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Impacts of Climate Change on Dengue Risk in Brazil

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IMPACTS OF CLIMATE CHANGE ON DENGUE RISK IN BRAZIL

Paula C. Pereda, Tatiane A. de Menezes and Denisard Alves

Abstract

Climate-sensitive health problems kill millions of people every year and undermine the physical and psychological well-being of millions more. In the case of infectious diseases such dengue fever, climate conditions affect the vectors' survival and reproduction and consequently the transmission of the disease. In order to identify the climate impacts on dengue risk in Brazil, a comparative case study is used based on the synthetic controls approach. The South and Northeast regions of Brazil are compared to the rest of the country in order to identify those impacts. The results suggest that the increase in temperature and humidity in temperate regions (South of the country) will increase the incidence of dengue in the region. On the other hand, the increase in rainfall in the tropical areas (Northeast) could diminish the disease's prevalence as standing water accumulations might be washed away. Therefore, due to the expected climatic changes in the future, the dengue fever distribution in the country might change, with the disease migrating to the south. The public policy's role in minimizing these effects in the country is mainly focused on integrated actions.

JEL Classification: I18 - Government Policy; Regulation; Public Health, Q54 - Climate; Natural Disasters; Global Warming.

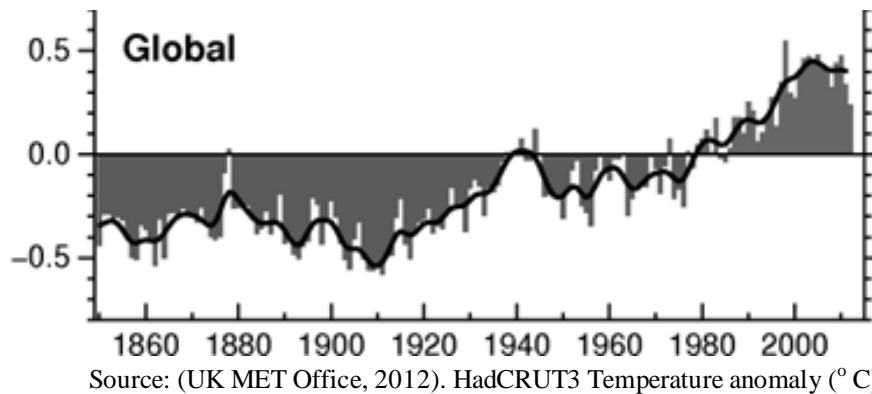
Keywords: dengue fever, synthetic control method, climate change impacts on health.

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1. Introduction

The observation of historical annual temperature values (and anomalies) from 1860 to 2006 supports the idea of climate evolution during the last 150 years (UK MET Office, 2012). Figure 1 indicates a rising trend in average temperature during the period. From 2000 to 2005, the average temperature was 0.48 °C above the long-term average; and 2005 was the second warmest year of the whole sample.

Figure 1 - Temperature deviation from long-term average in degrees Celsius (°C), 1860 to 2006.



Trends from 1900 to 2005 have also been observed in precipitation (IPCC, 2007). In South America, an increase in rainfall is observed for the eastern areas of the region. There is also evidence of an increase in extreme event frequency, such as droughts, floods, heat and cold waves, hurricanes and other storms (IPCC, 2001). Thus, the current climate change discussion is no longer about the existence of the phenomenon, but rather the magnitude of its longer term impacts and efficient adaptation measures.

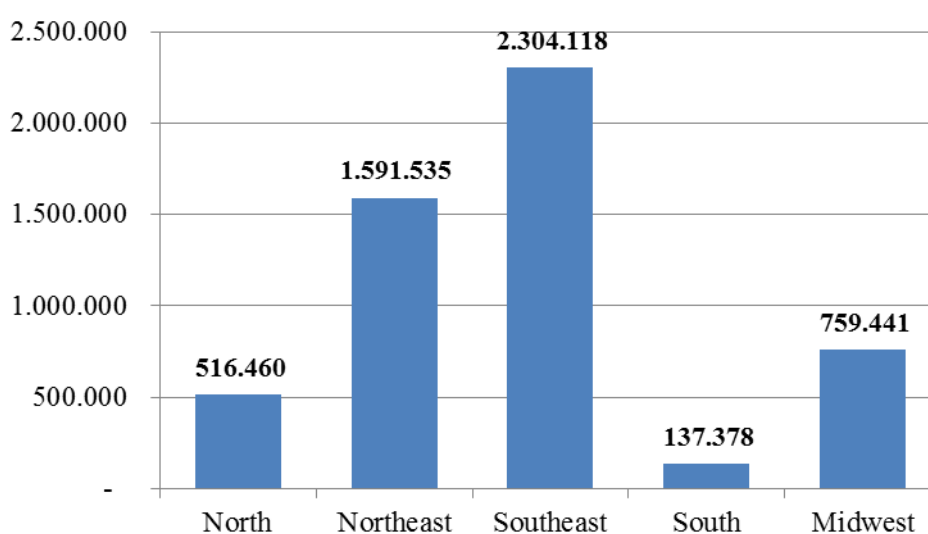
According to the World Health Organization (WHO), climate-sensitive health problems kill millions of people every year and undermine the physical and psychological health of millions more (WHO, 2012). In the particular case of vector-borne diseases, climate conditions assure the vectors' survival and reproduction and, consequently, the transmission of the diseases (Kelly-Hope and Thomson, 2008). Increases in heat, precipitation, and changes in humidity can allow insects to move from regions where infectious diseases thrive into new places.

The vector-borne disease analyzed by this paper is dengue fever. In Latin America, it is the most harmful infectious disease and it is considered an emerging mosquito-borne disease that is a major public health concern in Brazil. Dengue is transmitted to humans by

female *Aedes aegypti* mosquitoes, with high transmission rates throughout the day and night in urban areas. The cycle, reproduction and survival of mosquitoes are highly dependent on weather conditions – humid and warm environments – and the accumulation of water is necessary for the reproduction and spread of the mosquito population.

In Brazil, dengue has high annual incidence. According to the Ministry of Health's Information System for Disease Notification (MS/SINAN)¹, there were 5.3 million dengue fever notifications in Brazil between 2002 and 2013 (until September of 2013), regionally distributed as shown in Figure 2.

Figure 2 - Annual dengue Incidence, by region, 2001 to 2013^[1].



Source: Notifications of Dengue, Brazilian Ministry of Health's Information System for Disease Notification (MS/SINAN)

^[1] 2013 data from January to September.

In 2010, for example, a spate of dengue fever outbreaks occurred and almost one million cases of the disease were notified in the country. Due to the importance of the disease in Brazil, the goal of this study is to identify the climate relevance to dengue in the country in order to measure the impact of climate change on dengue risk, and to discuss the potential role of public policy in minimizing those effects in the country. The government influence in terms of public policy is mainly determined by the surveillance expenditures and sanitation measures (both urban infrastructure problems controlled by local governments, with federal and state support), by the type of housing, educational measures,

¹ SINAN is a national system for notification and investigation of diseases, in existence since 2001.

and by assuring the health assistance of the people affected by such diseases (availability of hospital beds, health expenditures).

In order to identify the climate impacts on dengue risk, a comparative case study is used, based on the comparison of cities that experienced specific climate conditions that increased the risk of dengue with cities whose climate conditions stayed the same (Section 2). The counterfactual is based on the synthetic controls approach, which generates control groups as a combination of units not exposed to the intervention (Abadie and Gardeazabal, 2003; extended by Abadie et al., 2010). Thus, the synthetic control is a weighted average of the available control units, which sum to one. As Brazil is a geographically large country subject to many climate patterns, there are many possibilities to obtain good control groups by using this methodology (Sections 4 and 5). Once the effect is identified, climate change simulations can be done in order to predict the expected effects of the changes in climate on the dengue fever spread in the country (Section 6).

2. Basic Model

Cavallo et al. (2010) analyzed the effect of natural disasters – such as floods, hurricanes and earthquakes – on countries' GDP in the short and long run. Following Abadie and Gardeazabal (2003) and Abadie et al. (2010), the authors performed a comparative analysis of countries from the construction of an appropriate counterfactual – a group of synthetic controls.

In this paper we apply a similar strategy to that of Cavallo et al. (2010) by trying to measure the consequences of global warming, an exogenous variable, on dengue incidence. Actually, the exogenous climate characteristics permit us to build a synthetic control using the cities where a strong impact of global warming cannot be observed.

According to Abadie and Gardeazabal (2003), Abadie et al. (2010) and Cavallo et al. (2010), a quasi-experimental design of this type is preferable to conventional methods for some reasons, such as the ability to explore the variability of the municipal rate of dengue fever using a time series model. However, this ignores the fact that the magnitude of mosquito proliferation can be different between regions. An alternative would be to control for the unobservable characteristics of city fixed effects, but this would lead to

extrapolations, since this model requires constant effects over time. Finally, the use of a difference-in-difference model would be inappropriate due to use of macro data as variables in the model.

One of the main determinants of dengue incidence is environmental features (Barcellos et al., 2009), dominated by the importance of climate on the incidence of dengue, as outlined previously. The relevant climate conditions for the dengue vectors' survival and reproduction are: average temperature not too low or high, sufficient humidity to regulate the temperature of mosquitoes, and a reasonable amount of precipitation for the deposition of eggs. Regarding the amount of rainfall, it is believed that large amounts of rain may have a reverse effect, since this can wash away standing water accumulations, reducing the number of surviving larvae.

The method to identify the climate impact on the health problem proposed is based on the comparison of areas affected and not affected by the climatic events considered to aggravate risk. When it comes to dengue, the Brazilian region so far not affected by dengue, as identified by Pereda (2012), is the South of the country. Hence, this area can be a target area in terms of the identification of climate impact on dengue.

Thus, the identification strategy will be to estimate the increase in dengue risk due to a warmer than average summer in those regions (or an extreme event observed in the mapped area). Cities that showed a deviation from the abovementioned climate conditions will be analyzed as the treatment group/city. As the cities cannot be observed in the situation of treated and non-treated simultaneously, the first step in assessing the impact of the climate event on the health problem is the construction of a counterfactual for evolution of this phenomenon. There is only one figure available very year with respect to the climate variable, dengue incidence and infrastructure and socioeconomic information.

Under such conditions, we employ the strategy of building a synthetic control variable according to the proposal of Abadie and Gardeazabal (2003), and extended by Abadie et al. (2010), to estimate the impact of climate on dengue fever incidence. A brief summary of this strategy starts with the recognition of the data structure necessary for the method. In this sense, consider the existence of a panel data set with observations for a range of cities $I_c + 1$ for a period of T years, in which I_c corresponds to the number of untreated cities considered. Assume also that the climate event is observed in year T_0 $1 \leq T_0 < T$, only in the city which is focus of evaluation. Suppose that Y_{it}^I and Y_{it}^N ,

respectively, denote the value of the focus variable of the evaluation (dengue incidence risk) in city i with and without the climate event. The aim is to obtain estimates for:

$$\tau_{it} = Y_{it}^I - Y_{it}^N = Y_{it} - Y_{it}^N, \text{ for } t > T_0 \quad (1)$$

In which $Y_{it}^I = Y_{it}$, since these are observed values.

Therefore, the aim is to estimate the values of Y_{it}^N from other I_c cities. In this sense, Abadie *et al* (2010) assume that such values are generated from a model of the type:

$$Y_{jt}^N = \delta_t + \theta_t Z_j + \gamma_t \mu_j + \varepsilon_{jt} \quad (2)$$

In which j indexes the I_c cities that did not undergo the climate event, δ_t is a unknown factor, common to the cities, Z_j is a vector of observed variables not affected by the event and θ_t is its parameter vector, μ_j is a specific effect vector of the city j and γ_t its unknown parameter vector, and ε_{jt} represents the unobserved random error.

This strategy aims to find a vector w^* , among the weight vector W ($I_c \times I$), $(w_1, w_2, \dots, w_{I_c})'$, in which $w_j \geq 0$ and $\sum_{j=1}^{I_c} w_j = 1$, such that:

$$\sum_{j=1}^{I_c} w_j^* Y_{jt} = Y_{it}, \text{ for } 1 \leq t \leq T_0, \text{ and } \sum_{j=1}^{I_c} w_j^* Z_j = Z_i \quad (3)$$

In other words, a vector is obtained that weights the dependent variables of the cities that did not experience the climate event in the period before the event and the observed independent variables of these cities in a way to obtain the dependent variable value of the treated city i in each period and the observed independent variables of this city. This vector represents a weighting structure of cities and corresponds to the untreated synthetic control city i , which observed the climate event.

Abadie *et al.* (2010) show that, under standard conditions, the expected value of $Y_{it}^N - \sum_{j=1}^{I_c} w_j^* Y_{jt}$, i.e, of the difference between the variable of interest from city I , that underwent the climate event for the period without this occurrence, and the weighted sum (using vector W^*) values of the cities without the climate event, is zero. Thus, $\sum_{j=1}^{I_c} w_j^* Y_{jt}$ is an unbiased estimator of Y_{it}^N . Estimates of the climate impact in city i in the periods after the climate event can be obtained by the following difference:

$$\hat{\tau}_{it} = Y_{it} - \sum_{j=1}^{I_c} w_j^* Y_{jt}, \text{ for } t > T_0 \quad (4)$$

In general, the conditions in (3) do not tend to be fully applied. Thus, the synthetic control represented by the weighting vector w^* is chosen so that these conditions are approximately assumed.

An interesting and useful aspect of this strategy is the fact that, unlike traditional applications of the difference-in-difference approach (where no specific control for the influence of units/cities varies in time), the model of equation (2), from the parameter γ_t , allows unobserved specific effects to vary in time. This stems from the fact that the conditions for a synthetic control satisfy the conditions in (3) only if the prevailing conditions $\sum_{j=1}^{Ic} w_j^* Z_j = Z_t$ e $\sum_{j=1}^{Ic} w_j^* \mu_j = \mu_t$ are approximately true (Abadie et al., 2010).

The calculation of the synthetic control (using the weighting vector W^*) involves the minimization of the distance measure between the values of the city variables, impacted by climate, X_1 (variable vector), and the same set of variables for cities that did not undergo the event in the same period weighted by W ($X_0 W$, vector of weighted variables): $\sqrt{(X_1 - X_0 W) \cdot V (X_1 - X_0 W)}$, where V is a positive semi-definite symmetric matrix affecting the Mean Squared Error Estimator (MSEE). We follow Abadie et al. (2003), choosing V so that the variable's MSEE (health risk variable) is minimized in the period before the event.

Finally, inferences can be made using results of placebos, which correspond to the evidence found from the application of the method over the cities considered as controls. The idea is to get results of false events/interventions for each of the considered cities in the same year of the event, generating a set of trajectories for the cities in relation to their alleged synthetic controls, which serve as comparison to the trajectory initially obtained for the city of interest.

Besides greater control for the influence of unobserved variables, the strategy of using synthetic control has other advantages over the non-experimental methods. Among these, it is possible to highlight the possibility of still drawing inferences when only one treated value is observed. In addition to that, the method only uses information about the period before the event, so the choice of control is not related to any direct results. Finally, there is transparency in the control choice, since the method involves consideration of the similarities of variables from the period before the event.

3. Data Sources and Description

This study uses annual municipal-level panel data for the period 2001-2010. The following table presents the description of data and sources used to gather the information:

Table 1 - General variables and sources

Variable(s)	Source	Description
<i>Observed climate data</i>	Brazilian Meteorology Institute (INMET)	Average temperature, average relative humidity and accumulated rainfall (in millimeters) per month by weather station from INMET. All data were transformed to municipalities by season ^[1,2] .
<i>Climate change projections</i>	Department for Weather Forecasting and Climate Studies (CPTEC/INPE)	Predictions of average temperature, relative humidity and rainfall are performed using three models run by INPE and the IPCC scenarios of emissions from 2040 to 2069 ^[3] .
<i>Dengue fever notifications</i>	Database of the National Public Health System (DATASUS)	Contains all notified cases of dengue in the year by municipality of residence reported and stratified by age or income.
<i>Socioeconomic data</i>	National Household Survey (PNAD)	Overall population characteristics: education, labor, income and housing, among other socioeconomic data (migration, fertility, health, food security, and other topics).

^[1] Brazil's network of weather stations covers much of the coast. To transform the data from the weather stations into municipal data, we used the kriging method of spatial interpolation (Haas, 1990), which allows the interpolation of data with flexibility to specify the covariance between the outputs.

^[2] The local political unit in Brazil is the municipality, which is similar to a county, except there is a single mayor and municipal council. There are no unincorporated areas in Brazil.

^[3] CPTEC/INPE uses regional models, which downscale the global models (HadRM3P Model; Eta/CPTEC Model; and RegCM3 Model). Correlation anomalies among the models are calculated in order to detect consistent signals for the predictions. The output of the models is an average of the combined results from three forecasting model. This is called the "multi-model ensemble technique" (UK MET Office, 2012).

In order to have the most wide-ranging dataset for the socioeconomic variables evolution, the data needed to be aggregated into the 27 capital cities of the Brazilian states, to enable using the sample from the yearly National Household Survey, which provides the most complete data about the country. The climate among these cities differs significantly. Table 2 shows that the temperatures in Brazil are typically very high, especially in the northern region. On the other hand, the south of Brazil has lower temperatures (and occasional frosts and brief snowfalls during the winter). The North region's cities are rainier, reaching approximately 3,000 mm of precipitation per year. The rainy season also lasts longer in this region, contrasting with the climate of the neighboring region, the Northeast, which has the highest temperatures and driest seasons in the country. The Table 3 shows the mean of the socioeconomic variables for the period 2001-2010, by Brazilian capital.

Table 2 - Climate description, seasonal long-term average (1980-2009), by capital city of Brazilian states^[1].

Capital cities	Altitude (in meters)	Average Temperature DJF	Average Temperature MAM	Average Temperature JJA	Average Temperature SON	Average Rel. Humidity DJF	Average Rel. Humidity MAM	Average Rel. Humidity JJA	Average Rel. Humidity SON	Avg. Monthly Precipitaion DJF	Avg. Monthly Precipitaion MAM	Avg. Monthly Precipitaion JJA	Avg. Monthly Precipitaion SON	
North	Porto Velho	85	25.53	24.91	23.97	25.66	87.92	86.22	75.02	78.14	262.34	229.05	85.43	147.55
	Rio Branco	153	25.47	24.89	23.51	25.55	89.91	87.65	76.10	79.89	276.60	195.86	45.59	145.58
	Manaus	92	26.32	26.32	26.78	27.48	86.84	86.32	75.21	76.77	264.25	276.56	86.62	107.58
	Boa Vista	85	27.72	27.82	27.31	28.88	85.57	85.52	76.93	76.00	88.79	203.56	274.41	84.07
	Belém	10	26.23	26.21	26.40	26.95	84.95	86.51	78.21	76.94	203.09	252.86	100.99	58.75
	Macapá	16	26.60	26.56	27.05	28.29	83.98	86.20	77.34	72.92	255.45	312.08	161.69	41.77
	Palmas	230	25.61	25.77	25.15	26.73	82.28	80.28	62.70	70.32	269.57	180.87	7.95	136.85
Northeast	São Luís	24	26.65	26.34	26.42	27.30	80.75	84.92	78.23	73.74	207.39	378.66	113.81	13.41
	Teresina	72	26.67	26.19	26.28	28.13	76.27	81.35	67.73	61.34	186.11	231.33	17.22	21.96
	Fortaleza	21	26.95	26.54	26.28	27.41	75.13	80.22	72.24	68.43	127.54	312.25	85.20	10.86
	Natal	30	26.81	26.43	25.09	26.50	74.29	79.30	75.93	71.80	81.93	208.88	235.38	23.92
	João Pessoa	47	26.92	26.33	24.85	26.35	72.97	77.57	78.11	71.51	82.90	219.92	262.34	34.40
	Recife	4	26.64	26.07	24.32	25.76	73.67	79.37	80.50	73.30	98.99	229.16	291.68	44.52
	Maceió	16	25.71	25.14	23.16	24.74	73.31	77.45	77.15	71.27	71.87	193.34	240.59	50.50
	Aracaju	4	26.19	25.70	23.73	25.29	74.88	77.58	75.84	72.46	62.55	148.50	143.44	49.24
	Salvador	8	25.92	25.21	23.02	24.80	76.61	79.82	77.11	74.06	94.57	206.55	172.77	80.65
Southeast	Belo Horizonte	858	23.20	21.68	18.65	21.96	75.65	74.45	68.21	68.47	274.28	90.71	10.06	125.94
	Vitória	3	25.48	23.94	20.90	23.15	75.65	77.12	74.23	73.65	149.47	108.42	52.13	121.89
	Rio de Janeiro	2	24.35	22.30	18.66	21.42	76.93	78.52	75.53	74.51	176.69	134.24	78.50	139.69
	São Paulo	760	22.65	20.29	16.67	19.65	77.03	77.41	73.18	74.14	240.05	119.26	42.58	121.47
South	Curitiba	934	21.21	18.06	14.00	17.28	81.09	83.14	80.33	80.31	172.03	114.94	72.32	147.55
	Florianópolis	3	23.46	20.77	15.73	19.59	78.84	79.58	78.56	77.04	188.66	137.57	61.64	164.06
	Porto Alegre	3	23.58	19.91	14.35	18.98	74.48	77.58	77.28	73.47	121.72	106.59	119.75	146.98
Midwest	Campo Grande	532	24.23	22.19	19.01	22.47	80.45	79.73	72.10	73.36	210.62	121.91	50.00	136.75
	Cuiabá	176	25.87	24.93	22.77	25.88	82.94	82.17	72.41	74.38	221.14	112.11	16.86	113.66
	Goiânia	749	24.08	23.73	22.09	24.77	75.90	70.59	53.68	62.77	251.98	136.95	8.08	131.00
	Brasília	1,171	21.86	21.17	19.48	22.10	77.69	73.71	55.60	64.55	226.16	122.72	10.80	125.38

^[1] Temperatures are measured in degrees Celsius, precipitation in millimeters, and humidity in percentage. Label of the periods:

DJF: December, January and February (summer);

MAM: March, April and May (fall);

JJA: June, July and August (winter);

SON: September, October and November (spring);

Table 3 - Descriptive variables from SINAN and PNAD, mean from 2001 to 2010, by the capital city of Brazilian states. Number of rooms in each household

Capital cities	Dengue cases per 100.000 habitants	Population of the city	% women in the city	Average Age, in years	% white and yellow people in the population	Years of schooling	Monthly real income, main job	Monthly per capita real income	% people working with agriculture	% people working at industry	% people working at service sector	% housesold with piped water in at least 1 room	% household which own bathroom	Number of rooms in the household	% roof material: tile or concrete slab	% households connected to the sewage system
<i>Porto Velho</i>	323.47	373,973	51.18	27.32	31.62	6.17	954	638	2.09	9.05	19.58	86.65	97.41	5.63	99.16	11.21
<i>Rio Branco</i>	1,937.11	294,369	51.75	26.67	28.27	5.72	885	656	4.81	6.86	18.89	71.48	93.36	5.13	93.09	50.61
<i>Manaus</i>	244.61	1,629,011	51.40	26.37	27.71	6.11	781	495	0.97	11.66	19.31	87.02	96.26	5.02	94.16	21.45
<i>Boa Vista</i>	990.84	243,423	50.28	24.85	24.00	5.65	737	503	3.28	7.14	17.89	91.47	97.16	4.92	99.46	17.65
<i>Belém</i>	152.01	1,385,389	52.64	29.59	28.45	6.50	718	528	1.45	7.69	23.00	91.20	96.78	5.25	98.27	39.96
<i>Macapá</i>	545.90	343,934	50.02	25.53	24.37	5.97	794	494	1.80	6.69	17.15	89.03	97.74	5.14	98.06	5.78
<i>Palmas</i>	950.13	188,026	51.79	25.73	34.28	6.88	981	760	2.56	8.81	20.32	96.99	98.10	5.80	99.15	42.50
<i>São Luís</i>	124.58	961,183	52.99	27.98	28.89	6.77	774	531	1.39	7.74	20.91	86.99	91.41	5.75	97.59	51.73
<i>Teresina</i>	312.04	777,789	54.56	29.68	25.34	6.25	669	566	2.79	8.13	24.20	92.11	93.82	6.49	98.99	14.71
<i>Fortaleza</i>	464.72	2,364,697	53.44	29.48	37.93	6.27	715	534	1.11	10.13	21.88	95.29	98.17	6.07	99.66	57.79
<i>Natal</i>	905.98	771,770	52.42	30.23	42.11	6.36	768	623	1.47	8.36	23.38	97.08	98.82	6.14	99.71	23.91
<i>João Pessoa</i>	120.34	663,121	52.65	29.88	42.77	6.10	807	656	1.26	7.86	21.01	97.99	98.97	6.39	99.75	49.12
<i>Recife</i>	364.93	1,503,350	53.90	31.44	40.26	6.58	863	629	0.94	6.14	21.27	95.16	97.80	6.07	98.27	51.34
<i>Maceió</i>	521.22	890,085	53.42	28.78	39.73	5.43	762	524	1.13	6.54	19.62	95.61	98.00	5.82	98.22	28.35
<i>Aracaju</i>	287.26	509,013	52.85	29.82	30.99	6.68	845	672	1.37	7.43	21.80	97.89	99.16	6.72	99.05	80.70
<i>Salvador</i>	176.09	2,709,711	53.12	30.01	18.83	6.75	768	598	1.03	8.16	24.69	97.58	98.29	5.67	98.49	87.44
<i>Belo Horizonte</i>	395.93	2,365,030	53.13	32.74	48.82	7.44	1,148	935	1.18	10.04	22.91	99.62	99.69	6.83	99.44	97.45
<i>Vitória</i>	720.91	311,772	52.81	33.86	49.26	8.38	1,390	1,178	0.87	8.55	21.54	99.28	99.26	7.09	99.22	94.16
<i>Rio de Janeiro</i>	544.30	6,085,273	53.91	36.03	61.43	7.63	1,241	976	0.84	7.19	22.50	99.38	99.61	5.77	99.37	93.28
<i>São Paulo</i>	19.96	10,900,000	52.81	32.48	65.69	7.17	1,289	909	0.85	10.60	22.48	99.12	99.40	5.67	99.03	89.30
<i>Curitiba</i>	3.28	1,743,811	52.31	32.36	82.00	7.67	1,253	1,027	1.35	11.49	23.78	99.48	99.46	6.87	98.65	91.33
<i>Florianópolis</i>	3.37	390,083	51.77	33.49	88.15	8.24	1,375	1,149	0.84	6.89	21.19	99.30	99.70	6.93	96.66	59.05
<i>Porto Alegre</i>	2.20	1,413,321	54.08	34.57	80.80	7.95	1,363	1,152	1.07	7.47	22.42	98.61	98.56	6.20	97.20	88.26
<i>Campo Grande</i>	1,323.64	734,060	51.59	30.66	52.53	6.57	997	767	2.46	9.25	24.77	98.20	99.69	6.26	97.41	24.34
<i>Cuiabá</i>	429.41	527,589	51.90	30.13	37.27	7.11	1,078	792	2.13	7.71	22.86	93.26	97.03	6.14	96.38	60.93
<i>Goiânia</i>	1,159.33	1,208,387	52.95	31.04	51.98	7.16	1,052	838	1.47	11.07	25.33	98.45	99.35	6.40	99.33	78.14
<i>Brasília</i>	102.16	2,362,212	52.81	28.73	43.54	7.11	1,566	1,139	1.05	5.50	20.71	98.35	99.48	6.40	98.99	84.50

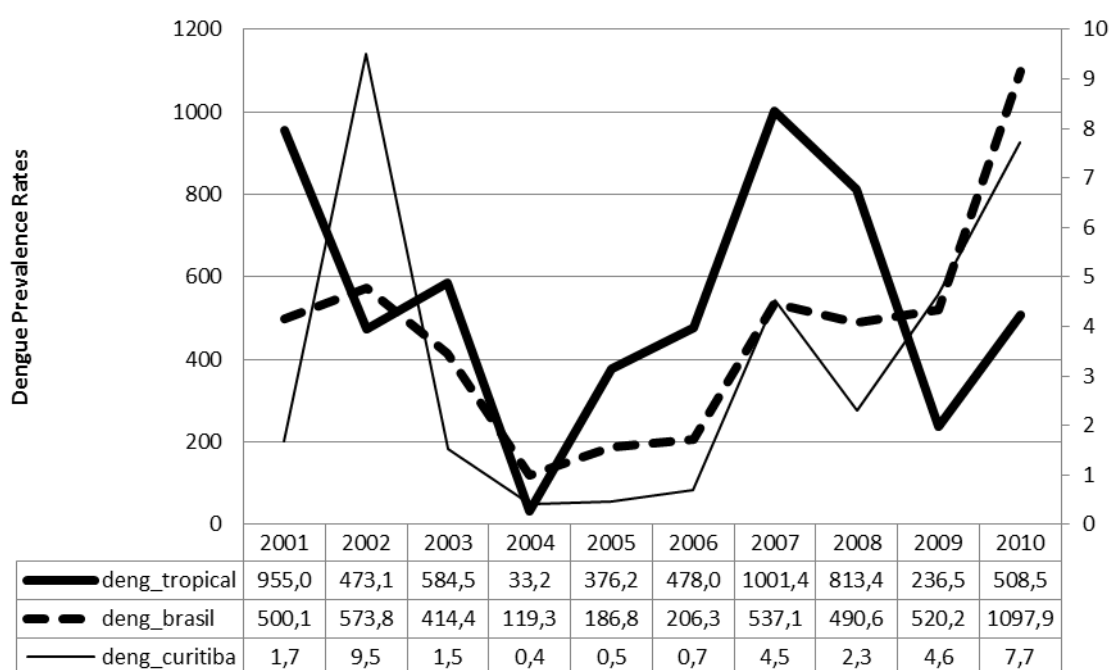
Table 3 shows some important differences among the Brazilian cities selected for the study. Cities of the South region show less dengue incidence than the cities of other regions, but have better average socioeconomic indicators, such as household income and infrastructure. The next section discusses some of these differences in order to select the cities of the treatment and control groups.

4. Empirical Strategy

Brazil's large dimension allows us to observe the effect of climate increase in cities with climates ranging from tropical (North) to temperate (South). The Brazilian states with the warmest capital cities among those in tropical areas are Maranhão, Piauí, Ceará, Rio Grande do Norte and Tocantins (respective capitals are Sao Luis, Teresina, Fortaleza, Natal and Palmas)². Among the temperate cities, Curitiba, capital of Paraná, has the highest relative temperature.

Besides the prevailing weather, the prevalence of dengue varies in Brazil between cities and time. Figure 3 shows the dengue prevalence rates for three groups of cities: the tropical capitals, the temperate city Curitiba and the entire country.

Figure 3 - Dengue prevalence rates for tree groups of cities: tropical, Curitiba and Brazil



² See Appendix A for details about the capital cities of the Brazilian states.

Figure 3 indicates the varied distribution of dengue among Brazilian cities. The temperate city Curitiba is too cold and dry to permit the mosquitoes to survive in large numbers. This city has natural protection against dengue, reflected in an average of just 4 cases in 100,000 inhabitants for 2001 to 2010. On the other hand, the tropical cities are warm and humid, perfect for mosquito reproduction. In this region, dengue prevalence averages 546 cases per 100,000 inhabitants. Figure 3 also indicates that for the three groups, dengue prevalence fell until 2004 when it increased again until 2008. In that year, the three groups had different movements. In tropical cities, the disease prevalence decreased, in Curitiba it increased and in Brazil as a whole there was virtually no change.

The year 2008 was marked by heavy rainfall in most Brazilian cities. Figures 4, 5, 6 and 7 present the cities' precipitation pattern change. Figure 4 and 5 show that the rainfall grew sharply in all three capitals of the temperate South: Curitiba, Florianópolis and Porto Alegre. However, as can be seen by comparing Figure 5 and 6, the rainfall pattern changes only affected the average relative humidity in Curitiba. In the two other capitals in the South, Florianópolis and Porto Alegre, the average humidity did not change in 2008.

As discussed above, dengue is a disease whose vector is a mosquito that proliferates more easily in humid environments. One of the hypotheses tested in this paper is whether the stronger precipitation followed by an elevation in the levels of humidity had the effect of increasing the prevalence of dengue in Curitiba.

Figure 4 - Rainfall in Curitiba before and after 2008.

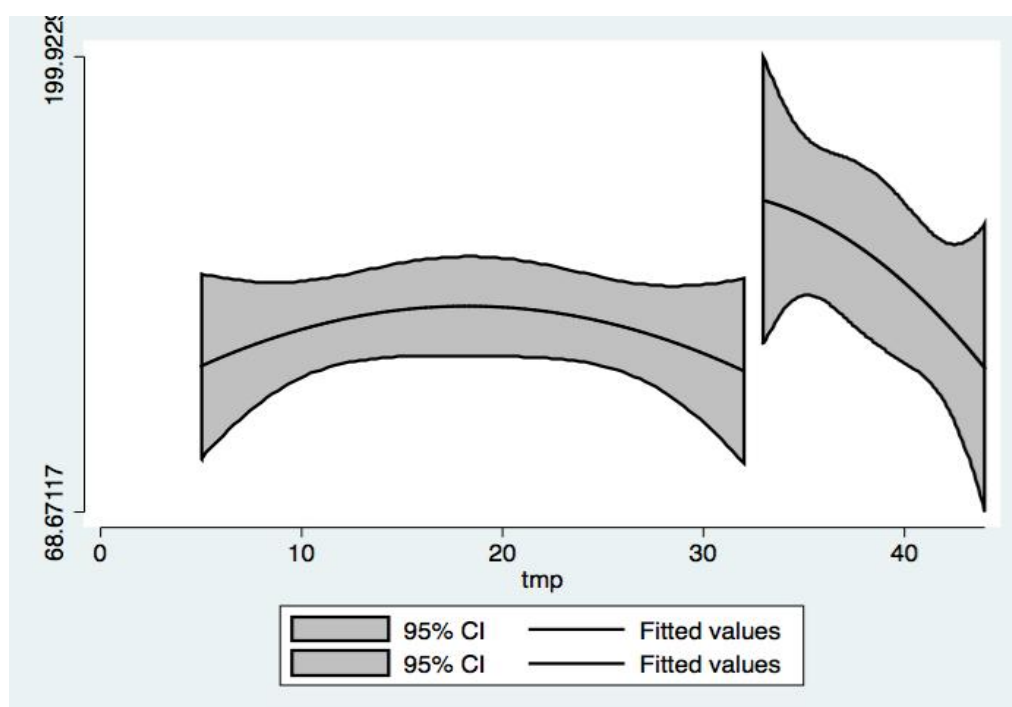


Figure 5 - Rainfall in others South capitals before and after 2008

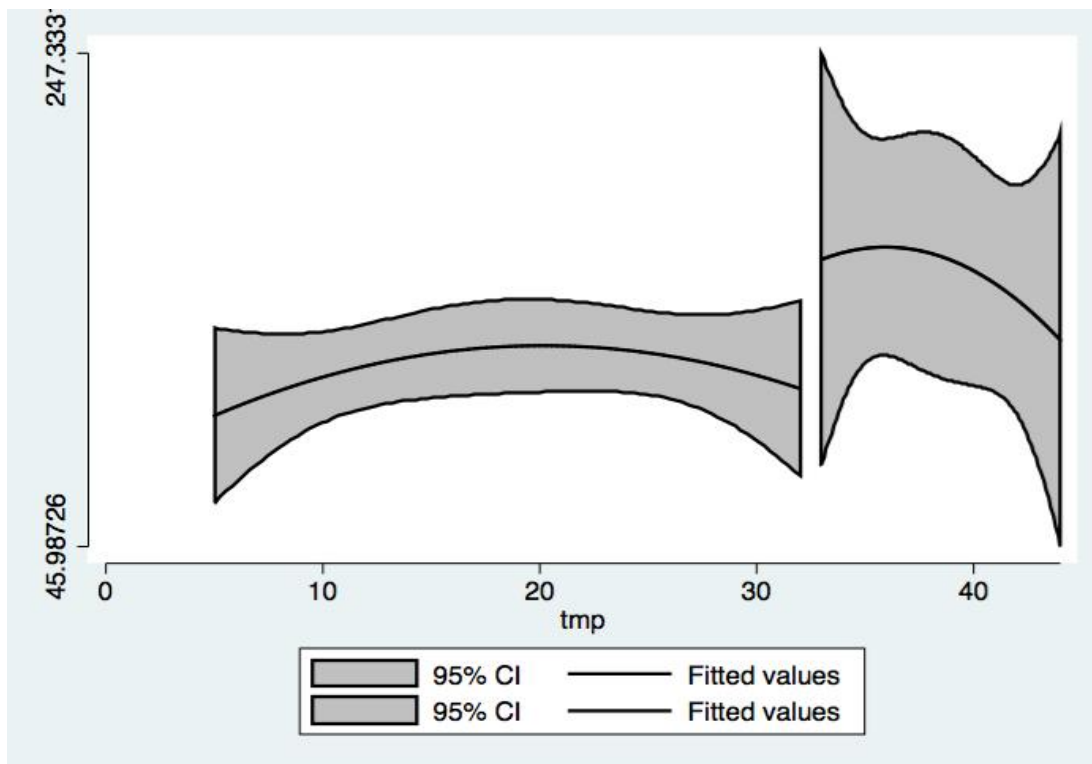


Figure 6 - Humidity in Curitiba before and after 2008

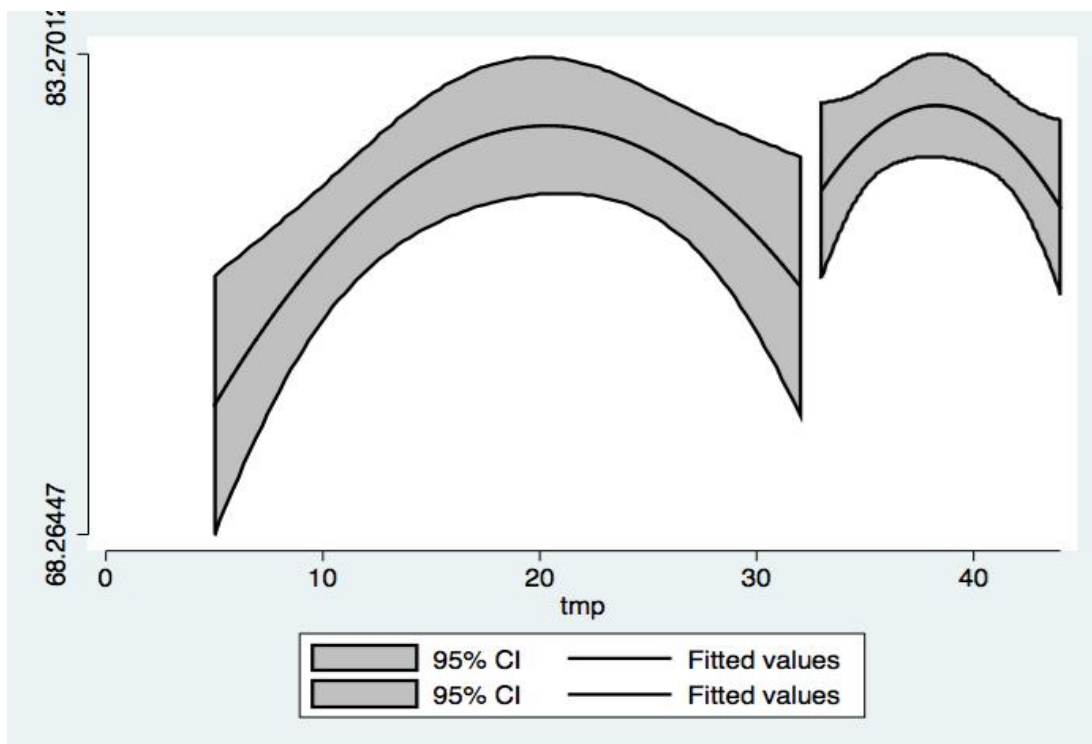
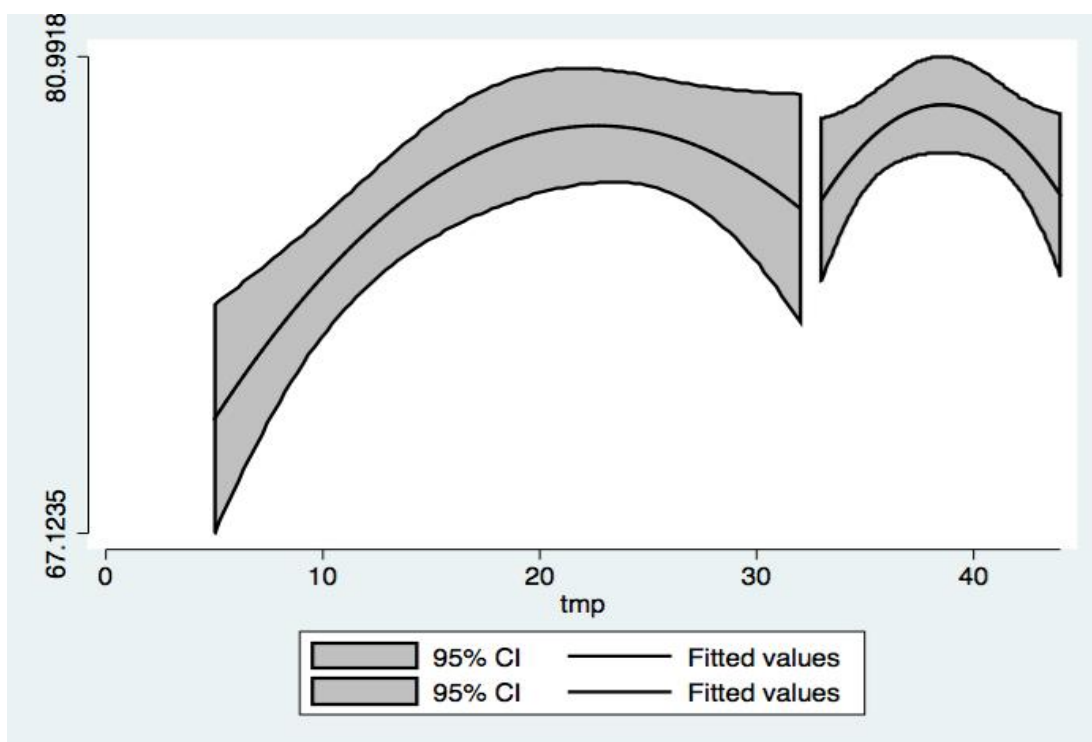


Figure 7 - Humidity in Florianopolis and Porto Alegre before and after 2008



Unlike the southern cities, which occupy temperate areas of the country, northeastern capitals have tropical weather. Despite the moderating factor of their location on the coast, their weather is still hot and humid, providing an ideal environment for *Aedes Aegypti* proliferation. It is no coincidence that the Brazilian cities with highest prevalence of dengue are mostly in this region (Figure 2). In 2008, the heavy rains that affected most of the country were more intense in warmer tropical capitals (Figure 8), respectively São Luis, Teresina, Fortaleza and Natal and Palmas. Figure 8 below describes the break in the average precipitation pattern of these cities. In 2008, the mean and the variance of the rainfall in these capitals increased in relation to the previous period. However, this phenomenon was not observed so sharply in the other Brazilian northeastern capitals (Figure 9): João Pessoa, Recife, Maceió, Aracaju and Salvador³.

³ See Table A.1 in Appendix A for details of the Brazilian states and their capital cities.

Figure 8 - Rainfall in the hottest Brazilian capitals: Tocantins, São Luis, Teresina, Natal and Fortaleza

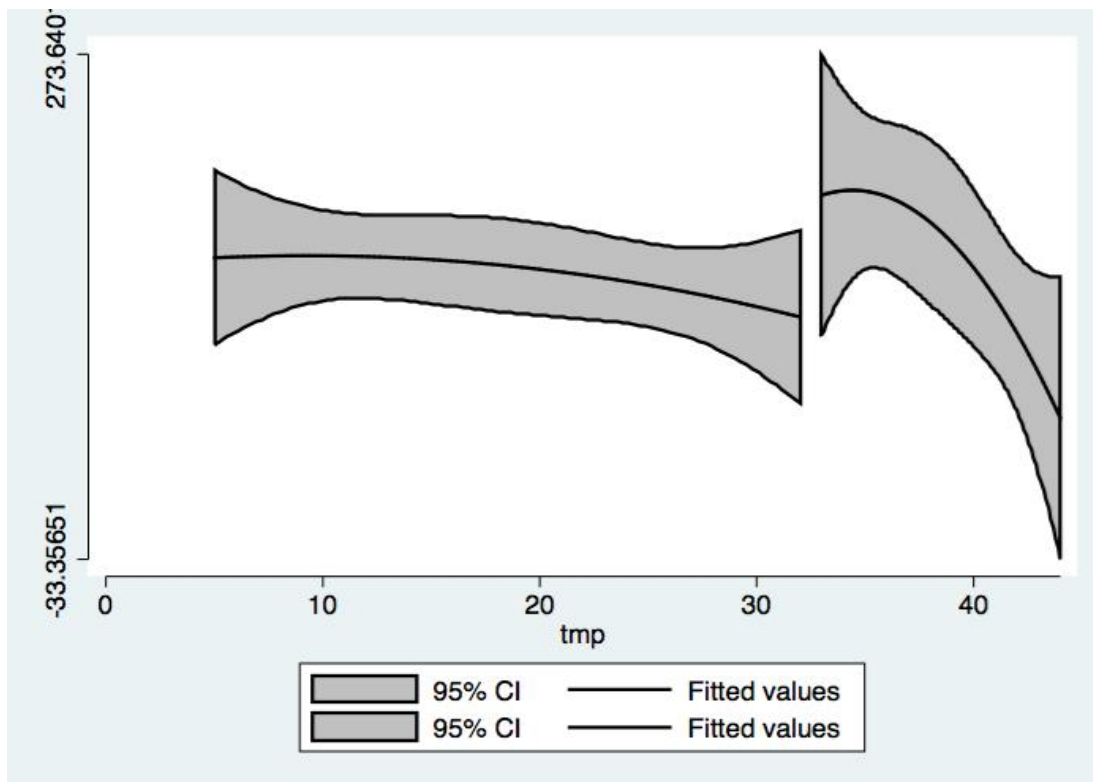
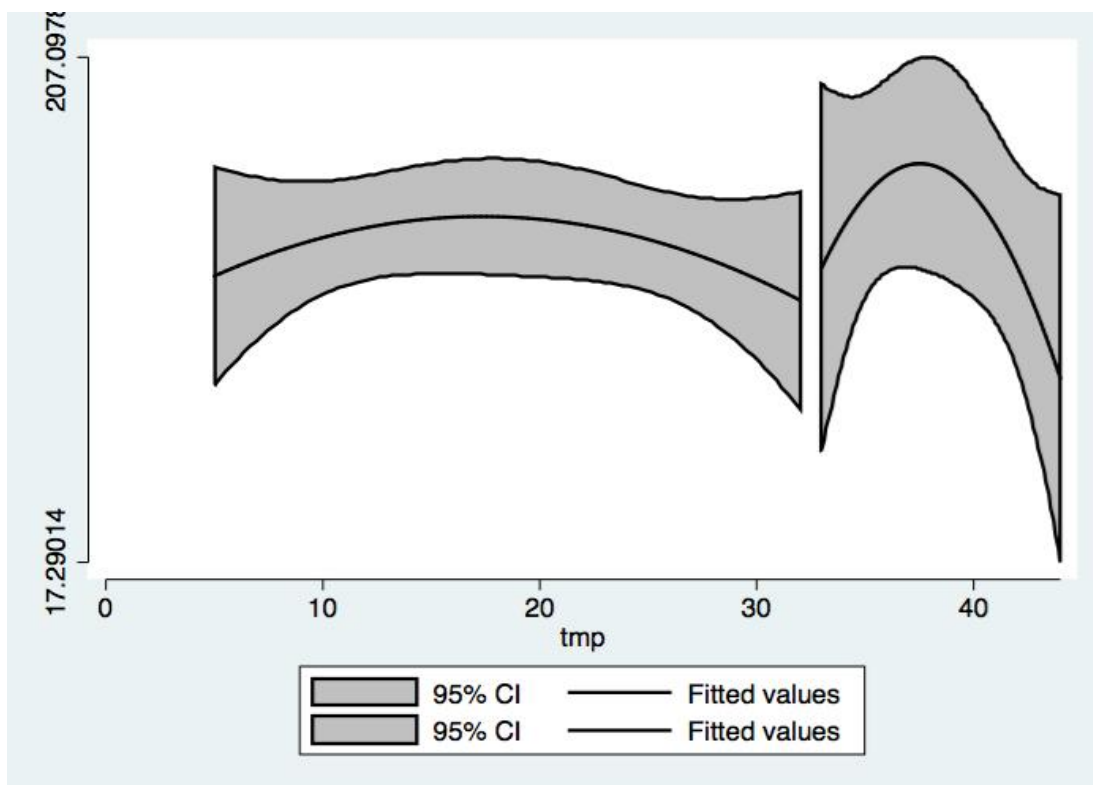


Figure 9 - Rainfall in the others Brazilian Northeast capitals: João Pessoa, Recife, Maceio, Aracaju and Salvador



The second hypothesis tested here is whether this increase in precipitation in areas where the conditions for mosquito survival were already ideal could have reduced the vector population and hence the disease prevalence in the respective cities.

To summarize, observing the average climate evolution in Brazil for the period 2001-2010, the rainfall in the warmest cities was above the historical average since 2007. Our hypothesis is that such high precipitation might have washed away standing water accumulations, reducing the number of larvae and therefore reducing the mosquito population and lowering the dengue prevalence in these tropical cities. On the other hand, in temperate cities, the higher humidity increased survival of mosquitoes, raising the risk of dengue in those regions.

Based on these hypotheses, recall that the synthetic group for each city is constructed as a weighted average of potential control states, with weights chosen so that the resulting synthetic cities best reproduce the values of a set of predictors of dengue before the temperature change. Because the synthetic group is meant to reproduce the dengue incidence that would have been observed for each city in the absence of temperature increase, we discarded from the sample the six cities mentioned above.

There is an emerging consensus on how to tackle a potential increase of dengue in new areas. Developing accurate models and surveillance to predict or detect disease outbreaks is central to this. Such systems will require both climate and disease data if they are to be rigorous enough to be reliable.

Using the techniques described at Section 3, a synthetic model was designed such that it mirrors the values of the predictors of dengue in Brazil's warmest and coldest cities before the temperature increase. The effect of increases in temperature on dengue is the difference in dengue case levels between each city and the corresponding synthetic versions in the years after the temperature increase. Placebo studies confirmed that the estimated effects for each city are unusually large relative to the distribution of the estimate obtained when the same analysis is applied to all cities in the sample.

5. Results

As explained above, from the convex combination of capital in the donor pool with greatest resemblance in terms of dengue prevalence predictors, we constructed the synthetic

controls for six capitals: Palmas, São Luis, Teresina, Fortaleza, Natal and Curitiba.

Tables 4a and 4b below highlight an important feature of synthetic control estimators. As describe in Abadie et al. (2010), similar to matching estimators, the synthetic control method forces the researcher to demonstrate the affinity between the cities exposed to the intervention of interest and the cities in the donor pool. As suggested by King and Zheng (2006), the synthetic control method safeguards against estimation of counterfactuals that fall far outside the convex hull of the data. The resulting value of the diagonal element described in section 3 associated to each logarithm of the per capita income variable is very high in all capitals, which indicates that, given the other variables in Tables 4a and 4b, log per capita income has substantial power in predicting the dengue rates in those cities before the change in rainfall pattern.

Table 4a - Dengue prevalence predictor means

	Palmas		São Luiz		Teresina	
	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic
Ln(income)	6.580	6.534	6.571	6.626	6.285	6.246
Rel. humid.	68.271	70.956	80.997	75.383		
Temperature	26.972	24.569	27.052	26.654	27.517	26.905
Dengue (2001)	951.805	936.292				
Dengue (2002)					612.494	535.972
Dengue (2003)			55.054	251.083		
Dengue (2004)			13.145	70.224		
Dengue (2005)	898.518	423.245	284.934	185.272		
Dengue (2006)			130.349	168.047		
Dengue (2007)	2714.681	2395.027	385.320	437.862	638.386	556.295

Table 4b - Dengue prevalence predictor means

	Natal		Fortaleza		Curitiba	
	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic
Ln(income)	6.245	6.280	6.388	6.349	6.753999	6.86581
Rel. humid.	77.029	74.345	78.125	75.356		
Temperature	26.826	26.127	26.508	26.847		
Dengue (2001)	608.543	724.681	2563.777	1355.918	18.53241	20.79042
Dengue (2002)			103.934	139.359		
Dengue (2003)	496.770	440.112				
Dengue (2004)	647.591	349.669				
Dengue (2005)			777.103	854.148	4.54352	3.720524

The climate variables temperature and humidity are the most important variables to fit the synthetic control. Despite the greater power of those variables to adjust the synthetic control, this is not the case of the models for all cities. Some cities, even though they have similar climates, have living standards that are too discordant to fit the model. For this reason, we chose not to include the humidity variable in the models for Teresina and Curitiba.

Table 5 displays the weights of each control city in the synthetic capital. The weights reported in Table 5 indicate that the dengue prevalence trend in the period before the rainfall pattern break is best reproduced for different cities. The number of synthetic controls depends on the capital that is analyzed.

Table 5 - Weights in the synthetic capitals

	Palmas	São Luis	Teresina	Natal	Fortaleza	Curitiba
Porto Velho	0	0	0	0	0	0
Rio Branco	0.052	0	0	0	0	0
Manaus	0	0	0	0	0	0
Boa Vista	0.202	0.096	0.243	0.362	0.578	0
Belém	0	0	0.612	0	0	0
Macapá	0	0	0	0	0	0
João Pessoa	0	0.818	0	0	0	0
Recife	0	0	0.076	0	0	0
Maceió	0	0	0	0.459	0	0
Aracaju	0	0	0	0	0	0
Salvador	0	0	0	0	0	0
Belo Horizonte	0	0	0	0	0	0
Vitória	0	0	0	0	0	0
Rio de Janeiro	0	0	0	0	0.31	0
São Paulo	0	0	0	0	0	0
Florianópolis	0	0	0	0	0	0.705
Porto Alegre	0	0	0	0	0	0.295
Mato Grosso do Sul	0.389	0	0.068	0	0.112	0
Mato Grosso	0	0	0	0	0	0
Goiás	0.357	0.086	0	0.179	0	0
Brasília	0	0	0	0	0	0

Figures 10 to 15 displays dengue prevalence rate for the cities and their respective synthetic counterparts during the period 2001-2010, namely Palmas, São Luis, Teresina, Fortaleza, Natal and Curitiba. Our estimates of the effect of rainfall pattern break on dengue rates are the difference between dengue rates in each capital and in their synthetic

version after the break. Immediately after the rainfall pattern break, the two lines begin to diverge noticeably for all cities. While dengue prevalence in the synthetic capitals continued on a moderate downward trend, the real tropical capitals experienced a sharp decline, while there was an increase in the temperate city of Curitiba. According to Abadie, Diamond and Hainmueller (2010), the discrepancy between the two lines suggests a reduction (increase) caused by the rainfall break on dengue prevalence in tropical cities (Curitiba).

Our results suggest that for the entire 2008-2009, period dengue cases per 100,000 inhabitants declined by an average of almost 576 cases. The biggest reduction happened in Natal, with 1,119 cases per 100,000 inhabitants, and the smallest reduction was in Teresina with just 48 cases per 100,000 inhabitants.

In order to assess the robustness of our results, we included additional predictors such as: log per capita wage income, average years of education, average number of rooms in homes, percentage of households with sewage disposal, percentage with piped water and number of bedrooms in homes. The results stayed virtually unaffected regardless of which and how many predictor variables we included. The lists of predictors used for robustness checks included are described in Table 4.

Figure 10 - Trends in dengue cases: Palmas vs. synthetic Palmas

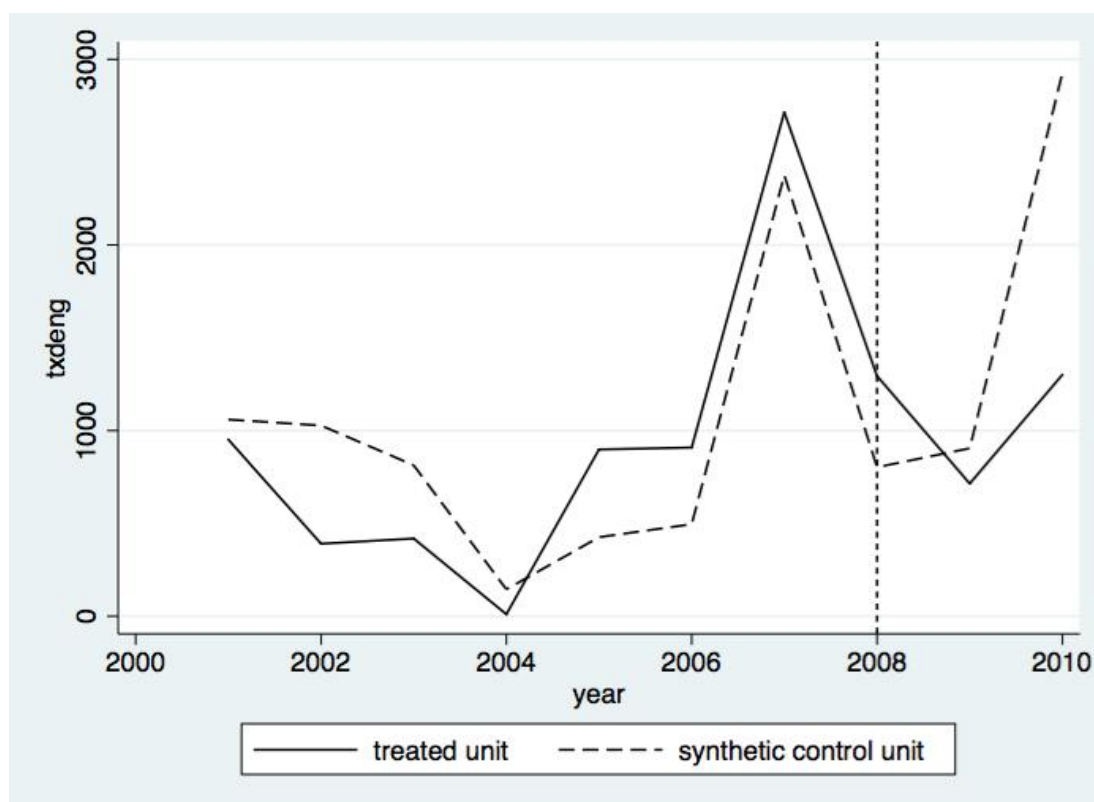


Figure 11 - Trends in dengue cases: São Luis vs. synthetic São Luis.

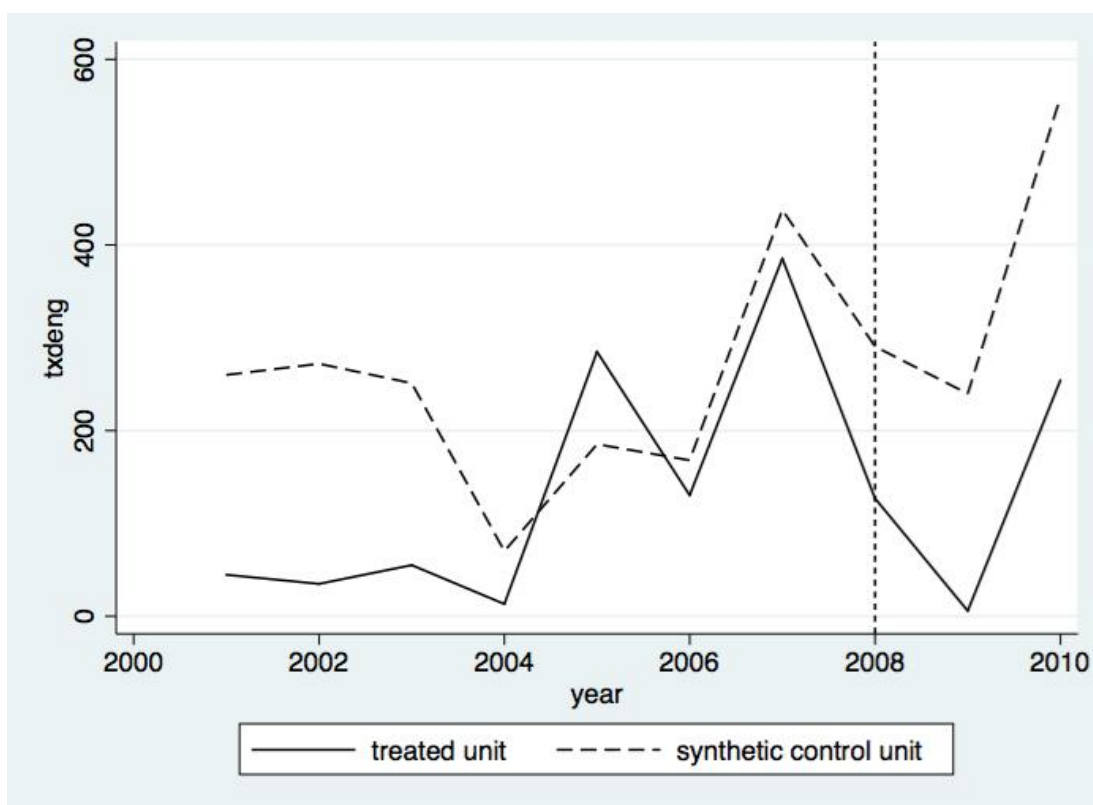


Figure 12 - Trends in Dengue Cases: Teresina vs. Synthetic Teresina

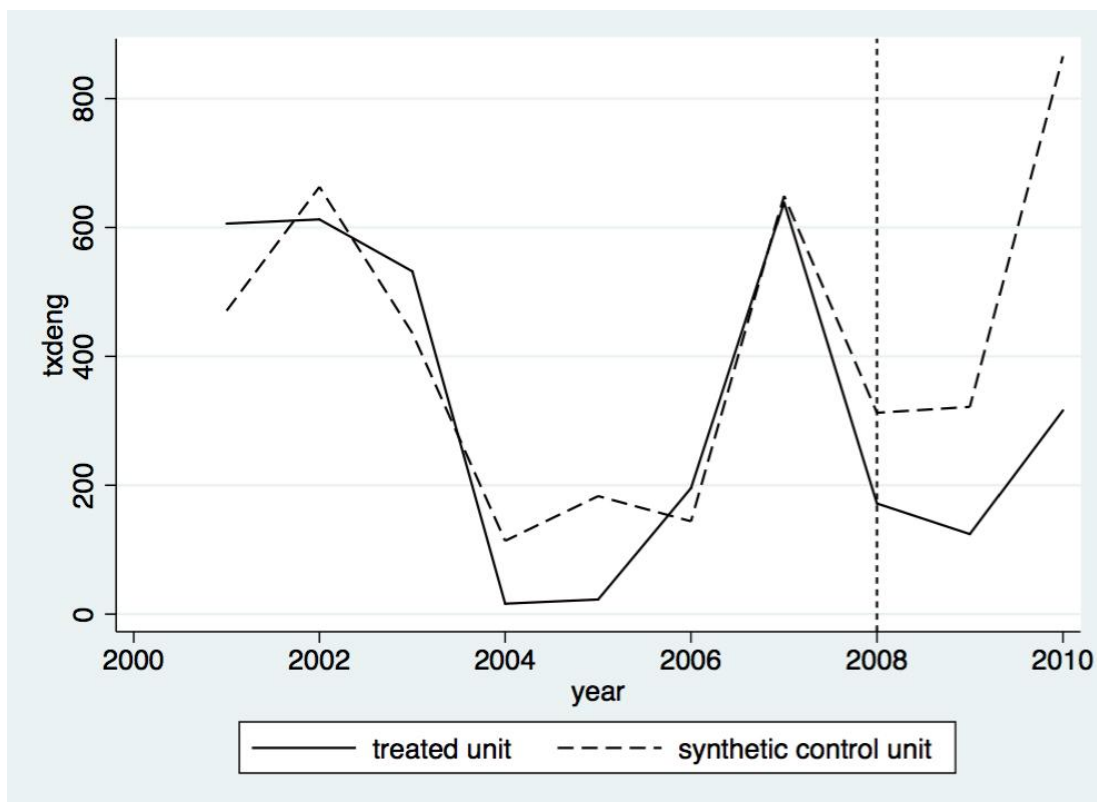


Figure 13 - Trends in dengue cases: Fortaleza vs. synthetic Fortaleza

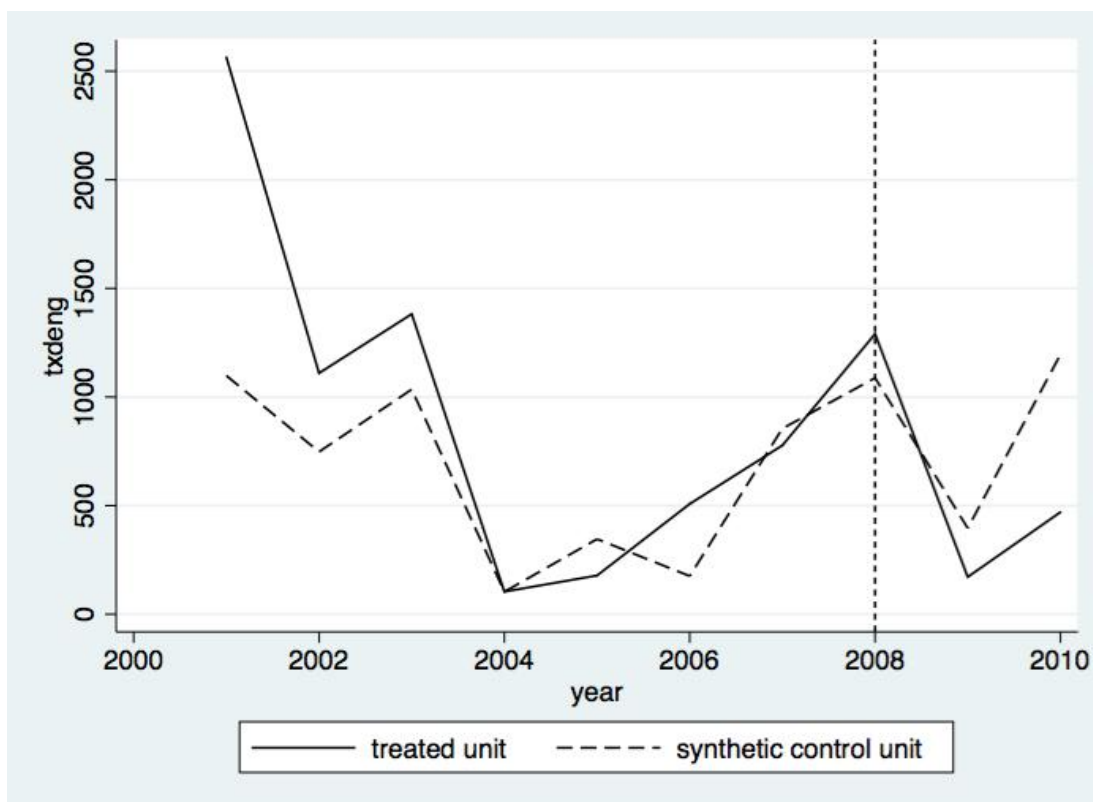


Figure 14 - Trends in dengue cases: Natal vs. synthetic Natal

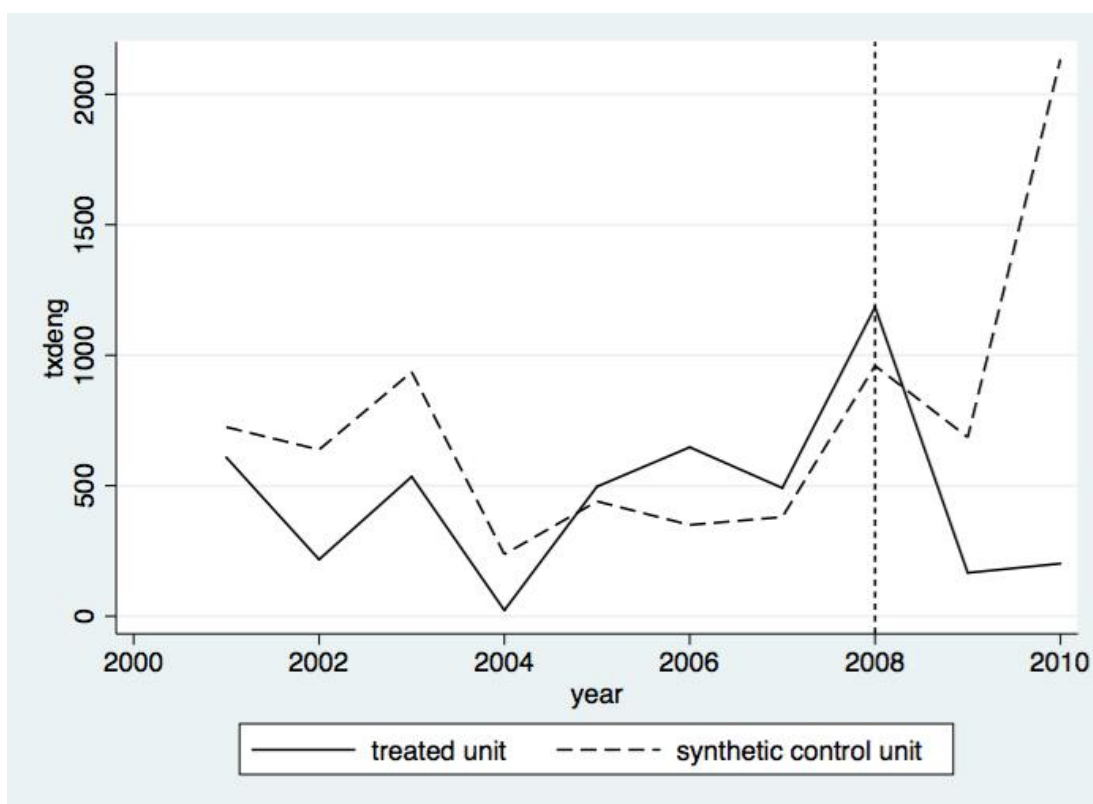
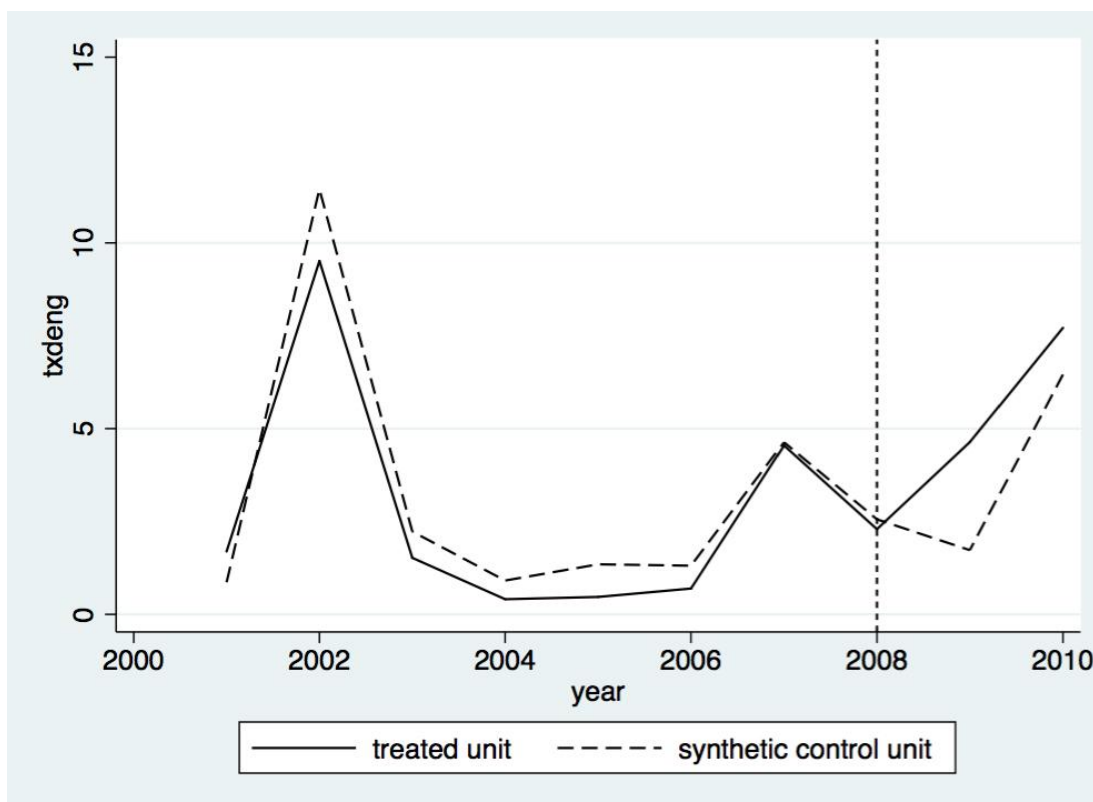


Figure 15 - Trends in dengue cases: Curitiba vs. synthetic Curitiba



Based on the climate impacts identified by this methodology, it is possible to calculate the climate change effects based on the rainfall increase expectations for the future.

6. Discussion

Dengue is transmitted to humans by the *Aedes aegypti* mosquitos, and this vector's prevalence is highly correlated with climate conditions. Very hot and dry environments as well as cold and dry ones do not allow the mosquitoes to survive, so the disease does not typically occur in these areas. The disease's high dependence on climate raises the question about the importance of global warming on the prevalence of dengue. Brazil is a country with continental size. Thus, global warming manifests itself in different ways among different cities.

As noted in Figures 4 to 9, in 2008, rainfall was in general more intense throughout the country, with some regions being more affected than others. Concurrently, as suggested by Figure 3, the prevalence of dengue varied unevenly: it declined in warmer regions,

where the rains were more intense, and increased in cooler regions, where the higher rainfall resulted in an increase in moisture.

Like Cavallo et al. (2010), who analyzed the causal effect of exogenous phenomena (natural disasters) on countries' GDP, our aim here is to analyze the impact of global warming on dengue prevalence. For this purpose, we built synthetic controls for cities where there was a significant variation in the prevalence of dengue fever after the high precipitation observed in 2008 (Figures 4 to 10). The other Brazilian state capitals, where the prevalence of dengue fever was not correlated with changes in rainfall pattern (Figure 3), were used to build these synthetic controls.

The differences between the observed rate of dengue and the estimated rate in the corresponding synthetic city are described in Figures 9 to 14, after the breaks in the rainfall pattern in 2008 in these cities. The results suggest that global warming affected the disease's prevalence. However, such impacts were not homogeneous among the tropical cities. For those located on the coast – São Luis, Fortaleza and Natal – the increase of rainfall reduced the rates of dengue by respectively 95%, 90% and 87%. In 2008, there were 127 cases of dengue registered in the city of São Luis for each 100,000 inhabitants. In the following year, this figure fell to only 6 cases per 100,000 inhabitants. In Fortaleza and Natal, the numbers of dengue cases per 100,000 inhabitants in 2008 were 1,184 and 1,290, respectively, while in 2009 these rates fell to 166 and 172 cases respectively.

For the two cities with tropical climate located in the interior of Brazil, Palmas and Teresina, the impact of higher rainfall was considerably smaller. In Palmas, the rate of dengue declined from 1,293 per 100,000 people in 2008 to 714 in 2009, a 45% drop, while in Teresina, the cases of dengue fell from 172 in 2008 to 124 in 2009, a decrease of only 28%.

Finally, Curitiba, a city located in southern Brazil, the increase of rainfall caused an increase in humidity, generating more dengue cases compared to its synthetic placebo (Figure 14). The temperate climate in the south of the country provides natural protection against dengue. Nevertheless, global warming has clearly increased the humidity in Curitiba, as can be identified in Figure 6. This phenomenon enables the existence of the climatic conditions, which are necessary for mosquito proliferation and, therefore, increased cases of the disease. In 2008, the number of dengue cases in the city was 2.3 per 100,000 inhabitants, while in 2009 this number rose to 4.6 and in 2010 grew further to 7.7, for a total increase in dengue of 70% between 2008 and 2010.

The results discussed clearly indicate the importance of climate in the prevalence of dengue. In the northern cities of the country, there was a reduction in the incidence of the disease, mainly after the period of higher rainfall. However, subsequently the rates reverted to the previous levels of incidence. This result suggests that although higher than normal rainfall may have eliminated the mosquito larvae for a short period, there was a subsequent reduction in the rainfall level leading to the return of the disease.

In the colder cities, located to the South of the country, the result is the opposite. The higher humidity caused by a warmer climate in cities of southern Brazil created conditions for the proliferation of mosquitoes, thus weakening these cities' natural shield against the disease.

In terms of public policy, these results must be seen as a warning call to policymakers about the moment to implement strategies to combat the disease. It is important to keep in mind that when high rainfall is expected, such phenomena will have a direct impact on policy aims.

7.1 Climate change

We also tried to demonstrate the importance of global warming on the prevalence of dengue in Brazil, mainly in the southern region where higher rainfall leads to an increase in humidity, creating the necessary conditions for the proliferation of the mosquito and consequent increase in the number cases. The next stage of this work is to create scenarios that will allow us to see the number of expected cases of disease for the country due to climate change. To do so, this section is divided into two parts: initially the coefficients that identify the impact of climate on the prevalence of dengue are estimated using regression analysis, and then scenarios are fitted with different climate conditions over which the previously estimated parameters are applied, projecting the number of cases in the country.

The forecast of dengue incidence is developed in two stages. The first consists of estimating the effect of climate parameters – temperature, rainfall and humidity – on the number of dengue cases per 100,000 inhabitants. The coefficients used in the prediction were derived from the estimation by OLS of the model described below⁴:

⁴ The OLS estimator with dummies for state and year corresponding to the fixed effect estimator (Cameron and Trivedi, 2005).

$$\ln(Dengue\ rate)_{kt} = \beta_0 + \sum_{j=1}^4 \beta_{1j} \ln(rain)_{jkt} * SeasonD_j + \sum_{j=1}^4 \beta_{2j} \ln(temp)_{jkt} * SeasonD_j + \sum_{j=1}^4 \beta_{3j} \ln(rel_hum)_{jkt} * SeasonD_j + \sum_{m=1}^8 \beta_m X_{mkt} \sum_{t=1}^9 \beta_{4t} D_t + \sum_{k=1}^{26} \beta_{5k} D_k + \zeta_{kt} \quad (5)$$

Here the dependent variable is the logarithm of dengue prevalence rate per 100,000 inhabitants, which varies by year (t) and capital city (k). The explanatory variables are the interactions between the logarithm of the three meteorological parameters, which vary by season (j), year (t) and capital city (k). The socioeconomics characteristics (m) are per capita income, per capita wage, years of education, number of bathrooms, quality of the roof, access to sewage system, access to running water, and dummies (j) for each season of the year. The database used in this step was the same as described in section 4.

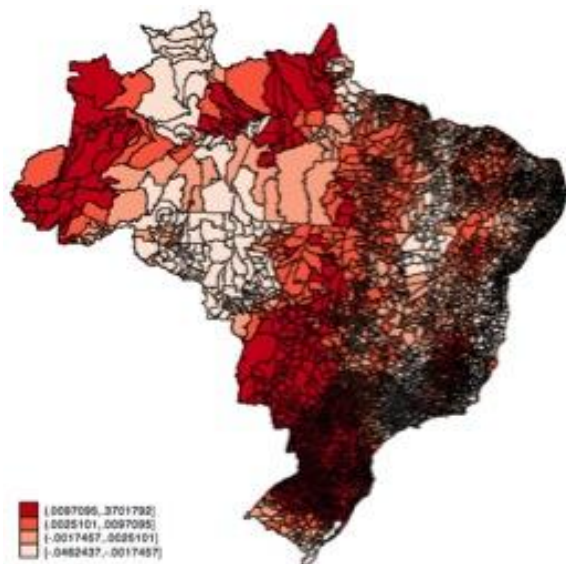
The climate information was calculated based on meteorological data provided by the Center for Earth System Science (CCST)⁵. The dataset provided by CCST contains monthly meteorological parameters: level of rainfall, temperature and average humidity for Brazilian municipalities between 2010 to 2100. The information was compiled considering the average scenario (Midi).

For each of the four seasons the dengue increase was calculated comparing the difference between current average climate and future climate (2041-2070), average scenario. Based on this information, we projected the growth rate of dengue for municipalities, as can be seen in Figures 5 to 8.

The results for the summer are in Map 1. These results suggest that warmer, more humid and rainier summers might decrease the disease in the cities to the Northeast located on the coast and increase the disease in the cities of the South, as predicted by the model results presented in section 6. In autumn, since the weather is milder and the extremes are closer, global warming does not cause much variance in the distribution of dengue among municipalities. The winter scenario is very close to that of the fall, which is expected since the probability of mosquito breeding rises in this season. As in the summer, high temperatures in the spring change the spatial distribution of dengue in the country, causing it to grow in the cities of the South region and decline in most cities located in the Midwest and the northeast coast.

⁵ Available at <http://dadosclima.ccst.inpe.br/>.

As already discussed, hot and rainy summers and springs kill the mosquito larvae in cities located further north. On the other hand, in the southern region such temperatures increase the humidity, which facilitates the proliferation of mosquitoes.



Map 1 - Dengue growth rate for next 70 years in summer



Map 2 - Dengue growth rate for next 70 years in autumn



Map 3 - Dengue growth rate for next 70 years in winter



Map 4 - Dengue growth rate for next 70 years in spring

The maps suggest a migration of dengue to the south of the country and a reduction of the epidemic in historically warmer areas. This phenomenon is observed in all seasons, becoming more present in the spring and fall.

7.2 Final Remarks

This paper aims to contribute to the measurement of climate impacts on health. Thus, dengue fever, the most relevant infectious disease in Brazil, is analyzed. We tested, and not rejected, the hypothesis that climate conditions affect the transmission of dengue fever in the country by using a synthetic control methodology.

In this way, this paper contributes by linking two relevant agendas: finding ways to manage the climate-related risks of today and improving the understanding of the future risks. The calculations performed suggested that as long-term temperatures increase, the southern and central southern states will become much more vulnerable to dengue, in accordance with the findings of Pereda (2012).

Thus, it is relevant to discuss potential adaptation instruments. Pereda (2012) found that expenditures for epidemiological surveillance are ineffective due to the delay in spending the funds. The current local system of monitoring dengue in Brazil is based on the observation of dengue cases in January and February, with occasional interventions by spraying insecticides to kill mosquitoes and their larvae where an increase in the number of cases is detected. This procedure, besides being more expensive, is not effective in reducing dengue locally. Moreover, those expenditures are also made at the municipal level, not controlling infected mosquitoes that cross municipal borders. Therefore, the author suggests that integrated actions are needed to control the dengue fever spread during epidemics.

When it comes to this article's contributions, the use of a synthetic control to identify the climate influence on dengue can be highlighted as the main contribution to the literature and to the study of dengue fever. Future research regarding dengue fever analysis could perform studies *in loco*, which could better identify inequality in sanitation infrastructure provision inside cities.

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Appendix

Figure A.1 – Brazilian states and capital cities



Source: <http://www.brazilmycountry.com/brazil-map/map-of-brazil-states/>.