The Impact of Water Scarcity on Educational Outcomes: Evidence from a Water Rationing in Brazil

Isabela Duarte *†
PUC- Rio and Harvard Kennedy School

This Version: October 22, 2020
Download Latest Version here

Abstract

We investigate whether water shortages caused by an extreme climate event impact educational performance. We answer this question exploring the consequences of a water rationing policy that affected some neighborhoods in Brazil's Distrito Federal. Comparing the academic performance of students enrolled in schools located in neighborhoods affected by the rationing against the performance of students enrolled in non-affected neighborhoods, we find that water rationing has a negative and significant impact on students' performance. In particular, we show that the impact is significantly stronger for students enrolled in schools with poor infrastructure.

*Isabela Duarte thanks Juliano Assunção for his continued guidance and support, and Claudio Ferraz, Michela Carlana, Cecília Machado, and Gustavo Gonzaga for helpful comments.

†Corresponding author: isabela_duarte@hks.harvard.edu

1 Introduction

As climate change unfolds, extreme climate events—and the direct and indirect losses caused by it—are likely to become more frequent. Understanding their consequences and how to mitigate their costs is crucial for effective policy making. In this paper, we investigate if water shortages caused by an extreme climate event have an impact on educational performance. We answer this question exploring the consequences of a water rationing policy in Brazil. In 2017, following a record-breaking drought, the regional government of Brazil's Federal District—the federal unit where the country's capital, Brasília, is located—implemented a water rationing schedule for neighborhoods served by two water reservoirs that were severely hit by the drought. We estimate the causal impact of the water rationing on academic outcomes evaluating its impact on students' performance in standardized evaluations. Through a difference-in-differences design, we compare the performance of students enrolled in schools located in areas subject to the rationing scheme against the performance of students enrolled in schools located in unaffected areas, controlling for differences in performance and other relevant factors that were present before the rationing. We find that the water rationing has a negative and significant impact on academic performance.

Similar shortages in water supply are likely to occur in Brazil's Federal District and other regions around the globe as climate change increases variability in precipitation (Pendergrass et al., 2017) and decreases the reliability of water supply systems in urban areas (O'Hara and Georgakakos, 2008). From a policy perspective, it is crucial to understand the consequences of such shortages and the mechanisms through which inadequate water supply can impact skill formation. Our results show that a predictable shortage in water supply caused by an extreme climate event has a significant negative impact on students' performance in standardized evaluations. This impact does not vary by students socioeconomic background, but it is significantly stronger for students enrolled in schools with poor infrastructure. There is a growing literature exploring what type of investments are needed to mitigate the consequences of climate change (Bento et al., 2020). We show that schools with good infrastructure can partially offset the negative impact of unreliable water supply systems on students' performance. Our results, thus, suggest the importance of investing in climate resilient infrastructure at the school level, as we adapt to the consequences of climate change.

Related Literature: We build upon three distinct strands of literature. First, our work contributes to a literature that evaluates the impact of extreme climate events on educational outcomes. According to this literature, climate shocks can impact educational performance through children's exposure to extreme temperatures or precipitation conditions. Many of the papers in this literature focus on the impact of being exposed to extreme climate during early childhood. Randell and Gray (2019) investigate the impact of climatic conditions experienced in utero and during early childhood on educational attainment using data from 30 countries. They find that children exposed to higher than average temperatures in Southeast Asia attain fewer years of education and that rainfall is positively correlated with attainment in Southeast Asia and West and Central Africa and negatively correlated with attainment in Central America and the Caribbean. Aguilar and Vicarelli (2018) explore exogenous extreme weather variations caused by the El Niño Southern Oscilation and find that children exposed to extreme climate events during early childhood present lower cognitive development between the ages of 2 and 6 years old. Shah and Steinberg (2017) show that positive rainfall shocks in India, if experienced during early childhood, improve educational outcomes. In this paper, we explore the impact of an extreme climate event that led to the implementation of a water rationing schedule on the academic performance of school-age children. We find a negative impact of rationing on academic performance, showing that older children in urban environments are also vulnerable to the consequences of extreme climate shocks.

Our work also contributes to a literature that explores the impact of school resources and investment in physical capital on educational attainment. The evidence on the relationship between infrastructure and educational attainment is mixed. In an extensive review of the early literature, Hanushek (1997) finds no systematic relationship between school resources and academic output. More recent studies also find mixed results. Neilson and Zimmerman (2014) evaluate the impact of a large infrastructure investment program in a poor, urban U.S. school district and find a positive impact on reading scores for elementary and middle school students. Martorell et al. (2016) explore discontinuities in the approval of school capital bonds at the school district level in Texas to estimate their impact on students' outcome. They find a significant impact of bond approval on capital investment, but no effect on achievement. Papers exploring the importance of infrastructure in regions with poor or non existent school facilities tend to find larger effects (Duflo (2001), Aaronson and Mazumder (2011), Jasper et al. (2012)).

Finally, our work contributes to a growing literature on climate adaptation and on the investments required to mitigate the impact of extreme climate events (Council (2010), Smith (2011), Deschênes and Greenstone (2011), Carleton et al. (2020) Bento et al. (2020)). We show that the negative impact of water rationing on students' performance is significantly stronger for students enrolled in schools with poor infrastructure. In this sense, our work is closely related to Goodman et al. (2018) and their evaluation of the impact of heat on educational attainment. Goodman et al. (2018) evaluate the relation between the performance of PSAT-retakers and their exposure to extreme heat in the years before the exam and concludes that cumulative heat exposure hinders cognitive development. Using data on air-conditioning at the school level, they conclude that infrastructure largely offsets the impact of heat. Both our work and Goodman et al. (2018) highlight how proper infrastructure at the school-level can serve an important role mitigating the impact of extreme climate events. As climate change increases the likelihood of such events, the relationship between investment in infrastructure and educational achievement is likely to become more pronounced.

2 Institutional Framework

To evaluate if shocks in water supply impact students' performance, we analyze the academic outcomes of students enrolled in schools subject to a water rationing scheme implemented by the regional government of Brazil's Federal District. The Federal District—or Distrito Federal (DF)—is one of Brazil's 27 federal units. It is the smallest federal unit in the country and it is where the capital of the country—Brasília—is located. The district is organized into 33 administrative regions (ARs) and all administrative regions are administered by a single elected official, the region's Governor.

Distrito Federal is located in an area of tropical savanna climate with two distinctive seasons: a rainy season from October to April and a dry season from May to September. The water supply in the region is organized at the Administrative Region level, i.e., all households within a given Administrative Region get their public water supply from the same system. Two large reservoirs—Descoberto and Santa Maria—serve 27 Administrative Regions. The other six Administrative Regions[1] get their water supply from independent systems.

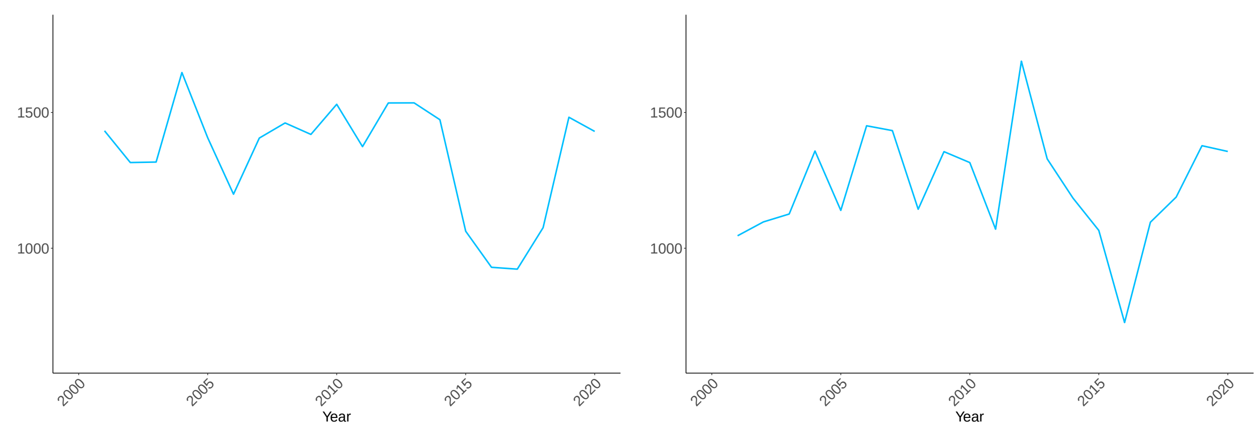
In the past decade, changes in regular rain schedules, a growing urban population, and insufficient investment in the systems for storage and distribution of water have seriously compromised the reliability of the region's water supply. In the years of 2016, 2017, and 2018 the water supply crisis reached its peak. Figure 1 illustrates the precipitation accumulated between rainy seasons on the reservoirs of Santa Maria and Descoberto through

[1] Brazlândia, Fercal, Planaltina, Sobradinho, Sobradinho II, and São Sebastião

the years between 2001 and 2019. Figure 1 shows that accumulated precipitation tends to average between 1000 and 1500 millimeters per year, with some variation between years. Lower than average rainfall years are usually followed by higher than average rainfall years. Figure 1 also shows that this was not the case for the years of 2015, 2016, and 2017. A lower than average rainfall year—2015—was followed by a record breaking drought in 2016 and by another lower than average rainfall year in 2017. Precipitation levels have a direct impact on the volume of the region's water reservoirs. Figure 2 shows the water volume of Descoberto—panel (a)—and Santa Maria—panel (b)—reservoirs as a percentage of total capacity in the years between 2010 and 2018. Between 2010 and 2015, water capacity in the two reservoirs followed a similar pattern reaching a peak of 100% during the rainy season and a minimum of approximately 50% at Descoberto and 75% at Santa Maria during the dry season. Starting in 2016, we see a clear change in this pattern. By the end of 2016, Descoberto reached 20% of capacity and Santa Maria 40%. With the rainy season, the water volume increased, but by less than what was needed to reach full capacity, with Descoberto and Santa Maria reaching only 50% of capacity by the end of the rainy season. By the end of 2017, Descoberto reached 6% of capacity and Santa Maria 20%.

Figure 1: Precipitation Accumulated Between Rainy Seasons (mm)

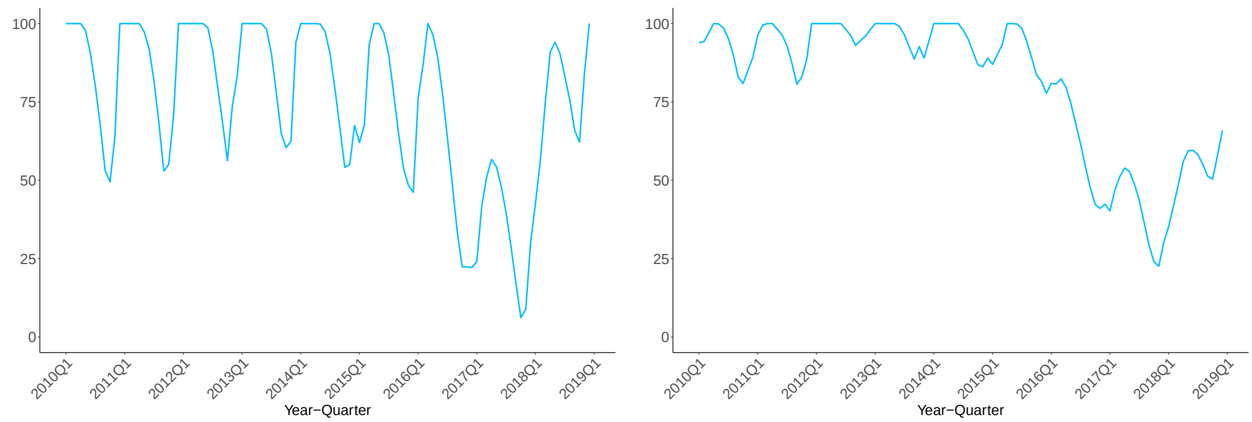
(a) Descoberto Reservoir (b) Santa Maria Reservoir



Notes: This figure illustrates the precipitation accumulated between rainy seasons on the reservoirs of Santa Maria and Descoberto through the years from 2001 to 2019. The data source is the Regulatory Agency of Water, Energy and Basic Sanitation of the Federal District (ADASA).

Figure 2: Water Volume at the End of the Month (% of Total Capacity)

(a) Descoberto Reservoir (b) Santa Maria Reservoir



Notes: This figure illustrates the water volume of Descoberto and Santa Maria reservoirs as a percentage of total capacity in the years between 2010 and 2018. The data source is the Regulatory Agency of Water, Energy and Basic Sanitation of the Federal District (ADASA).

As an initial response to the water crisis, the regional government established, in October of 2016, an emergency tariff, increasing the costs of water supply for consumers. The emergency tariff did not significantly decrease consumption and additional measures were needed to avoid a total collapse of the region's water supply system. In February of 2017, the regional government established a water rationing schedule for all Administrative Regions served by the Descoberto reservoir—16 ARs total. Three weeks later the water rationing schedule was extended to the regions served by the Santa Maria reservoir—11 ARs. The regions served by the independent systems were only included in the rationing schedule nine months later, by the end of the academic year. The water rationing lasted until June of 2018.

The rationing was established at the Administrative Region level. According to the rationing schedule, neighborhoods in the affected area would have their water supply shut down for a period of 24 hours every six days, possibly having to wait an additional 24 hours for normalized supply. Figure 3 presents a map of Distrito Federal that identifies the Administrative Regions impacted by the rationing—the Treatment Group. The rationing did impact water consumption. Detailed data on water consumption are not available, but according to a report from the local planning and development agency—CODEPLAN—the consumption of water in the region decreased by 9.5% between 2017 and 2016 (Codeplan, 2018). The report also shows that the Administrative Regions not initially included in the rationing—our Control Group—decreased their consumption of water at a significantly lower rate than affected ARs.

Figure 3: Distrito Federal Map - Treatment and Control Groups

3 Data

We evaluate the impact of water supply shortages on students' performance using data from Brazil's national evaluation of primary education schools, the *Sistema de Avaliação da Educação Básica* (SAEB). The SAEB evaluation is conducted every two years by INEP, an independent government agency linked to Brazil's Ministry of Education. All public schools that enroll at least ten students in fifth and ninth grade and a sample of private schools that meet these criteria are included in the evaluation. The SAEB data contains information on a set of surveys administered to students, teachers and principals. These surveys collect information on students' social economic background, schools' resources, safety and infrastructure and teachers perspective on learning environment and main challenges for education. SAEB data also provide information on student-level performance in a standardized test designed to evaluate students academic readiness in math and portuguese—the *Prova Brasil*. The data are publicly available.[2].

We use data from *Prova Brasil* to evaluate how shocks in water supply at the school level impact students' academic performance. We restrict our sample to students taking the *Prova Brasil* exam between 2007 and 2017 while enrolled in a school located at Distrito Federal.[3] SAEB data does not contain neighborhood or location information. From

[2]SAEB data is available through http://inep.gov.br/microdados

[3]According to SAEB rules[4], *Prova Brasil* results from schools in which less than ten students or less than

SAEB's school code, we are able to identify the neighborhood in which the school is located using data provided by INEP.[5] We present descriptive statistics on table A.1 of section A.1. We have information on 317,734 students. Students in our sample are mostly from public schools and from underprivileged backgrounds. 50% of the students are female, and 60% are black or brown. 30% of the students do not have access to a computer at home and 40% do not own a car. Only 13% (or 12%) of the students in our sample have a mother (or father) that completed higher education. 30% of the students in our sample have failed a grade in the past.

To explore mechanisms, we use information at the school level. Specifically, we collect information on school's physical infrastructure, safety measures, and available resources through SAEB's school survey. This survey is based on the evaluation of an external reviewer. We use this information to explore how different school-level factors impact students' performance. We present descriptive information on table A.2 of section A.1. 94% of the schools in our sample are public and 91% are located on urban areas. The quality of school infrastructure and available resources is measured in a scale from one—nonexistent—to four–good. Safety measures are evaluated as existent or nonexistent.

4 Empirical Strategy

The Administrative Regions originally included in the rationing schedule are different from the ones not included in several aspects. As table 1 details, students from the control region are on average poorer and from less educated households. They also have lower grades in both the portuguese and math exams from *Prova Brasil* and are more likely to have failed a grade in the past. To estimate the causal impact of the water rationing, we must control for observable and unobservable characteristics unrelated to treatment. We identify the causal impact of the water rationing on students' academic performance using a Difference-in-Differences (DD) framework.

80% of enrolled students took the exam are not made publicly available. We do not include these schools in our sample.

[5] http://idebescola.inep.gov.br/ideb/consulta-publica.

Table 1: Descriptive Statistics - Treatment vs. Control Groups

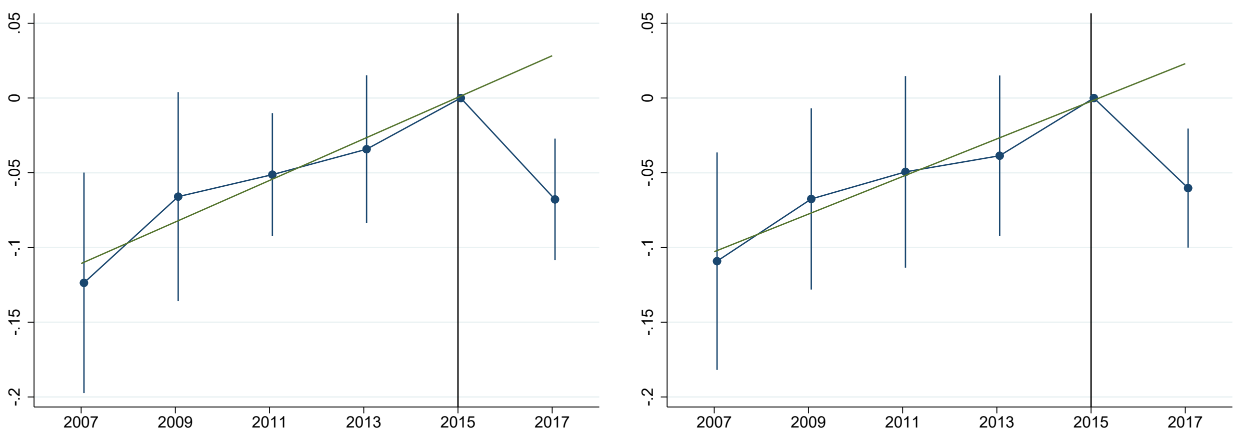
	Treatment Group		Control Group	
Variable	Mean	S.D.	Mean	S.D
Grade Mean - Portuguese (0,1)	-0.46	(0.92)	-0.56	(0.88)
Grade Mean - Math (0,1)	-0.24	(0.86)	-0.33	(0.81)
Female Student	0.50	(0.50)	0.50	(0.50)
Black Student	0.10	(0.31)	0.11	(0.31)
Brown Student	0.49	(0.50)	0.50	(0.50)
Does your family own a car? (Y/N)	0.62	(0.49)	0.57	(0.49)
Do you have a computer at home? (Y/N)	0.71	(0.46)	0.64	(0.48)
Mother Education - Never Studied or Less than elementary	0.05	(0.22)	0.07	(0.26)
Mother Education - Elementary School	0.13	(0.34)	0.16	(0.37)
Mother Education - College	0.14	(0.34)	0.10	(0.30)
Father Education - Less than elementary	0.07	(0.25)	0.09	(0.29)
Father Education - Elementary School	0.10	(0.30)	0.12	(0.33)
Father Education - College	0.13	(0.33)	0.09	(0.29)
Parents Incentive Score	4.39	(1.07)	4.38	(1.07)
Do you work? (Y/N)	0.09	(0.29)	0.10	(0.30)
Have you ever failed a grade (Y/N)	0.29	(0.45)	0.33	(0.47)
Have you ever dropout of school? (Y/N)	0.05	(0.21)	0.05	(0.22)
Observations	242382		70352	

Notes: This table presents descriptive statistics for the final students' sample. This sample includes students who took the math and portuguese *Prova Brasil* exam between 2007 and 2017 while enrolled at a school located at Distrito Federal. We do not include in our sample schools that are not identifiable in the date. We divide the sample by treatment status. In the treatment groups we include all students enrolled in schools located on a neighborhood subject to Distrito Federal's water rationing. In the control group we include students enrolled in non-affected schools.

Identification on a Difference-in-Differences framework relies on the assumption that the variable of interest—in our case, academic performance—was following a parallel trend for treatment and control units before the policy implementation—before the rationing schedule was implemented—and would have continued following a parallel trend if there had not been an intervention, i.e., in a counterfactual scenario. We cannot test how reasonable the counterfactual parallel trend hypothesis is. However, we can test the differential pre-trend hypothesis. In figure 4 we present the result of a event study analysis performed using our data. In this analysis, we compare students' performance in the *Prova Brasil* exam for students enrolled in schools that are part of the treatment group against students enrolled in schools part of the control group for every year with information available between 2007 and 2017. According to the results of this analysis, the difference in academic performance between units in the treatment and control group followed an increasing trend before the 2017 rationing, i.e., the difference between treatment and control units was decreasing through time at a constant rate. In 2017, we see a clear break from the previous trend, with a significant negative shock on the academic performance of students enrolled in schools located on neighborhoods affected by the rationing.

Figure 4: Impact of Water Rationing on Academic Performance

(a) Portuguese (b) Math



Notes: This figure shows the result of a event study analysis that represents the difference in academic performance on *Prova Brasil* of students enrolled in schools located in neighborhoods impacted by the water rationing (treatment group) against academic performance of students enrolled in non-affected schools (control group). The dots in the graph represent the point estimates of the treatment effect for each year. The vertical lines represent a 95% confidence interval. We also include in this figure a line representing the increasing trend that existed before treatment. The specification in this figure includes school and school-grade fixed effects. It also includes student level covariates, including information on gender, race, family income, parents' education, parents' support, and information on grade retention and school abandonment. Standard errors were computed with observations clustered at neighborhood level.

To obtain an estimate of the causal impact of being enrolled in a school located in a region subject to water rationing on students' academic performance, we run the following regression:

$$Grade_{ijt} = \alpha_1 + \alpha_2 D_t * Treatment_j + \alpha_3 D_t + \alpha_4 Treatment_j + \alpha_5 X_{ijt} + \alpha_6 t_{it} + \varepsilon_{ijt} \quad (1)$$

Here $Grade_{ijt}$ represents the outcome of interest, the performance of student i, enrolled at school j on year t in the *Prova Brasil* exam. $Treatment_j$ is a binary variable that takes the value of one if school j is located on a neighborhood impacted by the water rationing. The binary variable D_t takes the value of zero for the pre treatment period—the years of 2007, 2009, 2011, 2013, and 2015—and the value of one for the post treatment period, i.e., for observations in the year of 2017. We include student-level covariates (X_{ijt}) and time, school and school-grade fixed effects (ε_{ijt}). To control for the fact that the difference in academic performance of students in the treatment and control groups was following an increasing constant trend through time before treatment, we include the variable t_{it} representing years since the treatment for units in the treatment group (Gross et al., 2020). We present the results from this estimation on table 2. For all specifications considered, the treatment effect—the impact of being enrolled at a school located on a neighborhood affected by the water rationing—is negative and significant. Specifically, we find that students enrolled in affected schools get a grade 0.076 points smaller in the language exam and 0.08 smaller in the math exam, even after controlling for year, school, school-grade fixed effects and a set of covariates at the student level. In the next section, we explore some possible mechanisms for this result.

Table 2: Treatment Effect: Water Rationing on Academic Performance

	(1)	(2)	(3)	(4)	(5)	(6)
		Language			Math	
Treatment Effect	-0.0924***	-0.0962***	-0.0847***	-0.0761**	-0.0814***	-0.0738***
	(0.0303)	(0.0283)	(0.0277)	(0.0290)	(0.0269)	(0.0230)
Constant	-0.420***	-0.414***	-0.260***	-0.206***	-0.200***	0.108***
	(0.0166)	(0.0168)	(0.0377)	(0.0165)	(0.0168)	(0.0311)
Observations	312,734	312,734	312,734	312,734	312,734	312,734
R-squared	0.265	0.267	0.328	0.230	0.233	0.287
School FE	y	y	y	y	y	y
School-Grade FE	n	y	y	n	y	y
Student-level controls	n	n	y	n	n	y

Notes: This table presents the results of a difference-in-differences (DD) analysis that compares the academic performance on *Prova Brasil* of students enrolled in schools located in neighborhoods impacted by the water rationing against academic performance of students enrolled in non-affected schools (equation 1). In this DD, the pre-treatment period consists of the years that precede water rationing (2007, 2009, 2011, 2013, and 2015). The post-treatment period consists of the year the water rationing was implemented (2017) the expansion (2011 through 2014). The estimated coefficients associated with the "Treatment Effect" variable represent the impact of being enrolled in a school subject to rationing on academic performance. In columns (1), (2), and (3) we use students' grade on the *Prova Brasil* Language evaluation as a measure of academic performance. In columns (4), (5), and (6) we use students grade on the Math evaluation as a measure of academic performance. We include year fixed effects in all specifications. Student level controls include information on gender, race, family income, parents' education, parents' support, and information on grade retention and school abandonment. Standard errors were computed with observations clustered at neighborhood level. *** represents p-value<0.01, ** p-value<0.05, and* p-value<0.1.

5 Mechanisms

In section 4, we conclude that being enrolled at a school located on a neighborhood subject to the water rationing schedule cause students to get lower grades in *Prova Brasil*'s math and language evaluations. There are a few mechanisms through which water scarcity could affect students performance. In this section, we explore which factors are related to the negative impact of rationing on performance and discuss possible mechanisms. We start by collecting information on teachers' beliefs regarding the factors that affect students' academic performance and evaluating if these factors change for schools affected by the rationing. The *Prova Brasil* teachers' survey asks teachers to identify the factors they believe are relevant in explaining the poor performance of some of their students. According to the *Prova Brasil* survey, teachers believe that students' performance depend on students' individual characteristics, family and socioeconomic background, attendance, school-level resources, and teachers' work conditions and motivation. Table A.3 of section A.1 presents descriptive information on these data. To evaluate if there is a differential impact for any of these factors between treatment and control units after the treatment—i.e. after the beginning of the water rationing—we perform a difference-in-differences analysis for each factor mentioned in the teachers' survey. Table 3 presents the results of this analysis. Results show a significant impact for only one factor, school infrastructure. We find that teachers from schools in the treatment group significantly increased their likelihood of indicating schools' infrastructure as one of the culprits for the poor performance of their students.

Table 3: Treatment Effect : Reasons for Students' Poor Performance

Reason for Students' Poor Performance	Treatment Effect	N
School Infrastructure	0.062*	12125
	(0.034)	
Pedagical Supervision	0.050	7609
	(0.034)	
Inadequate Curriculum	0.042	12103
	(0.031)	
Past Learning	-0.035	12127
	(0.048)	
Excess Work for Teachers	0.008	12083
	(0.021)	
Teachers' Lack of Motivation	0.003	12019
	(0.029)	
Students' Social Environment	-0.002	12093
	(0.009)	
Parents' Cultural Level	0.026	12100
	(0.019)	
Parents' Lack of Assistance	-0.013	12107
	(0.012)	
Students' Low Self Esteem	-0.043	12128
	(0.030)	
Students' Poor Motivation/Effort	-0.015	12116
	(0.013)	
Students' Indiscipline	0.018	12113
	(0.037)	
Students' Poor Attendance	0.010	7611
	(0.050)	

Notes: Each line of this table present the results of a difference-in-differences (DD) analysis comparing how teachers' perception on different culprits for students' poor performance changed for teachers in the treatment group against teachers in the control group. We include in the treatment group teachers in schools located in neighborhoods impacted by the water rationing a and in the control group teachers in non-affected schools. In this DD, the pre-treatment period consists of the years that precede the water rationing (2007, 2009, 2011, 2013, and 2015). The post-treatment period consists of the year the water rationing was implemented (2017). The first column lists the different independent variables included in this analysis. The second column presents the estimated coefficients associated with "Treatment Effect" and standard errors (in parenthesis). The third column presents sample size. We include school and year fixed effects. Standard errors were computed with observations clustered at neighborhood level. *** represents p-value<0.01, ** p-value<0.05, and* p-value<0.1.

To evaluate if teachers' impression on the growing importance of infrastructure for the performance of students enrolled in schools affected by the rationing is consistent with the available information on the quality of infrastructure at the school level, we perform a heterogeneous treatment analysis. From the *Prova Brasil* data, we collect information on school-level characteristics.[6] From these characteristics, we build three different school-level factors that measure, first, the quality of infrastructure, second, school-level measures to guarantee safety and, finally, a factor that measures the quality of school resources. We then perform a heterogeneous treatment analysis to evaluate if the impact of the water rationing was distinct for schools with different characteristics. Specifically, for each factor, we run the specification of equation 1 including the possibility that treatment varies by school level factors. Table 4 presents the results of this analysis. Including the possibility that treatment effect varies with school characteristics does not significantly alter our previous conclusions. The treatment effect is negative for all specifications. When we include infrastructure and safety factors, results remain statistically significant for all specifications. When we consider the factor that measure schools' resources we loose a considerable number of observations and are no longer able to precisely estimate the treatment effect. Table 4 shows that the only characteristic that consistently impacts the effect of water rationing on students' performance is school infrastructure. Specifically, our results show that the water rationing has a significantly stronger negative impact on the academic performance of students enrolled in schools with poor infrastructure. In appendix A.2, we replicate this analysis for each individual school-level characteristics (tables A.4, A.5, and A.6). The results from this analysis largely corroborate our conclusions from the factor analysis.

[6] We detail these data on table A.2.

Table 4: Heterogeneous Treatment Effect by School Characteristics

Covariate	Language: Treatment Effect	Language: HTE.	Math: Treatment Effect	Math: HTE	Student Level Covariates	N
Infrastructure - PCA	-0.103**	0.029***	-0.091**	0.030***	n	276716
	(0.034)	(0.005)	(0.031)	(0.005)		
Safety - PCA	-0.152**	0.022	-0.136*	0.018	n	204696
	(0.066)	(0.018)	(0.066)	(0.019)		
Resources - PCA	-0.076*	0.016*	-0.086	0.006	n	132797
	(0.042)	(0.008)	(0.057)	(0.011)		
Infrastructure - PCA	-0.090**	0.031***	-0.080**	0.030***	y	276716
	(0.033)	(0.004)	(0.027)	(0.005)		
Safety - PCA	-0.146**	0.027	-0.123*	0.019	y	204696
	(0.067)	(0.016)	(0.061)	(0.018)		
Resources - PCA	-0.057	0.014	-0.079	0.003	y	132797
	(0.049)	(0.011)	(0.064)	(0.013)		

Notes: This table presents the results of a difference-in-differences (DD) analysis that: (i) estimates the difference in performance for students enrolled in schools located in neighborhoods impacted by the water rationing against academic performance of students enrolled in non-affected schools, i.e. the "Treatment Effect" and, (ii) estimates how the treatment effect varies with school level characteristics—the heterogeneous treatment effect or HTE. In this DD, the pre-treatment period consists of the years that precede water rationing (2007, 2009, 2011, 2013, and 2015). The post-treatment period consists of the year the water rationing was implemented (2017). From the *Prova Brasil* data we build three different school-level factors that measure the quality of infrastructure, school-level measures to guarantee safety and the quality of school resources. The first two columns consider performance in the Language evaluation as independent variable. The following two columns consider performance in the math evaluation. We include school, year and school-grade fixed effects in all specifications. Student level controls includes information on gender, race, family income, parents' education, parents' support, and information on grade retention and school abandonment. Standard errors were computed with observations clustered at neighborhood level. *** represents p-value<0.01, ** p-value<0.05, and* p-value<0.1.

Our results highlight the importance of school-level resources on mitigating the impact of negative shocks on students' performance and contributes to a growing literature on how school-level characteristics can have a significant impact on students learning function (Duflo (2001), Aaronson and Mazumder (2011), Neilson and Zimmerman (2014)). There are a few mechanisms through which water scarcity could impact the performance of students enrolled in schools ill prepared to deal with the challenges brought by a water rationing schedule. Schools with poor infrastructure might not be able to store water properly and, thus, be unable to serve students and teachers with a clean, hygienic environment on water rationing days. This could affect teachers' attendance rates. There is a literature exploring the impact of teachers' absenteeism on students' performance both at developed and developing countries. Suryadarma et al. (2006) collect data on teachers' absenteeism in Indonesia and find a strong negative correlation between teachers' absenteeism and students' performance. Duflo and Hanna (2005) evaluates the impact of a policy designed to reduce absenteeism among teachers in India and finds a positive strong impact of increased attendance on performance. Miller et al. (2008) find a strong impact of teachers' attendance on the performance in math of children enrolled in schools in the northern United States.

Water shortage can also impact schools' ability to prepare and serve lunch to students. All children enrolled in public schools in Brazil's Federal District are part of the country's national school meal program. Meals are usually prepared at the school kitchen and water scarcity can impact schools' ability to serve these meals or their quality. If students rely on school meals to obtain their daily nutritional needs, skipping meals or replacing high nutritional value meal for lower quality meals could impact their cognitive performance (Gómez-Pinilla (2008), Imberman and Kugler (2014) Frisvold (2015), Anderson et al. (2017)).

Finally, it is possible that water scarcity affects students through its impact on children's exposure to heat and dehydration. During the dry season, temperatures in the Federal District can reach 30 degrees Celsius with humidity levels as low as 10%. If drinking water is not available on rationing days, students can be more vulnerable to heat exposure which, in turn, can have an impact on cognitive functions and academic performance (Goodman et al. (2018) Isen et al. (2017)).

School-level characteristics are just one determinant of students' performance. Students background and socioeconomic status can influence how students cope with challenging scenarios. Student-level characteristics can also matter because the water rationing did not only affect schools, but also households. It is probably the case that students enrolled in schools located in neighborhoods affected by the water rationing reside themselves in those neighborhoods and, as such, also suffered the consequences of the water rationing in their homes. Living in a household with inconsistent access to running water could impact students performance if the water rationing impacts the general health, income or well-being of their families. It could also be the case that students reduce their school attendance on rationing days. If household level characteristics are to blame, we would expect to see a stronger effect for poorer students, whose family is unable to invest in a water storage system. To evaluate if treatment effect varies by students' characteristics, we replicate the previous heterogeneity analysis considering student-level factors. Table 5 presents the results from this analysis.[7] We do not find evidence that student-level characteristics have a differential impact on treatment effect. This result indicates that students from different backgrounds were equally affected by the rationing and suggests that factors equally affecting students from all backgrounds—for instance, school level factors—are the likely cause for our results.

[7] In appendix A.2, tables A.7 and A.8 we present a more detailed analysis. The results of this detailed analysis are consistent with the results from table 5.

Table 5: Heterogeneous Treatment Effect by Student Characteristics

	Language		Math		
Covariate	Treatment Effect	HTE.	Treatment Effect	HTE	N
Female Student	-0.097**	0.005	-0.089**	0.014	312734
	(0.029)	(0.018)	(0.024)	(0.023)	
Black Student	-0.098**	0.014	-0.077**	-0.042	312734
	(0.028)	(0.021)	(0.025)	(0.027)	
Brown Student	-0.104**	0.016	-0.097**	0.032	312734
	(0.032)	(0.034)	(0.031)	(0.020)	
Parents Incentive - PCA	-0.087**	0.002	-0.072**	0.012	271097
	(0.025)	(0.016)	(0.024)	(0.013)	
Income - PCA	-0.089**	-0.007	-0.077**	-0.006	276711
	(0.026)	(0.006)	(0.022)	(0.008)	
Mother Education	-0.113***	0.007*	-0.096***	0.007	312734
	(0.027)	(0.004)	(0.023)	(0.004)	
Father Education	-0.087**	-0.007	-0.081**	-0.002	312734
	(0.026)	(0.005)	(0.023)	(0.006)	

Notes: This table presents the results of a difference-in-differences (DD) analysis that: (i) estimates the difference in performance for students enrolled in schools located in neighborhoods impacted by the water rationing against academic performance of students enrolled in non-affected schools,i.e. the "Treatment Effect" and, (ii) estimates how the treatment effect varies with student level characteristics—the heterogeneous treatment effect or HTE. In this DD, the pre-treatment period consists of the years that precede water rationing (2007, 2009, 2011, 2013, and 2015). The post-treatment period consists of the year the water rationing was implemented (2017). We obtain student-level information from the *Prova Brasil* data. The first two columns consider performance in the Language evaluation as independent variable. The following two columns consider performance in the math evaluation. We include school, year and school-grade fixed effects in all specifications. Student level controls includes information on gender, race, family income, parents' education, parents' support, and information on grade retention and school abandonment. Standard errors were computed with observations clustered at neighborhood level. *** represents p-value<0.01, ** p-value<0.05, and* p-value<0.1.

6 Conclusion

In this paper, we explore the consequences of an extreme climate event that affected the supply of water in Brazil's Federal District to evaluate the impact of water scarcity on educational outcomes. After a record-breaking drought in 2017, Federal District's government imposed a water rationing schedule for neighborhoods served by the region's two main water reservoirs. According to the schedule, affected neighborhoods would have their water supply shut down for a period of 24 hours every six days, possibly having to wait an additional 24 hours for usual supply. We estimate the causal impact of water scarcity on academic performance comparing the educational outcomes of students enrolled in schools located in neighborhoods affected by the rationing against the outcomes of students enrolled in non-affected schools through a difference-in-differences design.

We find that water scarcity at the school level has a negative and significant impact on the performance of enrolled students in standardized language and math evaluations. Using information on a teacher-level survey, we find that teachers from affected schools increased their likelihood of blaming school infrastructure for students' poor performance. This results is consistent with the results we obtain exploring heterogeneities in treatment effect by school-level characteristics. Using data on school characteristics, we find that students enrolled in schools with poor infrastructure are more negatively affected by the water rationing. These results suggest that schools' inability to mitigate the impacts of the water rationing is the main mechanism through which water scarcity impacts academic outcomes. Our results highlight the importance of investing in school-level infrastructure for coping with the consequences of water scarcity caused by extreme climate events.

References

Aaronson, D. and Mazumder, B. (2011). The impact of rosenwald schools on black achievement. *Journal of Political Economy*, 119(5):821–888.

Aguilar, A. and Vicarelli, M. (2018). El niño and mexican children: Medium term effects ofearly-life weather shocks on cognitive and health outcomes. *Working Paper*.

Anderson, M. L., Gallagher, J., and Ritchie, E. R. (2017). School lunch quality and academic performance. Working Paper 23218, National Bureau of Economic Research.

Bento, A., Miller, N. S., Mookerjee, M., and Severnini, E. R. (2020). A unifying approach to measuring climate change impacts and adaptation. Working Paper 27247, National Bureau of Economic Research.

Carleton, T. A., Jina, A., Delgado, M. T., Greenstone, M., Houser, T., Hsiang, S. M., Hultgren, A., Kopp, R. E., McCusker, K. E., Nath, I. B., Rising, J., Rode, A., Seo, H. K., Viaene, A., Yuan, J., and Zhang, A. T. (2020). Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits. Working Paper 27599, National Bureau of Economic Research.

Codeplan (2018). Análise do consumo de Água tratada no período de racionamento no distrito federal. Technical report.

Council, N. R. (2010). *Adapting to the Impacts of Climate Change*. The National Academies Press, Washington, DC.

Deschênes, O. and Greenstone, M. (2011). Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the us. *American Economic Journal: Applied Economics*, 3(4):152–85.

Duflo, E. (2001). Schooling and labor market consequences of school construction in indonesia: Evidence from an unusual policy experiment. *American Economic Review*, 91(4):795–813.

Duflo, E. and Hanna, R. (2005). Monitoring works: Getting teachers to come to school. Working Paper 11880, National Bureau of Economic Research.

Frisvold, D. E. (2015). Nutrition and cognitive achievement: An evaluation of the school breakfast program. *Journal of public economics*, 124:91–104.

Gómez-Pinilla, F. (2008). Brain foods: the effects of nutrients on brain function. *Nature reviews neuroscience*, 9(7):568–578.

Goodman, J., Hurwitz, M., Park, J., and Smith, J. (2018). Heat and learning. Working Paper 24639, National Bureau of Economic Research.

Gross, T., Notowidigdo, M. J., and Wang, J. (2020). The marginal propensity to consume over the business cycle. *American Economic Journal: Macroeconomics*, 12(2):351–84.

Hanushek, E. A. (1997). Assessing the effects of school resources on student performance: An update. *Educational Evaluation and Policy Analysis*, 19(2):141–164.

Imberman, S. A. and Kugler, A. D. (2014). The effect of providing breakfast in class on student performance. *Journal of Policy Analysis and Management*, 33(3):669–699.

Isen, A., Rossin-Slater, M., and Walker, R. (2017). Relationship between season of birth, temperature exposure, and later life wellbeing. *Proceedings of the National Academy of Sciences*, 114(51):13447–13452.

Jasper, C., Le, T.-T., and Bartram, J. (2012). Water and Sanitation in Schools: A Systematic Review of the Health and Educational Outcomes. *International Journal of Environmental Research and Public Health*, 9(8):2772–2787.

Martorell, P., Stange, K., and McFarlin, I. (2016). Investing in schools: capital spending, facility conditions, and student achievement. *Journal of Public Economics*, 140:13 – 29.

Miller, R. T., Murnane, R. J., and Willett, J. B. (2008). Do teacher absences impact student achievement? longitudinal evidence from one urban school district. *Educational Evaluation and Policy Analysis*, 30(2):181–200.

Neilson, C. A. and Zimmerman, S. D. (2014). The effect of school construction on test scores, school enrollment, and home prices. *Journal of Public Economics*, 120:18 – 31.

O'Hara, J. K. and Georgakakos, K. P. (2008). Quantifying the Urban Water Supply Impacts of Climate Change. *Water Resources Management*, 22(10):1477–1497.

Pendergrass, A. G., Knutti, R., Lehner, F., Deser, C., and Sanderson, B. M. (2017). Precipitation variability increases in a warmer climate. *Scientific Reports*, 7(1):17966.

Randell, H. and Gray, C. (2019). Climate change and educational attainment in the global tropics. *Proceedings of the National Academy of Sciences*, 116(18):8840–8845.

Shah, M. and Steinberg, B. M. (2017). Drought of opportunities: Contemporaneous and long-term impacts of rainfall shocks on human capital. *Journal of Political Economy*, 125(2):527–561.

Smith, V. K. (2011). *How Can Policy Encourage Economically Sensible Climate Adaptation?*, pages 229–242. University of Chicago Press.

Suryadarma, D., Suryahadi, A., Sumarto, S., and Rogers, F. H. (2006). Improving student performance in public primary schools in developing countries: Evidence from indonesia. *Education Economics*, 14(4):401–429.

Appendix

A Appendix: The Impact of Water Scarcity on Educational Outcomes: Evidence from a Water Rationing Policy in Brazil

A.1 Descriptive Statistics

Table A.1: Descriptive Statistics - Students' Sample

Variable	Mean	S.D.	Min.	Max.	N
Grade Mean - Portuguese (0,1)	-0.48	0.91	-9.90	4.70	312734
Grade Mean - Math (0,1)	-0.26	0.85	-8.00	9.90	312734
Treatment Status	0.78	0.42	0.00	1.00	312734
Post-Treatment	0.14	0.35	0.00	1.00	312734
5th graders	0.58	0.49	0.00	1.00	312734
9th graders	0.40	0.49	0.00	1.00	312734
High school seniors	0.02	0.14	0.00	1.00	312734
Female Student	0.50	0.50	0.00	1.00	312734
White Student	0.22	0.42	0.00	1.00	312734
Black Student	0.11	0.31	0.00	1.00	312734
Brown Student	0.49	0.50	0.00	1.00	312734
Asian Student	0.04	0.19	0.00	1.00	312734
Indigenous Student	0.02	0.14	0.00	1.00	312734
Race - Unknown	0.12	0.32	0.00	1.00	312734
Does your family owe a car? (Y/N)	0.61	0.49	0.00	1.00	312734
Do you have a computer at home? (Y/N)	0.69	0.46	0.00	1.00	312734
Bathrooms at home (per capita)	0.33	0.23	0.00	4.00	312734
Number of people living at home	4.51	1.63	0.00	8.00	312734
Do you live with your mother/ female guardian? (Y/N)	0.91	0.29	0.00	1.00	312734
Mother Education - Never Studied or Less than elementary	0.06	0.23	0.00	1.00	312734
Mother Education - Elementary School	0.14	0.35	0.00	1.00	312734
Mother Education - Middle School	0.13	0.33	0.00	1.00	312734
Mother Education - High School	0.22	0.42	0.00	1.00	312734
Mother Education - College	0.13	0.33	0.00	1.00	312734
Mother Education - Don't Know	0.31	0.46	0.00	1.00	312734
Do you live with your father/ male guardian? (Y/N)	0.66	0.48	0.00	1.00	312734
Father Education - Never Studied or Less than elementary	0.07	0.26	0.00	1.00	312734
Father Education - Elementary School	0.11	0.31	0.00	1.00	312734
Father Education - Middle School	0.10	0.31	0.00	1.00	312734
Father Education - High School	0.16	0.37	0.00	1.00	312734
Father Education - College	0.12	0.32	0.00	1.00	312734
Father Education - Don't Know	0.44	0.50	0.00	1.00	312734
With what frequency do your parents attend PTA meetings	2.52	0.81	0.00	3.00	312734
Parents Incentive Score	4.39	1.07	0.00	5.00	312734
Do you work? (Y/N)	0.09	0.29	0.00	1.00	312734
Have you ever failed a grade	1.35	0.72	0.00	3.00	312734
Have you ever failed a grade (Y/N)	0.30	0.45	0.00	1.00	312734
Have you ever dropout of school?	1.02	0.35	0.00	3.00	312734
Have you ever dropout of school? (Y/N)	0.05	0.21	0.00	1.00	312734

Notes: This table presents descriptive statistics for the final students' sample. This sample includes

Table A.2: Descriptive Statistics - School Sample

Variable	Mean	S.D.	Min.	Max.	N
Public School	0.94	0.24	0.00	1.00	3008
School Located in Urban Area	0.91	0.29	0.00	1.00	3008
School Infrastructure - Roof	3.44	0.72	1.00	4.00	2925
School Infrastructure - Walls	3.61	0.60	2.00	4.00	2943
School Infrastructure - Floor	3.43	0.74	1.00	4.00	2923
School Infrastructure - Entrance	3.51	0.68	1.00	4.00	2928
School Infrastructure - Patio	3.46	0.76	1.00	4.00	2922
School Infrastructure - Corridors	3.49	0.78	1.00	4.00	2919
School Infrastructure - Classrooms	3.46	0.66	2.00	4.00	2924
School Infrastructure - Doors	3.39	0.71	1.00	4.00	2909
School Infrastructure - Windows	3.36	0.76	1.00	4.00	2907
School Infrastructure - Bathrooms	3.22	0.77	1.00	4.00	2886
School Infrastructure - Kitchen	3.43	0.75	1.00	4.00	2869
School Infrastructure - Plumbing	3.19	0.79	1.00	4.00	2895
School Infrastructure - Electric	3.16	0.80	1.00	4.00	2894
School Safety - Control Access - Students	0.44	0.50	0.00	1.00	2940
School Safety - Control Access	0.42	0.49	0.00	1.00	2938
School Safety - Security Presence- Day	0.36	0.48	0.00	1.00	2915
School Safety - Security Presence- Night	0.45	0.50	0.00	1.00	2912
School Safety - Security Presence- Weekends and Holydays	0.44	0.50	0.00	1.00	2900
School Safety - Police Presence- Violence Prevention	0.11	0.31	0.00	1.00	2916
School Safety - Police Presence- Drug Dealing (School)	0.11	0.31	0.00	1.00	2920
School Safety - Police Presence- Drug Dealing (Neighborhood)	0.10	0.30	0.00	1.00	2894
School Safety - Measures to Protect Students Around the School	0.37	0.48	0.00	1.00	2003
School Resources - Computers for Students	3.08	1.04	1.00	4.00	1649
School Resources - Internet for Students	2.63	1.23	1.00	4.00	1648
School Resources - Library	2.89	1.27	1.00	4.00	1640
School Resources - Reading Room	2.89	1.25	1.00	4.00	1649
School Resources - Gymnasium	2.69	1.21	1.00	4.00	1652
School Resources - Computer Lab	3.02	1.09	1.00	4.00	1644
School Resources - Science Lab	1.64	1.14	1.00	4.00	1658
School Resources - Auditorium	1.58	1.11	1.00	4.00	1663

Notes: This table presents descriptive statistics for the final schools' sample. This sample includes all schools located in Distrito Federal that participated in the *Prova Brasil* survey between 2007 and 2017. The quality of school infrastructure and available resources are measured on a scale from one—nonexistent—to four–good. Safety measures are evaluated as existent or nonexistent

Table A.3: Teachers' Survey - Reasons for Students' Poor Performance

Variable	Mean	S.D.	Min.	Max.	N
School Infrastructure	0.42	0.49	0.00	1.00	15299
Pedagical Supervision	0.21	0.41	0.00	1.00	8954
Inadequate Curriculum	0.23	0.42	0.00	1.00	15281
Past Learning	0.28	0.45	0.00	1.00	15293
Excess Work for Teachers	0.31	0.46	0.00	1.00	15256
Teachers' Lack of Motivation	0.37	0.48	0.00	1.00	15200
Students' Social Environment	0.84	0.37	0.00	1.00	15279
Parents' Cultural Level	0.80	0.40	0.00	1.00	15277
Parents' Lack of Assistance	0.95	0.22	0.00	1.00	15295
Students' Low Self Esteem	0.75	0.44	0.00	1.00	15313
Students' Poor Motivation/Effort	0.90	0.30	0.00	1.00	15304
Students' Indiscipline	0.73	0.44	0.00	1.00	15301
Students' Poor Attendance	0.48	0.50	0.00	1.00	8958

Notes: This table presents descriptive statistics for the teachers' survey sample. In this survey, teachers are asked if they believe certain factor are to blame for their students' poor performance. This sample includes respondents that were teaching in any of the Distrito Federal schools that participated in the *Prova Brasil* survey between 2007 and 2017.

A.2 Additional Results - Mechanisms

Table A.4: Heterogeneous Treatment Effect by School Characteristics - Infrastructure

	Language		Math		N
Covariate	Treatment Effect	HTE.	Treatment Effect	HTE	
Roof	-0.420***	0.091***	-0.432***	0.099***	300606
	(0.102)	(0.024)	(0.102)	(0.026)	
Walls	-0.434***	0.091**	-0.382***	0.080**	302253
	(0.105)	(0.029)	(0.100)	(0.027)	
Entrance	-0.352**	0.068**	-0.364**	0.076**	300902
	(0.124)	(0.031)	(0.125)	(0.033)	
Classrooms	-0.418***	0.092**	-0.382***	0.085***	301086
	(0.103)	(0.025)	(0.084)	(0.020)	
Doors	-0.266***	0.052**	-0.282**	0.060**	299163
	(0.070)	(0.019)	(0.084)	(0.022)	
Windows	-0.368***	0.079***	-0.411***	0.096***	298925
	(0.077)	(0.019)	(0.053)	(0.015)	
Bathrooms	-0.321***	0.069**	-0.287**	0.063*	296846
	(0.073)	(0.020)	(0.097)	(0.031)	
Kitchen	-0.228**	0.036	-0.301**	0.063**	296534
	(0.101)	(0.025)	(0.100)	(0.027)	
Plumbing	-0.366***	0.083***	-0.368***	0.089***	297719
	(0.051)	(0.015)	(0.056)	(0.020)	
Electric	-0.361***	0.088***	-0.354***	0.089***	297720
	(0.044)	(0.013)	(0.036)	(0.015)	

Notes: This table presents the results of a difference-in-differences (DD) analysis that: (i) estimates the difference in performance for students enrolled in schools located in neighborhoods impacted by the water rationing against academic performance of students enrolled in non-affected schools, i.e. the ''Treatment Effect" and, (ii) estimates how the treatment effect varies with school level characteristics—the heterogeneous treatment effect or HTE. In this DD, the pre-treatment period consists of the years that precede water rationing (2007, 2009, 2011, 2013, and 2015). The post-treatment period consists of the year the water rationing was implemented (2017). The first two columns consider performance in the Language evaluation as independent variable. The following two columns consider performance in the math evaluation. We include school, year and school-grade fixed effects in all specifications. We also include student level controls, such as information on gender, race, family income, parents' education, parents' support, and information on grade retention and school abandonment. Standard errors were computed with observations clustered at neighborhood level. *** represents p-value<0.01, ** p-value<0.05, and* p-value<0.1.

Table A.5: Heterogeneous Treatment Effect by School Characteristics - Safety

Covariate	Language		Math		N
	Treatment Effect	HTE.	Treatment Effect	HTE	
Control Access - Students	-0.170**	0.088	-0.206***	0.147**	302385
	(0.067)	(0.069)	(0.051)	(0.052)	
Control Access	-0.184***	0.112**	-0.148**	0.083*	302435
	(0.049)	(0.040)	(0.056)	(0.047)	
Security Presence- Day	-0.081*	-0.026	-0.079**	-0.012	300107
	(0.040)	(0.030)	(0.026)	(0.031)	
Security Presence- Night	-0.059	-0.041	-0.070*	-0.018	299794
	(0.052)	(0.044)	(0.036)	(0.036)	
Police Presence- Violence Prevention	-0.077**	-0.170***	-0.071**	-0.119**	300351
	(0.028)	(0.034)	(0.027)	(0.045)	
Police Presence- Drug Dealing (School)	-0.070**	-0.174***	-0.074**	-0.071**	301052
	(0.028)	(0.045)	(0.028)	(0.034)	
Police Presence- Drug Dealing (Neighborhood)	-0.069**	-0.156*	-0.067**	-0.034	297181
	(0.025)	(0.077)	(0.027)	(0.042)	
Measures to Protect Students Around School	-0.089**	0.000	-0.082**	0.000	221064
	(0.039)	(0.000)	(0.030)	(0.000)	

Notes: This table presents the results of a difference-in-differences (DD) analysis that: (i) estimates the difference in performance for students enrolled in schools located in neighborhoods impacted by the water rationing against academic performance of students enrolled in non-affected schools, i.e. the ''Treatment Effect" and, (ii) estimates how the treatment effect varies with school level characteristics—the heterogeneous treatment effect or HTE. In this DD, the pre-treatment period consists of the years that precede water rationing (2007, 2009, 2011, 2013, and 2015). The post-treatment period consists of the year the water rationing was implemented (2017). The first two columns consider performance in the Language evaluation as independent variable. The following two columns consider performance in the math evaluation. We include school, year and school-grade fixed effects in all specifications. We also include student level controls, such as information on gender, race, family income, parents' education, parents' support, and information on grade retention and school abandonment. Standard errors were computed with observations clustered at neighborhood level. *** represents p-value<0.01, ** p-value<0.05, and* p-value<0.1.

Table A.6: Heterogeneous Treatment Effect by School Characteristics - Resources

Covariate	Language: Treatment Effect	Language: HTE.	Math: Treatment Effect	Math: HTE	N
Computers for Students	-0.138**	0.019	-0.128**	0.013	143696
	(0.057)	(0.017)	(0.058)	(0.019)	
Internet for Students	-0.077**	-0.001	-0.078**	-0.002	144017
	(0.034)	(0.018)	(0.036)	(0.021)	
Library	0.016	-0.029*	0.051	-0.046***	142319
	(0.034)	(0.016)	(0.038)	(0.012)	
Reading Room	-0.104**	0.012	-0.135**	0.017*	143171
	(0.046)	(0.015)	(0.038)	(0.010)	
Gymnasium	-0.138**	0.023	-0.153**	0.026*	143689
	(0.044)	(0.015)	(0.046)	(0.015)	
Computer Lab	-0.203***	0.038***	-0.131***	0.011	142455
	(0.037)	(0.010)	(0.026)	(0.015)	
Science Lab	-0.078*	-0.001	-0.075*	-0.008	144243
	(0.043)	(0.027)	(0.041)	(0.021)	
Auditorium	-0.125**	0.036	-0.136**	0.038	145320
	(0.051)	(0.031)	(0.058)	(0.035)	

Notes: This table presents the results of a difference-in-differences (DD) analysis that: (i) estimates the difference in performance for students enrolled in schools located in neighborhoods impacted by the water rationing against academic performance of students enrolled in non-affected schools, i.e. the ''Treatment Effect" and, (ii) estimates how the treatment effect varies with school level characteristics—the heterogeneous treatment effect or HTE. In this DD, the pre-treatment period consists of the years that precede water rationing (2007, 2009, 2011, 2013, and 2015). The post-treatment period consists of the year the water rationing was implemented (2017). The first two columns consider performance in the Language evaluation as independent variable. The following two columns consider performance in the math evaluation. We include school, year and school-grade fixed effects in all specifications. We also include student level controls, such as information on gender, race, family income, parents' education, parents' support, and information on grade retention and school abandonment. Standard errors were computed with observations clustered at neighborhood level. *** represents p-value<0.01, ** p-value<0.05, and* p-value<0.1.

Table A.7: Heterogeneous Treatment Effect by Student Characteristics - Student

Covariate	Language		Math		N
	Treatment Effect	HTE.	Treatment Effect	HTE	
Female Student	-0.088**	0.005	-0.083**	0.014	312734
	(0.030)	(0.019)	(0.024)	(0.024)	
White Student	-0.085**	-0.007	-0.073**	-0.019	312734
	(0.029)	(0.020)	(0.027)	(0.018)	
Black Student	-0.089**	0.021	-0.072**	-0.038	312734
	(0.028)	(0.020)	(0.023)	(0.028)	
Brown Student	-0.095**	0.018	-0.092**	0.033*	312734
	(0.033)	(0.030)	(0.029)	(0.017)	
Asian Student	-0.088**	0.033	-0.078**	0.041	312734
	(0.030)	(0.051)	(0.025)	(0.029)	
Indigenous Student	-0.085**	-0.025	-0.075**	-0.026	312734
	(0.028)	(0.040)	(0.026)	(0.041)	
Does your family owe a car? (Y/N)	-0.097**	0.015	-0.083**	0.008	312734
	(0.027)	(0.020)	(0.025)	(0.018)	
Do you have a computer at home? (Y/N)	-0.093**	0.010	-0.077**	0.002	312734
	(0.028)	(0.012)	(0.023)	(0.016)	
Bathrooms at home (per capita)	-0.073*	-0.035	-0.060**	-0.044	312734
	(0.036)	(0.037)	(0.026)	(0.035)	
Number of people living at home	-0.162***	0.019***	-0.091**	0.004	312734
	(0.040)	(0.004)	(0.033)	(0.005)	
Do you work? (Y/N)	-0.084**	-0.030	-0.072**	-0.060	312734
	(0.031)	(0.054)	(0.027)	(0.040)	
Have you ever failed a grade	-0.108**	0.014	-0.073**	-0.004	312734
	(0.047)	(0.016)	(0.034)	(0.012)	
Have you ever dropout of school?	-0.110**	0.023	-0.104***	0.027	312734
	(0.031)	(0.023)	(0.027)	(0.026)	

Notes: This table presents the results of a difference-in-differences (DD) analysis that: (i) estimates the difference in performance for students enrolled in schools located in neighborhoods impacted by the water rationing against academic performance of students enrolled in non-affected schools, i.e. the ''Treatment Effect" and, (ii) estimates how the treatment effect varies with student level characteristics—the heterogeneous treatment effect or HTE. In this DD, the pre-treatment period consists of the years that precede water rationing (2007, 2009, 2011, 2013, and 2015). The post-treatment period consists of the year the water rationing was implemented (2017). The first two columns consider performance in the Language evaluation as independent variable. The following two columns consider performance in the math evaluation. We include school, year and school-grade fixed effects in all specifications. We also include student level controls, such as information on gender, race, family income, parents' education, parents' support, and information on grade retention and school abandonment. Standard errors were computed with observations clustered at neighborhood level. *** represents p-value<0.01, ** p-value<0.05, and* p-value<0.1.

Table A.8: Heterogeneous Treatment Effect by Student Characteristics - Parents

Covariate	Language Treatment Effect	Language HTE.	Math Treatment Effect	Math HTE	N
Mother Education - NLess than elementary	-0.086**	-0.049**	-0.077**	-0.023	312734
	(0.029)	(0.022)	(0.024)	(0.029)	
Mother Education - Elementary School	-0.082**	-0.059**	-0.073**	-0.044	312734
	(0.029)	(0.024)	(0.027)	(0.029)	
Mother Education - Middle School	-0.088**	0.018	-0.076**	-0.003	312734
	(0.029)	(0.028)	(0.026)	(0.023)	
Mother Education - High School	-0.088**	0.011	-0.080**	0.017	312734
	(0.031)	(0.036)	(0.025)	(0.015)	
Mother Education - College	-0.090**	0.003	-0.081**	0.011	312734
	(0.027)	(0.025)	(0.023)	(0.022)	
Father Education - Less than elementary	-0.085**	-0.028	-0.080**	0.018	312734
	(0.030)	(0.034)	(0.026)	(0.038)	
Father Education - Elementary School	-0.087**	0.010	-0.078**	0.019	312734
	(0.029)	(0.037)	(0.025)	(0.023)	
Father Education - Middle School	-0.085**	-0.012	-0.072**	-0.052**	312734
	(0.029)	(0.023)	(0.025)	(0.016)	
Father Education - High School	-0.082**	-0.024	-0.076**	0.001	312734
	(0.029)	(0.022)	(0.025)	(0.016)	
Father Education - College	-0.084**	-0.041	-0.078**	-0.015	312734
	(0.027)	(0.027)	(0.024)	(0.027)	
Frequency parents attend PTA meetings	-0.081**	-0.003	-0.119**	0.016	312734
	(0.036)	(0.014)	(0.044)	(0.018)	
Parents Incentive Score	-0.132*	0.010	-0.178**	0.023	312734
	(0.065)	(0.016)	(0.056)	(0.014)	

Notes: This table presents the results of a difference-in-differences (DD) analysis that: (i) estimates the difference in performance for students enrolled in schools located in neighborhoods impacted by the water rationing against academic performance of students enrolled in non-affected schools, i.e. the ''Treatment Effect" and, (ii) estimates how the treatment effect varies with student level characteristics—the heterogeneous treatment effect or HTE. In this DD, the pre-treatment period consists of the years that precede water rationing (2007, 2009, 2011, 2013, and 2015). The post-treatment period consists of the year the water rationing was implemented (2017). The first two columns consider performance in the Language evaluation as independent variable. The following two columns consider performance in the math evaluation. We include school, year and school-grade fixed effects in all specifications. We also include student level controls, such as information on gender, race, family income, parents' education, parents' support, and information on grade retention and school abandonment. Standard errors were computed with observations clustered at neighborhood level. *** represents p-value<0.01, ** p-value<0.05, and* p-value<0.1.