Climate Shocks and Human Capital

The Impact of Natural Disasters on Students' Performance in Standardized Tests

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Abstract

Using a difference-in-difference approach with repeated cross-sections, this paper investigates the impact of the climate shocks occurred in Colombia in 2010 on the results in the country's state standardized test, "Pruebas Saber 11", during the period 2010-2012. Even though cognitive skills variables have been recognized as better proxies for human capital than quantitative measures, the literature on the relationship between climate shocks and human capital has focused on the latter. By using two unique datasets, one linking test scores with students' socioeconomic characteristics, and the other containing the climate-related events at the municipal level, 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 of 2010 had a strong negative impact on the test outcomes, especially on those of low-income students; the impact was stronger on male and urban scholars; moreover, having experienced previous shocks seems to have lessened this impact, which points to the importance of adaptation and coping strategies; finally, health deterioration and physical capital destruction could have been two of the channels of transmission, due to the increase in the number of malaria and dengue cases, diseases that are related to weather conditions, and the damaged of school buildings, which might prevent students from attending classes.

Key words: Climate Shocks, Natural Disaster, Human Capital, Cognitive Skills, Colombia.

JEL codes: O12, I20.

Introduction

Using two unique datasets, and applying a difference-in-difference framework with repeated cross-sections, this paper investigates the impact of the severe weather shocks that affected Colombia in 2010-2011 on the results in the country's state standardized test "Pruebas Saber 11" in the period 2010-2012. Understanding the factors behind the performance of students in national standardized tests is important since these results operate as a market signaling of the student's skills and knowledge; they also allow some students to continue studying at a higher education level, as some universities not only require the test scores as part of their application process but also use them to rank students, and so they are important for promoting social mobility.

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By using a qualitative proxy of human capital, such as cognitive test results, this paper will contribute to the literature on the relationship between human capital and natural shocks. This literature has focused primarily on quantitative proxies of human capital, such as years of schooling, school enrollment ratios, students' attendance or adult literacy rates. However, recent research on human capital and educational systems is focusing more and more on qualitative measures of educational attainment, such as cognitive skills (test score results), at the individual level, or a country's quality of education, at the aggregate level, rather than on quantitative measures. This is because qualitative measures seem to be better predictors of economic growth and income distribution, but also of individual's future career success and productivity (Wößmann, 2003; Orazem, 2007; Baird, 2012). Moreover, time spent in school does not necessarily translate into more knowledge or better skills, since this variable is not a schooling outcome, but a component of the educational production process (Orazem, 2007). In fact, differences in adult earnings are better explained by cognitive achievements than by years of schooling (Glewwe, 2002, cited by Orazem 2007), as suggested by evidence for the United States and the United Kingdom (de Coulon et al., 2011). Plus, cognitive tests results account for differences in the quality of education, one of the cornerstones in the theory of human capital (Wößmann, 2003).

As argued by Orazem (2007), 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. So, 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 quality indicators of education. There is also a lack of studies on this relationship for Colombia, although this country has suffered from several natural disasters in its past. 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, similar to SAT) plus the personal characteristics and family background of each individual test-taker; and SNPAD dataset provides information on the natural disasters that have affected Colombia's municipalities since 1998.

The theory of human capital, proposed in the 1950s and 1960s by Schultz, Mincer, and Becker, brought to the spotlight of development economics the importance of education and accumulation of knowledge. From this theoretical point of view, education can be considered as an investment that would render benefits in the future, not only to the individual who invested in his education (micro level), but also to nations as a whole (macro level). In fact, the theory states that a great part of the differences in wages are due to differences in the productivity of individuals, but productivity is itself determined by previous investments made by these individuals in education and training (Cahu and Zylberberg, 2004). Human capital is then a key element in the development of nations; it enhances the welfare and the choices available to people (Nahapiet, 2011), but at the same time it fosters economic growth (Barro, 2001). As Becker states:

> The 21st century is clearly placing much greater emphasis than ever before on the importance of knowledge and information to the development of both countries and individuals (…) This means that it is more important than ever for both individuals and for nations to acquire knowledge, skills, and the experience to know how to acquire additional information (Becker, 2011, p. xv).

However, the stock and the accumulation of human capital can be threatened by the uncertainty of climate shocks. These shocks, similar to economic downturns, will have an influence not only on the returns of education for the people affected by the shock, but also on their attitudes towards acquiring human capital (Broomhall and Johnson, 1994). The issue of natural disasters is even more relevant to human capital if we consider the state of education in developing countries. In these countries, the limited capacity in human and financial resources is one of the main reasons why the quality of education is so low, with students learning much less than they should, according to their curriculums, and also learning less compared to students in developed countries (Glewwe and Kremer, 2006). In this scenario, climate shocks will make the convergence of these countries to the quality standards in education reached by the developed world even more difficult.

Over the last hundred years the world has experienced a serious threat to its existing forms of living: a significant warming, as a result of the increase in the emission of greenhouse gases. This phenomenon has had regional and global consequences, such as: reduced soil moisture, precipitation, droughts, sea level rise, high-temperature events, and floods, among others. Models projections conclude that the average annual global temperature for the period between 2007-2027 will rise about 0.2°C per decade, the average sea level will increase by 0.1 to 0.2 meters by 2090-2099 (relative to 1980-1999), and the frequency of climate shocks, such as heavy precipitations, hot extremes, and heat events, are very likely to increase in the next 100 years (IPCC, 2007). Moreover, the wide range of those projections generates uncertainty in terms of the regional and local socio-economic impacts of climate change (Yohe and Schlesinger, 2002).

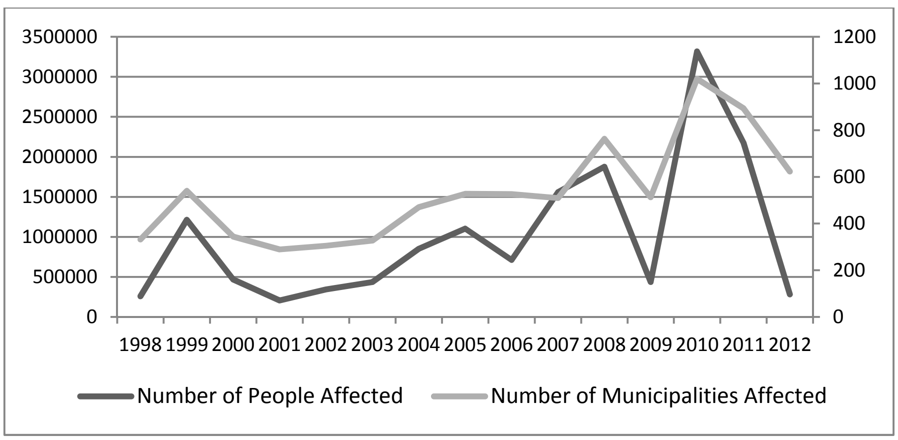
Even though climate shocks are part of the history of mankind, the increasing rate of occurrence of such events and its devastating effects on the lives of millions of people around the world have recently attracted attention to this issue (UNDP, 2007). In developing countries, a high percentage of the world population still depends on agriculture as its primary source of income, and many of the people living in the surroundings of the urban areas (slum dwellers) live in deplorable conditions. For these people, even small changes in climate can have an enormous impact, due to the nonlinearity response of economic and social systems (Sachs, 2006). Climate shocks might destroy crops and negatively affect not only people's assets and savings, but also their health, nutrition, and education. This implies uncertainty, vulnerability, and fewer opportunities to overcome their current living conditions, creating cumulative vicious cycles of disadvantages that are transmitted from generation to generation (UNDP, 2007).

What is more, those risks and vulnerabilities related to climate change are increasingly faced by poor people (UNDP, 2007; The World Bank, 2010). Indeed, during the period 2000-2004, 1 in 19 of the people affected by a climate shock was living in a developing country, compared with only 1 in 1,500 for OECD countries (UNDP, 2007, p.76). Additionally, the progressively frequency and intensity of such events might even compromise the historical resilience of some regions (Lacambra et al., 2008). In this context, understanding the links between natural shocks and human development —human capital, in particular, becomes important, 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 developing countries.

Colombia is a natural disaster hotspot. According to de la Fuente (2012), Colombia ranks at number 11 in the global ranking of population in areas of risk; 21.2% of its territory is at risk from two or more natural hazards; 84.7% of the population living in these areas could be potentially affected; plus 86.6% of the GDP of risk-prone areas is at stake. According to the National System for the Prevention and Attention of Disasters (SNPAD, 2013), since 1998, there has been an increasing rate of occurrence of climate shocks events in the country, as well as a raise in the number of people affected. From 1998 to 2011, the average annual increase in the number of climate-related events was 23%. Floods and landslides accounted for 50.6% and 20.5% of all events, respectively. While in 1998 258,341 people were victims of climate-related disasters, in 2010 this figure was 3,319,686.

What is more, the severe weather shocks of 2010 were the worst experienced by Colombia in its recent history. To mention just a few statistics, with respect to the previous year (2009), the number of people affected in 2010 increased in 661% (3,319,686), the number of families affected in 763% (764,274), the number of houses destroyed in 508% (12,297), the number of houses damaged in 519% (376,349), 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 was also felt in almost the whole territory. In 2009, 513 municipalities were affected by climate events; in 2010 this figure rose to 1,020 (more than 90% of all Colombian municipalities). Moreover, the shocks persisted in 2011, although to a lesser intensity. The Graph 1 shows the number of people (per 100,000 inhabitants) and the number of municipalities that were affected by climate-related events during the period 1998-2012. The year 2010 stands alone as the most intense year in terms of the severity of climate shocks. Therefore, this particularity provides a unique opportunity to conduct a natural experiment and apply an impact evaluation methodology, such as difference-in-difference, to assess the impact of this severe change in the intensity of climate events on the schooling achievement of high school students, as measured by the results in Saber 11 test.

Graph 1. *Intensity of Climate Shocks in Colombia, 1998-2012 (number of municipalities affected times number of people affected by climate-related disasters)*



Source: SNPAD, author calculations.

This paper is structured as follows. Section I presents a literature review on the relationship between climate shocks and human development, it also includes some illustrative empirical studies relating climate events and human capital, and the importance of perceived future risk in the human capital investment decisions of households; Section II identifies the main determinants of schooling outcomes, especially those related to student characteristics, parents' and peers' characteristics, and school and teacher characteristics; 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; Section VI introduces two possible channels of transmission: health deterioration and schools buildings destruction, and discusses the possible implications of credit constraints; finally, the last section concludes.

I. Literature Review

A. Climate Shocks and Human Development: Theory

The effects of natural disasters on economic growth (one of the components of human development) are not clear-cut, since both positive and negative effects are found in the literature, without providing definite conclusions (Chhibberet al., 2008; Baez et al., 2009; Ferreira and Schady, 2009; McDermott, 2012). In general, natural disasters reduce the stock of capital in the economy causing an immediate decrease in the GDP. But, what is the long-term impact of such disasters on the economic performance of the affected region? On the one hand, authors such as Cavallo et al. (2010) argue that natural disasters, either large or small, do not seem to have an apparent impact on the short/long-term economic growth. On the other hand, authors such as Chhibberet al. (2008), consider the possibility of such impact, by theoretically analyzing four different yet-to-test scenarios. In the first two scenarios, the long-term growth rate is not affected, meaning that after the natural shock, the economy will eventually return to its long-term growth path, either with (scenario 1) or without (scenario 2) a short-term expansion of its production levels. In the next two scenarios, the long-term growth rate is affected, either negatively (scenario 3), because of the permanent reduction in the stock of capital, or positively (scenario 4), due to the technological change introduced by the restitution of capital.

Therefore, the reduction in the stock of capital that results from a natural disaster is likely to produce a temporary decline in the income and production levels of the affected economy. Now, what are the possible effects of this chain of events on human capital, especially on schooling outcomes?

The answer to this question, according to Ferreira and Schady (2009), will depend on the magnitude of two opposite forces: the income and substitution effects. The income effect, by reducing households' available resources, has a negative impact on schooling; while the substitution effect, by affecting the opportunity cost of studying versus working (with more children studying after a shock, due to a reduction in child wage), has a positive impact on schooling. 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 authors claim, 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 economic crisis. Nevertheless, the authors state that the effects are heterogeneous within and across countries. In this sense, natural shocks have differential effects depending on gender (women usually suffer the most, Goh, 2012), race, socioeconomic status, occupation, and location, but the poor are always the most negative affected (Ferreira and Schady, 2009; Baez et al., 2009).

In fact, climate-related events increase the odds that a household remains or becomes poor (Glave et al. 2008, for the case of Peru); in fact, 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 and 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 et al., 2010). Moreover, the long-term effects of these events on human development are felt stronger on poorer 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 and Noy, 2010); plus, these regions usually have lower levels of infrastructural development, awareness, and coping capacities (Goteng et al., 2012). Accordingly, it is stated that economic and human development can counteract the negative effects of climate shocks on a certain region; that is, it increases its resilience (Toya and Skidmore, 2007).

The literature has also acknowledged the existence of direct and indirect effects on human capital derived from climate-related events. 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 and Seck, 2007; Baez et al., 2009; 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., 2009), which will negatively affect its future accumulation and, therefore, the human development possibilities of the affected region.

The negative impacts of the direct effects are certain, but the indirect effects can either counteract or reinforce these impacts. Contrary to the direct effects, the indirect effects will be affected by 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., 2009; Crespo-Cuaresma, 2010; McDermott, 2011). Plus, the destruction of infrastructure will require investment decisions by the affected households; but, poorer families will find it difficult to invest, because of credit restrictions or unavailability of credit to them. In such situation, credit-constrained households will be forced to disinvest, by selling-off productive assets, in order to cope with shock. Therefore, 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 on human and physical capital accumulation. In particular, the consumption of food, health and educational services will decline. Plus, parents might resort to children's time as a buffer mechanism to soften the shock. 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 temporary withdrawn from school (Baez et al., 2009; 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., 2009; Ferreira and 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., 2009). Finally, because of the discontinuation of schooling, children might not be able to keep up at a later time or will drop out of the educational system for good, creating a path-dependent effect (Baez et al., 2009). So, the short-term trade-offs faced by households in order to smooth consumption can have long-lasting negative 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 and Seck, 2007). In this sense, the evidence supports the fact that the net effect of the direct and indirect effects is strongly negative and long-lasting (Baez et al., 2009).

B. Climate Shocks and Human Capital: Empirical Evidence

As was stated in the previous section, the occurrence of natural disasters not only increases mortality risk, affecting the stock of human capital (because of the casualties of educated persons), but also affects the decisions of families regarding the use of child labor, in order to compensate for the income losses from the disaster. These hypotheses have been confirmed by different empirical studies. For example, using Bayesian Model Averaging methods, Crespo-Cuaresma (2010) finds a strong negative long-run effect of natural disasters on the rate of secondary school enrollment, a proxy for human capital accumulation. His results are consistent across countries and robust to different model specifications. The use of child labor to compensate for income losses is evidenced by Duryea et al. (2007) for the case of Brazil; in this study, the authors analyze the impact of household economic shocks on the reallocation of children's time from school to work; their results indicate that transitory unexpected economic shocks force families to increase children's labor in detriment of children's schooling.

Early life natural disasters have also been documented to have a negative effect on children's future human capital. Studying the case of rural Vietnam, Thai and Falaris (2011) find that negative climate shocks during gestation and early life affect households' income, by destroying crop production, and thus, have an indirect effect on children's nutrition, measured as height-for-age, and on schooling, measured as delayed entry to school and slower progress once enrolled. The effects vary by region, which shows dependence on specific region's constraints, with the regions where households face greater difficulties to smooth consumption being the most affected by the shock. In the case of Mozambique, a similar result in terms of children's nutrition was found by Prado (2009): Natural disasters negatively affect children's height-for-age for children between one and three years old. In the case of Mali, according to De Vreyer et al. (2011),early life shocks, like the one experienced by Malians in their early childhood back in the period 1987-1989, when a locust plague hit the country, have a long-lasting effect on nutrition and, thus, on educational enrollment and completion. The study shows a differential effect on girls and boys, confirming the gender-discrimination situation of the country, and a lack of insurance mechanisms that could have helped smoothing consumption.

Another case study, this time for Colombia, reaffirms the negative effects of climate shocks on human capital. In accordance with Bustelo et al. (2012), the 1999 earthquake on the coffeegrowing region of Colombia had a negative short-term impact on schooling and nutrition (the impact persisted in the medium-term, although with a lesser intensity), with parents reducing their investments in the human capital of their children. Their findings support the hypothesis that one of the households' mechanisms to cope with natural disasters is reducing their investment in their children's human capital, by withdrawing them from school or impoverishing their nutrition. Plus, even when remedial actions are taken right after the shock, a natural disaster might have persistent effects on the accumulation of human capital, with negative long-term welfare effects.

So far, most of the studies have focused on the negative effects of climate shocks on human capital. Still, climate shocks can also have positive consequences through a sudden increase in income. For example, for the case of Indonesian adults, Maccini and Yang (2009) studied the impact of early-life shocks (higher rainfall) on economic development variables, including health, education, and household's assets. Their results point out that higher early-life rainfall has a positive effect on women's variables (resulting in higher socioeconomic status), but not on men's, stressing the gender discrimination issues of the Indonesian society. The channel through which higher rainfall influence the future socioeconomic status of women is through its impact on agricultural production, which, in turn, will increase household's income, improving, later in life, their health status and schooling attainment.

C. Perceived Future Climate Risk and Human Capital

Human capital is not only affected by actual climate shocks; the perceived future risk, whether it materializes or not, can also have a profound impact on this variable. For instance, evidence from rural Indonesia suggests that parents' schooling decisions are affected by environmental risks; more precisely, under riskier environments parents tend to postpone their children's entry into school (Korkeala, 2012). Moreover, the effect of a perceived future risky environment, decomposed into household and village effects, on the stock of human capital of Indonesian rural children, indicate that village-level risk (the aggregate component), such as past fluctuations in rainfall, has a negative effect on children's educational attainment, while household-level risk (the idiosyncratic component), such as risk in parental income, has not significant effect (Fitzsimons, 2007). These findings point out the difficulty of households to insure against village-level risks, and therefore, their need to resort to child labor, in order to buffer against the shock; these results suggest also that the market for this insurance type might be incomplete (Fitzsimons, 2007).

So, focusing only on current shocks and the ex-post responses of households to them might not provide a full picture of the total costs derived from income risk, as a result of a climate shock, especially if education exhibits non-linear returns (Kazianga, 2012) or if the effect of future disaster risk on asset holding is not linear (Yamauchi et al., 2009). On the one hand, the results of Kazianga (2012) from rural Burkina Faso, although suffering from external validity, indicate that income uncertainty (income standard deviation) has a negative effect on household schooling decisions. This is because, in such uncertain environments, parents might decide not to enroll some of their children in school and put them to work, in order to minimize the impact of future shocks, even if these shocks do not materialize. On the other hand, if disaster probability is higher than a certain threshold, then asset holding will be positive; however, future risk has two opposite effects: it incentives investments, so as to lessen the impacts of future disasters; but it also disincentives investments, due to the uncertainty of the returns of these investments in front of a future risk (Yamauchi et al., 2009). In this line of reasoning, the study of Yamauchi et al. (2009), for Bangladesh, Ethiopia and Malawi, finds that the former effect is greater than the latter in disaster prone regions. In a similar study, these authors conclude that human capital investments and asset holding prior to a natural disaster shock help both increasing resilience and upholding investments in human capital in the aftermath of a shock (Yamauchi et al., 2009b).

II. Determinants of Schooling Achievement

According to the literature, schooling achievement is the result of student characteristics, parents' and peers' characteristics, and school characteristics.

A. Student Characteristics

This section describes the main factors associated to the student personal characteristics that have been found to be important in determining schooling outcomes, such as test scores. These characteristics include students' personality traits, health, time allocation, labor decisions, and gender.

Students' personality traits, although not easily measurable, have an important role in explaining schooling outcomes. For example, Baird (2012) argue that, while for some countries school characteristics (measured as school resources) still account for a great part of the performance gap between low and high socioeconomic status students, factors such as students' effort, interest, and motivation (usually, unmeasured characteristics) are generally more relevant to explain the achievement gap between these socioeconomic groups. In fact, students with high self-esteem tend to create virtuous circles of achievement, because, by trusting in their own abilities, these students put more effort when performing a task, and, therefore, tend to accomplish more, reinforcing the circle (Darolia and Wydick, 2011). A prior positive academic self-concept (students who think of themselves as being more able, effective, or confident) have also an important positive impact on different schooling outcomes, such as interest in the subjects, grades, and scores in standardized tests (Marsh et al., 2005).

Children's health has also strong and significant positive causal impact on their academic outcomes (Wolfe, 1985; Behrman, 1996; Glewwe and Miguel, 2008). One example is provided by Sabia (2007), who, after controlling for unobservable heterogeneity, finds that obesity, measured with a body mass index, has a negative impact on schooling outcomes (GPA) of white girls between 14 and 17 years old (the results are less significant for boys and nonwhite girls). Another case is given by Belot and James (2011), who exploit a shifting towards healthier meal options in Greenwich's schools in the UK; their results suggest that a better nutrition, which translates into better health, improves student's schooling outcomes and decreases absenteeism.

Similarly, Time allocation and labor decisions have an important effect on schooling achievement. Focusing on the effects of time allocation of undergraduate students on their academic results, although the results suffer from endogeneity, Grave (2011) finds that work group and attending tutorials has a negative impact on grades for below-average students, as well as for Engineering and Science students; attending courses has a positive effect only for certain groups of students (high-ability students and females) or certain programs (Engineering and Social Sciences); while, the time allocated to self-study or working as a tutor or academic assistant is positively related to higher grades for all students. Now, concerning labor decisions, Montmarquette et al. (2007) find that working less than 15 hours a week has not necessarily a negative impact on schooling outcomes; however, students who actually have an intensive work and non-worker students who show a preference for intensive work, which indicates a predisposition to a paid-job over studying, are related to low academic achievement (Staff et al., 2010). The preferences of studying over working have been found to be related to being female, having educated parents, and attending a private school (Montmarquette et al., 2007).

Finally, gender seems to have an important effect on academic results, which might stem from inherently gendered behaviors. Niederle and Vesterlund (2010), for example, argue that differences in the way men and women respond to competitive test-taking settings are responsible for the observed gender-related gap in mathematics achievement. These difference responses to competitive environments create a distorting picture of the math skills differences between men and women, which should actually be regarded, in the author's words, as "math skills under competitive pressure". In consequence, single-sex education can have a positive impact on females' math scores, by influencing their math studying decisions and improving their self-confidence in the subject (Fryer and Levitt, 2009, cited by Niederle and Vesterlund, 2010).

B. Parents' and Peers' Characteristics

People whom students interact with in their daily lives, basically parents and friends, play also a major role in school achievement.

In the case of rural students, Broomhall and Johnson (1994) analyze the value that people from rural areas place on education. Their results suggest that the value parents put on schooling together with the availability of local economic opportunities (or the willingness to find better opportunities somewhere else) exert an influence on the importance rural students place on education, which in turn translates into a better student's performance at school. Therefore, parents' perception of the benefits their children can reap from education combined with the socioeconomic conditions of the environment will have a say, in terms of incentives, in the student's and parent's decisions on how much to invest in education, and therefore, on the accumulation of human capital of individuals.

Apart from family income, which affects student's academic outcomes, mostly through the impacts of school choice proxies (Hoxby, 2001, cited by Krieg and Storer, 2008), the literature has found other parents-related variables that explain to a certain extent schooling performance. Parent's cognitive skills, for instance, are highly correlated with their children's academic achievement at school; plus, children of parents with higher cognitive skills are likely to perform better in tests and to have less behavioral and emotional complications (de Coulon et al., 2011). Literature for college performance indicates that parents' reward schemes will exert an influence on their children's academic effort and on their post-school achievement (Darolia and Wydick, 2011). Allowances seem to have a negative to neutral effect on these variables, except if the allowance was given upon the completion of a certain task (conditional allowances), in which case the effect was positive; purchasing a car in high school relates to a lower academic effort; but, children of parents who usually recognize their achievements, by influencing their self-esteem, will tend to exert greater effort in their undergraduate studies (Darolia and Wydick, 2011).

Research on parental closure found mixed effects of this variable on student's high school achievement, with positive effects for Catholic schools and no effects for public schools (Morgan and Todd, 2009). Paternal job loss has a negative impact on children's schooling outcomes, although not maternal job loss, which has a non-significant positive effect on the student's GPA, at least for the Norwegian case; this difference is explained by the claim that men experience more mental distress from a job loss experience than women (Rege et al., 2011). Birth order has no significant effect on test performance, but the number of siblings does negatively impact verbal IQ results (Steelman and Doby, 1983); the reasons provided by the authors are related to the importance for language development of parents' interaction with their children, in terms of stimulation and attention, which could be considerably affected by the number of siblings that would have to compete for their parent's time and dedication.

This latter result was also confirmed by Zimmerman (2003), when analyzing the effects of peer roommates on test scores. The author's results suggest that peer roommates have a more positive and significant effect on verbal tests scores than on math tests scores. Other studies have also remarked the importance of peers in schooling performance. Focusing on 11 years old British children, Robertson and Symons (2003) found a strong effect of peer groups, parents' education, and social class on children's academic achievement. Peer effects explain also, to a great extent, the reasons behind the performance gap between primary school students from Mexico and Cuba (with Cubans outperforming Mexicans) (McEwan and Marshall, 2004); in this study the socioeconomic variables of the student's family appear to be also important, although to a lesser degree; while school and teacher characteristics have no explanatory power when explaining differences in academic achievement across nations. Analyzing the United States case, Lee (2007) finds that both peer racial composition and school have significant effects on the student's academic outcomes.

C. School Characteristics

Most of the interaction between students and their peers and teachers occur in school environments, hence the importance of this variable in schooling performance. As in the case of the number of siblings, the number of students in a class might limit the time a teacher could spend with each of her pupils. In this respect, some research has found that class size reductions and teacher density (number of teachers per student) might exert a positive influence on cognitive skills and academic achievement (Fredriksson and Öckert, 2008; Ding and Lehrer, 2011), but the evidence is not clear-cut in the case of non-cognitive skills, such as motivation, listening, and self-concept, in which case family background seems to be more important (Ding and Lehrer, 2011). Results from a natural experiment and a field experiment suggest that attending a high-scoring school has a positive impact on the student's own academic achievement (Hastings and Weinstein, 2008), but, at the same time, it has been found that differences in school performance result to a great part from the socioeconomic characteristics of their students rather than from the school quality (Krieg and Storer, 2008). The literature points also to the importance of remedial summer schools and retention programs on academic achievement, especially for young disadvantaged students (Jacob and Lefgren, 2004).

Teacher quality has been considered an important factor affecting students' cognitive skills. In this respect, focusing on public elementary education, Rivkin et al. (2005) argue that teachers' quality have an important effect on student's mathematics and reading performance (and therefore on the school quality), and that being exposed to a higher quality teaching environment can counterbalance the negative effects of having a low socioeconomic status. However, the authors found that teacher quality is mostly explained by the unobservable characteristics of the teacher, since years of experience or having a master degree does not seem to have any significant impact. At the international level, Glewwe and Kremer (2006) highlight the importance of teacher's quality as the most important factor affecting school quality and its cross-country differences. Their claim is supported by random experiments conducted in different developing countries, where the substitution of technologies, such as radio education in Nicaragua or computer-assisted learning programs in India, for weak teachers have had a positive effect on the student's academic outcomes; this assertion is also supported by the results found after the implementation of teacher incentives in countries such as Israel and Kenya, where student's performance and test scores were significantly improved (although only on short-run outcomes, in the case of Kenya, and mainly for weaker students, in the case of Israel).

Lastly, central exit examinations have a positive impact on student's academic achievement, (Jürges et al., 2005), but this impact seems to have differential effects, depending on the ability of students; that is, central exit examinations have a lesser impact on low-ability students, compared to high-ability students, due to the characteristics of the labor market for less skilled workers (lower job mobility and limited grades-reading capacity of local employers) (Wößmann, 2005).

III. Data

This paper uses two different unique databases: 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 test is developed by the Instituto Colombiano para el Fomento de la Educación Superior —ICFES (Colombian Institute for the Promotion of Higher Education). The purpose of the test is to assess 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 country’s high schools performance. Now, regarding the contents of the Saber 11 test, the 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 in 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. Specifically, it uses the following information from the database: test results, student characteristics, and household characteristics. Test results include the test scores for each of the subjects of the common core (*language*, *mathematics*, *biology*, *chemistry*, *physics*, *philosophy*, *social science*, and *English*) —the *total score* was calculated as the arithmetic mean of the common core components. Student characteristics include: date of birth (three age variables were constructed from this information: *age* —the student age when the test was taken, *age 15-16* —a dummy variable if the student was 15 or 16 years old, and *age-squared*); *mother education* and *father education*, which ranks the student parents’ level of education on an ascending scale from 0 to 10 (where 0 means “none education” and 10 “graduate studies”); sex (male or female), from which the dummy variable *male* was created; and *work*, a dummy variable if the student had a job (paid or not) (the original database had different job classifications, which were recoded into just one category).

Household characteristics include: *social stratum* (the social stratification by law, ranging from 1 to 6 —1 indicating the lowest and 6 the highest, with each strata sharing similar socioeconomic characteristics; a few students classified as a strata 8 —not stratified, were omitted from the database); *Sisben* —El Sistema de Identificación de Potenciales Beneficiarios de Programas Sociales (The System for the Selection of Beneficiaries of Social Programs), ranging from level 1 to 4 (level 1, 2, and 3 means that the household is classified in any of these levels, whereas level 4 includes households that are classified at a different level and those that are not classified at all), monthly household income (*income*), ranging from 1 to 7, according to the number of minimum wages earned by the household unit on a monthly basis (1: less than 1 minimum wage; 2: between 1 and 2; 3: between 2 and 3; 4: between 3 and 5; 5: between 5 and 7; 6: between 7 and 10; 7: more than 10); number of bedrooms and number of people living in the house, from which the variable *No. of people per dormitory* and *overcrowding (d)* (dummy if the variable *No. of people per dormitory* was equal or greater than 2.5) were created; living zone (urban or rural), from which the dummy variable *urban* was constructed; and, finally, the dummy variables: *car*, *computer*, and *DVD player*, each indicating whether or not the household had at least one of these objects, and *Internet connection* and *cable TV*, each indicating if the household had the service installed (some variables in the original database specified the number of objects the household had, these were recoded to “having at least one”).

From the ICFES database, the variable *total score* is used as dependent variable, whereas the student and household characteristics are used as controls. The total number of students in the database for the period 2008-2012 is 2,669,540. Some summary statistics for some of the main variables as well as the total number of students per year are presented in Table 1.

Table 1. *Summary Statistics for ICFES Database Variables, 2008-2012*

Category	Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Saber 11 Scores	Total score	2,652,365	44.137	6.447	0.000	87.125
	Biology	2,653,386	45.292	8.172	0.000	100.000
	Social Science	2,653,386	44.759	9.237	0.000	112.930
	Philosophy	2,653,386	40.552	9.265	0.000	84.000
	Physics	2,653,386	43.875	8.407	0.000	112.000
	English	2,652,365	42.947	10.084	0.000	111.940
	Language	2,653,386	45.798	8.320	0.000	93.000
	Mathematics	2,653,386	44.763	10.644	0.000	126.000
	Chemistry	2,653,386	45.090	7.419	0.000	94.640
Year	2008	508,253	-	-	-	-
	2009	521,738	-	-	-	-
	2010	540,452	-	-	-	-
	2011	540,441	-	-	-	-
	2012	549,832	-	-	-	-

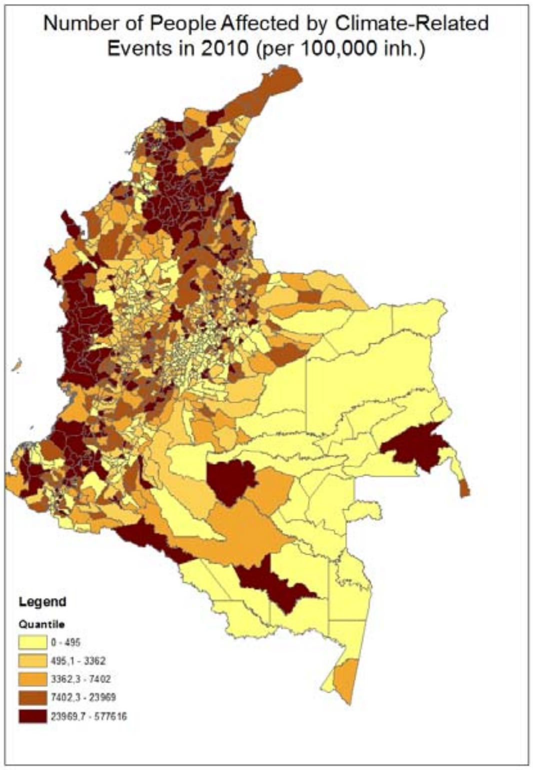
Source: ICFES, Saber 11 database, author calculations.

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). The database 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: date of the event; municipality code; type of event; number of casualties; number of people affected, wounded, or missing; number of houses destroyed or damaged; and number of different public infrastructure affected.

In order to create a shock variable (*shock*), the following variables were used from the SNPAD database: municipality code, number of people affected, and date of the event. The construction of the variable *shock* is detailed as follows. For each year and for each Colombian municipality, the number of people affected by natural disasters per 100,000 inhabitants was created (see Map 1 for the year 2010). This variable was used afterwards to calculate the average of the annual gross changes between 2004 and 2009, as well as the gross change between 2009 and 2010. The 2004-2009 average was then compared with the 2009-2010 gross change using the percentiles 50 and 99. This information was used to select the treatment and control groups. A municipality was considered treated with intensity 1 if the 2009-2010 gross change was greater than the percentile 50 but less than the percentile 99 of the 2004-2009 average (*shock*=1), and it was considered treated with intensity 2 if the 2009-2010 gross change was greater than the percentile 99 (*shock*=2) of the 2004-2009 average. If the 2009-2010 gross change was less than or equal to the percentile 50 of the 2004-2009 average, the municipality was included in the control group.

The reason why the *shock* variables were used as indicators of treatment is because the impact of the natural disasters on the test scores does not seem to follow a linear pattern (as suggested by Sachs (2006) in terms of the non-linear effects of climate change). In fact, the impact of the variable "number of people affected by 100,000 inhabitants", when included as a explanatory variable of the Saber 11 test scores, was close to zero and non significant, indicating that a natural shock might affect cognitive skills only if it surpasses a certain threshold.

Map 1. People Affected by Climate-Related Events in Colombia, 2010 (Per 100,000 Inhabitants)



Source: SNPAD, author calculations.

Table 2 shows some summary statistics for the SNPAD database. In particular, it shows the number of people affected by climate-related disasters, per 100,000 inhabitants, as well as the total number of people affected. The source of the municipalities' populations between 2006 and 2012 was "Departamento Administrativo Nacional de Estadística" DANE (National Administrative Department of Statistics).

Table 2. *Summary Statistics for SNPAD Database Variables, 2006-2012*

Variable	Mean	Std. Dev.	Min.	Max.	No. of people affected
Disasters 2006	3,100.3	9,149.0	0	135,656.8	711,447
Disasters 2007	6,271.9	22,320.0	0	275,423.9	1,559,377
Disasters 2008	8,932.6	22,490	0	214,432.4	1,877,504
Disasters 2009	2,274.7	12,593.3	0	345,651.6	435,851
Disasters 2010	16,614.01	31,605.4	0	577,616.1	3,319,686
Disasters 2011	11,263.16	26,875.1	0	348,439.5	2,178,557
Disasters 2012	1,560.78	7,421.7	0	128,402.6	282,333

Source: SNPAD, DANE, author calculations.

IV. 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 and 2011 on the test scores of the Saber 11 test in the period 2010-2012. The dummy variable *shock* indicates the treatment status of the individuals, that is, a student will belong to the treatment group if she lives in a municipality for which the change in the number of people affected by climate-related disasters (per 100,000 inhabitants) between 2009 and 2010 was either greater than the percentile 50 (*shock* intensity 1) or greater than the percentile 99 (*shock* intensity 2) of the average of the annual changes between 2004 and 2009. The student will belong to the control group if she lives in a municipality where the change in the number of people affected by climate-related disasters (per 100,000 inhabitants) between 2009 and 2010 was less than or equal to the median (percentile 50) of the average of the annual changes between 2004 and 2009 (*shock*=0). Even though *shock* varies at the municipality level, this paper uses student *i* as the unit of observation. The reason for this is the possibility to control for observables available in the ICFES database, as well as to examine heterogeneous effects. The baseline model is given by equation (1), whereas the time-heterogeneous effects model is given by equation (2):

$$score_{it} = \beta_0 + \beta_1 shock_j + \beta_2 Post + \beta_3 shock-2011_j * post + \boldsymbol{\gamma}\mathbf{C}_{it} + \boldsymbol{\delta}\mathbf{S}_{jt} + \boldsymbol{\theta}\mathbf{year}_t + \alpha_k + e_{it} \quad (1)$$

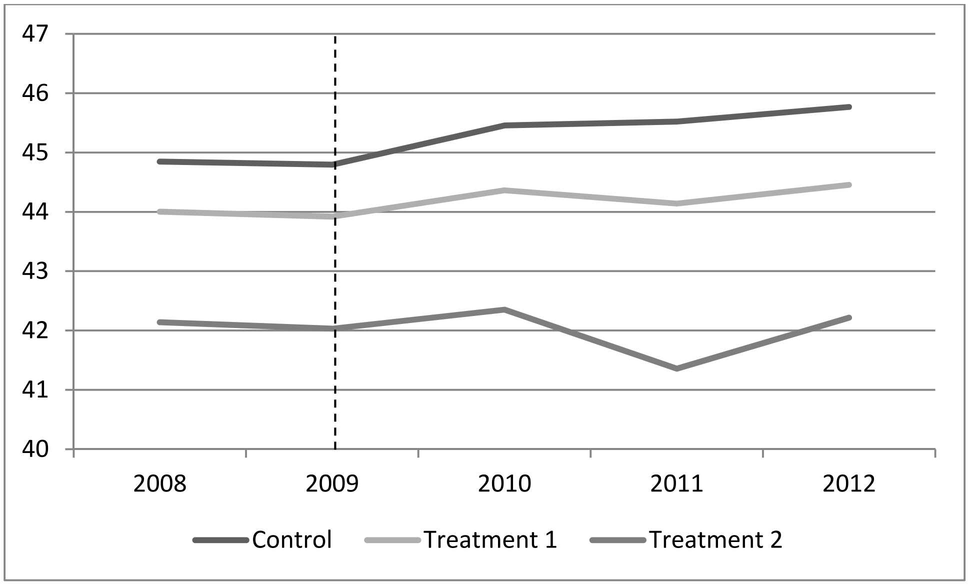
$$score_{it} = \beta_0 + \beta_1 shock_j + \beta_2 y2010 + \beta_3 y2011 + \beta_4 y2012 + \beta_5 shock_j * y2010 + \beta_6 shock_j * y2011 + \beta_7 shock_j * y2012 + \boldsymbol{\gamma}\mathbf{C}_{it} + \boldsymbol{\delta}\mathbf{S}_{jt} + y2008 + \alpha_k + e_{it} \quad (2)$$

where the outcome variable $score_{it}$ represents the test score of student *i* in time *t*; $shock_j$ is a dummy variable equal to 1 if the student lives in a municipality *j* where the shock intensity was 1, and equal to 2 if the shock intensity was 2 ; *post* is a dummy variable equal to one in the post-shock period (2010-2012); *y*2010, *y*2011, and *y*2012 represent dummy variables for the years 2010, 2011, and 2012; $\mathbf{C}_{it}$ is a vector of student and parents control variables (*age*, *age 15-16* —dummy for ages 15 or 16, *age-squared*, *mother education*, *father education*, *male* —dummy for student's sex, and *work* —dummy equal to one if the student works), household control variables (*social stratum*, *sisben*, *income* —monthly household income, *No. of people per dormitory*, *overcrowding (d)* —dummy equal to one if *No. of people per dormitory* is equal or greater than 2.5, *urban* —dummy equal to one if the student lives in an urban area, *car* —dummy equal to one if the household has at least one car, *computer* —dummy equal to one if the household has at least one computer, *DVD player* —dummy equal to one if the household has at least one DVD player, *Internet connection* —

dummy equal to one if the household has Internet connection, and *cable TV*, —dummy equal to one if the household has cable TV); $\mathbf{S}_{it}$ is a vector of climate shocks variables for the years pre and post 2010 (*disasters 2006*, *disasters 2007*, *disasters 2008*, *disasters 2009*, *disasters 2011*, *disasters 2012*), representing the number of people affected by climate disaster per 100,000 inhabitants; $\boldsymbol{\theta}\mathbf{year}_t$ is a vector of dummy variables to control for 2008, 2010, and 2011 year effects; *y2008* is a dummy variable for the year 2008; α_k represents school fixed effects; and, finally, e_{it} is an error term which satisfies $E(e_{it}|Shock2010_{it}) = 0$.

The difference-in-difference estimator ($\hat{\beta}_{DD}$) in equation (1) will be given by β_3; whereas the differential effect of years 2010, 2011, and 2012 in equation (2) will be given by β_5 ($\hat{\beta}_{2010DD}$), β_6 ($\hat{\beta}_{2011DD}$), and β_7 ($\hat{\beta}_{2012DD}$). Under the baseline model specification, β_1 represents the treatment group specific effect; β_2 is a time trend, which is common to treatment and control groups; and β_3 is the true effect of treatment. In order for the model to be correctly estimated, the following assumptions are required: (1) the error term must have mean zero, (2) the error term must not be correlated with any of the variables in the equation, and (3) the parallel-trend assumption, which guarantees that in the absence of treatment (*shock*), the average change in the test score for the treatment group would have been the same as the average change for the control group. Trends in the average Saber 11 scores for the years before the shock (2008, and 2009) for both treatment and control groups are presented in Graph 2. Before the shock, the trends in the average scores were similar for both groups; however, after the shock, the treatment group exhibited a different path. Graphically, the strongest effects of the 2010-2011 natural events were felt in 2011; but they were also felt in the 2012 test scores, although to a lesser extent.

Graph 2. *Parallel-Trend Assumption*



Source: ICFES, SNPAD, author calculations.

This paper implements also a triple-difference approach, in order to analyze the heterogeneous effects, as the literature has pointed out that the impacts of climate shocks on schooling outcomes vary according to certain characteristics, such as sex or living area, for example. The triple-difference model specification for the baseline model is given by equation (3), whereas the triple-difference for the time-heterogeneous effects model is given by equation (4); in both model specifications, Z_{it} represents a variable for which the expected outcome varies with:

$$score_{it} = \beta_0 + \beta_1 shock_j + \beta_2 Z_{it} + \beta_3 post + \beta_4 shock_j * Z_{it} + \beta_5 Z_{it} * post + \beta_6 shock_j * Post + \beta_7 shock_j * Z_{it} * Post + \boldsymbol{\gamma}\mathbf{C}_{it} + \boldsymbol{\delta}\mathbf{S}_{it} + \boldsymbol{\theta}\mathbf{year}_t + \alpha_k + e_{it} \quad (3)$$

$$score_{it} = \beta_0 + \beta_1 shock_j + \beta_2 Z_{it} + \beta_3 y2010 + \beta_4 y2011 + \beta_5 y2012 + \beta_6 shock_j * Z_{it} + \beta_7 Z_{it} * y2010 + \beta_8 Z_{it} * y2011 + \beta_9 Z_{it} * y2012 + \beta_{10} shock_j * y2010 + \beta_{11} shock_j * y2011 + \beta_{12} shock_j * y2012 + \beta_{13} shock_j * Z_{it} * y2010 + \beta_{14} shock_j * Z_{it} * y2011 + \beta_{15} shock_j * Z_{it} * y2012 + \boldsymbol{\gamma}\mathbf{C}_{it} + \boldsymbol{\delta}\mathbf{S}_{it} + y2008_t + \alpha_k + e_{it} \quad (4)$$

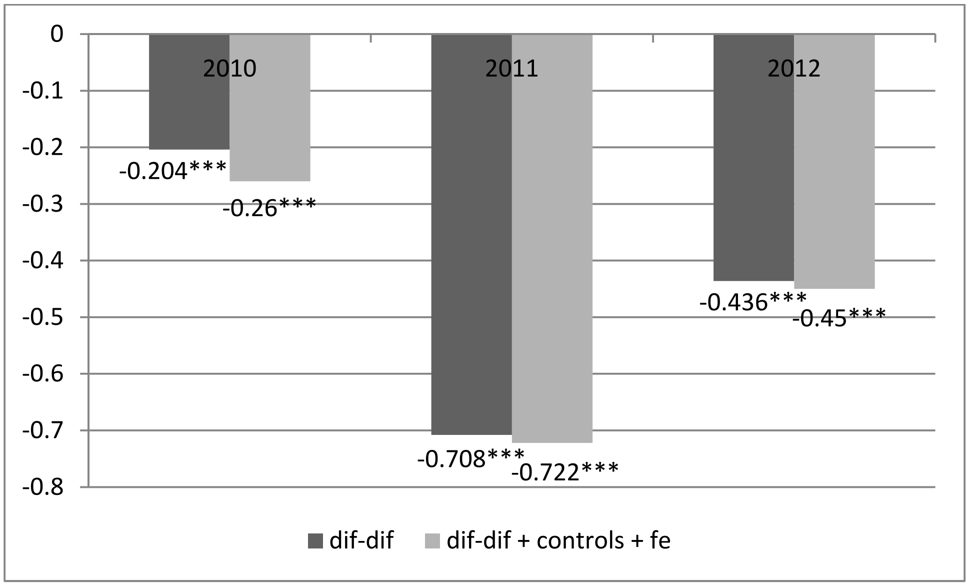
This paper estimates equations (3) and (4) to measure the differential impacts of shocks of 2010-2011 (*shock*) on the variables *male*, *urban*, *disasters 2006*, *disasters 2007*, *disasters 2008*, *disasters 2009*, *social stratum*, and *income*. The triple-differences estimator ($\hat{\beta}_{zDDD}$) in equation (6) is given by β_7; β_6 measures the impact of the variable *shock* when *Z* = 0, and $(\beta_6 + \beta_7)$ the impact when *Z* = 1; and so the estimator $\hat{\beta}_{ZDDD} = \beta_7$ identifies the differential impact of the variable *shock* for *Z* =

1 with respect to Z = 0. In the case of equation (4), the differential impact of *shock* on the different values of Z for the years 2010, 2011, and 2012 is given by $\beta_{13}(\hat{\beta}_{Z_{2010}DDD})$, $\beta_{14}(\hat{\beta}_{Z_{2011}DDD})$, and $\beta_{15}(\hat{\beta}_{Z_{2012}DDD})$, respectively.

IV. Results

Graph 3 presents the difference-in-difference estimations of $\hat{\beta}_{2010DD}$, $\hat{\beta}_{2011DD}$, and $\hat{\beta}_{2012DD}$, using two different model specifications of equation (2): (1) difference-in-difference without controls and school fixed effects and (2) difference-in-difference with controls and school fixed effects. In general, the estimators are quite similar in both cases. However, the negative effect gets a little bit stronger as controls and fixed effects are added to the simple difference-in-difference estimation. This fact would imply that the estimation of $\hat{\beta}_{DD}$ for the different post-years, without such controls and fixed effects, might be biased; that is, the control variables and the fixed effects help explain both the test scores and the fact that the municipality had suffered more from the 2010-2011 climate-related shocks than the national municipality average. However, the estimator would be biased downwards. For example, 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. By the same token, a high 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 effect of the omitted variables on the treatment indicator and on the outcome variable seems to follow opposite directions, and so not including control variables would underestimate the impact estimator.

Graph 3. *Impact of the Climate Shocks of 2010 on the Saber 11 Test Scores Using (1) Difference-in-Difference, and (2) Difference-in-Difference with Controls and School Fixed Effects, 2010-2011*



Source: ICFES, SNPAD, author calculations.

Note: All estimators are statistically significant at 1%. Standard errors were clustered at the school level.

The results shows that the climate shocks of 2010, as measured by the variable *shock*, had an important and significant impact on students' Saber 11 tests scores; the shock was more strongly felt in 2011, but its intensity had repercussions even in 2012, although to a lesser extent. Despite the fact that the climate shocks were intense in 2010, these weather-events did not have such great impact on the 2010 test results, compared to 2011 and 2012; the reason for this is that the 2010 Saber 11 test was taken on September 12th 2010, but (1) most of the natural disasters concentrated in just two months: August and November, and (2) in terms of the breadth and depth of the disasters, November stood alone as the time of the year when most municipalities suffered the most from these events.

Table 3 presents the complete results of the estimation of equations (1) and (2) using pooled OLS with clustered standard errors at the school level. Students' and parents' characteristics, as expected, have an important impact on the test score, result confirmed by the literature review of Section II, as well as by the studies on the determinants of academic performance in Colombia (Chica et al., 2011; Gaviria and Barrientos, 2001). Students' age is negatively related to test scores, but having the correct age for grade has positive impact on this outcome; having a job while studying is related to a lower test performance, and so is being female. All of these variables are important in the estimation and might help capture some of the students' unobserved skills and traits, such as interest or motivation, as well as their possible time allocation. Parents' level of education is also important, as it is related to higher levels of income; and by having higher salaries or belonging to a higher socioeconomic class, parents can have access to higher quality education, to a wider range of school choice (Gaviria and Barrientos, 2001; Krieg and Storer, 2008), and to school complements, such as personal teachers or assistive technology.

Now, concerning student's household characteristics, living in an overcrowded house (more than 2.5 people sharing a bedroom) has a slightly negative effect on test scores, possibly because the student might have more siblings or relatives living in the same place and so she might not receive enough parents' dedication and attention. Living in an urban area is positively correlated with a better scoring, since urban dwellers might not only enjoy a broader range of academic services, but put a greater value on education too, because the benefits of investing in education, in terms of the economic opportunities available after graduation, are broader if the student lives in an urban area. In this sense, rural students might put a lower value on education, as a result of the shortage of high quality schools, and the lack of proper incentives to have a good score, as argued by Broomhall and Johnson (1994). Having at least one computer and Internet connection has a positive impact on schooling outcomes; these household services can act as a complement of the education received at school, but also as a substitute for weak teaching (Glewwe and Kremer, 2006). In contrast, having at least one car, one DVD player, or cable TV is related to a negative score; cable TV and DVD player can take up time that would have otherwise been allocated to studying, while the negative effect of having at least one car could be related to the parents reward schemes discussed in Section II (Darolia and Wydick, 2011).

Table 3. *Impact of the Climate Shocks of 2010 on the Saber 11 Test Scores, 2010- 2012*

Dependent variable: Score Pooled OLS	**Baseline Model [eq. (1)]**	**Time-Heterogeneous Effects Model [eq. (2)]**
Shock.1	0.095 (0.051)	0.098 (0.051)
Shock.2	0.297** (0.096)	0.302** (0.096)
Shock.1*Post	-0.296*** (0.038)	
Shock.2*Post	-1.017*** (0.044)	
Post	0.925*** (0.032)	
Shock.1*y2010		-0.180*** (0.035)
Shock.2*y2010		-0.554*** (0.042)
Shock.1*y2011		-0.408*** (0.05)
Shock.2*y2011		-1.548*** (0.058)
Shock.1*yt2012		-0.306*** (0.044)
Shock.2*y2012		-0.955*** (0.051)
Age	-0.125***	-0.125***

	(0.008)	(0.008)
Age 15-16	1.280***	1.280***
	(0.01)	(0.01)
Age-squared	0.002***	0.002***
	(0.000)	(0.000)
Mother education	0.186***	0.186***
	(0.003)	(0.003)
Father education	0.191***	0.191***
	(0.002)	(0.002)
Social stratum	0.150***	0.150***
	(0.009)	(0.009)
Overcrowding	0.017**	0.017**
	(0.006)	(0.006)
Overcrowding	-0.069***	-0.068***
	(0.012)	(0.012)
Income	0.272***	0.271***
	(0.006)	(0.006)
Work	-0.236***	-0.236***
	(0.015)	(0.015)
Male	1.084***	1.084***
	(0.01)	(0.01)
Sisben	0.136***	0.136***
	(0.005)	(0.005)
Urban	0.490***	0.490***
	(0.016)	(0.016)
Car	-0.395***	-0.395***
	(0.012)	(0.012)
Computer	0.372***	0.373***
	(0.011)	(0.011)
DVD player	-0.251***	-0.249***
	(0.009)	(0.009)
Internet connection	0.114***	0.110***
	(0.012)	(0.012)
Cable TV	-0.248***	-0.249***
	(0.01)	(0.01)
y2008	-0.194***	-0.195***
	(0.018)	(0.018)
y2010	-0.116***	0.668***
	(0.015)	(0.029)
y2011	-0.403***	0.678***
	(0.016)	(0.039)
y2012		0.920***
		(0.036)
Disasters 2006	0.000	0.000
	(0.000)	(0.000)
Disasters 2007	0.000	0.000
	(0.000)	(0.000)
Disasters 2008	-0.000*	-0.000*
	(0.000)	(0.000)
Disasters 2009	0.000	0.000
	(0.000)	(0.000)
Disasters 2010	0.000	0.000
	(0.000)	(0.000)
Disasters 2011	0.000	0.000
	(0.000)	(0.000)
Disasters 2012	-0.000*	-0.000*
	(0.000)	(0.000)
Constant	41.551***	41.544***
	(0.118)	(0.118)
School Fixed Effects	YES	YES
R-squared	0.371	0.371
Obs.	2,422,673	2,422,673

Source: ICFES, SNPAD, author calculations.
Notes: (1) *p<0.05, **p<0.01, ***p<0.001, (2) standard errors in parenthesis are clustered at the school level.

Equations (1) and (2) were also estimated having as dependent variable each of the core subjects of the test. Table 4 presents the difference-in-difference estimator of the impact of the 2010 climate shocks on each of the core subjects evaluated in the Saber 11 test. In general, the effect of the shocks was negative and highly significant (except for Chemistry and English). As expected, the impact was greater in municipalities that experienced a stronger shock (*shock*=2). The most affected subjects were Philosophy, Language, Mathematics, and Biology; Language and Philosophy followed a similar trajectory, which could be an indicator that these subjects require similar skills and that these skills could have been in turn heavily affected by the climate shocks of 2010. According to ICFES, Language, Philosophy, and Social Science tests evaluate students' skills in interpretation, argumentation, and proposition; the reason why the effect was stronger in the first two subjects than in Social Science could be related to the fact that Philosophy might be closer to Language, since it is aimed at improving students' critical thinking, communication, and reading abilities. The literature review suggested that the lack of interaction between students' and their parents, peers, and teachers have a robust impact on the development of their language skills; then, one possible explanation for the strong effect of the climate disasters on Language and Philosophy is that these shocks could have prevented such interactions.

Relatively to other subjects, the effect of the shocks on Mathematics was important (it was the most affected subject in 2010). The skills evaluated in this subject are: communication, reasoning, and problem-solving. In the case of Natural Sciences (Biology, Chemistry, and Physics), which evaluate the identification, enquiring, and explanation skills, the strength of the effects was different for each subject, being stronger for Biology, and weaker for Chemistry, which was the second least affected of all common core subjects after English. The shock effect on Social Science, which assesses the same skills as Language and Philosophy, was comparatively low; while the impact on English, which evaluates grammar skills, textual skills, and textual coherence, was generally not significant and had a positive sign in 2011.

As was stated by Niederle and Vesterlund (2010) in Section II, males tend to outperform females in mathematics. This tendency is also confirmed in this study; in fact, although males outperform females in all subjects, except Philosophy, Mathematics exhibits the greatest score differences between males and females, followed by Physics, Social Science, and Biology. Girls tend to perform better in Philosophy, whereas the advantage of boys over girls in Language is the lowest among the boys-dominated subjects. This might provide new evidence that performance in Language and Philosophy might require the same kind of skills.

Now, if the skills evaluated by Saber 11 in Language and Philosophy (interpretation, argumentation, and proposition), and Mathematics (communication, reasoning, and problem-solving) were actually affected, the consequences of the climate shocks of 2010-2011 could have a long-term impact on the future academic outcomes of these students, since these skills are required by almost every undergraduate program, as well as on their future job performance. This is a hypothesis that needs to be researched by future studies.

Table 4. *Impact of the Climate Shocks of 2010 on the Saber 11 Test Scores, 2010- 2012, by Core Subjects*

Pooled OLS	Baseline Model [eq. (1)]		Time-Heterogeneous Effects Model [eq. (2)]						Male
Dependent Variable:	Shock.1*Post	Shock.2*Post	Shock.1*y2010	Shock.2*y2010	Shock.1*y2011	Shock.2*y2011	Shock.1*y2012	Shock.2*y2012	
Language	-0.475*** (0.049)	-1.621*** (0.057)	-0.157*** (0.041)	-0.369*** (0.051)	-0.843*** (0.087)	-3.313*** (0.102)	-0.442*** (0.048)	-1.196*** (0.057)	0.124*** (0.012)
Philosophy	-0.609*** (0.057)	-1.658*** (0.065)	-0.338*** (0.047)	-0.561*** (0.059)	-1.037*** (0.096)	-3.264*** (0.109)	-0.465*** (0.058)	-1.158*** (0.071)	-0.211*** (0.013)
Biology	-0.300*** (0.045)	-1.194*** (0.052)	-0.098* (0.040)	-0.566*** (0.050)	-0.420*** (0.064)	-1.923*** (0.075)	-0.398*** (0.053)	-1.105*** (0.062)	1.128*** (0.013)
Mathematics	-0.387*** (0.064)	-1.551*** (0.076)	-0.372*** (0.063)	-1.309*** (0.077)	-0.499*** (0.083)	-2.163*** (0.104)	-0.289*** (0.077)	-1.175*** (0.088)	2.800*** (0.019)
Physics	-0.246*** (0.051)	-1.001*** (0.057)	-0.183*** (0.047)	-0.640*** (0.057)	-0.387*** (0.072)	-1.541*** (0.082)	-0.170** (0.058)	-0.824*** (0.064)	1.962*** (0.014)
Social Science	-0.186*** (0.044)	-0.719*** (0.053)	-0.174*** (0.047)	-0.442*** (0.060)	-0.433*** (0.065)	-1.355*** (0.073)	0.055 (0.052)	-0.354*** (0.064)	1.133*** (0.015)
Chemistry	-0.025 (0.037)	-0.331*** (0.045)	0.037 (0.048)	-0.300*** (0.058)	0.009 (0.044)	-0.223*** (0.055)	-0.128** (0.045)	-0.477*** (0.052)	0.918*** (0.013)
English	-0.134** (0.047)	-0.044 (0.057)	-0.156** (0.060)	-0.237*** (0.069)	0.341*** (0.076)	1.416*** (0.080)	-0.599*** (0.066)	-1.336*** (0.079)	0.820*** (0.015)

Source: ICFES, SNPAD, author calculations.
Notes: (1) *p<0.05, **p<0.01, ***p<0.001, (2) standard errors in parenthesis are clustered at the school level, (3) all regressions include school fixed effects and control variables.

Table 5a and 5b shows the main results of the triple-difference estimation of equations (3) and (4) to account for the heterogeneous effects of the shock on sex, living area, and previous shocks. According to the international evidence presented in Section I, most of the effects of the shocks, at least for quantitative human capital variables, are suffered by women, due to gender-discrimination issues; however, the results in this paper indicate that there was a differential effect in favor of girls in the impact of the variable *shock* on the test scores. In fact, the scores for students living in a treated municipality with intensity 2 were almost 13% worse for boys than for girls. The reasons behind this result might be related to the differences in which men and women connect to and rely on their the social networks; it has been found that people responses in front of a disaster are affected by their connections within their social systems (Edwards, 1998). There is also evidence that not only women have wider and more supportive social networks than men, but their networks shield them better from depression, as compared to men (Kendler et al., 2005). In this sense, social networks might have lessen the impact of the climate shocks on female students, a reason that was also stated by Poutvaara and Ropponen (2010) when measuring the gender-differential effect of school shootings on young students' academic performance in Finland; however, more research is needed to support this claim.

On the same token, the literature states that rural inhabitants are more prone to suffer the consequences of climate shocks; however, the results of the estimations point to the opposite direction: urban dwellers were more affected by the 2010 shocks, in terms of test score results, than rural dwellers, comparing the results between the rural-urban differences between students that were affected by the variable *shock* (treatment) and those that were not (control). Actually, for the period 2010-2012, the impact was 76% higher for urban students than for the rural ones. Part of the divergence between these results and the ones found in the literature may stem from differences in the variables used as proxy of human capital; the literature in the review sections focused on quantitative measures, whereas this paper uses a qualitative proxy, and by doing so it not only broadens the understanding of the differential effects of the climate shocks on cognitive skills, but also highlights the importance of acknowledging the differential effects on human capital depending on which variable is used as a proxy of it. Another explanation for this divergence is related to adaptation and coping mechanisms: since the 2010-2011 climate-related events hit much harder than the previous climate shocks, the impact reached urban populations that had probably never experienced such events, and therefore had less coping skills, and so by being less prepared than their rural counterparts, the impact was stronger in these populations.

Now, are there differential effects of the variable *shock* on the test scores if the students lived in municipalities that were more affected by climate-related events in the previous years than the national municipality average? According to the results, the answer is yes. The differential impact of *shock* on students living in municipalities experiencing more shocks than the national municipality average in the years 2006, 2007, 2008, and 2009 was positive and significant. That is, having experienced previous natural-related shocks seem to be have lessened the impact of the 2010 shock. Now, the intuition behind these results are probably linked to the adaptation process and the coping mechanisms designed by the state, as well as by the engagement of communities in collective action efforts, that are put into motion once a severe climate shock have hit a region [see Adger (2003)]. So, having experienced more severe climate-related events than the average in previous years could have triggered actions to prevent the negative consequence of future shocks. In this scenario, populations that were hit by the variable *shock* and were not prepared had a greater impact on their human and physical resources, and therefore a stronger impact on their test scores.

Table 5a. *Heterogeneous Effects for Sex and Living Area, 2010-2012. Time-Heterogeneous Model*

	Time-Heterogeneous Effects Model [eq. (2)]			
Pooled OLS	**Sex**		**Urban**	
Dependent Variable: Score	Male (diff)	Female	Urban (diff)	Rural
Shock.1*y2010	0.056 (0.048)	-0.204*** (0.042)	0.093 (0.063)	-0.260*** (0.055)
Shock.2*y2010	0.016 (0.058)	-0.563*** (0.049)	-0.166* (0.071)	-0.412*** (0.058)
Shock.1*y2011	0.018 (0.064)	-0.415*** (0.059)	-0.119 (0.080)	-0.316*** (0.071)
Shock.2*y2011	-0.155* (0.073)	-1.481*** (0.067)	-0.638*** (0.092)	-0.997*** (0.076)
Shock.1*y2012	-0.121* (0.057)	-0.249*** (0.049)	-0.019 (0.071)	-0.290*** (0.063)
Shock.2*y2012	-0.254*** (0.064)	-0.841*** (0.056)	-0.439*** (0.080)	-0.586*** (0.066)

Table 5b. *Heterogeneous Effects for Sex, Living Area, and Previous Shocks, 2010-2012, Baseline Model*

	Baseline Model [eq. (1)]											
					Previous shocks							
Pooled OLS	**Sex**		**Urban**		**2006**		**2007**		**2008**		**2009**	
Dependent Variable: Score	Male (diff)	Female	Urban (diff)	Rural	Yes (diff)	no	Yes (diff)	no	Yes (diff)	no	Yes (diff)	no
Shock.1*Post	-0.015 (0.047)	-0.287*** (0.044)	-0.013 (0.058)	-0.290*** (0.051)	0.822*** (0.150)	-0.330*** (0.039)	1.155*** (0.185)	-0.331*** (0.038)	0.435* (0.182)	-0.306*** (0.038)	0.142 (0.136)	-0.375*** (0.039)
Shock.2*Post	-0.131* (0.053)	-0.959*** (0.049)	-0.412*** (0.066)	-0.666*** (0.054)	0.955*** (0.133)	-1.083*** (0.048)	1.140*** (0.138)	-0.996*** (0.049)	0.498** (0.160)	-0.958*** (0.049)	1.128*** (0.123)	-1.148*** (0.046)

Source: ICFES, SNPAD, author calculations.

Notes: (1) *p<0.05, **p<0.01, ***p<0.001, (2) standard errors in parenthesis are clustered at the school level, (3) all regressions include school fixed effects and control variables.

Even though the climate shocks of 2010 hit almost the entire country, some regions suffered more than others, and this is reflected on the regional effects of the variable *shock* on the Saber 11 test scores. Table 6 presents the regression results of equations (1) and (2) for each of the geographical regions of Colombia. In general, the most affected regions were: the Caribbean, the Central and Eastern Andean, and the Pacific; the difference-in-difference estimator was not significant for the Amazon and Eastern regions. The effect of the variable *shock* with intensity 2 on the Caribbean and Andean regions was significant and persistent in the years 2010, 2011, and 2012; whereas, in the case of the Pacific region, it was only significant in the years 2011 and 2012. The variable *shock* with intensity 1 was generally not significant and had a positive sign.

Table 6. *Impact of the Climate Shocks of 2010 on the Saber 11 Test Scores, 2010- 2012, by Geographical Region*

Dependent variable: Score Pooled OLS		**Caribbean**	**Pacific**	**Eastern Andean**	**Central Andean**	**Eastern**	**Amazon**
Baseline Model [eq. (1)]	**Shock.1*Post**	-0.03	-0.168	0.140*	0.279*	0.380*	-0.121
		(0.138)	(0.171)	(0.070)	(0.120)	(0.175)	(0.201)
	Shock.2*Post	-0.583***	-0.432**	-0.521***	-0.527***	0.034	0.128
		(0.136)	(0.160)	(0.077)	(0.152)	(0.263)	(0.218)
Time-Heterogeneous Effects Model [eq. (2)]	**Shock.1*y2010**	0.006	-0.269	0.099	0.125	0.083	0.005
		(0.118)	(0.170)	(0.070)	(0.099)	(0.153)	(0.216)
	Shock.2*y2010	-0.316**	-0.15	-0.263**	-0.414**	0.087	-0.115
		(0.116)	(0.159)	(0.082)	(0.132)	(0.231)	(0.216)
	Shock.1*y2011	-0.088	0.1	0.232*	0.284	0.793***	-0.194
		(0.204)	(0.210)	(0.096)	(0.177)	(0.227)	(0.282)
	Shock.2*y2011	-0.884***	-0.661**	-0.627***	-0.808***	-0.067	0.279
		(0.201)	(0.204)	(0.111)	(0.232)	(0.361)	(0.320)
	Shock.1*y2012	-0.003	-0.331	0.089	0.433**	0.263	-0.165
		(0.144)	(0.184)	(0.082)	(0.136)	(0.218)	(0.227)
	Shock.2*y2012	-0.543***	-0.467**	-0.691***	-0.351*	0.109	0.253
		(0.141)	(0.174)	(0.090)	(0.172)	(0.307)	(0.254)
	R-squared	0.364	0.312	0.334	0.354	0.28	0.267
	Obs.	540535	255343	590407	465473	86738	41485

Source: ICFES, SNPAD, author calculations.
Notes: (1) *p<0.05, **p<0.01, ***p<0.001, (2) standard errors in parenthesis are clustered at the school level, (3) all regressions include school fixed effects and control variables.

Finally, Tables 7 and 8 present the estimation of equations (1) and (2) by social stratum and income level. The results are coherent with the literature review, in the sense that the impact of the variable *shock* on the Saber 11 scores was strong for students from lower socioeconomic stratums as well as for students living in poorer households; however, the effects of the 2010 natural disasters reached also students belonging to middle and upper classes. Surprisingly, a closer look at the impact by household social stratum (Table 7) shows that the poorest (stratum 1 and 2) were not actually the most affected; in fact the impact was felt stronger in social strata 3, 4, and 5 (however, strata 1 and 2 were the only groups for which the intensity 1 *shock* variable was significant, which means that this population remains the most vulnerable). Once more, a probable explanation for this result is that the severity of the climate events of 2010 reached income levels that were not used to deal with this kind of situations. Moreover, these results underline the importance of recognizing the heterogeneities within broader social classes' categories, such as rich and poor, since there might be important difference in the responses of the different subgroups that comprises these income categories.

Table 7. *Impact of the Climate Shocks of 2010 on the Saber 11 Test Scores, 2010- 2012, by Social Stratum*

Dependent variable: Score Pooled OLS		Stratum 1	Stratum 2	Stratum 3	Stratum 4	Stratum 5	Stratum 6
Baseline Model [eq. (1)]	Shock.1*Post	-0.129**	-0.197***	-0.249***	-0.526***	-0.406	-0.094
		(0.048)	(0.039)	(0.060)	(0.131)	(0.278)	(0.455)
	Shock.2*Post	-0.447***	-0.474***	-0.754***	-0.633*	-1.378*	-0.741
		(0.050)	(0.059)	(0.119)	(0.267)	(0.670)	(1.005)
Time-Heterogeneous Effects Model [eq. (2)]	Shock.1*y2010	-0.091	-0.115**	-0.140*	-0.562***	-0.245	-0.138
		(0.048)	(0.040)	(0.061)	(0.153)	(0.317)	(0.533)
	Shock.2*y2010	-0.197***	-0.206**	-0.507***	-0.349	-0.804	-1.354
		(0.050)	(0.064)	(0.123)	(0.360)	(1.027)	(0.862)
	Shock.1*y2011	-0.165*	-0.231***	-0.378***	-0.424**	-0.653	0.34
		(0.068)	(0.055)	(0.078)	(0.164)	(0.342)	(0.573)
	Shock.2*y2011	-0.720***	-0.763***	-0.982***	-0.466	-1.608	0.045
		(0.072)	(0.082)	(0.158)	(0.490)	(0.909)	(1.413)
	Shock.1*y2012	-0.134*	-0.251***	-0.238**	-0.596***	-0.328	-0.519
		(0.056)	(0.049)	(0.078)	(0.171)	(0.338)	(0.593)
	Shock.2*y2012	-0.424***	-0.471***	-0.783***	-1.058**	-1.635*	-0.888
		(0.059)	(0.073)	(0.169)	(0.407)	(0.721)	(1.237)
	R-squared	0.215	0.238	0.33	0.413	0.431	0.491
	Obs.	914,092	909,059	464,293	92,672	29,112	13,445

Source: ICFES, SNPAD, author calculations.

Notes: (1) *p<0.05, **p<0.01, ***p<0.001, (2) standard errors in parenthesis are clustered at the school level, (3) all regressions include school fixed effects and control variables.

Table 8. *Impact of the Climate Shocks of 2010 on the Saber 11 Test Scores, 2010- 2012, by Monthly Household Income Level*

Dependent variable: Score Pooled OLS		Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7
Baseline Model	Shock.1*Post	-0.187***	-0.208***	-0.041	-0.095	-0.125	-0.079	-0.332
		(0.046)	(0.039)	(0.057)	(0.089)	(0.157)	(0.202)	(0.273)
	Shock.2*Post	-0.513***	-0.814***	-0.784***	-0.667***	-0.124	-0.98	-0.634
		(0.050)	(0.052)	(0.097)	(0.151)	(0.338)	(0.565)	(0.721)
Time-Heterogeneous Effects Model	Shock.1*y2010	-0.136**	-0.121**	-0.031	-0.065	0.104	0.014	-0.221
		(0.048)	(0.040)	(0.062)	(0.110)	(0.195)	(0.275)	(0.319)
	Shock.2*y2010	-0.267***	-0.376***	-0.466***	-0.662***	0.598	-0.284	-1.328
		(0.052)	(0.054)	(0.111)	(0.191)	(0.451)	(0.906)	(0.961)
	Shock.1*y2011	-0.226***	-0.284***	-0.049	-0.153	-0.372	-0.474	-0.336
		(0.066)	(0.055)	(0.079)	(0.115)	(0.204)	(0.263)	(0.338)
	Shock.2*y2011	-0.798***	-1.306***	-1.182***	-0.775***	-0.511	-1.063	-1.187
		(0.072)	(0.073)	(0.136)	(0.211)	(0.462)	(0.765)	(0.794)

Shock.1*y2012	-0.208*** (0.055)	-0.225*** (0.048)	-0.046 (0.073)	-0.066 (0.114)	-0.101 (0.203)	0.218 (0.262)	-0.435 (0.344)
Shock.2*y2012	-0.491*** (0.060)	-0.756*** (0.062)	-0.714*** (0.122)	-0.569** (0.195)	-0.394 (0.464)	-1.308 (0.789)	0.609 (0.870)
R-squared	0.214	0.25	0.301	0.366	0.393	0.4	0.46
Obs.	756,312	1,050,136	350,587	163,120	52,175	26,127	24,216

Source: ICFES, SNPAD, author calculations.

Notes: (1) *p<0.05, **p<0.01, ***p<0.001, (2) standard errors in parenthesis are clustered at the school level.

V. Possible Channels of Transmission

A. Health Deterioration

The deterioration of human health is an important issue regarding the costs of climate-related events on human capital, as well as one of the channels through which these events might affect students' test scores. In fact, this issue has been highlighted by the World Health Organization (2012):

> Climate change affects the social and environmental determinants of health – clean air, safe drinking water, sufficient food and secure shelter. (…) Many of the major killers such as diarrhoeal diseases, malnutrition, malaria and dengue are highly climate-sensitive and are expected to worsen as the climate changes. Areas with weak health infrastructure – mostly in developing countries – will be the least able to cope without assistance to prepare and respond.

According to the "Instituto Nacional de Salud" (National Health Institute), in 2010 the worst dengue epidemic in the previous 10 years hit Colombia, affecting 151,774 people (114% more than the previous year). Likewise, 116,914 people suffered from malaria the same year (38% more than in 2009). In order to get some insight on whether these epidemic events were caused by the weather-related hazards of 2010-2011, a simple difference-in-difference approach was implemented, focusing on the shocks of 2010.

Model specification for this approach is given by equations (5) and (6), for the baseline model and the time-heterogeneous effects model, respectively:

$$DiseaseCases_{it} = \beta_0 + \beta_1 ClimateShock2010_i * Post + \alpha_i + \boldsymbol{\theta}\mathbf{year}_t + e_{it} \quad (5)$$

$$\begin{aligned} DiseaseCases_{it} = {} & \beta_0 + \beta_1 ClimateShock2010_i * y2010 + \beta_2 ClimateShock2010_i * y2011 \\ & + \beta_3 ClimateShock2010_i * y2012 + y2010 + y2011 + y2012 + \alpha_i + \boldsymbol{\theta}\mathbf{year}_t \\ & + e_{it} \quad (6) \end{aligned}$$

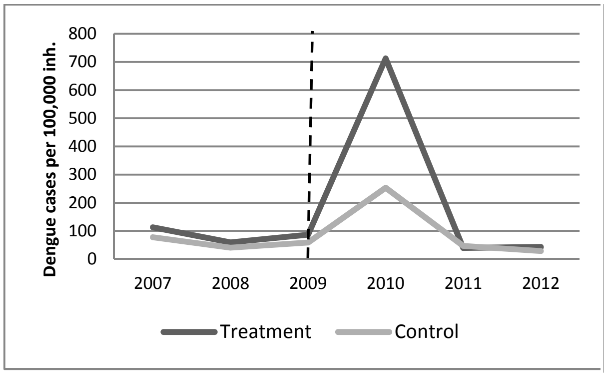
where $DiseaseCases_{it}$ is the outcome variable (number of infected people per 100,000 inhabitants in department *i* in time *t*); $ClimateShock2010_i$ is a treatment indicator; *post* is a dummy variable equal to one in the post-shock period (2010-2012); *y2010*, *y2011*, and *y2012* represent dummy variables for the years 2010, 2011, and 2012; α_i denotes department fixed effects; $\boldsymbol{\theta}\mathbf{year}_t$ is a vector of dummy variables for the years 2008 and 2009; and e_{it} is the error term. In this model, $\hat{\beta}_1$ measures the effect of treatment. The treatment indicator variable, $ClimateShock2010_i$, had two constructions, one for dengue and one for malaria. In the case of dengue, a rain measure was used as the treatment indicator; particularly, the annual precipitation was calculated for each department for the year 2010 and it was then compared with the median of the average of the previous five years for each department: If it was higher, then a dummy variable for the department was created, indicating treatment. In the case of malaria, a water-related disaster intensity variable was used as treatment indictor; this variable was the result of the number of water-related disasters per 100,000 inhabitants in 2010 times the number of municipalities that were affected by these disasters in each department. A department was then considered treated if it had a value for this variable that was higher than the median value of all departments.

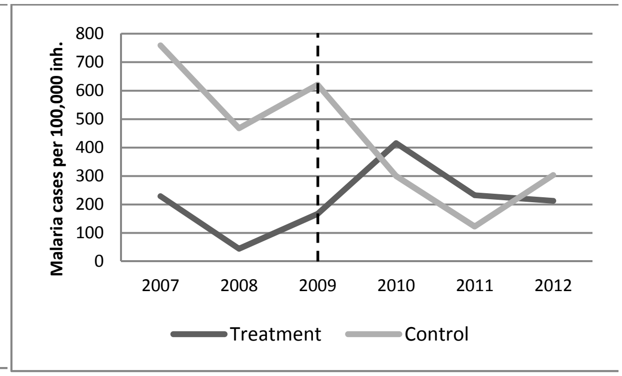
Graph 5 shows the average dengue and malaria cases per 100,000 inhabitants for the period 2007-2012. Before the 2010 shock, both control and treatment groups had similar trajectories; after the shock, dengue cases increased in the treatment group by more than twice the rate increase of the control group; malaria cases increased by 149% in the treatment group, but decreased by 52% in the control group. Table 9 presents the fixed-effects panel regression results of equations (5) and (6). As was shown graphically, the climate shocks of 2010 had a positive effect on the number of cases of dengue and malaria in 2010. Given the magnitude of these epidemic events, they were probably one of the channels of transmission from the climate-related shocks of 2010 to the students' Saber 11 test scores. However, a more detailed study at the municipality level is required in order to get more précised conclusions.

Graph 5. *Average Dengue and Malaria Cases for Treatment and Control Groups, 2007-2012*

(a) Dengue cases per 100,000 inhabitants, 2007-2012

(b) Malaria cases per 100,000 inhabitants, 2007-2012





Source: Instituto Nacional de Salud, author calculations.

Table 9. *Impact of the 2010 Climate Shocks on the Number of Disease Cases*

Dependent variable: Number of disease cases Panel estimation with fixed effects		**Malaria**	**Dengue**
Baseline Model [eq. (5)]	**2010-2012**	514.274*** (130.203)	127.832 (80.379)
Time-Heterogeneous Effects Model [eq. (6)]	**2010**	584.764** (184.935)	431.947*** (104.325)
	2011	579.150** (184.935)	-34.951 (104.325)
	2012	378.907* (184.935)	-13.5 (104.325)
	Obs.	198	96

Source: Instituto Nacional de Salud, author calculations. Notes: (1) *p<0.05, **p<0.01, ***p<0.001, (2) standard errors in parenthesis.

B. Schools Destruction

As discussed earlier, one of the direct effects of climate-related events is the destruction of physical capital. This section examines the destruction of schools as another possible channel of transmission from the climate shocks of 2010-2011 to the Saber 11 test results. Since many school buildings were destroyed as a consequence of the different natural disasters that hit Colombia in 2010, this section focuses on the climate shocks of this year. In total, according to SNPAD, 501 schools were damaged in 154 municipalities, 351% more than in 2009. In order to test whether this destruction of physical capital may have affected the test scores, a difference-in-difference approach was implemented. Model specification is given by equations (7) (baseline model) and (8) (time-heterogeneous effects model):

$$score_{it} = \beta_0 + \beta_1 School2010_j + \beta_2 post + \beta_3 School2010_j * post + \boldsymbol{\gamma}\mathbf{C}_{it} + \boldsymbol{\delta}\mathbf{S}_{jt} + \boldsymbol{\theta}\mathbf{year}_t + \alpha_k + e_{it} \quad (7)$$

$$score_{it} = \beta_0 + \beta_1 School2010_j + \beta_2 y2010 + \beta_3 y2011 + \beta_4 y2012 + \beta_5 School2010_j * y2010 + \beta_6 School2010_j * y2011 + \beta_7 School2010_j * y2012 + \boldsymbol{\gamma}\mathbf{C}_{it} + \boldsymbol{\delta}\mathbf{S}_{jt} + y2008 + \alpha_k + e_{it} \quad (8)$$

where $School2010_j$ is a dummy variable taking the value of one if the student *i* was living in one of the municipalities that had at least one of its schools destroyed in 2010, as the result of a natural disaster; *post* is a dummy variable for the period 2010-2012; *y2010*, *y2011*, and *y2012* are dummy variables for the years 2010, 2011, and 2012; $\boldsymbol{\gamma}\mathbf{C}_{it}$, $\boldsymbol{\delta}\mathbf{S}_{jt}$, $\boldsymbol{\theta}\mathbf{year}_t$ are control variables as described for equations (1) and (2); *y2008* is a dummy for the year 2008; α_k represents school fixed effects; and e_{it} is an error term.

Table 10 presents the pooled OLS regression results of equations (7) and (8). As expected, the destruction of physical capital, in this case the damage of school buildings, as a consequence of natural disasters, has a negative and significant impact on human capital, as measured by the score results of Saber 11 test. The impact is significant not only the year of the events, but also the years after. This fact may be related 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 not be able of teaching a class; 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 miss lessons, be given incomplete contents, and be taught classes in inappropriate spaces. All of which might finally affect their testing scores.

Table 10. *Impact of the 2010 School Buildings Climate-Related Destruction on Saber 11 Test Scores*

Dependent variable: Score Pooled OLS	**Baseline Model [eq. (7)]**	**Time-Heterogeneous Effects Model [eq. (8)]**
2010-2012 (β_3)	-0.155*** (0.041)	-
2010 (β_5)	-	-0.161*** (0.037)
2011 (β_6)	-	-0.182** (0.055)
2012 (β_7)	-	-0.121* (0.048)
R-squared	0.371	0.371
Obs.	2,422,435	2,422,435

Source: ICFES, SNPAD, author calculations.

Notes: (1) *p<0.05, **p<0.01, ***p<0.001, (2) standard errors in parenthesis are clustered at the school level, (3) all regressions include school fixed effects and control variables.

C. Credit Restrictions: Discussion for Future Research

Another possible channel of transmission, according to the literature, is the existence of credit restrictions both at the municipality and at the household level. However, due to data limitations, this channel is not detailed in this paper; it is rather suggested as a natural direction for future research in this topic. The importance of this channel, as well as its impacts on schooling outcomes is discussed in this section.

Although theoretically natural disasters should not have long-term impacts on economic development (more precisely on economic growth, Cavallo et al., 2010), the lack of financial resources in some emerging and poor countries can threaten the pace of the recovery, affect the accumulation of human capital, and therefore have medium and long-term negative impacts on the country's growth rate (McDermott, 2012). In fact, natural disasters can be a potential menace to the human development of poor countries, especially if households have limited or none access to credit. Therefore, access to credit can be an important determinant of the decisions of parents on whether or not to invest in their children's human capital (education and health) after a natural shock, which can be considered a long-term investment; and even though aid flows can soften the impact of disasters on human capital, schooling decisions will depend to a great extent on the existence of credit restrictions (McDermott, 2012).

Credit restrictions operate both at the macro level and at the micro level. At the macro level, according to Hallegatte and Dumas (2009), the capacity to fund and to carry out reconstructions after a natural shock plays an important role in preventing long-term negative consequences of natural disasters. Following their results, short-term constraints of this capacity intensifies the negative effect of a natural shock in the short-run, although not in the long-run, except when this capacity is below a certain threshold; in this latter case, the short-term constraints can result in vicious circles of poverty, hindering economic development in the long-run. At the micro level, it is stated that coping mechanisms to smooth consumption after a natural disaster can prevent households from eroding their human capital; and although this is not always the case (Skoufias and Vinha, 2012) most of the empirical evidence tend to support this claim.

For example, when analyzing the effect of Hurricane Mitch on children's secondary school attainment in rural Honduras, Gitter and Barham (2007) found that, without considering credit constraints, the hurricane had a negative impact on schooling, but once an interaction term between the natural shock and access to credit was included, the impact was significant only to credit-constrained households, as they tend to withdraw their children from school after a shock. This finding implies that providing access to credit or liquidity can counteract the negative effect of natural shocks on schooling, since the situation of quitting school, after a disaster, in order to work is a short term issue that can be lessen with money transfers. However, it is yet-to-prove whether access to credit can lessen the impact of natural disasters on qualitative measures of human capital, such as cognitive skills. This is a topic for future research.

V. Conclusions

This paper estimated the impact of the unprecedented climate shocks that hit Colombia in 2010 on the cognitive skills of high school students; in particular, the test scores in the Saber 11 test, a national standardized test for high school students prior to graduation, were used 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 on the impact on quantitative outcomes, such as years of schooling, school enrollment ratios, students' attendance or adult literacy rates. Using a difference-in-difference with repeated cross-section approach, it was found that the 2010 shocks had a strong impact on Saber 11 test scores, especially in 2011; the impact on the 2010 results was not as strong because students took the test in September and the shocks were more intense in the months after, especially in November. The strength of the shocks on the cognitive skills of high school students were reflected also in the 2012 score results, although to a lesser extent. The results of this paper provide new evidence of the non-monetary costs of natural disasters, in particular on the impact of these climate-related events on qualitative measures of human capital.

The climate-related events had a stronger effect on the Language, Philosophy, and Mathematics scores. It is then possible that the skills these particular subjects try to assess had been affected by the shocks, in particular, the interpretation, argumentation, and proposition skills evaluated in Language and Philosophy, and the communication, reasoning, and problem-solving skills evaluated in Mathematics. If, as suggested by the international evidence, climate shocks have a permanent impact on these skills, their effects can be reflected in the future college and job performance of the affected students. Moreover, the shocks had a stronger impact on male students and urban students, but the impact was less severe for students who were living in a municipality that experienced an above-average shock in the previous years. These facts can conceivably be related to the adaptation and coping mechanisms developed after a shock occurs. The impact of the disasters did not only affect the test scores of poor students, as suggested by the literature, they also had an important effect on the scores of middle and upper class students.

Two possible channels of transmission through which the shocks could have impacted the cognitive skills of students, as measured by the test scores, were identified. One of the channels is through the deterioration of human health. The WHO states that climate events might propitiate the propagation of epidemics and diseases, such as dengue and malaria. In 2010, Colombia experienced its worst dengue epidemic in a decade, affecting more than 140,000 people. This epidemic could have then affected students, parents, and teachers' health, impacting the performance of the students in the test. It was shown that there seems to be a link between the dengue and malaria epidemics and the climate shocks of 2010; however, a more detailed study at the municipality level is necessary to better support this claim. Another channel of transmission was through the destruction of physical capital, in particular through the damage of school buildings, which might have prevented students from attending classes under appropriate conditions. Future research should focus on (1) the assessment of the availability of credit constraints as another channel through which climate shocks might have affected cognitive skills, and (2) the long-term effects of the climate shocks of 2010, such as the impacts on the student performance in collage or on her income generation capacity.

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