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SERIE DOCUMENTOS DE TRABAJO

No. 180

Marzo de 2015

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March 15, 2015

Abstract

This paper makes use of a short, sharp, unexpected health shock in the form of the 2010 Colombian Dengue outbreak to examine the direct and indirect impact of negative health shocks on behaviour of households in affected areas. Our analysis combines data from several sources in order to obtain a comprehensive picture of the influence of the outbreak, and furthermore to understand the underlying mechanisms driving the effects. Our initial analysis indicates that the outbreak had a substantial negative effect on the health status of adults and adversely affected their ability to function as usual in their daily lives. In our aggregated school data, in areas with high levels of haemorrhagic Dengue we observe a reduction in national exam attendance (last year of secondary school) and on enrolment rates in primary education. Further analysis aims to exploit detailed individual level data to gain a more in depth understanding of the precise channels through which this disease influenced the behaviour and outcomes of the poor in Colombia.

JEL Codes: I12, I20

Keywords: Education, Dengue, Colombia

*Authors specially acknowledge Carmen Delgado for her assistance with data processing.

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1 Introduction

Climatic change is drastically reshaping the profile of tropical diseases around the world. The number of cases of Chikungunya or Dengue being reported in developed countries during recent years has grown exponentially, which indicates that vector-driven illnesses are increasingly important and should receive more attention. While, the influence of Malaria on economic activity and individual choices in areas where Malaria is in endemic has been studied in some depth, we do not have recent evidence of how this type of short, sharp negative health shock affects a population that was previously not well acquainted with the illness. In this document, we focus on one specific health shock in the form of a brief, unprecedentedly large outbreak Dengue fever. This outbreak provides an excellent natural experiment for assessing the impact of a short-run health shock. As we will discuss in depth, the suitability of this event for empirical analysis is due largely to the breeding patterns of the mosquito that carries Dengue, which can sometimes result in sudden unexpected enormous spikes in the prevalence of Dengue.

Due to the fact that individuals under the age of 15 are normally the most affected by Dengue, according to national statistics, in this paper we focus on the specific case of secondary school students and their families. Hence, the primary aim of this paper is to identify the impact of the Dengue epidemic on school attendance. However, the main project objective is aimed to understand the main mechanisms that might be driving the observed impact. For doing this we use administrative data from enrollment registries (C-600) at municipality level from 2008 to 2013, and SABER 11 test scores (ICFES) which allow us to understand the role of the outbreak using around 1 million test-takers. On top of that, we complement the analysis using microdata from the DHS survey for Colombia (Profamilia, 2011). These datasets are essential for understanding the impact of this short but intense health shock on household's behaviour.

The direct and indirect economic costs of this disease are considerable. However, its effect on human capital has not yet been estimated. According to Padilla et al (2012), institutional prevention and control costs of Dengue amounted to more than US$ 300 million during the last decade. It is informative to note that in 2010 alone, medical costs were about US$ 100 million, which is higher than those related to the control of rotavirus and Human papilloma virus (HPV). This is relevant as it reflects the fact that Dengue is rapidly becoming a massive worldwide health problem with prevalence increasing extremely quickly and currently no available vaccine. Infections are most commonly acquired in the urban environment and there is growing interest on how to reduce its impact via preventative interventions (see for instance, Dammert et al. (2014)). Furthermore, the influence of Dengue tends to be asymmetric along socio-economic dimensions, hurting the poor more. This is a result of low income households being more likely to use stagnant water in order to supply their daily needs, which provides a better opportunity for the spread of Dengue (Kovats et al., 2001).

2010 dengue outbreak in Colombia has been studied carefully. (De La Mata and Valencia-Amaya, 2014) have shown that the intensity of Malaria and Dengue outbreaks were related to drastic climatic events which varied in intensity across the country. Using as well SABER 11 information, (Valencia-Amaya, 2013) studied how that climatic events were also related to lower standardized test scores and suggest a link via higher incidence of Dengue and Malaria. Given this, he proposes that human capital accumulation might be affected due to the health shock. Rather than measuring the impact on human capital and its potential consequences, we are principally interested on how the epidemic might produce such affectations. This analysis is of primary importance as it might help to adjust policies that mitigate outbreaks' consequences.

Our initial analysis indicates that the outbreak had a substantial negative effect on the health status of adults and adversely affected their ability to function as usual in their daily lives. In our aggregated school data, we observe a reduction in exam attendance in areas with high levels of haemorrhagic Dengue. However, conditional on exam attendance, we don't observe a substantial influence of the disease on test scores. Further analysis aims to exploit detailed individual level data to gain a more in depth understanding of the precise channels through which this disease influenced the behaviour and outcomes of the poor in Colombia.

2 Characteristics of the Dengue disease

Dengue is one of the most common tropical diseases. It is transferred between people by the *Aedes Aegypti* mosquito. After an infected mosquito bites someone, the virus enters the white blood cells, and reproduces inside the cells while they move throughout the body. The main symptoms of the disease include fever, headache, as well as muscle and joint pains. Haemorrhagic dengue is a particularly severe, chronic strand of Dengue that can potentially lead to death. It produces bleeding and low levels of blood platelets that may potentially lead to death, although this is less common.

Aedes Aegypti benefits from the existence of stagnant water tanks and is active at the beginning and at the end of the day. This mosquito could be found was limited to the tropical and subtropical regions of the Americas, between latitudes 35° north and 35° south (Organización Panamericana de la Salud, 1995). The WHO notes that 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. Prevalence of Dengue is increasing extremely quickly, which is even more worrying in light of the fact that there is currently no available vaccine.

As discussed by Beatty et al. (2011), there is a substantial economic burden of the disease, not only on health care systems but also on households' budget constraints due to out-of-pocket health expenses and loss of productivity. Padilla et al. (2012) suggest that the prevalence of the disease has been increasing as a consequence of climate change, which has increased temperatures and lead to longer drought seasons, resulting in the reduction of alternative sources of water supply to water tanks. For example, this has resulted in a reduction of the use of aqueducts as a source of water. As mentioned earlier, because of the disease is spread mainly in areas with high levels of incidence of stagnant water, it tends to affect low-income households more than high-income households (Baylis and Risley, 2013). In addition, large Dengue outbreaks in a specific region tend to occur when the relevant health institutions are slow to respond efficiently to the disease with technical assistance and policies to detect and prevent its expansion. Furthermore, low income households often have reduced access to these institutions and tend to be located further away from them. It is clear that overall this disease poses a significant public health threat, particularly to low income households, and furthermore that the severity of this threat is increasing over time. The objective of this paper, however, is not to quantify the harm of this disease, but rather to examine the influence that it has on human behaviour, or more specifically, to examine the impact of a short, sharp, relatively unexpected health shock of particular contemporary importance.

In 2010, Colombia experienced a strong increase in Dengue incidence. According to the INS, *Instituto Nacional de Salud* (national health institute), which monitors the development of multiple diseases in Colombia (48 million inhabitants), there were 147.257 cases of classic Dengue reported (diagnosed by a laboratory), and 9.755 were haemorrhagic dengue. These figures correspond to a notorious sudden epidemic cycle as shown in Figure 1, where the number of reported new cases exploded dramatically in few weeks. Work by De La Mata and Valencia-Amaya (2014) provide evidence about the relationship between climatic conditions and Dengue incidence during the outbreak. While altitude provides some natural protection, due to its relation with the habitat of the *Aedes Aegypti*, the 'barrier' changes from 1200m to 1800m. This is reflected in Figure 2 where this relation is represented for years 2009 to 2011, using a local linear approximation. In fact, Table 1 shows that this rapid expansion was not only an increase on cases in some endemic municipalities[1]. For classic Dengue, the median incidence per 1.000 h per year jumped from .1 cases in 2009 to .6 in 2010, with 25% of them with rates above 3.4 new cases. Notice that in around

[1]Colombia is divided into 1123 Municipalities, which belong to 32 Departments.

68 of these administrative units (3.8 million inhabitants), the figure was above 10 new cases. A similar, but fortunately less common, expansion process took place for the case of Haemorrhagic dengue fever.

Figure 1: Municipal average incidence of Dengue fever per month

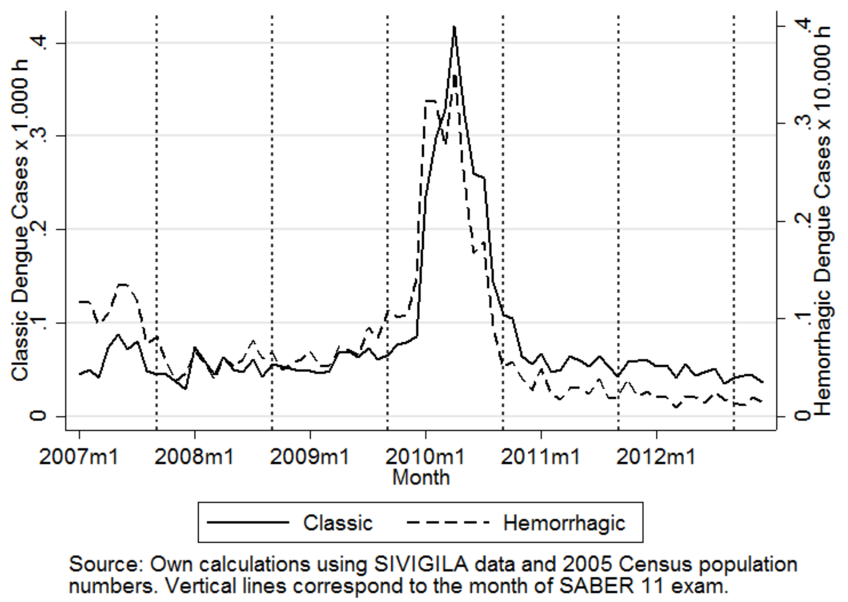
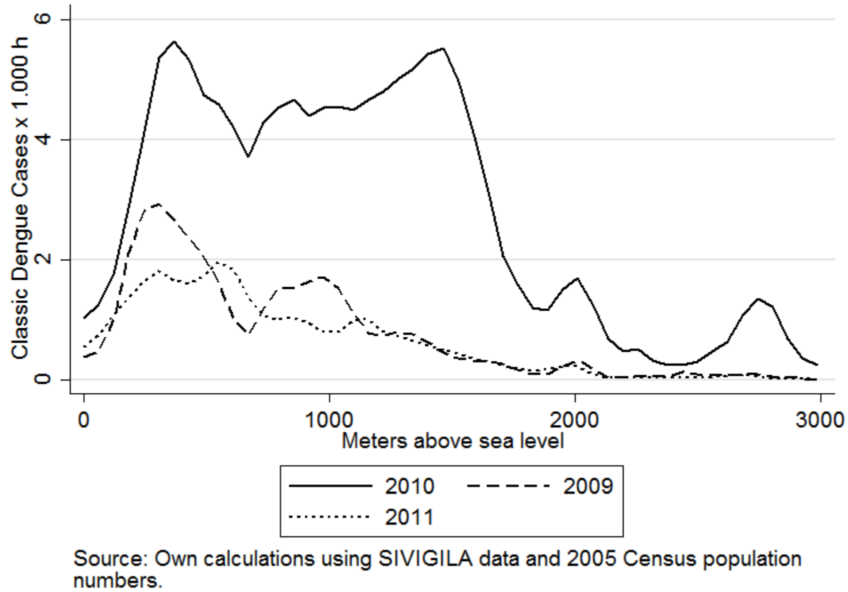


Table 1: Dengue Imcidemce Rates per Year

Statistic	2007	2008	2009	2010	2011	2012
Classic Dengue per 1000h						
Mean	.65	.66	.78	2.6	.68	.55
Stand. Dev	1.6	1.8	2.2	4.5	1.9	1.2
Minimum	0	0	0	0	0	0
Median	.043	.093	.1	.66	.14	.081
Percentile 75	.5	.52	.63	3.4	.7	.48
Percentile 95	3.5	3	3.9	11	2.9	2.6
Maximum	24	29	38	52	46	12
Hemorrhagic Dengue per 10.000h						
Mean	1.1	.7	1	2.1	.33	.2
Stand. Dev	4.5	2.4	3.2	5.8	1.3	.63
Minimum	0	0	0	0	0	0
Median	0	0	0	0	0	0
Percentile 75	.49	.39	.58	1.7	0	0
Percentile 95	5.9	3.6	4.6	11	1.7	1.3
Maximum	105	53	50	94	20	7.9

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

Figure 2: Municipal altitude and yearly incidence of Dengue fever



According to Padilla et al. (2012), there were 217 deaths associated with Dengue during this outbreak. The median age of those reported classic dengue cases was 14 and the average 13.5. A similar pattern was found for the Haemorrhagic version. In general, 51% of these reported cases occurred in individuals under the age of 15.

Colombian population was widely aware of the disease and public health services responded rapidly according to Padilla et al. (2012). They highlight that 62% of those affected attended primary care within 3 days of the first symptoms. They also highlight that 32% of the classic cases required hospitalization, in contrast with 79% of the severe version. However, other studies suggest that even though it is compulsory to register potential cases of Dengue in an electronic system, there might be some variation on adherence to such rule (Zea and Osorio, 2011), and on the correct classification and diagnosis of cases (Romero-Vega et al., 2014).

While it is clear that an outbreak of Dengue can have a large influence on the lives of those affected by the disease, it is important to understand the specific channels through which this disease can influence people's lives, as well as effect their behaviour. There are both direct and indirect channels through which Dengue can affect people. Firstly, Dengue can have a direct negative health effect on individuals who are themselves infected with the disease. As a result of the direct effects of poor health of these individuals, at the aggregate level we might expect school attendance rates and productivity to decrease, at least during the first phase of the fever.

Secondly, Dengue can have an indirect effect in terms of influencing the family or network of infected individuals. Its incidence may imply that families need to commit personal and family resources to take care of patients and abandon their daily duties (Boucekkine et al., 2009). The degree of harm of these indirect effects are also asymmetric along socio-demographic lines, since people who work in the informal sector are likely forego a greater percentage of their earnings in comparison to those in the formal sector when the disease causes them to miss work (although, it could be the case that those in the informal sector are therefore less likely to miss work in spite of being ill).

In summary, these direct and indirect effects might influence the time spent on both home production, work and educational activities through several channels. One of the objectives of this paper is to provide evidence on the magnitude of these different possible direct and indirect effects of the disease.

2.1 Data

For this analysis several sources of data are considered. The first source of data we use is administrative data, which contains useful information relevant to several aspects of our analysis. Firstly, we make use of information on the SABER 11 test scores for math and verbal analysis (language), which are administered by the ICFES (a government institution for the assessment of quality in education). SABER 11 is a compulsory test for every student who aspires to continue towards higher studies and a requirement imposed by the school system for all students in their last year of secondary education. This is generally taken by around a million students every year which serves as a signal of the quality of the school. We have a yearly time series of this test score data that can either be collapsed to construct of a longitudinal panel dataset at the school level, or alternatively allows us to create repeated cross-sections at the individual level. In addition, the SABER 11 data also provides information about some characteristics of the students.

All students in the dataset sit the exam at one of two dates within the year, with this choice being contingent on the when the start of the academic year for that school is. To be more precise, schools are divided into two groups, with the academic year either corresponding to the calendar year, or running from September to August as in many countries in the Northern hemisphere. The majority of the students in our dataset (85% to 95%) take part in the September examination and therefore we focus on this group in our analysis[2]. In addition, we will also restrict our analysis to schools which we can observe in both of the years 2007, 2008 so we can introduce a measure of average performance before the outbreak. Given these restrictions, we have 2.5 million observations

[2]This is done in order to ensure comparability of the tests every year. We also rule out schools which operate over the weekends or at night

available for the analysis. Table 2 presents variables used from this dataset.

Table 2: Descriptive Statistics: SABER 11

Variable	Mean (SD)	Obs
Girls	.55(.5)	2158609
Age	17(2)	2158416
SISBEN level 1 or 2	.66(.47)	1779436
Average Income of the families (school)	1.8(1.7)	1778927
Father Educ: None	.028(.16)	2158609
Father Educ: At most Primary	.3(.46)	2158609
Father Educ: Incomplete Secondary	.13(.33)	2158609
Father Educ: Complete Secondary	.19(.39)	2158609
Father Educ: Above Secondary	.14(.35)	2158609
Father Educ: Don't Know	.046(.21)	2158609
Mother Educ: None	.028(.16)	2158609
Mother Educ: At most Primary	.3(.46)	2158609
Mother Educ: Incomplete Secondary	.13(.33)	2158609
Mother Educ: Complete Secondary	.19(.39)	2158609
Mother Educ: Above Secondary	.14(.35)	2158609
Mother Educ: Don't Know	.046(.21)	2158609

Source: Own calculations based on SABER 11 registries.

Secondly, we include administrative enrolment records from C-600 (Ministry of Education) at municipality level. Table 3 present average enrolment figures by level for each year between 2007 and 2013. Even though these are unweighted averages which gives equal importance to small towns and big cities, the general trend is still valid: total number of students in primary education were decreasing (due to demographic transition) while secondary figures were increasing due to lower drop-out rates.

Third, we use is information regarding Classic Dengue cases reported to the INS. This information is collected weekly at a municipality level. Thirdly, we collect information on related covariates that may influence our results and therefore would be useful to control for, such as the incidence of other diseases and information on the influence of other natural disasters, compiled from the Government emergency reports. This latter information is particularly pertinent due to the substantial influence of natural disasters during the relevant period of study. This information helps us to control for potential confounding factors. A summary of these variables is presented in Table 4.[3]

[3]Population data comes from 2005 National Census. Emergencies data was derived from natural disasters records available at *Sistema Nacional de Información y Gestion del Riesgo* (SNIGRD) web page, which is the government institution that records such events.

Table 3: Enrolment per year

Variable	2007	2008	2009	2010	2011	2012	2013
Enrolment Primary (100s)							
Average	45.12	43.88	43.17	42.12	41.66	40.61	40.17
Std. Dev	221.84	219.88	213.37	207.63	201.82	197.34	193.86
N Obs	1119	1123	1122	1122	1122	1122	1122
Enrolment Secondary (100s)							
Average	36.78	37.68	38.39	38.77	38.94	38.39	38.13
Std. Dev	232.82	235.27	235.14	236.61	233.37	229.61	224.41
N Obs	1119	1123	1122	1122	1122	1122	1122

Source: C-600 data

Table 4: Municipality level data

Variable	Mean (SD)	Obs
General Characteristics		
Total population (1000s)	38(233)	1122
Distance to Department's capital	120(97)	1053
Capital of Department	.028(.16)	1126
Availability of water index	3.3(.55)	1061
Quality of soil index	2.7(1.2)	1061
Distance to the closest main market (4)	345(156)	1042
Altitude (meters above sea level)	1224(912)	1017
Average municipality precipitation in mm	1978(1071)	937
Current Road Density	.27(.62)	1119
Infant Mortality Rate	22(9.7)	1122
Other infectious diseases (INS, SIVIGILA)		
Influeza-like per 1000h	.21(.64)	1118
Emergencies due to natural events (SNIGRD, UNGRD)		
Total individuals	.98(7.2)	994
Total dwellings	378(921)	994
Total roads	1(2.9)	994
Total hectares	285(1762)	994

The last source of information pertinent to our analysis is the Demographic and Health Survey 2010 (DHS) collected by Profamilia (2011) under the international DHS program guidelines[4]. This survey is nationally representative 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 (see Figure 3). With this data we can explore how

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

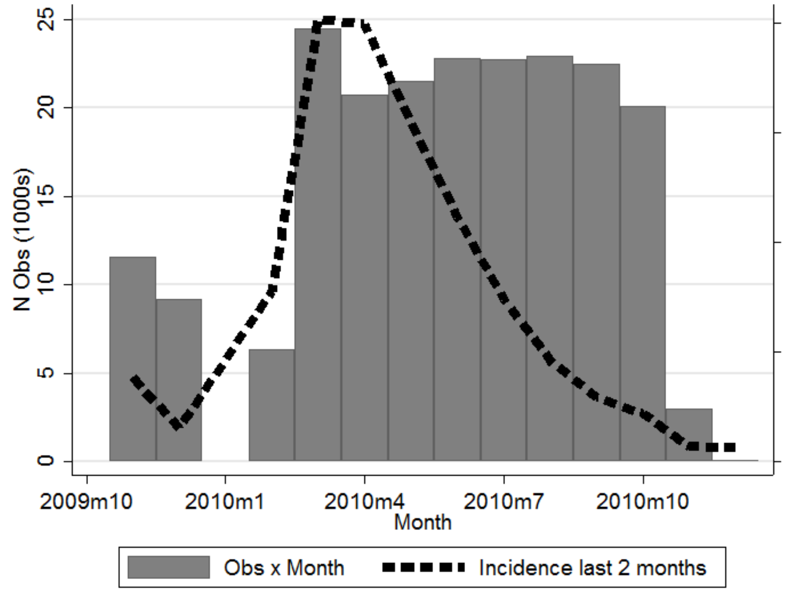
students and their family were affected by the disease. The main outcomes and controls used for our analysis are presented on table 5

Table 5: Descriptive Statistics DHS

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	.48(.5)	142060
Occupation Last Week: Studying	.17(.38)	142060
Hospitalized	.062(.24)	186974
Male Household Member	.48(.5)	186974
Age Of Household Members	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.

Figure 3: DHS date of interview and Dengue outbreak



2.2 Empirical Strategy

The identification strategy of Dengue impact relies on the key exogeneity assumption of its intensity with respect to other variables that might influence the outcomes of interest, conditional on some observed characteristics. While in general this would normally be a concern, the sharp rise of the epidemic in 2010 due to climate variations and natural protection provided by altitude provides a framework in which such restriction is plausible. This will be reflected in the econometric models used for the analysis.

Firstly, we analyse the impact of Dengue on health outcomes measured at individual level in the DHS. Here, we estimate the impact of an increase of 1 case per 1000h during the last 2 months, δ^Y, in outcome variable Y for an individual i living in a municipality j and who was surveyed in month m. For this, we take into account controls X at individual, household and municipality level, plus a fix effect dummy per period (Equation 1). Standard errors are clustered at municipality level as well. The strong identification assumption here says that our estimates might be affected by a selection bias: municipalities with higher prevalence might have some general conditions that are correlated to our outcomes.

$$Y_{ijm} = \delta^Y D_{jm} + \beta X_{ijm} + \gamma_m + u_{ijm} \tag{1}$$

Secondly, SABER 11 data set allows for a weaker assumption: Dengue rate has to be exogenous with respect to any unobserved shock which differs on time by municipality, but it could be endogenous to any characteristic that did not vary on time. As Dengue epidemic was just a spike of one year, and most of the conditions that are related to epidemic control are mostly fixed (health care and public health systems characteristics), this is not a very strong assumption. The only sort of variables that might follow the same patter are climatic factors, which might have direct impacts via natural disasters, information which is captured in our controls.

At student level, our specification is again an OLS estimator for δ^Y but it is possible to exploit the time dimension as discussed before. Hence, we allow for fix effects by municipality and analyse the impact over three test-taker cohort by introducing lags δ^Y_τ, as observed in Equation 2 where each student is observed in a school k (errors are clustered at such level) in calendar year t. Here our issue is selection: if students drop-out due to Dengue, our estimates on test-scores will be affected.

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

Finally, at school level we are able to contrast our previous results and stablish if selection is produced not. Equation 3 presents a linear fixed effects panel estimator. A similar strategy is used for municipality level data on enrollment.

$$Y_{kjt} = \sum_{\tau=0}^{T} \delta_\tau D_{kt-\tau} + \beta X_{kjt} + \gamma_k + \gamma_t + u_{kjt} \tag{3}$$

2.3 Preliminary Analysis

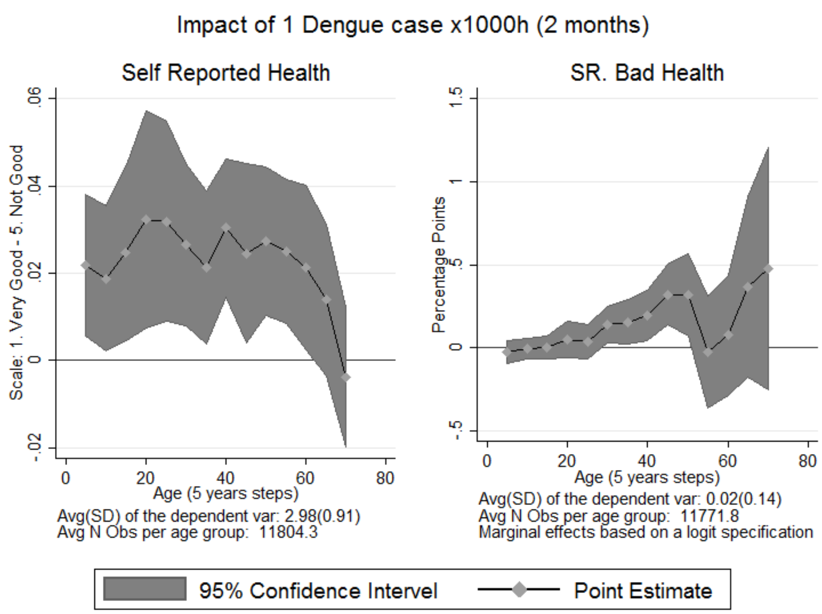
2.3.1 Health and activities impact

The first part of our analysis is based on the estimates from Equation 1. As mentioned above, there is evidence that Dengue incidence is higher among children under the age of 15, which motives an analysis by age groups of 5 years. It is important to remember that there is a strong identification assumption in place for the following estimates.

For ease of exposition, estimators for δ^Y are presented graphically. The y-axis shows the estimator in the units of the outcome and the x-axis the starting age of the group of individuals analysed. The figure also present some basic statistics for getting an impression of the size of the impact (mean and standard deviation of the outcome) and on the variance of the point estimate (confidence interval at 95% level and average number of observations per group).

The pair of outcomes related to own perception about health are shown in Figure 4. Even though the 1-to-5 scale does not have an intrinsic cardinal interpretation, the direction of the estimator shows that Dengue incidence appears to have had an impact on the perceptions about one's own health for people of all ages. However, interestingly, this effect does not seem to be concentrated on children under 15 years of age; it rather seems to be have stronger effects on adult population. For adults, an increase of 1 case per 1000h is associated with more or less 0.4 pp. increase on the likelihood to report to be in bad health. This is not a small number taking into account that only 2% of the respondents declared to be in bad health. Also, even though 1 case was around the average prevalence in the sample, this number jumped over 10 in some of the extreme scenarios.

Figure 4: Self-Reported Health



Aside from individuals perceptions regarding their health status, in order to obtain a better measure of the impact of the epidemic, we examine whether it stopped individuals from engaging in their usual daily activities. Figure 5 (right-side) shows that the bad-health reports are backed-up with a similar proportion of people of the same age who were temporally limited by disease (just 6% of the individuals were reported to be in such state). The left panel shows that the impact on the proportion of people who report to have been sick might be higher, and perhaps with different trends by age. Figure 6 shows that the temporal limitation is reflected on the likelihood to be working during the last week, but are not significant for being studying. These numbers are not reflected on the likelihood to be hospitalized, which indicates that most of the impact on the health system was concentrated on primary care, which is consistent with the guidelines for classic Dengue.

Figure 5: Health Problem Without Hospitalization Last 30 days

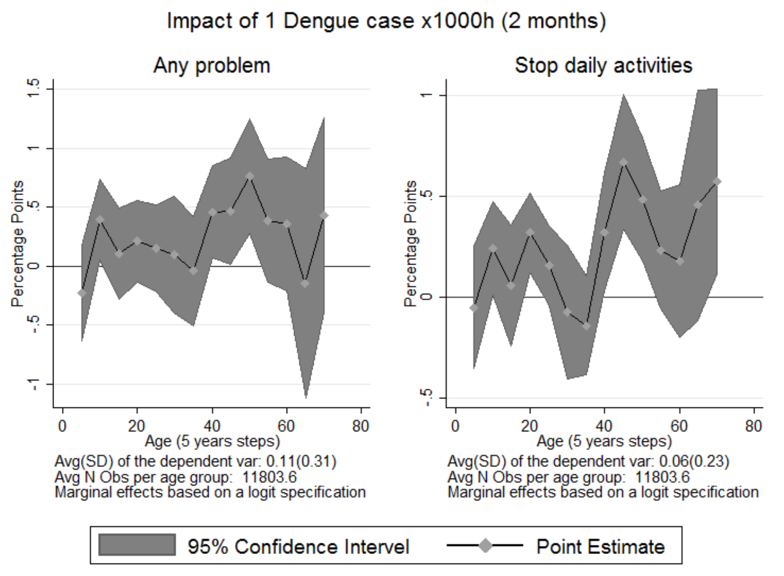
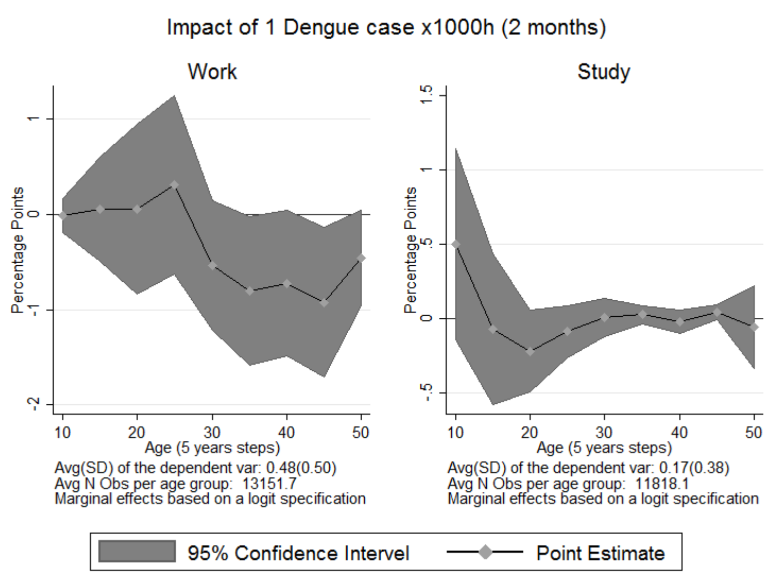


Figure 6: Main Activity Last Week



2.3.2 Impact on School Attendance and Test Scores

As discussed before, the longitudinal structure of the SABER 11 registries allows for a weaker identification assumption than the previous section. Table 6 briefly resume the impacts of both classic and haemorrhagic Dengue on yearly standardised test scores. While there is some evidence of a negative association with lower language scores, specially for the Haemorrhagic variation, estimated coefficients are very small in comparison with well known explanatory variables. For instance, an increase in 10 cases per 1000h in classic Dengue would be required in order to be in the same magnitude as the gender gap in such outcome (0.03). Moreover, such gender gap for language is normally irrelevant if we compare it with the gender gap in mathematics which is around 0.3 standard deviations. Moreover, some of the estimates for mathematics are positive and significant under some specifications. A similar pattern is observed when using mean test scores aggregated at school level (see Table 7). Therefore it does not seem that the epidemic had a relevant impact on test-scores, at least at a municipality-aggregate level. More work on this area, with individual level infection data might be required for this type of analysis, which is beyond the scope of this paper. It is also important to notice that there might be some selection in place: those students who were affected the most might have dropped out, or at least not presented the exam.

Table 6: Student Level Analysis

SABER 11 data: 2008-2012. Includes controls at student, school and municipality level, schools' average test scores from 2007-2008, year and department fix effects.

Specification	**Math**	**Math**	**Lang**	**Lang**
Dengue cases x1000h, same year	0.0007	0.0018	−0.0052***	−0.0049***
	(0.0007)	(0.0014)	(0.0007)	(0.0015)
Dengue cases x1000h, last year		0.0022		0.0016
		(0.0014)		(0.0015)
Dengue cases x1000h, 2 years ago		0.0009		−0.0016
		(0.0015)		(0.0016)
Dengue H cases x10.000h, same year	0.0024***	0.0018**	0.0004	−0.0014*
	(0.0006)	(0.0008)	(0.0006)	(0.0007)
Dengue H cases x10.000h, last year		0.0007		−0.0034***
		(0.0007)		(0.0006)
Dengue H cases x10.000h, 2 years ago		−0.0010		−0.0042***
		(0.0008)		(0.0008)
=1 if student is a girl	−0.3148***	−0.3148***	−0.0412***	−0.0412***
	(0.0025)	(0.0025)	(0.0022)	(0.0022)
N Observations	984765	984765	989189	989189
N Clusters	6516	6516	6516	6516
R^2	0.24	0.24	0.21	0.21

SE clustered at school level. Significance: * 10%, ** 5%, *** 1%

From the DHS, it was not possible to rule out that Dengue had a null impact on daily activities for children aged 10 to 14 or 15 to 19. Table 7 suggests that it might be possible that the number of test-takers was reduced due to the epidemic. While impacts due to classic Dengue are very sensible to the specification, that is not the case for the haemorrhagic version. In this case, An increase of 10 cases per 10.000h would be reflected on a reduction of 4% of the exam-takers, which is around 1.5 students for a median class of 38 pupils. It is important to stress that these cases are relatively rare, but during the 2010 epidemic around 10% of the municipalities had rates above 10.

Table 7: School Level Analysis: test scores

SABER 11 data: 2008-2012. Includes controls at student, school and municipality level, schools' average test scores from 2007-2008, year and department fix effects.

Specification	**LN(N.Est)**	**LN(N.Est)**	**Math**	**Math**	**Lang**	**Lang**
Dengue cases x1000h, same year	−0.0020	0.0018	0.0033***	0.0054***	−0.0039***	−0.0025
	(0.0016)	(0.0030)	(0.0008)	(0.0017)	(0.0009)	(0.0017)
Dengue cases x1000h, last year		0.0034		0.0042**		0.0027*
		(0.0028)		(0.0017)		(0.0016)
Dengue cases x1000h, 2 years ago		0.0046		0.0012		−0.0003
		(0.0030)		(0.0018)		(0.0017)
Dengue H cases x10.000h, same year	−0.0036***	−0.0061***	0.0008	0.0001	−0.0011	−0.0029***
	(0.0012)	(0.0016)	(0.0007)	(0.0009)	(0.0008)	(0.0009)
Dengue H cases x10.000h, last year		−0.0035***		0.0004		−0.0030***
		(0.0013)		(0.0008)		(0.0008)
Dengue H cases x10.000h, 2 years ago		−0.0046***		−0.0012		−0.0037***
		(0.0015)		(0.0010)		(0.0010)
% of SISBEN 1/2 of test-takers			−0.0006***	−0.0006***	−0.0006***	−0.0006***
			(0.0002)	(0.0002)	(0.0002)	(0.0002)
% of women of test-takers			−0.0024***	−0.0024***	−0.0002	−0.0002
			(0.0002)	(0.0002)	(0.0002)	(0.0002)
N Observations	26784	26784	26784	26784	26783	26783
Avg Periods	2.80	2.80	2.80	2.80	2.80	2.80
N Clusters	9564	9564	9564	9564	9563	9563
R^2	0.03	0.03	0.02	0.03	0.01	0.02

SE clustered at school level. Significance: * 10%, ** 5%, *** 1%

Finally, Table 8 shows that even though Dengue reduce the number of test-takers, there is no evidence that it reduces enrollment at secondary school. However, severe Dengue might have had an impact on enrollment at primary school level. Here, a rate of 10 would be required to reduce enrollment by 1%. Though this is quite a small number, average enrollment rates are on the order of 4200 students as seen in Table 3, or 3000 if we consider municipalities with less than half a million inhabitants.

Table 8: Total Enrolment Analysis

Enrolment data: 2008-2012. Linear fixed effects panel that includes controls at municipality level.				
Specification	**LN(N.Enrol Prim)**	**LN(N.Enrol Prim)**	**LN(N.Enrol Secu)**	**LN(N.Enrol Secu)**
Dengue cases x1000h, same year	0.0003	0.0007	0.0002	0.0006
	(0.0007)	(0.0008)	(0.0011)	(0.0012)
Dengue cases x1000h, last year		−0.0002		0.0008
		(0.0007)		(0.0008)
Dengue cases x1000h, 2 years ago		−0.0004		0.0006
		(0.0005)		(0.0006)
Dengue H cases x10.000h, same year	−0.0009**	−0.0014***	0.0001	0.0001
	(0.0004)	(0.0004)	(0.0005)	(0.0006)
Dengue H cases x10.000h, last year		−0.0018***		0.0003
		(0.0005)		(0.0005)
Dengue H cases x10.000h, 2 years ago		−0.0008***		−0.0003
		(0.0003)		(0.0004)
N Observations	4468	4468	4449	4449
Avg Periods	4.00	4.00	4.00	4.00
N Clusters	1117	1117	1113	1113
R^2	0.22	0.23	0.01	0.01

Robust SE. Significance: * 10%, ** 5%, *** 1%

3 Summary and next steps

In summary, we have shown that 2010 Dengue epidemic in Colombia is associated with temporary limitation of daily activities due to health, including working, for adult population. However, for individuals aged 10 to 20, there is no robust evidence of an aggregate impact on schooling activity. Also, there is no evidence that classic Dengue affect schooling enrollment, nor participation or results in standardized tests.

The only impacts for this population seem to be related to the incidence of haemorrhagic Dengue fever, which could be potentially lethal. If the number of cases increased by around 10 cases per 10.000h, this would imply a reduction of 1 student out of 38 attending the exam. It also seem to slightly reduce enrollment at primary school level, 1 children out of a 100 given the same rate increase.

Current results show that Dengue epidemic, from an aggregate point of view, did not have strong effects on the country. However, the picture might be different if we consider places were the epidemic was specially strong, where the haemorrhagic version might have produced deeper consequences both for students and their parents. Consequently, our next steps in this project will required to focus our attention in these municipalities potentially with measures of incidence below this aggregation level.

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