Too Hot to Learn? Evidence from High School Dropouts in Brazil

Francisco Costa* Diana Goldemberg†

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Abstract

This paper examines the impact of cumulative heat exposure on dropout rates for K10-12 students across Brazil, using data from over 30,000 schools and 80 million enrollments between 2007 and 2016. We find that a one-standard-deviation increase in the share of days above 34°C raises dropout rates by 0.36 percentage points, representing a 5.1% increase in the average dropout rate. The effects are concentrated in public schools, particularly in urban areas, where poor infrastructure amplifies the impact of heat. In contrast, private schools show no significant effects, likely due to better resources, such as air conditioning. These findings highlight the need to improve learning environments, particularly in public schools, to help students cope with rising temperatures and reduce dropout rates and educational inequality.

JEL codes: I20, J24, Q5.

Keywords: education, temperature, school dropout, climate change, Brazil.

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*FGV EPGE. E-mail: francisco.costa@fgv.br.

†Minerva University. E-mail: dgoldemberg@minerva.edu.

1 Introduction

Despite recent progress in global primary school enrollment, which has reached 91%, completion rates in developing countries remain low. In Latin America, only 48% of individuals aged 20-24 have completed secondary education, largely due to high dropout rates. In Brazil, our focus, 7.1% of K10-K12 students drop out each year.[1] Given the role of human capital in driving economic growth and the disproportionate impact of climate change on less developed countries, we study the link between temperature and school dropout.

Weather shocks are known to affect human capital. Research shows that high temperatures impair performance on high-stakes exams in both rich countries (Graff Zivin et al., 2018; Park et al., 2020; Park, 2022; Suzuki, 2024) and low- and middle-income countries (Zivin et al., 2020; Garg et al., 2020; Cho, 2017; Li and Patel, 2021; Arceo-Gomez and López-Feldman, 2024). In rural areas of developing countries, weather shocks can also influence schooling through agricultural income and health channels (Jensen, 2000; Björkman-Nyqvist, 2013; Shah and Steinberg, 2017). These studies primarily focus on learning or performance. Given the long-term consequences of dropping out on children's educational outcomes (Manacorda, 2012), our main contribution is to analyze how high temperatures affect this critical measure of educational attainment: school abandonment.

Using census data from over 30,000 schools and 80 million students enrolled in grades K10-12 in Brazil from 2007-2016, we analyze the impact of cumulative heat exposure on school dropout rates. While primary school enrollment is nearly universal, secondary school dropout rates remain high. We exploit both spatial and temporal variations in temperature over ten years to estimate the effect of heat on student dropout rates. Our identification strategy assumes that, conditional on a rich set of controls—including school-grade and year fixed effects—year-to-year weather variation is exogenous to dropout outcomes.

Our results provide strong evidence that heat negatively affects schooling. A one-standard-deviation increase in the share of days above 34°C raises dropout rates by 5.1% (0.36 percentage points). However, we cannot disentangle the mechanisms through which heat influences dropout. We perform placebo tests using off-school day temperatures, following-year temperatures, and data for grades K1-K9, where education is compulsory. None of these placebo tests show significant effects.

We find that the negative effects of heat are concentrated in public schools, particularly in urban areas. In contrast, private schools, mostly located in urban areas, show no significant effects, likely due to access to air conditioning or better infrastructure. Public schools, which

[1] Worldwide primary school enrollment and Latin American secondary education completion figures from UNICEF Global databases updated in December 2017 and available at http://data.unicef.org/topic/education/.

serve most of Brazil's students—especially those from lower-income backgrounds—struggle to cope with extreme temperatures, leading to worse educational outcomes.

While improving access to education is key for development (Duflo, 2001; Glewwe and Muralidharan, 2016; Muralidharan and Prakash, 2017), our findings suggest that factors like heat can undermine these efforts, particularly in urban areas of low- and middle-income countries. Adolescents who already face low perceived returns to education (Jensen, 2010) are more likely to drop out when small environmental factors like heat make school even more unpleasant. Given the long-term consequences of dropping out, understanding how these disruptions affect education is crucial.

2 Background and Data

We examine grade progression and dropouts in K10-12 schools across Brazil, using data from 80.7 million enrollments across 30,696 schools between 2007 and 2016. The education data come from Brazil's Annual School Census, which records student characteristics, school infrastructure, and grade outcomes. Our main focus is on dropouts, defined as students who fail to complete their grades and are not re-enrolled the following year. As shown in the summary statistics Table A1 in the Appendix, the average dropout rate in K10-12 is 7.1%.

We use ERA5 temperature data, which provides high-resolution daily maximum temperatures. Crucially, we focus only on temperatures during school days, as most schooling occurs during the hottest parts of the day. To identify school days, we exclude weekends and holidays based on the school calendar. By focusing on school-day temperatures, we isolate the effect of heat on educational outcomes, controlling for weather variability across Brazil.

To create our temperature exposure variable, we match each school year's temperature data to its county location. We then calculate the average maximum temperature on school days and categorize these into bins: below 22°C, 22-26°C, 26-30°C, 30-34°C, and above 34°C. This allows us to measure the cumulative heat exposure that students face during the academic year. Table A1 shows that the maximum temperature reaches 34°C about 5% of school days, with a standard deviation of 10%. Appendix Figure A1 shows an annual variation in the distribution of school days over 34°C.

3 Empirical Model

To estimate the effect of cumulative heat exposure on dropout rates, we exploit variations in temperature across counties and over time from 2007 to 2016. Our main identification assumption is that unobserved factors affecting student progression are uncorrelated with year-to-year variations in local weather. We implement this strategy using school-grade fixed effects regressions of the following form:

$$D_{sgy} = \sum_{j=1}^{4} \beta_j T_{j,c_s y} + \eta_{sg} + \gamma_{n_s gy} + \delta X_{sgy} + \epsilon_{sgy} \tag{1}$$

where D_{sgy} represents the dropout rate for students in school s, grade g, in year y. We include school-grade fixed effects η_{sg} to identify the impact of heat by comparing dropout rates within the same school and grade over multiple years. The grade-year by school-network[2] fixed effects $\gamma_{n_s gy}$ control for confounding factors such as evolving state policies and differences in promotion standards between public and private schools. We also add school-grade-level controls X_{sgy}, including student demographics (average class size and share of male students) and teacher demographics (average age, share of male teachers, and share of teachers with tertiary education). At the municipal level, we control for GDP per capita and local government spending on education. Standard errors are clustered at the municipality level, where the treatment variable varies (Abadie et al., 2023).

Our treatment variable $T_{j,c_s y}$ captures the share of school days in each temperature bin j experienced by the school's municipality in year y. The coefficient β_j represents the effect of 1% more days in each temperature bin, compared to 1% fewer days in the reference bin (26-30°C). In the absence of direct evidence on the mechanisms, we interpret β_j as the combined effect of cognition and income changes, which could influence both students and teachers.

To test the robustness of our findings, we perform three placebo exercises. First, we use non-school day temperatures to calculate heat exposure, which should have no effect on student outcomes. Second, we use future-year temperatures ($y + 1$) to verify whether weather conditions in the following year influence current dropout rates. Third, we examine dropout rates in K1-K9 grades, where education is compulsory, to see if heat affects students differently in this group.

4 Results

Our analysis shows clear effects of heat exposure on dropout rates, with notable differences across municipalities, school types, and urban and rural settings.

Main results. Table 1 presents the baseline results for the impact of cumulative heat exposure on dropout rates. The data show that school years with more days above 34°C

[2] School-network is defined as the pair state (27 states) and school type (public or private).

are linked to higher dropout rates. In our most rigorous specification (column 5), a one-standard-deviation (0.1) increase in the share of days above 34°C (and fewer days between 26-30°C) results in a 0.36 percentage point rise in dropout rates. With an average dropout rate of 7.1% in our sample, this translates to a 5.1% increase. These findings are consistent with existing research showing that high temperatures hinder cognitive performance.

Table 1: Results on School Dropout

	(1)	(2)	(3)	(4)	(5)
T<22C	-0.09	0.55	0.64	0.71	-0.57
	(0.67)	(0.94)	(0.94)	(0.96)	(1.09)
22≤T<26C	-0.13	0.20	0.14	0.36	-0.18
	(0.45)	(0.63)	(0.64)	(0.63)	(0.62)
30≤T<34C	0.98	2.01	1.92	1.90	2.45
	(0.48)**	(0.59)***	(0.59)***	(0.57)***	(0.69)***
T≥34C	2.10	2.56	2.53	2.39	3.64
	(0.91)**	(1.12)**	(1.11)**	(1.04)**	(1.27)***
Cohort controls	No	No	Yes	Yes	Yes
Munic Controls	No	No	No	Yes	Yes
Avg Max Temp	No	No	No	No	Yes
N	755,660	755,660	747,041	718,255	718,255
Clusters	5,563	5,563	5,563	5,551	5,551

The table shows the effects of temperature on dropout rates of students in K10-K12 based on the estimates of β_j from equation 1.

Placebo. To confirm the robustness of our findings, Table 2 presents three placebo tests. First, we calculate cumulative heat exposure using temperatures from off-school days, which should not impact student outcomes. Second, we use temperature data from the following year ($y + 1$) to check if future weather conditions affect current dropout rates and grade progression. Finally, we assess whether temperature influences dropout rates for younger students (K1-K9). In all placebo tests, the estimated coefficients for temperatures above 34°C are statistically insignificant and much smaller than in the main results. The absence of effects from off-school day and future year temperatures reinforces our confidence that the observed impacts are due to heat exposure during the school year, directly affecting students while they are in school.

Heterogeneity by school type. Table 3 columns 1 to 4 shows the results by school type. The impact of hot days on dropout rates is concentrated in public schools (columns 1-2), where the effects are both larger and more significant. In contrast, private schools display

Table 2: Placebo Results on School Dropout

	K10-K12			K1-K9
	Off-School Days Temperature	Temperature Year + 1		School Days Temperature
	(1)	(2)	(3)	
T<22C	0.61	-0.98		0.32
	(1.15)	(1.00)		(0.37)
22≤T<26C	0.45	0.11		0.37
	(0.75)	(0.65)		(0.30)
30≤T<34C	1.53	1.55		-0.14
	(0.60)**	(0.52)***		(0.26)
T≥34C	0.50	0.41		0.06
	(0.97)	(0.96)		(0.46)
Cohort controls	Yes	Yes		Yes
Munic Controls	Yes	Yes		Yes
N	718,255	718,255		7,217,764
Clusters	5,551	5,551		5,558

The table presents placebo estimates of the effects of temperature on dropout rates, using variations of equation 1. Columns 1 and 2 report dropout rates for students in K10-K12, while column 3 shows rates for K1-K9 students. Column 1 estimates the effects of temperatures on off-school days (i.e., weekends and holidays), and column 2 reports the effects of temperature in the following year ($y + 1$).

negative point estimates, which are statistically significant only at the 10% level. This pattern likely reflects private schools's superior resources for managing heat exposure, including air conditioning and improved infrastructure. For instance, 48% of private school classrooms and 24% of public school classrooms have climate control systems such as air conditioning or heating (2019 Education Census, which first documented classroom climatization). Resource disparities extend to basic amenities: while all private schools provide drinkable water, only 92% of public schools do so. Moreover, 13% of public schools lack connections to public water and sewage systems.

Heterogeneity by school location. While public schools are spread across the country, private schools are mostly located in urban areas. Heat may present different challenges in rural and urban public schools. In rural areas, heat could affect agricultural productivity and local income, while heat less directly impacts urban income.

Table 3 columns 5 to 8 presents the heterogeneity results for public schools in rural and urban areas. The negative effects of heat are concentrated in urban public schools. In rural areas, where schools face different challenges like access to basic resources such as water, the effects of heat are less pronounced. Despite having better infrastructure, urban schools appear more vulnerable to heat exposure.

Table 3: Results on Dropout by School Type and Location

	Public Schools		Private Schools		Public Rural		Public Urban	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T<22C	0.73	0.93	-0.63	-0.61	-7.10	-6.20	0.87	1.06
	(1.06)	(1.07)	(0.27)**	(0.28)**	(4.17)*	(4.40)	(1.08)	(1.09)
22≤T<26C	0.29	0.49	-0.59	-0.58	-5.90	-4.62	0.38	0.55
	(0.70)	(0.70)	(0.14)***	(0.14)***	(2.81)**	(2.76)*	(0.71)	(0.70)
30≤T<34C	2.25	2.10	-0.51	-0.49	-3.52	-5.01	2.48	2.37
	(0.65)***	(0.62)***	(0.16)***	(0.16)***	(2.01)*	(2.04)**	(0.65)***	(0.62)***
T≥34C	2.86	2.66	-0.51	-0.49	-0.95	-1.70	2.82	2.56
	(1.22)**	(1.13)**	(0.24)**	(0.25)*	(2.69)	(2.70)	(1.24)**	(1.14)**
Cohort controls	No	Yes	No	Yes	No	Yes	No	Yes
Munic. controls	No	Yes	No	Yes	No	Yes	No	Yes
N	548,092	520,813	207,568	197,442	62,170	56,643	485,922	464,170
Clusters	5,563	5,551	1,741	1,732	1,432	1,409	5,542	5,530

The table presents the heterogeneous effects of temperature on dropout rates for K10-K12 students, based on the estimates of β_j from equation 1. Columns 1 and 2 report results for public schools, while columns 3 and 4 focus on private schools. Columns 5 and 6 show results for public schools in rural areas, and columns 7 and 8 present findings for public schools in urban areas.

One possible explanation is that urban public schools, often overcrowded, may experience higher indoor temperatures, intensifying the physical discomfort caused by heat. In contrast, rural schools, though lacking some resources, may benefit from natural ventilation and lower student-to-teacher ratios, which lessen the impact of heat during school hours. Data confirm these disparities: urban schools average 31 students per classroom versus 22 in rural areas, and 14 students per teacher versus 9 in rural schools (2019 Education Census).

5 Conclusion

This study shows that cumulative heat exposure during the school year negatively impacts educational outcomes for K10-12 students in Brazil, increasing their likelihood of dropping out when temperatures rise. The effects are concentrated in public schools, particularly in urban areas, where poor infrastructure amplifies the impact of heat. Private schools, which likely have better resources, show no significant effects, suggesting that technology and improved learning environments can buffer against heat's impact.

Our results show that better learning environments could strengthen students' resilience to heat stress. Investment in public school infrastructure could help students manage environmental challenges, reduce dropouts, and narrow educational gaps – ultimately addressing economic inequality. Future research should identify the precise mechanisms driving these effects to inform targeted policies.

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Appendix (for online publication)

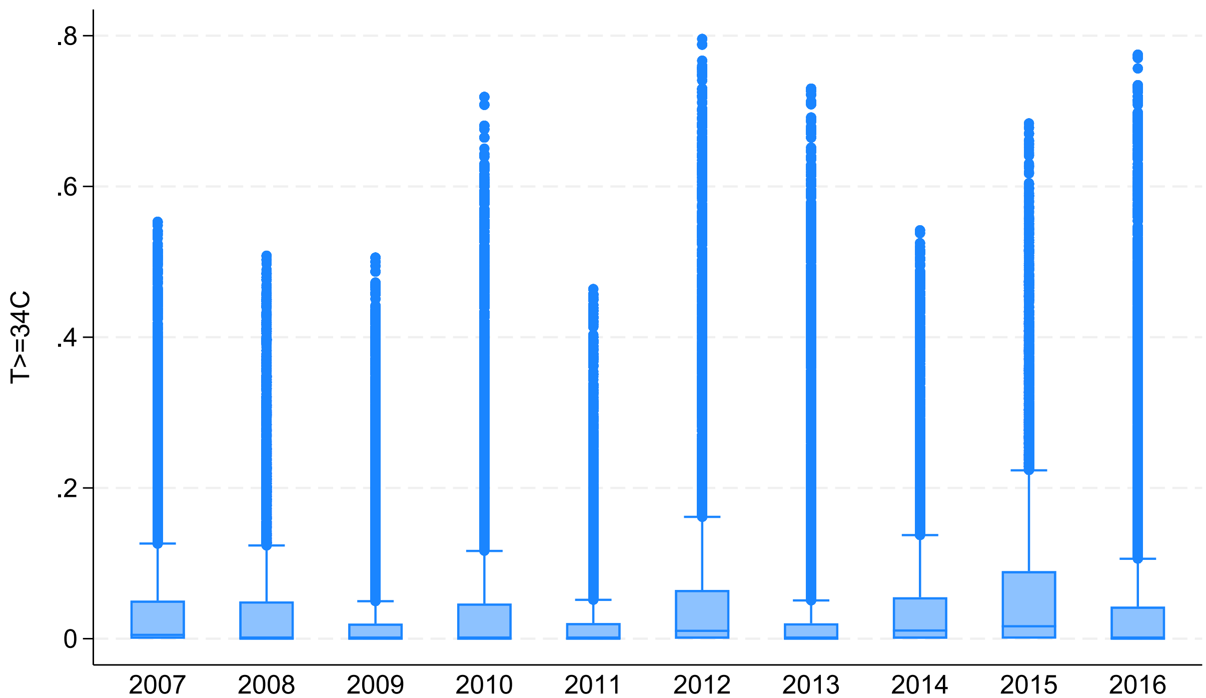
A Additional Figures and Tables

Table A1: Summary Statistics

	mean (1)	sd (2)	p1 (3)	p10 (4)	p50 (5)	p90 (6)	p99 (7)
Dropout Rate	7.10	9.78	0	0	3.20	20.20	41.50
T<22C	0.13	0.16	0	0	0.05	0.36	0.58
22≤T<26C	0.23	0.16	0	0.01	0.26	0.43	0.55
30≤T<34C	0.21	0.19	0	0.01	0.15	0.51	0.70
T≥34C	0.05	0.10	0	0	0.00	0.16	0.48
Students per class	29.50	10.42	6.00	16.00	30.06	40.83	53.00
Share of male students	0.47	0.11	0.19	0.35	0.46	0.58	0.78
Share male teachers	0.31	0.17	0	0.13	0.29	0.52	0.89
Avg teachers' age	39.14	4.56	28.12	33.21	39.32	44.62	49.50
Share teachers w/ college degree	0.88	0.17	0.17	0.67	0.94	1	1

This table presents the summary statistics of the variables used in our analysis.

Figure A1: Share of school days above 34°C by year



This graph presents the boxplot of the share of school days above 34°C by year.