NATURAL DISASTERS, ECONOMIC GROWTH AND SPATIAL SPILLOVERS: EVIDENCE FROM A FLASH FLOOD IN BRAZIL

ANTONIO VINÍCIUS BARBOSA* AND RICARDO CARVALHO DE ANDRADE LIMA*

Abstract. In this paper we use a flash flood that occurred in the Brazilian state of Santa Catarina in 2008 to investigate the existence of spatial spillovers from natural disasters in geographically linked areas. For that, we estimate a difference-in-differences model that explicitly allows for the existence of spatial interactions within affected and non-affected regions. Our results show that municipalities directly affected by the flood suffered a 8.47% decrease in GDP per capita on the year of the disaster. Three years after the flood however GDP per capita rebounded back to pre-disaster levels in all sectors but the Agricultural sector. Finally, our spatial estimations show that spillovers exist and are economically relevant.
Keywords: Natural disaster, spatial spillover, temporal dynamics.

Resumo. Este artigo utiliza as fortes chuvas ocorridas em Santa Catarina, no ano de 2008, para investigar a existência de *spillovers* espaciais em decorrência do desastre natural em regiões geograficamente relacionadas. Utiliza-se o método de diferença-em-diferenças que explicitamente permite a existência de interações espaciais entre regiões afetadas e não afetadas. Os resultados mostram que os municípios diretamente afetados sofreram uma queda de cerca de 8,47% no PIB per capita no ano do desastre. Três anos depois, no entanto, o PIB per capita retorna ao nível pré-disastre em todos os setores da economia, com exceção do setor agrícola. Por fim, os estimadores espaciais mostram que *spillovers* existem e são economicamente relevantes.
Palavras-chave: Desastres naturais, efeitos espaciais, dinâmica temporal.

JEL Codes: Q54, R211
Área ANPEC: Economia Regional e Urbana

1. Introduction

In this paper we use a flash flood that occurred in the Brazilian state of Santa Catarina in 2008 to investigate the existence of spatial spillovers from natural disasters in geographically linked areas. For that we compare the GDP trajectory of municipalities affected by the flash flood to the trajectory of municipalities not affected by the flood in the years immediately before and after the occurrence of the disaster using a difference-in-differences model that explicitly considers temporal dynamics (Autor et al., 2008; Husby et al., 2014) and allows for the existence of spatial interactions within affected and non-affected regions (along the lines of Delgado and Florax (2015)). While the literature analyzing the economic effects of natural disasters is quite large, spatial interactions – to the author's knowledge – have been largely overlooked and neglected in previous studies. Our study therefore aims at answering the following two questions: first, what was the economic effects of this natural disaster on directly affected municipalities? Second, and more importantly, how much (if any) were neighbouring regions indirectly affected by it?

*Universidade Federal de Pernambuco, Department of Economics.
Corresponding authors: CCSA, Universidade Federal de Pernambuco, Avenida dos Economistas, S/N, 50740-590, Recife, Brazil. aviniciusbb@hotmail.com; ricardocarvalho2009@gmail.com.

The direct impacts of environmental catastrophes have for long been in the research agenda of empirical economists, specially considering the huge effects that tsunamis, hurricanes, earthquakes and flooding may cause to economies throughout the world. For instance, according to the United Nations Office for Disaster Risk Reduction (UNISDR), between 2000 and 2012 natural disasters affected the lives of 2.9 billion people, killed around 1.2 million people and caused more than \$1.7 trillion worth of economic damage. In the United States, the Hurricane Katrina, one of the strongest storms to impact the coast of the country during the last 100 years, left about millions of homeless and an economic impact of approximately \$150 billion (Neumayer, Plümper, and Barthel, 2014).

These massive shocks led many to wonder about the true effect of a natural disaster. From a theoretical perspective, the notion that environmental disasters might have permanent long-run effects on income is not obvious (Hsiang and Jina, 2014). Income response to shocks may depend on the type and magnitude of the environmental disruption (Kahn, 2005) as well as on the level of development and institutional arrangement. More developed societies for instance may experience lower human and economic losses when compared to less well-off societies (Kahn, 2005; Toya and Skidmore, 2007; Noy, 2009).

Following this rationale, prior literature have laid out four competing possibilities for the growth trajectory succeeding a shock. The first, known as the "no recovery" possibility, argues that a natural disaster may result in damage to infrastructure and physical capital, which hinders the capital accumulation and thus negatively affects the rate of economic growth. In addition, the disaster can also alter business expectations, scaring away new investments and may trigger the migration of skilled and educated workers to unaffected areas (Barone and Mocetti, 2014), leaving post-disaster output to be permanently lower than its pre-disaster trajectory. A second possibility, the "recovery to trend" hypothesis, argues that a short-run negative shock exists but income levels should converge in the long-run back to their pre-disaster trend. According to Strobl (2011) and Yang (2008), the rebound back to pre-disaster trend may occur because individuals and wealth will migrate into devastated locations due to increases in the marginal product of capital when capital and labor become relatively scarce after the disaster due to destruction and mortality.

A third possibility, the "build back better" hypothesis, states that the shock may generate incentives for gradually building new and more efficient infra-structure compared to the capital that was destroyed in the disaster, leading to a positive net effect on long-run income levels (Cuaresma et al., 2008). A final possibility, known as "creative destruction" hypothesis, argues that income may increase in the short-run due to greater inflow of financial aid arising from donations and loans and to increases in demand for goods and services as destroyed capital is replaced with new assets. The environmental disruption may even provide the impetus to adopt new technologies, leading to improvements in total factor productivity (Skidmore and Toya, 2002).

From an empirical perspective, the debate however is far from settled. Cross-country evidence provide mixed empirical support for the hypotheses considered. Cavallo et al. (2013) for instance found no statistical relation between catastrophic natural disasters and economic growth, neither in the short nor long-run; the only exception occurring in extremely large disasters that were followed by radical political revolutions. More recently, Hsiang and Jina (2014), who analyzed 6,700 tropical cyclones during 1950-2008, showed that there was a long-term contraction in the income of affected countries.[1] The analysis based on cross-country data however may be subject to bias.

[1]See also Kahn (2005); Toya and Skidmore (2007); Noy (2009).

First, with few exceptions, natural disasters occur in very specific areas, making the assumption that the entire country has been affected a little implausible. Second, since in the cornerstone of these analysis is the assumption that treated and untreated countries can be compared, substantial unobserved, and difficult to control for, heterogeneity across countries may prevent one from obtaining a clean identification of causal effects. These motivated researchers to focus on investigating the economic impacts of natural hazards from a regional perspective, analyzing specific events and using more disaggregated data.

Along this line, Xiao et al. (2013) recently investigated the economic effects of the 1993 flood that occurred in the Midwest region of the United States using a matching algorithm to select non-flooded control counties and an ARIMA intervention model. They showed that the flood caused severe economic disturbances, mostly in the short-run, although a persistent contraction in the agricultural sector was observed. Barone and Mocetti (2014) examined two large-scale earthquakes that occurred in two different Italian regions in 1976 and 1980, one in the Friuli region (north of the country) and other in the Irpina region (south of the country). Using a synthetic control approach, the authors show that, discounting financial aid, both quakes had a negative impact in the short-term GDP. In the long-run however their findings indicate a positive effect in one case and a negative effect in the other. While the Friule region experienced increases to its per capita GDP, the Irpina region suffered a 12% decrease in GDP per capita. They suggest that differences in institutional quality between the regions may explain post disaster behaviors.

Using nightlight data from satellite images, Elliott et al. (2015) evaluated the impact of typhoons on economic activity in the coastal area of China. The results show that typhoons generated heavy short-term losses to the local economy. Their estimates also show a net economic loss of U$ 28.34 billion from 1992 to 2010. Tanaka (2015) investigated the economic impact of an Earthquake that struck the Japanese city of Kobe, in 1995. Using plant level data and a methodology based on a difference-in-differences strategy with matching, the author showed that the plants that survived in Kobe's most devastated districts experienced severe negative shocks to employment and value added growth during the following three years after the quake.

While the main motivation of these cross-country and cross-regional papers has been to investigate the positive/negative effects of natural disasters on economic outcomes,[2] issues related to spatial interactions have largely been overlooked. This is especially important in cross-regional analysis, since economies interact with each other, either through commercial transactions, labor mobility, technology diffusion and/or sharing of infrastructure assets (Ertur and Koch, 2007; LeSage and Fischer, 2008; Sardadvar, 2012). It is reasonable therefore to expect that neighbouring regions also suffer the consequences of a natural disaster, even indirectly. For instance, the destruction of important infrastructures, such as bridges and highways, might compromise economic growth of all economies that share its use in some way (Crescenzi and Rodríguez-Pose, 2012). Additionally, when a region suffers a negative shock, their ability to transact goods and disburse funds for new investments is reduced, compromising also the performance of neighbouring areas who would eventually benefit from spillover effects. Therefore, ignoring spatial interactions by treating regions as isolated islands may cause the model to (potentially) underestimate the economic consequences of natural disasters.

[2]Recently, researchers started using micro-level data to investigate the long run effects and inter-generational transmission of disasters on individual's outcomes. See, for instance, Vigdor (2008); Imberman et al. (2012); Caruso (2015).

Our study aims to contribute to this literature by explicitly considering the spatial interactions of natural disasters. We evaluate therefore not only the direct effect of the disaster, but allow our difference-in-differences model to capture also the indirect effects of the shock on neighbouring regions. For that, we apply the spatial extension of the difference-in-differences estimator recently proposed by Delgado and Florax (2015). As a case study, we investigate the economic impact of the flash flood that occurred on the northern coast of the Brazilian state of Santa Catarina in 2008. According to the state's Civil Defense, this was the worst disaster in the state history, with over 1.5 million people affected, 32,853 displaced, 5,617 homeless and 135 killed. This is an interesting case to be evaluated, since it occurred in a relatively rich region of a developing country[3]. In addition to considering spillover effects, our paper is among the few that use disaggregated data at municipality level to evaluate how each of the three economic sectors – agriculture, industry and services – respond to the flash flood.

Our difference-in-differences results show that municipalities directly affected by the flood suffered a 10% decrease in GDP per capita on the year following the disaster. Three years after the flood however GDP per capita rebounded back to pre-disaster levels; the only exception occurring in the agricultural sector, which experienced a decrease of about 22% in the first year after the shock and a statistically significant decrease of about 8% three years after the flood. Regarding our spatial estimations, our results show that spillovers exist and are economically relevant. We find an indirect impact of the flash flood of about -1.4% to -3.6%. In this way, ignoring the spatial spillovers leads to an underestimation of disasters effects and can generate sub-optimal recovery policies.

Our study is structured as follows: in section 2 we describe the study area and provide details about the natural disaster to be evaluated. Section 3 presents the empirical strategy and section 4 describes the data and variables used in the analysis. In section 5 we present the results and in section 6 we discuss the main empirical findings and policy implications.

2. The 2008 Flash Flood

Our study area comprises the Brazilian state of Santa Catarina, located in the southern part of Brazil. With an area of 95,736.165 km^2, the state has a population of 6.8 million inhabitants and is one of the most developed regions in the country, with a GDP per capita of R$ 29,350 (IBGE, 2013). Compared to other Brazilian states, Santa Catarina has the lowest illiteracy rate (3.2%), the lowest infant mortality rate (9.49%), the highest life expectancy (78.77 years) and the lowest levels of income inequality (Brazilian Demographic Census, 2010).

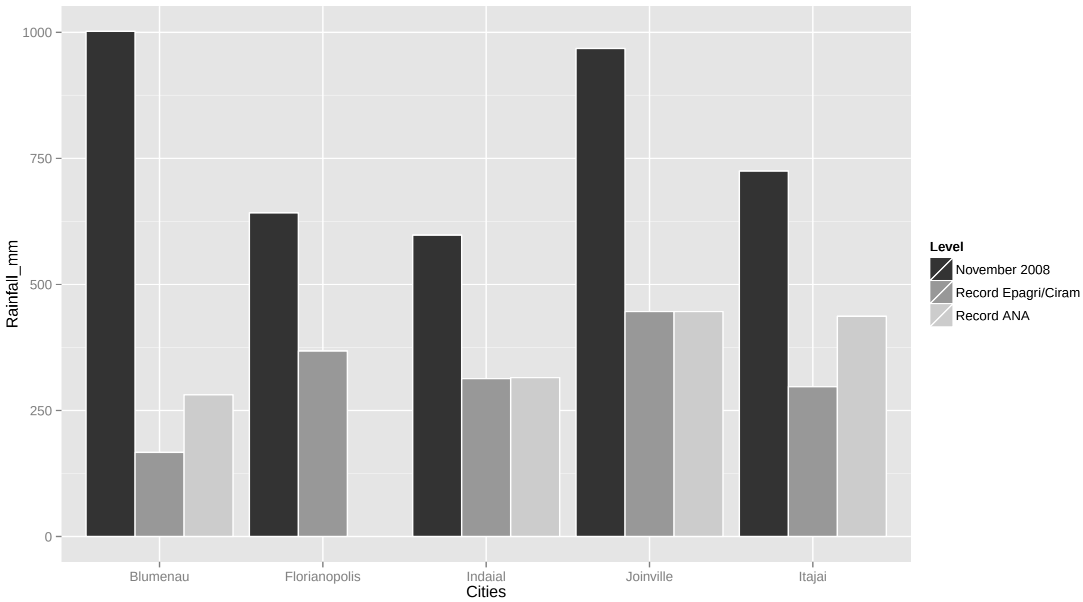
The state is located in a geographic area highly vulnerable to natural hazards. From 1992 to 2012, according to official records provided by Brazilian Atlas of Natural Disaster (2012), the state registered 4,999 natural disasters, 34% of those being flash floods, followed by dry spells and droughts (30%), windstorms (13%), hail (11%) and floods (9%). The flash floods and floods[4] occur predominantly in the basin of the Itajaí River (northeastern region of Santa Catarina) and its potential for destruction is amplified

[3]To our knowledge, the study of Ribeiro et al. (2014) is the only one that assesses the economic impact of this event. Using a synthetic control method, the authors show that the flash flood caused a monthly reduction of 5.13% in industrial production in the state of Santa Catarina. A drawback of their analysis is the use of aggregate data at the state level, which can lead to imprecise estimates, especially since the disaster occurred in a very specific and concentrated area of the state.

[4]The flash floods differ from floods due to their sudden occurrence, being caused by heavy rains (short time), having quick shifts and are more associated with hilly areas.

due to increasing urbanization pressures on the natural environment (Stevaux et al., 2009). These events often occur in the summer and spring seasons, due to increases in wet that facilitates tropical convections and to the mesoscale convective complexes (MCC), specifically favoring the occurrence of flash floods (Brazilian Atlas of Natural Disaster, 2012).

FIGURE 1. Cumulative Rain Level in Nov/2008 compared with the previous monthly records.



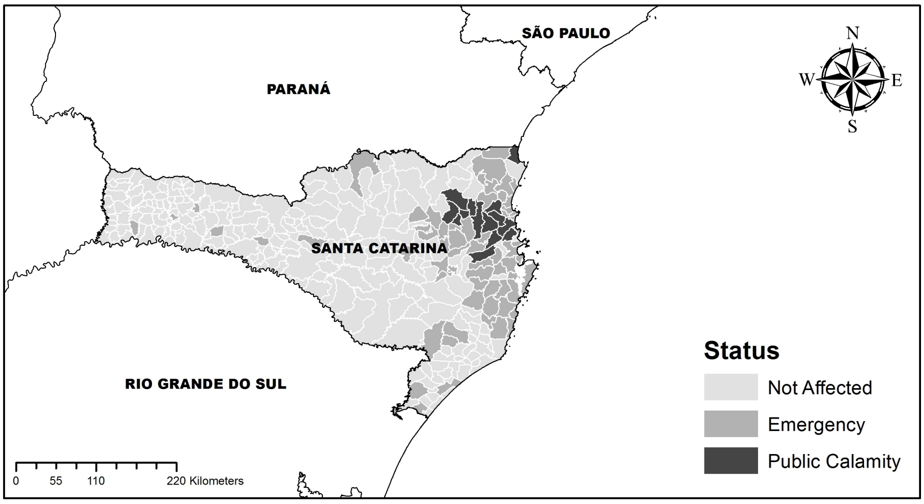
Source: Epagri/Ciram and National Water Agency (ANA).

In November 2008, the state of Santa Catarina was hit by a series of heavy rains that resulted in a catastrophic flash flood, impacting more than seventy cities concentrated in the northeast area of the state. In the affected municipalities, like Blumenau and Joinville, total rainfall of November 2008 almost surpassed 1,000 mm, way above Novembers' historic average of 150 mm. In the case of Blumenau, for instance, such volume exceeded total rainfall observed in October 2008 by 355%. Figure 1 gives us a clear picture of the magnitude of the phenomenon. The figure plots the monthly rainfall observed in November/2008 and the maximum historic values recorded by Epagri, a Santa Catarina government think tank, and the National Water Agency (ANA) for five affected cities.

According to Stevaux et al. (2009), the event was a result of two simultaneous weather events: a high pressure anticyclone that spread in the southern Atlantic Ocean coast and a cyclonic vortex of low pressure, which caused the ascension of air masses and the formation of rain clouds. The 2008 flash flood caused immense human damage due to landslides. According to the Civil Defense of Santa Catarina, 1.5 million people were affected by the event, 32,853 were displaced, 5,617 were homeless and 135 were killed. The severity of the 2008 event was such that it accounts for 80.3% of deaths from all flash floods that have occurred in the state during the period from 1992 to 2012 (Brazilian Atlas of Natural Disaster, 2012).

In terms of economic damage, the natural disaster occurred in an area with high industrial concentration and affected major urban centers like Florianópolis, Blumenau, Joinville and Itajaí, cities that concentrate 34.4% of the state GDP and 22.8% of its population (Brazilian Demographic Census, 2010). Regarding the infrastructure, the floods and landslides caused interceptions on roadways and highways, disrupted the Brazil-Bolivia gas pipeline (Gasbol), interrupted business in the Itajaí harbor, caused the destruction of agricultural assets and deteriorated most residential capital around the affected region. In the state, 63 municipalities declared state of emergency and 14 declared a state of public calamity. Figure 2 shows the geographical distribution of these municipalities.

FIGURE 2. Geographical Distribution of Affected Municipalities.



Source: Own elaboration based on information from the Civil Defense of SC.

Due to its tremendous socioeconomic consequences and the amount of lives affected, the November 2008 disaster is considered by the World Meteorological Organization (WMO) and by the United Nations (UN) as the worst catastrophe in the history of the state of Santa Catarina.

3. Empirical Strategy

In this section, we first present the empirical strategy we adopt to identify the impact of the 2008 Santa Catarina flash flood on GDP per capita of affected municipalities. We then describe the method through which we investigate the existence of potential spillover effects.

Direct effects. Regarding the direct effects of the 2008 Santa Catarina flash flood on GDP, we start with a standard municipal-level fixed-effects model that calculates the difference between the GDP before and after the flash flood for treated and untreated municipalities. This strategy, widely used in all areas of empirical economics, has recently been used to measure the economic impact of unanticipated natural disasters on a regional perspective by Husby et al. (2014) and Tanaka (2015). Our basic specification is given by the following equation:

$$y_{it} = \phi Flood_{i2008} + \sum_{k>2008} \eta_k Flood_{ik} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \tag{3.1}$$

where y_{it} is the log of GDP per capita of municipality i at year t, $Flood_{i2008}$ is a dummy variable that assumes the value of 1 if municipality i was affected by the natural disaster in 2008 and 0 otherwise, and $Flood_{ik}$, where $k > 2008$, are dummy variables representing treatment effects for k years after 2008. X_{it} is a vector of controls and μ_i and λ_t are, respectively, municipality and year fixed effects. ε_{it} is an error term, clustered at the municipality level in all estimations to allow for an arbitrary covariance structure within municipalities over time.

The municipality fixed effect included in the model control non-parametrically for municipality time-invariant unobservable characteristics, such as municipalities fixed geographical aspects. The time fixed effect control nonparametrically for yearly differences in GDP level common to all municipalities, such as macroeconomic aspects that can affect GDP. Finally, the vector of municipality characteristics, X_{it}, controls for time-varying characteristics that might be correlated with the shock and with municipalities GDP.[5]

The parameters of interest are given by ϕ and η_k, for $k > 2008$. ϕ represents the causal effect of the shock on GDP for the first year directly affected by the treatment. It calculates therefore the difference between the average of the outcome of interest for the first year after the shock minus the average of this outcome before the shock for treated and untreated municipalities. In a similar manner, η_k allows us to evaluate the time heterogeneity of the impact (temporal dynamics), assessing therefore if the impact of the natural disaster is temporary or persistent.

As is widely known, to interpret these parameters as causal we must rely on the assumption that there is no time-varying unobserved variable that is simultaneously correlated with our treatment and outcome variables, hence excluding the possibility of omitted variable bias (Angrist and Pischke, 2008). Although this assumption may seem strong for several empirical applications, we highlight that the natural disaster we analyze is hardly anticipated. Municipalities can predict rainfall a few days/hours before it happens, but not months before. Hence, simple comparison between affected and non-affected region may deliver the causal effect of interest.

We note however that a few natural disasters, such as floods and flash floods, may impact certain regions more frequently than others. It might be therefore that these regions may invest more in disaster preparedness, alleviating the potential impacts of a flood. If these investment differences changes between municipalities but are fixed across time, the municipality fixed effect we include in the model should be sufficient to allow for a causal interpretation of the estimates. If however investment changes across the time span we consider in our analysis, then we might face problems in identifying the isolated impact of the 2008 flash flood. We note however that preparedness tends to alleviate destruction, making our estimates likely to be a lower bound of the potential effect.

As it follows, although we cannot directly test if trajectories differ substantially between treated and control municipalities, since we cannot observe the treated group in the absence of treatment (Angrist and Pischke, 2008), we can test the robustness of our estimates to the existence of dynamic changes that might coincide with the occurrence of the flood. For that, we consider estimating model 3.1 with additional dummies indicating years before the disaster. We check therefore whether causes happen before consequences, in line with Granger (1969), by allowing the model to have heterogeneous anticipatory effects (leads), denoted by $Flood_{ik}$, where $k < 2008$, in addition to the heterogeneous post-treatment effects (lags) already included in the model (Autor, 2003). We estimate therefore:

$$y_{it} = \sum_{k<2008} \omega_k Flood_{ik} + \phi Flood_{i2008} + \sum_{k>2008} \eta_k Flood_{ik} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it}. \tag{3.2}$$

If the model we estimate in equation 3.1 incorrectly attributes pre-existing trends in the outcome to our treatment effect, then dummies indicating years before the

[5]In the next section we specify in more detail the variables included in this vector.

occurrence of the flash flood should matter in equation 3.2 and anticipatory effects, captured in ω_k, should show up as significant.

Indirect effects. Moving to estimates of potential spillover effects, we relax an important assumption required for the validity of the basic difference-in-differences estimator which is the Stable Unit Treatment Value Assumption (SUTVA). This assumption implies that potential outcomes for the unit i are unrelated to treatment status of units j (Angrist et al., 1996; Delgado and Florax, 2015). As we argue above, however, we expect to find significant spillover effects within the municipalities studied because of spatial dependence between local economies. In fact, there are strong evidences in favor of a positive spatial relation in the economic growth of Brazilian regional economies (Resende, 2011; Özyurt and Daumal, 2013; Lima and Silveira Neto, 2016).

Following this rationale, we apply the spatial extension of the difference-in-differences estimator recently proposed by Delgado and Florax (2015). This strategy allows us to explicitly consider the local spatial dependence of the treatment variable, so that the outcome of municipality i depends not only on their own treatment, but also on the treatment status of close neighbors. This framework has been increasingly adopted in the impact evaluation literature (Heckert and Mennis, 2012; Chagas et al., 2016; Dubé et al., 2014) to measure spatial treatment effects. The extension we consider is given by the following equation:

$$\begin{aligned} y_{it} = \phi Flood_{i2008} + \delta \sum_{j=1}^{n} w_{ij} Flood_{j2008} + \sum_{k>2008} \eta_k Flood_{ik} + \\ \sum_{j=1}^{n} w_{ij} (\sum_{k>2008} \theta_k Flood_{jk}) + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it}. \end{aligned} \tag{3.3}$$

This equation includes a spatial lag of the treatment dummy (second term on the right hand side) as well as spatial lags for post-treatment dummies (fourth term on the right hand side). The coefficient ϕ measures the average direct treatment effect (ADTE) and the coefficient δ multiplied by the average proportion of treated neighbors measures the average indirect treatment effect (AITE), or the spillover effect of the flash flood. In this case, the control group is composed of municipalities that are neither directly nor indirectly treated (Delgado and Florax, 2015).

The terms w_{ij} are elements of the spatial weight matrix W, which capture the neighborly relationship between municipality i and municipality j. In the present study, we use two types of spatial matrices: I) Binary Contiguity: w_{ij} takes the value of 1 if i borders j and 0, otherwise; II) k-Nearest Neighbors: w_{ij} takes the value of 1 if j is one of the k-nearest neighbors of i and 0, otherwise.

4. Variables and Data

The data we use to investigate the direct and indirect effects of the 2008 flash flood on the economic performance of the Santa Catarina municipalities consists of a balanced panel for the years between 2006 and 2010. Since our study area is often affected by natural disasters, we choose this small time interval to eliminate two less intense shocks that might affect/confound our estimates. In 2004 for instance the southern Brazilian states were hit by the "Catarina" hurricane, which affected about 40 municipalities in the State of Santa Catarina and caused four deaths. In January 2011 another flash flood occurred in the state and affected 83 cities and caused six deaths.

Treatment definition. An important issue when estimating the effects of disasters relates to the criteria used to define municipalities affected by the shock. A common choice has been to use rainfall levels and their deviations from historic averages as a measure of disaster exposure. As we argued in section 2, however, the 2008 flash floods were characterized by a combination of heavy rain, flooding and landslides. Since these floods and landslides were responsible for most of the damage, and these are not perfectly predicted by rainfall variation within municipalities, using rainfall as proxy for exposure may be inadequate. We choose therefore to use a more objective measure of disaster exposure: areas declared under a state of public calamity. Accordingly, the Brazilian Ministry of Integration establishes a few objective criteria that must be satisfied for cities to declare a state of public calamity: I) 10 or more individuals killed, or 100 individuals affected; II) 10 or more public health/education facilities destroyed; and III) economic loss above 8.33% of the municipality's net current revenue. Hence, due to these strict criteria, we expect only municipalities that were heavily affected by the floods to be considered as treated.

Aside from those who declared a state of public calamity, a few municipalities geographically far from the most heavily affected region (northeastern state) declared state of emergency. This is a milder signalling of a natural hazard, but more prone to endogeneity since no objective criteria has to be satisfied for those who declare an emergency status. There is in fact evidence that the recognition of emergency status by the federal government is related to partisan position (political alignment) of the municipality mayor (Cavalcanti, 2016), as a mechanism to facilitate federal transfers. In that regard, we add political controls (as described below) to test for this heterogeneity and perform sensitivity analysis. As a robustness exercise, we also define treatment based on a measure of human damage; we consider treated municipalities as those who had homeless or dead individuals.[6]

Outcome and control variables. The dependent variable is the municipality GDP per capita, constructed annually by the Brazilian Institute of Geography and Statistics (IBGE). The choice of covariates was based on the empirical literature of regional growth (Lall and Shalizi, 2003; LeSage and Fischer, 2008; Crescenzi and Rodríguez-Pose, 2012). From IBGE we use data on population size, urbanization rates[7] and the share of agricultural and manufacturing sector on the GDP. We also include public investment in capital as a proxy for physical capital investment, which is measured annually by the Department of National Treasury (STN), subordinated to the Brazilian Ministry of Finance. Related to urban infrastructure we use information on proportion of households with access to piped water, access to electricity and garbage collection. These information are available annually by the primary care information system (SIAB), from the Health Ministry.

In addition to the socioeconomic variables that might determine our outcome variable, we consider adding covariates related to local politics. Following Barone and Mocetti (2014), we include election turnout as proxy for civic engagement, which is a measure of institutional quality. In addition, as partisan alignment has been shown to affect local growth (Novosad and Asher, 2016), we add two dummy variables that link the political alignment between local and state (federal) governments. This variable assumes value equal to 1 when the mayor and the governor (president) share the same party and 0, otherwise. All political variables were obtained from the Brazilian Electoral Superior Court (TSE).

[6] There are 25 municipalities matching this criterion.

[7] As the urban population size is only available for the years 2007 and 2010, values for the other years were estimated via interpolation since it has a steady trend.

In table 1 we present descriptive statistics for the variables used in our analysis. We note that municipalities affected by the flash flood are richer when compared to unaffected municipalities. Also, they present higher volume of public investment, better urban infrastructure and are more industrialized.

TABLE 1. Descriptive Statistics

	Affected Municipalities		Not Affected Municipalities	
	Mean	SD	Mean	SD
GDP per capita (1000)	26.639	17.268	20.909	10.18
Population (1000)	58.388	80.722	18.751	45.933
Public Investment (in Million)	33.268	52.222	9.652	22.551
Share of Agriculture	0.050	0.047	0.265	0.177
Share of Manufacturing	0.344	0.114	0.229	0.148
Urbanization Rate	0.773	0.208	0.557	0.240
% Served by Piped Water	0.663	0.227	0.553	0.249
% Served by Garbage Collection	0.914	0.110	0.650	0.253
% Served by Electricity	0.991	0.006	0.979	0.035
Alignment with President	0.100	0.302	0.099	0.299
Alignment with Governor	0.386	0.490	0.387	0.487
Electoral Turnout	0.885	0.041	0.890	0.051

Note: SD corresponds to the standard deviation. The GDP per capita and public investment are deflated to R$ of 2000. Electoral turnout is the ratio between the number of voters who attended the elections and the total electorate.

5. RESULTS

In this section we present the direct and indirect effects of the 2008 Santa Catarina's flash flood on GDP per capita of the affected municipalities. We also present the effects taking into account the three economic sectors. At the end of the section we access the spatial spillover effects on geographically linked regions.

5.1. **Direct effects of the 2008 flash flood.** Table 2 presents the direct effect estimates of the Santa Catarina flash flood on GDP of the affected municipalities. As stated above, the empirical strategy consists in estimating the presence of short-run or persistent effects on GDP of the affected units. Column (1) refers to the model with time and municipality fixed effects, while in columns (2) and (3) we include socioeconomic and political control variables, respectively.

According to the column (1) the flash flood lead to an average fall of approximately 10% on GDP per capita in the year that municipalities were hit by the disaster. The same intense and significant result was obtained when we look at the year succeeding the flash flood. Only in 2010 the GDP per capita rebounded back to the patterns observed for the non affected municipalities. These findings suggest the existence of short-term negative effects on economic activity, with a quick recovery to pre-disaster levels. This is along the lines of the "recovery to trend" hypothesis, also observed in the recent cross-regional literature reported in Xiao et al. (2013); Husby et al. (2014); Elliott et al. (2015); Tanaka (2015). Results are quantitatively the same when we add socioeconomic controls in our main specification (column 2), and present marginal changes when political controls are added (column 3). The reduction of the magnitude of the damage observed in column (3) may indicate that the political alignment between the executive power of the different entities of the federation can facilitate the reception

Table 2. Impact of Natural Disasters on GDP: Benchmark Specification.

	(1)	(2)	(3)
Flood_{2008}	-0.1045***	-0.1027***	-0.0847***
	(0.027)	(0.028)	(0.028)
Flood_{2009}	-0.1053***	-0.0978***	-0.0771***
	(0.031)	(0.031)	(0.034)
Flood_{2010}	-0.0328	0.0113	0.0211
	(0.041)	(0.043)	(0.046)
Time Fixed Effects	Yes	Yes	Yes
Municipality Fixed Effects	Yes	Yes	Yes
Socioeconomic Controls	No	Yes	Yes
Political Controls	No	No	Yes
Observations	1465	1465	1465
Adjusted R^2	0.9259	0.9319	0.9326
F-Statistic	62.14	65.84	65.91

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. We use robust standard errors that were grouped at the municipal level. The standard deviations are presented in parentheses. The dependent variable is the logarithm of GDP per capita. The socioeconomic and political controls are reported in table 1. Non-dichotomous control variables are in logarithm format.

of transfers, political windfalls and donations, in line with the work of Cavalcanti (2016).

In order to capture any pre-trend differences between treated and control units, table 3 presents the results considering anticipatory effects, as depicted in equation 3.2. Here we consider the specification with one lead and two lags time periods. Column 1 represents the model with time-fixed effect, municipality fixed-effects, and socioeconomic control variables; and column 2 controls for political variables.

For both specifications, the coefficients measuring anticipatory effects are not statistically significant. Put another way, one can argue that there is no significant differences between the GDP trajectories for control and later affected municipalities. If there was another unobserved factor leading to a drop in GDP per capita of the affected municipalities, then it would have contemporaneous effects to the same economies, which is hardly credible. The lagged coefficients for 2009 and 2010 have the same pattern as the results obtained in table 2.

In table 4 we present the results of two robustness tests. In the first test we use as alternative treatment status municipalities that suffered some human damage, defined as rather homeless or dead people as consequence of the flood. This criterion is less restrictive than the state of public calamity declaration and comprises a larger number of affected municipalities. In the second robustness test, the control group is composed by municipalities with similar observable characteristics as the affected ones (columns 3 and 4). The matching procedure consists in estimating the propensity score for each municipality[8] before the parametric estimation (Ho et al., 2007). To improve balance between treated and control units, the matching estimation is useful to reduce the model dependence, remove outliers and minimize potential selection bias.

According to table 4, changes in treatment criteria and the composition of the control group do not change the results for the year the flash flood occurred, even tough the

[8]For more details about this methodology, see Caliendo and Kopeinig (2008). We employ a nearest neighbour algorithm for the construction of a new control group, composed by 14 municipalities.

Table 3. Impact of Natural Disasters on GDP growth: Leads and Lags Specification.

	(1)	(2)
$Flood_{2007}$	-0.0386	-0.0384
	(0.024)	(0.024)
$Flood_{2008}$	-0.1213***	-0.1031***
	(0.036)	(0.037)
$Flood_{2009}$	-0.1163***	-0.0956***
	(0.040)	(0.043)
$Flood_{2010}$	-0.0072	0.0026
	(0.050)	(0.053)
Time FE	Yes	Yes
Municipality FE	Yes	Yes
Socioeconomic Controls	Yes	Yes
Political Controls	No	Yes
Observations	1465	1465
Adjusted R^2	0.9319	0.9326
F-Statistic	65.62	65.7

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. We use robust standard errors that were grouped at the municipal level. The standard deviations are presented in parentheses. The dependent variable is the logarithm of GDP per capita. The time-varying controls are reported in table 1. Non-dichotomous control variables are in logarithm format.

Table 4. Impact of Natural Disasters on GDP growth: Robustness Checks.

	Human Damaged		Matched Sample	
	(1)	(2)	(3)	(4)
$Flood_{2008}$	-0.0897***	-0.0713***	-0.0777**	-0.0763**
	(0.023)	(0.024)	(0.038)	(0.039)
$Flood_{2009}$	-0.0878***	-0.0691***	-0.0658	-0.0472
	(0.025)	(0.027)	(0.044)	(0.049)
$Flood_{2010}$	0.0017	0.0097	-0.0030	0.0143
	(0.032)	(0.033)	(0.059)	(0.061)
Time FE	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Socioeconomic Controls	Yes	Yes	Yes	Yes
Political Controls	No	Yes	No	Yes
Observations	1465	1465	140	140
Adjusted R^2	0.9322	0.9327	0.9721	0.974
F-Statistic	66.1	66	113.8	114.4

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. We use robust standard errors that were grouped at the municipal level. The standard deviations are presented in parentheses. The dependent variable is the logarithm of GDP per capita. The time-varying controls are reported in table 1. Non-dichotomous control variables are in logarithm format. In column (1) and (2) the treated municipalities are those who have had some human damage, while in column (3) and (4) the treatment and control groups are composed after the matching estimation.

results are quantitatively smaller. Worth to note that the negative impact disappears one year before the natural disaster took place (columns 3 and 4) mainly because the sample size is drastically reduced after matching.

5.2. **Heterogeneity by intensity of damage and by economic sectors.** The use of public calamity declaration as a proxy for disaster exposure may be tricky because it does not reveal the intensity of the damage. Even if one knows weather the municipality was affected by the disaster there is no a clear picture about the size of the damage. An intuitive way to obtain some insights regarding the destruction level is creating an alternative treatment group composed by those municipalities affected by the flood, but at a lower magnitude than those that invoked for public calamity. As discussed in section 4, when a natural event occurs in a particular region the local government can claim for emergency or public calamity status. Thus, the use of the state of emergency dummies in equation 3.1 as treatment status is a reasonable strategy to attain the differences in shock intensity[9]. One can expect that municipalities that have enacted state of emergency also suffer from the shock, but less intensively than those who required for public calamity. Table 5 shows the results of this empirical exercise.

TABLE 5. Impact of Natural Disasters on GDP growth: the extent of the damage.

	(1)	(2)
Emergency_{2008}	-0.0356**	-0.0324*
	(0.017)	(0.017)
Emergency_{2009}	-0.0213	-0.0211
	(0.017)	(0.018)
Emergency_{2010}	-0.0056	-0.0075
	(0.019)	(0.021)
Calamity_{2008}	-0.1148***	-0.0966***
	(0.029)	(0.029)
Calamity_{2009}	-0.105***	-0.085**
	(0.033)	(0.036)
Calamity_{2010}	0.0079	0.0168
	(0.0439)	(0.0470)
Time FE	Yes	Yes
Municipality FE	Yes	Yes
Socioeconomic Controls	Yes	Yes
Political Controls	No	Yes
Observations	1465	1465
Adjusted R^2	0.9321	0.9327
F-Statistic	65.37	65.39

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. We use robust standard errors that were grouped at the municipal level. The standard deviations are presented in parentheses. The dependent variable is the logarithm of GDP per capita. The time-varying controls are reported in table 1. Non-dichotomous control variables are in logarithm format.

Municipalities that have enacted state of emergency status presented a 3.24 % reduction in the GDP per capita in the year that the flash flood occurred, while those

[9]The causal interpretation of the state of emergency dummies should be done with caution, since as discussed in section 4, this variable is potentially endogenous.

who enacted public calamity presented a drop of 9.66% (see column 2). It is worth to note that the effect fades away immediately in the year following the disaster in the case of emergency status. These evidences suggest the existence of heterogeneous effects in the disaster exposure and the use of emergency and calamity status resemble this fact.

The results presented so far show that the 2008 flash flood intensively harmed the economic activity of the affected municipalities. An important aspect for the design of damage management policies and financial aid plans is to understand how these effects spread out to different economic sectors. Although some quantitative research is focused in measuring the economic impact of natural disasters on the economic outcomes, little is known about their impact on distinct economic sectors. This gap in literature avoids the development of better mechanisms to promote the reestablishment of affect areas. In this sense, the shock affects the economic sectors in different ways and to test this hypothesis we re-estimated equation 3.1 considering the GDP per capita in different economic sectors: agriculture, manufacturing and services. Table 6 below summarizes the results.

Table 6. Impact of Natural Disasters on GDP growth: different sectors.

	Agriculture	Industry	Services
	(1)	(2)	(3)
Flood_{2008}	-0.1949***	-0.0952***	-0.0441**
	(0.048)	(0.039)	(0.020)
Flood_{2009}	-0.2066***	-0.0785	-0.0352
	(0.065)	(0.049)	(0.028)
Flood_{2010}	-0.0816**	-0.0524	0.0194
	(0.041)	(0.061)	(0.027)
Time FE	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes
Socioeconomic Controls	Yes	Yes	Yes
Political Controls	Yes	Yes	Yes
Observations	1465	1465	1465
Adjusted R^2	0.9466	0.9868	0.9969
F-Statistic	84.64	357.4	1535

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. We use robust standard errors that were grouped at the municipal level. The standard deviations are presented in parentheses. The dependent variable is the logarithm of GDP per capita. We exclude the sharing of agriculture and manufacture from the time-varying controls. Non-dichotomous control variables are in logarithm format.

All economic sectors are negatively affected by the natural disaster, although in different magnitudes. The agricultural sector is the most damaged by the flash flood[10]. In the year of the disaster, the agricultural GDP of the treated municipalities are reduced on average by 19.49%. This figure is twice as large as the impact size on

[10]As the share of manufacturing and services in the economy of the damaged areas is much higher than the share of agriculture, the absolute impact of the disaster is greater in the first sectors. Considering the average GDP of the affected municipalities and the coefficients described in table 6, it's estimated that the shock caused (per municipality) a reduction of R$ 3.71 million in agriculture, R$ 56.17 million in industry and R$ 49.7 million in services.

manufacturing GDP, and approximately four times the size on GDP of the tertiary sector.

Due to the nature of the shock, this result is quite expected. The floods can destroy completely the agricultural production systems, and it is almost impossible to protect the farms and agriculture assets from shocks like this. As mentioned in introduction, the study of Xiao et al. (2013), which investigated the economic consequences of a 1993 Midwest flood, also found that the impact on the agricultural sector were negative and long-lasting. Additionally, this evidence is also consistent with the finding of a recent report of the Food and Agriculture Organization of the United Nations (2015), which found that in developing countries, the agricultural sector absorbs about 22% of the economic damage caused by natural disasters.

5.3. **Spatial Spillovers.** The evidence shown above reveal that the flash flood caused a negative economic impact on the affected municipalities, but one may consider the existence of spillover effect in neighbouring areas. Due to the regional linkage between economic activity, it is feasible to expect that there is some spatial effects neglected by the previous results. A particular region may be directly affected by the disaster (when the event occurs in your own boundary) or may be affected indirectly (when the event occurs in the vicinity of the region). Additionally, the SUTVA is unlikely to hold in studies focused on the impact of disasters in a regional perspective. Following the methodology proposed by Delgado and Florax (2015), table 7 shows the estimated results from equation 3.3.

Column (1), (2) and (3) show model specifications similar to those estimated in section 5.1, while column (4) presents the specification that considers the spatial lags of the covariates. This model is widely used in spatial econometric literature[11] and is known as SLX model (Halleck Vega and Elhorst, 2015).

As can be observed, the results related to the direct impact remains unchanged when compared to the benchmark specification (see table 2). However, there is some evidences that a particular economy is also affected indirectly by the shock: the lags coefficients for the neighbour treatment variable are negative and statistically significant. Thus, one year after the event, municipalities that have a neighbour affected by the 2008 flash flood showed a decline in its per capita GDP of about 1.4% (0.27x0.0526)[12] and a contraction of 1.24% (0.2361x0.0526) two years after the event.These findings reveal that the municipalities indirectly affected by the natural hazard did not suffer the consequences immediately, only in years after the shock (2009 and 2010).

There are two possibilities that may help explain this result. Firstly, the intensity of economic interactions among directly affected and neighbouring areas can have some degree of time seasonality. For example, such interactions may occur predominantly in the early months of the year, so that in November 2008 (month that the flash flood occurred), most of the interactions had already been materialized. Secondly, it is likely that the economic effect of a demand drop for goods and services from the neighbours only be felt with a certain degree of delay.

[11]Besides adding spatial lag in the covariates, another option would also include the spatial lag in the dependent variable, specification known as Spatial Durbin Model (SDM). However, the consideration of global spatial dependence on a difference-in-differences framework is still a developing point (Delgado and Florax, 2015).

[12]As discussed in section 3, the average indirect treatment effect (AITE) is measured as the multiplication between the spatial lag coefficient and the respective average proportion of treated neighbours. Using the binary contiguity matrix, we observed this value is 0.0526 (Table 9).

Table 7. The Indirect Impact of Natural Disasters on GDP growth: spatial difference-in-differences specification.

	(1)	(2)	(3)	(4)
$Flood_{2008}$	-0.1098***	-0.1076***	-0.0895***	-0.0758***
	(0.0274)	(0.0281)	(0.0282)	(0.0250)
$Flood_{2009}$	-0.1192***	-0.1098***	-0.0888***	-0.0808***
	(0.0320)	(0.0319)	(0.0341)	(0.0307)
$Flood_{2010}$	-0.0450	-0.0001	0.0100	0.0165
	(0.0414)	(0.0440)	(0.0467)	(0.0425)
W^*Flood_{2008}	-0.0950	-0.0910	-0.1092	-0.1335
	(0.0863)	(0.0890)	(0.0894)	(0.0943)
W^*Flood_{2009}	-0.2521***	-0.2361***	-0.2492***	-0.2734***
	(0.0964)	(0.0936)	(0.0936)	(0.1012)
W^*Flood_{2010}	-0.2204*	-0.2220**	-0.2223**	-0.2361*
	(0.1163)	(0.1097)	(0.1122)	(0.1213)
Time FE	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Socioeconomic Controls	No	Yes	Yes	Yes
Political Controls	No	No	Yes	Yes
Neighborhood Controls	No	No	No	Yes
Observations	1465	1465	1465	1465
Avg. Prop. of Treated Neighbors	0.0526	0.0526	0.0526	0.0526
R^2	0.9266	0.9326	0.9333	0.9333
F-Statistic	62.18	65.9	66.04	61.18

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. We use robust standard errors that were grouped at the municipal level. The standard deviations are presented in parentheses. The dependent variable is the logarithm of GDP per capita. The time-varying controls are reported in table 1. Non-dichotomous control variables are in logarithm format. We use the binary contiguity matrix (weighted) in the estimations.

Finally, table A1 in the Appendix A shows that indirect impacts are insensitive to specifications with different spatial matrices (k-Nearest Neighbor), indicating robustness. Thus, the evidences showed in this section indicates that spillovers effects are far from negligible and neglect them may lead to undermined results of the real economic impacts of the natural disasters. Further, aid-relief policies should take into account the potential indirect effects of natural disasters.

6. Concluding Remarks

This paper access both direct and indirect effects caused by the flash flood that occurred in the Brazilian state of Santa Catarina. In order to deal with the endogeneity of the treatment definition of which municipalities were affected by the disaster we use as objective criteria of disaster exposure those municipalities declared under a state of emergency or public calamity status. We estimate contemporary and dynamic effects of the flash flood on the economic performance of the affected areas. Also, we allow the existence of spillover effects on unaffected but geographically related areas in the state.

We find that municipalities directly affected by the flash flood presented a significant drop of 8.5% on GDP per capita immediately after the disaster and a decrease of 7.71% in the year following. The economic performance of the municipalities rebounded to the pre-disaster level only after two year. When considering different economic sectors we observe that the agriculture sector does not present the same recovery pattern and has more permanent consequences. The results for spatial spillover suggest that indirect effects are far from negligible due the economic and social interactions between municipalities. These results are particularly important for aid policies aimed to mitigate overall loses, which also should consider the neighboring affected regions.

References

Angrist, J. D., Imbens, G. W., Rubin, D. B., 1996. Identification of causal effects using instrumental variables. Journal of the American statistical Association 91 (434), 444–455.

Angrist, J. D., Pischke, J.-S., 2008. Mostly harmless econometrics: An empiricist's companion. Princeton University Press.

Autor, D. H., Katz, L. F., Kearney, M. S., 2008. Trends in u.s. wage inequality: Revising the revisionists. Review of Economics and Statistics 90 (2), 300–323.

Autor, H., 2003. Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. Journal of Labor Economics, January.

Barone, G., Mocetti, S., 2014. Natural disasters, growth and institutions: a tale of two earthquakes. Journal of Urban Economics 84, 52–66.

Brazilian Atlas of Natural Disaster, 2012. Atlas brasileiro de desastres naturais 1991 a 2010: volume Brasil. Florianópolis: CEPED, UFSC.
URL http://150.162.127.14:8080/atlas/atlas.html

Brazilian Demographic Census, 2010. Características gerais da população, religião e pessoas com deficiência. Rio de Janeiro: Instituto Brasileiro de Geografia e Estatística.

Caliendo, M., Kopeinig, S., 2008. Some practical guidance for the implementation of propensity score matching. Journal of Economic Surveys 22 (1), 31–72.

Caruso, G. D., 2015. Intergenerational transmission of shocks in early life: Evidence from the Tanzania great flood of 1993. Available at SSRN 2560876.
URL http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2560876

Cavalcanti, F. L., 2016. The Brazilian "drought industry" revisited. Working paper.
URL https://goo.gl/SkDaX6

Cavallo, E., Galiani, S., Noy, I., Pantano, J., 2013. Catastrophic natural disasters and economic growth. Review of Economics and Statistics 95 (5), 1549–1561.

Chagas, A. L., Azzoni, C. R., Almeida, A. N., 2016. A spatial difference-in-differences analysis of the impact of sugarcane production on respiratory diseases. Regional Science and Urban Economics 59, 24–36.

Crescenzi, R., Rodríguez-Pose, A., 2012. Infrastructure and regional growth in the European Union*. Papers in Regional Science 91 (3), 487–513.

Cuaresma, J. C., Hlouskova, J., Obersteiner, M., 2008. Natural disasters as creative destruction? Evidence from developing countries. Economic Inquiry 46 (2), 214–226.

Delgado, M. S., Florax, R. J., 2015. Difference-in-differences techniques for spatial data: Local autocorrelation and spatial interaction. Economics Letters 137, 123–126.

Dubé, J., Legros, D., Thériault, M., Des Rosiers, F., 2014. A spatial difference-in-differences estimator to evaluate the effect of change in public mass transit systems on house prices. Transportation Research Part B: Methodological 64, 24–40.

Elliott, R. J., Strobl, E., Sun, P., 2015. The local impact of typhoons on economic activity in china: A view from outer space. Journal of Urban Economics 88, 50–66.

Ertur, C., Koch, W., 2007. Growth, technological interdependence and spatial externalities: Theory and evidence. Journal of Applied Econometrics 22 (6), 1033–1062.

Granger, C. W. J., 1969. Investigating causal relations by econometric models and cross-spectral methods. Econometrica 37 (3), 424–438.

Halleck Vega, S., Elhorst, J. P., 2015. The SLX model. Journal of Regional Science 55 (3), 339–363.

Heckert, M., Mennis, J., 2012. The economic impact of greening urban vacant land: a spatial difference-in-differences analysis. Environment and Planning A 44 (12), 3010–3027.

Ho, D. E., Imai, K., King, G., Stuart, E. A., 2007. Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. Political analysis 15 (3), 199–236.

Hsiang, S. M., Jina, A. S., 2014. The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones. Tech. rep., National Bureau of Economic Research.
URL http://www.nber.org/papers/w20352

Husby, T. G., Groot, H. L., Hofkes, M. W., Dröes, M. I., 2014. Do floods have permanent effects? evidence from the netherlands. Journal of Regional Science 54 (3), 355–377.

IBGE, 2013. Instituto Brasileiro de Geografia e Estatística, 2011 9, 2013.
URL http://www.ibge.gov.br/home/

Imberman, S. A., Kugler, A. D., Sacerdote, B. I., 2012. Katrina's children: Evidence on the structure of peer effects from hurricane evacuees. The American Economic Review, 2048–2082.

Kahn, M. E., 2005. The death toll from natural disasters: The role of income, geography, and institutions. Review of Economics and Statistics 87 (2), 271–284.

Lall, S. V., Shalizi, Z., 2003. Location and growth in the Brazilian Northeast. Journal of Regional Science 43 (4), 663–681.

LeSage, J. P., Fischer, M. M., 2008. Spatial growth regressions: Model specification, estimation and interpretation. Spatial Economic Analysis 3 (3), 275–304.

Lima, R. C. D. A., Silveira Neto, R. D. M., 2016. Physical and human capital and brazilian regional growth: A spatial econometric approach for the period 1970–2010. Regional Studies 50 (10), 1688–1701.

Neumayer, E., Plümper, T., Barthel, F., 2014. The political economy of natural disaster damage. Global Environmental Change 24, 8–19.

Novosad, P., Asher, S., 2016. Politics and local economic growth: Evidence from india. Tech. rep., Social Science Research Network.
URL http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2811187

Noy, I., 2009. The macroeconomic consequences of disasters. Journal of Development Economics 88 (2), 221–231.

Özyurt, S., Daumal, M., 2013. Trade openness and regional income spillovers in Brazil: A spatial econometric approach. Papers in Regional Science 92 (1), 197–215.

Resende, G. M., 2011. Multiple dimensions of regional economic growth: The Brazilian case, 1991- 2000. Papers in Regional Science 90 (3), 629–662.

Ribeiro, F. G., Stein, G., Carraro, A., Ramos, P. L., 2014. O Impacto Econômico dos Desastres Naturais: O Caso das Chuvas de 2008 em Santa Catarina. Planejamento e Políticas Públicas 43 (2), 299–322.

Sardadvar, S., 2012. Growth and disparities in Europe: Insights from a spatial growth model. Papers in Regional Science 91 (2), 257–274.

Skidmore, M., Toya, H., 2002. Do natural disasters promote long-run growth? Economic Inquiry 40 (4), 664–687.

Stevaux, J. C., Martins, D. P., Meurer, M., 2009. Changes in a large regulated tropical river: The Paraná River downstream from the Porto Primavera Dam, Brazil. Geomorphology 113 (3), 230–238.

Strobl, E., 2011. The economic growth impact of hurricanes: Evidence from u.s. coastal counties. Review of Economics and Statistics 93 (2), 575–589.

Tanaka, A., 2015. The impacts of natural disasters on plants' growth: Evidence from the Great Hanshin-Awaji (Kobe) earthquake. Regional Science and Urban Economics 50, 31–41.

Toya, H., Skidmore, M., 2007. Economic development and the impacts of natural disasters. Economics Letters 94 (1), 20–25.

Vigdor, J., 2008. The economic aftermath of Hurricane Katrina. The Journal of Economic Perspectives 22 (4), 135–154.

Xiao, Y., Wan, J., Hewings, G. J., 2013. Flooding and the Midwest economy: assessing the Midwest floods of 1993 and 2008. GeoJournal 78 (2), 245–258.

Yang, D., 2008. Coping with disaster: The impact of hurricanes on international financial flows, 1970-2002. The B.E. Journal of Economic Analysis & Policy 8 (1), Article 13.

Appendices

A. Tables

Table A1. The Indirect Impact of Natural Disasters on GDP growth: different spatial weight matrices.

	(1)	(2)	(3)	(4)
	$k = 2$	$k = 4$	$k = 6$	$k = 8$
$Flood_{2008}$	-0.0742***	-0.0775***	-0.0832***	-0.0813***
	(0.0225)	(0.0239)	(0.0258)	(0.0290)
$Flood_{2009}$	-0.0737***	-0.0724***	-0.0768***	-0.0700**
	(0.0288)	(0.0292)	(0.0314)	(0.0342)
$Flood_{2010}$	0.0229	0.0275	0.0213	0.0264
	(0.0402)	(0.0398)	(0.0412)	(0.0448)
$W*Flood_{2008}$	-0.0922	-0.1511*	-0.2466***	-0.3102***
	(0.0620)	(0.0863)	(0.1033)	(0.1217)
$W*Flood_{2009}$	-0.1320**	-0.2205**	-0.3306***	-0.3900***
	(0.0584)	(0.0913)	(0.1217)	(0.1461)
$W*Flood_{2010}$	-0.0929	-0.1818**	-0.2564*	-0.2730*
	(0.0599)	(0.0911)	(0.1320)	(0.1519)
Time FE	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Socioeconomic Controls	Yes	Yes	Yes	Yes
Political Controls	Yes	Yes	Yes	Yes
Neighbohood Controls	Yes	Yes	Yes	Yes
Avg. Prop. of Treated Neighbors	0.05631	0.0538	0.0552	0.0516
Observations	1465	1465	1465	1465
R^2	0.934	0.9336	0.933	0.9339
F-Statistic	63.47	62.1	60.65	60.62

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. We use robust standard errors that were grouped at the municipal level. The standard deviations are presented in parentheses. The dependent variable is the logarithm of GDP per capita. The time-varying controls are reported in table 1. Non-dichotomous control variables are in logarithm format. We use the k-nearest neighbor matrix (weighted) in the estimations.