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Abstract[*]

Climate-sensitive health problems kill millions every year and undermine the physical and psychological well-being of millions more. 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 dengue is more prevalent in warmer regions, but the humidity conditions and amount of rainfall seem fundamental for increase of the disease's prevalence in temperate climate regions or drier tropical regions of the country. On the other hand, the increase in rainfall in the rainiest tropical areas could diminish the disease's prevalence, as standing water accumulations might be washed away. Therefore, due to expected climate changes in the future, the dengue fever distribution in the country might change, with the disease migrating from the north to the south. Public policy's role in minimizing these effects in the country should be focused on anticipating the proper climate conditions for dengue incidence by using integrated actions among local authorities.

JEL classifications: I18, Q54

Keywords: Dengue fever, Synthetic control method, Climate change impacts on health

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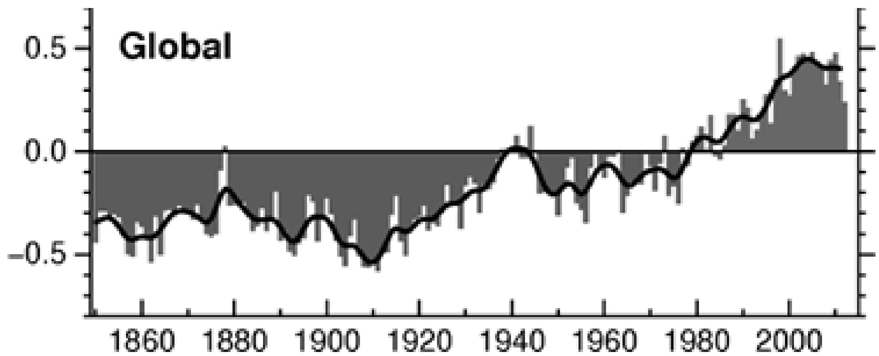
1. Introduction

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 ºC 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 (ºC), 1860 to 2006



Source: UK Met Office (2012).
Note: HadCRUT3 Temperature anomaly (º C)

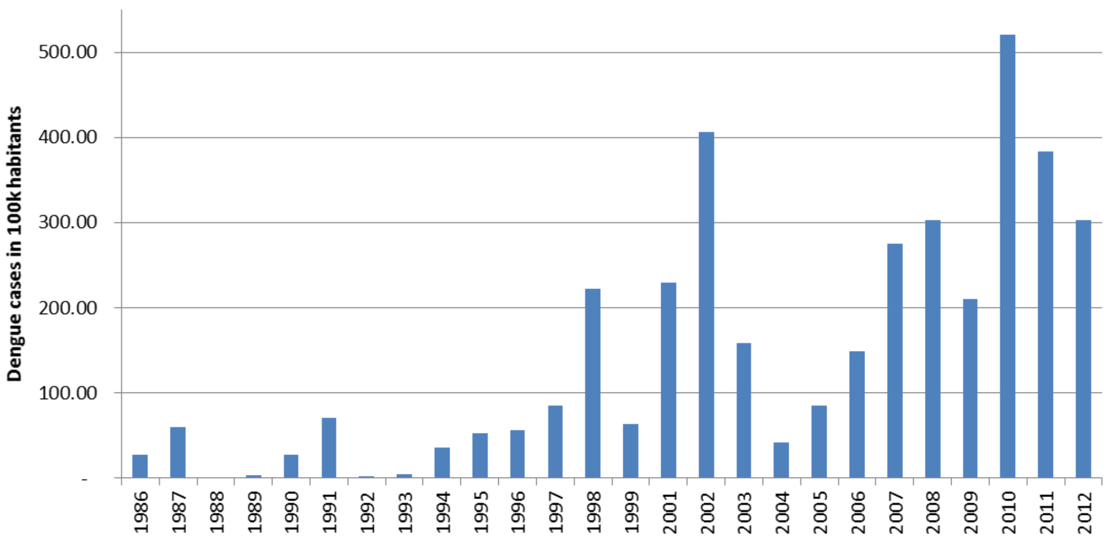
Trends from 1900 to 2005 have also been observed in precipitation (IPCC, 2007). In South America, increase in rainfall is observed for the eastern areas of the continent. There is also evidence of an increase in extreme event frequency, such as droughts, floods, heat and cold waves, hurricanes and other 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 (2012), climate-sensitive health problems kill millions of people every year and undermine the physical and psychological welfare of millions more. In the particular case of vector-borne diseases, climate conditions ensure vectors' survival and reproduction and, consequently, disease transmission (Kelly-Hope and Thomson, 2008). Increases in heat, precipitation, and changes in humidity can allow insects to move to new regions and spread diseases there.

The vector-borne disease analyzed in this paper is dengue fever. In Latin America, it is the most harmful infectious disease and 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—namely, humid and warm environments—and the accumulation of water is necessary for the reproduction and spread of the mosquito population.

In Brazil, the annual incidence of dengue between 1986 and 2012 was generally increasing, especially since 1998, albeit with a good deal of fluctuation. According to the Ministry of Health's Information System for Disease Notification (MS/SINAN),[1] there were 5.3 million reported cases of dengue fever in Brazil between 2002 and 2012.

Figure 2. Annual Dengue Cases per 100,000 Inhabitants, 1986 to 2012



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

In 2010, for example, a spate of dengue fever outbreaks occurred and almost one million cases of the disease were reported. Due to the importance of the disease in Brazil, the goal of this study is to identify the climate effect on 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. The government's influence on public policy is mainly determined by the

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

surveillance expenditures and sanitation measures (both urban infrastructure problems controlled by local governments, with federal and state support), by type of housing, educational measures, and by assuring health assistance to people affected by such diseases (availability of hospital beds, health expenditures).

The study uses a comparative case to identify the climate impacts on dengue risk, 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 for obtaining control groups by using this methodology (Sections 4 and 5). Once the effect is identified (Section 6), climate change simulations can be performed to predict the expected impacts of changes in climate on the spread of dengue fever in Brazil (Section 7).

2. Basic Model

Cavallo et al. (2013) 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 applied a comparative country analysis from the construction of an appropriate counterfactual—a group of synthetic controls. In this paper we apply a strategy similar to that of Cavallo et al. (2013) by trying to measure the consequences of climate change, an exogenous variable, on dengue incidence. The exogenous climate characteristics permit us to build a synthetic control using cities where a strong impact of climate change cannot be observed.

According to Abadie and Gardeazabal (2003), Abadie et al. (2010) and Cavallo et al. (2013), a quasi-experimental design of this type can be preferable to conventional methods for various 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 possibility 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. Relevant climate conditions for dengue vectors' survival and reproduction include average temperature not too low or high, enough humidity to regulate the temperature of mosquitoes, and a reasonable amount of precipitation for egg deposition. 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 for identifying the climate's impact on dengue is based on the comparison of areas affected and not affected by the climatic events believed to aggravate risk. When it comes to dengue, the South region of Brazil is the only one not being affected (Pereda, 2012). Hence, this area can be a target area in terms of the identification of climate impacts on dengue.

Thus, the identification strategy will be to estimate the increase in dengue risk due to a higher than average amount of rainfall (or relative humidity). Cities that showed a deviation from those 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 is the construction of a counterfactual for impact evaluation of this phenomenon. There is only one figure available every 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 $Ic + 1$ for a period of T years, in which Ic 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 the 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:

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

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 *Ic* cities. In this sense, Abadie et al. (2010) assume that such values are generated from a model of the type:

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

in which *j* indexes the *Ic* cities that did not undergo the climate event, δ_t is an 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 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 vectors *W* (*Ic x 1*), $(w_1, w_2, \ldots\ldots, w_{Ic})'$, in which $w_j \geq 0$ and $\sum_{j=1}^{Ic} w_j = 1$, such that:

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

In other words, a vector *w** is obtained such that the treated city (*I*) is reproduced by the *Ic* cities that did not experience the climate event in the period before the event. Abadie et al. (2010) show that, under standard conditions, the expected value of $Y_{it}^N - \sum_{j=1}^{Ic} w_j^* Y_{jt}$, i.e., of the difference between the variable of interest from city *I*, which underwent the climate event for the period without this occurrence, and the weighted sum (using vector *w**) of the values of the cities without the climate event, is zero. Thus, $\sum_{j=1}^{Ic} w_j^* Y_{jt}$ 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:

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

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 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 $\sum_{j=1}^{Ic} w_j^* Z_j = Z_i$ e $\sum_{j=1}^{Ic} w_j^* \mu_j = \mu_i$ are approximately true (Abadie et al., 2010).

The calculation of the synthetic control 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):

$$\sqrt{(X_1 - X_0 W)' V (X_1 - X_0 W)} \quad (5)$$

in which V is a positive semi-definite symmetric matrix affecting the mean squared error estimator (MSEE).

Following Abadie and Gardeazabal (2003) and Abadie et al. (2010), we choose 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 non-experimental methods. Among these are the possibility of still drawing inferences when only one treated value is observed; the fact the method only uses information about the period before the event, so the choice of control is not related to any direct results; and the fact 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

The dataset aggregates annual municipal-level panel data for the period 2001-2010 in Brazil. For the climate variables and for the dengue prevalence rates, information can be used by season of the year. The following table presents the description of data and sources.

Table 1. General Variables and Sources

Variable(s)	Source	Description
Observed climate data	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]
Climate change projections	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 2041 to 2070.[3]
Dengue fever notifications	Database of the National Health System (DATASUS)	Contains all notified cases of dengue in the season of the year by municipality of residence reported and stratified by age or income.
Socioeconomic data	National Household Survey (PNAD)	Overall population characteristics annually collected: 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 as 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 (in all cases the largest city in each state), to enable using the sample of socioeconomic data 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. 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	Average Temperature				Average Monthly				Average Relative			
			DJF	MA	JJA	SO	DJF	MA	JJA	SON			JJA	
North	*Porto Velho*		25.5	24.9	23.9	25.6	262.3	229.0	85.43	147.5	87.9	86.2	75.0	78.1
	Rio Branco		25.4	24.8	23.5	25.5	276.6	195.8	45.59	145.5	89.9	87.6	76.1	79.8
	Manaus		26.3	26.3	26.7	27.4	264.2	276.5	86.62	107.5	86.8	86.3	75.2	76.7
	Boa Vista		27.7	27.8	27.3	28.8	88.79	203.5	274.4	84.07	85.5	85.5	76.9	76.0
	Belém		26.2	26.2	26.4	26.9	203.0	252.8	100.9	58.75	84.9	86.5	78.2	76.9
	Macapá		26.6	26.5	27.0	28.2	255.4	312.0	161.6	41.77	83.9	86.2	77.3	72.9
	Palmas		25.6	25.7	25.1	26.7	269.5	180.8	7.95	136.8	82.2	80.2	62.7	70.3
Northeast	*São Luís*		26.6	26.3	26.4	27.3	207.3	378.6	113.8	13.41	80.7	84.9	78.2	73.7
	Teresina		26.6	26.1	26.2	28.1	186.1	231.3	17.22	21.96	76.2	81.3	67.7	61.3
	Fortaleza		26.9	26.5	26.2	27.4	127.5	312.2	85.20	10.86	75.1	80.2	72.2	68.4
	Natal		26.8	26.4	25.0	26.5	81.93	208.8	235.3	23.92	74.2	79.3	75.9	71.8
	João Pessoa		26.9	26.3	24.8	26.3	82.90	219.9	262.3	34.40	72.9	77.5	78.1	71.5
	Recife		26.6	26.0	24.3	25.7	98.99	229.1	291.6	44.52	73.6	79.3	80.5	73.3
	Maceió		25.7	25.1	23.1	24.7	71.87	193.3	240.5	50.50	73.3	77.4	77.1	71.2
	Aracaju		26.1	25.7	23.7	25.2	62.55	148.5	143.4	49.24	74.8	77.5	75.8	72.4
	Salvador		25.9	25.2	23.0	24.8	94.57	206.5	172.7	80.65	76.6	79.8	77.1	74.0
Midwest	*Campo*		24.2	22.1	19.0	22.4	210.6	121.9	50.00	136.7	80.4	79.7	72.1	73.3
	Cuiabá		25.8	24.9	22.7	25.8	221.1	112.1	16.86	113.6	82.9	82.1	72.4	74.3
	Goiânia		24.0	23.7	22.0	24.7	251.9	136.9	8.08	131.0	75.9	70.5	53.6	62.7
	Brasília		21.8	21.1	19.4	22.1	226.1	122.7	10.80	125.3	77.6	73.7	55.6	64.5
Southeast	*Belo*		23.2	21.6	18.6	21.9	274.2	90.71	10.06	125.9	75.6	74.4	68.2	68.4
	Vitória		25.4	23.9	20.9	23.1	149.4	108.4	52.13	121.8	75.6	77.1	74.2	73.6
	Rio de		24.3	22.3	18.6	21.4	176.6	134.2	78.50	139.6	76.9	78.5	75.5	74.5
	São Paulo		22.6	20.2	16.6	19.6	240.0	119.2	42.58	121.4	77.0	77.4	73.1	74.1
South	*Curitiba*		21.2	18.0	14.0	17.2	172.0	114.9	72.32	147.5	81.0	83.1	80.3	80.3
	Florianópol		23.4	20.7	15.7	19.5	188.6	137.5	61.64	164.0	78.8	79.5	78.5	77.0
	Porto		23.5	19.9	14.3	18.9	121.7	106.5	119.7	146.9	74.4	77.5	77.2	73.4

Label of the periods: DJF: December, January and February (summer); MAM: March, April and May (fall); JJA: June, July and August (winter); and 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

Region	Capital cities	Dengue cases per 100,000 habitants	Population of the city	% women in the city	Average Age, in years	% white people and asian descendents 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
North	*Porto Velho*	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
	Rio Branco	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
	Manaus	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
	Boa Vista	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
	Belém	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
	Macapá	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
	Palmas	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
Northeast	*São Luís*	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
	Teresina	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
	Fortaleza	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
	Natal	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
	João Pessoa	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
	Recife	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
	Maceió	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
	Aracaju	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
	Salvador	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
Midwest	*Campo Grande*	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
	Cuiabá	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
	Goiânia	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
	Brasília	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
Southeast	*Belo Horizonte*	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
	Vitória	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
	Rio de Janeiro	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
	São Paulo	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
South	*Curitiba*	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
	Florianópolis	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
	Porto Alegre	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

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.

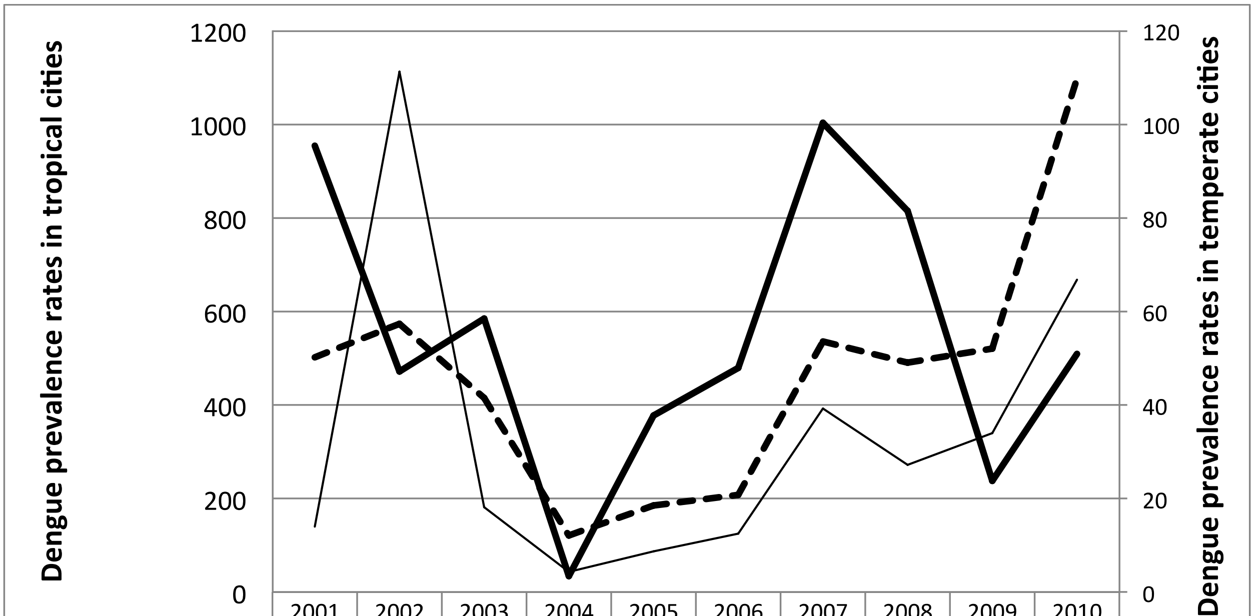
4. Empirical Strategy

Brazil's large extension 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[2] (capitals are São Luis, Teresina, Fortaleza, Natal and Palmas, respectively).[3] The temperate cities are Curitiba, Florianópolis and Porto Alegre, the capitals of Paraná, Santa Catarina and Rio Grande do Sul.

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: tropical cities, temperate cities and the entire country.

[2] We chose not to analyze the capital cities of the North region due to their equatorial climate (high temperatures, precipitation and humidity). The peculiar climate configuration does not allow proper comparison with other tropical cities. The equatorial capital cities are Acre, Amazonas, Roraima, Rondônia, Pará, and Amapá.
[3] See Appendix A for details about the capital cities of the Brazilian states.

Figure 3. Dengue Prevalence Rates for Three Groups of Cities:
Tropical, Temperate and All Brazil



	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
deng_tropical	955.0	473.1	584.5	33.2	376.2	478.0	1001.4	813.4	236.5	508.5
deng_brazil	500.1	573.8	414.4	119.3	186.8	206.3	537.1	490.6	520.2	1097.9
deng_temperate	14.0	111.3	18.0	4.3	8.7	12.3	39.3	27.3	34.0	66.7

Figure 3 indicates the varied distribution of dengue among Brazilian cities. The temperate cities are colder than the tropical cities, which decreases mosquitoes' survival. Therefore, these cities have natural protection against dengue, reflected in an average of just 33 cases per 100,000 inhabitants for 2001 to 2010. On the other hand, the tropical cities are warmer and more humid, which is suitable for mosquito reproduction. In this region, dengue prevalence averaged 546 cases per 100,000 inhabitants over the same period. Figure 3 also indicates that for the three groups, dengue prevalence fell to a low point in 2004 and slowly started to increase again until 2008. In that year, the three groups had different patterns of disease prevalence. In tropical cities, the disease prevalence decreased, in temperate ones it increased and in Brazil as a whole there was virtually no change.

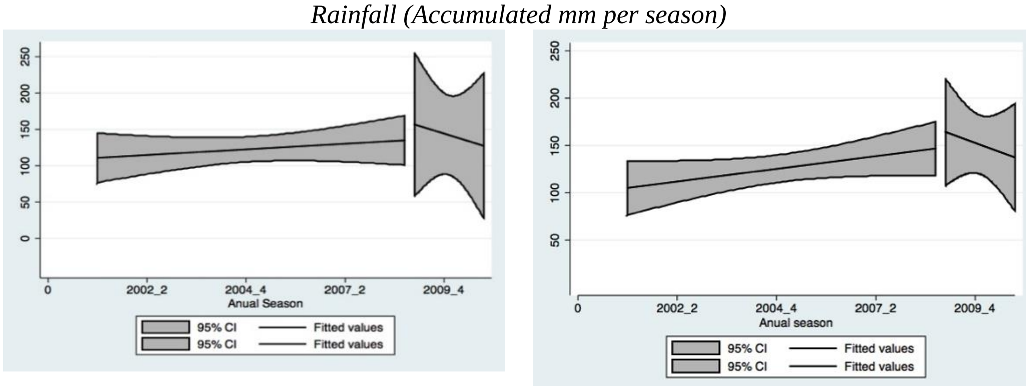
The years of 2008 and 2009 were marked by heavy rainfalls in most Brazilian cities. Figure 4 presents the cities' precipitation and average relative humidity pattern change in all three capitals of the temperate South: Curitiba, Florianópolis and Porto Alegre. The figure shows that rainfall grew in all three capitals in the summer of 2009. However, the rainfall pattern changes had a greater effect on the average relative humidity in Curitiba. In the two other capitals in the South, the average humidity did not change as much in that season.

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 in the summer of 2009 compared to the other years[4] had the effect of increasing the prevalence of dengue in Curitiba.

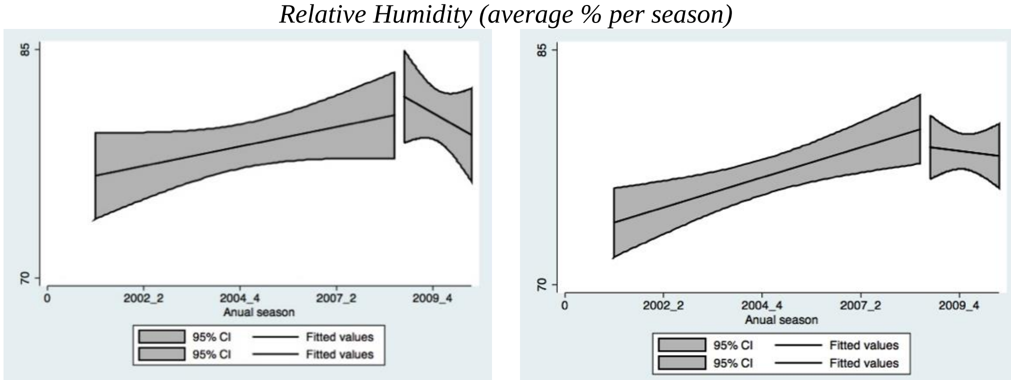
Figure 4. Rainfall in Temperate Cities before and after 2009

Curitiba **Florianópolis and Porto Alegre**

Rainfall (Accumulated mm per season)



Relative Humidity (average % per season)



Note: The horizontal axis corresponds to the annual information on the seasons of the year: summer (1), fall (2), winter (3) and spring (4)

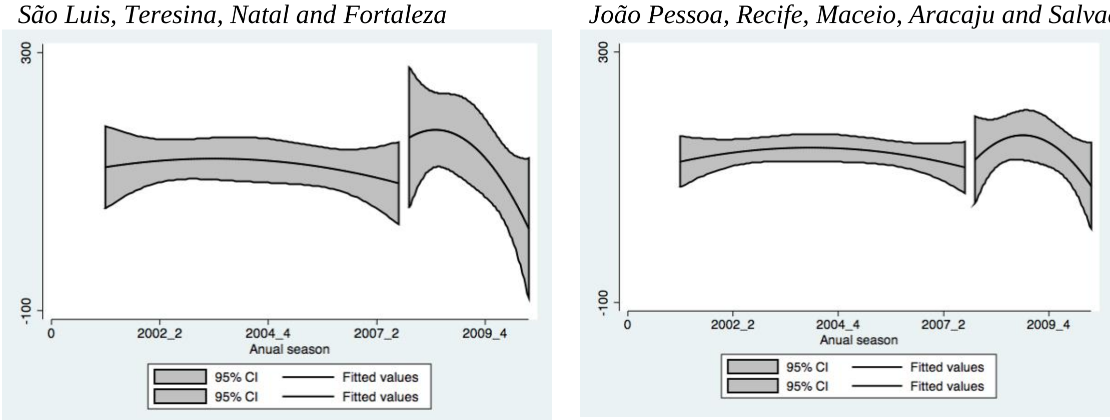
Unlike the southern cities, which occupy temperate areas of the country, northeastern capitals have tropical weather. Despite the moderating factor of their location on the coast, their weather is still hot and humid, providing an ideal environment for dengue proliferation. It is no

[4] Curitiba has already a higher relative humidity than the other temperate cities (probably because of the higher altitude). However, in 2008 the relative humidity increased more in Curitiba than in the other temperate cities.

coincidence that the region has high prevalence rates of dengue (Figure 2). In 2008, the heavy rains that affected most of the country were more intense in warmer tropical capitals (Figure 5), respectively São Luis, Teresina, Fortaleza, Natal and Palmas. Figure 5 describes the break in the average precipitation pattern of these cities. In the summer of 2008, the mean and variance of the rainfall in these capitals increased relative to the previous period. However, in the same season of 2008, this phenomenon was not observed so sharply in the other Brazilian northeastern capitals like João Pessoa, Recife, Maceió, Aracaju and Salvador.[5]

Figure 5. Rainfall in Northern Capitals[6] (in mm accumulated per season)

São Luis, Teresina, Natal and Fortaleza *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 per season in Brazil for the period 2001-2010, the rainfall in the tropical cities in the summer of 2008 was above the historical average until 2007. Our hypothesis is that such high precipitation might have washed away standing water accumulations in places where very high precipitation occurred, reducing the number of larvae and therefore reducing the mosquito population and lowering the dengue prevalence in some tropical cities. On the other hand, in temperate cities or tropical cities with less accumulated rain in normal conditions, the higher humidity and precipitation might have

[5] See Table A.1 in Appendix A for details of the Brazilian states and their capital cities.
[6] The negative values correspond to the minimum confidence intervals calculated for low values of observed rainfall.

increased survival of mosquitoes, raising the risk of dengue in those regions in the year highlighted by the figures.

Note that in the summer of the years of 2008 and 2009 there were climatic breaks in many Brazilian cities (change in relative humidity in Curitiba and a change in rainfall levels in some tropical cities). We use those breaks in order to identify if the dengue prevalence change in those years could be associated with the change in climatic conditions.

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 climatic 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 Palmas, São Luis, Teresina, Fortaleza, Natal and Curitiba and constructed synthetic controls for them.

Using the techniques described in 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 cities in Brazil with the greatest resemblance in terms of dengue prevalence predictors, we constructed the synthetic controls for five capitals: São Luis, Teresina, Fortaleza, Natal and Curitiba. To construct the synthetic control model, the full sample was not used; instead, we observe only the impact of the summer weather on the average rate of dengue in the first two seasons (summer and fall). Two reasons led us to proceed in this way: first, the fact that about 90 percent of dengue cases occur in the first half of the year (summer and fall seasons) in Brazil; and second, the fact that the summer weather determines the main conditions for mosquitoes' reproduction. The above reasons led us to conclude that using the annual average rates of dengue could have biased our results.

Table 4 below highlights an important feature of synthetic control estimators. As described in Abadie et al. (2010), similar to matching estimators, the synthetic control method forces demonstration of the affinity between the cities exposed to the intervention of interest and the cities in the sample. 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. Table 4 shows that for the variables used to reproduce the dengue pattern among the cities, the treated and synthetic control are close to each other. Per capita income, temperature and humidity are the variables that best adjusted the synthetic control for the majority of the cities.

Table 4. Dengue Prevalence Predictor Means for São Luís, Teresina, Natal, Fortaleza and Curitiba

	São Luís		Teresina		Natal		Fortaleza		Curitiba	
	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic
Ln(income)	6.230	6.235	6.285	6.413	6.245	6.249	6.388	6.528	6.806	6.903
Rel. humid.	81.635	81.088	76.180	77.583	77.472	80.036	77.156	76.989	21.346	24.452
Temperature	27.147	27.090	27.378	26.654	27.303	27.211	27.322	27.026		
Dengue (2001)										
Dengue (2002)	16.945	172.201	447.102	449.080	136.633	232.263				
Dengue (2003)			386.606	381.317	365.670	293.753	1013.60	919.558		
Dengue (2004)	5.300	40.103								
Dengue (2005)	148.793	87.735	6.180	35.561			59.468	114.639		
Dengue (2006)										
Dengue (2007)	249.298	218.567	298.881	300.321			313.295	287.956	4.371	4.268

Note: Dengue corresponds to the dengue prevalence rate per 100,000 inhabitants in the year.

Table 5 displays the weights of each control city in the synthetic capital. The weights indicate that the dengue prevalence trend in the period before the rainfall pattern break is best reproduced by different cities. The number of synthetic controls depends on the capital that is analyzed, and varies between two and seven cities.

Table 5. Weights in the Synthetic Capitals

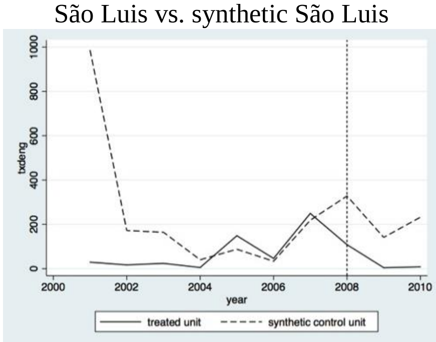
	São Luís	Teresina	Natal	Fortaleza	Curitiba
Porto Velho	0	0	0	0	0
Rio Branco	0.631	0.174	0.568	0.262	0
Manaus	0.215	0	0.238	0.301	0
Boa Vista	0	0	0	0	0
Belém	0	0	0	0	0
Macapá		0	0	0	0
João Pessoa	0.091	0.077	0.124	0	0
Recife	0	0	0	0	0
Maceió	0	0.31	0	0	0
Aracaju	0	0.222	0	0	0
Salvador	0	0.046	0	0	0
Belo Horizonte	0	0	0	0	0
Vitória	0	0.134	0.069	0.397	0
Rio de Janeiro	0	0	0	0	0
São Paulo	0	0	0	0	0
Florianópolis	0.038	0	0	0	0.888
Porto Alegre	0	0	0	0	0.112
Mato Grosso do Sul	0.026	0.038	0	0.04	0
Mato Grosso	0	0	0	0	0
Goiás	0	0	0	0	0
Brasília (Federal District)	0	0	0	0	0

Figure 6 displays dengue prevalence rate for the cities and their respective synthetic counterparts during the period 2001-2010, namely 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 its respective synthetic version after the break. In the 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 capitals experienced a sharp decline (São Luis and Teresina), or rise (Natal, Fortaleza and Curitiba). According to Abadie et al. (2010), the discrepancy between the two lines suggests a decrease (increase) caused by the rainfall break on dengue prevalence in São Luis and Teresina (Natal, Fortaleza and Curitiba).

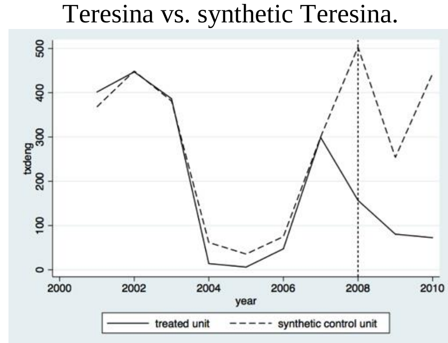
For the entire first six months of the 2007-2008 period in tropical treated cities, dengue cases per 100,000 inhabitants increase by an average of almost 261 cases. The largest increases happened in Fortaleza and Natal, with rises of 731 and 699, respectively. However, it was possible to observe a reduction at two other cities, São Luis and Teresina, with 103 and 76 fewer cases per 100,000 inhabitants, respectively. The different sign of the effect can be explained by the historical different rainfall observed in those cities, as São Luis and Teresina present greater historical rainfall in summer when compared to Natal and Fortaleza.

Figure 6. Trends in Dengue Cases, Capitals vs. Synthetic Capitals

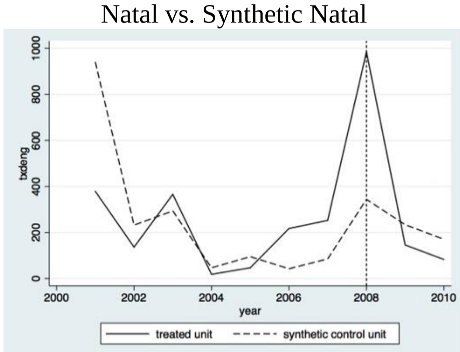
São Luis vs. synthetic São Luis



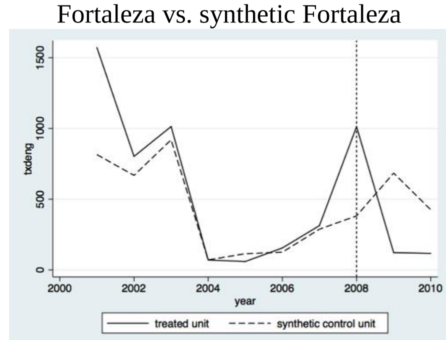
Teresina vs. synthetic Teresina.



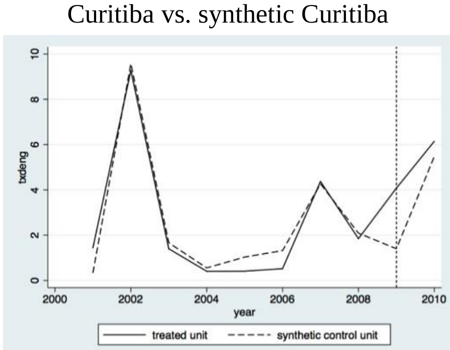
Natal vs. Synthetic Natal



Fortaleza vs. synthetic Fortaleza



Curitiba vs. synthetic Curitiba



In temperate cities the dengue cases per 100,000 inhabitants increased from 2008 to 2009 by 2 cases. However, this increase in Curitiba was almost 3 cases per 100,000 inhabitants. Table 6 below compares these real results with those predicted for the synthetic cities and then analyzes the impact of climate change.

Table 6. Accumulated Summer Rainfall: 2001-2010

Treated capitals	Accumulated summer rainfall 2001-2010 (mm)
São Luís	207.38
Teresina	186.11
Natal	127.53
Fortaleza	81.93

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 remained virtually unaffected regardless of which and how many predictor variables we included. The lists of predictors used for robustness checks are described in Table 4.

6. Discussion

The results suggest that climate affected dengue's prevalence for the cities where a climatic break occurred. However, such impacts were not homogeneous among the tropical cities. For those with less historical precipitation—Fortaleza and Natal—comparing these cities with their synthetics, the increase of rainfall in 2008 increased the rates of dengue by 36 percent and 22 percent, respectively. The projection for synthetic Fortaleza was 343 cases per 100,000 inhabitants in 2008, while the observed rate was 984. Likewise, the projection for synthetic Natal was 382 cases 100,000 inhabitants in 2008 against an observed rate of 1,012. We are arguing that the greater than expected increase of precipitation in these two cities in relation to their synthetic controls caused the dengue increase.

For the two cities with tropical climate but higher historical precipitation, São Luis and Teresina, the impact of higher rainfall was considerably smaller. In São Luis, the rate of dengue declined from 294 per 100,000 people in 2007 to 108 in 2008, a 56 percent drop, while in Teresina, the rate fell from 299 in 2007 to 157 in 2008, a decrease of only 47 percent.

Finally, in Curitiba, a city located in southern Brazil, the increase of rainfall caused an increase in humidity and generated more dengue cases compared to its synthetic placebo (Figure 6). The temperate climate in the south of the country provides natural protection against dengue. Nevertheless, climate is expected to get warmer and more humid in the southern region of the country. This change might enable the existence of the climatic conditions that are necessary for mosquito proliferation and, therefore, increased dengue cases. In 2008, the number of dengue cases in the city was 1.8 per 100,000 inhabitants, while in 2009 this number rose to 4.1. However, the number of projected cases for the synthetic was 1.4.

The results clearly indicate the importance of climate on the prevalence of dengue. 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.

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. Climate Change Forecast

7.1 Forecasting Strategy

Based on the work from the previous sections, we now analyze the potential impacts of climate change on the number of expected cases of disease in Brazil to 2041-2070. To do so, we divide this section into two parts: we first estimate the coefficients that identify the impact of climate on the prevalence of dengue, and then we fit scenarios with different climate conditions using those estimated parameters, to project the number of cases in the country into the future.

The first step 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 below:[7]

$$\ln(Dengue\ rate)_{kt} = \beta_0 + \sum_{j=1}^{4} \beta_{1j} ln(rain)_{jkt} * SeasonD_j + \sum_{j=1}^{4} \beta_{2j} ln(temp)_{jkt} * SeasonD_j + \sum_{j=1}^{4} \beta_{3j} ln(rel\_hum)_{jkt} * SeasonD_j + \sum_{m=1}^{8} \beta_m X_{mkt} \sum_{t=1}^{9} \beta_{4t} D_t + \sum_{r=1}^{4} \beta_{5r} D_r + \zeta_{kt} \qquad (6)$$

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

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

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 piped water, and dummies (*j*) for each season of the year and dummies (*r*) for Brazil's five regions. The database used here was the same as described in Section 4. The results are described in Table 7 below.

Table 7. Dependent Variable: Dengue Growth Rates for Brazilian States by Season, 2001-2010

Independent Variables	Estimated Coefficient	
Ln (Accumulated rain - Summer)	0.466	***
Ln (Accumulated rain - Fall)	-0.089	
Ln (Accumulated rain - Winter)	0.282	***
Ln (Accumulated rain - Spring)	-0.201	*
Ln (Avg. temperature - Summer)	2.255	
Ln (Avg. temperature - Fall)	4.319	***
Ln (Avg. temperature - Winter)	2.893	***
Ln (Avg. temperature - Spring)	1.578	*
Ln (Relative humidity - Summer)	0.17	
Ln (Relative humidity - Fall)	-0.596	
Ln (Relative humidity - Winter)	-0.069	
Ln (Relative humidity - Spring)	1.214	*
Head of household income	2.781	***
Total per capita income	-3.284	***
Head of household years of education	-0.255	
Number of bathrooms	1.803	
Number of rooms	0.399	***
Dummy for safe roof	5.892	***
Dummy for access to sewage system	-0.308	
Dummy for access to piped water	-1.311	
Constant	-7.447	
Time dummies	yes	
Regional dummies	yes	
R-squared	**0.513**	
Number of observations	**1078**	

The climate information was calculated based on meteorological data provided by the Center for Earth System Science (CCST).[8] The dataset provided by CCST contains monthly meteorological parameters: level of rainfall, temperature and average humidity for Brazilian municipalities between 2041 to 2070. The information was compiled considering the average scenario (Midi).

The climate change forecast used was generated from the data set boundaries of the global model (HadCM3), from the Met Office-Hadley Centre of the United Kingdom, A1B emission scenario for the entire area of South America considering 2041-2070 (the three scenarios considered indicate the level of human activity that influences climate: Low; Middle, or Midi; and High). The variables used as the average of the expected extreme weather events were calculated similarly to the independent variables of the models. The expected effects of climate change on dengue rates are reported in Table 8 and Figure 7.

Table 8. Climate Change Estimated Effect on Dengue Rates by Region, 2041-2070, Summer Scenario

Region	Dengue cases per 100,000 inhabitants		Incidence	Dengue growth rates
	Current	Projected		
		High		
North	150.229	137.130	-13.099	-1.107
Northeast	84.163	146.826	62.663	0.355
Midwest	94.874	248.163	153.289	0.704
Southeast	52.292	138.658	86.366	0.786
South	4.583	15.428	10.845	0.852
		Medium		
North	150.229	137.129	-13.100	-1.113
Northeast	84.163	147.702	63.539	0.360
Midwest	94.874	246.117	151.243	0.700
Southeast	52.292	142.179	89.887	0.800
South	4.583	15.183	10.600	0.850
		Low		
North	150.229	104.439	-45.790	-1.461
Northeast	84.163	121.279	37.116	0.196
Midwest	94.874	186.596	91.722	0.512
Southeast	52.292	105.429	53.137	0.574
South	4.583	11.224	6.641	0.615

[8] Available at http://dadosclima.ccst.inpe.br/.

Table 7 describes the forecast dengue prevalence rate per 100,000 inhabitants for the five Brazilian regions North, Northeast, South and Southeast, between 2041 and 2070. The results suggest that regardless of the scenario considered for climate change (high, medium or low), dengue is expected to increase in four of the five regions. The North region was the only one that showed a reduction in the prevalence of dengue in all scenarios. Between 2001 and 2010, the largest number of cases was observed in the North region (150 cases per 100,000 inhabitants). However, for the period 2041-2070, a reduction in prevalence to 137 cases per 100,000 inhabitants is projected in the medium and high scenarios, which corresponds to a negative growth rate of 1.1 percent in the region. In the scenario of low climate sensitivity, this reduction is even greater: the prevalence of dengue decreases to 104 cases per 100,000 inhabitants, corresponding to a growth rate of -1.46 percent.

Figure 7 shows that the northern states where there are the greatest reductions in prevalence rates of dengue due to climate change are Amapá, Amazonas and Rondônia, with respective percentages of -2.7 percent, -1.3 percent and -1.2 percent.

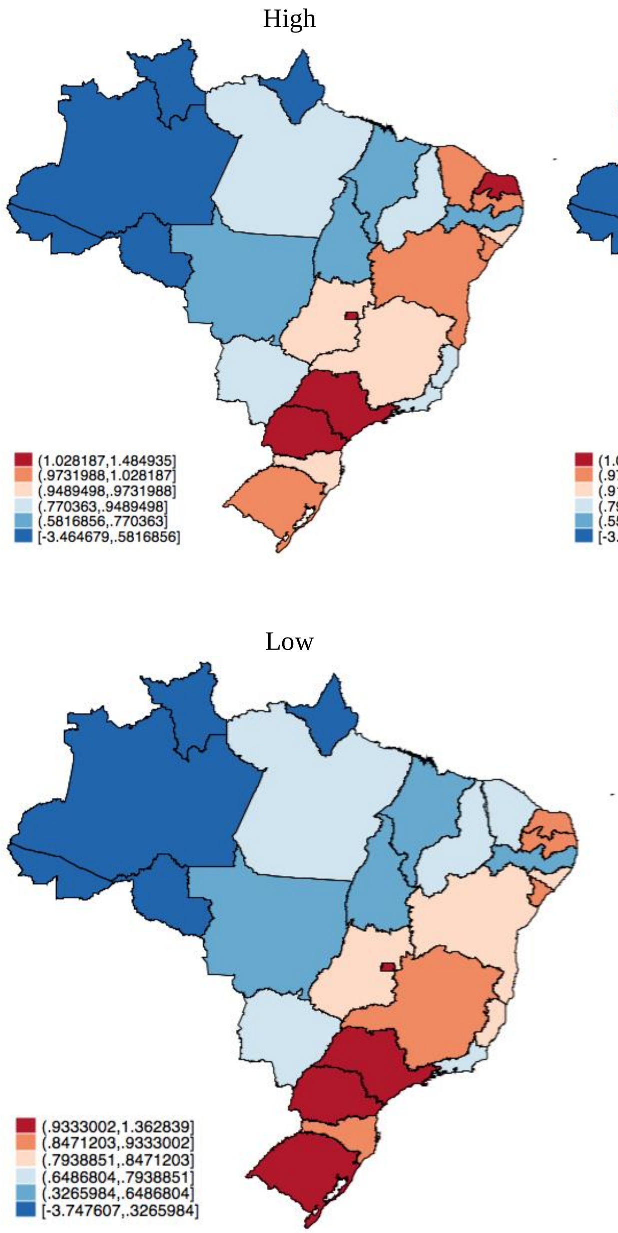
In relative terms, the biggest rise in dengue prevalence will be observed in the cities of the South, where the forecasts suggest an average rise in the number of cases exceeding 200 percent for the high and medium scenarios and somewhere around 150 percent for the low scenario (Table 6). Nowadays, in absolute terms, the lowest number of cases is also observed in the states of this region. The state that will present the largest growth in the number of dengue cases is Paraná, where the expected growth rate is around 1 percent (Figure 7), for all scenarios.

The Northeast region has historically high rates of dengue. Climate change might affect cities of this region differently. In the states of Maranhão, Piauí and Pernambuco, there will be lower growth rates of the disease in all scenarios, close to 0.5 percent (Figure 7). In the scenarios of high and medium climate change, the states of Ceará, Rio Grande do Norte, Paraíba, Alagoas, Sergipe and Bahia will present growth rates in disease prevalence of around 1 percent. With low climate change in the state of Ceará, the growth rate of the disease would be reduced to something closer to 0.6 percent.

In the Southeast and Midwest regions, the highest growth rates expected are observed in the Federal District, São Paulo and Minas Gerais, respectively: 1.06 percent, 1.02 percent and

0.96 percent. In these states,[9] the number of cases of dengue is expected to rise to around 140, 75 and 126 cases per 100,000 for the high and medium scenarios. For the scenario with low climate change, the number of dengue cases in these states is expected to rise to 90, 80 and 45 cases per 100,000, respectively, due to climate change.

Figure 7. Climate Change Estimate Effect on Dengue Rates Growth from 2041-2070 by Summer Scenarios



[9] The Federal District, location of the nation's capital, Brasília, is not strictly speaking a state, but it is treated as such here.

In this way, this paper contributes by linking two relevant agendas: finding ways to manage the climate-related risks of today and to improve the understanding of risks of tomorrow. The results suggest 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).

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 did not reject, the hypothesis that climate conditions affect the transmission of dengue fever in the country by using a synthetic control methodology.

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 allocated. 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 for infected mosquitoes that cross municipal borders. Therefore, the author suggests that integrated actions are needed to control the spread of dengue fever during epidemics.

When it comes to this paper’s contributions, the use of a synthetic control to identify the climate’s influence on dengue can be highlighted as the main contribution. Future research regarding dengue fever analysis could involve fieldwork, 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/.