Mosquito-Borne Disease and Newborn Health

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Abstract

While mosquito-borne diseases are currently most prevalent in mid-latitude countries, rising global temperatures are expanding their range. This paper investigates whether one such disease, dengue, harms newborns. Health at birth has been shown to impact economic outcomes throughout life. The empirical design exploits variation in lagged dengue rates in a town's closest neighbors and largest trading partner. The underlying source of exogeneity in this variation comes from two components: the uneven allocation, across municipalities, of funding to combat the mosquito vector and random weather patterns. Past disease rates in adjacent areas are used as instruments for the dengue rate in a newborn's municipality of residence. Using administrative individual data from birth records in Brazil, I find that a one standard deviation increase in the incidence of dengue in the third trimester of gestation reduces birth weight by 0.75 grams on average. The effect is more pronounced for baby girls and for children of more educated mothers. Moreover, there seems to exist a positive effect of dengue exposure during the early stages of gestation among children of mothers that do not receive scheduled prenatal care. The likely channel is that these women access pregnancy resources as a consequence of seeking medical treatment for dengue.

Keywords: Birth, Dengue, Municipality, Weather, Weight
JEL classification: J13, I14, I18, Q54

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1 Introduction

In the years to come warming temperatures will intensify the transmission of mosquito-borne diseases such as malaria, yellow fever and dengue, as latitudes currently too cool to sustain vectors become conducive to them (Patz et al., 1996; Khasnis and Nettleman, 2005). At the same time, we know very little about the effects of mosquito-borne diseases on fetal health. This paper studies the effects of *in utero* exposure to dengue on birth outcomes. Over 3.34 million cases of dengue were reported globally in 2016. The incidence of this disease, which is common in tropical areas, has grown dramatically in recent decades and about half of the world's population is now at risk (World Health Organization, 2019).

Public health deficits impose both short and long term economic cost on societies (See Bloom et al. 2019 for full discussion). More specifically, good health indicators at birth have been linked to positive long-term socioeconomic outcomes such as educational attainment, labor earnings, and physical health across the life-cycle (Behrman and Rosenzweig, 2004; Case and Paxson, 2008; Almond and Currie, 2011; Bharadwaj et al., 2018). Black et al. (2007) show that the positive effects of a healthy birth weight are especially strong for long term outcomes. Motivated by these findings, for the last decade economists have sought to understanding the impact on birth outcomes of maternal exposure to a variety of factors: violence and conflicts (Camacho, 2008; Mansour and Rees, 2012; Koppensteiner and Manacorda, 2016; Quintana-Domeque and Ródenas-Serrano, 2016), natural disasters (Simeonova, 2011; Torche, 2011; Currie and Rossin-Slater, 2013), weather shocks (Deschenes et al., 2009; Andalon et al., 2016), air pollution (Currie and Walker, 2011), water scarcity (Rocha and Soares, 2015), economic crisis (Bozzoli and Quintana-Domeque, 2014) and fasting (Almond and Mazumder, 2011). All these factors were found to have detrimental effects on newborn health as measured by weight, gestational length, or abnormal conditions at birth.

The expansion of mosquito-borne diseases due to climate change is likely to exacerbate preexisting inequalities in health and human capital. Determining the impact of these diseases on newborn health is useful because these are especially amenable to policy interventions. However, this literature is still in its nascent stages. A set of papers focuses on how early life exposure to malaria or influenza affects educational and income outcomes later in life (Almond, 2006; Barreca, 2010; Cutler et al., 2010; Venkataramani, 2012). Specifically focusing on fetal health, Kelly (2011) found that influenza had a negative effect on birth weight only for the offspring of mothers who smoked before pregnancy or were short. Schwandt (2018) found that maternal influenza leads to a doubling of prematurity. He also reported negative impacts on birth weight, but those cannot be disentangled from premature delivery. To the best of my knowledge no previous work has presented plausible estimates about the effect on birth outcomes of *in utero* exposure to mosquito-borne endemic disease such as dengue. This paper contributes greatly to the economic literature on the early origins of human capital development by documenting this causal relationship. It does so by utilizing a unique strategy that leverages the temporal and geographic aspects of disease proliferation. The approach is novel in testing and addressing endogeneity in the relationship between newborn health and maternal exposure to the disease that remains even after controlling for birth cohort and location fixed effects.

Dengue is a mosquito-borne tropical disease caused by a virus. Infection occurs when an infected female mosquito bites a human. Currently there is no effective commercial vaccine. While the disease is rarely fatal, sick individuals usually present muscular pain, fatigue, high fever and headache, with symptoms lasting from 3 to 10 days. There is no specific treatment, but patients are usually monitored and hydrated. Individuals do not acquire immunity after the initial infection. Two papers, Bhalotra et al. (2019) and Walsh (2016) looks at the short term impact of dengue outbreaks on labor market variables. The first uses data from Brazil, while the second uses data from Peru. Both find negative effects, with dengue epidemics lowering average hours worked and income. A paper by Barron et al. (2018) studies the relationship between dengue and educational outcomes in Colombia. They find that, mostly due to salience of the disease risks, a significant portion of students do not show up for an annual school examination when observed rate of severe dengue is high[1].

Measuring dengue infection's impact on birth outcomes is not straightforward because exposure to the disease is typically endogenous. Unobserved time variant factors like economic conditions and local policies can, at the same time, determine fetal health and affect dengue prevalence. Moreover, it is likely that the number of dengue cases is underreported, entailing measurement error. I overcome these issues with an instrumental variable research design, which exploits exogenous variation coming from past dengue infection in neighboring areas.

I use data from Brazil, a country where the disease is endemic and accounted for almost half of dengue cases worldwide in 2016. The Brazilian federal government helps finance mosquito-borne diseases prevention, which depends on effective vector control measures. I exploit the fact that the allocation of federal funding varies among localities. This, interacted with weather conditions, creates variability in the disease rate within regions. This variation, together with the fact that spread of disease is linked to patterns of human mobility (infected symptomatic or asymptomatic humans serve as a source of the virus for uninfected mosquitoes) makes past contagion rates in nearby areas an instrument for dengue cases in a given locality. The exclusion restriction is that lagged dengue contamination in adjacent municipalities, due the distribution of federal resources and weather patterns, only affects birth outcomes through its impact on local dengue cases. The validity of this restriction hinges on credibly partialling out seasonality and aggregate shocks.

The first stage equation is inspired by the work of Adda (2016), who modeled the proliferation of diseases as a function of past rates in a given locality and its neighboring areas. The unique approach of mapping out the advance of the disease across time periods and localities improves upon previous studies. Most existing papers with similar explanatory variables are based on longitudinal variation, or use weather conditions in the place of birth

[1] A small percentage of patients develops severe dengue, which is associated with bleeding, organ impairment and/or plasma leakage.

as instrument for disease contagion. However, the effect of local climate conditions on birth outcomes might not be exclusively through its potential effect on dengue exposure (See for instance Rosales-Rueda, 2018).

Using administrative individual data from birth records and monthly dengue notifications in Brazilian municipalities spanning from 2001 to 2015, I find that expected birth weight is reduced by 0.75 grams as the incidence of dengue during the third trimester of gestation increases by one standard deviation. The effect is more pronounced for baby girls (1.1 grams) and for children of more educated women (1.75 grams). Moreover, there seems to exist a positive effect of dengue exposure during early stages of the gestation among children of mothers that do not receive scheduled prenatal care. The likely channel is that, as a consequence of seeking medical treatment for dengue, these women access pregnancy resources that they would not have otherwise. The disease does not affect other outcomes at birth, except for increasing the probability of cesarean section delivery, which can be a potential indicator of complications during pregnancy.

The paper is organized as follows. The next section provides background information about dengue and other vector-borne diseases in Brazil. The third section details the data sources and provides some descriptive statistics. The empirical strategy is explained in section four and results are presented in section five. Section six discusses validity and robustness exercises results. Finally, the paper concludes with a discussion in section seven.

2 Mosquito-borne diseases in Brazil

2.1 Dengue

Dengue is a viral disease which has existed in Brazil since the late 19th century. The Aedes aegypti mosquito is the primary vector. The virus is transmitted to humans through the bites of infected female mosquitoes. Infected symptomatic or asymptomatic humans are the main carriers and multipliers of the virus, serving as a reservoir of the virus for uninfected mosquitoes. Patients who are already infected with the dengue virus can transmit the infection for 4 to 12 days after their first symptoms appear via Aedes mosquitoes (World Health Organization, 2019).

No licensed vaccine exists and antiviral drugs are not effective. Currently the best way to prevent contamination is to avoid the vector. However, the fact that the mosquito is well adapted to urban habitats and its eggs can remain dry for over a year before hatching contacted by water makes prevention harder. Nevertheless, public administrations can implement policies to prevent mosquito procreation through environmental management and modification.

The disease symptoms last from 3 to 10 days and include mild or severe headache, high fever, rash, and muscle and joint pain. A small proportion of infections progress to severe illness, resulting in shock and internal bleeding. There is no specific medication for dengue. Treatment includes proper hydration and careful monitoring. The patient should fully recover with rest, but does not acquire immunity.

In Brazil, the percentage of dengue cases in which the patient was reported to be pregnant was about 0.9% in 2016. In that year there were about 1.5 million dengue cases registered in the country, of those almost 14,000 were infected pregnant women. The disease can affect pregnancy by causing thrombocytopenia (platelet count of <50,000 cell/mm3) (Chitra and Panicker, 2011) and also pre-eclampsia (Pouliot et al., 2010). Vertical transmission to the fetus has also been documented in the medical literature (Tan et al., 2008; Ribeiro et al., 2013).

Figure 1A depicts the total number of cases reported in Brazil monthly from 2001 to 2016. The number of cases follows a periodic time series, where records are usually greater in the first semester of the year. It is worth noting the increase over time in the level of cases during dengue peaks.

2.2 Other diseases as potential confounders

Aedes aegypti, the dengue vector, can also transmit the Chikungunya, Zika fever, and Yellow fever viruses. All these diseases have symptoms similar to dengue. Here I discuss the efforts made to avoid attributing to dengue an effect that could belong to these other diseases. The results obtained for the robustness exercises discussed below are reported in Section 6.

Zika and Chikungunya

Zika and Chikungunya were found in Brazil only recently, after the 2014 Soccer World Cup. Both diseases have similar but milder symptoms than dengue. Notably, Zika virus contamination during pregnancy has been linked to microcephaly in babies, a birth defect in which the brain does not develop properly resulting in a smaller than normal head. Driven by the fear of Zika's consequences on the fetus, the socio-economic demographi composition of pregnant women could have changed due to the disease outbreak (e.g. women with means to delay pregancy mayhave chosen to do so). If Zika outbreaks are correlated to dengue cases, this would invalidate the strategy of comparing birth outcomes between periods with high and low dengue rates. In order to address this issue as a validity check, 2015 – the initial year of Zika outbreak – is dropped from my analysis.

Yellow Fever

In contrast to dengue and other diseases transmitted by the Aedes mosquito, there is an effective commercialized vaccine for yellow fever. The Brazilian government has historically provided free mass vaccination campaigns whenever outbreaks of the disease strike. As shown in Figure 2A, this strategy has successfully kept the disease level low. Given the constant low number of documented yellow fever cases, I will not treat it as a concerning confounder.

Malaria

Although malaria is transmitted by a different mosquito species, it is also a common arthropod-borne disease and patients present similar symptoms as dengue. In Brazil occurrence of the disease is mostly restricted to the northern extremes of the country in the Amazon region. Thus, to avoid attributing to dengue an effect that could belong to malaria, I add the malaria contamination rate in each municipality and month as a control variable.

3 Data

I use public administrative data about vital statistics from the Information System on Live Births (Sistema de informação de Nascidos Vivos - SINASC) collected by Brazilian Ministry of Health and available through Health Information Department (DATASUS). The data comes from birth certificates issued by the health institution where the birth occurred. This data carries information such as birth weight, Apgar score, pregnancy length, mother's education and municipality of residence.

Official monthly data on dengue prevalence comes from the Notifiable Diseases Information System (Sistema de Informacão de Agravos de Notificacão - SINAN), also available via the Health Information Department (DATASUS) (cases were confirmed by clinical and epidemiological evidence, and approximately 30% of them were also laboratory-confirmed). From the same source, I also collect data about hospitalization and official notifications regarding other types of diseases.

Monthly precipitation and temperature data is obtained from Willmott and Matsuura, at the University of Delaware. This data has spatial resolution of 0.5 degree by 0.5 degree latitude-longitude grids. In order to associate this information to municipalities I compute a weighted average of precipitation and temperature where the weights are inversely proportional to the distance between the municipality centroid and each four nodes of the grid where the the municipality centroid is located.

The data about constitutional transfers from federal to municipal sphere is collected from the Ministry of Treasury (Ministério da Fazenda). Other information at the municipality level such as annual per capita GDP, population and trade transaction networking were collected from the Brazilian Institute of Geography and Statistics (IBGE). I combine these different sources of information to form a rich monthly dataset of Brazilian births. The data period ranges from January, 2001 to December, 2015, a period in which almost 45 million births occurs.

3.1 Descriptive Statistics

Figure 3 displays the monthly average birth weight and dengue rate in Brazil. Despite showing how these two variables jointly move through months of the year, this plot helps to visualize seasonality in both series. As noted before, dengue cases are greater in the first semester and fall substantially in the second half of the year. Mean birth weight has a less clear pattern. It is mostly constant around 3182 grams from January through August, abruptly increases by about 10 grams in September, falls back to first semester levels in November, and decreases about 8 grams in December. In summary, there seems to exist a mild negative association between dengue rate and birth weight over the months of the year.

Table 1 displays summary statistics for all registered births in the period from 2001 to 2015 grouped into four panels: birth outcomes, newborn characteristics, mother characteristics, and pregnancy characteristics. It also provides a profile of variables measured at the municipality level. The mean birth weight is 3182 grams, and 3255 grams for full term birth, i.e., births after 37 weeks of pregnancy were completed. About 8% of babies are born below the threshold of 2500 grams, which qualifies as low weight according to the World Health Organization. Also about 8% of children are born premature (less than 37 weeks of gestation). In general, Brazil's numbers on birth outcomes are similar to the U.S. but below OECD averages.[2]

With respect to the explanatory variable of interest, it can be seen that, on average,

[2] In the United States percentage born with low birth weight is 8.3% (National Center for Health Statistics, 2019). On average across OECD countries about 6.5% of live births are recorded as low-weight births (OECD Family Database, 2019).

municipalities have 10 cases of dengue registered in a given month. In per capita terms, there are about 2.3 cases per 10,000 inhabitants monthly. Municipalities vary greatly in the disease incidence. Localities have average monthly temperature at 23°C, with 3.7°C standard deviation. It has been documented that Aedes aegypti females are able to sustainably fly between 15°C and 32°C (Reinhold et al., 2018). This range matches closely with the 95% confidence interval for monthly temperature in Brazilian municipalities, i.e. [15.6°C , 30.2°C], indicating that, in most places and seasons, temperatures are favorable to the vector. Precipitation varies quite a lot among municipalities-months, with mean at 117 millimeters and standard deviation of 100 millimeters. It has been registered that, during the Brazilian southeast raining season, the number of potential repository for the mosquito' eggs is six times greater than during dry season (Viana and Ignotti, 2013).

4 Empirical Strategy

The goal of this paper is to identify the causal effect of *in utero* exposure to dengue on birth outcomes. To do so, I use an analysis of intention-to-treat, where outcomes at birth are linked to dengue rate fluctuations during pregnancy. That is, a birth outcome of baby i born in month-year t is regressed on dengue rates during each trimester of the pregnancy in the mother's municipality of residence m. Consider the following equation,

$$y_{imt} = \sum_{j=1}^{3} \beta_j dengue_{jmt} + W_i\Omega + X_{mt}\theta + \gamma_{M\tau} + \gamma_{MT} + \gamma_t + \gamma_m + u_{imt} \tag{A}$$

in which y represents a birth outcome; *dengue* is the variable of interest and is measured by the proportion of the population in the mother's locality infected by new dengue cases in each trimester, j, of the pregnancy. W contains characteristics of the mother, pregnancy, and newborn. X contains time varying municipal characteristics, for example yearly per capita GDP and average weather conditions during each pregnancy trimester. $\gamma_{M\tau}$ represents a state-month fixed effect and accounts for monthly seasonality (τ denotes a calendar month).

γ_{MT} denotes state-year dummies and captures, for instance, annual state level policies that could impact health conditions. γ_t are time fixed effects and absorb national trends and overall conditions in each period. γ_m denotes municipality fixed effects and accounts for time invariant characteristics of each municipality. Finally, u represents unobserved time variant factors.

β_j are the parameters of interest and can be identified if, conditional on observable controls like weather conditions, seasonality, aggregate time trends and municipality fixed effects, birth outcomes in an area differ only because of differential exposure to dengue during pregnancy. This condition fails if time-varying individual or local characteristics affect both birth outcomes and dengue rates. For instance, individuals' selecting into pregnancy (or fertility postponement) in response to dengue rates would cause biased estimates if, due to the disease, women with better newborn health prospectus behave differently about fertility than other potential mothers. Given the endemic roots of dengue in Brazil, this type of selection is unlikely to happen[3]. Another concern is that there might be some relevant time-variant local characteristics unobservable to the econometrician. For example, local government quality is hard to measure and could directly affect mosquito-borne infections and health at birth. Another potential confounder is the strength of the local economy, which can directly affect diseases proliferation (Norris, 2004; Stoecker et al., 2016) and also indirectly affect newborn health. Additionally, panel data models also would not directly address measurement error. In municipalities where the supply of health centers has expanded over the years, diseases become more likely to be reported. At the same time, access to health facilities would also impact birth outcomes.

I overcome these concerns with an instrumental variable approach. Past dengue contamination in nearby areas and trading partners serve as instruments for dengue in municipality m in period t. Using gravity-style models which also account for climatic variation, Churakov et al. (2019) have shown that both human mobility and vector (i.e. mosquito) ecology

[3]Table 8 reports tests on whether the disease rate has any effect on birth records.

contribute to spatial patterns of dengue occurrence in Brazil. They find that seasonal patterns of human travel, within climatically conducive regions, are particularly strong predictors of dengue's path. Ultimately, their study provides evidence that dengue spreads from neighbor to neighbor over time.

In this case, the exclusion restriction is that past dengue rates in neighboring municipalities affect local birth outcomes only through their impact on dengue rate in the mother's home municipality. This assumption is plausible after conditioning on seasonality and time-variant regional attributes. However, this strategy will only work if there remains sufficient variation in dengue incidence among localities after discounting seasonality and aggregate shocks.

Of course, adjacent localities experience similar patterns of human travel and share similar climates which would on the whole imply similar rates of dengue. However, neighbors frequently differ in the implementation and effectiveness of policies for combating anti-mosquito borne diseases. Because the disease prevention depends crucially on avoiding mosquito reproduction, which in urban areas depends on citizens taking collective actions, government interventions on the local level are crucial to avoid the disease proliferation. Brazil's initial efforts to combat mosquito-borne illnesses were organized by the federal government, but by the beginning of 2000s this task was devolved to municipalities. Following devolution, the federal government provides financial resources to municipalities which then hire anti-endemic disease agents (Agentes Comunitário de Saúde and Agentes de Combate às Endemias, hereinafter denoted ACS). These workers visit homes for education and eradication purposes. They also inspect houses for places with standing water where mosquitoes could reproduce.

Figure 4A shows the geographic variation in dengue infection rates among Brazilian municipalities. Unsurprisingly, there exist a clear regional pattern. States in the southern area, where temperatures are milder, register lower rates, while those in the central-west region, where climate is often hot, present higher dengue rates. At the same time the picture shows that, despite the broad regional trends, municipal dengue rates vary widely within states, especially in the Southeast and Northeast regions (first and third most populous

Brazilian regions, respectively). This is evidence of the inter-municipal variation in dengue incidence required for identification.

The equation below describes the incidence rate of dengue and is inspired by the work of Adda (2016), which provides a model of diseases diffusion within and across regions:

$$dengue_{mt} = \alpha_1 dengue_{mt-1} + \sum_{n=1}^{N_m} \alpha_{2n} dengue_{nt-1} + X_{mt}\Phi + \delta_{M\tau} + \delta_{MT} + \delta_t + \delta_m + v_{mt} \quad \text{(B)}$$

This equation states the proportion of new dengue cases in municipality m in period t as a function of lagged cases in the locality, past cases in neighboring localities (n denotes a neighboring municipality or a trading partner), weather conditions (part of X_{mt}), seasonality ($\delta_{M\tau}$), regional aggregate conditions (δ_{MT}), and time and municipality fixed effects (δ_t and δ_m).

This equation differs from a first stage equation in a standard two stage least square (2SLS) system because it includes in its right-hand side the lagged dependent variable. If $\alpha_1 \neq 0$, Equation B exhibits state dependence, meaning that even after controlling for systematic time-constant municipality differences and seasonality, the dengue rate in the last period still helps to predict the current rate. Under this condition, the ability of differencing to remove unobserved heterogeneity and get consistent estimates of α's is jeopardized. A serious difficulty arises in using the fixed effects model because the demeaning process, which subtracts the municipality's mean value of the variables over time imparts correlation between regressor and error (Nickell, 1981). Another concern is measurement error that can cause endogeneity even after accounting for fixed effects. Hence, to overcome these issues I follow Adda's strategy and use a set of instruments to identify the parameters of Equation B.

Weather conditions are appropriate instruments for dengue rates because dengue transmission varies in response to temperature and rainfall (Lowe et al., 2011; de la Mata and Valencia-Amaya, 2014). The completion of the mosquito reproduction cycle requires its eggs to be in contact with water, which is usually facilitated by rainfall. At the same time, the virility and potency of the dengue virus oscillates with ambient temperature. It is important to highlight that climate conditions in the municipality could not be used directly as instrument for $dengue_{mt}$ in Equation A because climate conditions are not excluded variables[4]. That is, climate conditions during pregnancy have a direct effect on newborn health (See papers by Deschenes et al., 2009, Andalon et al., 2016). One obvious channel for this is through the propagation of other diseases or income shocks.

I also use as instruments for dengue rates in Equation B the interaction between weather variables and the annual monetary amount transferred by the federal government to finance the hiring of ACS. This resource is part of institutional transfers from the federal to municipal governments and is independent of current and transitory epidemic status. The average annual value (in U.S. dollars)[5] provided by the federal government to each municipality is mapped in Figure 4B. In general, municipalities in the North and Northeast regions of Brazil receive higher values per capita[6]. There seems to exist only a mild association between the dengue distribution across the country and the allocation of ACS funds.

After the funds are made available to municipalities, it becomes their responsibility to hire agents. Municipalities can also use their own funds to hire additional agents. However, a non-negligible number of municipalities hire fewer agents than sponsored by the federal government (possibly because they did not have the bureaucratic capacity or did not wish to expend resources to manage a team of agents) (Boas and Hidalgo, 2019). Given that the amount of final agents is likely endogenous to the municipality administration quality and current endemic status, I do not use information on the number of hired agents, but rather the number of potential ACS subsided by the federal government. In summary,

[4]Note that using weather conditions in neighbor municipalities as instruments for $dengue_{jmt}$ does not face this issue.

[5]Based on the wage value paid to an ACS worker, the average transfer affords about 8 workers.

[6]The criteria for ACS funds allocation among municipalities was not explicitly formalized until 2015. Besides being based on population size and historical epidemiological data, ACS funds are under transfers of the national public health system, which are used for alleviating regional inequalities such that more resources are directed to areas with worse health indicators (e.g. mortality rate or poverty rate).

heterogeneous distribution of this resource is likely to create variation in dengue rate among areas. Moreover, conditional on municipality fixed effects and yearly value of total transfers from the federal administration, transfer for ACS is likely exogenous to time variant health and epidemic condition in a given locality, which makes it a good candidate for instrument.

A key difference between this paper and previous work is that dengue's effect on birth outcomes is identified via exogenous variation in the past infection rates in adjacent areas generated from the interaction between funds for local vector-borne control policies and past weather conditions. This empirical strategy more closely resembles that of Aral and Nicolaides (2017). They leverage exogenous variation in weather patterns across geographies to identify social contagion in exercise behaviors across a social network.

4.1 The compliant population

The strategy identifies the average effect of dengue rate for individuals who are affected by the variation in dengue infection coming from neighbor municipalities or trading partners. That basically means that I am not able to capture the effect for areas where the disease is endemic or for individuals who are frequently exposure to it. Following the terminology from the treatment effect literature, the effects identified here are local average treatment effect (LATE), where the compliers – the population group that is affected by the instruments – are individuals exposed to the disease only because of outbreaks due to the collision of ACS funds and weather conditions in neighboring areas.

Table 2 shows the rate of infected individuals in a given municipality according to their education level and ethnicity separated by two mutually exclusive categories: during months when none of the neighboring localities registered outbreaks (more than 300 cases per 100K inhabitants) and when at least one neighbor has registered an outbreak and uncommon dengue rate (two standard deviations above the month average historical dengue rate in the municipality). It is worth mentioning that less educated individuals are more likely to acquire dengue. About 15% of the Brazilian population holds a college degree in 2016; however, from the overall number of dengue patients, only around 6% hold a college degree. By comparing columns one and two, one can see which types of individuals are mostly affected by outbreaks of the disease in adjacent areas. This information helps to characterize the subset of the population for which the causal effect can be identified. The composition of individuals infected in a given municipality changes during outbreaks of the disease in bordering areas. In particular, the rate of whites and college graduates among infected individuals is statistically higher. These are the type of mothers for who the contamination status is more likely to be switched by the instruments, and therefore are the group for which the identification strategy is able to retrieve the causal effect of *in utero* exposure to dengue.

4.2 Estimation details

The model is estimated in three steps which are schematically summarized below.

Variables:	weather conditions $\times$ ACS funds	$\Rightarrow$	dengue rate	$\Rightarrow$	dengue rate	dengue rate	$\Rightarrow$	birth outcome
Unit of analysis:	m and n's		m and n's		m	m		i and m
Time:	$t-2$		$t-1$		t	j		t
			(Equation B)			(Equation A)		

The first and second steps consist in estimating Equation B, which is estimated by fixed effects two stages least squared (FE-2SLS). Past dengue rate in the municipality and its neighbors are instrumented by past weather conditions and their interaction with ACS funds transferred by the federal government (this is the first step). Then, the endogenous variable, $dengue_{mt}$, is regressed on its predicted past value, the predicted past dengue rate in neighbor areas[7], observed characteristics and fixed effects (this is second step). The residuals of this

[7] Differently from Adda (2016) where disease rates in the neighbors are added in one variable, to estimate

regression are retained and used to calculate the control function. Finally in the third step, the equation of interest, i.e. Equation A, is estimated with the control function entering as extra variables.

I adopt the control function approach to estimate Equation A because it is an alternative to FE-2SLS given the dynamic structure in modeling dengue rate evolution in Equation B. Additionally, the control function approach offers a straightforward test for endogeneity of the variable of interest. The control function method requires that v_{mt} and u_{mt} are orthogonal to the instruments (past dengue rate in neighbor areas), but are related to each other. The key to this approach is that (under certain assumptions), conditional on v_{mt}, $dengue_{jmt}$ becomes appropriately exogenous (Wooldridge, 2015) in Equation A. The feasibility of the control function approach also depends on whether the practitioner is able to recover v_{mt} so it can be conditioned on when the parameters of interest, β's, are estimated (Petrin and Train, 2010). This is accomplished by estimating Equation B using an instrumental variable approach, which allows the computation of consistent estimates of α's and consequently of v_{mt}.

Birth weight can be thought of as a function of the gestation length and intrauterine growth (Kramer, 1987). It is appropriate to decompose the effect of dengue on outcomes at birth from the mechanic impact on these outcomes generated if the disease causes gestation to end earlier. An empirical challenge for estimating Equation A is dividing pregnancy into trimesters when the date of conception is not reported in the data. Retrospectively counting three trimesters from the time of birth without addressing the variation in the length of gestation across pregnancies would be incorrect. Although the exact week of conception is unknown, the gestational length (until birth) is reported in weeks range. Thus, I estimate the effect of dengue on birth outcomes of full term[8] pregnancy only. The disease's impact on gestational length is assessed separately.

Equation B I use separated explanatory variables about dengue rates in the three closest geographical neighbors to municipality m and the municipality largest business partner. Because partnership is measured in number of transactions, the largest business partner is usually the state capital city or a large city nearby.

[8]Full term pregnancy consists of at least 37 weeks of gestation completed.

5 Results

5.1 Dengue rate

Before discussing the estimates of key parameters, I test for the joint significance of the weather variables and ACS funds, which are used as instruments for past dengue rates in Equation B. The F statistic and its associated p-value are presented in Table 3. The set of instruments on the same municipality as the endogenous disease rate variable has p-value well below the 1% significance level (gray shaded cells in the table). This result demonstrates that the instruments explain the dengue rate in a given locality. On the other hand, with few exceptions, the set of instruments do not explain the dengue rates across localities. This fact is revealing in two ways. First, it helps to rule out underidentification of the endogenous variables. Second, it is a good indication that seasonality and regional aggregate trends are successfully being accounted for, such that the instruments only affect in dengue rate in its own locality.

Table 4 brings the estimates of Equation B's parameters before and after addressing endogeneity from possible measurement error and dynamic structure of the functional form. The first column shows the results of a naive linear regression. While the second column shows results controlling for seasonality, aggregate and regional trends and municipality time-invariant heterogeneity. In both cases the point estimates are similar. In particular $\hat{\alpha}_1$ is positive, smaller than one and statistically significant. Adjacent locations' effects on future dengue cases in a given municipality are also positive, but much smaller in magnitude.

The last column reports the estimates after instrumenting past dengue rates to account for potential time-variant confounders and measurement error. The coefficient of the lagged dependent variable increases and it is still statistically significant. With respect to lagged dengue rate in the main trading partner and neighbor areas, the estimates also increase after these variables are instrumented by weather conditions and ACS funds. For instance, one percentage point increase in the preceding month's dengue rate in the first neighbor is estimated to raise the current local infection rate by 0.094 percentage points respectively. Although the estimates are imprecise and the impact of past dengue rate in the municipality's largest business partner and closest neighbors are not statistically different from zero individually. Most importantly, a F-test points out past dengue rates in the largest trading partner and neighbor localities as jointly statistically relevant to explain present dengue rate in a given municipality. This test validates expectations about the diseases temporal and spacial transmission pattern, demonstrating that past dengue rate in nearby areas are determinants of current dengue rates in a certain municipality.

5.2 Birth weight

Table 5 presents the estimates when birth weight is the outcome variable. The first column displays estimates from a simple linear regression without controls or fixed effects. There is a positive correlation between the dengue rate during the first trimester of pregnancy in the mother's locale of residence and the newborn's weight at birth. Interestingly, there exist an association of similar magnitude in the third trimester of pregnancy, but it is negative. The second column shows the results when using the standard approach of controlling for location and cohort fixed effects. As expected the standard errors decrease and so did the point estimates. The positive association between dengue rate and birth weight in the first trimester is now of smaller magnitude, and the relationship is negative during the second and third trimesters of pregnancy, as one would expect.

However, as discussed previously, there may still exist time variant omitted factors not addressed by the fixed effects method that could cause endogeneity. The last column of Table 5 presents the estimates when a control function approach is applied in order to deal with time variant confounding variables. A simple F-test on whether the coefficients of the control function are jointly zero is rejected at 5% significance level, indicating the presence of endogeneity. Conditional on the instruments' validity, the values in the third column are the causal effect of exposure to dengue during each step of pregnancy on birth weight for babies affected by the disease due to contamination from neighbors localities. A one standard deviation rise in the dengue rate during the last trimester of pregnancy (33 dengue cases per 10,000 inhabitants in three months) leads to a reduction in birth weight of about 0.75 grams (-228.6×0.0033). The finding is consistent with other studies in the prenatal development literature, but slightly smaller in magnitude than in previous works that also investigate *in utero* exposure to a condition outside the control of the mother. For example, also using a sample from Brazil, Koppensteiner and Manacorda (2016) found that one standard deviation rise in the homicide rate during the first trimester of pregnancy leads to two grams reduction in birth weight. The effects for the first and second trimesters are not statistically significant to explain weight. Given that much of a fetus weight gain occurs during the last weeks of pregnancy, these results drive to the conclusion that maternal contamination by the mosquito-borne disease compromises fetal health through the growth channel.

In addition to the estimated parameters by gestation term, Table 5 also displays estimates for the trimesters before conception and after birth. These estimates are presented to validate the empirical strategy. In particular, for the post-birth period there should not exist any causal relationship between dengue rate and weight at birth. This is confirmed by the estimates in column three, my most preferred specification.

5.2.1 Heterogeneous Effects

In order to disentangle and better understand possible mechanisms behind the dengue effect, I examine heterogeneous treatment effects to understand some possible policy implications regarding the mitigation of mosquito-borne diseases spread.

The negative effects of *in utero* exposure to dengue are statistically higher for girls. One standard deviation increase in dengue rate during the third trimester of gestation decreases baby's weight by 1.1 grams for girls and by 0.6 grams for boys. Given that girls are on average lighter than boys (in my sample the difference is of 116 grams), the negative reduction in percentage of expected weight at birth is actually twice as large for female newborns. This finding is in line with results from previous work. For example, Rocha and Soares (2015) find that female newborns are more sensitive than males to the levels of rainfall during the gestation period. As Rocha and Soares mention, gender bias is not considered a significant problem in Brazil[9]. Thus it is difficulty to attribute the different result by sex to social factors. Given Brazilian institutional background, the difference is likely the result of biological causes.

I also examine results broken down by the baby's reported ethnicity. Brazil is considered a racially mixed country. As described in Table 1, almost half of newborns is identified as white. Within the non white group the composition is the following: 92% brown[10], 6% black, 1.3% native indigenous and 0.7% Asian. The effect is negative and statistically significant in all trimester of pregnancy for white newborns. For non white babies the effects are heterogeneous across gestation periods, being actually positive in the first and second trimesters and negative in the third trimester. The point estimates are also quite different between the two groups. My belief is that the difference in results is driven by the identification strategy, which captures the causal effect of dengue rates on babies of mothers that are more likely to get the disease due to variation in the instruments. As discussed before, the infection rate of whites is more responsive to outbreaks of the disease in the past month in adjacent areas. Another potential explanation is that, if race correlates to socioeconomic status such that non-white individuals are economically worse off and are less likely to receive prenatal care. Then, exposure to the dengue can cause expecting mothers to visit a doctor. Accessing formal health care during pregnancy could overcome the negative effect of dengue contamination.

In fact, that is confirmed when looking at the effect separately by number of prenatal visits. For mothers that do not record any visit, although not statistically significant, the

[9]Also, results shown in Table 8 confirm that dengue rate has no effect in the percentage of male birth

[10]Brown is the direct translation of *pardo*, which in the context of official surveys it may also refer to "racial mixture" (Loveman et al., 2011).

dengue effect is largely positive in the first two trimesters of gestation. That is probably because, after contracting the disease, these mothers receive health care and neonatal education that they would not receive otherwise, and prenatal care has been shown to have positive impact on birth outcomes (Joyce, 1999; Evans and Lien, 2005; Conway and Deb, 2005).

Finally the last panel of Table 6 shows the effect broken down by mother's schooling. The negative effect on birth weight of the dengue rate during the third trimester is smaller for babies of mothers with no college degree (less than 12 years of education). The effect more than doubles for newborns whose mother attended at least some college. A negative effect is also found during the first and second trimester of gestation for more educated mothers. Adding the effects in each gestational trimester, in total, one standard deviation increase in dengue rate during the gestation of mothers with some college reduces their newborn birth weight by about 3.4 grams. The larger impact for more educated mothers is probably due to the two factors discussed previously. First, these mothers are probably more likely to switch their status with respect to the disease due to outbreaks in nearby areas. That is, they are characterized as the compliers, for whom the causal effect can be estimated. Second, the vast majority of more educated mothers had at least one prenatal doctor appointment (Only 0.7% of mothers with some college degree reported zero prenatal visits. For mothers with 0 to 3 years of education, 7% do not have any prenatal visits during pregnancy). Thus, the estimates on birth weight for babies of more educated mother are not clustered with potential benefits generated from dengue contamination of seeing a doctor during pregnancy.

5.3 Other birth outcomes

Table 7 reports the results for additional birth outcomes using my most preferred specification, i.e., including the control function. Consistently with the continuous dependent variable, the dengue rate in the third trimester of pregnancy has a negative impact on birth weight by increasing the probability of low birth weight. However, this effect is not statistically significant. I do not find significant detrimental effects of *in utero* dengue exposure on Apgar scores, congenital anomaly and shorter gestation length. Apgar scores are known to be imprecise measures of health at birth and many studies fail to find effects on Apgar scores even when effects are found on birth weight (Koppensteiner and Manacorda, 2016). The fact that dengue does not affect congenital disability reassures that the estimates are not capturing a potential Zika virus effect, which has been linked to congenital disability. Interestingly, dengue infection does not seem to affect gestational length, strengthening the idea that the disease impacts fetal health through the growth channel.

There is statistically significant evidence that the dengue rate in the last trimester of pregnancy increases the probability of cesarean section delivery, which can be a potential indicator of complications during pregnancy. A one standard deviation increase in dengue rate during the last trimester of gestation raises the probability of C-section by 0.16 percentage points (0.477×0.0033). As in my sample about 48 out of 100 deliveries happen through C-sections, this effect means a 0.33% growth in the C-section rate. This number may not sound sizable, but in absolute terms, considering that Brazil has about three million births yearly, that translates to almost 5,000 extra deliveries by C-section.

5.4 Selection

Virus incidences may not only affect outcomes at birth but may also affect the conception and survival rate. For these topics, there are two dimensions of selection that could be interfering with my results. One source of concern is whether the dengue rate affects the composition of pregnant women, either due to biological factors or through the choices of potential parents. In order to verify or rule out the existence of this selection type I regress the number of births in a given municipality and month on dengue rate in the trimester before potential conception. I also test whether the disease incidence changes the educational composition of women giving birth. As presented in Table 8, both outcomes are unaffected by dengue rate in the pre-conception period.

At the same time the disease could cause some pregnancies to end with miscarriages. This dimension of selection would lead to underestimating the true effect of dengue on birth outcomes (e.g. assuming miscarried fetuses would experience worse outcomes at birth if they were to survive). To test this, I assess whether dengue incidence in the mother's municipality of residence in the current trimester affects spontaneous abortion rate[11] in the same period. Results are shown in the two last columns of the table. Without using the control function approach to account for possible endogeneity in dengue rate, I find that higher dengue rate is associated with lower rate of spontaneous abortion. However, the significance of this result disappears after addressing possible time-varying omitted factors. In conclusion, it does not seems that dengue increases the percentage of miscarriages in a given location.

6 Robustness and validity checks

I begin with a standard placebo test. Table 9 shows estimations of Equation B using different diseases as dependent variable. The idea is that, if valid exogenous variation is being used, then the incidence of other diseases in a given municipality should not be affected by past dengue rate in adjacent areas and trading partners after they are instrumented by weather conditions and federal funds for dengue combat. The F-statistic of a hypothesis test on whether past dengue rate in the three closest neighbors and the largest business partner are jointly statistical null in explaining current rates of leptospirosis, schistosomiasis and tuberculosis[12] in a given municipality are reported in the table for estimation using both FE and FE-2SLS. After controlling for a series of fixed effects, at 10% significance level or less, past dengue rates in neighboring and business partner localities are statistically significant to explain current rate of leptospirosis, schistosomiasis and tuberculosis in the FE

[11] I use data on hospitalizations for which the reported cause was spontaneous abortion. The miscarriage rate is created dividing the number of hospitalizations by a sum of this number, the number of birth and the number of fetal death in pregnancies advanced enough to not count as miscarriage.

[12] In the same way as dengue, cases of these diseases are required to be notified to the Brazilian Health Department. There are other diseases under the system of notification, but they were not included here because there were not enough cases or the data was not available by municipality.

estimates. However, these connections are erased when estimation is done using instruments for past dengue cases. These results confirm the endogeneity issues raised due to the dynamic structure and measurement error in Equation B. At the same time, these results are evidence in favor of the exclusion restriction. That is, after using exogenous variation from weather variables and funds for mosquito extermination, lagged dengue rates in neighbors and business partner do not affect diseases other than dengue in a given municipality.

Lastly, I performed three robustness checks about the impact of dengue rate on birth weight. First I control for malaria incidence. The second test excludes the year of 2015 to avoid periods with coexisting infection of Zika virus, which is known to cause permanent health damage on newborns. Finally, I investigate whether findings are sustained when a more conservative set of fixed effects (municipality-calendar month) is used. The coefficients of these exercises are reported in Table 10. In all specifications, the results hold in terms of both magnitude and significance level. These sensitivity tests bring confidence about the econometric approach adopted and that the dengue effect estimated in this paper is not due to other mosquito-borne diseases.

7 Conclusion

This work sheds light on an understudied and increasingly relevant relationship: mosquito-borne diseases and initial human capital stock. Health at birth is known to have important implications for human development and skills formation, which in turn affect economic outcomes in adulthood.

Besides documenting the relationship, this paper also presented an original approach to test and to address endogeneity that is left even after the application of well-used fixed effects techniques. The empirical design exploits variation in lagged dengue rates in a town's closest neighbors and largest trading partner. The underlying source of exogeneity in this variation comes from two components: the uneven allocation, across municipalities, of funding to combat the mosquito vector and random weather patterns.

My findings show that newborns are vulnerable to dengue, an endemic mosquito-borne disease. In particular *in utero* exposure to the disease jeopardizes fetal weight growth, especially for girls and babies of more educated mothers. Dengue does not seem to cause more serious consequences in term of miscarriage or shorting the gestational period. Additionally, there seems to exist a positive effect of dengue exposure during early stages of the gestation among children of mothers that do not receive scheduled prenatal care. The likely channel is that these women are exposure to pregnancy resources as a consequence of seeking medical treatment for dengue.

In 2015, Brazil's transfer per newborn in ACS funds was around 225 dollars. Ignoring macroeconomic effects, a back-of-the-envelop analysis using Black et al. (2007) estimates about birth weight returns[13] finds that, in 20 years of a newborn's labor supply, the aggregate return in terms of earnings growth due to dengue reduction and better health at birth overcomes the per birth ACS expenses. Thus, Brazil's investment in staff to combat the mosquito vector is justifiable from a cost-effectiveness perspective.

With climate change the occurrence of mosquito-borne diseases is likely to become a more recurrent phenomenon. Therefore, the results obtained here have even more important implications for health and environmental policies. Future research could invest in studying longer-term follow-up outcomes such as educational attainment or earnings later in life. This type of research could help to better understand whether and how the disease impacts human capital and income inequalities in the long run.

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[13] Using a sample of twins in Norway, Black et al. (2007) estimates that 10% percent increase in birth weight raises full-time earnings by about 1%

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Tables

Table 1: Descriptive statistics: birth and monthly municipality data 2001–2015.

	Mean	Std. Dev.
Birth outcomes		
Birth weight	3,182	550
Birth weight full term	3,255	461
Birth weight<2500 grams	0.08	0.28
Weeks gestation $\leq$ 36 weeks	0.08	0.28
Apgar 1 min	8.20	1.31
Apgar 5 min	9.27	1.00
Congenital anomaly	0.01	0.08
Newborn characteristics		
Male	0.51	0.50
White	0.43	0.50
Mother characteristics		
Single	0.62	0.49
Age	25.4	6.5
Years of edu. 0-3	0.10	0.31
Years of edu. 4-7	0.30	0.46
Years of edu. 8-11	0.45	0.50
Years of edu. $\geq$12	0.15	0.36
Birth and pregnancy characteristics		
Prenatal visits 0	0.03	0.16
Prenatal visits 1-6	0.40	0.49
Prenatal visits $\geq$ 7	0.57	0.49
Multiple births	0.02	0.14
C-section	0.48	0.50
Births	44,330,805	
Municipality characteristics		
Monthly Dengue cases	10.1	208.7
Monthly dengue rate	2.3	14.1
Annual ACS funds ($)	31,175.2	22,215.6
Temperature	22.9	3.7
Precipitation	117.1	100.1
Population	34,278	203,095
Municipalities	5,565	

Table 2: Heterogeneity in dengue infected individuals.

	Outbreak and $> 2SD$ in at least one neighbor in the past period		
	No	Yes	Diff.
Patient's education level			
Not reported	0.342	0.353	0.011***
	(0.382)	(0.349)	(0.003)
Not applicable	0.091	0.063	-0.029***
	(0.214)	(0.134)	(0.002)
Secondary or less	0.268	0.262	-0.006**
	(0.335)	(0.266)	(0.002)
High school	0.239	0.258	0.018***
	(0.317)	(0.26)	(0.002)
College or more	0.059	0.065	0.005***
	(0.175)	(0.14)	(0.001)
Patient's ethnicity			
Not reported	0.152	0.156	0.004*
	(0.293)	(0.271)	(0.002)
Asian or Native	0.014	0.014	-0.001
	(0.087)	(0.064)	(0.001)
Black	0.050	0.049	-0.001
	(0.155)	(0.116)	(0.001)
Mixed	0.419	0.371	-0.049***
	(0.395)	(0.333)	(0.003)
White	0.364	0.411	0.047***
	(0.388)	(0.342)	(0.003)
# of cases in the municipality	5,263,447	2,193,339	
Observations	170,332	20,141	

Note: * p<0.1, ** p<0.05 and *** p<0.01.

Table 3: F-test for instruments of the endogenous variables of Equation B.

	Dependent variable				
	$dengue_{mt-1}$	$dengue_{nbt-1}$	$dengue_{n1t-1}$	$dengue_{n2t-1}$	$dengue_{n3t-1}$
Weather variables$_{mt-2}$	9.28	0.86	3.40	1.24	2.29
$\times$ ACS fund$_{mT}$	(0.000)	(0.459)	(0.017)	(0.293)	(0.076)
Weather variables$_{nbt-2}$	1.72	177.36	3.55	1.54	1.08
$\times$ ACS fund$_{nbT}$	(0.161)	(0.000)	(0.014)	(0.203)	(0.356)
Weather variables$_{n1t-2}$	4.62	2.32	10.02	2.30	0.47
$\times$ ACS fund$_{n1T}$	(0.003)	(0.074)	(0.000)	(0.075)	(0.706)
Weather variables$_{n2t-2}$	0.86	0.20	1.84	12.08	0.15
$\times$ ACS fund$_{n2T}$	(0.463)	(0.893)	(0.137)	(0.000)	(0.929)
Weather variables$_{n3t-2}$	2.12	3.02	0.80	0.40	8.87
$\times$ ACS fund$_{n3T}$	(0.096)	(0.029)	0.491)	(0.750)	(0.000)
R^2-adjusted	0.125	0.189	0.121	0.132	0.129
Observations	956,970	956,970	956,792	956,080	956,436

Note: Each column reports separated regression. Each cell provides the F statistic and p-value about the jointly statistical significance of a set of instrumental variables. A set of instrument consists in the following variables: temperature, precipitation, temperature×precipitation, temperature×ACS funds, precipitation× ACS funds and temperature×precipitation×ACS funds. The regressions also include the same controls and fixed effects as those in Table 4.

Table 4: Estimates of Equation B parameters. Dependent variable: $dengue_{mt}$

	OLS	FE	FE-2SLS
$dengue_{mt-1}$	0.587***	0.564***	0.809***
	(0.010)	(0.011)	(0.067)
$dengue_{nbt-1}$	0.031***	0.023***	0.037
	(0.004)	(0.004)	(0.035)
$dengue_{n1t-1}$	0.037***	0.027***	0.094
	(0.004)	(0.004)	(0.061)
$dengue_{n2t-1}$	0.043***	0.031***	0.067
	(0.005)	(0.004)	(0.081)
$dengue_{n3t-1}$	0.039***	0.028***	0.138*
	(0.004)	(0.004)	(0.077)
Coeffs of dengue in nb, $n1$, $n2$ and $n3 = 0$			
F-stat(4, 5368)	85.76	49.10	5.13
p-value	(0.000)	(0.000)	(0.000)
Control variables	No	Yes	Yes
State-Month FE	No	Yes	Yes
State-Year FE	No	Yes	Yes
Month-Year FE	No	Yes	Yes
Municipality FE	No	Yes	Yes
R^2	0.392	0.422	0.239
Observations	961,409	960,732	955,368

Note: * p<0.1, ** p<0.05 and *** p<0.01. Robust standard deviation clustered by municipality in parenthesis. Control variables at the municipality level are: annual per capita GDP, annual total transfers and ACS transfers from the federal government, monthly number of hospitalization per capita, average temperature and precipitation and their interaction in the current and past month. I also include average temperature and precipitation and their interaction in the past month in each neighbor and trading partner.

Table 5: Estimates of Equation A parameters. Dependent variable: $birth\ weight_{imt}$

	(I)	(II)	(III)
Trimester			
3	-278.5***	-146.9***	-228.6**
	(88.9)	(38.6)	(89.6)
2	111.4	-106.1**	73.2
	(112.2)	(42.9)	(123.0)
1	252.1***	66.6	-22.9
	(97.2)	(41.1)	(96.3)
-1 (pre-conception)	88.9	-79.8**	-77.3
	(137.5)	(39.7)	(61.9)
4 (post-birth)	-38.8	-86.7**	-61.6*
	(109.4)	(34.3)	(37.4)
CF p-value	-	-	0.017
Control variables	No	Yes	Yes
State-Month FE	No	Yes	Yes
State-Year FE	No	Yes	Yes
Month-Year FE	No	Yes	Yes
Municipality FE	No	Yes	Yes
R^2	0.000	0.061	0.061
Observations	37,380,088	36,252,406	34,916,885

Note: * p<0.1, ** p<0.05 and *** p<0.01. Robust standard deviation clustered by municipality in parenthesis. Control variables at the individual level are: male, white, multiple pregnancy dummies, dummies for numbers of prenatal visits, dummies for mother's schooling, mother's age, mother's age squared. Control variables at the municipality level are: annual per capita GDP, annual total transfers and ACS transfers from the federal government, monthly number of hospitalization per capita, and average temperature and precipitation and their interaction in each trimester of pregnancy.

Table 6: Dengue's heterogeneous effects in Equation A. Dependent variable: *birth weight*$_{imt}$

	Trimester 1	2	3
Girl	-117.9	103.9	-332.6***
	(87.7)	(122.0)	(90.6)
Boy	-71.2	122.2	-184.8*
	(89.5)	(120.3)	(97.2)
Non white	90.9	249.5**	-132.1
	(100.5)	(122.4)	(99.0)
White	-363.7***	-47.6	-414.3***
	(91.1)	(124.8)	(104.1)
Prenatal visits 0	585.5	462.2	-262.9
	(413.3)	(283.5)	(409.1)
Prenatal visits 1-6	-40.8	140.7	-269.1**
	(114.7)	(131.9)	(108.2)
Prenatal visits >=7	-131.1	97.8	-253.5**
	(92.5)	(121.3)	(104.8)
Years of ed. 0-3	-71.0	125.4	-113.3
	(164.0)	(158.7)	(168.5)
Years of ed. 4-7	92.6	202.5	-206.9*
	(127.9)	(126.9)	(112.7)
Years of ed. 8-11	-61.4	155.0	-197.5**
	(91.4)	(116.6)	(98.8)
Years of ed. >=12	-427.2***	-79.6	-532.7***
	(119.1)	(160.2)	(129.1)

Note: * p<0.1, ** p<0.05 and *** p<0.01. Robust standard deviation clustered by municipality in parenthesis. The regressions have the same explanatory variables and fixed effects as the specifications in the last column of Table 5.

Table 7: Estimates of Equation A parameters. Several birth outcomes as dependent variable.

	Weight <2500g	Apgar 1 > 8	Apgar 5 > 8	Congenital Anomaly	C-section	Gestation <37 weeks
Trimester						
3	0.043	-0.140	0.038	-0.036	0.477***	-0.137
	(0.035)	(0.273)	(0.095)	(0.025)	(0.173)	(0.084)
2	-0.052	-0.079	-0.128	0.002	0.226	-0.076
	(0.052)	(0.213)	(0.082)	(0.019)	(0.153)	(0.086)
1	0.035	-0.324*	0.097	-0.029	0.047	0.038
	(0.035)	(0.169)	(0.067)	(0.018)	(0.114)	(0.060)
-1 (pre-conception)	0.032*	-0.119	-0.068	-0.009	-0.124	-0.056
	(0.019)	(0.168)	(0.068)	(0.012)	(0.083)	(0.062)
4 (post-birth)	0.007	-0.050	-0.005	-0.012	0.127	-0.007
	(0.013)	(0.122)	(0.036)	(0.009)	(0.080)	(0.035)
CF p-value	0.404	0.261	0.181	0.416	0.119	0.379
R^2	0.037	0.140	0.060	0.002	0.189	0.070
Observations	34,916,885	33,424,002	33,343,747	33,492,191	34,974,479	38,128,926

Note: * p<0.1, ** p<0.05 and *** p<0.01. Robust standard deviation clustered by municipality in parenthesis. The regressions have the same explanatory variables and fixed effects as the specifications in the last column of Table 5.

Table 8: Selection variable regressions - Observations at the municipality level.

Dengue rate in trimester	# of births	birth mother college/births	% of boys	miscarriage rate	miscarriage rate
3 (or current)			-0.023	-0.156***	-0.077
			(0.028)	(0.049)	(0.076)
2			0.000		
			(0.033)		
1			0.040		
			(0.031)		
-1 (pre-conception)	14,051.833	0.027	0.009		
	(9,798.799)	(0.054)	(0.033)		
4 (post-birth)			-0.021		
			(0.028)		
CF p-value	-	-	-	-	0.146
Observations	1,007,264	922,947	922,947	970,289	937,901

Note: * p<0.1, ** p<0.05 and *** p<0.01. Robust standard deviation clustered by municipality in parenthesis. The regressions have the same explanatory variables and fixed effects as the specifications in the second column of Table 5, expect for variables at the individual level.

Table 9: The significance of past dengue rates in adjacent areas on other diseases.

	# of cases		FE	2SLS-FE
Leptospirosis	53,928	F stat	2.08	0.12
		p-value	(0.080)	(0.975)
Schistosomiasis	372,027	F stat	3.25	0.19
		p-value	(0.011)	(0.945)
Tuberculosis	1,206,102	F stat	1.93	1.57
		p-value	(0.102)	(0.179)
Observations			960,732	955,368

Note: * p<0.1, ** p<0.05 and *** p<0.01. Robust standard deviation clustered by municipality in parenthesis. The regressions have the same explanatory variables and fixed effects as the specifications in the second and third columns of Table 4.

Table 10: Validity test results. Dependent variable: $birth\ weight_{imt}$.

	Malaria as control		Dropping 2015		Conservative FE	
Trimester						
3	-151.4***	-265.7***	-174.4***	-200.6*	-135.7***	-237.5**
	(43.4)	(76.3)	(40.2)	(114.2)	(40.7)	(92.9)
2	-108.3**	-45.9	-127.6***	17.0	-127.9***	61.6
	-47.7	(78.7)	(49.3)	(156.8)	(44.2)	(127.5)
1	61.4	-35.7	41.9	-46.4	62.2	-12.2
	(43.3)	(83.5)	(55.2)	(116.6)	(41.8)	(99.0)
CF p-value	-	0.03	-	0.025	-	0.019
R^2	0.058	0.059	0.100	0.100	0.062	0.063
Observations	27,702,497	26,608,896	33,687,574	32,447,358	36,252,406	34,916,885

Note: * p<0.1, ** p<0.05 and *** p<0.01. Robust standard deviation clustered by municipality in parenthesis. Expect for the "Conservative FE" columns, the regressions have the same explanatory variables and fixed effects as the specifications in the second and third columns of Table 5.

Figures

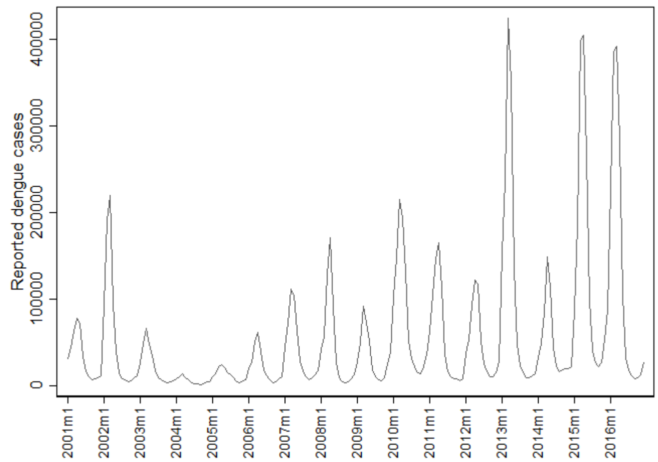
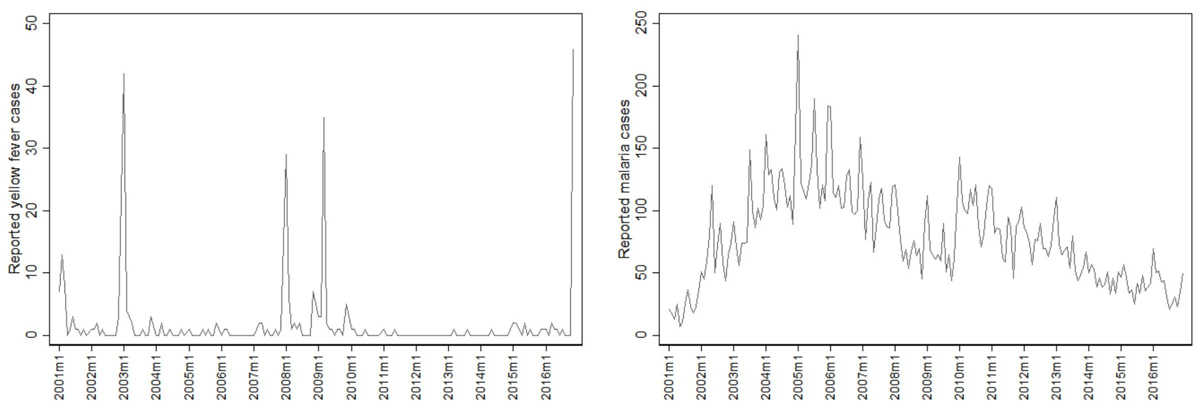


Figure 1: Times series of dengue profile in Brazil.



A: Yellow fever cases reported in Brazil.

B: Malaria cases reported in Brazil.

Figure 2: Yellow fever and malaria times series.

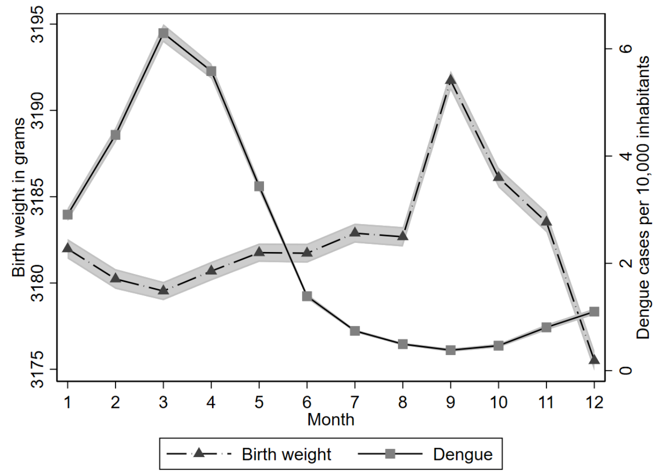
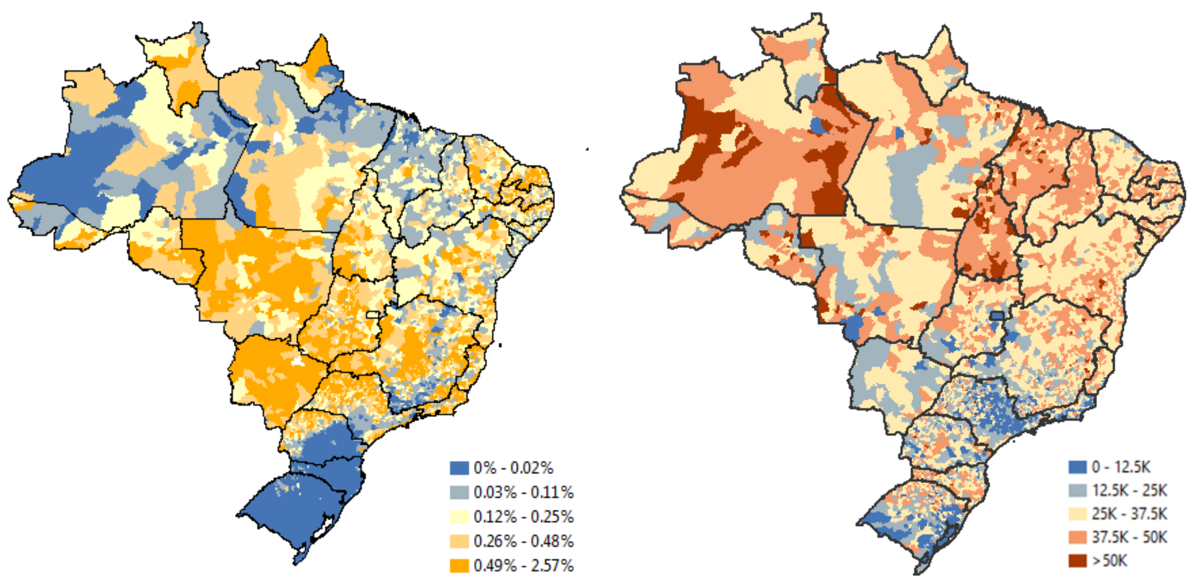


Figure 3: Monthly average dengue cases and birth weight.



A: Average from 2001 to 2015 of yearly infection rate (as % of the population).

B: Average from 2001 to 2015 of annual per capita ACS funds transferred in thousand dollars.

Figure 4: Municipalities distribution of dengue cases and health agents.