.0048***
	(0.005)	(0.006)	(0.006)	(0.003)	(0.003)	(0.001)
R^2adj	0.0463	0.0479	0.0462	0.0832	0.0198	0.1696
Drought	-0.0637***	-0.1172***	-0.1343***	-0.0473***	-0.0306***	-0.0060**
	(0.008)	(0.010)	(0.010)	(0.005)	(0.007)	(0.002)
R^2adj	0.0434	0.0448	0.0416	0.0777	0.0194	0.1693
Moderate Drought	-0.0216**	-0.0694***	-0.0960***	-0.0255***	-0.0138*	-0.0039
	(0.009)	(0.010)	(0.010)	(0.006)	(0.008)	(0.003)
Severe Drought	-0.1410***	-0.2049***	-0.2047***	-0.0871***	-0.0614***	-0.0100***
	(0.010)	(0.020)	(0.020)	(0.006)	(0.009)	(0.003)
R^2adj	0.0486	0.0495	0.0441	0.0816	0.0207	0.1695
Observations	38799	38742	38741	38853	38817	38853
	Panel B: Urban Municipalities					
	(7)	(8)	(9)	(10)	(11)	(12)
SPEI	-0.0184	-0.0061	0.0019	0.0093	0.0151**	0.0047**
	(0.050)	(0.040)	(0.040)	(0.010)	(0.007)	(0.002)
R^2adj	0.0238	0.0239	0.0239	0.0797	0.3041	0.1340
Drought	0.0426	0.0214	-0.0013	-0.0277**	-0.0239***	-0.0066
	(0.070)	(0.060)	(0.050)	(0.010)	(0.008)	(0.004)
R^2adj	0.0242	0.0241	0.0239	0.0809	0.3037	0.1335
Moderate Drought	0.0731	0.0483	0.0330	-0.0276**	-0.0236**	-0.0098**
	(0.080)	(0.080)	(0.060)	(0.010)	(0.010)	(0.004)
Severe Drought	-0.0098	-0.0248	-0.0604	-0.0278	-0.0245**	-0.0005
	(0.050)	(0.050)	(0.070)	(0.020)	(0.010)	(0.005)
R^2adj	0.0259	0.0254	0.0258	0.0808	0.3037	0.1341
Observations	9812	9799	9798	10367	10381	10386
Municipality FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Note: This table presents the estimation of the impact of prolonged droughts conditions on agriculture outputs and local economy. Each column represent a different outcomes. All outcomes are expressed in the logarithmic scale Panel A reports the results for rural municipalities, and Panel B for urban ones. The SPEI (Standard Precipitation-Evapotranspiration Index) is used as the measure of drought. *Drought* is defined as SPEI < -1, *Moderate Drought* as -1.5 <SPEI<-1, and *Severe Drought* as SPEI <-1.5. Standard errors are clustered at the municipality level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.5.3 Discussion

Our results indicate that droughts significantly increase IPV rates and negatively affect agricultural and economic outputs in rural municipalities. In contrast, in urban areas there are only transitory effects on IPV, with no significant impact on agricultural outcomes and smaller effects on economic activity compared to rural areas.

These findings suggest a causal pathway linking droughts and IPV. In rural areas, droughts reduce family income, which is heavily dependent on agricultural production, thereby increasing the likelihood of women becoming victims of IPV. In contrast, urban areas benefit from more diversified income sources that are less reliant on agriculture, making the population less vulnerable to weather shocks and, consequently, reducing the probability of women experiencing IPV in response to droughts.

The evidence that the risk of IPV increases with drought duration and intensity in rural areas can be understood through both the family stress model and bargaining models. According to the family stress model, prolonged economic pressure caused by long-term droughts can accumulate household tensions, which may trigger violence. Bargaining models, on the other hand, provide insight into how these economic shocks affect power dynamics within families. As income becomes scarce, women's outside options may decline, particularly due to reduced access to off-farm income opportunities. With men often retaining greater control over economic resources and women becoming more dependent on family income, women's bargain power is reduced, which contributes to an increase in IPV.

Moreover, in rural areas, gender roles are often more rigid, and violence against women is more socially accepted. Many of these women live in isolated areas, where protection and support services, such as women's shelters or specialized police stations, are scarce, making it even more difficult for them to seek help. The combination of economic challenges imposed by droughts, social norms unfavorable to women, and a lack of support services makes rural women particularly vulnerable to IPV.

In terms of identification, the comparison between rural and urban areas helps address concerns about omitted variable bias. Droughts are often correlated with high temperatures, raising the possibility that our results might reflect the influence of heat rather than drought. Previous research has shown that high temperatures can increase interpersonal violence by heightening discomfort, frustration, and aggression Henke & chi Hsu (2020); Mahendran *et al.* (2021). However, if temperature were the primary driver, we would expect the predominance of short-term effects, as well as similar impacts in both rural and urban areas. The fact that we observe stronger and greater effects in rural areas—particularly during medium and long-term droughts—suggests that droughts and their impacts on the local economy, rather than high temperatures, play a more significant role in driving IPV.

3.5.4 Robustness Checks

In this section, we perform two key robustness checks to validate our findings, focusing on rural municipalities.

First, we show that the results are robust when using an alternative drought indicator. In Table 3.4, we compare the estimation of drought effects on rural municipalities between the SPI and SPEI indices, applying the same thresholds to define droughts. The analysis focuses on long-term droughts (12 months). When using the SPI index, we also control for monthly average maximum temperature. The consistency in results across both indices, with similar coefficients and significance levels, underscores the reliability of our drought indicators.

Tabela 3.4: The Effect of Long Term Drought on IPV in Rural Brasil - Alternative Drought Index

	SPI	SPEI
Index	-0.0191***	-0.0247***
	(0.006)	(0.007)
R^2	0.0379	0.0378
Drought	0.0526***	0.0582***
	(0.010)	(0.010)
R^2	0.0380	0.0379
Moderate Drought	0.0365***	0.0428***
	(0.010)	(0.010)
R^2	0.0380	0.0379
Severe Drought	0.0734***	0.0765***
	(0.020)	(0.010)
R^2	0.0380	0.0380
Observations	465,912	466,236

Notes: This table compares the effects of long-term droughts on IPV using the SPI and SPEI indices at 12-month time scale. SPEI is the Standardized Precipitation-Evapotranspiration Index, while SPI is the Standardized Precipitation Index. The dependent variable is IHS transformation of the rate of IPV notifications per 100,000 women. *Drought* is defined as Index < -1, *Moderate Drought* as $-1.5 \leq$ Index < -1, and severe drought as Index< -1.5. Standard errors are clustered at the municipality level. Significance values: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Next, we test the robustness of our results by allowing flexibility in the main model. In Table 3.5, each column represents a different specification: the benchmark model, an unweighted regression, clustering at the microregion level, and using the raw IPV rate as the dependent variable instead of its IHS transformation. The main results remain consistent across all specifications. The unweighted regression suggests that the estimated impacts are not disproportionately influenced by larger municipalities. Clustering at the micro-region level accounts for potential spatial dependence between IPV rates and drought by allowing error correlation across broader geographic areas. Finally, using the raw IPV rate instead of the IHS transformation simplifies result interpretation and suggests larger drought effects, although this approach may be more sensitive to extreme values, potentially introducing distortion.

Tabela 3.5: The Effect of Prolonged Droughts on IPV in Rural Brazil - Alternative Model Specifications

	(1) Benchmark Model	(2) Unweighted Regression	(3) Microregion Cluster	(4) Dep Var: IPV Rate
SPEI	-0.0247***	-0.0381***	-0.0247***	-0.2318***
	(0.007)	(0.004)	(0.008)	(0.07)
Drought	0.0582***	0.0716***	0.0582***	0.4467***
	(0.01)	(0.007)	(0.01)	(0.1)
Moderate Drought	0.0428***	0.0484***	0.0428***	0.2343**
	(0.01)	(0.007)	(0.01)	(0.1)
Severe Drought	0.0765***	0.0976***	0.0765***	0.7001***
	(0.01)	(0.009)	(0.02)	(0.2)
Municipality FE	X	X	X	X
Time FE	X	X	X	X
Observations	466236	466236	466236	466236

Notes: This table presents the effects of droughts on IPV estimated using alternative specifications for the benchmark model. Each columns represents implements a different modification of the benchmark model. SPEI is the Standardized Precipitation-Evapotranspiration Index, while SPI is the Standardized Precipitation Index. *Drought* is defined as Index < -1, *Moderate Drought* as $-1.5 \leq$ Index < -1, and severe drought as Index< -1.5. Standard errors are clustered at the municipality level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.6 Conclusion

This study sheds light on the significant impact of droughts on IPV in Brazil, particularly in rural municipalities. Our analysis reveals that prolonged and intense droughts are associated with higher rates of IPV in rural areas. In contrast, in urban areas, the effects of drought appear to be transitory, with impacts diminishing within one month.

By comparing the effects on IPV rates, agricultural outcomes, and economic activity in rural and urban municipalities, we provide strong evidence that the economic channel plays a crucial role in driving IPV. This disparity highlights the economic vulnerabilities faced by rural households, where livelihoods are heavily dependent on agriculture and thus more susceptible to adverse weather shocks.

Drawing from theoretical models, we argue that in rural areas, economic hardship leads to heightened stress, exacerbates household tensions, and reduces women's bargaining power, ultimately contributing to an increase in IPV. Conversely, in urban municipalities, where income sources are more diversified, the economic consequences of droughts are less severe, resulting in a weaker link between droughts and IPV.

These findings suggest the need for targeted interventions to support women during times of drought. Interventions such as direct cash transfers to women, vocational training programs, and improved access to essential services—such as police protection, shelters, healthcare, and legal assistance—can help strengthen women's resilience to droughts, thereby reducing their vulnerability to IPV.

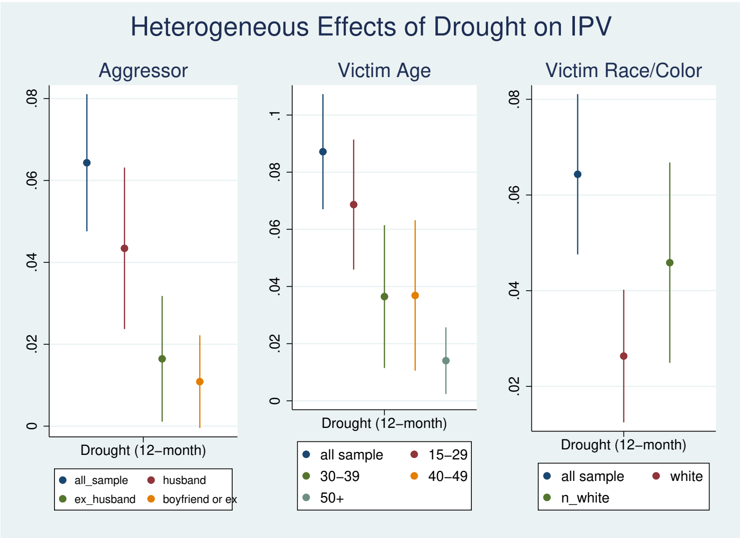
While this study offers valuable insights, it is important to acknowledge its limitations. Our measure of IPV is based on compulsory healthcare notifications, which may underreport less severe cases. Furthermore, the limited availability of healthcare services and protection for women in rural areas could lead to further underreporting. Nevertheless, we believe our results represent a lower bound on the actual impact of drought on IPV.

This study explores the intersections of climate extremes, economic stress, and gender-based violence, highlighting the heightened vulnerabilities faced by rural women in the context of climate change.

Appendix B

Additional Results

Figura B.1: Heterogeneous Effect of Drought on IPV



Notes: This figure shows the heterogeneous effects of droughts on IPV by the relationship between the victim and the aggressor, the victim's age, and the victim's race or color.

4
The Impact of Extreme Rainfall on Learning: Evidence from Southern Brazil

4.1
Introduction

Do temporary disruptive shocks affect student achievement? In this paper, we explore the short-term impacts of extreme rainfall shocks on student learning outcomes. Education is a process shaped by a wide range of inputs that contribute to the development of knowledge and skills. Although learning is cumulative, we demonstrate that even brief disruptions—such as those caused by extreme weather events—can hinder this process. With the increasing frequency of extreme weather events, these short-term effects may accumulate, leading to broader consequences both at the individual level—impacting future earnings and productivity—and at the aggregate level, influencing economic growth and income distribution (Hanushek & Woessmann, 2008).

In the empirical setting of Southern Brazil, where heavy rainfall is one of the most frequent and disruptive hazards, we examine the impact of extreme rainfall on student performance in a national standardized exam—the SAEB (*Sistema Nacional de Avaliação da Educação Básica*). [4.1] The exam is administered every two years to public school students, being part of a system designed to assess the quality of education in Brazil. Our focus is on 9th-grade students who are at a critical point in their school journey, marking the transition from middle school (*Ensino Fundamental*) to high school (*Ensino Médio*).

We combine student-level data from the SAEB exam with municipality-level measures of extreme rainfall, derived from high-resolution gridded daily precipitation data. Extreme rainfall is defined as the number of days in the school year when precipitation exceeds specific thresholds. We test 10 mm, 20 mm and 50 mm thresholds, with the main focus on the latter. The final sample includes test scores for 1,144,385 students attending 6,048 schools across 1,169 municipalities.

[4.1] Brazilian South encompasses three states: Paraná, Santa Catarina, and Rio Grande do Sul. This region is home to almost 15% of the Brazilian population. Historically, it has been one of the most impacted areas by natural disasters in Brazil

To identify the causal impact of extreme rainfall, we estimate a linear regression model that leverages within-municipality variation in extreme rainfall episodes across years. While we cannot track students over time, we can track schools, which allows us to incorporate school fixed effects into the model, and control for time-invariant school-level inputs and municipality-specific characteristics that could correlate with both student outcomes and rainfall. Additionally, year fixed effects absorb common time trends that may influence all students. By controlling for time-varying student characteristics, we further mitigate the risk that systematic differences in observable student traits could influence our results. The combination of school fixed effects, year fixed effects, and time-varying student controls provides a robust framework to isolate the effect of extreme rainfall on student performance.

Our results show that extreme rainfall disrupts student learning. Specifically, we find that three additional days of rainfall above 50 mm (the sample median) reduce math scores by 0.023 standard deviations and language scores by 0.017 standard deviations. Although these effects may seem modest, we demonstrate that they increase with both the intensity of rainfall and duration of rainfall exposure. Furthermore, heterogeneous analysis reveals that extreme rainfall exacerbates existing educational inequalities, disproportionately affecting vulnerable groups such as non-white students, students from lower socio-economic backgrounds, and lower-achieving students—

Next, we explore whether students attending schools located near areas at risk for rainfall-related disasters are more vulnerable to the impacts of severe rainfall. However, we do not find evidence that proximity to these risk zones exacerbates the adverse effects of extreme weather on student outcomes. This could suggest the presence of adaptation efforts by schools and municipalities.

We also investigate whether loss of instructional time is a mechanism through which extreme rainfall affects student performance. The findings suggest that extreme rainfall is associated with an increased likelihood of school principals reporting temporary interruptions of school activities, although we do not observe significant effects on proxies for student or teacher absences or school physical infrastructure quality.

To ensure the robustness of our results, we conduct several checks. First, we show that future rainfall shocks do not affect current test scores, suggesting that we are not capturing a spurious correlation between rainfall and academic performance. We also examine the possibility of selection bias among students taking the exam. Our analysis shows no significant association between rainfall and the observable characteristics of students who attended the exam, indicating that selection bias is unlikely to drive our results.

Our paper is closely related to studies on how natural disasters affect student outcomes. Past literature has shown that events like earthquakes, hurricanes, and floods significantly impact student achievement, enrollment, dropout, and other educational outcomes(e.g Sacerdote (2012); Marchetta *et al.* (2019); Thamtanajit (2020); Segarra-Alméstica *et al.* (2022)). We extend this evidence by examining the direct effect of rainfall—an event that typically causes less damage than major disasters but that occurs more frequently. Studies focusing on rainfall typically define extreme shocks as temporary deviations in precipitation accumulated over a period (e.g., a month or year) from the long-term averages for a specific location (e.g Rosales-Rueda (2018); Aguilar & Vicarelli (2022); Palacios & Rojas-Velásquez (2023)). However, we argue that such measures can smooth out the effects of short-term, high-intensity rainfall days, leading to an underestimation of their immediate and disruptive impact on the education system. By focusing on absolute daily rainfall thresholds, our approach more accurately captures the critical, localized disruptions caused by single-day or few-days of heavy rainfall.

In the Brazilian context, our paper closely relates to Ferreira de Lima *et al.* (2024), who also estimate the impact of rainfall shocks on SAEB exam performance. Nevertheless, our works differ in terms of empirical context, methodology, and results. While they restrict their analysis to 826 Brazilian municipalities with mapped risk areas and compare the performance of students attending schools near and far from these areas, we focus on the Southern region and analyze short-term, high-intensity rainfall events across all municipalities in the region. Ferreira de Lima *et al.* (2024) measure rainfall shocks as monthly deviations from local averages, finding that students with higher socioeconomic status and better prior academic performance are more negatively affected. In contrast, we focus on absolute daily thresholds and find that vulnerable students are more impacted. These differences may reflect both methodological choices and differences in empirical context.

The remainder of this paper is structured as follows: Section 4.2 reviews the literature on mechanisms through which rainfall shocks may negatively affect learning. Section 4.3 describes the data, defines learning outcome variables,the construction of extreme rainfall indicator, and presents descriptive statistics. Section 4.4 details the empirical strategy and the identification hypothesis. Section 4.5 presents and discusses the main results, including heterogeneous analyses, and potential mechanisms. Section 4.6 covers the robustness checks and Section 4.7 concludes.

4.2
Literature Review: How Do Rainfall Shocks Disrupt Learning?

Drawing from past literature, we identify three key channels through which severe rainfall episodes can undermine learning: loss of instructional time, income losses, and health-related issues. In this section, we discuss and present evidence of each one of these mechanisms.

The most direct way that extreme rainfall affects student outcomes is through the loss of instructional time. Heavy rainfall can force school closures due to damage or destruction of infrastructure or by disrupting essential services such as electricity and transportation. Even when schools remain open, rainfall often leads to increased absenteeism among students and teachers. For instance, a study in Brazil by Santana *et al.* (2013) find that student attendance dropped from 77% on non-flood days to just 27% on flood days, primarily for transportation challenges. Furthermore, past research has consistently demonstrated that loss of instruction time impact academic performance. Goodman (2014) observes that snow-related absences reduced math achievement in Massachusetts, while Bekkouche *et al.* (2023) show that exposure to rainy days in Sub-Saharan Africa led to lower test scores, likely due to increased teacher absenteeism. Similarly, Monteiro & Rocha (2017) note that violence shocks in Rio de Janeiro are related to higher teacher absenteeism and lower math performance in the SAEB exam.

Rainfall shocks can also affect student achievement by reducing household income. Much of this literature explores the relationship between rainfall shocks during early stages of life and later outcomes, especially in rural environments. Rainfall anomalies—whether droughts or excessive rainfall—reduce family incomes, which in turn lowers investments in crucial human capital inputs, such as nutrition, thereby compromising children's cognitive development. For example, Aguilar & Vicarelli (2022) show that children from rural communities in Mexico exhibit lower cognitive development four years after being exposed to exogenous precipitation anomalies during early childhood. Additionally, another part of the literature focuses on the trade-off between schooling and working, as income losses may lead families to prioritize work over education and reduce attendance and the probability of advancing in school (Marchetta *et al.*, 2019; Duryea *et al.*, 2007).

Finally, extreme rainfall can deteriorate student health. Flooding from excessive rainfall can damage water and sewage systems, leading to the spread of diseases such as diarrhea, leptospirosis, and vector-borne diseases. In addition, student mental health may also be affected if children develop post-traumatic stress disorder as a consequence of natural disasters triggered by heavy rain. Previous research has shown a strong association between health status and educational outcomes (Bleakley, 2007; Currie *et al.*, 2010).

In summary, while all three mechanisms—loss of instructional time, income losses, and health-related issues—are important, this study primarily focus on the disruption of instructional time. However, it is important to recognize that these mechanisms often overlap, making it challenging to isolate their individual impacts on student outcomes.

4.3 Data

To conduct the empirical analyses, we combine student-level data on SAEB exam performance and student characteristics with annual indicators of extreme precipitation at the municipality level. We also incorporate school-level data on infrastructure quality and proxies for school closures, as well as student and teacher absenteeism, extracted from surveys linked to SAEB. The data spans the years 2011, 2013, 2015, 2017, and 2019 — the SAEB exam years. In this section, we describe each data source, define the outcome variables, explain the construction of extreme rainfall indicators, and present descriptive statistics.

4.3.1 Education

To measure educational outcomes, we use student-level data from the SAEB exam, a nationwide standardized test that assesses the math and language (Portuguese) performance of 5th- and 9th-grade students in Brazil. The exam is mandatory for public schools with more than 20 students enrolled in each grade and is administered every two years, typically in late October or November. Data from the exam are provided by the National Institute for Research on Education (*Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira, INEP*), which is also responsible for the exam's development. We use data from five exam editions: 2011, 2013, 2015, 2017, and 2019.

The indicators of student achievement are the 9th-grade student scores in math and language, which are standardized by INEP to ensure comparability across different years. Importantly, the primary goal of the SAEB exam is to evaluate the quality of public education in Brazil. Notably, students' performance on the exam has no direct academic consequences for them, meaning it does not impact students' promotion or retention.

Students, teachers, and principals from schools participating in the SAEB exam also complete surveys. The student survey collects information on socio-demographic characteristics, such as race, gender, age, family background and household assets. This data allows us to explore the heterogeneous effects of rainfall and serves as control variables in different model specifications. The principal survey includes questions such as “Has the functioning of the school been hindered by any of the following issues ?", covering topics like interruption of school activities, teacher and student absenteeism These responses help us assess whether rainfall disrupts normal school functions.

Moreover, between 2011 and 2017, the SAEB included a survey evaluating the physical conditions of school infrastructure, conducted by an external reviewer. The condition of infrastructure components, such as electricity, water supply, walls, and roofs, and rated on a scale from zero (nonexistent) to three (good). We obtain a simple average of these ratings to create an infrastructure quality index, allowing us to study the potential impact of rainfall on school infrastructure. For instance, we classify infrastructure as “good"if the index is above the median.

4.3.2 Rainfall

The source of our weather data is the Brazilian Daily Weather Gridded Data (BR-DWGD) from Xavier *et al.* (2022). The current version of BR-DWGD provides daily rainfall data at a spatial resolution of 0.1×0.1 degrees, obtained by interpolating observational rainfall records.

To obtain daily rainfall series at the municipality level, we average the grid cell values that fall within the municipality boundaries. Since our goal is to identify the impact of rainfall during the school year on students' performance, we use only precipitation records from the months between February and October, which we define as the school year; January is excluded because it is the school vacation month, and November and December are excluded as they may fall after the test dates. For each municipality, we count the number of days during the school year when precipitation amounts exceed 10 mm/day, 20 mm/day, and 50 mm/day. These thresholds are recommended by the Expert Team on Climate Change Detection and Indices (ETCCDI) to classify rainfall extremes. [4.2]

To account for climate heterogeneity across municipalities, we also rely on an alternative definition of extreme rainfall: days that fall within the upper range of the historical distribution of rainy days (i.e., days with precipitation

[4.2] https://etccdi.pacificclimate.org/list_27_indices.shtml

$\geq$ 1mm/day) at each location, calculated over the 1981–2010 period. In this approach, extreme rainfall is defined as rainy days that exceed the 90^{th}, 95^{th}, or 99^{th} percentiles.

4.3.3 Other Data

We complement our analysis by incorporating additional sources of school and municipality data. To identify schools located near risk areas for rain-related disasters, we merge data from the Statistical Territorial Base of Risk Areas (BATER) with the schools' locations provided by INEP. BATER results from a partnership between the *Instituto Brasileiro de Geografia (IBGE)* and the *Centro de Monitoramento e Alerta de Desastres Naturais (CEMADEN)*. It consists of vector data (shapefiles), where each polygon represents a distinct risk area. In the South Region, there are 1,293 risk areas across 144 monitored municipalities.

We calculate the distance of each school to the nearest risk area and consider them to be within a risk zone if the distance is less than B meters from the risk area. For robustness, we use different values for B, specifically 250 and 500 meters.

4.3.4 Sample Selection and Summary Statistics

The estimation of the impact of severe rainfall episodes on student achievement is always conditional on school and year fixed effects. Therefore, we exclude from the sample schools that only participated in a single SAEB edition. Notably, in 2019, the student surveys did not include a question about gender. To avoid losing data, we impute the missing gender information for 2019 using the school's average gender distribution from previous editions in our regression. The final sample includes test scores for 1,444,385 students attending 6,048 schools across 1,169 municipalities. We present summary statistics of the sample in Table 4.1. The number of observations varies across variables due to some students or principals not responding to certain survey questions.

Tabela 4.1: Descriptive Statistics

	Mean	SD	Min	Max	N
Student Data					
Math	0.19	0.81	-9.50	9.80	1,144,385
Language	0.083	0.85	-9.60	7.20	1,144,385
Non White	0.40	0.49	0.00	1.00	1,034,273
Female	0.51	0.50	0.00	1.00	926,782
Low Educated Mother	0.57	0.50	0.00	1.00	913,815
Poor	0.22	0.41	0.00	1.00	1,135,495
Previously Repeated	0.30	0.46	0.00	1.00	1,117,815
Previously Dropped Out	0.038	0.19	0.00	1.00	1,119,278
School Data					
Infrastructure Index	2.42	0.49	0.00	3.00	1,209,654
Good Infrastructure	0.50	0.50	0.00	1.00	1,209,654
Teacher Absence	0.58	0.49	0.00	1.00	1,404,208
Student Absence	0.54	0.50	0.00	1.00	1,404,570
School Closure	0.28	0.45	0.00	1.00	1,403,866
Weather Data					
# R10	43.4	8.50	11.00	72.00	1,456,881
# R20	21.1	5.78	4.00	40.00	1,456,881
# R50	2.98	2.07	0.00	14.00	1,456,881
# Rp90	13.4	4.66	0.00	28.00	1,456,881
# Rp95	7.29	3.29	0.00	20.00	1,456,881
# Rp99	1.77	1.44	0.00	9.00	1,456,881

Note: The table presents summary statistics for students and schools participation in SAEB exam, as well municipality-level conditions in 2011, 2013, 2015, 2017 and 2019. Data from SAEB exam are provided by INEP, while daily precipitation information comes from BR-DWGD. The number of observations varies across variables due to missing information.

4.4 Empirical Strategy

To identify the causal impact of extreme rainfall, we exploit within-municipality variations in extreme rainfall episodes across years. More specifically, we estimate a linear model with fixed effects, as described by the equation below:

$$y_{ismt} = \alpha + \beta R_{mt} + \lambda X_{ismt} + \gamma_t + \mu_s + \varepsilon_{ismt} \tag{4.1}$$

In equation 4.1, i indexes students, s denotes school, m indicates municipality, and t corresponds to the year. The dependent variable, y_{ismt}, is the student's test score on the math or language test. The variable of interest, R_{mt}, represents the number of days with precipitation exceeding a predetermined threshold (we use 10 mm, 20 mm, and 50 mm) during the school year (March - October). The term X_{ismt} is a set of student-level socio-demographic controls, including dummy variables for student gender, race/ethnicity, whether the student has repeated a grade or dropped out of school before, and whether the student's mother is low-educated (i.e.,did not complete middle school). The term μ_s represents school fixed effects, which account for any time-invariant factors at the school (and municipality) level, such as the school's geographic location, baseline educational quality, and long-term rainfall patterns in the municipality. Year fixed effects, represented by γ_t , capture time trends common to all municipalities in the region, such as economic activity, regional weather phenomena (like El Niño), and common educational policies. Finally ε_{ismt} is a random error term. We cluster standard errors at the municipality level, the level in which rainfall is observed.

The parameter of interest β estimates the effect of extreme rainfall days on student test scores. Identification requires that, conditional on school and year fixed effects, and on student-level controls, intense precipitation episodes are uncorrelated with any other determinants of student performance on the SAEB exam. Since we focus on short-term, intense rainfall episodes, it is unlikely that these events are systematically related to other factors influencing student outcomes. Furthermore, we conduct a robustness checks showing that future rainfall does not affect current proficiency, reinforcing that we are not capturing a spurious correlation.

Another potential issue regarding identification is the possibility that extreme rainfall introduces selection bias among the students who take the exam. For instance, if low-ability students are more likely to miss the SAEB exam in response to heavy rainfall, we may underestimate the effect on test scores. Conversely, if high-ability students are more likely to miss the test, we could be capturing a worsening of the pool of students taking the exam rather than the actual causal impact of intense precipitation on academic achievement. Since we do not observe the characteristics of students who do not participate in the exam, we investigate whether rainfall is correlated with the socioeconomic characteristics of students who do take the exam. We do not find evidence of selection bias.

Lastly, to address concerns regarding spatial and temporal correlation in rainfall, we demonstrate that our estimates are robust to two-way clustering at the municipality and microregion-year levels. Municipality-level clustering addresses serial correlation, while microregion-year clustering mitigates potential correlations in rainfall across municipalities within the same microregion (Assunção *et al.*, 2023).

4.5 Results

In this section, we present the impact of extreme rainfall on student performance in the SAEB exam. We explore how these effects vary based on student background, school infrastructure quality, and proximity to areas at risk for natural disasters.

4.5.1 Main Results

Table 4.2 presents the results of the estimation of equation 4.1. The first three columns show the impact on math scores, while the last three focus on language scores. We estimate separate regressions for days with precipitation exceeding 10 mm/day, 20 mm/day, and 50 mm/day. All specifications include school and year fixed effects. Columns (1) and (4) control for school and year fixed effects, columns (2) and (5), add student-level controls. Columns (3) and (6) report the results of the full specification using the two-way clustering method.

The results reveal a clear negative relationship between extreme rainfall and performance in both math and language tests, with the effect being more pronounced for math. The coefficients for the number of days with precipitation above 10 mm/day, 20 mm/day, and 50 mm/day are consistently negative across all specifications, indicating that an increase in the number of intense rainfall days is associated with lower test scores. Furthermore, the impact intensifies as the rainfall threshold increases, suggesting that more severe rainfall events have a greater detrimental effect on student learning outcomes.

Importantly, the effect is not driven by student selection on observed characteristics, as the coefficients remain statistically significant when controlling for student covariates. Moreover, the effects are robust to the two-way clustering method.

In our preferred specification, we estimate that three additional days with rainfall above 50 mm/day (the sample median) reduce math scores by 0.023 standard deviations and language scores by 0.017 standard deviations.

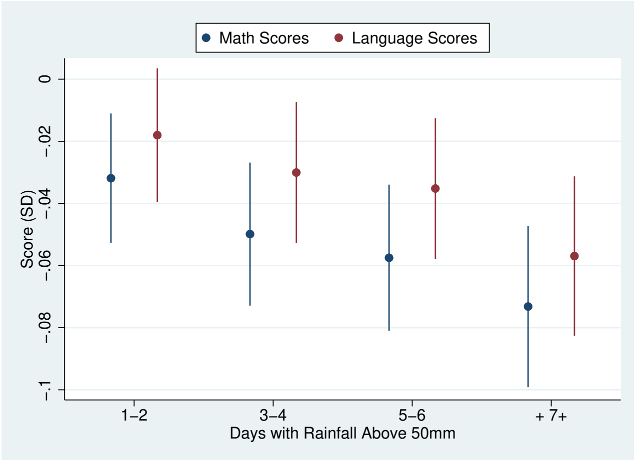
Tabela 4.2: The Impact of Extreme Rainfall Days on SAEB Test Scores

	Math Scores			Language Scores		
	(1)	(2)	(3)	(4)	(5)	(6)
# R10	-0.0013***	-0.0019***	-0.0019***	-0.0005	-0.0012***	-0.0012**
	(0.0004)	(0.0004)	(0.0006)	(0.0004)	(0.0004)	(0.0005)
R^2adj	0.1283	0.2137	0.2137	0.1153	0.2115	0.2115
# R20	-0.0025***	-0.0030***	-0.0030***	-0.0019***	-0.0026***	-0.0026***
	(0.0007)	(0.0006)	(0.0008)	(0.0006)	(0.0006)	(0.0007)
R^2adj	0.1283	0.2137	0.2137	0.1153	0.2115	0.2115
# R50	-0.0079***	-0.0078***	-0.0078***	-0.0055***	-0.0058***	-0.0058***
	(0.0010)	(0.0010)	(0.0020)	(0.0010)	(0.0010)	(0.0010)
R^2adj	0.1284	0.2138	0.2138	0.1154	0.2116	0.2116
Observations	1,144,385	827,935	827,935	1,144,385	827,935	827,935
School FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Student-Level Controls	N	Y	Y	N	Y	Y
Two-Way Clustering	N	N	Y	N	N	Y

Notes: This table presents the estimation of the effects of extreme rainfall on students performance in the SAEB exam. The dependent variable in columns (1)-(3) is math score, while in columns (4)-(6), it is language scores. The independent variables are the number of days during the school year with precipitation exceeding 10 mm/day, 20 mm/day, and 50 mm/day. We run separate regressions for each of these precipitation thresholds. Student-level controls include information on gender, race, family income, mothers' education, and whether the student has repeated a grade or dropped out of school before. The inclusion of student-level controls reduces the number of observations, as some information is missing. In columns (1)-(2) and (4)-(5), standard errors are clustered at the municipality level. In columns (3) and (6), the standard errors are clustered at the municipality and micro-region-year levels. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We provide additional evidence on how increased exposure to intense rainfall shocks negatively impacts student test scores by categorizing the number of days with rainfall above 50 mm/day into intervals: 1-2 days, 3-4 days, 5-6 days, and 7 or more days. We estimate the full specification of equation 4.1, using these groups as independent variables. The reference group consists of students who experienced zero days of rainfall above 50 mm in a given school year. Figure 4.1 illustrates this analysis. The results show a clear and significant decline in math scores as the number of intense rainfall days increases. Specifically, students exposed to 7 or more days of rainfall above 50 mm during the school year experience a reduction in math scores of approximately 0.075 standard deviations. For language scores, a negative trend is also observed, though the effect is smaller, with an estimated reduction of around 0.055 standard deviations for 7 or more days of intense rainfall.

Figura 4.1: The Impact of Extreme Rainfall on SAEB Test Scores by Number of Days with Rainfall above 50 mm



Notes: This figure shows the effect of the number of days during the school year with precipitation exceeding 50 mm on student scores in math and language. We categorize this variable into intervals: 1-2 days, 3-4 days, 5-6 days, and 7 or more days. The specification includes school and year fixed effects, as well as student-level controls. The dots represent the point estimates, and the lines represent the 95% confidence intervals. Standard errors clustered at the municipality level.

To better contextualize these effects, we compare our findings with other studies examining the relationship between weather and academic performance in standardized exams. For instance, in the United States, Park *et al.* (2020) find that a 1°F increase in temperature during the year prior to the PSAT test lowers scores by approximately 0.2 percent of a standard deviation. Bekkouche *et al.* (2023) report a reduction of 0.05 standard deviations in test scores for each additional rainy day among students in Sub-Saharan Africa. Thamtanajit (2020) estimate that floods lead to reductions in test scores ranging from 0.03 to 0.11 standard deviations. In Brazil, Ferreira de Lima *et al.* (2024) find that rainfall reduce math performance by 0.055 standard deviations for students attending schools near high-risk areas. Our coefficients align with these findings, indicating a significant negative impact of extreme rainfall on student achievement, although the magnitude of the effect in our context appears smaller.

4.5.2 Heterogeneity Analyses

4.5.2.1 Students Socioeconomic Characteristics

Adverse weather conditions may disproportionately affect certain groups of students. Table 4.3 explores the heterogeneous effects of extreme rainfall on math scores across different socioeconomic characteristics. Each column presents the results of a regression in which a specific student characteristic is interacted with the number of rainy days with precipitation exceeding 50 mm/day, while controlling for the remaining characteristics.

The analysis reveals that heavy rainfall has a more pronounced negative impact on non-white students, those from low socioeconomic backgrounds—such as students from poor families and with less-educated mothers—and students who have previously repeated a grade or dropped out of school. On average, these groups already have weaker academic performance, and heavy rainfall further exacerbates existing educational inequalities.

One concern is the potential endogeneity of poverty in our setting, as it may be affected by rainfall shocks. However, we address this issue in Section 4.6.

Tabela 4.3: Heterogeneous Effects of Extreme Rainfall on Math Test Scores by Student Characteristics

	Dependent Variable: Math Scores					
	(1)	(2)	(3)	(4)	(5)	(6)
# R50	-0.0053***	-0.0060***	-0.0063***	-0.0075***	-0.0069***	-0.0075***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Female	-0.1638***					
	(0.009)					
Female × #R50	-0.0031					
	(0.002)					
Non White		-0.0953***				
		(0.004)				
Non White × # R50		-0.0047***				
		(0.001)				
Low Educated Mother			-0.1309***			
			(0.006)			
Low Educated Mother × # R50			-0.0027*			
			(0.001)			
Poor				-0.0502***		
				(0.006)		
Poor × # R50				-0.0053***		
				(0.002)		
Previously Repeated					-0.4376***	
					(0.009)	
Previously Repeated × # R50					-0.0034*	
					(0.002)	
Previously Dropped Out						0.0376***
						(0.010)
Previously Dropped Out× # R50						-0.0113***
						(0.003)
Observations	686,853	827,935	827,935	827,314	827,935	827,935
R^2 Adj.	0.2089	0.2138	0.2138	0.2142	0.2138	0.2138
School FE	Y	Y	Y	Y	Y	X
Year FE	Y	Y	Y	Y	Y	Y
Student-Level Controls	Y	Y	Y	Y	Y	Y

Notes: This table investigate heterogeneity of extreme rainfall by students characteristic. Dependent Variable is math test score. Independent variable of interest is the number of days in the school year with precipitation exceeding 50 mm/day. The sample size varies across columns due to missing information on students characteristics. The standard errors are clustered at the municipality level. Significance Levels:
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.5.2.2 Schools Location

Are students attending schools near rainfall-related risk areas more vulnerable to the impacts of extreme precipitation? We investigate this question using two different approaches.

First, we compare the effects of rainfall on students in municipalities with and without mapped risk areas (RA), providing a broad assessment of whether living in risk-prone municipalities leads to lower SAEB exam performance. In our sample, 144 out of 1,169 municipalities have identified risk areas. Although these municipalities represent only 12.3% of the total, they account for 40.81% of the students. Second, within municipalities with risk areas, we analyze the proximity of schools to these zones, comparing students attending schools within 250 meters and 500 meters to those farther away. This more granular approach allows us to assess whether closer proximity to risk areas exacerbates the negative effects of extreme rainfall on student outcomes due to increased risks of floods, landslides, and other disruptions.

However, as reported in Table 4.4, we do not identify significant differentiated effects based on the proximity to risk areas on student performance in either of these analyses. These null effects may be due to several factors, including adaptation policies implemented by schools and municipalities that mitigate the adverse impacts of rainfall, and limitations in the study's design or data, such as the reduced sample size when restricting the analysis to municipalities with mapped risk areas. A deeper investigation is necessary to fully understand these results.

Tabela 4.4: Heterogeneous Effects of Extreme Rainfall on SAEB Test Scores by Distance to Risk Areas

	Math Scores			Language Scores		
	(1)	(2)	(3)	(4)	(5)	(6)
# R50	-0.0074***	-0.0107***	-0.0101***	-0.0052***	-0.0084***	-0.0084***
	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)
Risk Municipality × # R50	-0.0013			-0.0018		
	(0.002)			(0.003)		
Schools Within 250m of RA × # R50		0.0030			0.0022	
		(0.004)			(0.004)	
Schools Within 500m of RA × # R50			-0.0001			0.0015
			(0.003)			(0.003)
Observations	827,314	316,902	316,902	827,314	316,902	316,902
R^2_{adj}	0.2147	0.2110	0.2110	0.2119	0.2025	0.2025
School FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Student-Level Controls	Y	Y	Y	Y	Y	Y

Notes: This table investigates whether students attending schools in localities near risk zones are disproportionately affected by extreme rainfall. The dependent variable in columns (1)-(3) is students' math scores, while in columns (4)-(6) it is language scores. The independent variable is the number of days in the school year with precipitation exceeding 50 mm/day. Risk municipalities are those with mapped risk areas.from schools Student-level controls include information on gender, race, mothers' education, and whether the student has repeated a grade or dropped out of school before. The inclusion of student-level controls reduces the number of observations, as some information is missing. The standard errors are clustered at the municipality level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.5.3 Mechanisms

Loss of instructional time is likely the most direct mechanism through which extreme rainfall undermines learning. To explore this channel, we use principal surveys to investigate whether rainfall is associated with a higher likelihood of principals reporting student and teacher absences, as well as interruptions to school activities. In addition, we examine the impact of heavy rainfall on the physical condition of school infrastructure, based on evaluations conducted by external reviewers. Table 4.5 summarizes the results, with each column (1)-(4) representing a different outcome. For this analysis, we aggregate the data at the school-level.

Our findings indicate that extreme rainfall increases the likelihood of principals reporting concerns about interruptions to school activities. However, there is no significant effect on student or teacher absences, nor on the quality of school infrastructure. This suggests that while severe weather disrupts the normal operation of schools, leading to a loss of instructional time, it may not directly result in increased absenteeism or immediate deterioration of physical infrastructure. Since these outcomes are based on survey responses rather than actual attendance, the findings remain inconclusive, but they point to a potential area for further investigation.

Tabela 4.5: The Impact of Extreme Rainfall on Loss of Instructional Time

	(1) School Interruption	(2) Student Absence	(3) Teacher Absence	(4) Good Infr
# R50	0.0158***	0.0009	0.0018	0.0017
	(0.0050)	(0.0020)	(0.0020)	(0.0030)
Observations	22,099	22,118	22,109	18,332
R^2adj	0.1130	0.2292	0.2907	0.2243
School FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
School Level Controls	Y	Y	Y	Y

Notes: This table investigates the effect of rainfall on school instructional time loss. The dependent variables are dummies indicating whether the school principal reported issues with school activity interruptions, student absence, teacher absence, and whether the school was evaluated as having good infrastructure quality. The independent variable is the number of day with rainfall exceeding 50 mm/day. Controls include average characteristics of students taking the exam at that school. Standard errors are clustered at the municipality level. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.6 Robustness Checks

In this section, we investigate the robustness of our estimation in three ways: (i) placebo analysis: we examine whether future rainfall shocks impact current student outcomes, (ii) student selection, and (iii) alternative rainfall shock definitions.

4.6.1 Lagged and Lead Effects

Table 4.6 presents a robustness check for the impact of extreme rainfall on student performance by analyzing both lagged and led effects of rainfall. In columns (1) and (2), the dependent variable is math scores, while in columns (3) and (4), is language scores. We find no association between past or future days of intense rainfall and student performance. The null coefficients for past shocks suggest that, at least in terms of academic achievement, the effects of rainfall are transitory. Additionally, the absence of significant lead effects supports the credibility of the identification strategy, indicating that our findings are not driven by unobserved factors or spurious correlations.

Tabela 4.6: Lagged and Lead Effects of Extreme Rainfall on SAEB Test Scores

	Math Scores		Language Scores	
	(1)	(2)	(3)	(4)
# R50	-0.0080***	-0.0077***	-0.0058***	-0.0059***
	(0.001)	(0.001)	(0.001)	(0.001)
# R50 (t-1)	0.0024*		0.0007	
	(0.001)		(0.002)	
# R50 (t+1)		-0.0014		0.0011
		(0.002)		(0.002)
Observations	827314	827314	827314	827314
R^2adj	0.2142	0.2142	0.2119	0.2119
School FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Student-Level Controls	Y	Y	Y	Y

Notes: This table presents the placebo of extreme rainfall on student performance. The dependent variables are math and language test scores. The independent variables are the number of days with precipitation exceeding 50 mm/day in the current year, past year, and following year. Standard errors are clustered at the municipality level. All regression include year, school and student level controls. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.6.2 Selection

Another concern regarding identification is the possibility that rainfall might influence which students take the SAEB exam. If this were true, our estimator could be capturing differences in student characteristics rather than the causal effect of rainfall. Since we do not have data on the characteristics of students who did not participate, we address this issue by demonstrating that there is no association between rainfall and the observed characteristics of the students who did take the exam in Table 4.7. This finding strengthens the argument that our analysis is not compromised by selection bias.

Tabela 4.7: Student Selection at the SAEB Exam

	(1) Female	(2) Non White	(3) Low Educated Mother	(4) Poor	(5) Previously Repeated	(6) Dropped Out
#R50	-0.0003	0.0002	0.0007*	0.0003	0.0008	0.0001
	(0.0004)	(0.0004)	(0.0004)	(0.0006)	(0.0010)	(0.0002)
Observations	926,782	1,034,273	913,815	1,135,495	1,117,815	1,119,278
R^2adj	0.0023	0.0692	0.1172	0.0680	0.0432	0.0124
School FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Notes: The table presents the test for selection-bias among students taking the SAEB Exam. Each column is different dependent variable, corresponding for represents a observed characteristic of students participating in the exam. Independent variable is number of days in school year with precipitation exceeding 50 mm/day. Standard Errors are clustered at the municipality level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.6.3 Alternative Rainfall Measures

In table 4.8, we estimate the benchmark model using measures of rainfall that accounts for municipalities heterogeneity in what is considered of extreme. We use as independent variables the number of days in school year when precipitation amount exceed the 90^{th}, 95^{th}, and 99^{th} percentiles of the municipality-specific distribution of precipitation in rainfall days. The advantage of using these relative measures is that they address the possibility that municipalities with frequent high rainfall may have already adapted by developing infrastructure and policies that make them more resilient to the effects of extreme precipitation. By defining extreme rainfall in this way, we ensure that the rainfall classified as extreme is genuinely unexpected and disruptive for that specific location. The results confirm the adverse impacts of rainfall on student performance and show that the findings are robust to alternative definitions of extreme rainfall.

Tabela 4.8: Impact of Extreme Rainfall on Math and Language Scores Using Alternative Rainfall Measures

	Math Scores			Language Scores		
	(1)	(2)	(3)	(4)	(5)	(6)
#Rp90	-0.0027***			-0.0029***		
	(0.0007)			(0.0007)		
#Rp95		-0.0050***			-0.0046***	
		(0.0009)			(0.0010)	
#Rp99			-0.0096***			-0.0071***
			(0.002)			(0.002)
Observations	827,314	827,314	827,314	827,314	827,314	827,314
R^2Adj	0.2146	0.2147	0.2146	0.2119	0.2120	0.2119
Municipality FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Student Controls	Y	Y	Y	Y	Y	Y

Note: In the first three columns, the dependent variable is the math score, and in the last three columns, it is the language score. The independent variables are Rp90, Rp95, and Rp99, representing the number of days in the school year with precipitation amounts exceeding the 90^{th}, 95^{th}, and 99^{th} percentiles of the municipality-specific distribution of precipitation on rainy days. All regressions include year, school, and student-level controls. Standard errors are clustered at the municipality level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.7 Conclusion

In this paper, we analyzed the short-term impact of extreme rainfall events on student achievement in Southern Brazil, focusing on the performance of 9th-grade students in standardized math and language exams. Our identification strategy exploits within-municipality variations in extreme rainfall episodes across years, which, after controlling for school fixed effects, time fixed effects, and school-level controls, can be plausibly considered exogenous.

Importantly, these disruptions are not uniform across all students. Vulnerable groups—such as non-white students, those from disadvantaged backgrounds (with low-educated mothers and from poor families), and students with lower academic performance—are disproportionately affected. These students already face educational disadvantages, and rainfall shocks appear to exacerbate these existing inequalities.

We show evidence that rainfall leads to school interruptions, likely resulting in a loss of instructional time. We did not observe significant effects on student absenteeism, teacher attendance, or the physical condition of school infrastructure. However, since these measures are based on individuals' perceptions, we cannot entirely rule out the importance of these channels.

Robustness checks support the causal relationship between rainfall and student outcomes. We show that future rainfall shocks do not affect current test scores, reducing concerns regarding spurious correlations. We also find no evidence of student selection bias related to rainfall events. Testing alternative definitions of extreme rainfall based on municipality-specific historic precipitation distribution yielded consistent results.

Overall, this study underscores the negative effects of extreme rainfall on student performance in Southern Brazil. While our evidence suggests these effects are transitory, with no lasting impact from past rainfall episodes, as extreme weather becomes more frequent and intense, cumulative disruptions in the education process may lead to more persistent and long-term deterioration in academic achievement.

Appendix C

Asset Index

The asset index is constructed by standardizing responses to questions about the number of household items, as described in the table below. For each question, the student's response is normalized by subtracting the average response of all students in the same year and dividing the result by the standard deviation of those responses. These standardized responses are then summed to create the Asset Index. Students classified as "poor"are those in the bottom 20% of the distribution.

Tabela C.1: Student Survey: Household Assets

Item	**Does Your House Have?**				
Refrigerator	No	Yes, One	Yes, Two	Yes, Three	Yes, Four or more
Freezer	No	Yes, One	Yes, Two	Yes, Three	Yes, Four or more
Washing Machine	No	Yes, One	Yes, Two	Yes, Three	Yes, Four or more
Car	No	Yes, One	Yes, Two	Yes, Three	Yes, Four or more
Computer	No	Yes, One	Yes, Two	Yes, Three	Yes, Four or more
Bathroom	No	Yes, One	Yes, Two	Yes, Three	Yes, Four or more
Bedroom	No	Yes, One	Yes, Two	Yes, Three	Yes, Four or more

School Survey

Tabela C.2: School Survey - Evaluation of Building Items and Equipment

	Item	Rate			
1	Roof	Good	Regular	Poor	Noxistent
2	Walls	Good	Regular	Poor	Nonexistent
3	Floor	Good	Regular	Poor	Nonexistent
4	Building Entrance	Good	Regular	Poor	Nonexistent
5	Courtyard	Good	Regular	Poor	Nonexistent
6	Hallways	Good	Regular	Poor	Nonexistent
7	Classrooms	Good	Regular	Poor	Nonexistent
8	Doors	Good	Regular	Poor	Nonexistent
9	Windows	Good	Regular	Poor	Nonexistent
10	Bathrooms	Good	Regular	Poor	Nonexistent
11	Kitchen	Good	Regular	Poor	Nonexistent
12	Hydraulic Installations	Good	Regular	Poor	Nonexistent
13	Electrical Installations	Good	Regular	Poor	Nonexistent

Additional Results

Tabela C.3: Impact of Extreme Rainfall on Language Scores

	Dep Var: Language Scores					
	(1)	(2)	(3)	(4)	(5)	(6)
R50	-0.0058***	-0.0058***	-0.0035*	-0.0056***	-0.0056***	-0.0054***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Female	0.2283***					
	(0.008)					
Female × R50	-0.0001					
	(0.002)					
Non White		-0.1027***				
		(0.004)				
Non White × R50		-0.0000				
		(0.001)				
Low Educated Mother			-0.1312***			
			(0.006)			
Low Educated Mother × R50			-0.0042**			
			(0.002)			
Poor				-0.0382***		
				(0.007)		
Poor × R50				-0.0036*		
				(0.002)		
Previously Repeated1					-0.4393***	
					(0.009)	
Previously Repeated × R50					-0.0006	
					(0.002)	
Previously Dropped Out						0.0537***
						(0.01)
Previously Dropped Out × R50						-0.0110***
						(0.004)
Observations	686838	827314	827314	827314	827314	827314
R^2 adj.	0.2075	0.2119	0.2119	0.2119	0.2119	0.2119
School FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Notes: This table investigate heterogeneity of extreme rainfall by students characteristic. Dependent Variable is language score. Independent variable of interest is the number of days in the school year with precipitation exceeding 50mm/day. The sample size varies across columns due to missing information on students characteristics. The standard errors are clustered at the municipality level. Significance Levels: * denotes $p < 0.10$, ** denotes $p < 0.05$, and *** denotes $p < 0.01$.

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