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Kai Barron
Luis F. Gamboa
Paul Rodriguez-Lesmes

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Wissenschaftszentrum Berlin für Sozialforschung gGmbH
Reichpietschufer 50
10785 Berlin
Germany
www.wzb.eu

Affiliation of the authors:

Kai Barron, University College London and WZB (kai.barron.10@ucl.ac.uk)

Luis F. Gamboa, Universidad Jorge Tadeo Lozano (luisfw.gamboan@utadeo.edu.co)

Paul Rodriguez-Lesmes, Universidad del Rosario (paul.rodriguez@urosario.edu.co)

Abstract

Behavioural response to a sudden health risk: Dengue and educational outcomes in Colombia*

Epidemics tend to have a debilitating influence on the lives of directly afflicted families. However, the presence of an epidemic can also change the behaviour and outcomes of those not directly affected. This paper makes use of a short, sharp, unexpected epidemic to examine the behavioural response of the general public to a sudden shift in the perceived risk to an individual's health and mortality. Our analysis finds that unafflicted school students change their behaviour substantially, affecting important life outcomes. In particular, we find that close to 4 fewer students, out of a typical class of 47 pupils, sit their school leaving examination for every additional 10 cases of severe Dengue per 10 000 inhabitants in a municipality. We rule out several possible mechanisms, leaving an increase in the salience of the disease's risks as a plausible explanation for our findings.

JEL classifications: I12, I15, I20, D80

Keywords: Health, health risks, education, human capital, Dengue, Colombia

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1 Introduction

Confronted with a new epidemic, the general public must decide how to respond. Often information about the risks is scarce and imperfect, and people respond by adjusting their daily lives and taking extreme preventative action, such as avoiding public places and reducing hospital visits (Bennett et al., 2015). In this paper, we ask whether this shift in behaviour can lead to a change in important life outcomes. In particular, we study the influence of an epidemic on the schooling outcomes of unafflicted students.

The sudden and unprecedented spike in the incidence of Dengue disease in Colombia during 2010 provides a good opportunity for studying how the public change their behaviour when there is a sudden outbreak of an epidemic. Dengue is currently the most prevalent mosquito-borne viral disease in humans, with a 30-fold increase in incidence in the last 50 years and an estimated 50 million annual infections worldwide (WHO, 2009). During the 2010 epidemic, there was an increase of over 200 percent in the incidence in comparison to the previous year (Villar et al., 2015). Dengue can manifest as one of two strands - either as *classic Dengue*, a more common, but milder version of the disease akin to an episode of flu, or *severe Dengue*, a rarer, but far more serious condition that requires hospitalisation for around 80 percent of cases and can lead to death (Villar et al., 2015). While it is well documented that epidemics of this nature can have sizeable direct negative economic consequences for the families of those who fall ill (Clark et al., 2005), it is also of considerable interest to understand how this unexpected change in the profile of health risks faced by the population affects their behaviour, and thereby has an indirect effect on the economic outcomes of individuals who are not directly affected by the disease.

We make use of this "natural" experiment to study the influence of the Dengue epidemic on the participation in school leaving examinations (SABER 11 test) of approximately 1 million students. Saber 11 is the most important educational examination in Colombia because it is used as the main admission requirement in almost all the higher education institutions in Colombia (similar to the SAT in the USA). Therefore, taking this examination is essential for progressing to any form of further education facility after completing school.

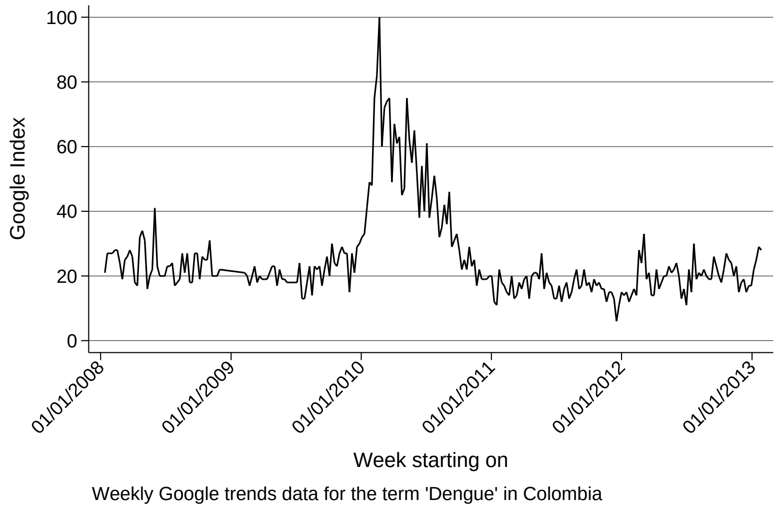
In addition to being unexpected and widespread, the 2010 Colombian Dengue epidemic is particularly suitable for the study of public response to health risks for the following reason. While the relatively benign *classic Dengue* may cause students to miss school temporarily when someone in the household is infected, it is similar to a flu and unlikely to cause fear. Therefore, it is unlikely to substantially change the behaviour of individuals outside the households directly affected. In contrast, *severe Dengue* is a dangerous illness that is likely shift the perceived mortality risk and lead families to change their behaviour and take preventative actions before anyone in the household is directly affected by the epidemic.

We use the temporal and geographic variation in the incidence of the two strands of the disease to estimate the impact of *classic Dengue* and *severe Dengue* on school attendance and test score attainment in the SABER 11 school leaving examinations. We find that an increase in the incidence of *classic Dengue* during the four months prior to the exam in 2010 in a particular municipality did not have a substantial effect on exam attendance or test taking behaviour. In contrast, however, we find that a higher incidence of *severe Dengue* in a municipality in the months preceding the exam led to a substantial reduction in the number of students who sat the examination. It is particularly striking that the estimated reduction in the number of students sitting the exam in a municipality with one additional case of *severe Dengue* per 10.000 individuals in the population in 2010 is, on average, substantially higher than the number of individuals (of any age) who actually had *severe Dengue* in the municipality. This suggests that the higher incidence of *severe Dengue* in the municipality led to a general reduction in the propensity of individuals to attend the exam, even amongst those unaffected by the disease.

There are several possible mechanisms that could explain this finding. We consider three leading candidates, namely that (i) the **supply of schooling** may have been reduced due to temporary school closures, (ii) older students may have missed school because they were **caring for ill relatives** (e.g. younger siblings), and (iii) there may have been an **increase in awareness** of the risks and severity of the disease when an additional member of the community became seriously ill, leading to preventative actions being taken by others in the community. In the discussion below, we present evidence suggesting that the supply of schooling remained relatively unaffected, and high school aged students did not change their time allocation at home substantially in response to the epidemic. An increase in public awareness of the risks of the disease remains as a leading plausible explanation for the behavioural response that we observe.

The general public's increased awareness and concern is reflected in Figure 1, which shows google searches for the term "Dengue" over five years in Colombia. Furthermore, news headlines from this period, such as "*El Dengue asesino al alza*" ("Dengue, a rising killer"), published by El Tiempo on June the 20th, 2010) were likely to induce fear and uncertainty in the public.

Figure 1: Web searches for ”Dengue” in Colombia



The epidemic can therefore be viewed as a natural experiment that shifted the level of perceived mortality risk. In regions where only the incidence of *classic Dengue* increased, and people in the municipality were only afflicted by mild symptoms, the shift in the level of perceived mortality risk was likely to be small. However, one would expect that a spike in *severe Dengue*, along with the corresponding hospitalisation or death of several members of a community would result in a significant shift in the level of perceived mortality risk in that community. This paper studies the response to this heterogeneous shift in the perceived mortality risk across municipalities.

Our paper relates closely to the economic epidemiology literature demonstrating a “prevalence response”, whereby behaviour is a function of the underlying prevalence of a disease. The majority of this literature has focused on HIV, and has studied the behavioural response to the receipt of public and private information pertaining to own and community risk of HIV (Ahituv et al., 1996; Lakdawalla et al., 2006; Thornton, 2008, 2012; Delavande and Kohler, 2012; de Paula et al., 2014; Gong, 2015). In addition, in work close in spirit to ours, Adda (2007) uses the 1996 “Mad Cow” crisis to show that there was a sharp drop in the amount of beef bought by French consumers once they became aware of the possible health risk, and the reduction was strongest amongst those who were medium risk individuals. Bennett et al. (2015) studies how public information, and peer-to-peer information transmission led to a large reduction in hospital outpatient visits in response to the outbreak of the SARS epidemic in Taiwan in 2003.

In an early experiment in this literature, Viscusi (1997) provides evidence showing that when there is uncertainty regarding a new health risk and the public receives several different risk assessments, they tend to place inordinate weight on the high risk assessment[1]. The author terms this behaviour an ‘alarmist reaction’ in response to the uncertainty regarding a new health risk. More generally, there is considerable literature exploring the behavioural response to different types of risks, including crime (Linden and Rockoff, 2008; Pope, 2008), smoking (Viscusi and Hakes, 2008; Gerking and Khaddaria, 2012), risky sexual behaviour (Lakdawalla et al., 2006; Chesson et al., 2006), and existing asymptomatic diseases (Oster et al., 2013; Thornton, 2012). Lastly, this paper speaks to the fairly thin, but important, literature that considers the educational implications of a disease outbreak: Archibong and Annan (2017) show that the 1986 meningitis epidemic in Niger increased the gender gap in the number of years of education attained by men and women, and Goulas and Megalokonomou (2016) study how high school students academic outcomes were affected by an increase in the laxity of school attendance policies due to the swine flu outbreak in 2009-10.

We contribute to this literature in several ways. Firstly, we provide support for the experimental results of Viscusi (1997) by showing that a new health risk of uncertain severity (e.g. an epidemic) can lead to a strong behavioural response amongst the general public, with important long-term negative consequences. More specifically, we show that each additional case of severe Dengue per 10 000 inhabitants in a municipality reduced attendance in the school leaving examination in 2010 by 1 percent.[2] This implies that the influence of a single case extends far beyond the individual and household directly afflicted by the illness.[3] There is a large literature documenting the substantial cost of reducing (or delaying) educational attainment (see, for example Card (1999); Carlsson et al. (2015); Light (1995); Krueger and Ashenfelter (1994); Angrist and Krueger (1991); Hansen et al. (2004)). This suggests that a drop in educational attainment due to an epidemic will lead to long-term negative outcomes.

Secondly, we explore the heterogeneity in the reduction in examination attendance observed in administrative data. Interestingly, we find that in municipalities where the proportion of poor

[1]This finding is consistent with a large body of evidence from the non-expected utility literature, which argues that individuals tend to behave as if they overweight the probabilities associated with the ‘best’ and ‘worst’ outcomes from the feasible set of outcomes, such as Choquet-expected utility (CEU) and cumulative prospect theory (CPT) (Schmeidler, 1989; Tversky and Kahneman, 1992; Wakker and Tversky, 1993).

[2]These results are robust to alternative specifications, and a placebo test shows that they are not driven by the empirical strategy.

[3]In the average municipality, there are 41 000 inhabitants. Of these, 21 percent are enroled in primary or secondary school. The school leaving examinations are taken by students in the last year of secondary school - in the average municipality, there are 464 students enrolled in this final year of school, and 363 of them took the SABER 11 examination. Therefore, 4.1 extra cases 4 months before the exam of *severe Dengue* in the entire municipality (i.e. one additional case per 10 000 gives 41 000 / 10 000 = 4.1) would imply that 3.6 fewer students sat their SABER 11 examination in the municipality (i.e. one percent of 363 is approximantely 3.6).

students is lower, the effect is far stronger, while in municipalities with a high proportion of poor students, an additional case of Dengue per 10 000 inhabitants does not have a significant effect in reducing examination attendance. This could be interpreted as providing suggestive evidence that wealthier families panic more and change their behaviour more when faced with substantial uncertainty regarding a risk to their health and mortality. There is scope for more work in this area.

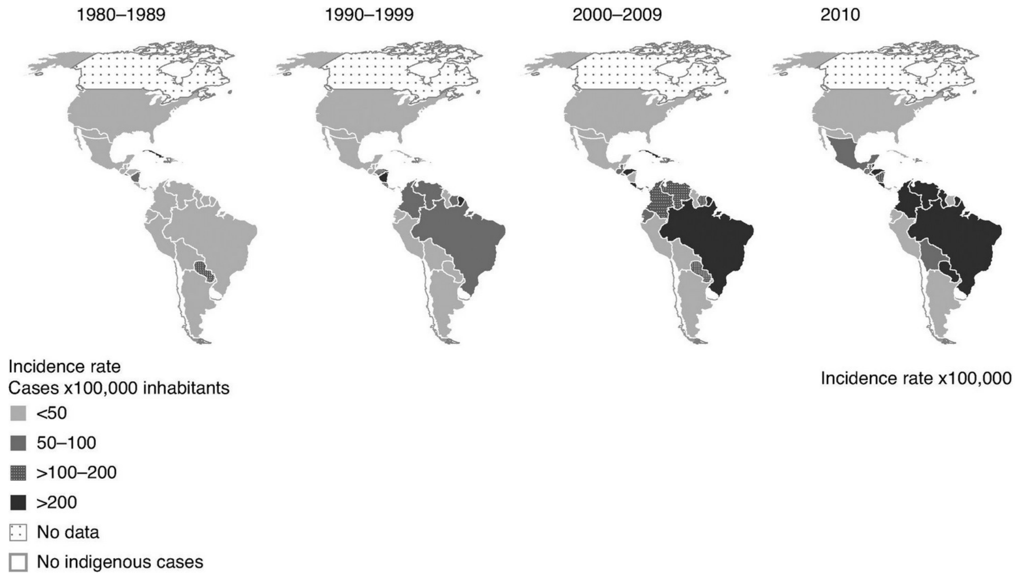
Overall, the results show that the impact of a sudden epidemic are not fully captured by the direct influence on the afflicted families. Rather, other members of society are confronted with reports regarding a threat to their wellbeing and tend to take extreme preventative action. We demonstrate that this shift in behaviour as a result of the epidemic can exert a potentially long-lasting negative influence on the lives of the unafflicted. This evidence serves to make the point that in assessing the true impact of an epidemic, and designing policies to address it, it is very important to take into consideration the behavioural response and the implications of that response.

The remainder of the paper is structured as follows. Section 2 briefly describes the nature of dengue epidemics and their occurrence in Colombia during the recent past. Section 3 presents the data employed in the empirical strategy, which includes a school and student-level analysis and some exercises intended to assess the heterogeneous effects. Section 4 summarizes the main results and outlines some robustness checks that were carried out as a precaution against biased inference. Section 5 discusses the main findings and limitations. Finally, section 6 concludes.

2 Dengue: An Overview

Dengue is the most prevalent mosquito-borne viral disease in the world. It is fast becoming one of the primary worldwide public health concerns due to its extremely rapid rate of expansion over the last decades. This expansion has taken place along both the extensive margin, with the mosquitos migrating to new countries and new altitudes, and along the intensive margin, with the incidence increasing in regions that were already affected. This trend is reflected in Figure 2. The WHO estimates that there are more than 50 million new Dengue infections and more than 22 000 deaths attributable to Dengue every year, worldwide (WHO, 2009).

Figure 2: Dengue Incidence in the Americas, 1980-2010 (reproduced from Tapia-Conyer et al. (2012))



Dengue is transmitted between individuals primarily by the *Aedes aegypti* (Linnaeus) mosquito and can be caused by any one of four distinct dengue virus serotypes (Villar et al., 2015). According to the WHO classification, cases of Dengue fall into two categories, *severe Dengue* (previously referred to as dengue haemorrhagic fever) and *non-severe Dengue*, which we refer to as *classic Dengue* in this paper. *Classic Dengue* is comparable to the flu, with symptoms that are very unpleasant, but temporary and not life threatening (including: severe headache, abdominal pain, muscle and joint pain, mucosal bleeding, lethargy, nausea and vomiting (WHO, 2009)). In contrast, *severe Dengue* results in serious illness, and sometimes death. During 2010, it resulted in hospitalisation in approximately 80 percent of cases and death in approximately 2 percent of cases in Colombia. However, the mortality rate has been substantially higher in the past - e.g. between 1990 and 1999 in Colombia, the mortality rate of *severe Dengue* was sometimes as high as 40 percent (Villar et al., 2015).[4] This history has contributed to the perception of the disease in Colombia as one to be feared.

According to Padilla et al. (2012), one of the primary reasons for the extremely rapid expansion of Dengue is climate change. This has contributed to the expansion of Dengue in two ways. Firstly, it has increased temperatures and allowed mosquitoes to thrive in new regions and at higher

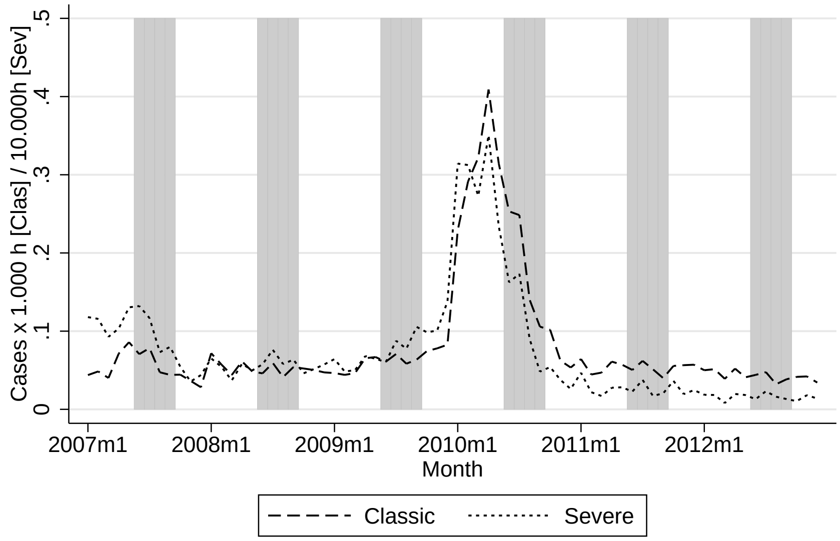
[4]For detailed reviews, particularly in relation to Colombia and the Americas, see Dick et al. (2012), Villar et al. (2015), Teixeira et al. (2013) and WHO (2009).

altitudes. Secondly, there has been an increase in the frequency of droughts, resulting in an increase in reliance on water tanks as a means of water supply. Unfortunately, these stagnant water tanks provide ideal conditions for the *Aedes aegypti* reproduction. In particular these water tanks provide *Aedes aegypti* with a place to lay its eggs during dry periods and keep the baseline population level high while waiting for more favourable conditions[5]. The high prevalence of these water tanks means that when favourable climatic conditions do arrive, the mosquito population is in a position to multiply rapidly. This can result in a sharp spike in Dengue incidence.

In 2010, Colombia experienced a sharp spike of this nature when there was an unprecedented increase in Dengue incidence due, partially to unexpectedly high rainfall variability (De La Mata and Valencia-Amaya, 2014). According to the *Instituto Nacional de Salud* (National Health Institute, or INS), which monitors the status of multiple diseases in Colombia, in 2010 there were 147257 reported cases of *classic Dengue*, and 9755 cases of *severe Dengue*. The estimated incidence was 577 per 100 000 individuals for *classic Dengue* and 38.3 per 100 000 individuals for *severe Dengue* (Villar et al., 2015). Figure 3 shows clearly that the 2010 epidemic was both extremely sudden and sizeable, with the baseline incidence of Dengue in the years around the epidemic (2008, 2009, 2011, and 2012) being nearly flat.

[5]The average lifespan of the *Aedes aegypti* mosquito is two weeks, however, the eggs of the mosquito can lie dormant in dry conditions for up to nine months. They can then hatch if they are exposed to favourable conditions. *Aedes Aegypti* benefits from the existence of stagnant water tanks and is active at the beginning and end of the day. Previously, the areas in which this mosquito could be found were limited to the tropical and subtropical regions of the Americas, between the latitudes of 35°north and 35°south (Organización Panamericana de la Salud, 1995). The WHO notes that due to rapid geographical expansion dengue now ranks as the most harmful mosquito-borne viral disease in the world, affecting different geographic areas in the Americas, South-East Asia, the Eastern Mediterranean as well as the Western Pacific.

Figure 3: Municipal average incidence of Dengue fever per month



Source: Own calculations using SIVIGILA data and 2005 Census population numbers. Vertical lines correspond to the 4 months prior to SABER 11 exam.

Aside from requiring sufficient rainfall for reproduction, altitude is the second factor that is important for determining whether a particular area is suitable for inhabitation by *Aedes aegypti*. Figures 4 and 5 show the incidence of *classic Dengue* and *severe Dengue* in 2008 - 2011 at different altitudes using a local linear approximation. These figures show that in 2010 there was a substantial increase in incidence at all altitudes, but perhaps more surprisingly, there was a considerable expansion of the disease to municipalities at altitudes above 1500m (Colombia is divided into 1123 Municipalities, which belong to 32 Departments), which in prior years were relatively unaffected[6]. Furthermore, Figure 6 shows that approximately 10% of municipalities transitioned from having 0 cases of *severe Dengue* in 2009 to being affected by the disease in 2010. A similar pattern is observed for *classic Dengue*. The geographical variation in *severe Dengue* incidence is illustrated in Figure 7. This figure presents the *severe Dengue* incidence rates in 2010, colour coded according to the 2008 incidence, a pre-outbreak year. It shows that in 2010, the epidemic spread from endemic areas (shades of blue) to the areas where there were no cases in 2008 (shades of red).

[6]The evidence provided by Figures 4 and 5 is supported by Table 1, which shows that this rapid expansion was not only due to an increase in incidence in endemic municipalities. Rather, for *severe Dengue*, 2010 was the only year in which the 75th percentile municipality was affected; while for *classic Dengue*, the incidence per 1 000 inhabitants for the municipality at the 75th percentile jumped dramatically from 0.15 to 1.1.

Table 1: Dengue Incidence Rates 4 months before September SABER 11 test

Statistic	2007	2008	2009	2010	2011	2012
C. Dengue 1000h (4M)						
Mean	.28	.19	.26	.96	.22	.16
Stand. Dev	.78	.55	.87	1.8	.63	.44
Minimum	0	0	0	0	0	0
Median	0	0	0	.21	0	0
Percentile 75	.18	.17	.15	1.1	.21	.12
Percentile 95	1.7	.91	1.3	4.3	.96	.81
Maximum	10	8.4	13	22	13	5.2
1 year variation	.	-.087	.062	.7	-.74	-.056
S. Dengue 10000h (4M)						
Mean	.45	.24	.29	.66	.11	.071
Stand. Dev	1.7	.99	1	2.4	.55	.32
Minimum	0	0	0	0	0	0
Median	0	0	0	0	0	0
Percentile 75	0	0	0	.37	0	0
Percentile 95	2.7	1.4	1.8	3.3	.59	.43
Maximum	26	21	12	44	8.9	4.4
1 year variation	.	-.21	.049	.37	-.55	-.035

Source: Own calculations based on SIVIGILA data and DANE national census 2005 population numbers.

Figure 4: Municipal altitude and yearly incidence of classic Dengue fever

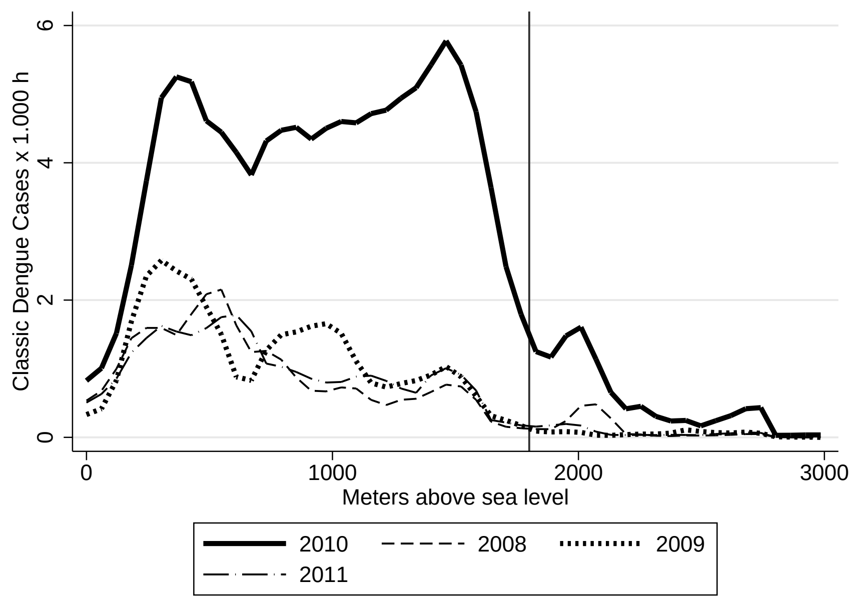
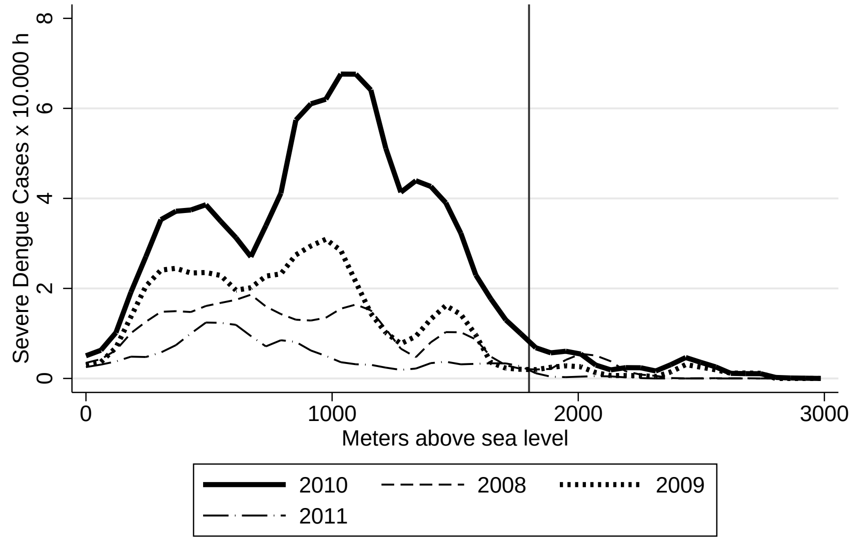


Figure 5: Municipal altitude and yearly incidence of severe Dengue fever



Source: Own calculations using SIVIGILA data and 2005 Census population numbers. Incidence rates are per calendar year.

Figure 6: Distribution of classic and severe Dengue Incidence

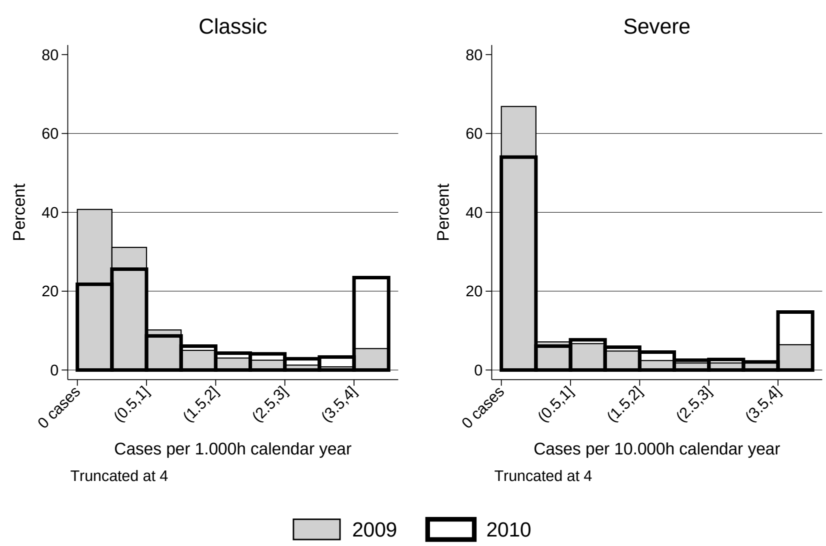
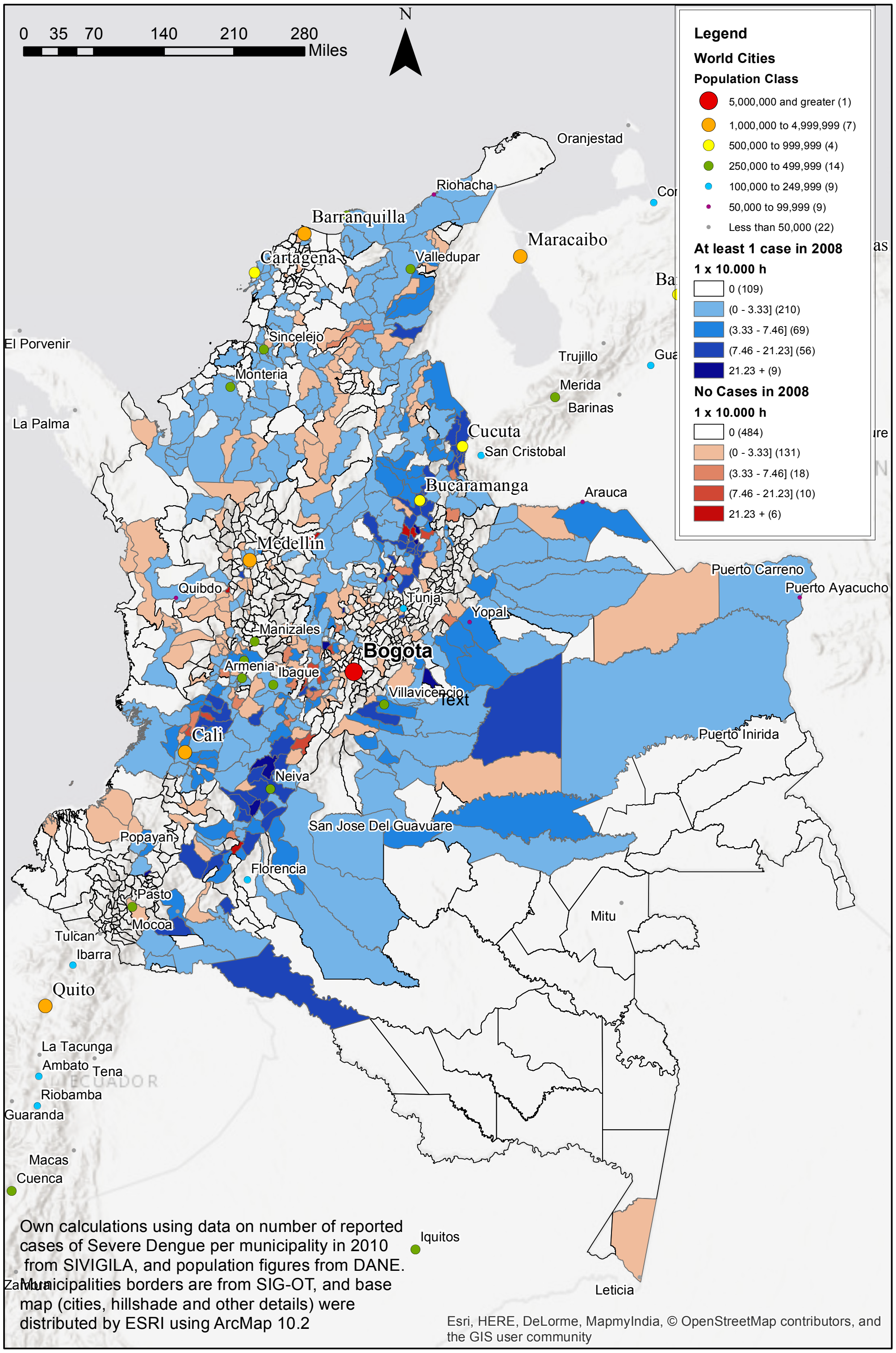


Figure 7: Geographical Distribution of severe Dengue Incidence in Colombia, 2010



Comparing the number of infections to the size of the Colombian population (approximately 46 million inhabitants in 2010), it is clear that the 2010 Dengue epidemic had a substantial effect. The direct economic costs of the disease were considerable, with Padilla et al. (2012) estimating that medical costs related to the disease during this year alone amounted to about US$100 million. In addition to the public health costs, epidemics also place substantial pressure on households' budgets due to out-of-pocket health expenses and loss of productivity (Beatty et al., 2011).

Unfortunately, the burden of the epidemic is not equally distributed between the poor and the wealthy. One implication of the higher incidence of water tanks used by low-income households for their water supply is that these low-income households therefore tend to be at higher risk of Dengue than high-income households (Baylis and Risley, 2013). This implies that the poor are disproportionately afflicted by the disease (although, this may not be reflected in people's perceptions). While these direct effects are certainly very serious, the objective of this paper is to examine the influence that it has on human behaviour, or more specifically, to examine the indirect impact that a short, sharp, relatively unexpected and uncertain health shock can have via a behavioural response.

3 Methods

3.1 Data

We use administrative data containing individual level schooling outcomes (e.g. examination attendance, and test scores for mathematics and language) from the end of high school examination (named "SABER 11"), managed by ICFES[7]. The data also contains demographic information about the students and their families.

SABER 11 is the most important educational test taken during high school in Colombia because of its extensive use as a measurement of educational attainment. Each school student in the final (i.e. eleventh) year of high school is expected to take this examination. The test provides a national ranking that is used by universities in order to determine admission. Therefore, SABER 11 is important not only for students, as it is a requirement to continue their academic career, but also for schools as the average result is used by the government (and families) in order to determine the quality of the institution.

There are two dates for taking the test in the year. The decision regarding the timing of test-taking is typically contingent on the academic calendar followed by the school. In Colombia

[7] ICFES is a government institution for the assessment of quality in education.

the academic year usually corresponds to the calendar year, but a minority of schools follow the northern hemisphere academic year (September to June).[8] We focus on those schools where the academic year corresponds to the calendar year as the majority of the students (around 90%) attend these schools. In Figure 3, vertical lines correspond to the four months prior to the September exam date. As a result, it is plausible that the participation and performance in the 2010 exam was affected by the outbreak.

With respect to the SABER 11 test data, we also exclude schools that operate over the weekends or at night, which typically cater to young adults who are already working and want to finish their secondary education. After these exclusions, we have approximately 2 million observations available for the analysis, covering the years 2007 to 2012. Table 2 describes the variables that we use from this dataset.

In our main analysis, we use the examination and demographic data at two levels of aggregation: (i) firstly, we use it as a longitudinal panel dataset at school level; and (ii) secondly, we use it as a repeated cross-sections at the individual level.

In order to assess the impact of the epidemic, we combine the data described above with information regarding *severe Dengue* and *classic Dengue* cases collected weekly at the municipality level by the INS. From it we construct the incidence of the illness for the four months prior to the exam date.

Last, in parts of our analysis, it will be useful to have measures of exogenous factors that tend to exacerbate or moderate the intensity of the epidemic in a particular region. In particular, we have collected rainfall and temperature data, measured across time and geographic location, spanning the period of the epidemic. This weather data provides us with exogenous shocks that vary across time and space, and can be used to instrument for the intensity of the epidemic. In addition, we also collect altitude data, which is also predictive of the intensity of the epidemic, but does not vary across time, and is therefore only useful in certain instances within our analysis. This data, along with other relevant municipality level variables are summarised in Panel C of Table 2.[9]

[8]These schools are concentrated in a few cities, especially in the capital which was unaffected by the outbreak because of its location.

[9]The general municipal characteristics data is sourced predominantly from the 2005 National Census. Data regarding natural disasters was compiled from the *Sistema Nacional de Informacion y Gestion del Riesgo* (SNIGRD) webpage, a government institution.

Table 2: Descriptive Statistics for year 2010

Variable	Mean	SD	Obs
Municipality: general characteristics (CEDE, DNP, SIHO, ERA-Interim ECMWF)			
Total population (1000s)	41	250	1122
Altitude (meters above sea level)	1168	917	1086
Avg. 2m temperature (C), last 8 months (Aug)	20	3.6	1081
Avg. Precipitation (mm)*100, last 8 months (Aug)	.5	.35	1081
NBI Poverty Index x (year=2010)	45	21	1122
Subsidized Health Care / Population	.7	.48	1118
Log income per capita	-.39	.46	1092
Municipality dependence on central Gov. transfers	.58	.19	1118
Log-population	9.5	1.1	1122
Inpatient Beds per 10.000h	7.2	11	855
A&E positions per 10.000h	1.1	1.2	855
Certified x (year=2010)	.45	.5	1098
Municipality: other infectious diseases (SIVIGILA)			
Influeza-like per 1000h, Cal Y	.2	.65	1122
Municipality: emergencies due to natural events (SNIGRD)			
Total individuals	.87	6.7	1123
Total dwellings	334	875	1123
Total roads	.92	2.7	1123
Total hectares	227	1429	1123
School characteristics			
Private management	.27	.44	8463
Public management	.73	.44	8463
Full-day shift	.36	.48	8463
Morning shift	.47	.5	8463
Afternoon shift	.17	.37	8463
Female-only	.041	.2	8463
Male-only	.0093	.096	8463
Mix gender	.95	.22	8463
% of women test-takers	53	18	8463
% of SISBEN 1/2 of test-takers	69	35	8463
Average Income of the Families	1.6	1.3	8456
Number of test-takers	47	44	8463

Source: Own calculations based on ICFES data, *Sistema Nacional de Informacion y Gestion del Riesgo* (SNIGRD), *Sistema de Informacion de Hospitales Publicos* (SIHO), *Departamento Nacional de Planeacion* (DNP), *Sistema de Vigilancia en Salud Publica* (SIVIGILA), CEDE municipality dataset, and ERA-Interim (ECMWF) weather and altitude data. Certified municipalities are those who are able to determine how they spend part of their education and/or certain health care resources according to previous performance assessments by Central Government. For those non-certified, such expenses are controlled directly by the departmental authorities. This classification depends on population size and on some administrative quality indicators. The NBI is a government multidimensional poverty index which considers quality of life and access to public goods.

3.2 Empirical Strategy

Across all of our empirical specifications, we exploit the variation that we observe in the Dengue incidence over time and across geographic area. The identification of causal effects relies on the exogeneity of idiosyncratic time-shocks to Dengue incidence. We will exploit the variation in Dengue incidence generated during the 2010 outbreak. Further, we argue that part of this variation in the intensity of the epidemic across time and geographical area was driven by exogenous weather triggers that exacerbated or dampened the intensity of the epidemic. We will use measures of rainfall and temperature variation to capture the variation generated by these weather triggers.

Importantly, our empirical strategy will include both time and school (or municipality) fixed effects[10]. These will capture all variables at the school or municipality level that do not change over time, as well as all shocks that might affect the entire country at a particular point in time. Therefore, time-invariant factors such as altitude and poverty in a particular region which do tend to be related to the intensity of the outbreak in the area are captured by these fixed effects. However, we do consider the influence of the interaction between these time-invariant variables and the incidence of Dengue (e.g. we ask questions of the type: Does an additional case of Dengue have a different impact in an impoverished area, in comparison to an additional case in a richer area?).

The identification strategy relies on the assumption that the time-spatial variation in the intensity of Dengue is exogenous with respect to other time-varying variables that might affect the outcomes of interest. In general, this assumption would only be violated if there were some unobserved factor that varied both temporally and geographically and explained the variation in the 2010 Dengue epidemic, as well as variation in our outcomes of interest. We will discuss the main factors associated with the intensity of the outbreak, in order to make it clear that this assumption is credible.

Our analysis considers the impact of both *severe* and *classic* Dengue, but the primary focus is on the results for *severe Dengue* due to our interest in the behavioural effects of the epidemic. As primary unit of analysis, we will consider outcomes at both the school and student level.

3.3 Analysis of the outbreak intensity

3.3.1 Municipality Level Specification

Table 3 provides the estimates from a linear panel regression of the *severe Dengue* incidence on an array of municipality level covariates that shows which municipality characteristics are correlated with the incidence of *severe Dengue*. Municipality level fixed effects control for time-invariant factors. As one might expect, there is a clear relationship between *severe Dengue* and the economic profile of the municipality, summarized here by the poverty index; this will be further discussed in the results section. Interestingly, altitude, which has a strong influence on local climatic conditions, has a different sign at low altitudes and high altitudes (Columns 4 and 5). At low altitudes (Column 4) an increase in altitude is positively correlated with *severe Dengue*, whereas at higher altitudes

[10]Specifications at the school level include school fixed effects, while specifications at the municipality level include municipality fixed effects.

(Column 5), it is negatively correlated. This implies an inverse-U shaped conditional correlation between altitude and *severe Dengue* in 2010.

Table 3: Determinants of Severe Dengue Incidence (cases per 10.000h in the 2010 calendar year)

	$\bar{X}$	Below 2000 masl (1)	Below 2000 masl (2)	Below 2000 masl (3)	Below 1000 masl (4)	1000-2000 masl (5)
Altitude x (year=2010)	89.860	0.0005***	−0.0004	−0.0004**	0.0034***	−0.0065***
		(0.0002)	(0.0002)	(0.0002)	(0.0011)	(0.0016)
Avg. 2m temperature (C), last 12 months (Aug)	19.800	−0.7638***	−0.7921***	−0.3952***	−0.7673***	−0.8761***
		(0.0736)	(0.0735)	(0.0832)	(0.0784)	(0.1355)
Avg. Precipitation (mm)*100, last 12 months (Aug)	0.528	−3.4004***	−2.9169***	−2.3260***	−1.3342*	−3.6475***
		(0.6158)	(0.5819)	(0.5320)	(0.7089)	(1.1033)
NBI Poverty Index x (year=2010)	3.492		−0.0650***	−0.0327***	−0.0352***	−0.0735***
			(0.0119)	(0.0113)	(0.0080)	(0.0281)
Certified x (year=2010)	0.034		0.0014	0.4011	0.1099	0.0771
			(0.4101)	(0.3769)	(0.3895)	(0.7313)
Year = 2009	0.077	0.6770***	0.6906***	0.4470***	0.9570***	0.0476
		(0.1199)	(0.1200)	(0.1041)	(0.1373)	(0.2364)
Year = 2010	0.077	2.1203***	5.8752***	2.6510***	3.1655***	15.4000***
		(0.2070)	(0.8968)	(0.8629)	(0.7154)	(3.8813)
Year = 2011	0.077	0.1627**	0.1393*	−0.1163	0.1466**	0.0420
		(0.0765)	(0.0774)	(0.1003)	(0.0715)	(0.1954)
Year = 2012	0.077	−0.0062	−0.0174	−0.2064***	−0.0395	0.0008
		(0.0514)	(0.0520)	(0.0606)	(0.0500)	(0.1090)
Classic Dengue per 1000h, Cal Y	0.441			0.4994***		
				(0.0816)		
N Observations		5118	5022	5022	2826	2166
N Clusters (Departments)		853	837	837	471	361
Adjusted R^2		0.114	0.139	0.254	0.177	0.184

† Linear panel fixed effects regression at municipality level with Severe Dengue Incidence (10.000 cases per hab., calendar year) as a dependent variable. Certified municipalities are those who are able to determine how they spend part of their education and/or certain health care resources according to previous performance assessments by Central Government. For those non-certified, such expenses are controlled directly by the departmental authorities. This classification depends on population size and on some administrative quality indicators. The NBI is a government multidimensional poverty index which considers quality of life and access to public goods. A summary of the variables included in this table is presented in Table 2.
Robust standard errors in parenthesis. Significance: * 10%, ** 5%, *** 1%.

Lower rainfall levels, which assist in the reproduction of the mosquito (as it is more likely to find stagnant water), are a strong predictor of the intensity of the outbreak. Other variables such as the municipality's degree of control over health expenses (i.e. being a 'certified' municipality[11]) are irrelevant once poverty levels are taken into account.

Taken together, these results provide support for the validity of our main identification assumption (i.e. that our results are not driven by another variable that covaried with Dengue in 2010). Firstly, the outbreak comprised a sharp and unexpected increase in Dengue that occurred over a relatively short period of time. Secondly, the majority of factors that one would expect to drive an

[11]Certified municipalites are those who are able to determine how they spend part of their education and/or health care resources. This clasification depends on previous performance assessments by the national government. For those that are non-certified, such expenses are controlled directly by the departmental authorities. This classification depends on population size and some administrative quality indicators.

epidemic of this nature are fixed over the short period of time we are considering (e.g. altitude, demography of population, health care and public health system characteristics). Furthermore, the main type of variable that we may expect to vary across time and also influence the epidemic are climatic factors. However, we are able to control for both climatic variation and natural disaster information with our control variables.

3.3.2 School Level Specification

The school level impacts of Dengue are estimated using the panel of school level variables obtained by collapsing the SABER 11 administrative examination data at school level. For this specification, we exploit the fact that we observe the same schools over time to control for school level fixed effects. Therefore, we estimate the impact of Dengue incidence by using the following linear fixed effects panel estimator:

$$Y_{kjt} = \sum_{\tau=0}^{T} \delta_{\tau}^{Y} D_{jt-\tau} + \beta X_{kjt} + \gamma_k + \gamma_t + u_{kjt} \tag{1}$$

where Y_{kjt} is the outcome of interest for school k, in municipality j, in year t; γ_k and γ_t are fixed effects for school and time respectively; and X_{kjt} is a vector of school and municipality level controls. The parameter that we are primarily interested in estimating is δ_{τ}^{Y}, which reflects the impact of Dengue incidence, lagged by τ periods, on the outcome of interest. Notice, we include the lags to assess whether past Dengue incidence in the municipality plays any role in influencing the current outcomes.

3.3.3 Student Level Specification

Using the student level test data from SABER 11, we employ a similar specification to assess the influence of Dengue incidence on test scores. In this specification, we observe each student i in school k (where the errors are clustered at the school level), and estimate the following equation:

$$Y_{ikjt} = \sum_{\tau=0}^{T} \delta_{\tau}^{Y} D_{jt-\tau} + \beta X_{ikjt} + \gamma_k + \gamma_t + u_{ikjt} \tag{2}$$

Equation 2 follows a similar rationale to equation 1, with the exception of examining individual level outcomes, and the inclusion of individual level variables in the set of controls, X_{ikjt}.

3.3.4 Heterogeneous Effects

It is also of considerable interest to examine whether we observe heterogeneity in terms of the type of municipalities which were most affected by *severe Dengue* as this can help us to understand the mechanism driving the influence of the epidemic. The following specification allows us to interact a polynomial in a given observable characteristic with the treatment variable (Dengue incidence):

$$\begin{aligned} Y_{kjt} = \delta_1 D_{kt} + \sum_{z=1}^{\#Z} \big(& \delta_{2,z} D_{kt} * Z_{zkjt} + \delta_{3,z} D_{kt} * Z_{zkjt}^2 + \delta_{4,z} D_{kt} * Z_{zkjt}^3 \\ & + \varphi_{1,z} Z_{zkjt} + \varphi_{2,z} Z_{zkjt}^2 + \varphi_{3,z} Z_{zkjt}^3 \big) + \beta X_{kjt} + \gamma_k + \gamma_t + u_{kjt} \end{aligned} \tag{3}$$

where we consider heterogeneous effects in $\#Z$ observable variables, indexed by z; and Z_{zkjt} refers to a specific one of these variables for school k, municipality j and year t. As in equations 1 and 2, we include fixed effects for the municipality and year, as well as a vector of controls, X_{kjt}.

4 Results

4.1 Test Attendance

We begin our analysis by examining the impact of 1 additional case of Dengue (per 10 000 inhabitants for *severe Dengue* and per 1 000 inhabitants for *classic Dengue*) on the number of students who took the school leaving examinations in 2010 using equation 1.

The results are displayed in Table 4. Firstly, columns (2) and (4) show that an increase in *classic Dengue* has no significant effect on participation in the SABER 11 examination. However, columns (1) and (3) show that there is a large contemporaneous effect of *severe Dengue* on attendance in the examination. More specifically, the magnitude of the estimates suggests that for each additional case of *severe Dengue* per 10 000 inhabitants in the municipality, 1 percent fewer students attended the examination. This implies that if there is an increase in *severe Dengue* cases by 10 per 10 000 inhabitants, in the average class of 38 pupils, 3.8 - 4.2 fewer pupils attended the examination (using the estimates from column (1) and (3) respectively). While it is important to stress that having 10 cases of *severe Dengue* per 10 000 inhabitants is in general fairly rare, over 10 percent of municipalities in Colombia had an incidence rate at least this high during the 2010 epidemic.

Table 4: Number of test takers per school and Dengue Incidence

	LOG(Number of students who presented the test)				LOG(Number of schools per municipality with at least 1 SABER 11 test taker)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
S. Dengue 10000h (4M)	-0.010**		-0.011**		-0.036		-0.003	
	(0.005)		(0.005)		(0.034)		(0.021)	
L.S. Dengue 10000h (4M)			-0.005				0.033	
			(0.004)				(0.025)	
L2.S. Dengue 10000h (4M)			-0.000				0.055	
			(0.003)				(0.040)	
C. Dengue 1000h (4M)		0.002		0.004		-0.068		-0.023
		(0.005)		(0.005)		(0.059)		(0.037)
L.C. Dengue 1000h (4M)				0.003				0.036
				(0.005)				(0.047)
L2.C. Dengue 1000h (4M)				0.005				0.080
				(0.007)				(0.083)
Observations	37299	37299	30862	30862	3935	3935	2998	2998
Schools/Municipalities	8839	8839	8746	8746	837	837	836	836
Municipalities	837	837	836	836	837	837	836	836
Adj. R squared	0.02169	0.02087	0.02412	0.02297	0.04243	0.04247	0.01906	0.01906

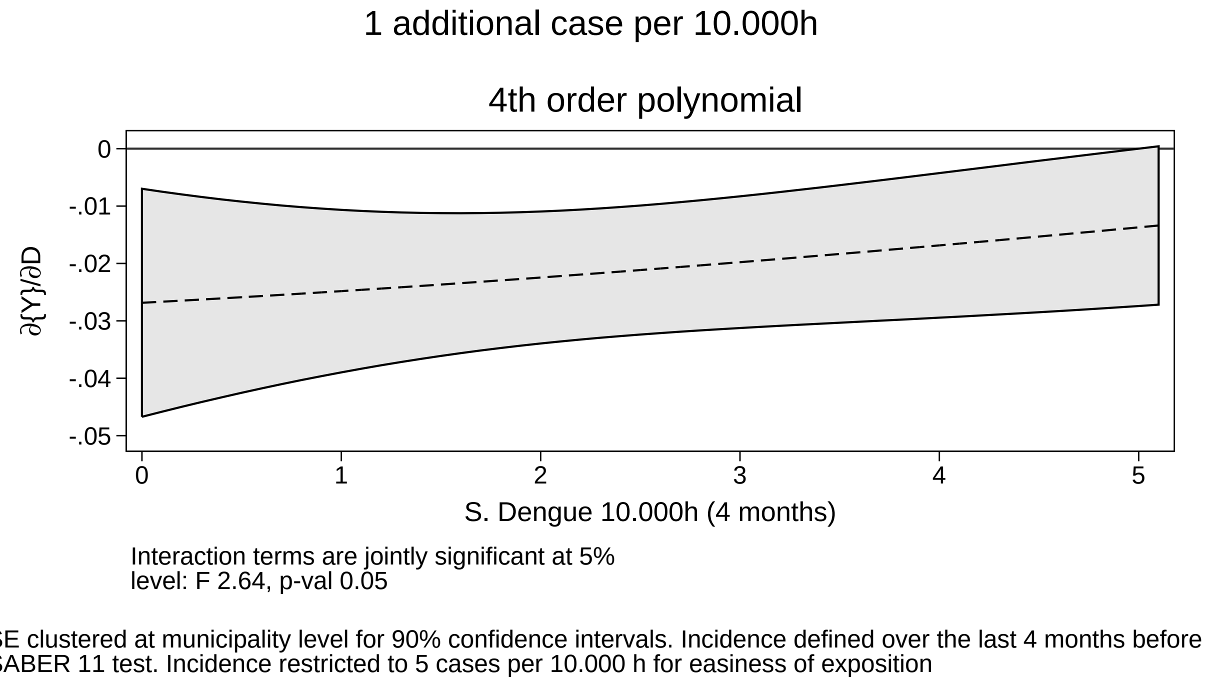
Linear fixed effects panel regression at school level (see Equation 1). S. Dengue is the reported incidence of Severe Dengue in the last 4 months (4M) at municipality level and C. Dengue is the incidence of Classic Dengue at the same level. L.S. Dengue and L.C. Dengue are the lag of Severe and Classic Dengue, respectively. On top of the fixed effects by school and by year, these controls for Inpatient beds and AE positions per 10.000h, Subsidized Health Care registry as a percentage of Population, municipality dependence on central government transfers, municipality per capita income, the incidence rate of influenza-like cases per 1.000h in the municipality during the calendar year, avg. temperature and rainfall for the last 8 months, log-population and the standardized number of people, houses and roads affected by natural disasters. See Table 2 for further details. See Table 2 for further details.
Clustered at municipality level SD in parenthesis. Significance: * 10%, ** 5%, *** 1%.

One potential explanation is that entire schools closed during the epidemic, and consequently the students did not sit the examination. This could be the case if they had to close because of public health considerations.[12] Columns 5 to 8 in Table 4 consider as an outcome the number of schools per municipality for which at least one student took the test. As a result, there is no evidence of Dengue leading to school closures.

While the discussion of Table 4 above showed that on average an increase in *severe Dengue* implied a decrease in examination attendance, it is interesting to consider whether this impact was non-linear. To explore this, the marginal effects of *severe Dengue* at different levels of *severe Dengue* intensity are plotted in Figure 8 using a polynomial of order 4. The non-linear terms are jointly different from 0, but the difference between the point estimates at intensity level 0 and 5 are not statistically different from one another at the 90% level.

[12]We are not aware of any such closure in Colombia, but it is a real possibility. In a Dengue outbreak in Paraguay (2009), at least one school was temporarily closed in the Bugaba district because of the high incidence of classic Dengue and the occurrence of two severe cases Vásquez (2009).

Figure 8: Marginal effect of severe Dengue on the LOG number of Test Takers: non-linear effects



4.2 Test Scores

We explore the impact of Dengue incidence (*classic* and *severe*) on mathematics and language scores, conditional on having taken the exam in these subjects. Table 5 indicates very small estimates for the impact at student and school level, respectively. The size of these estimates for the impact of Dengue is put into perspective if we compare them to the magnitude of the influence of other characteristics that are known to be related to test scores, such as gender for mathematics. While, the gender gap in mathematics is 0.3 standard deviations, an additional case of *severe Dengue* is associated with a decrease of only 0.003 standard deviations in language, and does not have a significant effect on mathematics at all, conditional on examination attendance. A similar pattern is observed when using the mean test scores aggregated at the school level. Therefore, we conclude that the epidemic had a negligent effect on test scores, conditional on participation.

Table 5: Test scores

	Student level				School level			
Variable	**Math**	**Math**	**Lang**	**Lang**	**Math**	**Math**	**Lang**	**Lang**
S. Dengue 10000h (4M)	0.0007		-0.0034^{**}		0.000		-0.005*	
	(0.0011)		(0.0014)		(0.002)		(0.002)	
S. Dengue 10000h (4M), 1 year ago	0.0014		-0.0059^{***}		0.002		-0.005**	
	(0.0013)		(0.0012)		(0.002)		(0.003)	
S. Dengue 10000h (4M), 2 years ago	-0.0008		-0.0030^{***}		-0.000		-0.002	
	(0.0012)		(0.0010)		(0.002)		(0.002)	
C. Dengue 1000h (4M)		0.0031^{*}		0.0074^{***}		0.006**		0.002
		(0.0017)		(0.0020)		(0.002)		(0.004)
C. Dengue 1000h (4M), 1 year ago		0.0002		0.0165^{***}		0.002		0.010**
		(0.0019)		(0.0024)		(0.003)		(0.004)
C. Dengue 1000h (4M), 2 years ago		-0.0045^{**}		0.0170^{***}		-0.005		0.007
		(0.0020)		(0.0022)		(0.004)		(0.006)
=1 if student is a girl	-0.3106^{***}	-0.3106^{***}	-0.0319^{***}	-0.0319^{***}				
	(0.0021)	(0.0021)	(0.0017)	(0.00172				
N Observations	1501868	1501868	1508018	1508018	30862	30862	30864	30864
N Clusters (Schools)	8746	8746	8743	8743	8746	8746	8746	8746

For the first four columns, reported coefficients come from an OLS over a repeated cross section, with fixed effects at school level (see Equation 2). For the last four columns, the estimated model is a linear fixed effects panel regression at school level (see Equation 1). In each case, the two left-hand columns employ standardised mathematics scores as dependent variables and the two remaining are standardised language scores. S. Dengue is the reported incidence of Severe Dengue in the last 4 months (4M) at municipality level and C. Dengue is the incidence of Classic Dengue at the same level. On top of the fixed effects by school and by year, these controls for Inpatient beds and AE positions per 10.000h, Subsidized Health Care registry as a percentage of Population, municipality dependence on central government transfers, municipality per capita income, the incidence rate of influenza-like cases per 1.000h in the municipality during the calendar year, avg. temperature and rainfall for the last 8 months, log-population and the standardized number of people, houses and roads affected by natural disasters. See Table 2 for further details.
Clustered at municipality level SD in parenthesis. Significance: * 10%, ** 5%, *** 1%.

These results are comparable to those of Goulas and Megalokonomou (2016), who found that the swine flu outbreak (2009-10) in Greece triggered an increase in high school students' absenteeism. However, in their case this behavioural change resulted in an increase in average test scores, indicating a stronger pattern of selection (i.e. it suggests that in their case relatively more weaker students than stronger students selected into absenteeism).

4.3 Heterogeneous effects

In this section, firstly, we examine whether the impact of *severe Dengue* varied according to the prior incidence of the disease. More specifically, we consider the impact in municipalities which had no cases of *severe Dengue* in 2007 and 2008 separately from municipalities that were already afflicted in these previous years. Secondly, we assess whether the characteristics of the municipalities and the school affected the impact of Dengue on students who attended that school.

Table 6 compares the behavioural response to *severe Dengue* in municipalities that were not affected by *severe Dengue* prior to the epidemic (i.e. in 2007, 2008) to endemic municipalities. This is done by interacting the intensity variable with an 'endemicity' indicator. While the coefficient for those places that normally do not have severe Dengue seems to be larger, these coefficients are not statistically different from one another. Furthermore, Figure 9 shows that for those municipalities with at least 1 case of *severe Dengue* in 2008, there was no differential effect according to prior intensity level.

Table 6: S. Dengue Impact by Prior Intensity

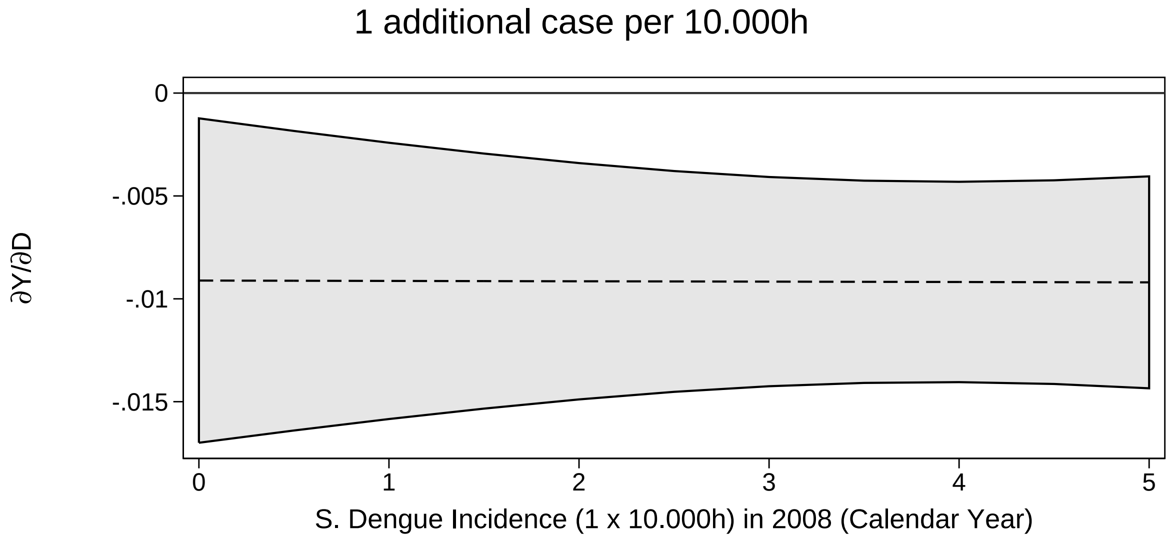
	LOG(Takers)	Maths	Lang
	(1)	(2)	(3)
S. Dengue x No Cases 2007, 2008	-0.011**	0.001	-0.003
	(0.005)	(0.004)	(0.004)
S. Dengue x At least 1 Case 2007, 2008	-0.006**	0.000	-0.003
	(0.003)	(0.002)	(0.002)
Observations	37299	37299	37301
Schools	8839	8839	8839
Avg. periods per school	4.22	4.22	4.22
Municipalities	837	837	837
Adj. R squared	0.02	0.02	0.01
H0: impact is the same	0.4561	0.8680	0.9590

Linear fixed effects panel regression at school level (see Equation 1). In Column 1, the dependent variable LOG(Takers) is the logarithm of the number of students who presented the test per school. In Columns 2 and 3, the dependent variables are the standardised test result in mathematics (Maths) and language (Lang). S. Dengue is the reported incidence of Severe Dengue in the last 4 months (4M) at municipality level, and it is interacted with a couple if dummies that indicates the presence or not of Dengue cases in the past. On top of the fixed effects by school and by year, these controls for Inpatient beds and AE positions per 10.000h, Subsidized Health Care registry as a percentage of Population, municipality dependence on central government transfers, municipality per capita income, the incidence rate of influenza-like cases per 1.000h in the municipality during the calendar year, avg. temperature and rainfall for the last 8 months, log-population and the standardized number of people, houses and roads affected by natural disasters. See Table 2 for further details.
Clustered at municipality level SD in parenthesis. Significance: * 10%, ** 5%, *** 1%.

Using the same specification from equation 3, we estimate the heterogeneous effects of *severe Dengue* by school and municipality characteristics. In line with the analysis above, we focus only on municipalities below 1800m since these are the municipalities that are most affected. Figure 10 presents these estimates of heterogeneous effects for indicators of the capacity of the health system in the municipality, as well as for measures of the wealth level of the children in a given school.[13]

[13]The rationale for the former is to consider whether people respond more in avoiding public spaces when there is a weaker health system that they might perceive as providing protection. The latter considers whether the wealthy respond to the epidemic differently to the poor.

Figure 9: Marginal effect of severe Dengue on the LOG number of Test Takers: by S. Dengue Incidence in 2008

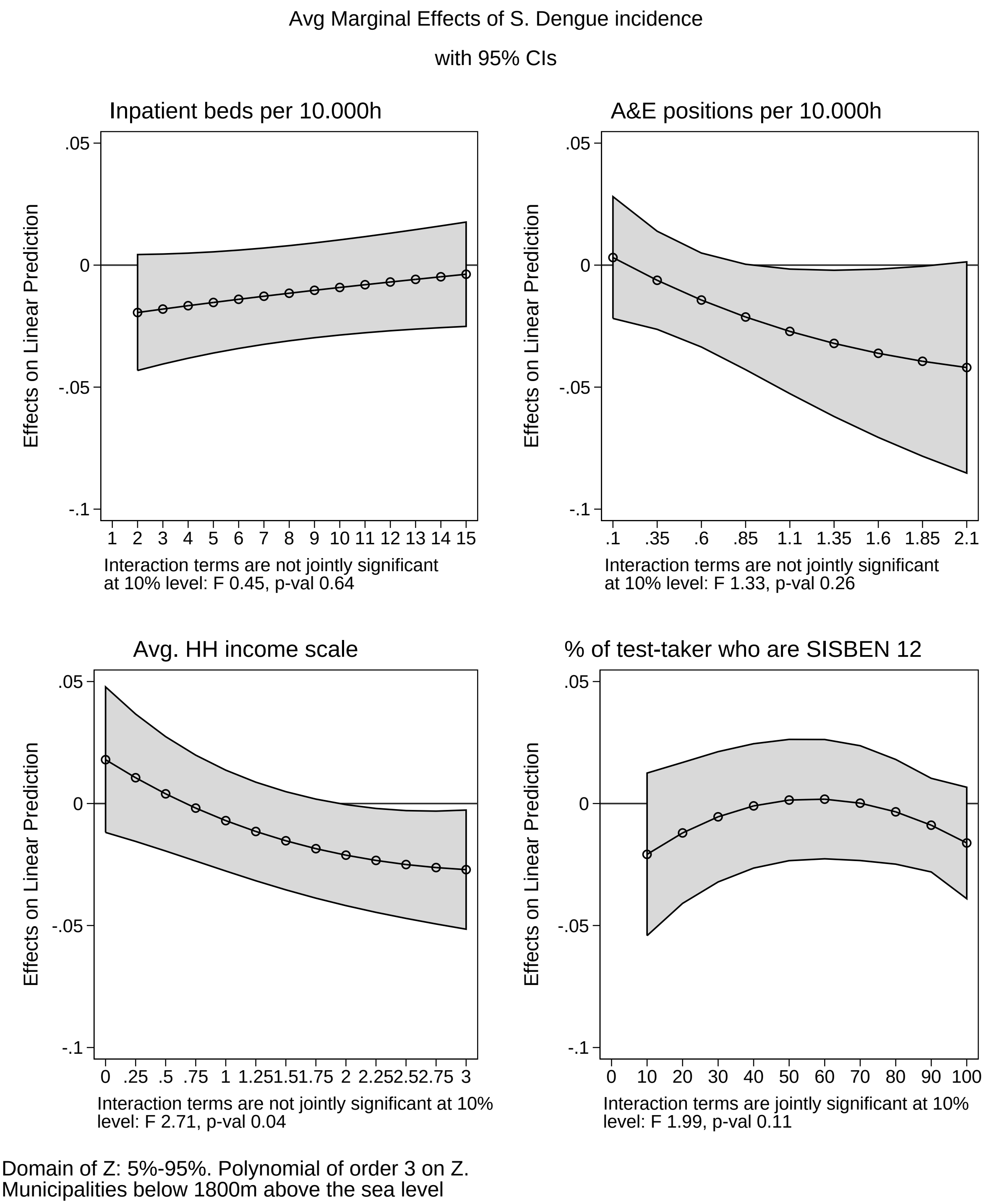


Linear interaction term between outbreak (2010) and pre-outbreak (2008) incidence was not different from 0 (p-val: 0.99). SE clustered at municipality level for 90% confidence intervals. Incidence of the vertical axis is defined over the last 4 months before SABER 11 test. Incidence restricted to 5 cases per 10.000 h for easiness of exposition

The rationale for examining the influence of the health capacity of the municipality is that one might expect the public's perception of the ability of the municipality to contain an epidemic may affect the beliefs of members of the community regarding their mortality risk due to the epidemic. This could then affect their behaviour in response to the epidemic. Furthermore, one would expect that the public's perceptions regarding the efficacy of the health system would be related to measures of the true efficacy. The upper panels of Figure 10 do not provide much evidence in favour of a heterogeneous impact due to variation in the characteristics of the health system. While the point estimates for the coefficients are negative everywhere, these interactions terms are not jointly different from 0.

Interestingly, in the lower panel, there appears to be a clear pattern when considering heterogeneity in the self-reported income index. The impact is not significantly different from 0 when considering schools with low average income levels, but the point estimate of the impact decreases to nearly -4 pp for schools with high average income levels. This pattern arises even after controlling for SISBEN status, a means-test used for classification in allocating conditional cash transfers.

Figure 10: Marginal effect of severe Dengue on the LOG number of Test Takers: heterogeneous effects



4.4 Robustness Checks

In order to test our identification assumptions, we conducted several robustness exercises. The main results of these exercises are summarised in Table 7, while we also provide a more detailed discussion of the exercises and results in Section B of the Supplementary Material associated with the paper.

First, we conducted a placebo test in which we assessed the impacts of future Dengue shocks (two years leads of incidence rate) on current outcomes. It showed no evidence of any anticipatory effects. Secondly, we varied the incidence window used in our estimation to ensure that was not driving our results. Thirdly, we estimated our specifications for the restricted sample of municipalities with non-zero *severe Dengue* incidence. Finally, we performed a matching exercise in which we use a synthetic control strategy to approximate an experiment in which some municipalities are randomly treated with additional cases of *severe Dengue*.

Table 7: Robustness checks exercises

	MAIN (1)	**PLACEBO** (2)	**NZI** (3)	**SYNC** (4)
S. Dengue 10000h (4M)	-0.011**	0.005	-0.011**	-0.008**
	-0.005	-0.006	-0.005	-0.003
L.S. Dengue 10000h (4M)	-0.005	-0.003	-0.010*	-0.001
	-0.004	-0.003	-0.006	-0.003
L2.S. Dengue 10000h (4M)	0	0.004	-0.001	-0.002
	-0.003	-0.003	-0.004	-0.003
Observations	30862	26956	12682	13108
Schools	8746	8064	5095	0.019
Avg. periods per school	3.53	3.34	2.49	0.018
Municipalities	836	836	363	3721

In all columns the dependent variable LOG(Takers) is the logarithm of the number of students who presented the test per school. **MAIN:** This column reproduces the main result discussed above. **PLACEBO:** In this exercise, future variation on dengue incidence is used in order to explain the variation on the number of students who present the test. It includes variation of incidence rates from 2009 to 2012, and on SABER 11 participation from 2007 to 2010. **NZI:** The exercise was restricted municipalities with at least one case of severe dengue. **SYNC:** A synthetic control strategy was used in this specification in order to obtain a more balanced control group.
Linear fixed effects panel regression at school level (see Equation 1). S. Dengue is the reported incidence of Severe Dengue in the last 4 months (4M) at municipality level. L.S. Dengue is the lag of Severe Dengue. On top of the fixed effects by school and by year, these controls for Inpatient beds and AE positions per 10.000h, Subsidized Health Care registry as a percentage of Population, municipality dependence on central government transfers, municipality per capita income, the incidence rate of influenza-like cases per 1.000h in the municipality during the calendar year, avg. temperature and rainfall for the last 8 months, log-population and the standardized number of people, houses and roads affected by natural disasters. See Table 2 for further details.
Clustered at school level SD in parenthesis. Significance: * 10%, ** 5%, *** 1%.

The results of all of these exercises, available as supplementary materials, are strongly supportive of our main results.[14]

5 Discussion

Our results show that the Dengue outbreak had a strong impact on the number of students who took the SABER 11 test. To put the size of the estimates into perspective, if we consider an average school with a cohort of 47 students in an average municipality, which has around 7.7 schools, for each additional case of *severe Dengue* per 10 000 inhabitants during the 4 months prior to the examination, 0.47 fewer students took the examination. As the average increase in incidence between 2009 and 2010 was 0.37, the mean impact of the outbreak on test taking was a reduction of around 1.34 students per municipality. If we consider only municipalities affected by the epidemic (i.e. non-zero cases), the average change in *severe Dengue* incidence was 2.11, implying a substantial reduction of 7.63 students. However, we should bear in mind that in some municipalities the epidemic was even more harmful, with the incidence increasing by more than 10.

Overall, it does not appear that the epidemic had a relevant impact on the scores that students achieved in the examinations. In order to have an impact of a similar magnitude, there would need to be an unrealistic increase of over 100 cases per 10 000 inhabitants in severe Dengue.[15] Therefore, we conclude that the estimated short-run effect of Dengue incidence on test scores, conditional on exam attendance, should be treated as being zero, for practical purposes. It is important to qualify this statement by mentioning that this observed zero effect may be driven by the fact that severe Dengue causes some students not to attend the exam. If these students tend to be poorly prepared students, then this selection effect would imply an underestimation of the effect of Dengue on test scores.

This impact that we observe seems to be an indirect effect due to a behavioural response to the epidemic: given the estimates, the number of students affected could be 100 times larger than the number of individuals who contracted *severe Dengue* if we compare the 1/100 impact with the 1/10.000 change in the incidence rate.[16]

However, it is worth mentioning a few caveats to this interpretation of the results. Firstly, the

[14] We also conducted an exercise that considers alternative incidence windows (instead of the 4 months used in the main results above). This exercise indicates that the choice of incidence window width is not relevant for the results.

[15] Similarly, the effects for *classic Dengue* are also small but positive.

[16] If one student in 10.000 contracts *severe Dengue*, the results suggest that this implies that 100 fewer students in 10.000 sit their examination, which is an incredibly large effect. As discussed below, the true effect size is likely to be smaller than this, but still strikingly large.

impact on students is likely to be smaller than this as the incidence rate could have been underestimated due to the fact that the age group incidence for students tends to be larger than the entire municipality average (Padilla et al., 2012). Secondly, there is the possibility that underreporting and misclassification between *severe* and *classic* Dengue might also be an issue. However, underreporting of *severe Dengue* is unlikely to be substantial due to the severity of the disease.

Nevertheless, our results indicate that the observed behavioural response is not due to a direct effect of illness: we do not find any impact of *classic Dengue*, even with much higher incidence rates of nearly 1/1000 inhabitants. While it is true that it is milder than the *severe* version, it is still debilitating. In some areas, the disease is known as the *'bone breaker fever'* (Fajardo et al., 2001), which gives an idea of the temporary debilitating effect that it generates.

Our behavioural explanation relies on the assumption that households considered it to be riskier to send their children to school than for them to stay at home. This is consistent with the high degree of uncertainty and fear that is often generated when there is a sudden and severe new epidemic. Support for this argument comes from web searches for Dengue that coincided with the epidemic.[17]

The effect of *severe Dengue* in a municipality extended far beyond its direct influence on the afflicted households. Furthermore, the fact that the effect had a strong income gradient is striking. The following are potential explanations for this finding. Firstly, as discussed above, it may be driven by the fact that wealthier areas are more likely to be integrated into trade networks and to contain a highly mobile population. This would increase the transmission of the disease, as well as the likelihood of contracting both strands. Secondly, wealthier families are likely to have greater savings and be able to afford to delay the school leaving examination in order to reduce the perceived risk of being exposed to the epidemic by staying out of school. Thirdly, the examination is more likely to be pivotal for wealthier students, in the sense of being on the borderline between being accepted into tertiary education and not being accepted. These pivotal students might be more likely to delay the examinations by a year if they think the disease will negatively influence their performance.

[17] In our supplementary material, using an additional dataset, the 2010 DHS, we present estimates for the impact of Classic Dengue on household activity using an instrumental variables approach. In this exercise, we do not find any effect on general health perceptions or demand for health care services in affected communities apart from higher hospitalization rates of children aged 5 or younger.

6 Conclusion

This paper provides new evidence regarding the behavioural response to a short, sharp, unexpected increase in the incidence of both *classic* and *severe* Dengue fever in Colombia on students' outcomes. The striking finding is that the likelihood that final year secondary students attend their school leaving examination is reduced on average by 1 pp. if the incidence of *severe Dengue* increases by 1 case per 10.000 inhabitants in the 4 months prior to the exam. This is not the case for *classic Dengue*, which has no impact. These results are estimated using the geographic and temporal variation in *severe Dengue* incidence between 2008 and 2012.

These results suggest a behavioural risk-prevention response to the high degree of uncertainty generated by a sudden and severe epidemic and that substantial benefit can be obtained by ensuring that the public is well-informed regarding the facts pertaining to the channels of transmission and good practices for reducing the development and spread of the disease. It does not seem plausible that the results are driven by either the direct or indirect consequences of illness of family members. This conclusion is drawn from the fact that while *classic Dengue* is far more prevalent, it had no impact, and furthermore, the estimated reduction in the number of students who missed or delayed their school leaving examination was larger than the number of individuals afflicted by *severe Dengue*. The behavioural response may be explained by the fact that contracting *severe Dengue* resulted in death in 2 percent of cases in 2010. Furthermore, the fact that it had mortality rates of up to 40 percent during the preceding two decades in Colombia would have contributed to the fear and uncertainty generated by the 2010 epidemic.

The results, in conjunction with those from the preceding literature, suggest that in addition to addressing the direct health concerns generated by an epidemic, substantial benefit may be obtained from ensuring that the public is well-informed regarding the facts pertaining to the channels of transmission and good practices for reducing the development and spread of the disease.

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Supplementary Material A: SABER 11

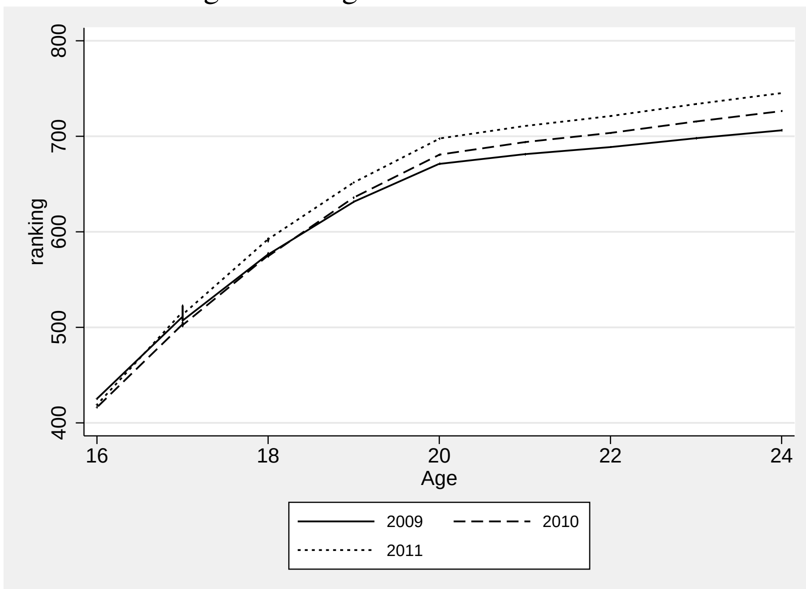
The main result of our study shows that fewer students participated in the SABER 11 examination during their last year of secondary education due to the 2010 peak in severe dengue incidence. However, this clearly doesn't imply that these students never completed the exam at all. Many of these students may have simply participated in the exam 6 or 12 months later[18]. Therefore, while permanent non-completion of the examination is likely to have a large negative impact on life outcomes[19], it is important to also consider the likely implications of a temporary delay in the completion of the examination.

Unfortunately, to the best of our knowledge, there exists no study that directly considers this question for the Colombian context, however, Fortin and Ragued (2016) show that in the Canadian context, similar temporary interruptions in post-secondary education are relevant for wages, conditional on the activity undertaken during the interruption. Furthermore, in order to provide some suggestive evidence for the Colombian context, in Fig 11 we plot the relationship between a students' age at time of completing the examination and their rank in the examination (for 2009, 2010, 2011). As one might expect, there is a strong negative correlation. Taken together, this evidence suggests that there may have been negative implications for human capital formation and other lifetime outcomes for those who temporary delayed participation in the examination, as well as for the those who dropped out permanently. At minimum, it implied a 6 month period of non-employment for many students. This short-run cost is non-negligible and should not be disregarded.

[18]Unfortunately, our data does not permit us to estimate the fraction of students who missed SABER 11 in 2010 that then participated the following year.

[19]This is because non-completion of the examination implies that these students will never have completed secondary school, and will not be eligible for tertiary education. Furtherfore, it is viewed as a negative signal to potential employers.

Figure 11: Age and rank at Saber 11



Source: Own calculations using SABER 11

Supplementary Material B: Robustness checks

Placebo Test

One may be concerned that there is a common factor that is driving both the variation in the incidence of *severe Dengue* across municipalities, as well as the variation in the number of test takers. However, as discussed above, our empirical specification includes both municipality level and year fixed effects and therefore, this should rule out the influence of any common factor that is not varying across both time and space and driving both *severe Dengue* incidence and test attendance. However, in order to provider stronger evidence of our results, we conduct a placebo test using variation in the incidence between 2009 and 2011.

This placebo test involves estimating the same specification as in Table **??**, but here using the Dengue incidence (*classic* and *severe*) as predictors of test attendance two years before. For example, testing whether the severity of the outbreak of 2010 in a municipality is related to the number of students who attended the test in 2008. Notice that, while the timing should invalidate the relationship, there are still chances of detecting an effect as Dengue incidence is geographically persistent. However, if the impact we observe on test taking is connected to the media storm generated by the epidemic in 2010, then we should not observe a large correlation with test taking in 2008.

The results from this placebo exercise are summarized in Table 8 and they indicate clearly that future severe Dengue incidence was not predictive of exam attendance. The results of this table therefore provide further support for the validity of our main results regarding the impact of *severe Dengue* on exam attendance in 2010.

Table 8: Placebo: Number of test takers per school two years ago and Dengue Incidence

LOG(Number of students who presented the test two years ago)
Includes variation of incidence rates from 2009 to 2012, and on SABER 11 participation from 2007 to 2010

	(1)	(2)	(3)	(4)
S. Dengue 10000h (4M)	0.005		0.005	
	(0.006)		(0.006)	
L.S. Dengue 10000h (4M)			-0.003	
			(0.003)	
L2.S. Dengue 10000h (4M)			0.004	
			(0.003)	
C. Dengue 1000h (4M)		-0.004		-0.009
		(0.004)		(0.006)
L.C. Dengue 1000h (4M)				-0.012
				(0.009)
L2.C. Dengue 1000h (4M)				-0.005
				(0.011)
Observations	26956	26956	26956	26956
Schools	8064	8064	8064	8064
Avg. periods per school	3.34	3.34	3.34	3.34
Municipalities	836	836	836	836
$\bar{Y}$	3.55	3.55	3.55	3.55
Adj. R squared	0.0194	0.0193	0.0198	0.0197

Linear fixed effects panel regression at school level (see Equation 1). Main independent variable: Reported incidence of Dengue in the last 4 months (4M) at municipality level. On top of the fixed effects by school and by year, these estimates include as controls: Inpatient beds and AE positions per 10.000h, Subsidized Health Care registry as a percentage of Population, municipality dependence on central government transfers, municipality income per capita, avg. temperature and rainfall for the last 8 months, log-population, std. of the number of people, houses and roads affected by natural disasters, and the incidence rate of influenza-like cases per 1.000h in the municipality during the calendar year. See Table **??** for further details.
Clustered at school level SD in parenthesis. Significance: * 10%, ** 5%, *** 1%.

Impacts using alternative incidence windows

For our main exercises we have presented data using incidence during the 4 months preceding the main SABER 11 test date (May, June, July and August). It is important to know what the implications of this choice are, and further to know the influence of Dengue incidence earlier in the year. Columns 1 - 3 of Table 9 present the estimates for different incidence windows: one year, 8 months, and 4 months. These estimates suggest that while much of the impact of *severe*

Dengue is driven by the variance in the incidence in the 4 months preceding the exam, the earlier months may also have influence.[20] We split up the cumulative incidence for the last year into three four-month windows, with column 4 displaying the results when we include the incidence for each of the following windows: 0 to 4, 5 to 8, and 8 to 12 months. While all three coefficients have a negative sign, the most recent trimester has the strongest impact. The 2nd trimester has almost zero impact, highlighting that the shocks are exerting a short-term influence. The last trimester also has a negative impact, which is plausible as it would be reflecting impacts on enrolment for the school calendar year which typically starts in January.

Table 9: Number of test takers per school and Severe Dengue: different incidence periods

	LOG(Number of students who presented the test)			
	All municipalities			
	(1)	(2)	(3)	(4)
Severe Dengue per 10.000h, 4M August				-0.008***
				(0.003)
Severe Dengue per 10.000h, 5-8 months from August				-0.001
				(0.003)
Severe Dengue per 10.000h, 9-12 months from August				-0.005
				(0.003)
Avg. Monthly Incidence S. Dengue, 4M August			-0.040***	
			(0.010)	
Avg. Monthly Incidence S. Dengue, 8M August		-0.039***		
		(0.009)		
Avg. Monthly Incidence S. Dengue, 12M August	-0.048***			
	(0.011)			
N Obs	37299	37299	37299	37299
N schools	8839	8839	8839	8839
Avg. periods	4.22	4.22	4.22	4.22
Adj. R2	0.02	0.02	0.02	0.02
p-val for Wald test on H0: I04 - I58=0				0.14
p-val for Wald test on H0: I04 - I912=0				0.41

Linear fixed effects panel regression at school level (see Equation 1). Main independent variable: Reported incidence of Dengue in the last 4 months (4M), 8 months (8M) and year (12M), or the stated period, at municipality level. On top of the fixed effects by school and by year, these estimates include as controls: Inpatient beds and AE positions per 10.000h, Subsidized Health Care registry as a percentage of Population, municipality dependence on central government transfers, municipality income per capita, avg. temperature and rainfall for the last 8 months, log-population, std. of the number of people, houses and roads affected by natural disasters, and the incidence rate of influenza-like cases per 1.000h in the municipality during the calendar year. See Table **??** for further details. Wald tests of hyphotesis were performed in order to asses if the coefficients for incidence of the last 4 months and 5-8 months were the same (H0: I04 - I058 =0). A similar procedure was done for the incidence between 9 to 12 months (H: I04 - I912 =0). Results are presented in the last two rows of the table.
Clustered at school level SD in parenthesis. Significance: * 10%, ** 5%, *** 1%.

[20]Note, in order to make these estimates comparable to one another, the estimates are for the average monthly incidence over the period. This is why the estimate in column 3 is four times as large as the estimate in the main Table which corresponds to a three months incidence.

Estimates for subsample with non-zero *severe Dengue* incidence

Table 10 presents the estimates for the impact of *severe Dengue* on attendance, when we restrict our sample to the subsample of schools in municipalities with at least one case of *severe Dengue* per 10 000 inhabitants. Here, we observe that the effect persists and the magnitude of the effect is only slightly dampened when we consider this subsample.

Table 10: Number of test takers per school and Dengue Incidence

	LOG(Number of students who presented the test) Only for municipalities with at least 1 case of Dengue			
	(1)	(2)	(3)	(4)
S. Dengue 10000h (4M)	-0.008		-0.011**	
	(0.005)		(0.005)	
L.S. Dengue 10000h (4M)			-0.010*	
			(0.006)	
L2.S. Dengue 10000h (4M)			-0.001	
			(0.004)	
C. Dengue 1000h (4M)		0.003		0.002
		(0.006)		(0.006)
L.C. Dengue 1000h (4M)				-0.002
				(0.006)
L2.C. Dengue 1000h (4M)				0.005
				(0.009)
Observations	15502	25730	12682	21652
Schools	5287	8109	5095	8017
Avg. periods per school	2.93	3.17	2.49	2.70
Municipalities	392	671	363	661
$\bar{Y}$	0.0248	0.0245	0.0299	0.0256

Linear fixed effects panel regression at school level (see Equation 1). Main independent variable: Reported incidence of Dengue in the last 4 months (4M) at municipality level. On top of the fixed effects by school and by year, these estimates include as controls: Inpatient beds and AE positions per 10.000h, Subsidized Health Care registry as a percentage of Population, municipality dependence on central government transfers, municipality income per capita, avg. temperature and rainfall for the last 8 months, log-population, std. of the number of people, homes and roads affected by natural disasters. See Table **??** for further details.
Clustered at school level SD in parenthesis. Significance: * 10%, ** 5%, *** 1%.

Synthetic Control Strategy

In this exercise, we match municipalities on an array of pre-outbreak observable characteristics. The basic idea is to try to approximate an experiment in which the sole difference between two areas is that one of them is suddenly afflicted by some additional cases of *severe Dengue*, while the other is not. We do this by using the group of municipalities with zero incidence of Dengue to construct a synthetic control group for municipalities with positive incidence of *severe Dengue*. Furthermore, we divide the municipalities with positive *severe Dengue* incidence into three groups according to the intensity of the disease in the municipality.

The synthetic control group for each of these three groups is constructed by re-weighting the control group observations (those without cases of severe Dengue in 2010) using a kernel propensity score matching (Heckman et al., 1997).[21] In essence, we want to compare municipalities that were as likely to have cases of severe Dengue, given their pre-outbreak observable characteristics, as those who reported them, but did not.[22]

Table 11 shows the result of this matching procedure. Column C displays the average values for each of the variables of interest at municipality level for the control group, before re-weighting. Columns T show the average values for each of the three treated groups. Notice the variation in the incidence of *severe Dengue* across these three groups (see the row, third from the bottom). The stars appended to the figures in columns T come from a t-test of difference of means between each of the treatment groups and the control group, before reweighting. Columns MC show the average values of the control group after reweighting, using the weights that are calculated for the relevant treatment group. Again, stars reflect a t-test comparison between the treatment group and the re-weighted control group. In order to ensure, common support municipalities for which there is no valid counterpart (too low or high propensity scores) are omitted. This will reduce the sample size of our estimates as we will see in the following tables.

[21] Implemented using psmatch2 in STATA (Leuven and Sianesi, 2014)The matching was done between each set of municipalities and the control group separately. Then, the weights were combined to construct a single measure to be used in all the regressions below.

[22] While this methodology follows the logic of the synthetic control strategy (Abadie and Gardeazabal, 2003) (See Rodríguez-Lesmes et al. (2014) for other applications of this strategy using SABER11 data.), one concern would be that we might be inducing a bias in the estimates: there might be unobserved characteristics of the health system that could be related to under-reporting of *severe Dengue* which are exacerbated by the matching procedure. However, provided these characteristics are uncorrelated to the intensity of the behavioral response to new cases of Dengue, this strategy will ensure that we are comparing municipalities which are generally similar.

Table 11: Matching: Balance Table

	Municipality average						
		Group 1		Group 2		Group 3	
Variable	C	T	MC	T	MC	T	MC
C. Dengue 1000h (4M)	0.66	1.43***	1.28	1.76***	1.37	3.03***	3.16
Population in 100.000	0.17	1.21***	0.43	0.53*	0.24	0.48***	0.26
Current Road Density	0.15	0.44***	0.21	0.38**	0.23	0.32***	0.25
Distance to Department's capital	143.14	114.81**	133.40	117.31***	111.84	92.60***	94.05
Altitude (meters above sea level)	845.64	553.58***	476.31	748.57	711.87	841.71	861.56
Avg. precipitation in mm/1000	2.18	1.91**	1.87	2.04	2.04	1.82***	1.84
Subsidized Health Care / Population: 2009	0.78	0.68***	0.73	0.75	0.77	0.75*	0.79
Total Municipality Income per capita: 2009	0.74	0.56***	0.50	0.72	0.70	0.91**	0.84
Municipality dependence on central Gov. transfers: 2009	0.61	0.62	0.64	0.56**	0.57	0.55***	0.56
% of female test-takes: 2007	0.49	0.48	0.49	0.48	0.48	0.51	0.51
% of female test-takes: 2008	0.49	0.48	0.48	0.49	0.48	0.52**	0.52
% of female test-takes: 2009	0.49	0.48	0.49	0.48	0.49	0.51	0.51
% of SISBEN 12 test-takers: 2009	0.84	0.74***	0.81	0.78*	0.80	0.81	0.84
% of SISBEN 12 test-takers: 2008	0.83	0.70***	0.78	0.77*	0.79	0.81	0.83
Avg. Family Income Index: 2009	0.96	1.17***	1.11	1.12***	1.08	1.13***	1.12
Avg. Family Income Index: 2008	0.97	1.23***	1.18	1.16***	1.10	1.16***	1.17
Avg. Maths Score: 2009	0.03	0.03	0.02	0.03	0.02	0.11***	0.09
Avg. Maths Score: 2007	0.03	0.03	0.03	0.04	0.02	0.09***	0.08
Avg. Maths Score: 2008	0.03	0.04	0.04	0.05	0.03	0.11***	0.10
Avg. Language Score: 2009	0.02	0.04**	0.03	0.02	0.01	0.07***	0.04
Avg. Language Score: 2007	0.03	0.04	0.02	0.04	0.03	0.07***	0.07
Avg. Language Score: 2008	0.03	0.04	0.02	0.05	0.04	0.07***	0.06
Avg. N test takers: 2009	128.10	1027.62***	331.51	252.61**	192.65	403.88***	173.85
Avg. N test takers: 2007	122.51	1075.80***	331.79	261.84**	191.92	441.89***	178.12
Avg. N test takers: 2008	120.81	1008.09***	315.13	243.92**	180.85	380.56***	159.91
S. Dengue Incidence		0.02 to 0.70		0.71 to 1.78		1.80 to 44.31	
No. Municipalities	523	108		107		108	
No. Municipalities Common S	444	88		93		92	

Municipalities were matched using Kernel Propensity Score matching (bandwidth for the kernel: 0.06). T: municipalities with positive Severe Dengue incidence in 2010. C: municipalities with zero Severe Dengue incidence in 2010. MC: re-weighted average of group C. The stars show the significance of a t-test of difference of means: In column T the test is between groups T and C, and in column MC, between groups T and C but after matching.
Significance: * 10%, ** 5%, *** 1%.

Overall, the matching procedure works very well, with the only remaining significant differences between the treatment and synthetic control being the number of test takers for group 3 (high *severe Dengue* intensity), which is only significant at the 10 percent level. Interestingly, looking at the pre-weighted groups, we see that there are correlations between many of the observable variables and pre-outbreak Dengue incidence, as one would expect. For example, it is unsurprising that the population density is lowest for municipalities with no *severe Dengue* and for the municipalities with the highest incidence of *severe Dengue*. It is perhaps more surprising that the proportion of poor students (SISBEN 1 and 2) varies so little across the three treatments and control group, with the proportion only changing by 12 percentage points between the lowest and highest of the groups.

With our matching weights in hand, Table 12 below presents the estimates for the impact of *severe Dengue*, with each school weighted using the appropriate municipality weight. The results are very similar to our main results, with *severe Dengue* causing a sizeable reduction in test attendance, and no significant impact of *classic Dengue*. This serves as a further validation of the estimated impact of the 2010 epidemic on test taking behaviour.

Table 12: Matching: Number of test takers per school and Dengue Incidence

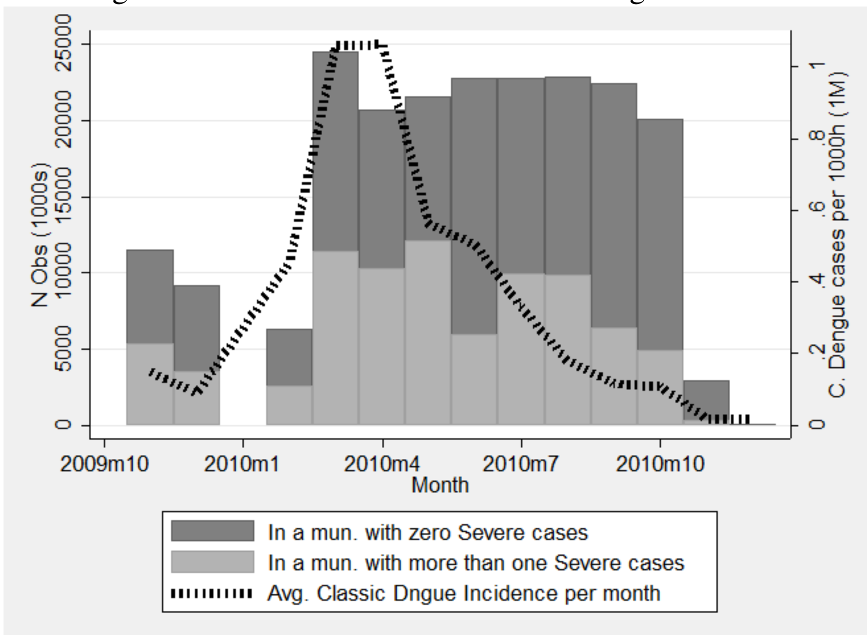
	LOG(Number of students who presented the test)			
	(1)	(2)	(3)	(4)
S. Dengue 10000h (4M)	-0.007**		-0.008**	
	(0.003)		(0.003)	
L.S. Dengue 10000h (4M)			-0.001	
			(0.003)	
L2.S. Dengue 10000h (4M)			-0.002	
			(0.003)	
C. Dengue 1000h (4M)		-0.005		-0.002
		(0.005)		(0.007)
L.C. Dengue 1000h (4M)				0.008
				(0.006)
L2.C. Dengue 1000h (4M)				0.005
				(0.007)
Observations	15777	15777	13108	13108
R^2	0.027	0.026	0.019	0.019
Adjusted R^2	0.026	0.025	0.018	0.018
N_g	3746	3746	3721	3721

Clustered at school level SD in parenthesis. Significance: * 10%, ** 5%, *** 1%.
Schools are weighted so municipalities ared matched on fix and pre-outbreak characteristics

Supplementary Material C: Impact of Dengue on household activity

In this appendix we explore the influence that the Dengue fever outbreak had on households' daily activities. In particular, we want to determine if the outbreak produced serious disruptions economic activity or to health-related activities and outcomes at the population level. In order to do this, we use information from the DHS 2010. This is a cross-section dataset and for that reason our main identification strategy presented in section 3.2 cannot be used. In contrast, we instrument the incidence of both versions of the disease.

Figure 12: DHS date of interview and Dengue outbreak



The Demographic and Health Survey 2010 (DHS) os collected by Profamilia (2011) under the international DHS program guidelines[23]. This survey is representative at the state level (*Departamento*) and was collected between October 2009 and October 2010. One very attractive feature of this dataset is that this collection period effectively covers the entire start, peak and decline of the epidemic, both in municipios with and without Severe Dengue (see Figure 6). With this data we can explore how students and their family were affected by the disease. The main outcomes and controls used for our analysis are presented in Table 13.

[23]Recoded datasets COPR61FL, COHR61FL. Colombia 2010 is a standard DHS-VI version.

Table 13: Descriptive Statistics DHS 2010

Variable	Mean (SD)	Obs
Self Reported Health (1: Very Good, 5: Very Bad)	3(.91)	186974
Sr Health: Regular Or Bad	.02(.14)	186974
Any Health Problem (Outpatient)	.11(.31)	186974
Stop Activities Due To A Health Problem (Outpatient)	.058(.23)	186974
Occupation Last Week: Working, 12+ Years (P16)	.48(.5)	142060
Occupation Last Week: Studying, 12+ Years (P16)	.17(.38)	142060
Hospitalized	.062(.24)	186974
Male Household Member	.48(.5)	186974
Age In Years	29(21)	186929
Member Is A Native Colombian	.11(.32)	186974
Member Is An Afro-Descen	.11(.31)	186974
Member Attended School During Previous School Year	.29(.45)	186974
Number Of Household Members	5.1(2.4)	186974
Number Of Children 5 And Under	.67(.89)	186974
Female Household Head	.31(.46)	186974
Access To Piped Water	.79(.41)	186974
Access To Sewer	.64(.48)	186974
Age Of Head Of Household	47(15)	186974
Head Of Household Is Male	.69(.46)	186974
Wealth Index Factor Score (5 Decimals)	-10816(105736)	186974

Source: Own calculations based on the DHS 2010 for Colombia.

While the DHS is a rich dataset, its design does not allow for the fixed effects regression used for the SABER 11 analysis.[24] In contrast, we exploit the discussed environmental diversity of the country to instrument the incidence of classic Dengue during the outbreak. Equation 4 presents the first stage, and Equation 5 the second stage of this instrumental variables approach.

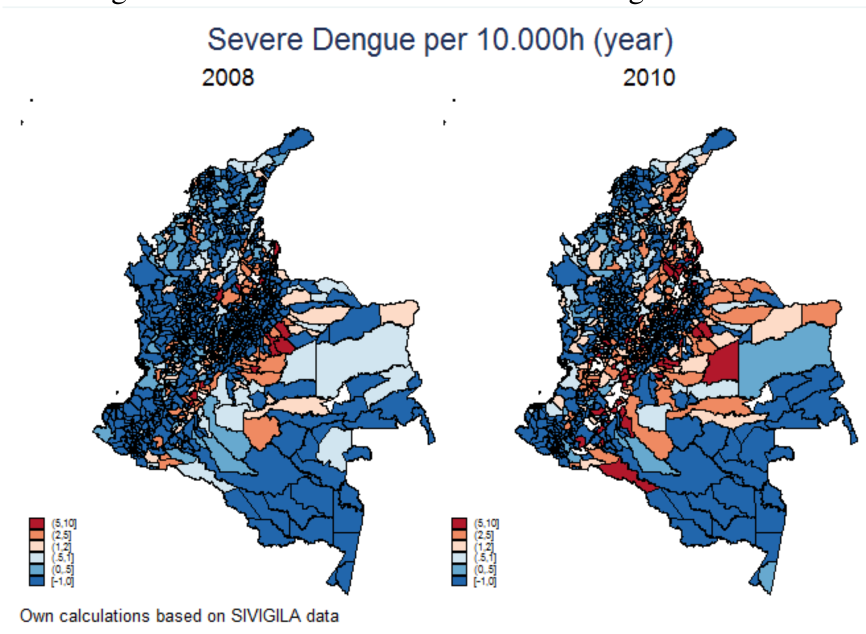
$$CD_{jt} = \iota_1 \mathbb{1}\{Alt_j < 1800\} \cdot Ep_t + \iota_2 \mathbb{1}\{Alt_j < 1800\} + \iota_3 Ep_t + \iota X_{jt} + u_{jt} \tag{4}$$

$$Y_{ijt} = \eta_1 CD_{jt} + \eta_2 \mathbb{1}\{Alt_j < 1800\} + \eta_3 Ep_t + \eta X_{ijt} + v_{ijt} \tag{5}$$

where i is the individual living in municipality j and surveyed in month t. CD_{jt} is the classic Dengue incidence per month at municipality level per 10.000 inhabitants. Alt_j is the altitude over the sea level of the municipality, and the focus is on 1800 meters as above this altitude the mosquito cannot develop (see Section 2). Ep_t is a dummy variable that indicates that the survey was carried on during the main epidemic time (February 2010 to August 2011). Finally, X_{ijt} includes controls at individual, household and municipality level; including altitude in meters, temperature and precipitation.

[24] Its previous wave is from 2005 and given that is not representative at municipality level, many of these administrative divisions are not covered in both surveys.

Figure 13: DHS date of interview and Dengue outbreak



For severe Dengue, in order to disentangle it from classic Dengue, we consider as an instrument the incidence of the disease in the non-epidemic period (total number of cases between 2007 and 2008 per 10.000 inhabitants, ySD_j). The idea behind this is that Severe Dengue tends to be persistent in certain areas of the country, thus, during the outbreak it was more likely that those areas where Severe Dengue is endemic, again suffered from this strand of the disease. The maps in Figure 6 illustrate this argument. Equations 6 and 7 shows that once again, the instrument is the interaction between space and time.

$$SD_{jt} = \zeta_1 ySD_j \cdot Ep_t + \zeta_2 ySD_j + \zeta_3 \mathbb{1}\{Alt_j < 1800\} + \zeta_4 Ep_t + \zeta_5 CD_{jt} + \zeta X_{jt} + u_{jt} \quad (6)$$

$$Y_{ijt} = \omega_1 SD_{jt} + \omega_2 ySD_j + \omega_3 \mathbb{1}\{Alt_j < 1800\} + \omega_4 Ep_t + \omega_5 CD_{jt} + \omega X_{ijt} + v_{ijt} \quad (7)$$

Tables 14, 15 and 16 present the estimates for the coefficients of the equations explained above for several outcomes of interest. Students who are finishing their secondary school are in general 14 to 18 years old, covered in Table 14. Children under the age of 5, typically the most affected by the disease, are covered in Table 15, and all the others are grouped in Table 16. In particular, our interest relies on coefficients η_1 and ω_1, which are interpreted as the causal effect of increased incidence of Dengue on the outcomes of interest. Each of the tables also presents the first stage results, showing the power of the particular instrument.

In these tables we see that Classic Dengue is related to a slight increase in the probability of hospitalization for children under the age of 5 (4 pp., with respect to a 22% mean) and for those aged 19 and older, but has no significant impact on health status perception of the overall population. In the case of Severe Dengue, there is no additional effect on top of the Classic Dengue incidence. For the 14 to 18 year olds, the age at which students typically participate in the SABER 11 test, there is a negative coefficient on the probability of reporting that one studied last week, but it important to note that it is not significant, so we cannot draw conclusions from this.

Table 14: Dengue Incidence and Households' activity: 14 to 18 years old

	Dependent variable						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	cstud	**work**	**hprob**	**hosp**	**stopact**	**badHe**	**Dengue**
Panel A: Classic Dengue							
C. Dengue 1000h (1M)	-0.00206	0.0124	0.00523	0.0123	0.00705	0.000292	
	[-0.11]	[0.68]	[0.18]	[1.02]	[0.36]	[0.08]	
Below 1800 masl	-0.000212	-0.0298	-0.00678	-0.0360**	-0.00693	0.00274	0.547*
	[-0.01]	[-1.12]	[-0.14]	[-2.29]	[-0.23]	[0.49]	[1.74]
Outbreak period	0.0128	-0.0283***	0.000900	-0.0133*	-0.00371	0.00244	-0.0171
	[1.20]	[-2.94]	[0.05]	[-1.91]	[-0.29]	[1.15]	[-0.19]
Below 1800 masl × Outbreak period							0.696***
							[3.65]
Observations	20282	20470	20482	20482	20482	20482	20282
N of clusters (municipios)	250	250	250	250	250	250	250
F-stat First Stage	13.32	13.32	13.30	13.30	13.30	13.30	
Average of the dependent variable	0.741	0.134	0.0765	0.0466	0.0442	0.00644	
R Squared	0.477	0.221	0.0143	0.0187	0.00646	0.00537	0.373
Panel B: Severe Dengue							
S. Dengue 10.000h (1M)	-0.0522	-0.0356	0.00894	-0.00484	0.00985	0.000418	
	[-1.30]	[-0.72]	[0.33]	[-0.20]	[0.48]	[0.05]	
C. Dengue 1000h (1M)	0.0259	0.0149	-0.00275	0.000627	-0.00381	-0.000414	0.470*
	[1.21]	[0.59]	[-0.18]	[0.05]	[-0.32]	[-0.10]	[1.75]
S. Dengue incide 2007-08 per 10.000h	-0.0000649	0.00179**	-0.00180***	-0.000208	-0.000845**	-0.0000856	-0.0169
	[-0.08]	[2.08]	[-3.96]	[-0.51]	[-2.52]	[-0.69]	[-1.00]
Below 1800 masl	-0.0337	-0.0291	-0.00316	-0.0244	0.00276	0.00326	-0.557
	[-1.14]	[-0.83]	[-0.14]	[-1.36]	[0.17]	[0.55]	[-1.52]
Outbreak period	0.0125*	-0.0221***	0.00516	-0.00531	0.000556	0.00282**	-0.0636
	[1.90]	[-2.78]	[0.83]	[-1.51]	[0.13]	[2.33]	[-1.07]
S. Dengue incide 2007-08 per 10.000h × Outbreak period							0.0331**
							[2.22]
Observations	20282	20470	20482	20482	20482	20482	20282
N of clusters (municipios)	250	250	250	250	250	250	250
F-stat First Stage	4.93	4.89	4.88	4.88	4.88	4.88	
Average of the dependent variable	0.741	0.134	0.0765	0.0466	0.0442	0.00644	
R Squared	0.473	0.217	0.0149	0.0209	0.00603	0.00543	0.396

Notes: Own calculations based mainly on DHS-2010, SIVIGILA, population projections by DANE, emergency cases from *Sistema Nacional de Informacion y Gestion del Riesgo* (SNIGRD). This table presents coefficients of a instrumental variables regression in columns 1 to 6, estimated via two-stage least squares. Column 7 presents the first stage for the sample used in column 1. t-statistic from clustered standard errors presented in brackets. * p¡0.10, ** p¡0.05, *** p¡0.01.
Municipio Controls: 2nd order polynomial of Municipio's altitude in meters above the sea level; average month temperature, precipitation and their interaction; Standarized total individuals, dwellings, roads and agriculture hectares affected by natural events in the year. Inpatient Beds per 10.000h, A&E positions per 10.000h, Subsidized Health Care per capita, Municipality dependence on central Gov. transfers. Influenza-like per 1000h, Cal Y, Log-population, log income per-capita, categories of a poverty index based on quality of life (NBI). *Household Controls:* number of household members, number of children under the age of 5, access to piped water and sewer, household head age and gender; 2nd order polynomial wealth index. *Individual Controls:* 2nd order polynomial of age in years; gender, black or native american ethnicity dummies; and a dummy that indicates if the individual was studiying the previous academic year.

Table 15: Dengue Incidence and Households' activity: 0 to 5 years old

	Dependent variable						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	fever	**mediAtt**	**hprob**	**hosp**	**stopact**	**badHe**	**Dengue**
Panel A: Classic Dengue							
C. Dengue 1000h (1M)	-0.00760	0.0122	-0.0342	0.00739	-0.0247	0.00754*	
	[-0.16]	[0.28]	[-0.91]	[0.59]	[-0.95]	[1.87]	
Below 1800 masl	0.0272	-0.0342	0.0190	0.00252	0.0209	-0.00735	0.475
	[0.34]	[-0.58]	[0.29]	[0.16]	[0.49]	[-1.15]	[1.58]
Outbreak period	0.0211	0.0205	0.00685	-0.00163	0.00777	-0.00374**	-0.0965
	[0.68]	[0.97]	[0.30]	[-0.25]	[0.50]	[-2.02]	[-1.27]
Below 1800 masl × Outbreak period							0.758***
							[4.11]
Observations	16107	8812	22714	22714	22714	22714	16107
N of clusters (municipios)	250	250	250	250	250	250	250
F-stat First Stage	16.85	15.55	16.24	16.24	16.24	16.24	
Average of the dependent variable	0.271	0.434	0.139	0.0676	0.0726	0.00616	
R Squared	0.0231	0.0333	0.0192	0.0213	0.00620	0.00146	0.350
Panel B: Severe Dengue							
S. Dengue 10.000h (1M)	0.0719	0.181*	0.0847	-0.00942	0.0240	-0.000921	
	[0.89]	[1.80]	[1.57]	[-0.46]	[0.59]	[-0.12]	
C. Dengue 1000h (1M)	-0.0242	-0.0582	-0.0471	0.00492	-0.0115	-0.000103	0.447*
	[-0.61]	[-1.25]	[-1.54]	[0.51]	[-0.56]	[-0.03]	[1.84]
S. Dengue incide 2007-08 per 10.000h	-0.00133	-0.000968	-0.00317***	0.0000197	-0.00153**	0.0000606	-0.0144
	[-0.88]	[-0.44]	[-2.73]	[0.05]	[-2.12]	[0.50]	[-0.97]
Below 1800 masl	0.0395	0.0363	0.0232	0.00499	0.00237	0.000776	-0.446
	[0.71]	[0.54]	[0.55]	[0.32]	[0.09]	[0.15]	[-1.36]
Outbreak period	0.0124	0.0156	-0.00507	0.00210	-0.00378	0.000434	-0.0544
	[0.91]	[0.90]	[-0.42]	[0.44]	[-0.53]	[0.29]	[-1.03]
S. Dengue incide 2007-08 per 10.000h × Outbreak period							0.0305**
							[2.37]
Observations	16107	8812	22714	22714	22714	22714	16107
N of clusters (municipios)	250	250	250	250	250	250	250
F-stat First Stage	5.61	5.76	5.82	5.82	5.82	5.82	
Average of the dependent variable	0.271	0.434	0.139	0.0676	0.0726	0.00616	
R Squared	0.0133	0.00893	0.00379	0.0217	0.00718	0.00628	0.388

Notes: Own calculations based mainly on DHS-2010, SIVIGILA, population projections by DANE, emergency cases from *Sistema Nacional de Informacion y Gestion del Riesgo* (SNIGRD). This table presents coefficients of a instrumental variables regression in columns 1 to 6, estimated via two-stage least squares. Column 7 presents the first stage for the sample used in column 1. t-statistic from clustered standard errors presented in brackets. * p¡0.10, ** p¡0.05, *** p¡0.01.
Municipio Controls: 2nd order polynomial of Municipio's altitude in meters above the sea level; average month temperature, precipitation and their interaction; Standarized total individuals, dwellings, roads and agriculture hectares affected by natural events in the year. Inpatient Beds per 10.000h, A&E positions per 10.000h, Subsidized Health Care per capita, Municipality dependence on central Gov. transfers. Influenza-like per 1000h, Cal Y, Log-population, log income per-capita, categories of a poverty index based on quality of life (NBI). *Household Controls:* number of household members, number of children under the age of 5, access to piped water and sewer, household head age and gender; 2nd order polynomial wealth index. *Individual Controls:* 2nd order polynomial of age in months; gender dummy, and WHO height-for-age z-score.

Table 16: Dengue Incidence and Households' activity: older than 19

	Dependent variable						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	stud	**work**	**hprob**	**hosp**	**stopact**	**badHe**	**Dengue**
Panel A: Classic Dengue							
C. Dengue 1000h (1M)	0.00361	0.0129	-0.00197	0.0150*	-0.00349	-0.00849	
	[0.71]	[0.75]	[-0.11]	[1.88]	[-0.46]	[-1.06]	
Below 1800 masl	-0.00288	-0.0373	0.0269	-0.0189*	0.0206*	0.0186*	0.555*
	[-0.35]	[-1.35]	[1.00]	[-1.82]	[1.85]	[1.74]	[1.87]
Outbreak period	-0.00305	-0.00623	0.00524	-0.00602*	0.00272	0.00542	-0.0494
	[-1.03]	[-0.67]	[0.49]	[-1.68]	[0.61]	[1.11]	[-0.57]
Below 1800 masl × Outbreak period							0.732***
							[3.91]
Observations	122564	122564	122628	122628	122628	122628	122564
N of clusters (municipios)	250	250	250	250	250	250	250
F-stat First Stage	15.28	15.28	15.28	15.28	15.28	15.28	
Average of the dependent variable	0.0351	0.572	0.115	0.0731	0.0604	0.0300	
R Squared	0.321	0.262	0.0194	0.0149	0.00754	0.0378	0.395
Panel B: Severe Dengue							
S. Dengue 10.000h (1M)	0.0117	0.00592	0.0477*	0.00236	0.0171	0.00208	
	[1.62]	[0.16]	[1.66]	[0.18]	[1.14]	[0.16]	
C. Dengue 1000h (1M)	-0.00366	-0.00600	-0.0190	-0.00131	-0.00393	-0.0000649	0.404*
	[-1.13]	[-0.37]	[-1.35]	[-0.23]	[-0.54]	[-0.01]	[1.71]
S. Dengue incide 2007-08 per 10.000h	-0.000260	0.00131*	-0.00239***	-0.000440	-0.000946***	0.0000709	-0.0166
	[-1.55]	[1.89]	[-3.39]	[-1.64]	[-3.10]	[0.32]	[-0.95]
Below 1800 masl	0.00481	-0.0123	0.0403**	-0.00232	0.0190**	0.00974	-0.473
	[0.89]	[-0.54]	[2.07]	[-0.29]	[2.06]	[1.07]	[-1.44]
Outbreak period	-0.00178	0.000232	0.00578	0.00248	0.000129	0.000449	-0.0562
	[-0.92]	[0.04]	[0.94]	[0.85]	[0.04]	[0.22]	[-1.03]
S. Dengue incide 2007-08 per 10.000h × Outbreak period							0.0347**
							[2.22]
Observations	122564	122564	122628	122628	122628	122628	122564
N of clusters (municipios)	250	250	250	250	250	250	250
F-stat First Stage	4.94	4.94	4.94	4.94	4.94	4.94	
Average of the dependent variable	0.0351	0.572	0.115	0.0731	0.0604	0.0300	
R Squared	0.321	0.263	0.0133	0.0167	0.00636	0.0393	0.373

Notes: Own calculations based mainly on DHS-2010, SIVIGILA, population projections by DANE, emergency cases from *Sistema Nacional de Informacion y Gestion del Riesgo* (SNIGRD). This table presents coefficients of a instrumental variables regression in columns 1 to 6, estimated via two-stage least squares. Column 7 presents the first stage for the sample used in column 1. t-statistic from clustered standard errors presented in brackets. * p¡0.10, ** p¡0.05, *** p¡0.01.
Municipio Controls: 2nd order polynomial of Municipio's altitude in meters above the sea level; average month temperature, precipitation and their interaction; Standarized total individuals, dwellings, roads and agriculture hectares affected by natural events in the year. Inpatient Beds per 10.000h, A&E positions per 10.000h, Subsidized Health Care per capita, Municipality dependence on central Gov. transfers. Influenza-like per 1000h, Cal Y, Log-population, log income per-capita, categories of a poverty index based on quality of life (NBI). *Household Controls:* number of household members, number of children under the age of 5, access to piped water and sewer, household head age and gender; 2nd order polynomial wealth index. *Individual Controls:* 2nd order polynomial of age in years; gender, black or native american ethnicity dummies; and a dummy that indicates if the individual was studiying the previous academic year.

In general, the results highlighted above show that despite the high incidence of Dengue, this is not a disease that generates a massive real health consequences and causes a disruption to all aspects of life. Rather, it is a transitory health event, and it is likely that the channel of influence is related to the fear of potential health consequences, rather than real observed overall health deterioration.

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