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Behavioural Response to a Sudden Health Risk: Dengue and Educational Outcomes in Colombia[1]

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Abstract

This paper makes use of a short, sharp, unexpected health shock to examine the indirect behavioural response of the general public to a sudden shift in the perceived risk of a substantial deterioration of health and mortality. While existing work has been done estimating the direct effects of an epidemic on the afflicted families, we instead focus on assessing the indirect effect of a sudden epidemic on the population as a whole, mediated by the behavioural response to the sudden shift in the perceived risks of engaging in certain activities. Our analysis finds that the influence of the epidemic extends far beyond those directly afflicted: it essentially comprises a behavioural response to the fear of contracting the disease. Strikingly, 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, but the response to classic Dengue is inconclusive.

JEL Classification: I12, I15, I20, D80

Keywords: health risks, health and education, dengue outbreaks

Resumen

Este documento utiliza un evento de salud corto e inesperado para analizar la existencia de respuestas indirectas de la población frente a cambios repentinos en el riesgo percibido de un deterioro de salud. El trabajo se enfoca en evaluar los efectos indirectos de un brote epidémico repentino sobre la población como un todo, reconociendo la existencia de otros trabajos que evalúan los efectos directos. El análisis encuentra que la influencia de la epidemia va más allá de los directamente afectados, mostrando que existe un comportamiento particular en respuesta al temor de contraer la enfermedad. En particular, se encuentra que en un curso con un tamaño aproximado de 47 estudiantes, faltan aproximadamente 4 estudiantes a la prueba Saber 11 por cada 10 casos adicionales de dengue hemorrágico por 10.000 habitantes, pero la respuesta a casos de dengue clásico no es concluyente.

Palabras clave: riesgos de salud, salud, educación, dengue

[1] An earlier draft of this paper was circulated as "Short Term Health Shocks and School Attendance: The Case of a Dengue Fever Outbreak in Colombia".

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1 Introduction

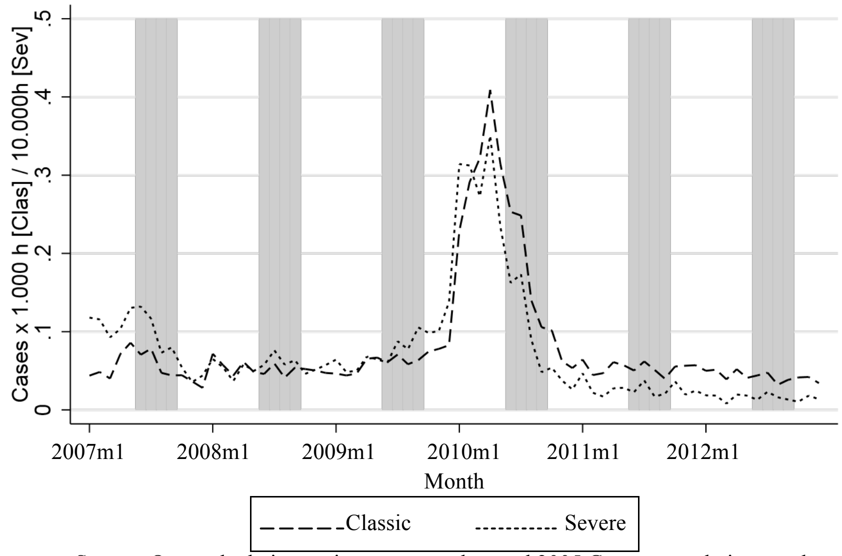
Dengue is currently the most prevalent mosquito-borne viral disease in humans, with an estimated 50 million infections annually worldwide (WHO, 2009). Its expansion has taken place at an extremely rapid rate over the last few decades along both the extensive margin as well the intensive margin. In America, Dengue is transmitted between individuals primarily by the *Aedes aegypti* mosquito (Villar et al., 2015), which is also the vector of diseases like *Zika* and *Chikungunya*. According to Padilla et al. (2012) climate change has contributed to the expansion of Dengue by increasing temperatures and allowing mosquitos to thrive in new regions and at higher altitudes. While it is well documented that epidemics of this nature can have dire 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 has an *indirect* effect on the economic outcomes of individuals who are not directly influenced by the disease.

Dengue can manifest 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 in many cases[2] (Villar et al., 2015). We make use of a "natural" experiment to study the direct and indirect effects of the dengue epidemic on human capital formation. Temporal and geographic variation in the incidence of dengue allow us to assess the direct impact of both strands of dengue on school attendance and test score attainment in the Saber 11 school leaving examinations.

In 2010, Colombia experienced an unprecedented increase in dengue incidence due, partially to unexpectedly high rainfall variability (De La Mata and Valencia-Amaya, 2014), with rainfall and average temperatures having been identified as predictive of *Aedes aegypti* prevalence. According to the *Instituto Nacional de Salud* (National Health Institute or INS), in 2010 there were 147 257 reported cases of *classic dengue*, and 9 755 cases of *severe dengue*. The estimated incidence was 577 per 100 000 for *classic dengue* and 38.3 per 100 000 for *severe dengue* (Villar et al., 2015). The 2010 epidemic therefore was substantially worse than the 2002 outbreak, with nearly double the 78 618 cases recorded in 2002. Figure 1 shows that the 2010 epidemic was both extremely sudden and sizeable. Moreover, it generated a sudden increase in the public's concern and awareness regarding dengue as reflected in Figure 2, which shows Google searches for the term "Dengue" over five years in Colombia.

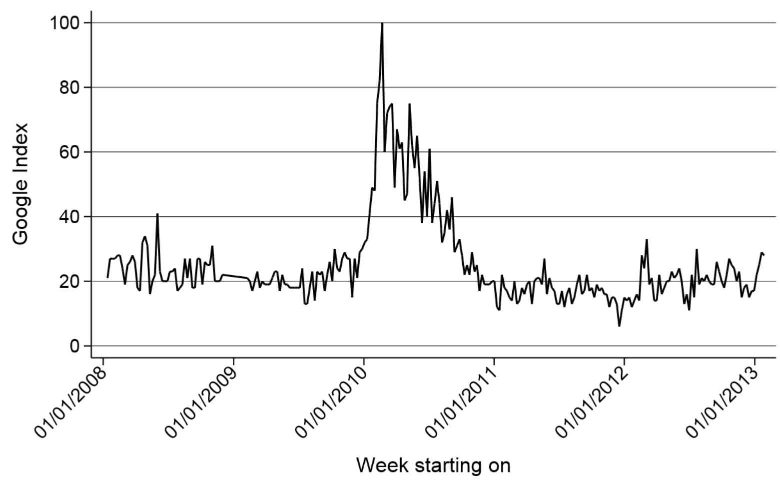
[2] According to the WHO classification, dengue appears as *severe dengue* (previously referred to as dengue haemorrhagic fever) and *non-severe dengue*, which we refer to as *classic dengue* in this paper. *Classic dengue* is comparable to the flu, with symptoms that are very unpleasant, but temporary 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. During 2010, it resulted in hospitalization in approximately 80% of cases and death in approximately 2% 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% (Villar et al., 2015). 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).

Figure 1: 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.

Figure 2: Web searches for "Dengue" in Colombia



Weekly Google trends data for the term 'Dengue' in Colombia

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 *classic dengue* may cause students to miss school temporarily when someone in the household is infected, it is unlikely to cause fear and therefore substantially change the behaviour of individuals outside the directly affected households. In contrast, *severe dengue* is a dangerous illness that is likely shift the perceived mortality risk and lead families to take preventative actions before anyone in the household is directly affected by the epidemic.

In line with this, we find that a higher incidence of *severe dengue* in a municipality in the months preceding the exam leads 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.

The most plausible explanation for this behavioural response is that given that the 2010 dengue epidemic resulted in a media storm, the public were suddenly made acutely aware of a new health risk of unknown severity. The epidemic can therefore be viewed as a natural experiment that shifts 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, this 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 hospitalization or death of several members of a municipality would result in a significant shift in the level of perceived mortality risk in that municipality.

The existing literature examining the behavioural response to a sudden health risk is scarce. For example, Adda (2007) uses the 1996 "Mad Cow" crisis to show that there was a strong reduction in the amount of beef bought by French consumers once they became aware of the possible health risk. Furthermore, 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.[3] The author terms this behaviour an 'alarmist reaction' in response to the uncertainty regarding a new health risk. Other authors explore 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).

By studying the response to a heterogeneous shift in the perceived mortality risk across municipalities, 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 can lead to a strong, preventable behavioural response with significant 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%. This implies

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[3] 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 (Schmeidler, 1989; Tversky and Kahneman, 1992; Wakker and Tversky, 1993).

that the influence of a single case extends far beyond the individual and household directly affected by the illness.[4] There is a large literature documenting the substantial cost of reducing (or delaying) educational attainment, including Card (1999); Carlsson et al. (2015); Light (1995); Krueger and Ashenfelter (1994); Angrist and Krueger (1991); Hansen et al. (2004). Secondly, we explore the heterogeneity in the reduction in examination attendance observed in the administrative data. Interestingly, we find that in municipalities where the proportion of poor students is lower, the effect is far stronger, while in municipalities with a high proportion of poor students, an additional case of severe dengue per 10 000 inhabitants does not have a significant effect in reducing examination attendance.

Overall, the results show that the impact of a sudden epidemic is not fully captured by the direct influence on the afflicted families and the strain put on the health system, rather, the behavioural response of the general population in the face of substantial uncertainty regarding the new risk to their health is another important channel through which the epidemic can exert a long-lasting influence.

The remainder of the paper is structured as follows. Section 2 presents the data employed in the empirical strategy and some exercises intended to assess heterogeneous effects. The next section summarizes the results of the main estimations. Finally, section 6 discusses and concludes.

2 Methods

2.1 Data

We use administrative data containing individual level schooling outcomes (e.g. test scores for mathematics and language and examination attendance) from the Saber 11 examinations managed by ICFES[5] as well as demographic information regarding the students and their families. Saber 11 is a compulsory examination for all students in their last year of secondary education and is used for private universities as an input of their selection process. We use this test score data in two ways: (i) as a longitudinal panel dataset at school level; and (ii) as a repeated cross-section at the individual level.

We focus on those schools whose the academic year correspond to the calendar year that represent the majority of the students (85% to 95%).[6] Then, we have approximately 2 million

[4] In the average municipality, there are 41 000 inhabitants. Of these, 21% are enrolled 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 (an additional case per 10 000) would imply that 3.6 fewer students sat their Saber 11 examination in the municipality.

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

[6] 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.

observations available for the analysis. Tables 1 and 2 present the variables that we use from this dataset.

In addition, we use information regarding *severe dengue* and *classic dengue* cases collected weekly at the municipality level by the INS. From it we construct the prevalence of the illness for the four months prior to the exam date.

Last, we control for the intensity of the shocks that triggered the outbreak, namely rainfall and temperature. This is because they might have other direct consequences as a surge of other diseases and be related with the incidence of natural disasters, compiled from the Government emergency reports.[7] A summary of these variables is presented in Table 3.[8]

2.2 Empirical Strategy

Across all our empirical specifications, we exploit the geographical variation that we observe in dengue incidence over time. Identification of causal effects is based on the exogeneity of idiosyncratic time-shocks in such variable. We will argue that the main source of such variation is the unanticipated outbreak, where exposition to its intensity is given by pre-determined characteristics once we condition on the triggers of the shock (rainfall and temperature variations). We do the analysis for 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 both school and student levels.

The identification strategy relies on the assumption that the geographical 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. For this reason, it is important to discuss the main factors associated to the intensity of the outbreak.

2.3 Analysis of the outbreak intensity

Figures 3 and 4 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, that 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

[7] 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.

[8] Population data comes from 2005 National Census. Emergencies data was derived from natural disasters records available at the *Sistema Nacional de Información y Gestión del Riesgo* (SNIGRD) webpage, which is the government institution that records events of this nature.

relatively unaffected. Table 4 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.

Figure 3: Municipal altitude and yearly incidence of classic dengue fever

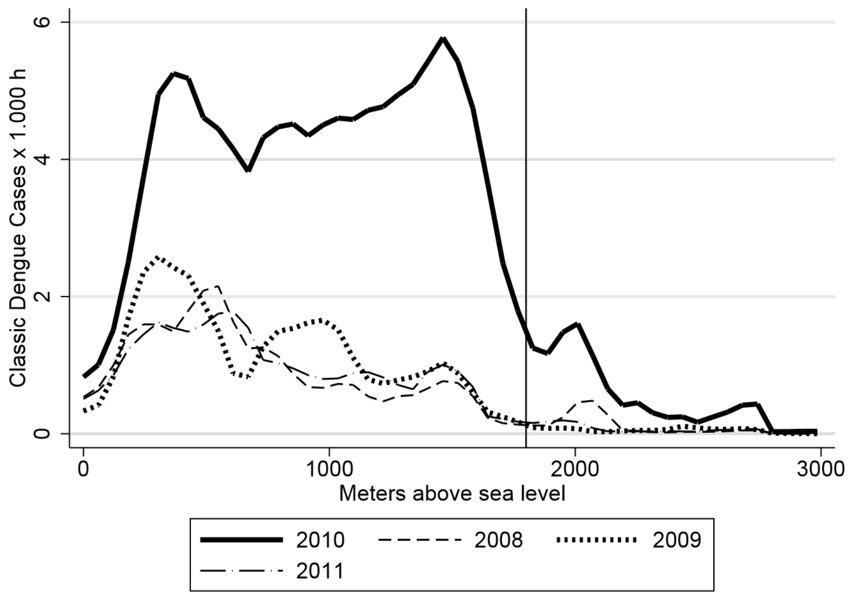
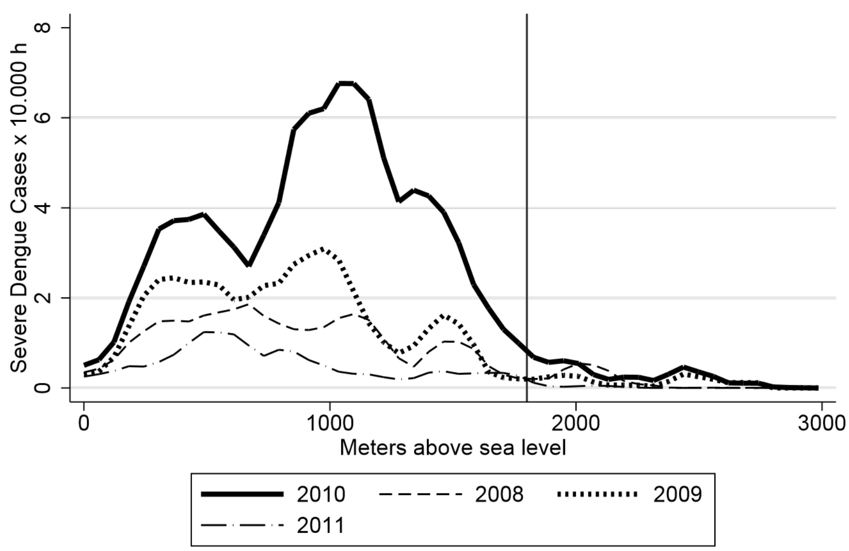


Figure 4: Municipal altitude and yearly incidence of severe dengue fever



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

Furthermore, Figure 5 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 6. It presents the *severe dengue* incidence rates in 2010, colour coded according to the 2008 incidence, a preoutbreak 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).

Figure 5: Distribution of classic and severe dengue incidence

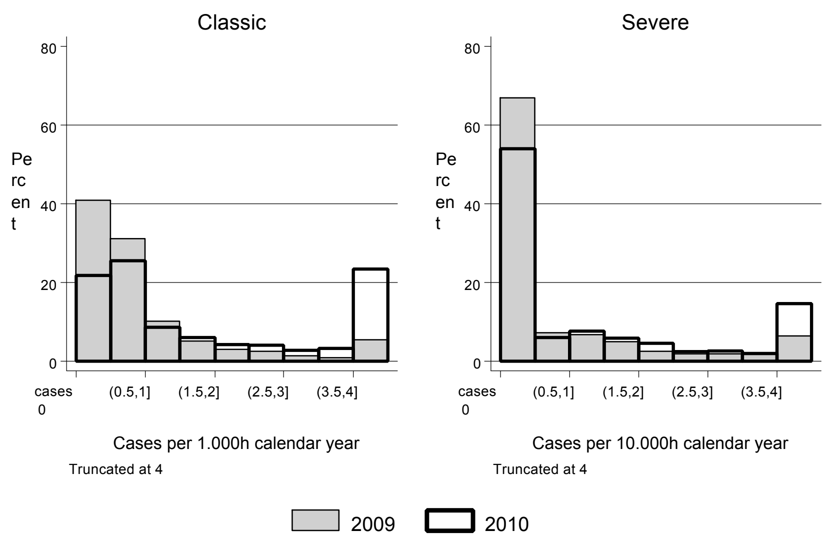


Figure 6: Geographical distribution of severe dengue incidence in Colombia, 2010

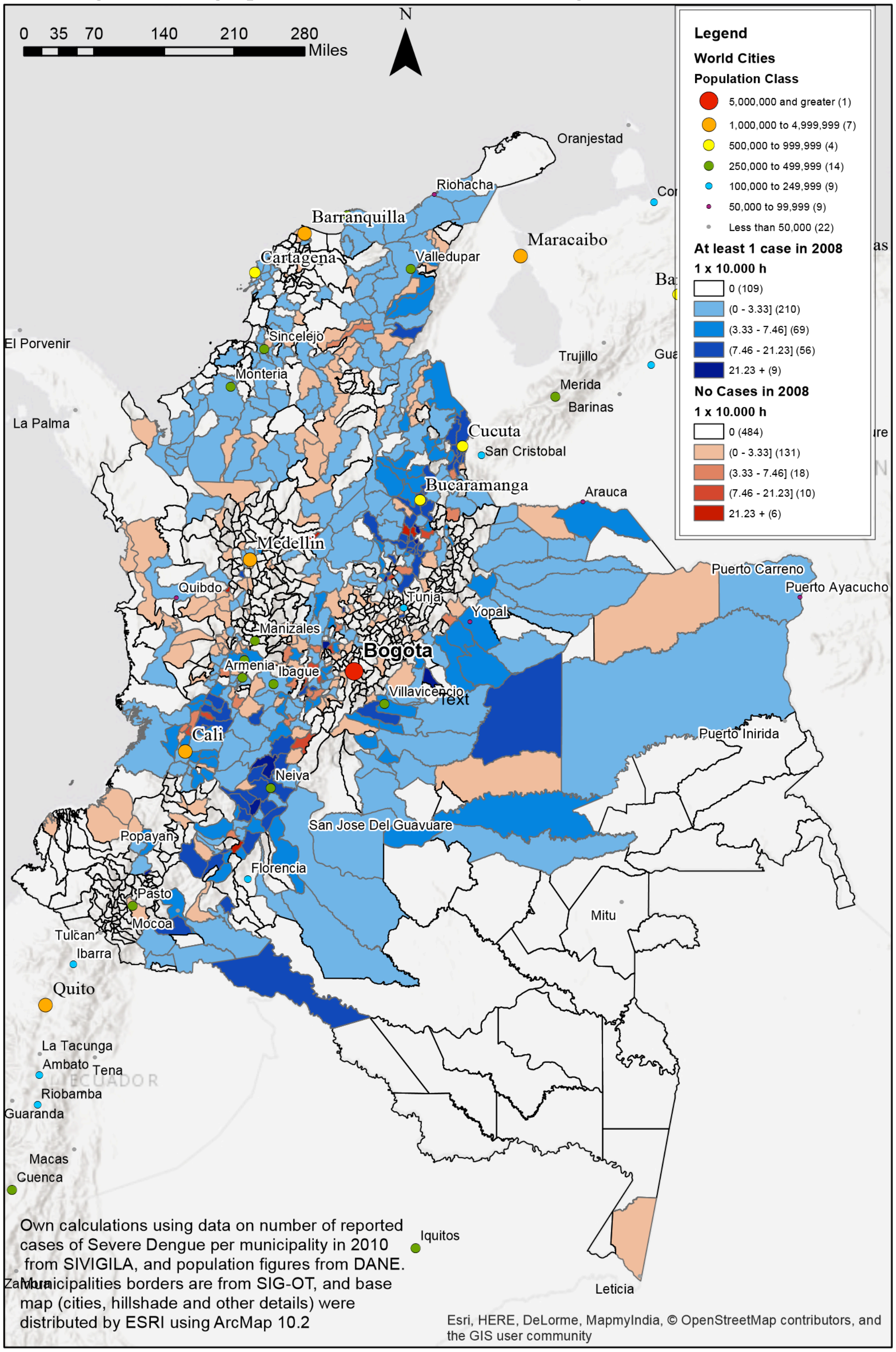


Table 5 provides the estimates from a linear panel regression with municipality fixed effects for *severe dengue* incidence on an array of municipality level covariates that allow us to know which municipality characteristics are correlated with the incidence of *severe dengue*. In general, there is a clear relationship between *severe dengue* and economic characteristics, here summarized 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 (Column 5), it is negatively correlated.

Lower rainfall levels, which assist 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) or the level of school enrolment as a proportion of the population, are irrelevant once poverty levels are taken into account.

As a result, we consider that our main identification assumption is valid. Firstly, this is due to the sharp and unexpected increase in dengue incidence in 2010, and secondly to the fact that the majority of factors that one would expect to drive an 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, which could have some influence via natural disasters. However, we are able to control for both climatic variation and disaster information with our control variables.

2.3.1 *School Level Specification*

The school level impacts of dengue are obtained using the panel of schools resulting from 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 schooling 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 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.

2.3.2 *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:

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

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}.

2.3.3 *Heterogeneous Effects*

It is also of considerable interest to examine whether we observe heterogeneity in terms of which types of municipalities 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):

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

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}.

3 Results

3.1 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.

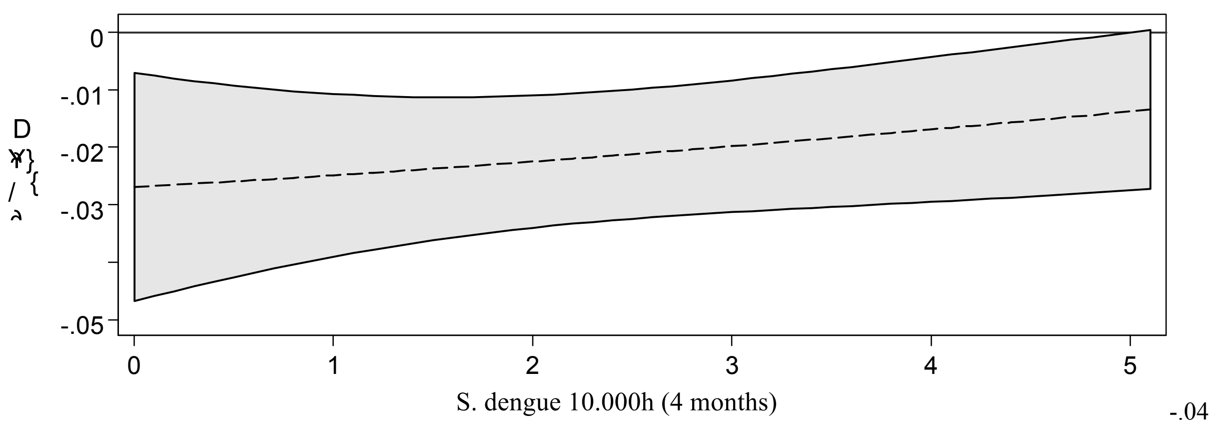
The results are displayed in Table 6. Firstly, columns (2) and (4) show that an increase in *classic dengue* has no significant effect on participation in the Saber 11 examination. However, columns (1) and (3) show that there is a large contemporaneous effect of *severe dengue* on attendance in the examination. More specifically, the magnitude of the estimates suggests that for each additional case of *severe dengue* per 10 000 inhabitants in the municipality, 1% fewer students attend 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% of municipalities in Colombia had an incidence rate at least this high during the 2010 epidemic.

Non-linearities of this impact of *severe dengue* might be an important element to consider. The marginal effects of *severe dengue* at different levels of *severe dengue* intensity are plotted in Figure 7 using a polynomial or 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.

Figure 7: Marginal effect of severe dengue on the LOG number of Test Takers: non-linear effects

1 additional case per 10.000h

4th order polynomial



Interaction terms are jointly significant at 5% level: F 2.64, p-val 0.05

SE clustered at municipality level for 90% confidence intervals. Incidence defined over the last 4 months before Saber 11 test. Incidence restricted to 5 cases per 10.000 h for easiness of exposition

3.2 Test Scores

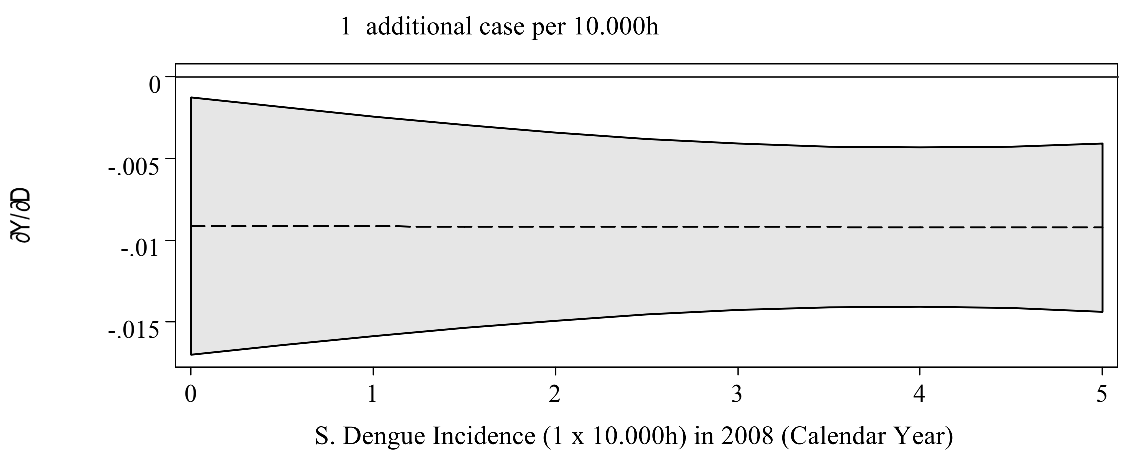
We explore the impact of dengue incidence (*classic* and *severe*) on mathematics and language scores, conditional on having taken the exam along this section. Table 7 and Table 8 indicate very small estimates at student and school level, respectively. The size of these estimates for the impact of dengue is put into perspective if we compare them to 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 (see Table 8).

3.3 Heterogeneous effects

We examine whether this impact varies according to the prior incidence of the disease due to the potential variation in behavioural response according to previous exposure to the disease. Secondly, we assess whether the characteristics of the municipalities and the school affect the impact of dengue on students attending that school. In order to check whether the behavioural response to *severe dengue* differed between municipalities that were not affected by *severe dengue* prior to the epidemic (e.g. in 2008) relative to endemic areas, Table 9 presents the results from an exercise that interacts 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 numbers are not statistically different. Furthermore, Figure 8 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.

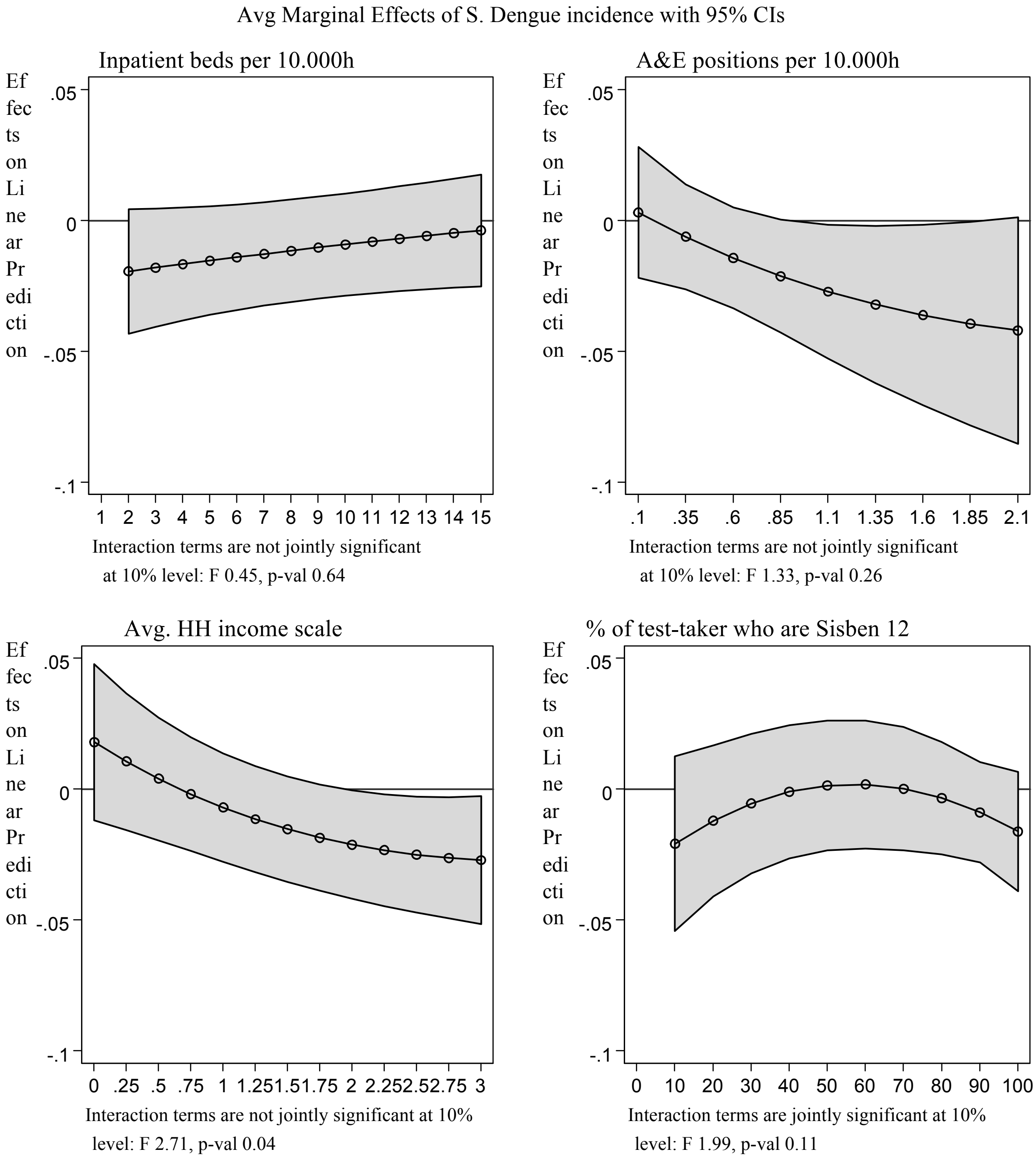
Using the same specification from equation 3, we estimate the heterogeneous effects of severe dengue by school and municipality characteristics. In line with the analysis above, we focus only on municipalities below 1800m since these are the municipalities that are most affected. Figure 9 presents these 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.

Figure 8: 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

Figure 9: Marginal effect of severe dengue on the LOG number of Test Takers: heterogeneous effects



Domain of Z: 5%-95%. Polynomial of order 3 on Z
Municipalities below 1800m above the sea level

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 from 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 9 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 everywhere negative, 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.

3.4 Robustness Checks

In order to test our identification assumptions, we conducted several tests. First, we found no impact on observed characteristic of students who presented the test. Second, we conducted a placebo test in which we assessed the impacts of future dengue shocks (two years leads of prevalence rate) on current outcomes. It showed no evidence of any anticipatory effects. We also run our specifications for the restricted sample of municipalities with non-zero *severe dengue* incidence and 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*. The results of all these exercises, available in a previous version, are strongly supportive of our main results.

3.4.1 *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 6, 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 10 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.

3.4.2 *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 11 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.[9] 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 2^{nd} 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.

3.4.3 *Estimates for subsample with non-zero* severe dengue *incidence*

Table 12 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.

3.4.4 *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.

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[9] 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.

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).[10] 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.[11]

Table 13 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.

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 14 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.

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[10] 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.

[11] 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 Saber 11 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.

4 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 which had a cohort of 47 students in an average municipality, which had 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 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, 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.[12] 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 is causing some students not to attend the exam. If these students tend to be poorly prepared, then this selection effect would imply an underestimate 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.[13]

However, it is worth mentioning a few caveats to this interpretation of the results. Firstly, the impact on students is likely to be smaller than this as the incidence rate could be 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

[12] Similarly, the effects for *classic dengue* are also small but positive.
[13] If one student in 10 000 students contract *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.

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 the 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. Suggestive support for this argument comes from web searches for dengue that coincided with the epidemic.

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 two strands of the disease. Secondly, wealthier families are likely to have greater savings and be able to afford delaying 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 would negatively influence their performance.

5 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 a substantial benefit to 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% during 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, there may be a substantial benefit in 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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Tables

Table 1: Descriptive Statistics for year 2010: student level data

Variable	Mean (SD)	Obs
Saber 11		
=1 if student is a girl	.54(.5)	368264
Age in years	17(2)	368264
=1 if Sisben level 1 or 2	.67(.47)	368264
Avg. Household Income Index (self-reported)	1.6(1.5)	368264
Father Educ: None	.036(.19)	368264
Father Educ: At most Primary	.37(.48)	368264
Father Educ: Incomplete Secondary	.16(.36)	368264
Father Educ: Complete Secondary	.23(.42)	368264
Father Educ: Above Secondary	.15(.36)	368264
Father Educ: Don't Know	.061(.24)	368264
Mother Educ: None	.02(.14)	368264
Mother Educ: At most Primary	.35(.48)	368264
Mother Educ: Incomplete Secondary	.19(.39)	368264
Mother Educ: Complete Secondary	.26(.44)	368264
Mother Educ: Above Secondary	.16(.37)	368264
Mother Educ: Don't Know	.026(.16)	368264

Table 2: Descriptive Statistics for Year 2010: School level data

Variable	Mean (SD)	Obs
Saber 11		
Private managment	.27(.44)	8463
Public managment	.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

Table 3: Descriptive Statistics for year 2010: Municipality level data

Variable	Mean (SD)	Obs
General Characteristics 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
Urban-total population	.43(.24)	1122
Current Road Density	.27(.62)	1119
Distance to Department’s capital	120(97)	1053
Poverty Index based on quality of life (NBI)	45(21)	1122
Sewer coverage (%)	41(27)	1113
Piper Water Coverage (%)	65(23)	1113
Subsidized Health Care / Population	.7(.48)	1118
Total Municipality Income per capita	.76(.6)	1118
Municipality dependence on central Gov. transfers	.58(.19)	1118
Certified Municipality (Health) 2006	.45(.5)	1098
Inpatient Beds per 10.000h	7.2(11)	855
A&E positions per 10.000h	1.1(1.2)	855
Education Characteristics Enrolment Primary (1000s)	4.2(21)	1122
Enrolment Secondary (1000s)	3.9(24)	1122
Enrolment/Population	.21(.05)	1122
Last year of secondary school	464(3112)	1122
Number of schools which participate in Saber 11	7.7(41)	1095
Number of Saber 11 test takers	363(2427)	1095
Other infectious diseases (INS, SIVIGILA) Influeza-like per 1000h, Cal Y	.2(.65)	1122
Emergencies due to natural events (SNIGRD, UNGRD) Total individuals	.87(6.7)	1123
Total dwellings	334(875)	1123
Total roads	.92(2.7)	1123
Total hectares	227(1429)	1123

Table 4: 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 (4 1)						
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

Table 5: Determinants of severe dengue

	$\bar{X}$	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	0.0003*	−0.0004**	−0.0005**	0.0032**	−0.0064***
		(0.0002)	(0.0002)	(0.0002)	(0.0012)	(0.0016)
Avg. 2m temperature (C), last 12 months (Aug)	19.800	0.1443	−0.0490	0.1300	0.1991	−0.4076
		(0.2759)	(0.2948)	(0.2913)	(0.3220)	(0.5587)
Avg. Precipitation (mm)*100, last 12 months (Aug)	0.528	−5.0086***	−4.3449***	−3.4462***	−2.7823***	−4.7986***
		(0.7783)	(0.7249)	(0.6744)	(1.0278)	(1.1724)
Enrolment/Population x (year=2010)	0.042	−2.3893	−2.2350	0.5377	1.6122	−2.7374
		(2.8795)	(3.2442)	(2.9015)	(3.7693)	(6.5082)
NBI Poverty Index x (year=2010)	3.492		−0.0583***	−0.0314***	−0.0300***	−0.0710**
			(0.0117)	(0.0108)	(0.0078)	(0.0280)
Certified x (year=2010)	0.034		0.0533	0.3905	0.0625	0.2148
			(0.4086)	(0.3778)	(0.3863)	(0.7267)
Year = 2009	0.077	0.1899	0.2763	0.1534	0.4313**	−0.1835
		(0.1749)	(0.1837)	(0.1773)	(0.2039)	(0.3819)
Year = 2010	0.077	1.6562**	5.1382***	1.9308*	1.4548	14.8870***
		(0.7026)	(1.0392)	(1.0510)	(1.2135)	(3.8054)
Year = 2011	0.077	−0.3574*	−0.2959	−0.4205*	−0.4145*	−0.2354
		(0.2039)	(0.2170)	(0.2219)	(0.2154)	(0.4402)
Year = 2012	0.077	−0.5987***	−0.5205**	−0.5640***	−0.6428***	−0.3803
		(0.2043)	(0.2189)	(0.2087)	(0.2238)	(0.4157)
Classic Dengue per 1000h, Cal Y	0.441			0.4610***		
				(0.0786)		
N Observations		4265	4185	4185	2355	1805
N Clusters (Departments)		853	837	837	471	361
Adjusted R^2		0.111	0.132	0.228	0.161	0.176

† Linear panel fixed effects regression at municipality level with Severe Dengue Incidence (10.000 cases per hab., calendar year) as a dependent.
Robust standard errors in parenthesis. Significance: * 10%, ** 5%, *** 1%.

Table 6: Number of test takers per school and dengue incidence

	LOG(Number of students who presented the test)			
	(1)	(2)	(3)	(4)
	-0.010**		-0.011**	
	(0.005)		(0.005)	
			-0.005	
L.S. Dengue 10000h (4M)			(0.004)	
L2.S. Dengue 10000h (4M)			-0.000	
			(0.003)	
C. Dengue 1000h (4M)		0.002		0.004
		(0.005)		(0.005)
L.C. Dengue 1000h (4M)				0.003
				(0.005)
L2.C. Dengue 1000h (4M)				0.005
				(0.007)
Observations	37299	37299	30862	30862
Schools	8839	8839	8746	8746
Avg. periods per school	4.22	4.22	3.53	3.53
Municipalities	837	837	836	836
$\bar{Y}$	0.02	0.02	0.02	0.02

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, roads affected by natural disasters. See Table 3 for further details.

Clustered at municipality level SD in parenthesis. Significance: * 10%, ** 5%, *** 1%

Table 7: Student Level Analysis

Specification	Math	Math	Lang	Lang
S. Dengue 10000h (4M)	0.0007		−0.0034**	
	(0.0011)		(0.0014)	
S. Dengue 10000h (4M), 1 year ago	0.0014		−0.0059***	
	(0.0013)		(0.0012)	
S. Dengue 10000h (4M), 2 years ago	−0.0008		−0.0030***	
	(0.0012)		(0.0010)	
C. Dengue 1000h (4M)		0.0031*		0.0074***
		(0.0017)		(0.0020)
C. Dengue 1000h (4M), 1 year ago		0.0002		0.0165***
		(0.0019)		(0.0024)
C. Dengue 1000h (4M), 2 years ago		−0.0045**		0.0170***
		(0.0020)		(0.0022)
=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
N Clusters	8746	8746	8743	87436
$R2$	0.25	0.25	0.20	0.20

Ordinary least squares over a repeated cross section, with fixed effects at school level (see Equation 2). 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 3 for further details.
Clustered at municipality level SD in parenthesis. Significance: * 10%, ** 5%, *** 1%

Table 8: Avg Test Scores per school and dengue incidence

	Maths	Maths	Lang	Lang
		(2)		
S. Dengue 10000h (4M)	0.000		-0.005	
	(0.002)		(0.002)	
L.S. Dengue 10000h (4M)	0.002		-0.005**	
	(0.002)		(0.003)	
L2.S. Dengue 10000h (4M)	-0.000		-0.002	
	(0.002)		(0.002)	
C. Dengue 1000h (4M)		0.006**		0.002
		(0.002)		(0.004)
L.C. Dengue 1000h (4M)		0.002		0.010**
		(0.003)		(0.004)
L2.C. Dengue 1000h (4M)		-0.005		0.007
		(0.004)		(0.006)
Observations	30862	30862	30864	30864
Schools	8746	8746	8746	8746
Avg. periods per school	3.53	3.53	3.53	3.53
Municipalities	836	836	836	836
$\bar{Y}$	0.01	0.01	0.01	0.01

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, nomes and roads affected by natural disasters. See Table 3 for further details.
Clustered at municipality level SD in parenthesis. Significance: * 10%, ** 5%, *** 1%

Table 9: S. Dengue Impact by Prior Intensity

	LOG(Takers)	Maths	Lang
	(1)		
	-0.011** (0.005)		
	-0.006** (0.003)		
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). 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, nomes and roads affected by natural disasters. See Table 3 for further details.

Clustered at municipality level SD in parenthesis. Significance: * 10%, ** 5%, *** 1%

Table 10: 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 3 for further details.
Clustered at school level SD in parenthesis. Significance: * 10%, ** 5%, *** 1%

Table 11: 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 3 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%

Table 12: 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			
		(2)		
S. Dengue 10000h (4M)	-0.008		-0.011	
	(0.005)		(0.005)	
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 3 for further details.
Clustered at school level SD in parenthesis. Significance: * 10%, ** 5%, *** 1%

Table 13: 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%.

Table 14: Matching: Number of test takers per school and dengue incidence

	LOG (Number of students who presented the test)			
	(1)	(2)	(3)	(4)
	-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
$R2$	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 are matched on fix and pre-outbreak characteristics

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