Mosquito-Borne Disease and Newborn Health

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Abstract

While mosquito-borne diseases are today most prevalent in mid-latitude countries, rising global temperatures are expanding their range. This paper investigates whether one such disease, dengue, harms newborns. Poor health at birth has been shown to adversely impact economic outcomes throughout life. The empirical design exploits temporal and spatial variations in dengue incidence. Since a mosquito must acquire dengue virus from an infected human host before it becomes a disease vector, human mobility plays a key role in spreading dengue among localities. Exploiting these epidemiologic patterns, I instrument the dengue rate to which a newborn was exposed *in utero* with exogenous factors that determine dengue incidence in municipalities that have tight social connections to the newborn's municipality of residence. Using a large dataset of Brazilian birth records, I find that a higher dengue rate during the third trimester of gestation has a detrimental effect on birth weight. The effect is more pronounced for baby girls. *In utero* exposure to dengue also increases the probability of cesarean delivery and can lead to more serious consequences as it increases fetal and maternal mortality rates.

Keywords: Birth, Dengue, Mortality, Virus, Weather, Weight
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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 the 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. 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). Over 3.34 million cases of dengue were reported globally in 2016 alone.

Sickness and poor health impose both short and long term collective costs on society (See Bloom et al., 2019 for full discussion). According to the fetal origins hypothesis (Barker, 1990), certain chronic health conditions can be traced back to fetal development. Thus, individuals' health at any point in time depends not only on investments they choose to make throughout their lifetime, but also on their health stock at birth. Moreover, strong health indicators at birth have been linked to positive long-term socioeconomic outcomes such as physical health in adulthood, educational achievements, and labor earnings (Behrman and Rosenzweig, 2004; Case and Paxson, 2008; Almond and Currie, 2011; Bharadwaj et al., 2018). Black et al. (2007) show that a healthy birth weight has an especially strong positive effect on long term outcomes. Motivated by these findings, for the last decade economists have sought to understand the impact on birth outcomes of maternal exposure to a variety of external 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 of these factors were found to have detrimental effects on newborn health as measured by weight, gestational length, or the presence of abnormal conditions at birth.

The expansion of mosquito-borne diseases due to climate change is likely to exacerbate pre-existing inequalities in health and human capital. At the same time, these diseases are especially amenable to policy interventions. Therefore, determining the impact of mosquito-borne viral diseases on newborn health is a useful endeavor. However, the economic literature on this subject, which might inform policymakers, is still in its nascent stages. A set of papers focuses on how early life exposure to malaria or influenza affects income and education outcomes later in life (Almond, 2006; Barreca, 2010; Bleakley, 2010; Cutler et al., 2010; Venkataramani, 2012). Examining infant mortality, Kudamatsu et al. (2012) find that children born in areas with epidemic malaria who *in utero* experience malarious conditions worse than the site-specific seasonal means face a higher risk of death. Two papers, Bhalotra et al. (2019) and Walsh (2019), examine 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 severe dengue[1] 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 the observed rate of severe dengue is high.

Specifically focusing on fetal health, Kelly (2011) found that influenza had a negative effect on birth weight for the offspring of mothers who smoked before pregnancy. Schwandt (2018) found that maternal influenza leads to a doubling of prematurity. The author also reported negative impacts on birth weight, but those cannot be disentangled from premature delivery. In the medical literature, a large body of work has documented negative aspects of the relationship between maternal dengue and pregnancy outcomes such as higher incidence of cesarean delivery, shorter terms and lower birth weight (See Pouliot et al., 2010 and Paixão et al., 2016 for a literature review). However, many of these studies were conducted on small

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

samples or are simply comparative case studies where endogeneity in dengue exposure is not addressed.

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 and correlates to the local supply of healthcare, entailing measurement error. To address endogeneity, Karimova (2019) uses data from Puerto Rico and an identification strategy relying on rainfall as an instrument for dengue. The author finds evidence that prenatal dengue exposure decreases birth rates. A concern with this type of study is that rainfall may not be a valid instrument. As documented in the literature, rainfall is not an excluded variable since it can affect birth outcomes through channels other than its direct effect on dengue incidence (See for instance Rosales-Rueda, 2018).

This work takes advantage of richer, fine-grained data to apply a robust identification strategy. Specifically, I employ an instrumental variable research design that rests on two main components. To begin, the Brazilian federal government helps finance mosquito-borne disease prevention. In practice this takes the form of vector control measures. I exploit the fact that the allocation of federal funding is not uniform among localities. That is, some municipalities receive and spend more funding than others. This spending, interacted with weather conditions, creates variability in the disease rate *within* localities. Of course, while these drivers affect the vector life cycle in a given locality, they may violate the exclusion restriction by having a direct impact on fetal health or by being correlated with other unobservables which affect fetal health within that locality.

Therefore, I combine this local variation in disease rates with the fact that the spread of viral diseases *across* localities is linked to patterns of human mobility (Adda, 2016). Infection occurs when a dengue positive female mosquito bites a healthy human. Once infected, humans become the main reservoirs and carriers of the virus. As symptomatic or asymptomatic human hosts travel, they serve as a source of the virus for uninfected mosquitoes and thus spread outbreaks to new areas. This makes the past infection rates in nearby areas determinants of dengue cases in other localities. In practice, nearness can be defined on a variety of dimensions other than distance, for example commercial linkages. In unison, these facts form a valid and relevant set of instruments for the dengue rate in a newborn's municipality of residence: past weather conditions and allocation of funds for mosquito combat in socially connected localities. The exclusion restriction is that past dengue rates in socially connected municipalities, due the distribution of federal resources and weather patterns, only affect birth outcomes through their impact on local dengue cases. The validity of this restriction hinges on credibly partialling out seasonality, aggregate regional shocks and weather conditions in the newborn's municipality.

To the best of my knowledge no other previously published work has presented causal estimates of the effect of *in utero* exposure to an endemic mosquito-borne disease such as dengue (or malaria) on birth outcomes. This paper contributes 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 both the temporal and geographic aspects of disease proliferation. This is a novel approach in testing for and addressing endogeneity in the relationship between newborn health and maternal exposure to the disease that would otherwise remain even after controlling for birth cohort and location fixed effects. Thus, this paper also offers a methodological contribution.

I apply this method to data from Brazil, a country where the disease is endemic and accounted for almost half of the dengue cases reported worldwide in 2016. Using the universe of birth records and monthly dengue reports from all Brazilian municipalities from 2001 to 2015, I find that the average birth weight for babies whose municipalities experienced a one standard deviation increase during their mother's third trimester of gestation decreases by 0.85 grams. This effect is more pronounced for baby girls (1.07 grams). The disease also increases the probability of cesarean delivery, which can be a potential indicator of complications during pregnancy. *In utero* exposure to dengue can also lead to more serious consequences, increasing the fetal mortality rate by 1% and the probability of maternal death in 3%.

The paper is organized as follows. The next section provides background information about dengue and other mosquito-borne diseases in Brazil. Section 3 details the data sources and provides some descriptive statistics. The empirical strategy is explained in section 4 and results are presented in section 5. Finally, the paper concludes with a discussion in section 6.

2 Mosquito-borne diseases in Brazil

2.1 Dengue

Dengue is a disease, caused by the dengue virus (DENV), which has been present in Brazil since the late 19th century. There are four distinct DENV serotypes, meaning that it is possible for humans to be infected up to four times. Recovery from an infection of one serotype conveys lifelong immunity against that particular serotype. Infected symptomatic or asymptomatic humans are the main carriers and multipliers of the virus, serving as a reservoir. Dengue's primary vector is the Aedes aegypti mosquito. Female mosquitoes become carriers when they bite an infected human, and transmit the virus to new hosts when they bite previously uninfected humans. Infected patients can transmit the infection, via the mosquitoes, for four to 12 days after their first symptoms appear (World Health Organization, 2019). Symptoms last from three 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[2]. There is no specific medication for dengue. Treatment includes proper hydration and careful monitoring. Most

[2]In 2016 1% of the dengue cases in Brazil were registered as non-classical or involving more serious medical complications.

patients make a full recovery with rest.

No licensed vaccine exists and antiviral drugs are not effective. As such, the best way to prevent dengue virus transmission is to effectively control the mosquito vector. However, the Aedes aegypti is difficult to combat because it is well adapted to urban habitats and its eggs remain viable for over a year until contacting water and hatching. Nevertheless, public administrations can implement policies to prevent mosquito procreation through environmental management and modification. For example, community-based programs encouraging proper solid waste disposal and improved water storage practices, such as covering containers to prevent access by egg-laying female mosquitoes, can be effective.

Despite such efforts, Brazil reported approximately 900 deaths from dengue infections in 2016. In the same year, there were almost 14,000 recorded cases of pregnant women contracting dengue. This is about 0.9% of the approximately 1.5 million total dengue cases registered in 2016. Medically, dengue is known to 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 1 depicts the total number of cases reported monthly in Brazil from 2001 to 2016. The number of cases follows a periodic time series, where records are usually greater in the first half of the year. It is worth noting the peaks of dengue outbreaks have been increasing over time. Whereas Figure 1 shows temporal variation of the disease, Figure 2(a) displays geographic variation in dengue infection rates among Brazilian municipalities. Unsurprisingly, there exists a clear regional pattern. States in the southern area, where temperatures are milder, register lower rates while those in the west-central region, where the climate is warmer, 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 (the first and third most populous Brazilian regions, respectively).

2.2 Public health program for dengue combat

Dengue prevention hinges on controlling the mosquito vector. In Latin America, the most successful interventions attack live mosquitoes with insecticide while simultaneously taking actions to reduce mosquito reproduction (Gubler, 2005). In Brazil, initial efforts to combat mosquito-borne illnesses were organized by the federal government, but this task was delegated to the municipalities in the early 2000s . The federal government, through the Ministry of Health (Ministério da Saúde), provides financial resources to municipalities which then have the responsibility for and autonomy in implementing mosquito-borne disease prevention programs. Technically, these funds are institutional grants from the federal to municipal governments under the National Public Health System (Sistema Único de Saúde, SUS), which was created to alleviate regional inequalities. For this reason, SUS devotes more resources to areas with worse health and economic indicators, such as child mortality and the illiteracy rate (Mendes et al., 2011).

Brazil's mosquito-borne disease control efforts were incorporated into SUS in an attempt to improve the coverage, quality, and regularity of fieldwork for combating the vector (Pessoa et al., 2016). In 2002, the Ministry of Health defined national guidelines for the prevention and control of dengue. These guidelines called for a set of complementary actions to be implemented by community health agents (Agentes Comunitário de Saúde hereafter denoted ACS) and anti-endemic disease agents (Agentes de Combate às Endemias, hereafter denoted ACE). These professionals visit households to provide education and to inspect for mosquito breeding sites. ACSs work closely with communities on diseases prevention and health promotion. They also serve as “eyes”, reporting potential sources of water accumulation, such as abandoned houses or wasteland, to ACEs. The ACEs are responsible for developing large-scale mosquito control plans and actively combating larvae and adult mosquitoes, for example by applying larvicides (Ministério da Saúde, 2009). The work of ACSs and ACEs must strictly adhere to SUS guidelines and agents are hired through competitive public selection. There are no temporary or outsourced agents, except during extreme outbreaks.

Annual data on funding for ACSs in each municipality is available from 2001 to 2015. The ACS program falls under the Variable Basic Attention Floor (Piso de Atenção Básica Variável) funding mechanism, which ties transfers to the implementation of program requirements. On the other hand, explicit information on funding for ACEs is not available prior to 2015. In that year, the Ministry of Health formally defined the criteria by which ACE funding is distributed to municipalities. While pre-2015 allocations are known to have been made according to municipal population sizes and epidemiological histories, the actual amount given to each municipality is unknown or entangled with the financing of other health programs.[3] Moreover, after the funds are made available to municipalities, it becomes their responsibility to hire ACEs. However, a non-negligible number of municipalities hire fewer agents than the federal government transfer would allow for (possibly because they did not have the bureaucratic capacity or did not wish to spend resources to manage a team of agents) (Boas and Hidalgo, 2019). Due to unclear information about the amounts provided for and spent on finance ACEs before 2015, and in order to consistently track anti-dengue resources throughout the period of observation, this paper only uses measures of transfers to the ACS program.

The average annual value, in U.S. dollars per capita, transferred from the federal government to each municipality over the years is mapped in Figure 2(b). In general, municipalities in the north and northeast regions of Brazil receive higher values per capita. While municipalities in the southeast and south of the country receive less funds. Comparing this map with Figure 2(a), there seems to exist a mild positive association between the dengue distribution across the country and the allocation of ACS funds.

[3] During these years, municipalities could opt to pay for ACEs with resources from the Fixed Health Surveillance Floor (Piso Fixo Vigilância em Saúde, PFVS) funding mechanism. The PFVS transfers a per capita amount from the federal to state governments, with some adjustments to account for local conditions, which then finance municipal agencies that monitor and manage health and disease information systems. In many, but not all, municipalities about 70% of the PFVS was committed to hiring ACEs (Confederação Nacional de Municípios, Recursos financeiros no Sistema Único de Saúde, Brasília, 2014).

2.3 Other diseases as potential confounders

Aedes aegypti, the dengue vector, can also transmit the zika fever and yellow fever viruses. Malaria is transmitted by a different mosquito species, but it is also a common mosquito-borne disease and patients present similar symptoms as dengue. In this section I discuss the efforts made to avoid attributing to dengue an effect that could belong to these other diseases.

Malaria

Although malaria's main mosquito vector, Anopheles darlingi, is present in about 80% of the country, the presence of malaria in Brazil is currently almost exclusively restricted to the region of the Amazon Basin which accounts for 99.8% of cases (Oliveira-Ferreira et al., 2010). This region lies in the northern extreme of the country as displayed in Figure 3(a) and is home to only approximately 13% of the Brazilian population. Outside of the Amazon Basin the vast majority of the few recorded malaria cases are imported, meaning that the disease was acquired outside the region where the individuals live or where the diagnosis was made. Imported malaria comprised 89% of the cases found outside the area of active transmission in 2013 (Pina-Costa et al., 2014). The fact that malaria infections are restricted to the Amazon Basin makes it possible to avoid overlapping the effects of malaria and dengue. To ensure that my findings are not driven by areas where both diseases are endemic, I also report results using a reduced sample without the municipalities in Brazil's northern region.

Yellow Fever

In contrast to dengue and other diseases transmitted by the Aedes mosquito, there is an effective commercial vaccine for yellow fever. The Brazilian government has historically launched free mass vaccination campaigns whenever outbreaks of the disease flare up. As shown in Figure 3(b), this strategy has successfully kept the disease level low. Given the consistently low number of documented yellow fever cases, I will not treat it as a concerning confounder.

Zika

Zika virus was discovered in Brazil only recently, after Brazil hosted major international sports events. The virus was almost certainly brought to Brazil by a traveler from French Polynesia, as molecular studies have shown that viral specimens from the two countries were virtually identical. The first cases were positively identified in Rio de Janeiro in January 2015, but retrospective investigations show that the virus first began circulating in northeastern Brazil near the end of 2014. Within a year of its arrival, the virus was detected in nearly every territory infested with Aedes aegypti mosquito (World Health Organization, 2019).

In general, zika's symptoms are similar to but milder than dengue's. A notable difference is that zika infection during pregnancy has been linked to microcephaly (Victora et al., 2016), a severe 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 socioeconomic demographic composition of pregnant women could have changed due to the disease outbreak (e.g. families with the means to plan parenthood and to delay pregnancy may have chosen to do so). If zika outbreaks are correlated with dengue cases, this would invalidate the strategy of comparing birth outcomes between periods with high and low dengue rates. To rule out this potential issue, I also report results from a reduced sample that drops the year 2015, the initial year of the zika outbreak in Brazil.

3 Data

I obtain data on birth outcomes from the Information System on Live Births (Sistema de informação de Nascidos Vivos - SINASC) collected by Brazilian Ministry of Health and publically available through the Health Information Department (DATASUS). The data are gathered from documentation issued by the health institution where the birth occurred.

These data contain information such as birth weight, Apgar score[4], pregnancy length, mother's education and municipality of residence.

Also from DATASUS I collect mortality data from the National System of Mortality Records (Sistema de informações de Mortalidade - SIM), which gathers information on every death officially registered in Brazil. It contains data on cause of death, date of death, individual's age and municipality of residence. In these data records are also classified as cases of maternal death or fetal death.

Official monthly data on dengue prevalence come from the Notifiable Diseases Information System (Sistema de Informação de Agravos de Notificação - SINAN), also available via DATASUS. All 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 on the prevalence of all other diseases considered in this study.

To control for the supply of public health care in each municipality, I collect information on all visits to hospitals within Brazil's public health care network. These data are from the National System of Information on Hospitalizations (Sistema de Informação Hospitalares - SIH), and are also available through DATASUS. From this source I construct a count of hospitalizations, excluding those due to dengue, that occurred each month in each municipality. The DATASUS also contains information about public health staffing levels and the quantities of medical equipment. However, these data are available only after August 2005 which is after the onset of the period of observation. For this reason to collect other time variant control on the supply of public health I obtained from a different source, the RAIS (Relação Anual de Informações Sociais) dataset collected by the Ministry of Labor, the number of registered nurses in each municipality and year is used as a control.

Monthly precipitation and temperature data are obtained from Willmott and Matsuura's (2018) Terrestrial Air Temperature and Precipitation: Monthly and Annual Time Series

[4] The Apgar score was introduced by Virginia Apgar, MD (1909-1974) in 1952 and is a quick method to summarize the health of newborn children. The test ranges from zero to 10 and is performed on a baby at one and five minutes after birth.

(1900–2017). These data report the average weather conditions within grid cells that are squares 0.5 degrees in latitude and 0.5 degrees in longitude. 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 municipality centroid is located.

The data about fiscal transfers from the federal to municipal governments made through SUS are collected from the Ministry of Health. Other municipality-level information, such as annual per capita GDP and population, were collected from the Brazilian Institute of Geography and Statistics (IBGE). Also from the IBGE, I obtain information on firms' territorial networks to measure commercial connectedness among municipalities. The data are reported in a special study, 2014 Territory Management, which uses data from the 2011 Central Register of Enterprises (Cadastro Central de Empresas - CEMPRE) to count ties among firms and their branches. In addition to the commercial closeness score, I also construct a measure of connectedness based on the proportion of residents that commute for education purposes from one municipality to another. This measure is built from data in the 2010 population census conducted by the IBGE.

I combine these different sources of information to form a rich monthly dataset of Brazilian births. The period of observation runs from January, 2001 to December, 2015[5]. The final sample includes almost 40 million births and 5,555 municipalities for which all variables are available.[6]

3.1 Descriptive Statistics

Figure 4 displays the average birth weight by month of conception and monthly dengue rate in Brazil. This plot shows how these two variables move throughout the year, and

[5]Since the variable of interest is dengue rates over the whole gestational period, births in the first nine months of 2001 are not considered.

[6]In 2015 there were 5,570 municipalities in total. Not all of them are contained in my sample because five were only created recently, and for the other 10 municipalities I do have enough information to identify their main school attractor.

visualizes the seasonality in both series. As noted before, dengue cases are greater in the first and second quarters of the year and fall substantially in the second half of the year. Average birth weight displays a less striking pattern. It is about eight grams higher during the summer rainy season (November to February) than during the dry winter and spring seasons (June to October). Interestingly, the average birth weight for children conceived in March is clearly less, by about six grams, than those conceived in February and April. This may owe to the fact that Carnival, a national festivity believed to increase the number of unplanned pregnancies and sexually transmitted diseases (Kadhel et al., 2017), is generally held from late February to early March. In summary, there seems to exist a mild negative association between the dengue rate and birth weight over the months of the year.

Table 1 displays standard measures of birth outcome for all births (top panel) and a wide set of summary statistics for full term births[7](middle panel) from 2001 to 2015 which are observed in my sample. Throughout the paper I work with two samples. The full sample includes virtually all Brazilian municipalities from 2001 to 2015, while the reduced sample excludes municipalities in the northern region to avoid overlap with areas of endemic malaria. The reduced sample also excludes all observations from the year 2015, the first year of zika outbreaks in Brazil.

About 8% of children are born premature, meaning with less than 37 weeks of gestation. Also 8% of babies are born with weights below the threshold of 2,500 grams, which qualifies as low weight according to the World Health Organization. In general, Brazil's percentage of low birth weight is similar to the U.S. but higher than OECD averages.[8] The average full term birth weight is 3,256 grams. Full term babies are less likely to be born below the threshold of 2,500 grams, only 4% of them classified as low birth weight. In summary, birth weights in Brazil are within the norm for more developed countries.

Regarding the explanatory variable of interest, the average mother resides in areas where

[7]Full term births have delivery after 37 weeks of pregnancy were completed.

[8]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).

nine out of every 10,000 residents will become infected with dengue during some point in her last trimester. This translates to roughly three infections per 10,000 residents during each of the last three months of pregnancy, which is higher than the average monthly rate in municipalities of 2.1 cases per 10,000 inhabitants. This implies that there are more pregnancies in areas with a higher prevalence of dengue. However, there is great variation in dengue incidence among municipalities at any point in time. In a given month, about three quarters of them register zero cases. On the other hand, in an average month about 1.5% of Brazilian municipalities face outbreaks, defined as more than 30 dengue cases per 10,000 inhabitants. In terms of anti-mosquito resources, the federal government transfers, through the ACS program, 4.3 dollars per inhabitant to the average municipality. This amount is about 1.6% of the total transfers from the federal government and 0.1% of the average municipality's per capita GDP.

Weather conditions are important determinants of the mosquito population, and are described in the bottom panel of Table 1. The average municipality has an average monthly temperature of 23°C, with a standard deviation of 3.7°C. Aedes aegypti females are only able to sustain flight at temperatures between 15°C and 32°C (Reinhold et al., 2018). This range closely matches the 95% confidence interval for monthly temperature in Brazilian municipalities, i.e. 15.6°C to 30.2°C, indicating that temperatures are generally favorable to the vector throughout the year in much of Brazil. Another important factor for the mosquito life cycle is rainfall. For example, Viana and Ignotti (2013) found that during the rainy season the number of viable mosquito breeding pools in southeastern Brazil is six times greater than during the dry season. Monthly precipitation varies greatly among municipalities in my sample, with an average of 118 millimeters and a standard deviation of 100 millimeters.

4 Empirical Strategy

The goal of this paper is to estimate the causal effect of *in utero* exposure to dengue on birth outcomes. To do so, I use an analysis of intention-to-treat in which outcomes at birth are linked to fluctuations during pregnancy in dengue rate at the mother's residential area. Even when longitudinal data are available, estimating the dengue effect is difficult because exposure to the disease is typically endogenous. That is, unobserved time-varying individual or local factors 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 prospects behave differently about fertility than other potential mothers. Given the endemic roots of dengue in Brazil, this type of selection is unlikely to occur in my sample[9]. However, it is impossible to rule out entirely. 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 or be affected by disease proliferation (Norris, 2004; Stoecker et al., 2016) and also indirectly affect newborn health (through income shocks or environmental conditions, see Duncan et al., 2017 for instance). Additionally, panel data methods on their own may not be enough to address all types of measurement error. In municipalities where the supply of health centers has expanded over the years, diseases become more likely to be reported and counted. At the same time, access to health facilities would also impact birth outcomes (presumably positively).

I overcome these concerns with an instrumental variable approach. In short, I employ an instrumental variable research design that rests on two main components. First, I find needed variability in dengue incidence within localities. However, factors affecting dengue incidence within a given locality may plausibly affect fetal outcomes in that same locality. Therefore,

[9]Table 9 reports tests on whether the disease rate has any effect on birth rate.

the second component of my approach is the fact that dengue spreads geographically across localities. As symptomatic and asymptomatic human hosts travel, they serve as a source of the virus for uninfected mosquitoes and thus spread outbreaks to new areas. This makes past outbreaks in one locality a determinant of dengue cases in other localities that it is interconnected with. These two components construct a valid instrument for the dengue rate in the newborn's municipality of residence: lagged weather conditions and funds to finance local programs for disease combat in closely socially related areas are used as instruments for the current dengue rate in the maternal municipality of residence. The exclusion restriction is that past dengue rates in socially connected municipalities, due the distribution of federal resources and weather shocks, only affect birth outcomes through their impact on local dengue cases. The remainder of the section explains each part of the strategy in detail.

4.1 Determinants of dengue

Changes in weather, especially in humidity, temperature, and precipitation, alter the incidence of mosquito-borne diseases (de la Mata and Valencia-Amaya, 2014). First, the life-cycle of the mosquito vector itself is affected by climatic conditions. Completion of the mosquito reproduction cycle requires its eggs to be in contact with water, which is facilitated by rainfall. Additionally, Yang et al. (2009) have documented, through controlled experiments, that temperature directly affects the mosquito's oviposition rate and the mortality rate of female mosquitoes. Second, weather conditions also affect human behavior and social interactions, influencing the infection rate. Thus, dengue transmission varies in response to temperature and rainfall (Lowe et al., 2011).

On the other hand, dengue prevention depends on controlling the vector. Sustained community involvement is known to substantially improve vector control outcomes, and policy interventions at the local level are crucial to avoid disease proliferation. Consequently, in the early 2000s the Brazilian federal government began providing financial resources to municipalities to hire health agents (ACSs). These workers make house calls to provide vector control education and inspect for mosquito breeding grounds. The resources for ACSs are one of the fiscal transfers from the federal to municipal governments. Allocation criteria are based on the municipality's population size and health indicators. After the funds are made available to municipalities, it becomes their responsibility to hire agents. The heterogeneous distribution and application of this resource is likely to create variation in dengue cases among municipalities over the years.

Based on the discussion above, dengue rate in municipality m and month-year t is determined by variation in precipitation, temperature (which in the equation below are labeled as *weather*) and public resources available to hire agents to combat the disease (labeled ACS):

$$dengue_{mt} = f(weather_{mt}, ACS_{mT}) + \gamma_{m\tau} + \gamma_{MT} + \gamma_t + e_{mt} \tag{1}$$

in which γ denotes fixed effects such that municipality's invariant characteristics and seasonality in each calendar month ($\tau = 1, 2, \ldots, 12$) are denoted by $\gamma_{m\tau}$, yearly conditions at the state level are represented by γ_{MT} (M denotes the state where municipality m is located and T denotes year), and overall monthly conditions are denoted by γ_t. e_{mt} denotes all other factors that could determine the dengue rate in a municipality and month-year.

Although weather conditions are exogenous after controlling for seasonality, they cannot be used as instruments for the dengue rate in an equation with a birth outcome as dependent variable because weather is not an excluded variable. That is, weather conditions during pregnancy have a direct effect on newborn health (See papers by Deschenes et al., 2009, Andalon et al., 2016). Obvious channels are through the propagation of other diseases or income shocks. Likewise, even after controlling for municipality fixed effects, the exogeneity of ACS funds is compromised if its allocation criteria changes over the years based on underlying trends in local health, emerging viruses, or political conditions.

4.2 Transmission

Because the disease is carried from infected to healthy individuals via a mosquito's bite, the rate of its transmission is linked to human interactions. For this reason, the infection rate depends not only on local factors, as stated in Equation (1), but also on dengue status in connected areas. Using gravity-style models[10] which also account for climatic variation, Churakov et al. (2019) shows that both human mobility and vector (i.e. mosquito) ecology 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.

My second equation builds off of their findings. For each municipality m I examine the dengue rate in localities connected to m, and I define connectedness based on two measures. First, I examine the disease rate in the closest connection in terms of commercial management networks. This connection is referred to as the commercial partner and denoted by superscript c. Commercial management intensity is measured as the count of firms which have headquarters in one member and a branch in the other member of a pair of municipalities. For instance, suppose municipality m is home to the headquarters of firms A, B, and C, and that A and C maintain a branch office in municipality n. Then there are two connections from m to n. At the same time, municipality n is the headquarters of firm D which has a branch office in municipality m. This forms one connection from n to m. Commercial management intensity is the sum of these ties between municipalities, which is three in this example.[11] Second, I examine infection rates in the municipality where the plurality of municipality m's residents hold education ties, which I refer to as the school attractor and denote by superscript s. The school attractor of municipality m

[10]Gravity-style models contain some elements of mass and distance, which lends them to the metaphor of physical gravity. A gravity model holds that the interaction between two places can be determined by the product of the population of both places, divided by the square of their distance from one another.

[11]This measure is obtained from a special study done by the IBGE. In this study, about 20% of municipalities have no commercial ties to any other municipalities. In these cases I assign the state capital, which is usually the largest metropolitan area in the region, as their commercial partner.

is the municipality (excluding m) where the most residents of m reported to attend school in the 2010 census[12]. These measures capture patterns of movement between municipalities and I refer to these economically and socially connected municipalities as interconnected. In practice, these two measures of connectedness are quite different. The commercial partner and school attractor are different for about 80% of municipalities.

Adda (2016) provides a model of viral diseases diffusion within and across regions. In his equation the growth of a disease in a given region and time period is a function of lagged cases in the region itself and lagged cases in "neighboring" regions. The equation below is inspired by Adda's epidemiological work, but is not a structural equation. It simply models dengue incidence in municipality m in month-year t as a linear function of the past rate of the disease in the two other municipalities that have the closest commercial and educational ties to municipality m.

$$dengue_{mt} = \alpha_1 dengue^c_{mt-1} + \alpha_2 dengue^s_{mt-1} + \eta weather_{mt} + \psi ACS_{mT} + X_{mt}\Phi + \delta_{m\tau} + \delta_{MT} + \delta_t + v_{mt} \tag{2}$$

in which $weather_{mt}$ includes precipitation, temperature and the interaction of them, ACS_{mT} is the annual value transfers for the ACS program, X_{mt} contains observed time varying municipal characteristics such as public health indicators, municipality's yearly per capita GDP and the total yearly amount of federal fiscal transfers. δ denotes fixed effects, and as before $\delta_{m\tau}$ captures monthly municipal seasonality and a municipality's time-invariant factors, δ_{MT} captures yearly conditions at the state level, and δ_t accounts for time aggregate conditions. v_{mt} denotes an error term and all other unobserved factors that affect dengue rate in time t and municipality m.

Equation (2) links the dengue rate in municipality m in period t with past rates of the disease in municipalities closely connected to m.[13] So long as $\alpha' s \neq 0$, past levels of

[12] This measure is constructed from responses to question V6364 "Em que município estuda?" in english, "In which municipality do you attend school?".

[13] It is worth mentioning that past dengue rates in connected areas should not directly serve as instruments because of spatial correlation. If dengue rate exhibits state dependence (i.e. even after controlling for

dengue in the interconnected communities will affect contamination rates in municipality m. Then combining Equation (1), calculated for municipality m's main commercial partner and school attractor, and Equation (2) reveals natural candidates for instruments: weather fluctuations in the previous period and the allocation of ACS funds in municipalities closely interconnected to the newborn's municipality of residence.

4.3 Birth outcomes and dengue incidence

Finally, the ultimate equation of interest is stated below. Since the literature on the determinants of birth weight suggests that the effect of external shocks varies according to the stages of gestation, the equation models a birth outcome of baby i born in month-year t as a function of dengue rates during each trimester, j, of pregnancy in the mother's municipality of residence m.

$$y_{imt} = \sum_{j=1}^{3} \beta_j dengue_{j,mt} + W_i \Omega + \sum_{j=1}^{3} \pi_j weather_{j,mt} + \rho ACS_{mT} + X_{mt}\Theta + \lambda_{m\tau} + \lambda_{MT} + \lambda_t + u_{imt} \tag{3}$$

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 municipality of residence infected by new dengue cases in each trimester, j, of the pregnancy. W contains characteristics of the mother, pregnancy, and newborn. *weather* includes average precipitation, average temperature and the interaction of them in each trimester of pregnancy. ACS is the annual value transfers for the mosquito-borne combat program. As before X contains time varying municipal characteristics and λ denotes fixed effects. $\lambda_{m\tau}$ represents a municipality-month fixed effects, which accounts for monthly seasonality and for time invariant characteristics of each municipality. λ_{MT} denotes state-year dummies and captures, for instance, annual

systematic time-constant municipality differences, lagged dengue rate in the municipality helps to predict its current rate), $dengue^{c}_{mt-1}$ and $dengue^{s}_{mt-1}$ will be correlated to v_{mt}.

state level policies that could impact health conditions. λ_t are time fixed effects and absorb national trends and overall conditions in each period. Finally, u represents unobserved time variant factors.

β_j's are the parameters of interest and can be identified if, conditional on 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. As discussed in the beginning of this section, there likely exist time-variant factors that affect dengue rate and health at birth which I am not able to account for in Equation (3). I overcome this concern with an instrumental variable approach. This approach 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 network.

The exclusion restriction is that past dengue rates in interconnected municipalities generated from weather fluctuations and the distribution of ACS funds only affect birth outcomes at municipality m through their impact on municipality m's dengue rate. This assumption is plausible after conditioning on seasonality, aggregate regional factors, weather conditions and other time variant variables and fixed effects of the mother's residential municipality.

However, there are two possible alternative channels through which the instruments could affect birth outcomes, violating the exclusion restriction. First, even after controlling for weather variations in the mother's municipality of residence, weather in interconnected municipalities could still affect economic conditions, which could then impact incomes in the newborn's municipality and consequently outcomes at birth. This channel is unlikely because the profile of relationships among municipalities used to measure connectedness is not obviously sensitive to weather shock. For instance, weather shocks in school attractors are unlikely to impact birth outcomes through the income channel stated above. A second potential concern comes from using ACS funds in interconnected municipalities as instruments. Because ACSs also provide general health guidance to households, they could reduce the incidence of other diseases besides dengue in interconnected municipalities. If these diseases are also transmitted through human interactions then the exclusion restriction would fail.

Since there are more instruments than endogenous variables, the exogeneity of the instruments is testable. In order to rule out these alternative channels through which the instruments could correlate to birth outcomes I also perform two additional checks. First, I include weather variables in interconnected municipalities during each trimester of pregnancy as controls in Equation 3. This means that only ACS funds and the interactions between weather variables and ACS funds are used as instruments for dengue rate. Then following similar idea, to assess whether ACS fund allocated to interconnected municipalities have a direct effect on birth weight, I add it as a regressor in Equation 3. This means that only the interactions between ACS funds and weather variables are used as instruments in this specification. The results show that after instrumenting dengue rates, weather conditions and ACS funds in interconnected municipalities on their own are not statistically significant predictors of birth weight in the newborn's municipality. Moreover, the estimates of the dengue effect in each trimester of pregnancy from these alternative specifications remain statistically the same as those assuming exogeneity of all the instruments. These results strengthen the argument that the instruments are uncorrelated to outcomes at birth, except through their impact on the dengue rate.

4.4 Estimation details and inference

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

Equation:		(1)		(2)			(3)	
Variables:	weather conditions + ACS funds	$\Rightarrow$	dengue rate	$\Rightarrow$	dengue rate	dengue rate	$\Rightarrow$	birth outcome
Unit of analysis:	c and l		c and l		m	m		i and m
Time:	$t-1$		$t-1$		t	j		t

Estimation procedure consists of three stages. The fitted value from estimating Equation (1) serve as inputs to Equation (2) and the residuals values obtained from estimating Equation (2) are inputs to Equation (3). Equations (1) and (2) are estimated by fixed effects two stages least squared (FE-2SLS). In the first stage, past dengue rates in interconnected municipalities are instrumented by their past monthly temperature, past monthly precipitation, and annual ACS funding inflows.[14] Then in the second stage the endogenous variable, $dengue_{mt}$, is regressed on fitted values of past dengue rates in interconnected municipalities, weather variables, ACS funds, others observed time-variant municipality characteristics and fixed effects. The residuals of this second regression are retained and used to construct a control function. Finally in the third stage, the equation of interest, i.e. Equation (3), is estimated with the control function entering as an additional regressor.

While endogeneity of the monthly dengue rate is addressed by the instrumental variable approach, the variables of interest in Equation (3) are dengue rates during a particular trimester. For a full term baby born in time t whose mother resides in municipality m, the dengue rate in the third trimester of gestation is calculated as $dengue_{3,mt} = dengue_{mt} + dengue_{mt-1} + dengue_{mt-2}$. While the dengue rate in the first trimester of gestation is given by $dengue_{1,mt} = dengue_{mt-6} + dengue_{mt-7} + dengue_{mt-8}$. That means that the equation of interest has three endogenous variables, $dengue_{1,mt}$, $dengue_{2,mt}$, $dengue_{3,mt}$ and each of them is formed by the summation of three endogenous variables at the monthly level. Therefore, the control function will be composed of nine variables, which are the residuals of monthly dengue rate as modeled in Equation (2). Specifically, the control function will be formed by $\hat{v}_{mt}, \hat{v}_{mt-1}, \ldots, \hat{v}_{mt-8}$.

I adopt the control function approach to estimate Equation (3), as opposed to FE-3SLS, due to the dynamic and aggregate nature of modeling dengue incidence evolution in Equation 3. The control function approach offers the additional advantage of a straightforward test for endogeneity of the variable of interest. The control function method requires that v_{mt}

[14]For estimation purpose $f(\cdot)$ in Equation 1 is an additively separable function of the monthly temperature, monthly precipitation, yearly ACS transfers and all the interactions across these three variables.

and u_{mt} are orthogonal to the instruments, but are related to each other. The key to this approach is that (under certain assumptions), conditional on v_{mt}, $dengue_{j,mt}$ becomes appropriately exogenous (Wooldridge, 2015) in Equation (3). The feasibility of the method 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 (2) using an instrumental variable approach, which allows the computation of consistent estimates of α's and consequently of v_{mt}.

Turning to outcomes of interest, birth weight can be thought of as a function of gestation length and intrauterine growth (Kramer, 1987). Therefore dengue could affect weight by weakening fetal growth, shortening the gestation period, or some combination and it is appropriate to disentangle these effects if possible. In many studies, this is impossible as the date of conception is unknown and simply retrospectively subtracting three trimesters from the time of birth could yield incorrect gestation times. Fortunately the Brazilian data contain information about gestational length, which is reported in number of weeks. This allows me to estimate dengue's effect on birth outcomes through intrauterine growth by considering only full-term pregnancies. The disease's impact on gestational length is assessed separately.

Valid inference must account for the fact that the empirical strategy uses interconnected municipalities and explores geographical variation in addition to longitudinal variation in dengue rate. To address any spatial and temporal correlation among observations, I adopt clustered standard errors at a geographic unit larger than municipality. A natural candidate would be states[15], but Brazilian states are quite large in size and heterogeneous in character. Alternatively, the IBGE divides states into sub-units called micro regions. There are a total of 556 micro regions and each one contains ten municipalities on average. Since interconnected municipalities are commonly within the same region, I cluster at the smaller and more uniform region level. Another inference challenge is posed by the fact that the control function approach uses generated regressors. This is problematic in terms of

[15] Brazil has 26 states plus the federal district.

covariance matrix estimates because the generated regressor is a function of the sample and the assumption of independent identically distributed observations does not hold. To overcome this problem I bootstrap standard errors (clustered at the regional level).

4.5 The compliant population

The strategy identifies the average effect of changes in the dengue rate only for individuals who are affected by the changes in the dengue rate driven by conditions in interconnected municipalities. Essentially, this means that I am not able to capture the effect for areas where the disease is always widespread or for individuals who are frequently exposed to it regardless (i.e. the always takers). In the terminology of the treatment effect literature, the effects identified here are local average treatment effects (LATEs), where the compliers – the population group that is affected by the instruments – are fetuses exposed to the disease because of dengue infections coming from other municipalities that have considerable business and social interaction with the maternal municipality of residence.

Table 2 shows how infections break down by socioeconomic characteristics of the patients. Educational characteristics are listed in the upper panel, and racial characteristics are in the lower half. The first column lists the percentage of cases accruing to each subgroup during months when there are no uncommonly large outbreaks (i.e. months where the dengue rate is within two standard deviations of the locality historical average dengue rate) in interconnected municipalities. The second column lists percentages during months when there is a large outbreak (more than 30 cases per 10,000 and greater than two standard deviations above the historical monthly incidence of the dengue) in at least one interconnected municipality. So, for example, during months without large-scale outbreaks in interconnected municipalities, about 24% of dengue patients reported attending high school. It is worth noting that less educated individuals are more likely to acquire dengue. About 15% of the Brazilian population holds a college degree in 2016; however, only 9% $(0.06/(1-0.342))$ of patients who reported their education level held a college degree.

A comparison of the first and second columns shows which types of individuals are most affected by dengue shocks in interconnected areas. This information helps to characterize the subset of the population for which the causal effect can be identified. The composition of infected individuals in a given municipality changes during outbreaks in commercial partners and school attractors. In particular, the proportion of whites, high school and college graduates among infected individuals becomes statistically higher. These are the type of mothers for whom infection status is more likely to be switched by the instruments, and therefore the group for which the identification strategy is able to retrieve the causal effect of *in utero* exposure to dengue.

5 Results

5.1 Dengue rate

Before discussing estimates of the main equation, I present estimates of Equations (1) and (2) in order to assess the instruments' relevance and validity. Table 3 presents the effects of a one standard deviation increase in precipitation, temperature, and ACS funding on dengue rates in the main commercial partner and school attractor. The estimates are first stage results and should not be interpreted as causal effects. Rather, they demonstrate the power of weather and funding to predict dengue rates in municipalities most intensely connected to the newborns' municipality of residence.

The estimates are of meaningful magnitude given that the average municipality has a monthly dengue rate around two cases per 10,000 inhabitants. For instance, a one standard deviation increase in precipitation in the commercial partner is associated with 0.20 additional cases of dengue per 10,000 inhabitants, a 10% increase in dengue incidence in that partner locality. A one standard deviation increase in ACS transfers, which finances community health agents that educate residents about dengue and also inspect for mosquito breeding sites, is associated with a significant reduction of dengue incidence in interconnected municipalities.

The table also presents the results of a test on the joint significance of the weather variables and ACS transfers to predict the dengue rate in the interconnected municipalities. The instrumental variables set has a p-value well below the 1% significance level. In summary, these estimates show that weather conditions and ACS transfers are determinants of dengue rates in the interconnected municipalities, even after controlling for time variant variables at the municipality level and a series of fixed effects.

Table 4 displays the estimates of Equation 2's parameters using different specifications and samples. The first column shows the results of a naive linear regression. The second and third columns show estimates after fixed effects and control variables are added. The point estimates are similar. In particular $\hat{\alpha}$'s are positive, smaller than one and statistically significant. That is, higher dengue rates in interconnected localities in the previous month increases dengue cases in the mother's municipality of residence. The fourth column reports estimates after instrumenting dengue rate in interconnected localities by past weather conditions and ACS transfers in those municipalities. The coefficients increase in magnitude and remain statistically significant. For the full sample, one additional case of dengue in the previous month in the main commercial partner is associated with 0.33 cases of dengue in the mother's municipality of residence. Most importantly, a hypothesis test confirms that dengue rates in the interconnected localities are jointly statistically relevant predictors of dengue rates in the mother's municipality. These findings validate the narrative about patterns of temporal and spatial transmission of dengue.

Finally, I present results of a placebo test designed to assess the validity of the instruments. The idea is that if external dengue rates are valid instruments, then the incidence of other diseases inside a given municipality should not be affected by lagged dengue rates in interconnected localities after they are instrumented by weather conditions and ACS transfers. The F statistic of hypothesis tests on whether past dengue rates in the interconnected localities are jointly statistically null for explaining current rates of leptospirosis, schistosomiasis and tuberculosis[16] in the mother's residential municipality are reported in Table 5 for FE and FE-2SLS estimation. In general, past dengue rates in interconnected municipalities have low statistical power to predict other diseases in a given municipality. This is taken as evidence in favor of the exclusion restriction.

5.2 Birth weight

Table 6 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 exists a correlation of similar magnitude, but negative, in the third trimester of pregnancy. The second column shows the results after controlling for fixed effects. As expected the standard errors decrease and so do the point estimates (in absolute terms). The positive association between dengue rate and birth weight in the first trimester is now of smaller magnitude and statistically insignificant, and the relationship is negative during the second and third trimesters of pregnancy, as one would expect if dengue fever has a detrimental effect on birth weight. In columns III and IV some control variables at the individual and at the municipal levels are added and results remain stable. Specifically, IV differs from III in that it includes prenatal medical appointments reported by the mother. This variable could be endogenous to dengue infection and may not be an appropriate control. However, point estimates are only changed slightly by its addition. Later on I also present results treating prenatal visits as an outcome variable[17].

As discussed previously, there may still exist time variant omitted factors not addressed by controls and the fixed effects that could cause endogeneity. The fifth column of Table 6

[16] In the same way as dengue, cases of these diseases are required to be notified to the Brazilian Health Department. There are other diseases in the reporting system, but they were not included here because there were not enough observations or the data were not available by municipality and month.

[17] I do not detect an effect of dengue exposure on prenatal visits, which indicates that this variable is unlikely a source of post-treatment bias.

presents the estimates when the control function approach is applied in order to deal with time variant confounding variables. A hypothesis 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 column V are the causal effect of exposure to dengue during each step of pregnancy on birth weight. This is a LATE for babies affected by the disease due to contamination from interconnected localities. The effects for the first and second trimesters are not statistically significant to explain weight. On the other hand, exposure to dengue during the third trimester of gestation has a markedly adverse effect on weight at birth.

Columns VI and VII present results using the reduced sample that avoids overlapping malaria endemic areas and the 2015 zika outbreak. The estimates are similar to those obtained using the full sample. In particular, my most preferred specification, which includes the control function, shows that a one standard deviation (29 dengue cases per 10,000 inhabitants) rise in the dengue rate during the last trimester of pregnancy decreases birth weight by 0.85 grams (-293.5×0.0029) on average. This effect is only slightly smaller than in the full sample, in which one standard deviation increase in the dengue rate during the last trimester of pregnancy (34 dengue cases per 10,000 inhabitants) leads to an average reduction in birth weight of about one gram (-294.4×0.0034) on average. Given that most fetal weight gain occurs during the last weeks of a pregnancy, these results lend themselves to the conclusion that maternal exposure to the mosquito-borne disease compromises fetal health through the growth channel. The finding is consistent with other studies in the prenatal development literature, but slightly smaller in magnitude than reported in previous work that also investigate *in utero* exposure to a condition outside the mother's control. For example, also using a sample from Brazil, Koppensteiner and Manacorda (2016) found that a one standard deviation increase in the homicide rate during the first trimester of pregnancy leads to two grams reduction in birth weight.

With some assumptions, the direct effect of a mother contracting dengue during pregnancy can be conjectured. Assuming that dengue impacts the fetus only through the maternal health channel, one can infer that when the infection rate in the municipality of residence goes to one, then the probability of a mother contracting dengue is one, and the reduction in her baby's weight at birth would be 293.5 grams (-293.5×1). This implied effect is substantial, being 60% larger than the effect of smoking during pregnancy of 182 grams estimated by Lien and Evans (2005).

In addition to the parameters estimated by gestation term, Table 6 also displays estimates for the trimesters before conception and after birth. These estimates support the validity of the empirical strategy. In particular, there should be no causal relationship between dengue rate in the post-birth period and weight at birth. This is confirmed by the estimates in column V and VII, my most complete specifications. This result is reassuring, since it serves as a falsification test of the empirical strategy. While dengue incidence during pregnancy matters for health at birth, birth weight is not affected by the disease before conception or after birth.

5.2.1 Heterogeneous Effects

In order to disentangle and better understand possible mechanisms behind the dengue effect, I examine heterogeneous treatment effects. This also uncovers some possible policy implications regarding the mitigation of mosquito-borne disease spread. Table 7 reports the results using the reduced sample and my most preferred specification which contains the control function approach.

The negative effects of *in utero* exposure to dengue are statistically higher for female babies. One standard deviation increase in dengue incidence during the third trimester of gestation decreases a baby's weight by 1.07 grams for girls and by 0.67 grams for boys. Given that girls are on average lighter than boys (in my sample the difference is 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 these authors mention, newborn gender bias is not considered a significant problem in Brazil[18]. Thus it is difficult to attribute the different findings 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 are identified as white. Within the non white group the composition is the following: 92% brown[19], 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 contract 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 interconnected areas. Another potential explanation is that if race correlates to socioeconomic status such that non-white individuals are economically worse off, then they may be less likely to receive prenatal care. If so, exposure to dengue could cause mothers to visit a doctor who would not otherwise do so. This access to formal health care early in pregnancy could overcome the negative effect of dengue contamination.

This hypothesis is confirmed when examining the effect of dengue broken down by the number of prenatal visits. For mothers that do not record any prenatal care visits the dengue effect is largely positive in the first two trimesters of gestation, although not statistically significant. That is probably because, after contracting the disease, these mothers access

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

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

health care and neonatal education that they would not receive otherwise and prenatal care has been shown to have a positive impact on birth outcomes (Joyce, 1999; Evans and Lien, 2005; Conway and Deb, 2005).

Finally the last panel of Table 7 shows the effect broken down by mother's schooling. The negative effect of the dengue rate during the third trimester on birth weight 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 trimester, in total, a one standard deviation increase in dengue rate during the gestation of mothers with some college reduces their newborn's birth weight by about 4.2 grams on average. 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 dengue infection status due to outbreaks in interconnected areas. That is, they are characterized as the compliers, the population most likely to be affected by instruments. If dengue is endemic among socioeconomically worse off individuals, the identification strategy, which relies on external shocks of the disease rate, is not able to capture the effect for those who are frequently exposed to the disease. Second, the vast majority of highly educated mothers had at least one prenatal visit (Only 0.7% of mothers with some college degree reported zero prenatal visits. For mothers with zero to three years of education, 7% do not have any prenatal visits during pregnancy). Thus, the estimates on birth weight for babies of more educated mothers are not conflated with potential benefits of seeing a doctor during the pregnancy due to contracting dengue.

5.3 Other birth outcomes

Table 8 reports the results for additional birth outcomes using the most preferred specification, i.e., including the control function and using the reduced sample. Consistent 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 only slightly statistically significant. I do not find significant detrimental effects of *in utero* dengue exposure on Apgar score, congenital disability[20] 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 gives reassurance that the estimates are not capturing a potential zika virus effect, which has been linked to congenital disability. Dengue infection does not seem to affect gestational length, strengthening the conjecture 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 an indicator of complications during pregnancy. A one standard deviation increase in dengue rate during the first trimester of gestation raises the probability of C-section by 0.15 percentage points (0.555×0.0028). About 49 out of every 100 deliveries in the sample are cesarean deliveries, so this effect means a 0.31% 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, it translates to almost 4,700 extra deliveries by C-section.

5.4 Selection and mortality rate

Virus incidence may not only affect outcomes at birth but also the conception and survival rates. These are two dimensions of selection that could interfere with birth weight estimated. 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 type of selection I regress birth rate (number of births

[20] Congenital disability refers to developmental disorders of prenatal origin present at birth, and can be structural, functional or metabolic.

per 10,000 inhabitants) 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 (percentage of mothers with some college). As presented in Table 9, both outcomes are unaffected by dengue rates 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 analyze whether dengue incidence in the mother's municipality of residence in the current trimester affects the spontaneous abortion rate[21] in the same period. Results are shown in the fourth column of Table 9. A higher dengue rate is associated with a higher rate of spontaneous abortion. However, the estimate is not statistically different from zero.

Finally I present results about the dengue effect on fetal death and non zero maternal mortality rate. Fetal deaths, for example stillbirths, occur at later stages of development than miscarriages. Although positive and statistically significant, the effect of dengue on fetal death is small. Fetal death rate increases 1% ($0.04 \times 0.0028/0.01$) when the dengue rate in the municipality of residence during the first trimester of gestation increases by one standard deviation. The average maternal mortality (number of maternal deaths divided by number of births and fetal deaths) in my sample is 54 deaths per 100,000 births[22]. Because most of the observations are zero I use a dummy dependent variable equal to one if maternal mortality in the municipality-month was not zero. Based on the findings in the sixth column of Table 9, the probability of maternal death increases by 0.78 (2.71×0.0029) percentage points or 3% ($0.0078/0.26$) when the dengue incidence in the third trimester of gestation is one standard deviation higher.

[21] I use data on hospitalizations for which the reported cause was spontaneous abortion. The miscarriage rate is created dividing the number of these hospitalizations by the "pregnancies stock", i.e., a sum of hospitalizations due to spontaneous abortion, the number of births and the number of fetal deaths in pregnancies advanced enough to not count as miscarriage.

[22] In the United States in 2015 the maternal mortality was three times smaller, 15 deaths per 100,000 live births (World Bank, 2015).

As a benchmark I also present results of the dengue infection effect on the overall death rate, measured as the number of deaths per 10,000 inhabitants. As the dengue rate increases by one standard deviation in the current trimester, mortality grows by 0.05 cases per 10,000 inhabitants (15.87×0.0029) or 1% (0.05/4.8). At last, dengue's effect on deaths due to external causes (deaths due to intentional and unintentional injury, poisoning, drug overdose, and complications from medical or surgical care) is presented as a validity test. This relationship should be null if endogeneity has been properly addressed and the instrumental variable approach is valid. As shown in the last column of the table, trimester dengue rates are individually and jointly (joint test p-value equals to 0.50 reported on the bottom of the table) not statistically significant predictors of deaths due to external causes.

6 Conclusion

This work sheds light on an understudied and increasingly relevant relationship: the effect of mosquito-borne diseases on the initial human capital stock. Health at birth is known to have important implications for human development and skill formation, which in turn affect economic outcomes in adulthood. This paper also presents an original approach to address endogeneity that is left even after the application of commonly applied fixed effects techniques. The empirical design exploits variation in lagged dengue rates in a town's most important commercial and social partners. 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 fluctuations.

My findings show that newborns are vulnerable to dengue, which is endemic in Brazil and in several other tropical countries. In particular *in utero* exposure to the disease jeopardizes fetal weight growth, even more so for female newborns. This result is worrisome because it shows that dengue inflicts a health deficit right from the very first moment of life. Since individuals living in worse housing arrangements or with less means to avoid the mosquito are more affected by dengue, these findings indicate that the disease contributes to the exacerbation and perpetuation of inequality.

Owing to rising global temperatures, mosquito-borne diseases are likely to become a more prevalent phenomenon in many parts of the world. Therefore, these results have important implications for future health and environmental policies. Future research could study longer-term follow-up outcomes for affected newborns such as educational attainment or earnings later in life. This line of research could enable a better understanding of whether and how disease impacts human capital and income inequalities in the long run.

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Tables and Figures

Table 1: Descriptive statistics: birth records and monthly municipality data.

	Full sample		Reduced sample	
	Mean	Std. Dev.	Mean	Std. Dev.
All records				
Weeks gestation <37 weeks	0.08	0.28	0.08	0.27
Birth weight<2500g	0.08	0.28	0.08	0.28
Full term pregancies only				
Birth outcome				
Birth weight	3,256	461	3,253	459
Birth weight¡2500g	0.04	0.20	0.04	0.20
Agpar 1 min	8.28	1.20	8.29	1.21
Agpar 5 min	9.33	0.88	9.34	0.89
Congenital anomaly	0.01	0.08	0.01	0.08
Newborn characteristics				
Male	0.51	0.50	0.51	0.50
White	0.44	0.50	0.48	0.50
Mother characteristics				
Single	0.62	0.48	0.60	0.49
Age	25.4	6.4	25.5	6.4
Years of ed. 0-3	0.10	0.30	0.10	0.30
Years of ed. 4-7	0.29	0.46	0.29	0.46
Years of ed. 8-11	0.45	0.50	0.45	0.50
Years of ed. $\geq$12	0.15	0.36	0.16	0.36
Birth and pregnancy characteristics				
Prenatal visits 0	0.02	0.14	0.02	0.13
Prenatal visits 1-6	0.38	0.49	0.36	0.48
Prenatal visits $\geq$7	0.60	0.49	0.62	0.49
Multiple births	0.01	0.11	0.01	0.11
C-section	0.49	0.50	0.49	0.50
Dengue exposure				
Dengue rate 3^{rd} trimester	8.5	34.0	7.5	29.4
Dengue rate 2^{nd} trimester	8.1	33.1	7.2	28.7
Dengue rate 1^{st} trimester	7.7	32.0	6.8	27.7
Births	35,436,465		29,365,227	
Municipality characteristics				
Monthly dengue cases per 10k	2.1	13.0	1.8	11.7
% monthly outbreak (>30 cases per 10k)	1.5	12.3	1.3	11.4
% zero monthly dengue cases	73.5	44.1	75.7	42.9
Monthly hospitalization per 10k (exclude dengue)	54.3	25.1	54.9	24.6
Nurses per 10k	25.7	25.0	25.6	24.7
Yearly ACS per capita	4.3	3.2	3.9	2.9
Yearly per capita federal total transfers	274	224	260	214
Yearly per capita GDP	3,388	4,590	3,265	4,465
Precipitation (in ml)	117.7	100.2	112.8	95.0
Temperature (in Celsius)	22.9	3.7	22.6	3.7
Population	33,641	199,772	33,489	205,444
# Municipalities / # Micro regions	5,555 / 556		5,108 / 492	

Table 2: Heterogeneity in dengue infected individuals.

Patient's characteristics (education level and ethnicity)	Outbreak and >2SD in at least one interconnected municipality in the past period: No	Yes	Diff.
Not reported	0.342	0.360	0.018***
	(0.38)	(0.348)	(0.004)
Less than secondary	0.09	0.058	-0.032***
	(0.212)	(0.123)	(0.002)
Secondary	0.268	0.261	-0.007**
	(0.332)	(0.26)	(0.003)
High school	0.24	0.256	0.016***
	(0.315)	(0.253)	(0.003)
College or more	0.06	0.064	0.005***
	(0.173)	(0.135)	(0.002)
Not reported	0.152	0.156	0.003
	(0.292)	(0.266)	(0.003)
Asian or Native	0.014	0.014	-0.001
	(0.086)	(0.063)	(0.001)
Black	0.05	0.049	-0.001
	(0.153)	(0.112)	(0.001)
Mixed	0.418	0.364	-0.054***
	(0.392)	(0.327)	(0.004)
White	0.366	0.419	0.052***
	(0.386)	(0.34)	(0.004)
# of dengue cases	6,024,233	1,432,553	
Observations	178,885	11,588	

Note: * p<0.1, ** p<0.05 and *** p<0.01. Data for municipality-month-year with positive dengue cases. To keep consistency in patient's education classification, only data from 2007 and after are considered.

Table 3: The effect of one standard deviation increase in the instruments on dengue rate in interconnected municipalities.

	Full sample		Reduced sample	
	Business partner	School attractor	Business partner	School attractor
Precipitation	0.20***	-0.13	0.16***	-0.36**
	(0.04)	(0.14)	(0.04)	(0.15)
Temperature	-0.16**	-0.07	-0.22***	-0.07
	(0.08)	(0.35)	(0.08)	(0.34)
ACS Funds	-0.14**	-0.75***	-0.20***	-0.36***
	(0.07)	(0.15)	(0.07)	(0.13)
R^2-adjusted	0.209	0.198	0.206	0.207
Observations	994,026	994,026	852,717	852,717
Test joint significance weather variables and ACS funds				
	9.27	10.99	10.10	6.61
	(0.000)	(0.000)	(0.000)	(0.000)

* p<0.1, ** p<0.05 and *** p<0.01. Robust standard deviation clustered by micro region in parenthesis. Number of clusters is 556 in the full sample and 492 in the reduced sample. Excluded variables in Equation (1) and not in Equation (2) are: precipitation, temperature, and first order interactions between them and ACS funds in the main commercial partner and school attractor at time $t-1$. Control variables are precipitation, temperature, interaction of precipitation and temperature, ACS funds in municipality m and its interconnected municipalities at time t. I also control for precipitation, temperature and their interaction in municipality m and time $t-1$, municipality m's annual per capita GDP, annual total federal transfers, monthly per capita hospitalization excluding those due to dengue diagnose and annual number of nurses per capita. The regressions also include municipality-calendar month fixed effects, state-year fixed effects and month-year fixed effects.

Table 4: Estimates of Equation 2 parameters. Dependent variable: $dengue_{mt}$

	Full sample				Reduced sample	
	OLS	FE	FE	FE-2SLS	FE	FE-2SLS
dengue$_{t-1}$ at	0.18***	0.13***	0.13***	0.33**	0.11***	0.55***
commercial partner	(0.01)	(0.01)	(0.01)	(0.13)	(0.01)	(0.14)
dengue$_{t-1}$	0.21***	0.15***	0.15***	0.27***	0.17***	0.14
school attractor	(0.01)	(0.01)	(0.01)	(0.07)	(0.01)	(0.09)
F(2, clusters-1)	402.39	262.51	263.80	15.1	226.26	17.54
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Fixed effects	No	Yes	Yes	Yes	Yes	Yes
Control variables	No	No	Yes	Yes	Yes	Yes
R^2 adjusted	0.09	0.22	0.22	-0.00	0.22	-0.07
Observations	994,062	994,062	994,026	994,026	852,717	852,717

Note: * p<0.1, ** p<0.05 and *** p<0.01. Robust standard deviation clustered by micro region in parenthesis. Number of clusters is 556 in the full sample and 492 in the reduced sample. Control variables are precipitation, temperature, interaction of precipitation and temperature, ACS funds in municipality m and its interconnected municipalities at time t. I also control for precipitation, temperature and their interaction in municipality m and time $t-1$, municipality m's annual per capita GDP, annual total federal transfers, monthly per capita hospitalization excluding those due to dengue diagnose and annual number of nurses per capita. The regressions also include municipality-calendar month fixed effects, state-year fixed effects and month-year fixed effects.

Table 5: F-test, significance of past dengue rates in interconnected municipalities on other diseases.

	Full sample			Reduced sample		
	FE	FE-2SLS	# of cases	FE	FE-2SLS	# of cases
Leptospirosis	2.39	0.05	53,928	2.03	0.57	43,354
	(0.09)	(0.95)		(0.13)	(0.57)	
Schistosomiasis	1.25	0.65	372,027	0.76	0.65	364,314
	(0.29)	(0.52)		(0.47)	(0.52)	
Tuberculosis	0.14	0.21	1,206,102	0.74	0.48	1,021,414
	(0.87)	(0.81)		(0.48)	(0.62)	
Obs/Clusters	994,026/556			852,717/492		

Note: The table shows F statistics, F(2,clusters-1), and their p-values about the joint statistical significance of $dengue^{c}_{mt-1}$ and $dengue^{l}_{mt-1}$ to explain a disease rate in municipality m and time t. The specifications in columns FE and FE-2SLS have the same explanatory variables and fixed effects as those displayed Table 4.

Table 6: Estimates of Equation 3 parameters. Dependent variable: $birth\ weight_{imt}$

	Full sample					Reduced sample	
	I	II	III	IV	V	VI	VII
Trimester							
3	-285.4**	-167.4***	-153.2***	-128.2***	-294.4**	-129.0***	-293.5**
	(127.3)	(42.6)	(42.9)	(42.8)	(114.9)	(47.0)	(115.4)
2	91.4	-125.0**	-146.6***	-126.1***	-11.6	-147.7***	-50.2
	(153.3)	(50.0)	(49.1)	(46.9)	(105.4)	(50.4)	(108.1)
1	235.8*	53.4	40.9	67.7	77.3	73.1	78.0
	(132.3)	(45.5)	(46.4)	(45.7)	(117.6)	(64.8)	(114.5)
-1 (pre-conception)	58.6	-57.5	-60.5	-46.8	-65.9	-67.0	-79.6
	(186.7)	(47.0)	(43.3)	(42.8)	(42.7)	(56.6)	(54.6)
4 (post-birth)	-46.0	-84.3**	-87.0**	-67.5*	-47.8	-43.0	-23.0
	(157.5)	(39.5)	(39.1)	(39.1)	(42.9)	(46.6)	(49.8)
Joint test	0.000	0.000	0.000	0.001	0.020	0.003	0.023
CF p-value	-	-	-	-	0.008	-	0.003
Fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	No	No	Yes	Yes	Yes	Yes	Yes
Control for prenatal	No	No	No	Yes	Yes	Yes	Yes
R^2	0.0	0.0	0.1	0.1	0.1	0.1	0.1
Observations			35,436,465			29,365,227	

Note: * p<0.1, ** p<0.05 and *** p<0.01. Bootstrap standard deviation clustered by micro region in parenthesis. Number of clusters is 556 in the full sample and 492 in the reduced sample. Control variables at the individual level are: male, white, multiple pregnancy dummies, 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 federal transfers, annual ACS transfers, monthly per capita hospitalization excluding those due to dengue diagnose, annual number of nurses per capita, and average temperature and average precipitation and their interaction in each trimester of pregnancy. Fixed effects refereed to are municipality-calendar month fixed effects, state-year fixed effects and month-year fixed effects. Joint test displays the p-value of a joint significance test of dengue in the three trimesters of gestation. CF p-value refers to the p-value about the statistical significance of the control function.

Table 7: Dengue's heterogeneous effects in Equation 3. Dependent variable: *birth weight*$_{imt}$

Girl	36.5	-86.1	-368.6***
	(121.7)	(111.5)	(122.4)
Boy	52.1	5.7	-230.3*
	(126.5)	(108.4)	(121.9)
Non white	324.1***	86.4	-136.0
	(123.8)	(102.9)	(128.3)
White	-337.0**	-217.7*	-510.6***
	(137.7)	(124.4)	(125.9)
Prenatal visits 0	770.5	371.6	-152.7
	(469.2)	(379.3)	(501.7)
Prenatal visits 1-6	261.6*	91.3	-178.9
	(149.9)	(125.0)	(156.2)
Prenatal visits $\geq$7	-65.3	-112.7	-361.1***
	(134.9)	(109.6)	(133.7)
Years of ed. 0-3	102.9	-32.5	-80.3
	(220.8)	(171.5)	(176.3)
Years of ed. 4-7	363.4**	0.2	-251.6*
	(164.8)	(120.2)	(129.6)
Years of ed. 8-11	39.6	50.3	-268.5**
	(129.1)	(105.6)	(133.7)
Years of ed. $\geq$12	-447.3**	-426.1**	-617.8***
	(204.4)	(168.4)	(195.0)

Note: * p<0.1, ** p<0.05 and *** p<0.01. Bootstrap standard deviation clustered by micro region in parenthesis. The regressions have the same explanatory variables and fixed effects as the specification in column VII of Table 6.

Table 8: Estimates of Equation 3 parameters. Several birth outcomes as dependent variable.

	Weight <2500g	Apgar 5 > 8	Congenital disability	C-section	Prenatal	Gestation <37 weeks
Trimester						
3	0.067	-0.116	-0.020	0.425*	-0.022	
	(0.041)	(0.221)	(0.022)	(0.225)	(0.097)	
2	-0.003	-0.111	-0.041**	0.307	0.027	-0.148*
	(0.039)	(0.164)	(0.019)	(0.209)	(0.075)	(0.077)
1	-0.031	0.144	-0.018	0.555***	0.021	-0.024
	(0.036)	(0.120)	(0.020)	(0.206)	(0.100)	(0.080)
-1	0.019	-0.029	-0.012	-0.014	-0.051	
(pre-conception)	(0.019)	(0.060)	(0.010)	(0.145)	(0.034)	
4	-0.011	-0.039	-0.026**	0.183	-0.042	
(post-birth)	(0.018)	(0.067)	(0.012)	(0.127)	(0.036)	
Average	0.043	0.916	0.006	0.493	0.978	0.076
Joint test	0.260	0.408	0.183	0.058	0.868	0.111
CF p-value	0.614	0.196	0.695	0.068	0.781	0.116
R^2	0.039	0.058	0.004	0.188	0.066	0.034
Observations	29,569,822	28,200,459	28,206,595	29,613,460	29,613,460	32,840,391

Note: * p<0.1, ** p<0.05 and *** p<0.01. Bootstrap standard deviation clustered by micro region in parenthesis. The regressions have the same explanatory variables and fixed effects as the specification in column VII of Table 6. Average refers to the average of the dependent variable. Joint test displays the p-value of a joint significance test of dengue in the three trimesters of gestation. CF p-value refers to the p-value about the statistical significance of the control function.

Table 9: Selection and mortality variables regressions - Observations at the municipality level.

Dengue in trimester	Births	% college	% of boys	Misca-rriage	Fetal death	Maternal death>0	All deaths	Ext. cause death
3 (or current)			-0.00	0.08	0.01	2.71**	15.87***	1.17*
			(0.04)	(0.10)	(0.02)	(1.35)	(2.08)	(0.68)
2			0.05		-0.03	-0.86	-2.51	0.11
			(0.04)		(0.02)	(1.14)	(1.90)	(0.68)
1			0.05		0.04**	-0.34	0.58	1.11
			(0.04)		(0.02)	(1.10)	(1.91)	(0.73)
-1 (pre-conception)	0.47	0.06	0.04		0.01	-0.73	-0.16	0.24
	(0.32)	(0.08)	(0.04)		(0.01)	(0.51)	(1.03)	(0.37)
4 (post-birth)			-0.01		0.01	0.65	3.68**	-0.07
			(0.03)		(0.01)	(0.62)	(1.49)	(0.33)
Average	1.34	0.15	0.51	0.07	0.01	0.26	4.80	0.60
Joint test	-	-	0.54	-	0.04	0.07	0.00	0.50
CF p-value	-	-	-	0.01	0.25	0.01	0.00	0.38
R^2	0.55	0.64	0.08	0.44	0.11	0.61	0.50	0.23
Observations	787,521	787,521	772,485	796,228	771,252	771,252	771,216	771,252

Note: * p<0.1, ** p<0.05 and *** p<0.01. Bootstrap standard deviation clustered by micro region in parenthesis. The regressions have the same explanatory variables and fixed effects as the specification in the last column of Table 6, except for control variables at the individual level. Average refers to the average of the dependent variable. Joint test displays the p-value of a joint significance test of dengue in the three trimesters of gestation. CF p-value refers to the p-value about the statistical significance of the control function. Estimations are weighted by municipality number of births per month.

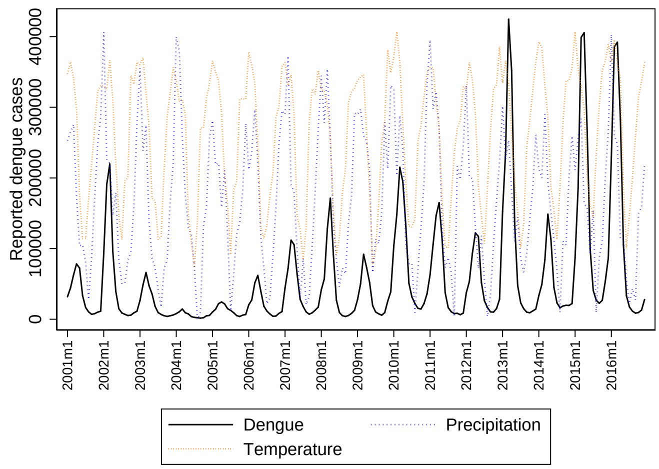
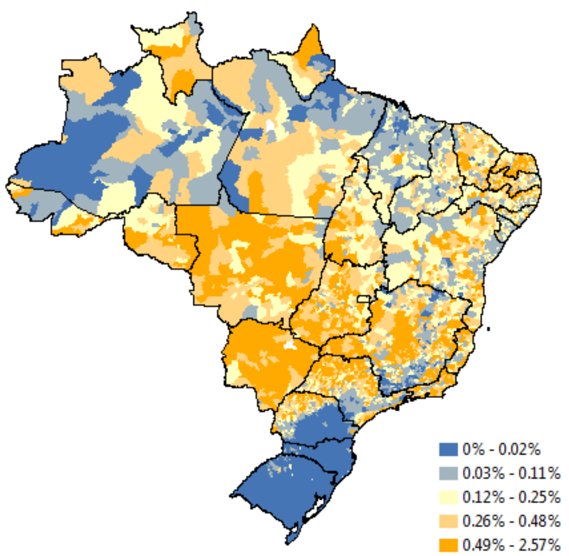
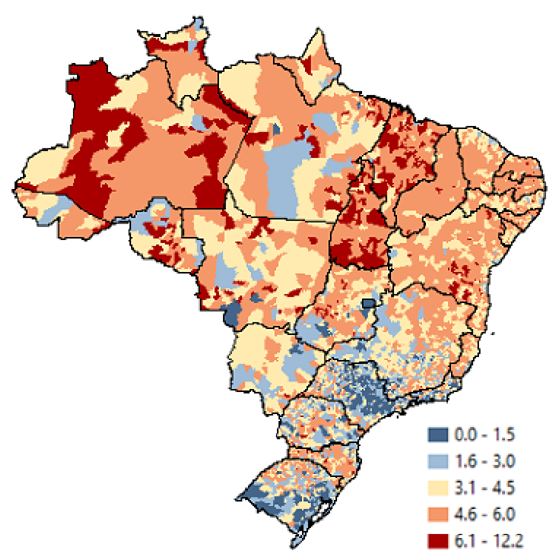


Figure 1: Times series of dengue profile in Brazil.

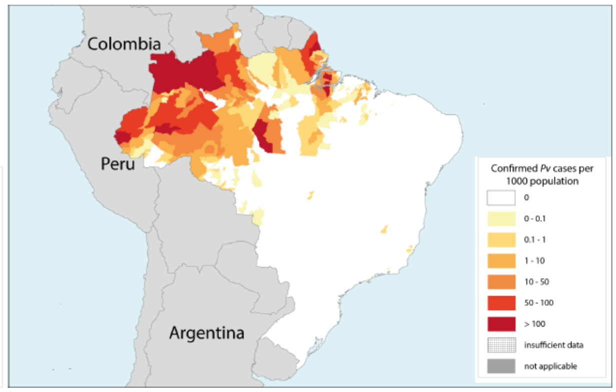


(a) Average from 2001 to 2015 of yearly infection rate (as % of the population).

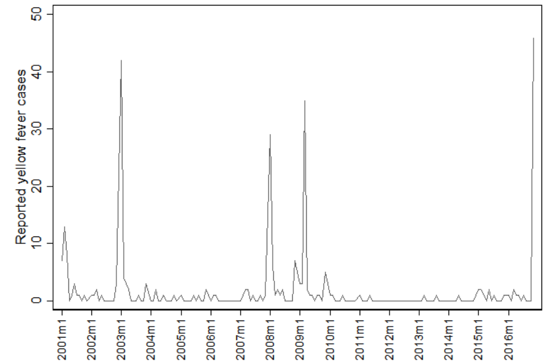


(b) Average from 2001 to 2015 of annual per capita ACS funds transferred in dollars.

Figure 2: Municipalities distribution of dengue cases and health agents.



(a) Areas with confirmed malaria cases in Brazil, major plasmodium: P.vivax.
Source: World Malaria Report (World Health Organization, 2018).



(b) Month yellow fever reported cases.

Figure 3: Malaria map and yellow fever time series.

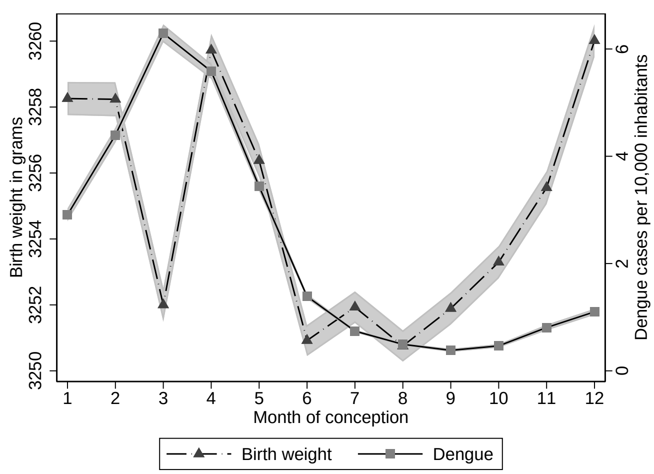


Figure 4: Monthly average dengue cases and birth weight.