ARTÍCULO

CLIMATE SHOCKS AND HUMAN CAPITAL: THE IMPACT OF THE NATURAL DISASTERS OF 2010 IN COLOMBIA ON STUDENT ACHIEVEMENT

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Valencia Amaya, M. G. (2020). Climate shocks and human capital: The impact of the natural disasters of 2010 in Colombia on student achievement. *Cuadernos de Economía*, *39*(79), 303-328.

This paper investigates the impact of the unprecedented climate shocks of the 2010 in Colombia on the results of the Saber 11 standardized test for the 2010-2012 period. By using two unique datasets, this paper contributes to the literature by providing a better estimate of the human capital costs of climate shocks. The findings indicate that the climate shocks occurred on 2010 decreased Saber 11 test scores. The impact was stronger for female students, students from rural areas and students from low-income families. A possible channel of transmission is identified: the destruction of schools.

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Valencia Amaya, M. G. (2020). Choques climáticos y capital humano: El impacto de los desastres naturales de 2010 en Colombia sobre el desempeño académico de los estudiantes. *Cuadernos de Economía*, *39*(79), 303-328.

Este artículo investiga el impacto de los choques climáticos de 2010 en Colombia sobre los resultados en las pruebas Saber 11 del período 2010-2012. El artículo contribuye a la literatura sobre cambio climático y capital humano al proporcionar una mejor estimación de los costos de capital humano debidos a desastres climáticos. Los resultados indican que los choques climáticos de 2010 disminuyeron los puntajes en las pruebas Saber 11. El impacto fue mayor para estudiantes mujeres, de áreas rurales y pertenecientes a familias de ingresos bajos. Se identifica un posible canal de transmisión: la destrucción de escuelas.

Palabras clave: choques climáticos, desastres naturales, capital humano, habilidades cognitivas, Colombia.
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Cet article enquête sur l'impact des chocs climatiques en Colombie sur les résultats dans les épreuves Saber 11 de la période 2010-2012. L'article est un apport aux publications sur le changement climatique et le capital humain en offrant une meilleure estimation des coûts de capital humain dus aux désastres climatiques. Les résultats montrent que les chocs climatiques de 2010 ont fait baisser les notes dans les épreuves Saber 11. L'impact a été plus important pour les étudiantes de zones rurales et appartenant à des familles de faibles revenus. On peut identifier une cause possible : la destruction des écoles.

Mots-clés: chocs climatiques, désastres naturels, capital humain, habilités cognitives, Colombie.
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Este artigo pesquisa o impacto dos choques climáticos de 2010 na Colômbia sobre os resultados nas provas Saber 11 do período 2010-2012. O artigo contribui para a literatura sobre mudança climática e capital humano ao proporcionar uma melhor estimação dos custos de capital humano devidos a desastres climáticos. Os resultados indicam que os choques climáticos de 2010 diminuíram as pontuações nas provas Saber 11. O impacto foi maior para estudantes mulheres, de áreas rurais e pertencentes a famílias de ingressos baixos. Identifica-se um possível canal de transmissão: a destruição de escolas.

Palavras-chave: choques climáticos, desastres naturais, capital humano, habilidades cognitivas, Colômbia.
JEL: O12, I20, I21, Q54.

INTRODUCTION

This paper investigates the impact of the severe weather shocks that affected Colombia in 2010 on the national standardized test *Pruebas Saber 11* scores, by using two unique datasets and applying a difference-in-difference framework with repeated cross-sections. Understanding the factors behind the performance of students in national standardized tests is essential since some universities require the test results as part of their application process and use them to rank students —as they are proxies of students' skills and knowledge—. Those grades allow, then, some students to continue studying at a higher education level, and so they are a keystone for promoting social mobility.

The use of measures of learning attainment in economics is still a nascent field, subject to the availability of periodic academic datasets linking student's scores with student and family characteristics (Orazem & King, 2007). Previous studies on the relationship between climate shocks and human capital have analyzed the impact of natural disasters only on quantitative indicators of human capital, but so far there have been no studies to account for the effects of these disasters on qualitative indicators of education. There is also a lack of studies on this relationship for Colombia (see Brando & Santos, 2015, for early life impacts of rainfall variation), although this country has suffered from several natural disasters during its history. In this sense, the use of two unique datasets for Colombia, ICFES dataset and SNPAD dataset, allows this paper to measure the impact of natural shocks on a qualitative proxy of human capital, such as learning attainment (cognitive skills). ICFES dataset comprises "Saber 11" test scores (a national standardized test like the SAT) plus the personal characteristics and family background of each test-taker; whereas SNPAD dataset provides detailed information on the natural disasters that have affected Colombia's municipalities since 1998.

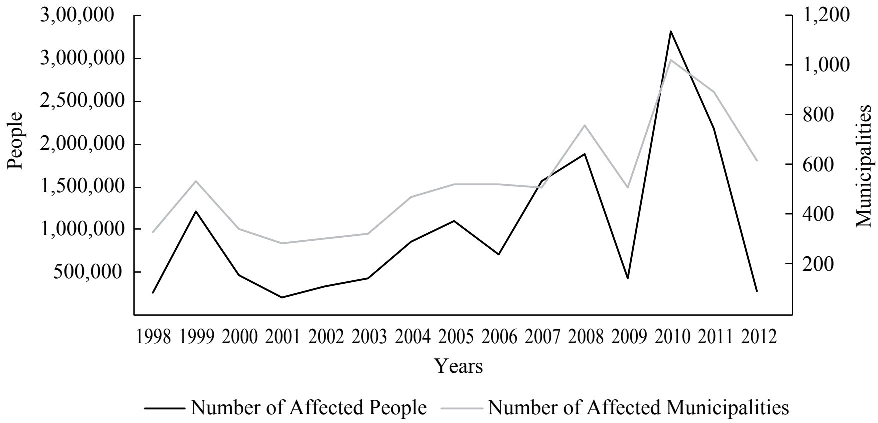
This paper contributes to the literature on the relationship between human capital and natural shocks, by using a qualitative proxy of human capital, such as cognitive test results. On the one hand, the literature on this topic has focused primarily on quantitative proxies of human capital, such as years of schooling, school enrollment ratios, students' attendance or adult literacy rates (see Bustelo, Arends-Kuenning, & Lucchetti, 2012, for the Colombian case). Qualitative measures of educational attainments, such as cognitive skills (test score results) or a country's quality of education seem to be better predictors of productivity, economic growth, income distribution and individuals' future career success (Wößmann, 2003; Orazem & King, 2007; Baird, 2012). For instance, time spent in school does not necessarily translate into more knowledge or better skills —for this variable is not a schooling outcome but a component of the educational production process (Orazem & King, 2007)—, but cognitive tests results account for differences in the quality of education, one of the cornerstones in the theory of human capital (Wößmann, 2003). In fact, differences in adult earnings are better explained by cognitive achievements than by years of schooling (Glewwe, 2002, cited by Orazem & King, 2007; de Coulon, Meschi, & Vignoles, 2011).

On the other hand, climate shocks will complicate the convergence of developing countries to the quality standards in education reached by the developed world. Their limited capacity in human and financial resources affects negatively the quality of the education imparted. As a result, students learn much less than they should, according to their curriculums, and compared to students in developed countries (Glewwe & Kremer, 2006). Natural shocks, akin to economic downturns, worsen the situation for these countries, as these shocks will influence the returns of education for the people affected as well as their attitudes towards acquiring human capital (Broomhall & Johnson, 1994). Poor people living in developing countries are also more prone to climate-related events (UNDP, 2007; The World Bank, 2010) and their historical resilience is even at risk, due to the increasing frequency and intensity of such events (Lacambra, Möller, & Spencer., 2008). In this context, understanding the links between natural shocks and human capital becomes essential, especially when designing policies aimed at reducing vulnerability and enhancing the inherent resilience of regions and communities. To sum up, climate change will increase the risk of exposure to climate shocks, mainly for the people living in poor countries, and therefore, will become an obstacle to the development goals of these countries.

For Colombia, the year 2010 stands as a remarkable year in terms of the severity of the climate shocks that hit the country (see Figure 1). According to the National System for the Prevention and Attention of Disasters (SNPAD), with respect to 2009, the number of people affected in 2010 increased by 661% (3,319,686), the number of houses damaged in 508% (12,297), the number of roads destroyed in 358% (1,104), and the number of schools affected in 351% (501). The shock was not only intense but also broad in scope. In 2009, 513 municipalities were affected by climate events; in 2010 this figure rose to 1,020 (more than 90% of all Colombian municipalities). The shocks persisted in 2011, although to a lesser intensity. The most common disasters were landslides (48% of the events) and floods (31% of the events). In terms of capital destruction, together these two disasters accounted for the damages of 93% of the roads, 92% of the houses, and 78% of the schools. In terms of the direct impacts on humans, 43% of the death toll was caused by landslides, and 74% of the number of people affected suffered floods.

The severe and unexpected change in the intensity of climate events provides a unique opportunity to assess its impact on the schooling achievement of high school students, as measured by the results in the Saber 11 test. The results of a difference-in-differences estimation suggest that the 2010 climate shock decreased students' test scores. The size of the impact was larger for females, rural, and poorer students. Health deterioration, through vector-borne diseases, and the destruction of physical capital, proxied by schools' damages, are explored as two possible channels of transmission. The paper is structured as follows. Section II presents a literature review on the relationship between climate shocks and human

Figure 1.
Climate Shocks in Colombia, 1998-2012: Number of Municipalities and Number of People Affected by Climate-Related Disasters.



Source: author's calculations based on data from SNPAD (2013).

development; Section III introduces the datasets used in this paper and some summary statistics; Section IV explains the empirical strategy of difference-in-difference estimation with repeated cross sections; Section V presents the main results; the last section concludes.

CLIMATE SHOCKS AND HUMAN DEVELOPMENT: THEORY

The literature on the effects of natural disasters on economic growth (one of the components of human development) points out to both positive and negative impacts (Chhibber & Laajaj, 2008; Baez, de la Fuente, & Santos, 2010; Ferreira & Schady, 2009; McDermott, 2012). In the short run, natural disasters reduce the stock of capital in the economy causing an immediate decrease in the GDP. In the long term, some authors argue that natural disasters do not seem to have an apparent impact on the rate of economic growth (Cavallo, Galiani, Noy, & Pantano, 2013). Some others highlight a long-term positive effect on income and welfare (Gignoux & Menéndez, 2016), as well as on wage growth (Kirchberger, 2017). The reduction in the stock of capital that results from a natural disaster is likely to produce a temporary decline in income and production levels. But, how does a natural disaster affect human capital, especially schooling outcomes? Its effect will depend on the magnitude of two opposite forces: the income and substitution effects (Ferreira & Schady, 2009).

By reducing households' available resources, the income effect harms schooling; while the substitution effect has a positive impact on it by affecting the opportunity cost of studying versus working (with more children studying after a shock, due to a reduction in children wage). As a result, the total impact of a natural shock on schooling is not clear cut, especially if households are credit-constrained; however, in the case of poorer countries, the income effect is expected to be larger because the marginal utility of consumption is higher in these countries (contrary to the case of richer countries). For middle-income countries, like those of Latin America, empirical evidence suggests that education outcomes are counter-cyclical to economic downturns, meaning that more children are enrolled in school during an economic crisis. Nevertheless, the effects are heterogeneous within and across countries. In this sense, natural shocks have differential effects depending on gender —women usually suffer more than men (Goh, 2012)—, race, socioeconomic status, occupation, and location, but the poor are always the most negatively affected (Ferreira & Schady, 2009; Baez et al., 2010).

Climate-related events, in fact, increase the odds that a household remains or becomes poor (Glave, Fort, & Rosemberg, 2008, for the case of Peru). These events increase the chances of poverty persistence (poverty lock-in) and downward mobility (downward consumption trajectories), hindering the capacity of households for rising to a higher socioeconomic position (Premand & Vakis, 2010). To this effect, natural disasters (especially floods and droughts) have negative impacts on both human development (deterioration in the human development index) and poverty (food poverty, capacities poverty, and asset poverty) (Rodríguez-Oreggia, de la Fuente, de la Torre, Moreno, & Rodríguez, 2010). Moreover, the long-term effects of these events on human development are felt stronger on more impoverished regions because, even though these regions are more prone to natural catastrophes, they are also less likely to mobilize reconstruction funds, by, for example, implementing counter-cyclical fiscal policies (Cavallo & Noy, 2010). These regions, in addition, usually have lower levels of infrastructural development, less awareness, and inferior coping capacities (Goteng, Census, & Alikeju, 2012). Accordingly, it is stated that economic and human development can counteract the adverse effects of climate shocks on a region by increasing its resilience (Toya & Skidmore, 2007).

The literature has also acknowledged the existence of direct and indirect effects on human capital derived from climate-related disasters. Direct effects include the destruction and depletion of physical and human capital. One of the immediate consequences of climate shocks is the destruction of physical capital, such as schools, health centers, households' assets and public and private infrastructure; as well as of human capital, in terms of the casualties, disabilities, illness and injuries of students, teachers and health professionals (Fuentes & Seck, 2007; Baez et al., 2010; Crespo-Cuaresma, 2010; McDermott, 2011). Wounds and illness keep children from attending school; death translates into a loss in previous investments in human capital; and disease or epidemics eruption, which results from contamination or scarcity of water and food supplies, combined with the favorable conditions for microorganisms to emerge and spread, could permanently decrease the cognitive skills of children (McDermott, 2011). Together, the destruction of physical and human capital increases the marginal cost of acquiring human capital (Baez et al., 2010), which will deteriorate its future accumulation and, therefore, the social development possibilities of the affected regions.

The negative impacts of the direct effects are indubitable, but the indirect effects can either counteract or reinforce these impacts. The indirect effects are related to the decisions taken by households after the natural disaster (McDermott, 2012). The loss of households' assets, the illness or death of households' members, which could potentially cut their available time to generate income, together with the migration and evacuation decisions, will most probably reduce the family income (Baez et al., 2010; Crespo-Cuaresma, 2010; McDermott, 2011). Plus, the destruction of infrastructure will require investment decisions by the affected households; but more impoverished families will find it difficult to invest because of credit restrictions or unavailability of credit to them. In such a situation, credit-constrained households will be forced to disinvest, by selling-off productive assets to cope with the shock. This situation will trigger a vicious circle, since the reduction of productive assets will diminish their ability to generate income in the future, and this will translate into more vulnerability to future climate shocks (McDermott, 2011).

In consequence, when households are credit-constrained, this shock on income will lead family units to reduce their investment in human and physical capital accumulation. The consumption of food and health and educational services will decline. Plus, parents might resort to children's time as a buffer mechanism to soften the shock (Fitzsimons, 2007; Kazianga, 2012). In this scenario, adding the possible health impacts derived from the disaster and the possibility that income losses might increase the opportunity cost of studying, children will be permanent or temporarily withdrawn from school (Baez et al., 2010; McDermott, 2011).

Prices and wages, the amount of parental time, and the discontinuation of schooling are other indirect channels through which natural disasters affect human capital. The impact of a natural disaster on prices and wages is unclear because it will depend on the direction and size of the income and substitution effects (Baez et al., 2010; Ferreira & Schady, 2009). Additionally, there is uncertainty about the amount of parental time with children available after a shock, as well as of its effects on the production of human capital (possibly increasing its marginal cost, Baez et al., 2010). Finally, because of the discontinuation of schooling, children might not be able to keep up later or will drop out of the educational system for good, creating a path-dependent effect (Baez et al., 2010). So, the short-term tradeoffs faced by households to smooth consumption can have long-lasting adverse effects on the accumulation of human capital, even more when human development follows a non-linear path, and can potentially create poverty traps in the long run (Fuentes & Seck, 2007). In this sense, the evidence supports the fact that the net effect of the direct and indirect impact is strongly negative and long-lasting (Baez et al., 2010).

DATA

This paper uses two unique datasets: ICFES database for Saber 11 test and SNPAD database for natural disasters. The ICFES database contains the test results from the examination Saber 11: a standardized national test applied to high school Colombian students prior to graduation. The Instituto Colombiano para el Fomento de la Educación Superior—ICFES (Colombian Institute for the Promotion of Higher Education)— is the institution in charge of developing the test, which has the purpose of assessing the academic skills of grade 11 high school students. The test is administered twice a year, according to the academic year of the school; however, for most of the institutions the academic year starts in late January or early February and ends in mid or late November; this calendar is known as "calendar A". The test results are required by some universities as part of their application process; they also serve as a quality indicator that allows comparing the performance of the country's high schools. Saber 11 test has two components: a common core, which evaluates the students' knowledge in eight (8) different subjects: language (Spanish), mathematics, biology, chemistry, physics, philosophy, social science, and foreign language (English); and a flexible core, which allows students to choose one subject out of the six available options, divided into four in-depth subjects: language, mathematics, biology, or social science, and two interdisciplinary subjects: environment or violence and society.

This paper uses the Saber 11 (calendar A) database for the period 2008-2012. The ICFES database variables were merged with some variables from the SNPAD national disasters database. This database was developed by the governmental institution "Sistema Nacional para la Prevención y Atención de Desastres" (National System for the Prevention and Attention of Disasters) and contains the records of the different natural events that have affected Colombia since 1998 at a municipality level. Some of the variables included in the database are the date of the event; municipality code; type of event; the number of casualties; the number of people affected, wounded, or missing; the number of houses destroyed or damaged, and the number of different public infrastructure affected.

EMPIRICAL STRATEGY: DIFFERENCE-IN-DIFFERENCE ESTIMATION WITH REPEATED CROSS SECTIONS

This paper uses a difference-in-difference estimation with repeated cross sections to measure the impact of the climate shocks of 2010 on the test scores of the Saber

11 test in the period 2010-2012. The following equation (1) molds the baseline model:

$$Score_{ijt} = \beta_0 + \beta_1 Post + \beta_2 \left(Shock_j * Post\right) + \beta_3 \mathbf{X}_{it} + \alpha_k + \theta_t + e_{ijt} \qquad (1)$$

Where the outcome variable $Score_{ijt}$ represents the z-score test result —total, reading, and math— of the student *i* living in the municipality *j* in the year *t*. The dummy variable *Shock* indicates the treatment status of the municipality. Both treatment and control groups share the fact that the average number of people affected by climate-related disasters (per 100,000 inhabitants) in the years 2006, 2007, 2008, and 2009 was less than or equal to the average of all municipalities for each year. A municipality belongs to the treatment/control group if in 2010 this indicator was *higher than/less than or equal to* the 2006-2009 average at the municipality level. *Post* is a dummy variable equal to 1 if a student's score is observed in the post-shock period (2010-2012). $\mathbf{X}_{it}$ is a vector of students' and households' control variables (age, sex, parents' education, student's employment status, socioeconomic stratum, household's income, overcrowding status, living area, household's appliances, and Internet and cable TV access). α_k and θ_t represent school and time fixed effects. e_{ijt} is an error term.

Under the definition of the variable *Shock*, there are 95 municipalities in the treatment group and 555 municipalities in the control group. Even though the variable *Shock* varies at the municipality level, this paper uses student *i* as the unit of observation, as this allows to control for observables available in the ICFES database, as well as to examine heterogeneous effects.

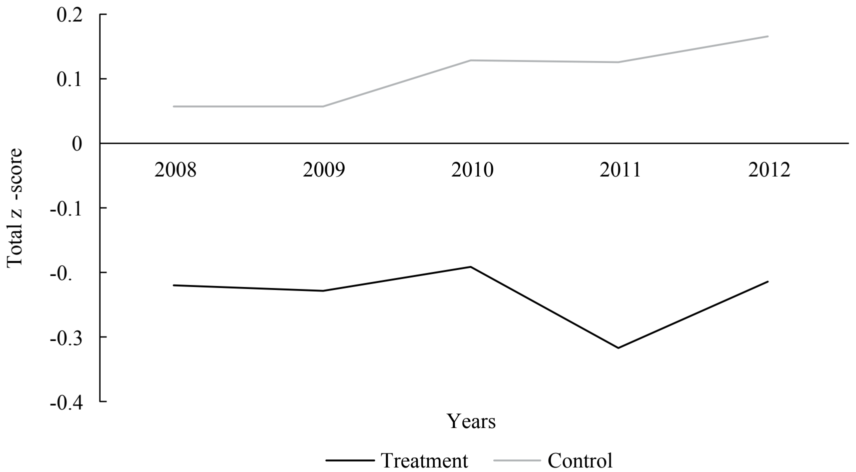
The difference-in-difference model requires the satisfaction of the parallel trend assumption, which guarantees that in the absence of treatment (*Shock*), the average test score of the treatment group would have followed the same trend as the average test score of the control group. Table 1 shows that both groups differ in all but one of the control variables (*male*). However, three different tests show that the common-trends assumption is satisfied in this case. First, visual inspection indicates that the trends in the average Saber 11 *z*-scores for the years before the shock (2008 and 2009) were similar for both groups but diverge after the shock (2010, 2011, and 2012) (Figure 2). These results are further confirmed with a formal test on common pre-dynamics for the two groups (see Mora & Reggio, 2012 and 2014). The null hypothesis of this test is that both treatment and control groups have similar dynamics in the outcome variable during the pre-treatment period. The null is not rejected in this case (p-value: 0.378) (Table 2). Finally, the regression results of the treatment variable (*Shock*) interacted with the time dummies for the years 2008 and 2009 show that the coefficients are not significant and close to zero (Figure 3). The parallel-trend assumption is then fulfilled.

Table 1.
Summary Statistics: Treatment and Control Groups.

Variable	Control	Treatment	Difference
Altitude	1544.25	867.47	676.78***
Area	923.09	664.04	259.05***
Temperature	20.19	23.67	-3.48***
Age	17.68	17.77	-0.09***
Age (15-16)	0.40	0.36	0.04***
Male	0.45	0.45	0.00
Work	0.11	0.12	-0.01***
Mother's Education	4.58	3.74	0.84***
Father's Education	4.45	3.56	0.90***
Social Strata	2.15	1.43	0.72***
Income	2.27	1.59	0.68***
Overcrowding	0.18	0.28	-0.10***
Urban	0.83	0.65	0.18***
Car	0.20	0.10	0.10***
Computer	0.54	0.25	0.29***
DVD	0.69	0.50	0.19***
Internet	0.40	0.13	0.27***

Note: (a) *** p<0.01, ** p<0.05, * p<0.1.
Source: author's calculations based on data from ICFES.

Figure 2.
Parallel-Trend Assumption: Graphic Inspection.



Source: author's calculations based on data from ICFES and SNPAD (2013).

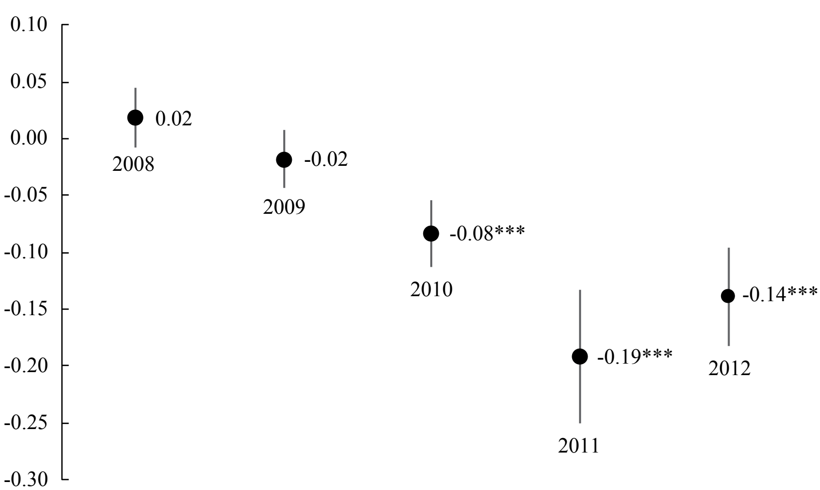
Table 2.
Parallel-Trend Assumption Test.

Unconditional Fully Flexible Model						
Output: Total Score (z-score)				Number of obs.:		1,984,402
Sample Period: 2008:2012				H0: Common Pre-dynamics:		0.778
Treatment Period: 2010:2012					p-value:	0.378
Post-treatment (s)		s=2010	s=2011	s=2012	H0: q=q-1	H0: s=s-1
Pre-treatment (q)	q=2008	-0.035	-0.158	-0.094		364.170
		(0.007)	(0.008)	(0.007)		[0.0000]
	q=2009	-0.029	-0.146	-0.076	-0.006	259.700
		(0.012)	(0.019)	(0.026)	[0.3778]	[0.0000]

Notes: (1) Parallel-trend assumption test based on Mora and Reggio (2012) and Mora and Reggio (2014); (2) robust standard errors in parenthesis; (3) p-values in brackets.

Source: author's calculations based on data from ICFES and SNPAD (2013).

Figure 3.
Regression Coefficients of Treatment (*Shock*) Interacted with Year Dummies.



Note: *** p<0.01, ** p<0.05, * p<0.1.
Source: author's calculations based on data from ICFES and SNPAD (2013).

RESULTS

Baseline

Table 3 presents the results of the estimation of equation (1) using pooled OLS with clustered standard errors at the municipality level. The climate shocks of 2010, as measured by the variable *Shock*, decreased students' average test scores in treatment municipalities by 0.13 standard deviations during the post-treatment period (2010-2012). By subject area, the size of the negative effect was greater for language (0.15 standard deviations) than for mathematics (0.10 standard deviations). The results are robust across three different model specifications. However, the coefficients increase in size as controls and fixed effects are added to the simple

Table 3.
Effects of the 2010 Climate Shocks on Saber 11 Z-Scores.

Dependent variable: Z-score	Model	(i)	(ii)	(iii)
Total	Treat*Post	-0.102***	-0.116***	-0.129***
		(0.026)	(0.020)	(0.022)
	Observations	1,806,831	1,806,831	1,806,831
	R-squared	0.013	0.254	0.366
Language	Treat*Post	-0.132***	-0.140***	-0.153***
		(0.029)	(0.025)	(0.027)
	Observations	1,807,594	1,807,594	1,807,594
	R-squared	0.01	0.136	0.194
Math	Treat*Post	-0.0867***	-0.101***	-0.105***
		(0.024)	(0.019)	(0.019)
	Observations	1,807,594	1,807,594	1,807,594
	R-squared	0.011	0.168	0.246
Controls			X	X
Year fixed effects			X	X
Municipality and School fixed effects				X

Notes: (1) The coefficient *Treat*Post* corresponds to the estimated parameter β_2 of equation (1), which is the difference-in-difference estimation of the effect of the 2010 climate shocks on the test scores. *Treat* indicates whether a student belongs to the control group (*Shock*=0) or the treatment group (*Shock*=1). (2) *** p<0.01, ** p<0.05, * p<0.1. (3) Standard errors in parenthesis are clustered at the municipality level. (4) Control variables include dummy variables for male, urban area, being 15 or 16 years old, social strata, income levels, mother education levels, father education levels, student employment status, ownership of household's appliances, internet access at home, age, and age squared. (5) All scale variables were converted into z-scores.
Source: author's calculations based on data from ICFES and SNPAD (2013).

difference-in-differences estimation. In this case, the control variables and the fixed effects help explain both the test scores and the fact that a municipality had suffered more from the 2010 climate-related shocks. Yet, the estimator would be biased downwards. For instance, studying in a school with poor infrastructure increases the chances of being affected by a landslide or a flood, augmenting the possibility of being treated, but it also relates to a lower test score. A higher household income decreases the chances of being affected, perhaps by living in a house better equipped to annual floods or by having access to credit and insurance markets, but it also has a positive effect on the test scores. Therefore, the impact of the omitted variables on the treatment indicator and the outcome variable seems to follow opposite directions, and so not including control variables would underestimate the impact estimator.

Heterogeneous Effects

This section presents the estimation of equation (1) that accounts for the heterogeneous effect of the variable *Shock* by year, sex, living area, and household income.

Disaggregating the post-treatment period by year shows that the effect was short-lived and concentrated in the year 2011 (Table 4). That is, the shock affected to a higher extend students who were studying the 10th year of school in 2010 and took the Saber 11 test in 2011. Both the instant impact —for students who took the test in 2010— and the delayed effect —for students who were studying the 9th year of school in 2010— were relatively small. By subject area, the *Shock* hit harder the results on math than on language for students who took the test in the year of the climate events. However, for those who were in the 10th and 9th grade in 2010, the impact was greater on language.

Table 4.
Effects of the 2010 Climate Shocks on Saber 11 Z-Scores, by Year.

Dependent variable: Z-score	Total	Language	Math
Treat*Post: 2010	-0.0744*** (0.015)	-0.0354*** (0.013)	-0.0843*** (0.018)
Treat*Post: 2011	-0.183*** (0.030)	-0.299*** (0.051)	-0.143*** (0.025)
Treat*Post: 2012	-0.130*** (0.022)	-0.123*** (0.023)	-0.0875*** (0.017)
Observations	1,806,831	1,807,594	1,807,594
R-squared	0.366	0.195	0.246

(*Continued*)

Table 4.
Effects of the 2010 Climate Shocks on Saber 11 Z-Scores, by Year.

Dependent variable: Z-score	Total	Language	Math
Controls	X	X	X
Year fixed effects	X	X	X
Municipality and School fixed effects	X	X	X

Notes: (1) The coefficient *Treat*Post* corresponds to the estimated parameter β_2 of equation (1), which is the difference-in-difference estimation of the effect of the 2010 climate shocks on the test scores. In this case, the post-treatment period is disaggregated by year. *Treat* indicates whether a student belongs to the control group (*Shock*=0) or the treatment group (*Shock*=1). (2) *** p<0.01, ** p<0.05, * p<0.1. (3) Standard errors in parenthesis are clustered at the municipality level. (4) Control variables include dummy variables for male, urban area, being 15 or 16 years old, social strata, income levels, mother education levels, father education levels, student employment status, ownership of household's appliances, internet access at home, age, and age squared. (5) All scale variables were converted into z-scores.
Source: author's calculations based on data from ICFES and SNPAD (2013).

The results show a differentiated effect of the 2010 *Shock* on males and females (Table 5). Females' scores decreased more vis-à-vis males' scores throughout the post-treatment period, but the difference was greater in the year 2010. That is, relative to males, the climate shocks hit harder female students who took the test in 2010 (11th-grade students). The difference persisted for the 9th and 10th-grade students, although to a lesser degree. By subject area, the effect on language and math also differs between males and females, but for language, the difference disappears steadily in the following years, whereas for math the gap endures.

The heterogeneous results by living zone also show a differentiated impact (Table 6), although less striking than in the results by sex. Students from rural areas suffered a more significant loss in their test scores compared with students from urban areas. The total scores attest a big difference between the two groups in the year 2011, especially in the language component of the test. In this subject area, the negative impact on rural students was 0.12 standard deviations higher vis-à-vis urban students.

Table 7 shows the results related to the income levels of students' households. In general, the impact of the 2010 *Shock* decreases in magnitude the higher the income level of the student's family. That is, poor and middle-class students experienced a greater loss in their test scores, whereas students from wealthier families lived through the climate disasters having their scores either barely affected or unaltered by the events.

Table 5.
Effects of the 2010 Climate Shocks on Saber 11 Z-Scores, by Sex.

Dependent variable: Z-score		Total	Language	Math
Treat*Post: 2010	Males	-0.0337** (0.016)	0.0125 (0.014)	-0.0539*** (0.021)
	Females	-0.109*** (0.015)	-0.0756*** (0.014)	-0.110*** (0.018)
Treat*Post: 2011	Males	-0.162*** (0.032)	-0.249*** (0.052)	-0.135*** (0.027)
	Females	-0.201*** (0.030)	-0.341*** (0.051)	-0.151*** (0.025)
Treat*Post: 2012	Males	-0.112*** (0.024)	-0.119*** (0.023)	-0.0625*** (0.020)
	Females	-0.145*** (0.022)	-0.126*** (0.023)	-0.109*** (0.017)
Observations		1,806,831	1,807,594	1,807,594
R-squared		0.366	0.195	0.246
Controls		X	X	X
Year fixed effects		X	X	X
Municipality and School fixed effects		X	X	X

Notes: (1) The coefficient *Treat*Post* corresponds to the estimated parameter β_2 of equation (1), which is the difference-in-difference estimation of the effect of the 2010 climate shocks on the test scores. In this case, the post-treatment period is disaggregated by year. *Treat* indicates whether a student belongs to the control group (*Shock*=0) or the treatment group (*Shock*=1). (2) *** p<0.01, ** p<0.05, * p<0.1. (3) Standard errors in parenthesis are clustered at the municipality level. (4) Control variables include dummy variables for male, urban area, being 15 or 16 years old, social strata, income levels, mother education levels, father education levels, student employment status, ownership of household's appliances, internet access at home, age, and age squared. (5) All scale variables were converted into z-scores.
Source: author's calculations based on data from ICFES and SNPAD (2013).

Table 6.
Effects of the 2010 Climate Shocks on Saber 11 Z-Scores, by Living Zone.

Dependent variable: Z-score		Total	Language	Math
Treat*Post: 2010	Urban	-0.0744*** (0.016)	-0.0383*** (0.014)	-0.0733*** (0.020)
	Rural	-0.0765*** (0.016)	-0.0334** (0.015)	-0.106*** (0.020)
Treat*Post: 2011	Urban	-0.166*** (0.032)	-0.259*** (0.052)	-0.126*** (0.027)
	Rural	-0.215*** (0.031)	-0.378*** (0.052)	-0.175*** (0.027)
Treat*Post: 2012	Urban	-0.130*** (0.025)	-0.118*** (0.023)	-0.0995*** (0.020)
	Rural	-0.132*** (0.022)	-0.135*** (0.024)	-0.0682*** (0.018)
Observations		1,806,831	1,807,594	1,807,594
R-squared		0.366	0.195	0.246
Controls		X	X	X
Year fixed effects		X	X	X
Municipality and School fixed effects		X	X	X

Notes: (1) The coefficient *Treat*Post* corresponds to the estimated parameter β_2 of equation (1), which is the difference-in-difference estimation of the effect of the 2010 climate shocks on the test scores. In this case, the post-treatment period is disaggregated by year. *Treat* indicates whether a student belongs to the control group (*Shock*=0) or the treatment group (*Shock*=1). (2) *** p<0.01, ** p<0.05, * p<0.1. (3) Standard errors in parenthesis are clustered at the municipality level. (4) Control variables include dummy variables for male, urban area, being 15 or 16 years old, social strata, income levels, mother education levels, father education levels, student employment status, ownership of household's appliances, internet access at home, age, and age squared. (5) All scale variables were converted into z-scores.
Source: author's calculations based on data from ICFES and SNPAD (2013).

Table 7.
Effects of the 2010 Climate Shocks on Saber 11 Z-Scores, by the Income Levels of Students' Households.

Dependent variable: Z-score		Total	Language	Math
Treat*Post: 2010	Low	-0.0888*** (0.015)	-0.0383*** (0.014)	-0.110*** (0.018)
	Medium	-0.0682*** (0.017)	-0.0341** (0.015)	-0.0760*** (0.022)
	High	-0.0468* (0.025)	-0.0596** (0.025)	0.0042 (0.024)
Treat*Post: 2011	Low	-0.225*** (0.030)	-0.383*** (0.052)	-0.191*** (0.025)
	Medium	-0.161*** (0.032)	-0.242*** (0.051)	-0.115*** (0.027)
	High	-0.0429 (0.045)	-0.0424 (0.059)	0.00849 (0.044)
Treat*Post: 2012	Low	-0.153*** (0.022)	-0.141*** (0.023)	-0.103*** (0.017)
	Medium	-0.125*** -0.0242	-0.117*** (0.023)	-0.0913*** (0.020)
	High	-0.0361 (0.034)	-0.0664** (0.030)	-0.0122 (0.034)
Observations		1,806,831	1,807,594	1,807,594
R-squared		0.366	0.195	0.246
Controls		X	X	X
Year fixed effects		X	X	X
Municipality and School		X	X	X

Notes: (1) The coefficient *Treat*Post* corresponds to the estimated parameter β_2 of equation (1), which is the difference-in-difference estimation of the effect of the 2010 climate shocks on the test scores. In this case, the post-treatment period is disaggregated by year. *Treat* indicates whether a student belongs to the control group (*Shock*=0) or the treatment group (*Shock*=1). (2) *** p<0.01, ** p<0.05, * p<0.1. (3) Standard errors in parenthesis are clustered at the municipality level. (4) Control variables include dummy variables for male, urban area, being 15 or 16 years old, social strata, income levels, mother education levels, father education levels, student employment status, ownership of household's appliances, internet access at home, age, and age squared. (5) All scale variables were converted into z-scores.

Source: author's calculations based on data from ICFES and SNPAD (2013).

Sensitivity Analysis

Table 8 presents a sensitivity analysis to examine how changes in the definition of treatment and control groups affect the overall results. Both groups share the fact that for the years 2006, 2007, 2008, and 2009, the average number of people affected by climate-related disasters (per 100,000 inhabitants) in a municipality was less than or equal to the average of all municipalities for each year. Now, the 2010 figure defines whose students belong to each group. If it was less or equal to the 2006-2009 average of the municipalities' average, they belong to the control group, but if it was higher, they belong to the treatment group. Columns (i) to (iv) of Table 6 show alternative criteria for defining treatment and control groups, having as cutoff point four different percentiles (75th, 80th, 85th, and 90th percentiles) of the distribution of the 2006-2009 municipalities' average of the people affected by climate-related disasters. In general, the results are robust to the four different definitions of treatment and control groups, both for the total score, as well as for the language and math scores.

Possible Channel of Transmission: Schools' Destruction

One of the direct effects of climate-related events is the destruction of physical capital. This section examines the destruction of schools as a possible channel of transmission from the climate shocks of 2010 to the Saber 11 test results. According to SNPAD, in 2010, 501 schools were damaged in 154 municipalities, 351% more than in 2009. A difference-in-difference approach was implemented to test whether this destruction of physical capital might have affected the test scores. The model specification is given by equation (2).

$$Score_{ijt} = \beta_0 + \beta_1 Post + \beta_2 \left(School2010_j * Post \right) + \beta_3 \mathbf{X}_{it} + \alpha_k + \theta_t + e_{ijt} \quad (2)$$

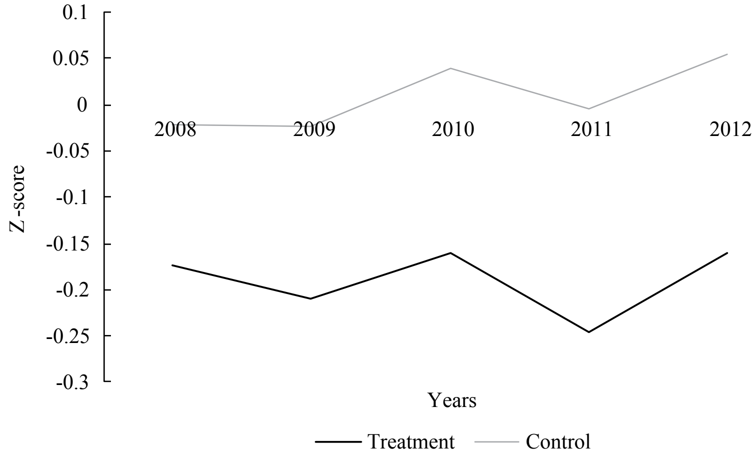
Where $Score_{ijt}$ represents the Saber 11 average test score of the student i living in the municipality j in the year t. $School2010_j$ is a dummy variable taking the value of 1 if the student i was living in a municipality where the number of schools destroyed per 100,000 people in 2010 —as the result of a natural disaster— was greater than the 95th percentile of the distribution. *Post* is a dummy variable for the period 2010-2012; $\mathbf{X}_{it}$ is a vector of control variables; α_k and θ_t represent school and time fixed effects, and e_{ijt} is an error term. The common trend assumption is shown graphically in Figure 4.

Table 8.
Effects of the 2010 Climate Shocks on Saber 11 Z-Scores: Alternative Definitions of Treatment and Control Groups.

Dependent variable: Z-score	**Percentile criteria for defining treatment and control groups**	**(i) p.75**	**(ii) p.80**	**(iii) p.85**	**(iv) p.90**
Total	Treat*Post	-0.129*** (0.021)	-0.131*** (0.022)	-0.128*** (0.025)	-0.127*** (0.025)
	Observations	1,806,831	1,806,831	1,806,831	1,806,831
	R-squared	0.366	0.366	0.365	0.365
Language	Treat*Post	-0.150***	-0.152***	-0.151***	-0.155***
		(0.027)	(0.027)	(0.029)	(0.031)
	Observations	1,807,594	1,807,594	1,807,594	1,807,594
	R-squared	0.194	0.194	0.194	0.194
Math	Treat*Post	-0.106***	-0.107***	-0.104***	-0.109***
		(0.019)	(0.020)	(0.023)	(0.026)
	Observations	1,807,594	1,807,594	1,807,594	1,807,594
	R-squared	0.246	0.246	0.246	0.246
Controls		X	X	X	X
Year fixed effects		X	X	X	X
Municipality and School fixed effects		X	X	X	X

Notes: (1) The coefficient *Treat*Post* corresponds to the estimated parameter β_2 of equation (1), which is the difference-in-difference estimation of the effect of the 2010 climate shocks on the test scores. *Treat* indicates whether a student belongs to the control group (*Shock*=0) or the treatment group (*Shock*=1). (2) *** p<0.01, ** p<0.05, * p<0.1. (3) Standard errors in parenthesis are clustered at the municipality level. (4) Control variables include dummy variables for male, urban area, being 15 or 16 years old, social strata, income levels, mother education levels, father education levels, student employment status, ownership of household's appliances, internet access at home, age, and age squared. (5) All scale variables were converted into z-scores.
Source: author's calculations based on data from ICFES and SNPAD (2013).

Figure 4.
School Destruction: Parallel-Trend Assumption, 2008-2012.



Source: author's calculations based on data from ICFES and SNPAD (2013).

Table 9 presents the pooled OLS regression results of equation (2). The destruction of school buildings, because of natural disasters, decreased Saber 11 test scores. The impact was long-lasting as it dropped not only the 2010 test scores but also the results of the years after. This result could be due to restrictions of economic resources or unavailability of credit at the municipality level, which deters reconstruction efforts and lengthens the initial effect of the shock. Because of the damages or destruction of school buildings teachers might be unable of lecturing and, in some cases, the reallocation to a temporary building might not provide the optimal conditions in terms of space, comfort, or resources. In consequence, students might have missed lessons, be given incomplete contents, and be taught classes in inappropriate places. All of which could ultimately affect their Saber 11 test scores.

Table 9.
Effects of the 2010 School Buildings Destruction on Saber 11 Z-Scores.

Dependent variable: Z-score	Total	Language	Math
School2010*Post	-0.0600**	-0.0627**	-0.0483**
	(0.026)	(0.030)	(0.023)
Observations	2,283,721	2,284,525	2,284,525
R-squared	0.37	0.198	0.247
School2010*2010	-0.0405**	-0.00831	-0.0368*

(*Continued*)

Table 9.
Effects of the 2010 School Buildings Destruction on Saber 11 Z-Scores.

Dependent variable: Z-score		Total	Language	Math
		(0.018)	(0.013)	(0.021)
School2010*2011		-0.0818**	-0.123**	-0.0610*
		(0.037)	(0.059)	(0.032)
School2010*2012		-0.0579**	-0.0574**	-0.0472**
		(0.027)	(0.025)	(0.020)
Observations		2,283,721	2,284,525	2,284,525
R-squared		0.37	0.198	0.247
Controls		X	X	X
Fixed effects	Year	X	X	X
	Municipality	X	X	X
	School	X	X	X

Notes: (1) The coefficient *School2010*Post* corresponds to the estimated parameter β_2 of equation (2), which is the difference-in-difference estimation of the effect of the 2010 school destruction on the test scores. The dummy variable *School2010* is equal to 1 if the student was living in a municipality where the number of schools destroyed per 100,000 people in 2010, as the result of a natural disaster, was greater than the 95th percentile of the distribution. (2) *** p<0.01, ** p<0.05, * p<0.1. (3) standard errors in parenthesis are clustered at the municipality level. (4) control variables include dummy variables for male, urban area, being 15 or 16 years old, social strata, income levels, mother education levels, father education levels, student employment status, ownership of household's appliances; internet access at home; age; age squared. (5) all scale variables were converted into z-scores.
Source: author's calculations based on data from ICFES and SNPAD (2013).

Discussion

According to the results, the 2010 *Shock* decreased students' Saber 11 test scores. It is then possible that the extreme natural events could have affected some of the language and math skills assessed by the test. These skills include interpretation, argumentation, and proposition—in the case of language—, and communication, reasoning, and problem-solving —in the case of math—. Since the lack of interaction between students' and their peers/relatives/teachers affects language skills (Graham & Perin, 2007; Wentzel, 2012), a likely explanation for the strong effect on the language test scores is that the shock could have prevented or diminished such interactions. The heterogeneous results are in line with the literature, as natural disasters and climate change affect strikingly more women, rural dwellers, and poorer households. Because of gender-discrimination issues, women are more affected than men by natural disasters, and suffer most of the negative consequences of these events, including, for example, a greater decrease in their life expectancy (Neumayer & Plümper, 2007) and a larger deterioration of their human capital (Goh, 2012). Rural dwellers' income depends on agricultural production, which is greatly affected by climate variations and natural disasters. A possible response of rural households, to soften the impact of the income losses derived from the shock, is to resort to children's help (Fitzsimons, 2007; Kazianga, 2012), affecting their amount of time dedicated to studying. Finally, although climate shocks can cause severe damages to both rich and poor households, income levels play an essential role in the ability to cope and respond with the negative impacts of a natural disaster, as well as in the possibilities to recover in the aftermath of the events (Masozera, Bailey, & Kerchner, 2007). Therefore, having less monetary resources magnifies the harmful effects of a natural disaster.

CONCLUSIONS

This paper estimated the impact of the unprecedented climate shocks that hit Colombia in 2010 on the cognitive skills of high school students. It used Saber 11 test scores (a national standardized test for high school students prior to graduation) as a qualitative proxy for human capital. This approach is new in the literature of the relationship between climate shocks and human capital since this literature has focused mainly on the impact on quantitative outcomes, such as years of schooling, school enrollment ratios, and students' attendance or adult literacy rates. According to the findings, the 2010 shocks decreased Saber 11 test scores during the period 2010-2012, especially in 2011. The negative impact was greater on female and rural students' test scores than on those of male and urban students. The shocks did not only decrease the test scores of poor students, as suggested by the literature; they also did it on the test scores of middle-income students.

A possible channel of transmission was explored. The destruction of physical capital, through the damage of school buildings, might have prevented teachers from lecturing and students from attending classes under appropriate conditions. Missed classes, incomplete contents, and unsuitable classrooms could have decreased students' Saber 11 test scores. The results of this paper provided new evidence of the non-monetary costs of natural disasters, especially on the impact of these climate-related events on qualitative measures of human capital. Future research in this topic should focus on (1) credit restrictions, both at the municipality and at the household level, as a possible additional channel of transmission since it is yet to prove whether access to credit can lessen the impact of natural disasters on qualitative measures of human capital; and on (2) studying the long-term effects of 2010 shocks on college performance and labor market outcomes.

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