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# Local effects of climate change: how voters react to natural disasters


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# Local effects of climate change: how voters react to natural disasters*

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**Abstract**

In this article, the effects of natural disasters on the political participation of the population, measured both by turnout and by votes for incumbents, are studied. Based on the premise that natural disasters have an endogenous character, this article aims to consistently identify their effects on the political participation of the electorate and the electoral performance of incumbent politicians. Furthermore, this study aims to identify public policies with the potential to reduce the effects of extreme weather events and to understand how the population assesses these policies when casting their vote. That is, mapping heterogeneous effects of disasters makes it possible to establish the relationship between the reaction of the electorate and the local supply of public goods. The electoral effects of disasters are estimated based on the fact that census tracts are heterogeneously affected. Thus, an empirical strategy based on a Difference-in-Differences model is adopted to estimate the causal effect of natural disasters that occurred during the mandate of incumbents on their share of votes when running for re-election and on voter turnout by census tract. Nevertheless, disasters are not exogenous to unobservable characteristics that vary in time. Policies such as removing houses from slopes, basic sanitation and river dredging, for example, may affect the willingness to vote for mayors running for re-election, despite the effects of these measures on natural disasters. Thus, by recognizing the possibility of endogeneity, this study also uses instrumental variable estimation to obtain a consistent estimator of the effect of disasters on electoral performance. Results show that the occurrence of disasters leads to (i) a lower level of political participation and (ii) stronger punishment of incumbent politicians.
**Keywords**: Natural Disasters, Climate Change, Electoral Accountability
JEL Classification: Q54, Q58.

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# 1 Introduction

Natural disasters affect millions of people. Between 2000 and 2015, disasters related to extreme rainfall, such as landslides and floods, are estimated to have killed 295,000 people and left 23 million homeless worldwide (EM-DAT, 2010). In Brazil, 2600 deaths occurred in the same period, including 900 in the disaster in the mountainous region of Rio de Janeiro in 2011 alone (World Bank, 2012). Given the prediction that climate change tends to increase the intensity of extreme weather events (Seneviratne et al., 2012), the concern with natural disasters and their effects on the population has become a priority issue.[1]

Because environmental policies emerge from a political balance between voters and lobby groups (Aidt, 1998), the political participation of the population plays a key role in the adoption of more restrictive environmental policies (Fredriksson et al., 2005). Thus, the effects of disasters on voters' voting decisions have the potential to rewrite the political balance toward the adoption of appropriate policies for adaptation to climate change. Accordingly, it is fundamental to understand how the population has reacted from an electoral standpoint to the more frequent and intense occurrence of these events.

In this article, the effects of natural disasters on the political participation of the population, measured both by turnout and by votes for incumbents, are studied. Several studies assessing the effects of natural disasters on electoral results have been published. This literature is part of the theoretical tradition of retrospective voting. This theory assumes that voters, even without all relevant information for decision making, effectively hold incumbents accountable by focusing on simple performance metrics (Fiorina, 1981; Healy and Malhotra, 2013). Accordingly, natural disasters function as one of these simple metrics.

Although extreme weather events are a key risk factor for the occurrence of disasters, this relationship is not necessarily unequivocal.[2] A set of public policies may prevent the extension of damages related to natural disasters or even mitigate their occurrence (World Bank and United Nations , 2010). Accordingly, Kahn (2005) reports that rich countries, despite experiencing just as many natural disasters, have a lower number of deaths related to natural disasters because investments in infrastructure and appropriate land-use zoning reduce the risk associated with extreme weather events Boustan et al. (2012).

Based on the premise that natural disasters have an endogenous character, this article aims

[1] Noy (2015) documents a significant increase in lives lost annually as a result of natural disasters from 1980 to 2012.

[2] In fact, in 2012 the IPCC published a report on adaptation to climate change focused on addressing risks of extreme events (Field, 2012).

to consistently identify their effects on the political participation of the electorate and the electoral performance of incumbent politicians. Furthermore, this study aims to identify public policies with the potential to reduce the effects of extreme weather events and to understand how the population assesses these policies when casting their vote. That is, mapping heterogeneous effects of disasters makes it possible to establish the relationship between the reaction of the electorate and the local supply of public goods.

To investigate the relationship between disasters and elections, this article builds a database of natural disasters and elections for Rio de Janeiro – note that 66% of deaths due to hydrological disasters between 2000 and 2014 occurred in this state. This database geographically identifies, based on documents from the Brazilian Ministry of National Integration, which is responsible for managing the National System of Civil Protection and Defense (Sistema Nacional de Proteção e Defesa Civil - SINPDEC), the occurrence of landslides, floods and flash floods between 2005 and 2016, by census tract, in the state of Rio de Janeiro.[3] These data are cross-referenced with voting information for mayors, by polling station, for 2008, 2012 and 2016, thereby creating a panel database of census tracts and electoral years that makes it is possible to assess, to the largest geographical breakdown possible, the effects of natural disasters on the electoral performance of incumbent politicians and voter turnout.

The electoral effects of disasters are estimated based on the fact that census tracts are heterogeneously affected. Thus, an empirical strategy based on a Difference-in-Differences model is adopted to estimate the causal effect of natural disasters that occurred during the mandate of incumbents on their share of votes when running for re-election and on voter turnout by census tract.

Nevertheless, disasters are not exogenous to unobservable characteristics that vary in time. Policies such as removing houses from slopes, basic sanitation and river dredging, for example, may affect the willingness to vote for mayors running for re-election, despite the effects of these measures on natural disasters. Thus, by recognizing the possibility of endogeneity, this study also uses instrumental variable estimation to obtain a consistent estimator of the effect of disasters on electoral performance.

This article is part of the literature that analyzes electoral effects related to natural disasters. Its main contribution is providing an identification strategy that eliminates estimation problems when disregarding that disasters have an endogenous component. Furthermore, this study investigates how heterogeneity in the provision of public infrastructure affects voters' perceptions of disasters. Finally, in line with the study by Healy and Malhotra

[3]Census tract is the smallest territorial area used by the Brazilian Institute of Geography and Statistics (Instituto Brasileiro de Geografia e Estatística – IBGE) in the interpretation of census data (IBGE, 2011).

(2009) of counties in the United States, this study tests how the electorate reacts to disaster prevention and response policies. Thus, this article allows for a detailed mapping of the relationship between natural disasters and electoral performance of politicians in re-election campaigns.

To investigate these relationships, this article is structured into six sections, in addition to this introduction. In section 2, this article is framed within the literature on the political economy of natural disasters, and the purpose of the study is explained based on the empirical context used in the article, notably the state of Rio de Janeiro. In section 3, the data used are presented, describing in detail the construction of the database of this project, in addition to descriptive statistics. Section 4 describes the empirical strategy. In section 5, the results are presented and discussed. Section 6 presents the main conclusions of the study.

# 2 Literature Review and Empirical Context

## 2.1 Literature Review

In a context of climate change, one of the most striking features is the inability of governments to coordinate their actions on a subject with global consequences. Part of the literature highlights the coordination difficulties stemming from the different historical responsibilities of countries and the costs associated with those responsibilities (Friman and Strandberg, 2014; Pauw et al., 2014). Tirole (2012) highlights issues related to free-riding and to the strategic positioning of countries in future negotiations.[4]

In addition to these issues, a key point concerns the impact of domestic policy on climate change decisions. Dietz et al. (2012) argue that the theory of international environmental agreements considers that governments perform a cost-benefit analysis based on collective interests. However, the authors argue that domestic policies play a crucial role in the stance taken by governments in international negotiations. Accordingly, Dietz et al. (2012) show how domestic interest groups may influence the international position of a country. Habla and Winkler (2013) analyze the influence of lobby groups on emissions trading mechanisms. The authors argue that the international policy adopted depends on two factors: the influence of interest groups on incumbent politicians and the actions of national

[4]In this case, the author argues that climate change negotiations should be understood under the framework of the incomplete contract theory: incentives to invest in a low carbon economy are low because they reduce the chances of a country obtaining a good deal in future negotiations.

governments in the international arena.[5]

Thus, environmental policies clearly derive from the political balance in force. However, according to Fredriksson et al. (2005), the political participation of the population, understood as participation in elections,[6] plays a key role in the adoption of more restrictive environmental policies.

In fact, assessment of the performance of those in power at the polls functions as an important mechanism of political accountability in democracies (Ashworth, 2012). Thus, given the role of democratic participation in shaping policies, the effects of natural disasters on the population's voting decisions may sway the political balance towards adopting suitable policies for adaptation to climate change. Accordingly, Fair et al. (2017) show that the voters most affected by the great flood of 2010-2011 in Pakistan were more likely to participate politically.

Climate change is a complex phenomenon whose causes are unclear to the population (Millner and Ollivier, 2016).[7] The most striking expression of climate change is the more frequent and intense occurrence of extreme weather events (Seneviratne et al., 2012).[8] Thus, the performance assessment of incumbent politicians regarding climate change will presumably be based primarily on the occurrence and extension of damages resulting from natural disasters.

The literature assessing the effects of natural disasters on electoral results is based on the premise that the response of incumbents to disasters is a simple performance metric of the incumbent. A possible interpretation for this type of voter behavior, according to Healy and Malhotra (2013), is based on the idea that it is virtually impossible to process the entire set of information and that individuals thus use their limited cognitive resources on a relevant subset of information.[9]

Abney and Hill (1966) started this line of research when assessing the effects of floods caused by hurricane Betsy, which hit the American state of Louisiana in 1965. The authors compared the electoral results from 1962 and from 1966 in flood-affected and unaffected

[5]It is worth noting that the effects of the policy need not be driven only by special interests. As Rodrik (2014) argues, the ideas of politicians should be considered in political economy analyses.

[6]Note that there are complementary ways of participating in political democracy other than voting. In this sense, Campante and Chor (2014) show how protests, driven by a more educated population with no economic opportunities, were central to the Arab Spring.

[7]According to Lee et al. (2015), educational level and local dimensions, such as the perception of temperature, are key factors in the perception of climate risk by the public.

[8]Spence et al. (2011) show that the population that suffered from flooding in England is more concerned with climate change and consumes less energy than the unaffected population.

[9]In this sense, the theory approaches "Salience theory", proposed in Bordalo et al. (2012).

districts and found no significant difference in electoral performance. Achen and Bartels (2012) analyzed the effects of a series of shark attacks on the New Jersey coast and show how president Woodrow Wilson was punished in the affected locations, although the attacks were outside the purview of his public policies. Malhotra and Kuo (2008) show how voters blamed officials of the opposite party for the damages caused by hurricane Katrina. According to the authors, they primarily blamed president George W. Bush. Regarding the same event, Sinclair et al. (2011) show evidence of decreased electoral participation after hurricane Katrina.

These ambivalent results may reflect the fact that voter assessment depends on the response of incumbent politicians to natural disasters. Accordingly, Healy and Malhotra (2009) show that voters reward spending on disaster assistance *ex post*, whereas spending on disaster prevention has no effect on the electoral performance of incumbents, and that this occurs despite the efficacy of prevention spending in reducing damages.[10] More specifically, the authors show that spending on individual disaster assistance determines the electoral reward of incumbents.

Similarly, Chen (2013), assessed the effects of federal aid to Florida residents after the 2004 hurricane season and demonstrates that disaster relief funds benefited the incumbent party by reducing the participation (turnout) of voters of the opposite party and by increasing the participation of its voters. Eriksson (2016) also examines municipal variation in the exposure to a storm that hit half the Swedish territory in 2005: the inaction of the Swedish Social-Democratic Party had long-lasting effects. The party lost its electoral base in the affected places in the 2006, 2010 and 2014 parliamentary elections. Gallego (2012) analyzed the effects of landslides and floods resulting from extreme rainfall that hit part of Colombia in 2010 and found a positive effect on the probability of mayors' reelections in the country. The author associates this positive result with patronage, whereby voters are more likely to sell their votes and incumbents have larger budgets to buy votes.[11] Fuchs (2014) also finds positive results when analyzing Mexican drought relief payments and the performance of the incumbent president. The analysis is based on the discontinuity in payments slightly deviating from a pre-established rainfall threshold that determines federal aid to estimate the effects on electoral results. Bodet et al. (2016) use a flood that occurred in June 2013, four months before the elections, in the city of Calgary, Canada, to assess the effects on the electoral performance of the incumbent mayor. The authors argue that the mayor's re-

[10] Healy and Malhotra (2009) show that each US$ 1 spent on prevention results in a US$ 15 reduction in future damages.

[11] Cooperman (2017) discusses how drought declarations in the Brazilian Northeast are motivated by the political agenda of mayors.

sponse was perceived as exemplary, and he even won the 2014 World Mayor Award. Nevertheless, Bodet et al. (2016) estimate, using difference in differences, that when controlling for observable socioeconomic characteristics of the voting areas, there was no difference in voting for the incumbent mayor between treatment and control areas.

In general, this literature examines natural disasters as exogenous events. Although the risks derive from nature,[12] disasters should not be regarded as exclusively natural events (World Bank and United Nations , 2010). Ultimately, the choice of public policies, such as investments in infrastructure, affects the extent and even the occurrence of disasters and is related to the quality of the incumbent politician (Ashworth et al., 2016). Thus, this article is also related to the literature that discusses the effects of economic development on natural disasters. In a comparison between countries, Anbarci et al. (2005) argue that higher income levels and equity are important for establishing stricter construction standards to reduce the effects of earthquakes. Similarly, Kahn (2005) show that richer countries do not suffer fewer disasters than poor countries. However, the number of deaths are much lower. Kellenberg and Mobarak (2008) present a non-linear relationship between the extent of damage related to various types of natural disasters and per capita income. The authors argue that some policies change with the income level. Finally, a part of the natural sciences literature discusses the importance of extreme rainfall as a trigger for disasters and the importance of public infrastructure and forest cover as determinants of the occurrence and intensity of landslides and floods (Vasantha Kumar and Bhagavanulu, 2008; Liao et al., 2012). Accordingly, omitted variable bias may occur when the endogeneity between disasters and votes is disregarded.

If the relationship between natural disasters and public policies is understood by the population, institutional improvement and enhanced ability of the State to promote development may be induced (Besley and Persson, 2011). Accordingly, Kahn (2007) show how some environmental catastrophes (e.g., Exxon Valdez, Chernobyl) led to stricter environmental regulations in the United States.[13]

As described above, literature findings are unclear and indicate the need for understanding the mechanisms linking natural disasters to electoral performance. The present study contributes to this literature by providing an identification strategy that eliminates estimation problems when the endogenous component of disasters is disregarded. For this purpose, instrumental variable estimation will be used to isolate the exogenous component of the

[12] These exogenous events are considered locally. In a global perspective, this would not be valid, since the frequency of events of this type is related to climate change (Seneviratne et al., 2012).

[13] It is worth noting that these catastrophes, unlike the natural disasters evaluated in this project, were the result of human action.

hydrological disasters studied. The instrument used will be a measure of extreme rainfall at the census tract level. The main contribution of this article, therefore, is to consistently identify the effects of natural disasters on the electoral performance of incumbent politicians.

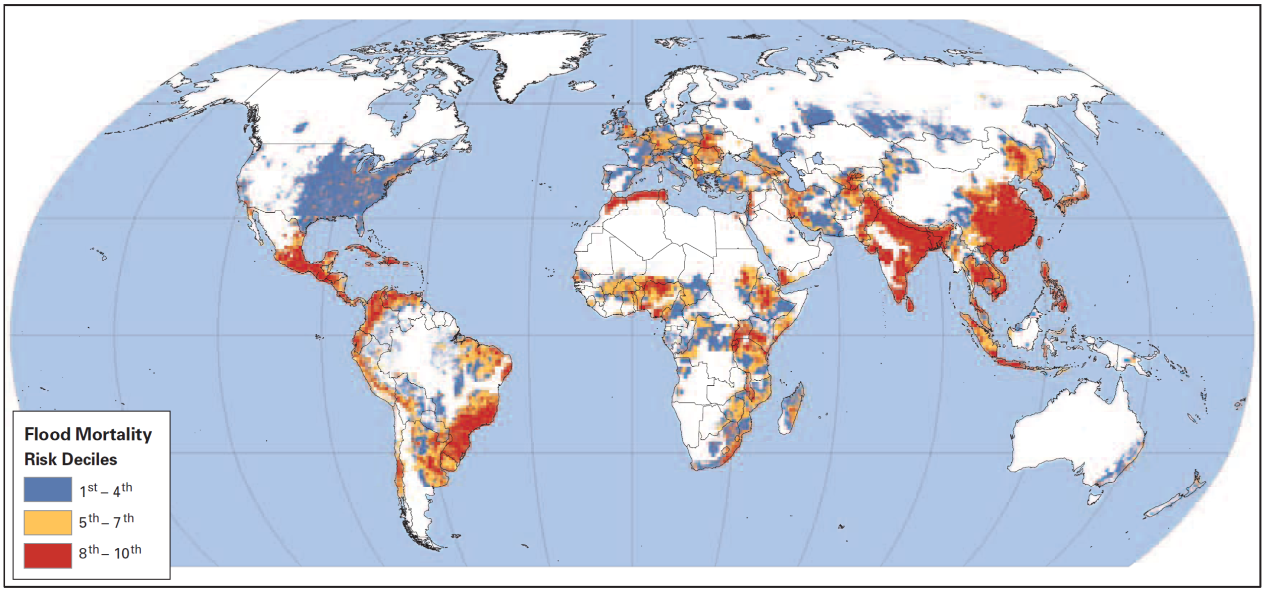
Furthermore, this article evaluates possible mechanisms that help to understand how disasters can affect voters' voting decisions. The adoption of public policies for natural disaster prevention and assistance is frequently used in the literature to understand the mechanisms that relate natural disasters to the electoral performance of incumbents (Healy and Malhotra, 2009; Gallego, 2012; Chen, 2013). In addition to those policies, this study tests how public policies not directly related to natural disasters have heterogeneous effects on the occurrence of natural disasters and on the response of the electorate at the polls. For this purpose, variables related to public infrastructure – for example, basic sanitation, urban drainage and garbage collection as well as land use and healthcare provision are used, which allows for a more comprehensive mapping of the relationship between natural disasters and the electoral performance of incumbents.

## 2.2 Empirical Context

Estimates indicate that, between 2000 and 2015, natural disasters related to landslides, floods and storms caused the death of 295,000 people and left 23 million people homeless worldwide (EM-DAT, 2010). In Brazil alone, according to the same database from the EM-DAT (The International Disasters Database), 2,600 deaths occurred and 600,000 people were left homeless in the same period. Regarding economic losses, CEPED/UFSC (2016) estimates that hydrological disasters have caused losses of R$ 72 billion at 2014 prices, from 1995 to 2014. This is equivalent to losses of R$ 3.6 billion per year.

As shown in Figure 1, which indicates the risk of flood-related mortality, some areas of Brazil – particularly the South and Southeast regions – are among the highest risk areas on the planet.

Figure 1: Global distribution of flood mortality risk




Source: Dilley (2005)

A significant portion of these regions is in the highest risk deciles, which is particularly worrisome considering the high population density. Furthermore, the number of hydrological disasters has increased in recent years. According to a survey conducted by CEPED/UFSC (2016), since 2008, the extent of damage was above average in 1995-2014. This pattern may be related to the predicted effects of climate change on extreme weather events (Lehmann et al., 2015).[14]

In this region, the state of Rio de Janeiro has experienced a significant number of natural disasters related to mass movements, flash floods and floods. Although its area accounts for only 0.5% of the national territory, the state of Rio de Janeiro concentrated, from 1990 to 2010, 4% of flash floods and 31% of mass movements occurring in Brazil during this period (CEPED, 2012). Thus, local factors that increase the susceptibility of Rio de Janeiro to intense rainfall must be understood in more detail.

The risk of the occurrence of a disaster is related to the vulnerability of a given location and to the level of risk (in the case in question, extreme rainfall) to which the specific location is exposed (Hallegatte et al., 2016). The concept of vulnerability is defined as the set of con-

[14] Natural disasters cause harm to the population, not only through deaths directly linked to them but also through subsequent harm to the health of the inhabitants of affected areas.do Carmo and Anazawa (2014) analyze the mortality pattern related to natural disasters.Guimarães et al. (2014) and Pereira et al. (2014) find, respectively, a positive association between disasters and diseases such as leptospirosis and dengue fever.

ditions determined by physical, social, environmental and economic factors that increase the susceptibility of a community to the impact of extreme weather events Gencer (2013). Hazards are defined as natural phenomena that cause economic, environmental and health damages, according to the Hyogo Framework for Action (HFA).[15]

Among Brazilian states, Rio de Janeiro is particularly prone to hydrological disasters, such as landslides, flash floods and floods. This also translates into extensive economic losses. According to estimates by CEPED/UFSC (2016), the state of Rio de Janeiro lost R$ 10.8 billion from 1995 to 2014, or 15% of the national losses due to hydrological disasters.[16] Furthermore, according to numbers from the Brazilian Ministry of Health, 66% of deaths due to natural disasters from 2000 to 2014 occurred in Rio de Janeiro.[17]

Given the clear predisposition of Rio de Janeiro to be hit by extreme weather events, it is important to understand how vulnerability and natural phenomena combine to make the region a global hotspot for hydrological disasters, as shown in Figure 1.

The state of Rio de Janeiro stretches from the 20.5 to the 23.5 latitude of the southern hemisphere and between the 41 West and 45 West meridians. The state comprises mountainous and lowland regions. Three mountain ranges cross the state in an east-west direction (Serra do Mar, Serra da Bocaina and Serra da Mantiqueira). The lowlands are located to the south of the mountains and have a high population density (e.g., Baixada Fluminense). The eastern most part of the state also includes the Baixada Campista.

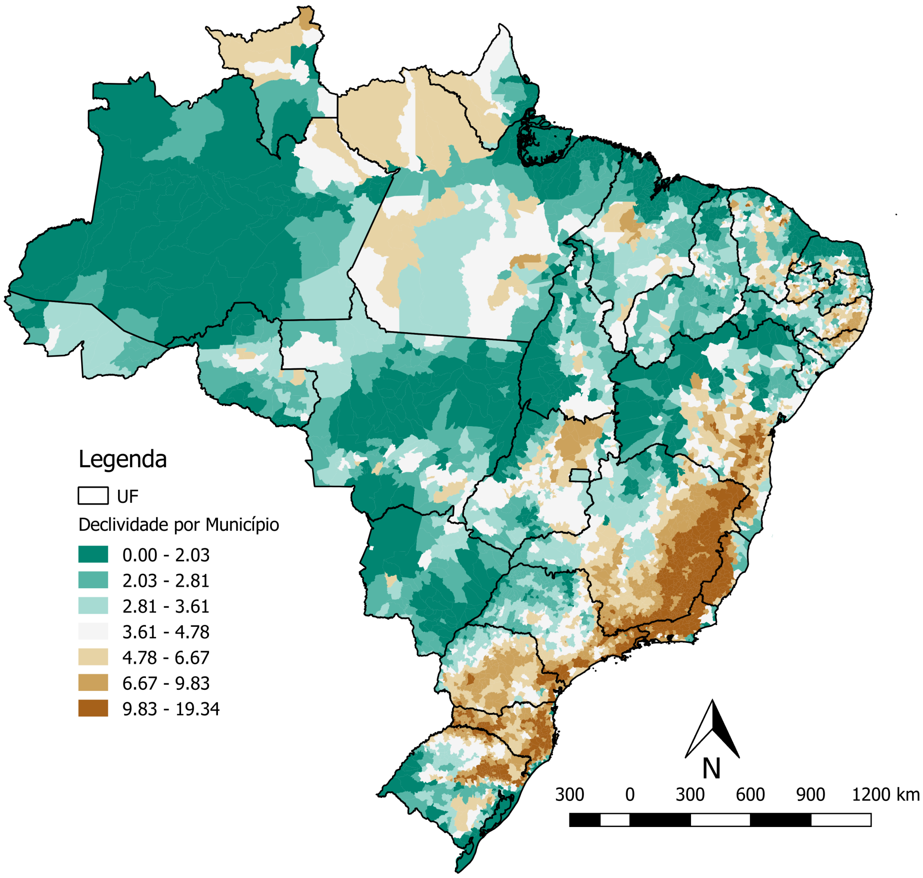
From this combination of relatively high mountains – their highest point reaches 2,971 meters above sea level – and lowlands, a rugged terrain emerges, with several locations with high terrain slope. In fact, Rio de Janeiro has the highest altitude standard deviation/mean ratio of all Brazilian states. Furthermore, as shown in Figure 2, the state has the highest terrain slope values of the country.

[15] The Hyogo Framework for Action is a plan designed to reduce losses from disasters. This framework was developed after the World Conference on Disaster Reduction coordinated by the United Nations in 2005.

[16] This estimate considers only *direct* losses.

[17] http://tabnet.datasus.gov.br/cgi/deftohtm.exe?sim/cnv/ext10uf.def

Figure 2: Mean slope by municipality




Source: IBGE

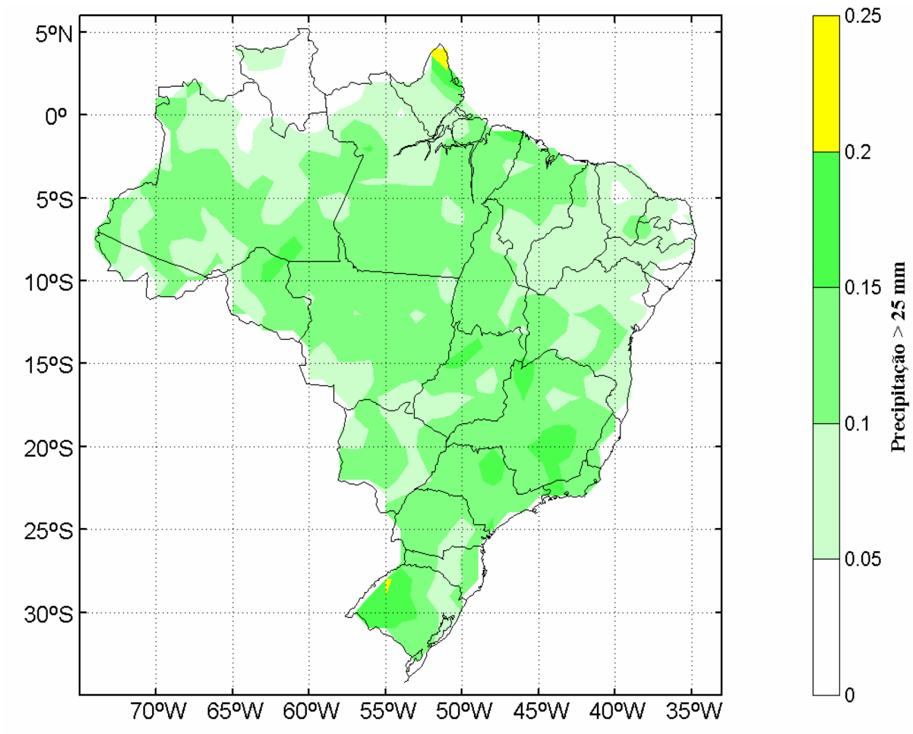
From the standpoint of its geomorphological features, Rio de Janeiro has a combination of factors that make it a place of high vulnerability to climatic events. Moreover, socioeconomic factors contribute to increasing this vulnerability. The type of land use is particularly important in this context. Throughout the state, slopes are deforested and used for housing. According to Bahia Schlee (2013), this type of occupation pattern plays a key role in reducing the resilience of cities in the state of Rio de Janeiro. Accordingly, in a report commissioned by the Brazilian Ministry of the Environment on the tragedy of the Serrana Region,[18] Schäffer et al. (2013) argue that non-compliance with the Forest Code, particularly regarding the maintenance of Permanent Preservation Areas, played a key role in the scale of this disaster. The literature on the risk profile related to floods and landslides highlights the importance of factors such as terrain slope, land use type and soil type in the ability to predict the vulnerability of a location (Dapples et al., 2002; Kamp et al., 2008;

[18] In January 2011, seven municipalities in the Serrana Region of Rio de Janeiro were hit by extreme rains, which caused landslides, leading to the death of more than 900 people and affecting more than 300,000 inhabitants of the region.

Vasantha Kumar and Bhagavanulu, 2008; Liao et al., 2012).

The combination of high vulnerability with climatic characteristics renders the state highly prone to hydrological disasters. As shown in Figure **??**, based on climatic data from 1981 to 2000, the state of Rio de Janeiro has a relatively high probability of experiencing heavy rainfall (>25mm/day) during the summer.

Figure 3: Probability of intense rainfall - summer




Source: Obregon and Marengo (2007)

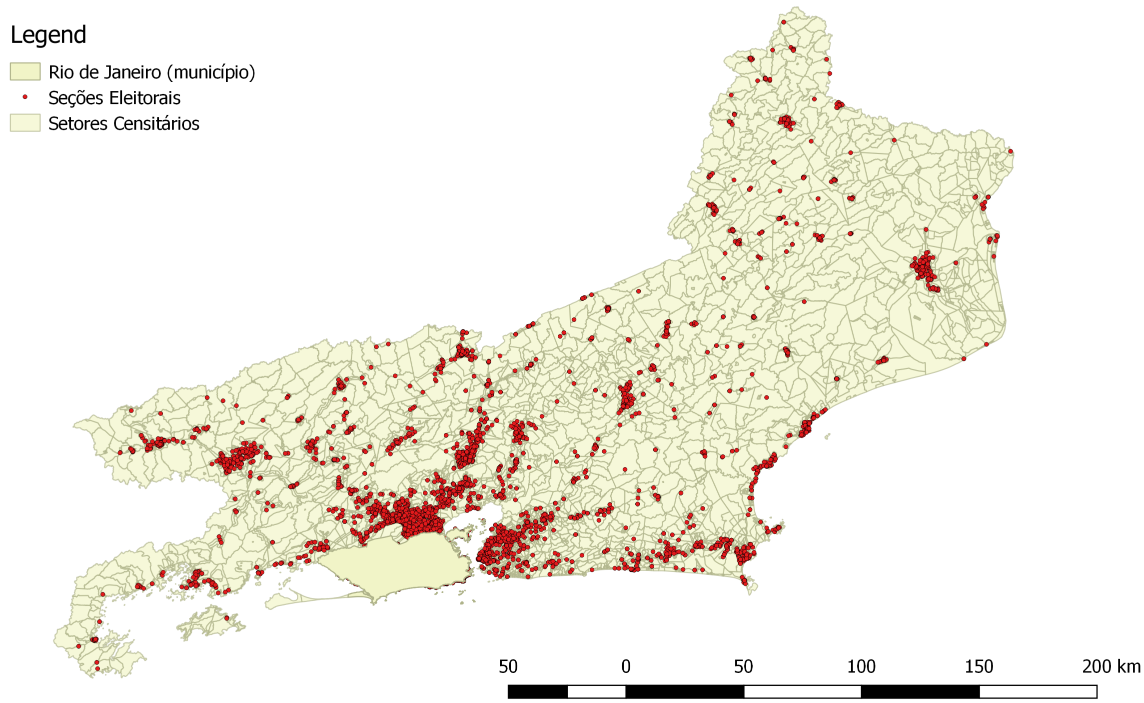
Thus, the state of Rio de Janeiro has geographic and socio-economic factors that lead to a situation of high vulnerability. In addition, Rio de Janeiro is exposed to extreme weather events more frequently than other Brazilian states. Considering this combination between vulnerability and natural hazards, the reason why the state is hit by numerous landslides, flash floods and floods is clearly understood. In fact, in an analysis of the vulnerability to expected increases in the number of landslides and floods, Debortoli et al. (2017) classify Rio de Janeiro as one of the regions most vulnerable to the effects of climate change. After discussing the empirical context contextualizing the susceptibility of Rio de Janeiro to the occurrence of natural disasters, the following section presents and describes the data used in this study.

# 3 Data

The basic unit of analysis used in this study is the urban census tract that includes the polling station. The sample will be based on census tracts of the state of Rio de Janeiro, excluding the capital, for the 2008, 2012 and 2016 electoral years. The city of Rio de Janeiro, the state capital, was excluded from the sample for two reasons. First, only one natural disaster, in 2010, was registered in the Integrated Disaster Information System (Sistema Integrado de Informações de Desastres – S2ID) maintained by the Brazilian Ministry of National Integration. Thus, there is no temporal variation allowing for panel data analysis. Furthermore, the geographic quality of the 2010 disaster information is unsuitable for the purposes of this study because only neighborhoods were identified, and each neighborhood has, on average, 65 census tracts in the city of Rio de Janeiro.

Data on elections are originally collected at the polling station. Information on urban infrastructure is retrieved from the Population Census, which defines the census tract as the smallest territorial area used for census data interpretation. Thus, information on disasters, rainfall and forest remnant areas were analyzed at the census tract level. Finally, considering that election information is based on polling stations and the other information is based on census tracts, geographical matching is required. The state of Rio de Janeiro, excluding the capital, has 5,548 addresses with polling stations and 17,702 census tracts. Figure **??** shows the map of polling stations and census tracts of the state of Rio de Janeiro. As shown, polling stations are distributed in only a few census tracts: 2.956 or 16.7% of the total.

Figure 4: Polling stations and census tracts



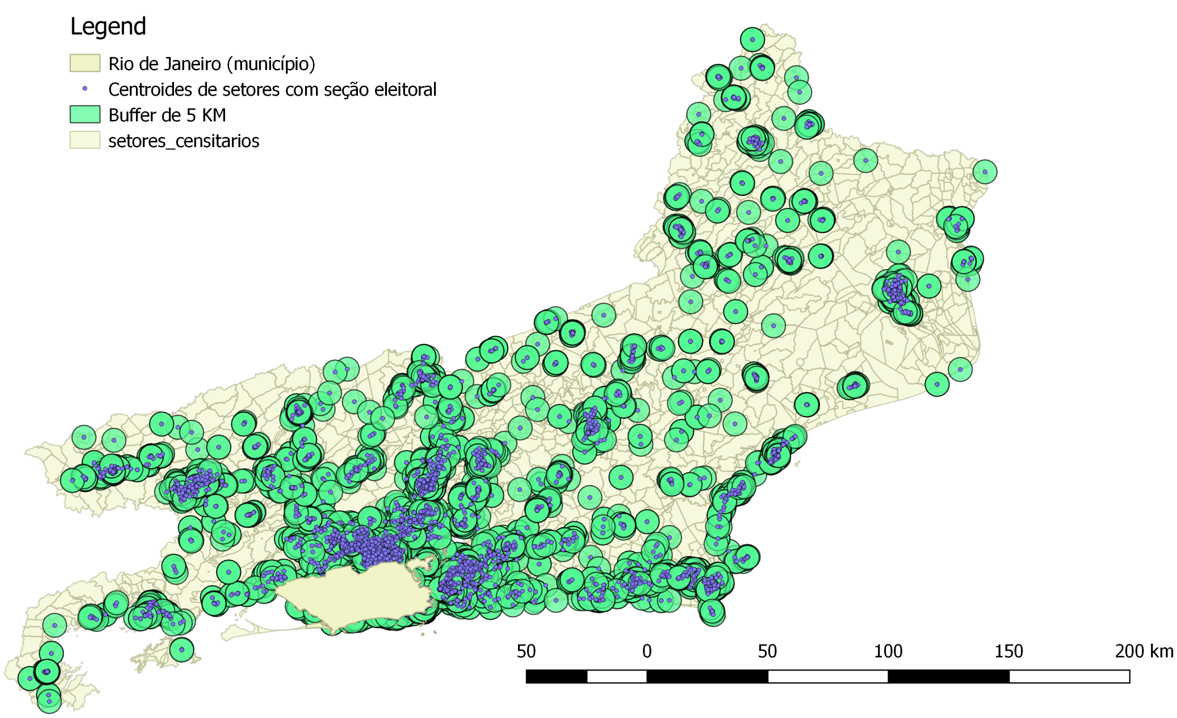

Source: TSE and IBGE

Moreover, polling stations are concentrated in more urbanized locations, and the mean number of polling stations per census tract is 4.75. Thus, because the basic unit of analysis is the census tract, data on all polling stations within a given census tract were grouped to create an electoral database by tract.

Finally, natural disasters may have occurred in any of the 17,702 census tracts and not just in those with polling stations. To incorporate this information, radii of different distances (1, 2, 3, 4 and 5 kilometers) were drawn from the centroids of tracts with polling stations.[19] Thus, the independent variables incorporate information from all census tracts that are inside a predefined radius of the unit of analysis. Figure 5 shows the map with census tracts used in the sample. A 5-km radius was drawn around these tracts. The method used to construct the variables is detailed below.

[19] The choice of a maximum buffer of 5 km is due to the fact that 96.9% of the urban census tracts are within this radius.

Figure 5: Census tracts used with a 5-km buffer




Source: TSE and IBGE

## 3.1 Dependent Variables

The database of voting by polling station of the Superior Electoral Court (Tribunal Superior Eleitoral – TSE) is available online.[20] A voting machine is allocated to each polling station, by which votes are recorded. Accordingly, the polling station represents the most disaggregated level of electoral data in Brazil.

Based on this information, data on the 2008, 2012 and 2016 mayoral elections in the state of Rio de Janeiro were compiled. Because the objective is to understand the effect of disasters on the performance of incumbent politicians, the main dependent variable used is the percentage of votes for the incumbent in the primary election race, in the polling stations of each census tract with a polling station $i$, in election year $t$. This variable captures the performance of the incumbent candidate locally, thereby capturing spatial heterogeneities

[20]http://www.tse.jus.br/eleicoes/estatisticas/repositorio-de-dados-eleitorais

that analyses at more aggregate levels cannot. It should also be noted that politicians who already completed their second term were excluded from the analysis because in Brazil incumbents are only allowed to run for re-election once. Thus, polling stations of municipalities in which the incumbents could not run for reelection, in electoral year $t$, are excluded from the sample.

In addition, a variable that measures the percentage of invalid votes (blank and null) in the primary, by census tract $i$, in election year $t$, will be used to assess whether possible voter dissatisfaction with the incumbent translates into votes for rivals or into invalid votes: because the sum of invalid votes for the incumbent and for rivals must total 100%, understanding the effects on votes for incumbents and invalid votes sheds light on voter response to the occurrence of natural disasters. Finally, voter turnout, measured by the variable $Turnout_{it}$, is a measure that translates how political participation is affected (Chen, 2013).

## 3.2 Independent Variables

The Ministry of National Integration maintains the S2ID (http://s2id.mi.gov.br/). This system gathers all information on official records of state and municipal calls for a declaration of a state of emergency or state of public calamity by the federal government. This documentation is filled out by municipalities affected by natural disasters and is a legal requirement for disaster declaration by the federal government. These documents have a rich set of information that includes type of disaster and its causes, area affected, number of people affected, financial losses and economic sectors affected. Regarding the areas affected, which is the most relevant information for this study, the level of detail varies by municipality, although the affected streets are commonly identified.

Once a disaster is declared, upon publication in the Diário Oficial da União - Official Journal of the Union -, the municipality is entitled to request financial aid, which can be used for rebuilding and response measures.[21] Thus, because the documentation is part of the institutional framework required for the release of resources – from the Federal Government, which can only be used in initiatives related to the disaster – problems related to under-reporting of natural disasters are expected to be minor.[22]

[21]Response actions are emergency measures to rescue and transport victims, provide humanitarian assistance and re-establish essential services. Rebuilding actions aim to rebuild areas destroyed by disasters. For more details see http://www.mi.gov.br/web/guest/defesa-civil/solicitacao-de-recursos

[22]Nevertheless, it is possible that municipalities with less institutional capacity tend to register fewer natural disasters. In any case, this will not be a problem since in the empirical part, the estimation will be

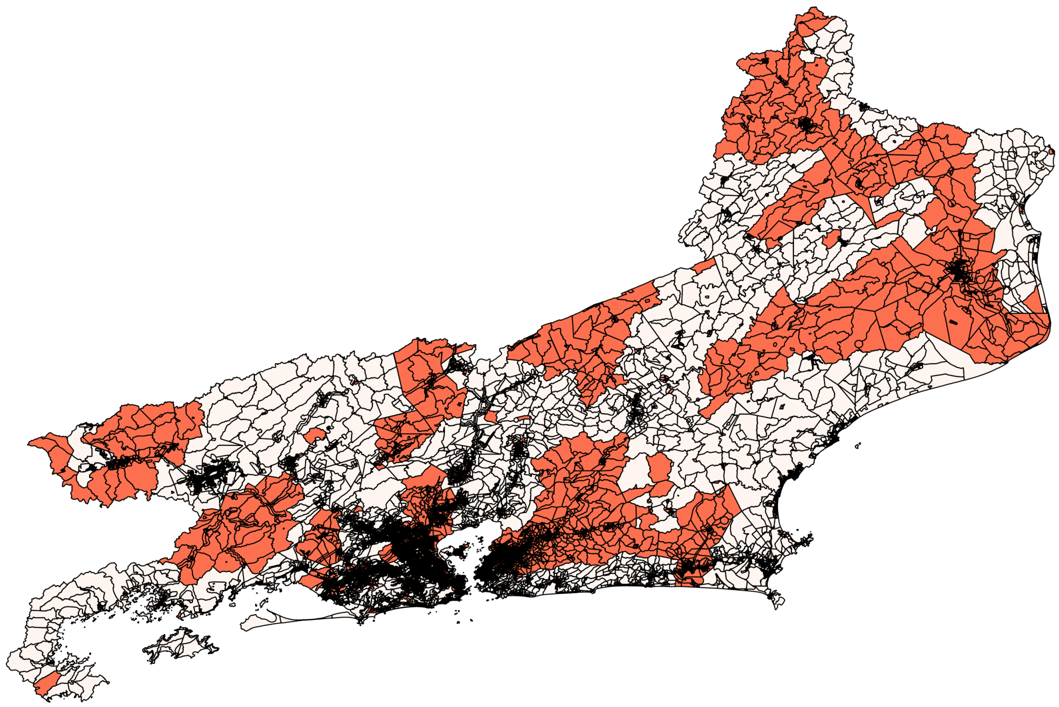
From the consultation of this document base, a database of hydrological disasters (landslides, floods and flash floods) georeferenced by census tract that occurred in the state of Rio de Janeiro from 2005 to 2016 was created. For such purpose, a Brazilian Institute of Geography and Statistics (Instituto Brasileiro de Geografia e Estatística – IBGE) census tract shapefile layer was added to the software QGis. Thus, each address mentioned in the municipal documents can be searched for and georeferenced by census tract. It should be noted that the quality of data reported by municipalities varies widely. Some municipalities even report the street where the disaster occurred, whereas others only present aggregate data, requiring the use of secondary sources of information.[23]

After creating this database, the variable of interest for this study could be constructed. The variable $Disaster_{it}$ is a dummy that indicates whether some disaster occurred in the census tract – with a polling station – $i$, in a four-year election cycle, which ends in the election year $t$. Figure 6 shows the map with hydrological disasters by census tract that occurred from 2005 to 2016. The red areas are census tracts hit by at least one disaster during the entire period.

performed with fixed-effects of the census sector.

[23]These cases occur, in general, when only the Ministerial Ordinance is disclosed. Often, the ordinances disclose only the name of the municipalities where a state of emergency was declared. In these cases, municipal documents or even newspaper reports were used to obtain information that would spatially segregate the places where disasters occurred.

Figure 6: Hydrological disasters by census tract between 2005 and 2016



Source: Ministry of National Integration and IBGE

As described at the beginning of this section, the basic unit of analysis is the census tract $i$ with a polling station. Hence, the disaster-related variable is constructed so as to consider only disasters that occurred in census tracts that are within a previously established radius from the census tract $i$ with a polling station. Thus, the variable $Disaster_{it}$ is defined so that:

$$Disaster_{it} = 1\, if \sum_{j} \mathbf{1}(D_{ij} < B) Disaster_{jt} = 1,\ and\ 0\ otherwise$$

where $Disaster_{jt}$ is a dummy that measures the occurrence of natural disasters in any census tract $j$ of the state of Rio de Janeiro, over the four-year period that ends in election year $t$. The term $\mathbf{1}(D_{ij} < B)$ is a function that indicates whether the distance $D_{ij}$ between the census tracts $i$ having a polling station and the census tracts $j$ is shorter than $B$ kilometers.[24] The estimates use five values for B: 1, 2, 3, 4 and 5 km.

Two other alternative variables will be used in this study to capture the effects of recurrence and election proximity on the electoral performance of incumbents. The variable $NumDisasters_{it}$ measures the number of disasters that occurred *buffers* around cen-

[24]This method is used in (Monteiro and Rocha, 2017).

sus tract $i$, in the four-year electoral cycle, which ends in election year $t$. This variable allows for understanding the effects of disaster recurrence and, accordingly, may help elucidate retrospective voting mechanisms after a natural disaster. Locations where disasters occur recurrently may also lack infrastructure, for example. The other variable, $Weighted\ sum\ Disasters_{it}$, calculates a weighted sum, with greater weight for years closer to elections. This measure is used to capture the effects of election proximity on voter behavior.[25]

### 3.3 Instrumental Variable

As discussed in the previous section, hydrological disasters are not fully exogenous. Even considering fixed effects, there may be unobservable characteristics that vary in time, making it necessary to introduce instrumental variables.

The occurrence of high levels of rainfall concentrated in a period of time is the main triggering factor of natural disasters such as landslides, flash floods and floods (Hong et al., 2007; Van Westen et al., 2008). Regarding landslides and flash floods, excess water, particularly in places with low natural protection, such as areas without forest cover and with irregular occupations, soaks and erodes the soil and leads to the occurrence of landslides (Tominaga et al., 2009). Regarding floods, heavy rains tend to increase the likelihood of soil flooding, particularly in locations with silted rivers and lowland areas (Bradshaw et al., 2007).

Although the literature on the rainfall threshold above which the risk of hydrological disasters increases is inconclusive, de Oliveira et al. (2016) show that, under strict criteria, the threshold of 100mm/24h rainfall is relevant for the occurrence of catastrophic disasters in Rio de Janeiro. Similarly, Paulais (2012) reports the same level of rainfall as a limit after which the risk of hydrological disasters with significant damage increase.

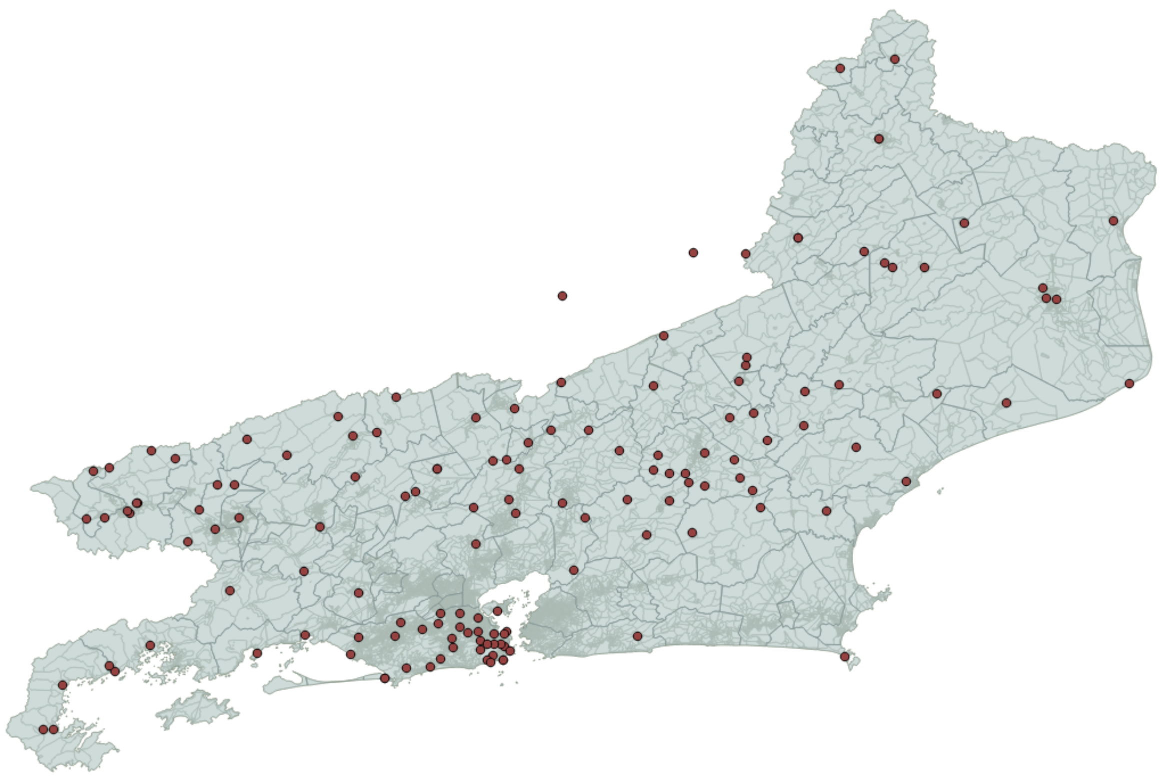
Thus, the instrumental variable used in this article, $Extreme\ Rainfall_{it}$ considers the number of days in a year with rainfall above 100mm/day, weighted by the difference between the calculated value and the 100 mm/day threshold, so that:

$$Extreme\ Rainfall_{it} = \sum_{1}^{365} \frac{x}{100}\ if\ Rainfall/day = x > 100mm/day$$

[25] Miron-Shatz et al. (2009) find that individuals, when performing retrospective evaluations, exaggerate the effects of intense pain, which would indicate possible divergence between experience and memory.

Data on daily rainfall were collected from 137 rainfall stations located in the state of Rio de Janeiro and bordering states, from 2005 to 2016. Three different sources were used to collect data: National Water Agency (Agência Nacional de Águas – ANA), National Institute of Meteorology (Instituto Nacional de Meteorologia – INMET) and Alerta Rio, the meteorological institute of the municipality of Rio de Janeiro.[26] Figure 7 shows the map of Rio de Janeiro, divided by census tracts, and the rainfall stations used for data interpolation.

Figure 7: Rainfall Stations and Census Tracts



Source: ANA, INMET, Alerta Rio and IBGE

After computing the variable $Extreme\ Rainfall$ at the rainfall station level, the data were interpolated using the Inverse Distance Weighting (IDW) method to obtain data on extreme rainfall by census tract $i$ and calendar year $a$.[27] Next, to calculate the number of weighted days of extreme rainfall per electoral period $t$, the number of days of extreme rainfall in the four-year electoral cycle were added. Finally, the variable $Extreme\ Rainfall$ had to be established for the basic unit of analysis, census tract $i$ with polling station. For this pur-

[26]Although the city of Rio de Janeiro was not included in the sample, its rainfall information was considered in order to obtain a more reliable data interpolation.

[27]This method is used by Currie and Neidell (2005) to interpolate atmospheric pollution data. Chen and Liu (2012) use the IDW for rainfall.

pose, the maximum value of $Extreme\ Rainfall$ among the census tracts within the defined distance radius was considered.

### 3.4 Heterogeneity: provision of public services

Urban infrastructure is crucial for reducing vulnerability related to extreme weather events (Andrew, 2012). Thus, the effects of those events may be heterogeneous, depending on some characteristics of the census tracts. More specifically, the adequate provision of public service, such as adequate sewage and garbage collection and urban drainage, may be important in reducing the effects and even the occurrence of hydrological disasters because they affect erosive processes and river siltation (Tominaga et al., 2009).

To assess the heterogeneous effects of the provision of public services, three variables related to urban infrastructure are used: $Sewage_i$, which refers to exposure to open sewage; $Garbage_i$, which refers to exposure to garbage in vacant lots and $Drainage_i$, which refers to the existence of storm drains connected to underground waterways. The three variables reflect the percentage of street fronts in the census tracts located within the area circumscribed by each distance buffer from the census tract $i$ with polling station. All of these variables are available online by census tract, for 2010, at the IBGE website (IBGE, 2011).

In addition to urban infrastructure, land use plays a key role in risk distribution related to extreme weather events. The literature on landslides and floods shows the important role of forest cover in defining terrain risk (Dapples et al., 2002; Kamp et al., 2008; Vasantha Kumar and Bhagavanulu, 2008; Liao et al., 2012). Regarding landslides, Dapples et al. (2002) argue that vegetation suppression reduces slope stability by increasing erosive processes. Gentry and Lopez-Parodi (1980) argue that deforestation also increases the probability of floods because less vegetation implies less water retention. Accordingly, to estimate the effects of forest remnants on the occurrence of disasters, the variable $Forest_i$, which reflects the percentage of the area covered by forest remnants of the census tracts within the respective distance buffers from census tract $i$, will be used. For this purpose, the shapefile of Atlantic Forest remnants, in 2012, provided by the non-governmental organization SOS Mata Atlântica, was used.

Another issue related to land use relevant to developing countries is urban occupation regulation. As discussed in the previous section, the state of Rio de Janeiro is characterized by a high percentage of its population living in substandard settlements. The IBGE registers census tracts classified as substandard according to the following definition: set with more than 50 housing units without deeds and (i) irregularities in traffic lanes and in the size and shape of lots and/or (ii) lack of essential public services (such as garbage collection, public lighting, sewerage and water and electricity) (IBGE, 2010). Smyth and Royle (2000) analyze how the growth of slums affects environmental degradation, particularly considering slope occupation, thereby increasing the risks related to hydrological disasters, primarily due to increased soil erosion. Accordingly, the variable $Substandard_i$, which represents the area occupied by substandard settlements of the census tracts within the defined distance radius from the unit of analysis, will be used.

Other public policies may also affect voter response to natural disasters. de Freitas et al. (2014) analyze various possible effects of disasters on human health. The authors estimate that from 1991 to 2010, hydrological disasters in Brazil led to 1,567 deaths and 309,529 sick and minor and severely injured. Thus, close proximity to primary care units, such as emergency room hospitals and emergency care units that ensure a rapid response, can function as a cooling mechanism of negative assessments of incumbent mayors. Hence, the variable - $Health_i$ – which relates the number of health units (per 100,000 inhabitants) around – as previously defined –the census tract $i$, will be used.

## 3.5 Mechanisms

The literature discusses possible mechanisms that may reveal how disasters affect the electoral performance of incumbents. Healy and Malhotra (2009) and Gallego (2012) demonstrate the positive effects of disaster assistance policies on the performance of incumbents. To test this type of effect, this article will use data on transfers of resources to municipalities and states from the Brazilian Ministry of National Integration. These transfers are performed by the National Secretariat of Civil Protection and Defense (Secretaria Nacional de Proteção e Defesa Civil – SEDEC) and aim to help federal agencies conduct prevention, rebuilding and response. Resources for prevention are provided through voluntary agreements or transfers. In such cases, the municipality or state must actively search for resources. For rebuilding and response measures, the institutional framework ensures mandatory transfers of resources once the federal government has decreed and recognized the emergency situation.

The variable $Prevention_{mt}$ indicates the volume of resources per capita transferred and effectively spent on prevention initiatives in municipality $m$, in term $t$ of the incumbent government. Similarly, the variable $Response_{mt}$ indicates the volume of resources per capita transferred and spent on response and rebuilding initiatives in municipality $m$. The purpose is to test whether and which type of transfer affects electoral performance.

Both variables are measured at the municipal level and not at the census tract level because the allocation of transferred resources cannot be identified geographically. Thus, the variables are defined as:

$$Prevention_{mt} = Ln(1 + \frac{Prevention\ Costs_{mt}}{Population_{mt}})$$

wherein $Prevention\ Costs_{mt}$ represents the total expenditure on prevention by municipality $m$ and by term $t$ and $Population_{mt}$ represents the average municipal population during term $t$. The same applies to response and rebuilding expenses.

### 3.6 Descriptive Statistics

Table 1 outlines the descriptive statistics of the sample of census tracts used in this study. As previously mentioned, electoral performance variables are measured at the level of census tracts with polling stations. The remaining variables, except for response and prevention expenditures, are grouped and weighted and refer to all census tracts within a 5-km (maximum distance) radius from the census tracts with polling stations. Expenditure variables are measured at the municipal level and are available only for the first two years of the sample – 2008 and 2012.

The mean percentage of votes obtained by incumbents is 34 %, with a wide range of variation, from 0.3% to 86.8%. The mean turnout is 83.7%, whereas the percentage of invalid votes is 11.1%.[28] The statistics on disasters show that 32.1% of the sample census tracts, or their surroundings (this equals an area of 78.5 square kilometers),[29] were hit by at least one landslide or flood event during the electoral cycles. The number of days (weighted) in the year with rainfall higher than 100mm/day is, on average, 3.5. However, it reached 16.5 days in the census tract of the municipality of Cachoeira de Macacu during the 2012 election year.

[28]The percentage of invalid votes shows an increasing trend over time: 8.6% in 2008, 10.4% in 2012 and 14.3% in 2016, while the turnout shows a decreasing trend. The combination of both shows less political participation in the state of Rio de Janeiro over the years.

[29]This area corresponds to a circle with a 5 km radius.

Table 1: Descriptive Statistics

| VARIABLES | (1) mean | (2) sd | (3) min | (4) max | (5) N |
|---|---|---|---|---|---|
| **A. Electoral Performance** | | | | | |
| Share of votes for the incumbent | 33.99 | 17.26 | 0.306 | 86.76 | 4,836 |
| Share of invalid votes s | 11.06 | 5.479 | 0.901 | 37.79 | 4,836 |
| Turnout | 83.70 | 4.691 | 53.03 | 100 | 4,836 |
| **B. Natural Disasters and Extreme Rainfall** | | | | | |
| (Dummy) Disaster | 0.321 | 0.467 | 0 | 1 | 4,836 |
| Disaster (unweighted sum) | 0.364 | 0.566 | 0 | 3 | 4,836 |
| Disaster (weighted sum) | 0.182 | 0.314 | 0 | 2.250 | 4,836 |
| Extreme Rainfall | 3.545 | 2.689 | 0.002 | 16.52 | 4,836 |
| **C. Heterogeneous Effects and Mechanisms** | | | | | |
| Open sewage | 5.988 | 10.95 | 0 | 92.80 | 4,836 |
| Garbage in Vacant Lots | 0.759 | 2.368 | 0 | 35.82 | 4,836 |
| Lack of Drainage | 43.07 | 30.78 | 0 | 100 | 4,836 |
| Forest Cover | 5.407 | 13.02 | 0 | 85.74 | 4,836 |
| Substandard Settlement | 4.318 | 14.957 | 0 | 100.0 | 4,836 |
| Health Unit (per 100,000 inhab) | 25.86 | 98.46 | 0 | 4,545 | 4,836 |
| (Ln) Expenditures per capita - Response | 0.784 | 1.547 | 0 | 6.655 | 3,158 |
| (Ln) Expenditures per capita - Prevention | 0.355 | 0.991 | 0 | 5.583 | 3,158 |

Note: sample include election years 2008, 2012 and 2016. Observations comprise census tracts that exclude the state capital..

The means comparison is shown in Table 2, with the sample divided into tracts with and without natural disasters. Overall, the differences between means are significant, except for the main dependent variable – Share of incumbents. The other electoral performance variables indicate significant differences, with an increased number of invalid votes and decreased turnout in locations with natural disasters. The mean number of weighted days of extreme rainfall differ significantly (2.675 and 5.395), indicating that the instrumental variable chosen is appropriate.

Regarding the provision of public services, unsurprisingly, more census tracts with poor garbage collection, lower forest cover, more substandard settlements and lower primary care coverage are found in locations where disasters occurred. This reinforces the view that landslides and floods are related to infrastructure and land use, as discussed above.

Table 2: Difference in means between census tracts with and without disasters

| | *No Disaster* | | *Disaster* | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| VARIABLES | mean | sd | mean | sd | diff |
| Share of votes for the incumbent | 34.19 | 17.11 | 33.56 | 17.56 | 0.629 |
| Share of invalid votes | 10.87 | 5.86 | 11.43 | 4.53 | -0.561*** |
| Turnout | 83.77 | 4.77 | 83.54 | 4.50 | 0.226* |
| Extreme Rainfall | 2.675 | 1.941 | 5.395 | 3.085 | -2.719*** |
| Open sewage | 6.000 | 11.00 | 5.954 | 10.83 | 0.051 |
| Garbage in Vacant Lots | 0.675 | 2.105 | 0.937 | 2.837 | -0.263*** |
| Forest Cover | 5.689 | 13.38 | 4.810 | 12.22 | 0.878** |
| Substandard Settlement | 4.120 | 14.73 | 4.737 | 15.40 | -0.617* |
| Lack of Drainage | 44.82 | 31.19 | 39.39 | 29.56 | 5.421*** |
| Health Unit (per 100,000 inhab) | 27.23 | 96.07 | 22.94 | 103.29 | 4.287* |
| (Ln) Expenditures per capita - Response | 0.603 | 1.315 | 1.039 | 1.796 | -0.436*** |
| (Ln) Expenditures per capita - Prevention | 0.285 | 0.937 | 0.454 | 1.054 | -0.169*** |

Note: sample include election years 2008, 2012 and 2016. Columns (1) and (2) provide descriptive statistics the census tracts that did not suffer any disaster in the whole period and columns (3) and (4) provides descriptive statistics for the census tracts that did suffer at least one natural disaster in the period analyzed. Column (5) provides the difference between the means. Observations comprise census tracts that exclude the state capital, as the main results of the paper are presented. *** p<0.01, ** p<0.05, * p<0.1.

# 4 Empirical Strategy

To understand the type of relationship established between natural disasters and the electoral performance of politicians, this article examines the 2008, 2012 and 2016 elections for mayors.

Thus, the sample comprises a panel with census tracts with at least one polling station in the 2008, 2012 and 2016 election years. Because the database is organized into a panel of census tracts by electoral year, the effect of natural disasters on the electoral performance of incumbents can be assessed. For such purpose, the following equation will be estimated:

$$Incumbent\ Share_{it} = \beta_0 + \beta_1 Disaster_{it} + \alpha_t + \lambda_i + \varepsilon_{it} \ (1)$$

wherein $Incumbent\ Share_{it}$ is the vote share of the incumbent in census tract $i$, in election year $t$. The variable of interest, $Disaster_{it}$, is a dummy that indicates whether a natural disaster occurred in census tract $i$ during term $t$ of the incumbent, that is, 2005-2008, 2009-2012 and 2013-2016. The term $\alpha_t$ is a time fixed effect, which captures trends common to census tracts, $\lambda_i$ is the census tract fixed effect, which captures effects of unobservable and invariant variables in time of census tract $i$. The model error term is $\varepsilon_{it}$. In addition to the equation above, similar equations will be estimated, albeit with other dependent variables and with the alternative natural disaster variables.

Although the triggering factor for a hydrological disaster, controlled for census tract fixed effects, is random (e.g., storms, extreme temperatures or any other weather event), the occurrence of the disaster itself depends on local characteristics, such as infrastructure, institutions and income level (Healy and Malhotra, 2009). Thus, the first identification strategy to be adopted will be using a panel with time and census tract fixed effects, thereby enabling solving endogeneity problems regarding time-fixed unobservable variables of the census tracts.

Nevertheless, natural disasters may not be exogenous to unobservable characteristics that vary in time. Accordingly, policies such as removing homes from slopes, basic sanitation and river dredging, for example, may affect the willingness to vote for the incumbent mayor, despite their effects on natural disasters. Furthermore, as reported by Cooperman (2017), the disaster declaration itself may depend on the quality of the mayor. Because these characteristics of census tracts may vary in time and are unobservable,[30] an alternative strategy is needed to address this possible endogeneity. In addition, as discussed in the data description, the disaster georeferencing data have a heterogeneous quality. Accordingly, the instrumental variable is also crucial to correct problems related to measurement errors.

The occurrence of intense and time-concentrated rainfall is the main trigger for the natural disasters discussed in this article (Stanley and Kirschbaum, 2017). To credibly identify the effects of hydrological disasters on electoral outcomes, an estimation strategy based on an instrumental variable is used. Accordingly, this study uses a measure of concentrated rainfall intensity to define an instrumental variable for natural disasters. The variable $Extreme\ Rainfall_{it}$, defined in the previous section, will be used to identify the effects of disasters on electoral performance.

The first stage equation is defined by:

$$Disaster_{it} = \gamma_0 + \gamma_1 Extreme\ Rainfall_{it} + \alpha_t + \lambda_i + \epsilon_{it} \ (2)$$

Where, in addition to the variables described above, $Extreme\ Rainfall_{it}$ represents the

[30] Some of these characteristics are observable for only one point in time - 2010 - and, therefore, will be object of heterogeneity analysis of the results.

weighted number of days with rainfall higher than 100mm/day in term $t$ of the incumbent, by census tract $i$. The instrument is validated based on the premise that the exclusion constraint suffices. That is: the variable $Extreme\ Rainfall_{it}$ cannot affect voters' decisions in ways other than through the occurrence of natural disasters. From the reverse causality standpoint, the exogeneity of the instrumental variable is guaranteed because politicians cannot affect nature.[31] However, as discussed by Cole et al. (2012) regarding India, deviations from the optimal rainfall level affect electoral results and agricultural production. Because the effects on agricultural production and voter behavior may be associated, the exclusion constraint may become invalid. To address this issue, only urban census tracts are considered in the estimations. Moreover, the municipal agricultural production value is added as a control. Finally, the use of detailed data at the census tract level allows for a more accurate identification of census tracts affected by extreme weather events.

The second stage of the estimation using an instrumental variable is given by:

$$Incumbent\ Share_{it} = \beta_0 + \beta_{IV} Dis\hat{a}ster_{it} + \alpha_t + \lambda_i + \varepsilon_{it}\ (3)$$

As discussed above, when assessing the effects of natural disasters on the electoral performance of incumbent politicians, the possible retrospective voting mechanisms and the heterogeneity of some census tract characteristics must be analyzed. Hence, two-stage least squares (2SLS) regression analysis will be performed to examine the interaction between natural disasters and variables related to local heterogeneity.

The variables $Disaster_{it}$ and $Extreme\ Rainfall_{it}$ potentially have spatial correlation problems. To overcome spatial correlation problems in the independent variable, standard errors are adjusted using the procedure proposed by Conley (1999), Hsiang (2010) and Fetzer (2014). Regarding rainfall measurements, there is spatial dependence by definition. Ultimately, the original data is collected at the level of the rainfall stations and then interpolated to obtain results by census tract. Thus, the variable that measures extreme rainfall at the census tract level is related to extreme rainfall measurements from the nearest rainfall stations. In this case, the attribution of values by census tract is clustered. Furthermore, because interpolation is calculated by the inverse of distance, the treatment is heterogeneous between census tracts within the same cluster. In these cases, as emphasized by Abadie et al. (2017), the standard errors must be adjusted, even when the estimate consid-

[31]On a global scale, mitigation policies can affect the climate. However, on a local scale, politicians can only rely on "magic" forces. In this sense, the city of Rio de Janeiro maintained a contract with a foundation that claims to be able to control the weather: http://oglobo.globo.com/rio/cobrada-pelo-mau-tempo-fundacao-cacique-cobra-coral-diz-que-nao-falhou-19894579

ers fixed effects. Hence, the inference of standard errors for the rainfall measurement will be performed with clusters per rainfall station, which is the original source of variation in the rainfall measurement.[32]

# 5 Results

The main results from this study are outlined in Table 3. Columns (1) to (5) refer to the different distance buffers used, as explained in section 3. The table is divided into four panels. The results based on Ordinary Least Squares (OLS) estimation with location and time fixed-effects are shown in panel A. Thus, time-constant unobservable variables can be controlled for, in the case of location fixed-effects, and for common shocks between census tracts, in each period, in the case of time fixed-effects. Moreover, considering the spatial correlation in the data structure, standard errors are corrected using the method proposed by Conley (1999). In this case, it is considered that there is a correlation between different units in the covariance matrix up to a distance limit (in this study, from 1 to 5 km). Abbreviated results are shown in panel B. Thus, the effects of extreme rainfall events on electoral outcomes can be estimated. The results from the second stage of instrumental variable estimation are shown in panel C. Finally, the results from the first stage of instrumental variable estimation are shown in panel D. As discussed in the previous section, the OLS estimation coefficient is inconsistent because natural disasters are subject to measurement error and omitted variable bias. To overcome spatial correlation problems, clusters at the rainfall station level are used.

[32] Angrist and Pischke (2008) discuss the need to use clustering when the data structure is not independent.

Table 3: OLS (Conley), Reduced Form and Second Stage

| VARIABLES | (1)<br>1 KM | (2)<br>2 KM | (3)<br>3 KM | (4)<br>4 KM | (5)<br>5 KM |
|---|---|---|---|---|---|
| | Panel A: OLS with Conley correction - Dep. Var: Incumbent Share | | | | |
| (Dummy of) Disaster | -0.598 | -0.659 | -0.659 | -0.561 | -0.570 |
| | (0.965) | (1.469) | (1.846) | (2.092) | (2.272) |
| | Panel B: Reduced Form - Dep. Var: Incumbent Share | | | | |
| Extreme Rainfall | -1.975** | -1.973** | -1.971** | -1.973** | -1.983** |
| | (0.963) | (0.964) | (0.964) | (0.964) | (0.966) |
| | Panel C: Second Stage - Dep. Var: Incumbent Share | | | | |
| (Dummy of) Disaster | -17.247* | -17.170* | -17.134* | -17.112* | -17.275* |
| | (9.265) | (9.218) | (9.211) | (9.189) | (9.253) |
| | Panel D: First Stage - Dep. Var: (Dummy of) Disaster | | | | |
| Extreme Rainfall | 0.114*** | 0.115*** | 0.115*** | 0.115*** | 0.114*** |
| | (0.025) | (0.025) | (0.026) | (0.026) | (0.025) |
| Observations | 3,888 | 3,888 | 3,888 | 3,888 | 3,888 |
| Number of Census Tract | 1,657 | 1,657 | 1,657 | 1,657 | 1,657 |
| Census tract FE | Y | Y | Y | Y | Y |
| Period FE | Y | Y | Y | Y | Y |
| Sanderson-Windmeijer first stage F | 20.08 | 20.27 | 20.33 | 20.42 | 20.11 |
| Number of clusters | 70 | 70 | 70 | 70 | 70 |
| Cluster | Rainfall Station | Rainfall Station | Rainfall Station | Rainfall Station | Rainfall Station |
| Mean of Share of Incumbent | 33.99 | 33.99 | 33.99 | 33.99 | 33.99 |
| Mean of (Dummy of) Disaster | 0.3180 | 0.3201 | 0.3201 | 0.3207 | 0.3209 |

Note: sample include election years 2008, 2012 and 2016. All regressions include period and census tract fixed effects. OLS estimates include, as proposed by Hsiang (2010) and Fetzer (2014), Conley corrected standard errors for spatial dependence, with distance cutoffs similar to the buffers utilized. Instrumental variable: Extreme Rainfall. Robust standard errors are clustered by rainfall station. Significance: *** p<0.01, ** p<0.05, * p<0.1.

The results shown in panel A and estimated by OLS show a negative relationship, albeit non-significant, between the occurrence of at least one natural disaster during the electoral cycle, in the area defined by the distance buffer, and the share of votes for the incumbent politician. As discussed in the previous section, it is not possible to assume that the covariance between the share of votes for the incumbent and the residual is equal to zero. Therefore, a strategy of instrumental variable estimation is used. In Panel B, the abbreviated results show a negative and significant ($p < 0.05$) relationship between extreme rainfall and votes for the incumbent. The relationship remains stable in different radii of distance from the census tract centroids in the sample. This result, similar to Cole et al. (2012), shows that voters tend to punish incumbents when extreme weather events occur.

The results from the instrumental variable estimation are shown in panels C and D. The results from the second stage of instrumental variable estimation are shown in panel C. As shown, when controlling for endogeneity of the variable that measures the occurrence of natural disasters, a negative and significant ($p < 0.1$) correlation is found between the occurrence of hydrological disasters and the electoral performance of incumbent politicians in mayoral elections. The estimated coefficient represents a significant mean treatment effect: approximately 17 percentage points of vote share loss in each census tract used as unit of analysis. These results suggest that voters strongly react at the local level.[33] Finally, the results from the first stage are presented in Panel D. As shown, there is no difference in estimated coefficients between different buffers due to the stability of the variable regarding the occurrence of natural disasters: as shown in the last row, the variation in the mean of the disasters dummy is very small throughout the columns.[34] In all estimates, the values of the partial F statistic, measured as proposed by Sanderson and Windmeijer (2016), are satisfactory.

Because instrumental variable estimation identifies the effects resulting from the exogenous variation of natural disasters, the results suggest that the impact of extreme weather events – in the specific case, extreme rainfall – on votes occur through disasters. Because these weather events are random and highly salient, the electoral sanction may be related to the introduction of new and relevant information on the managerial quality of the politician (Ashworth et al., 2016).

In this context, it is important to understand which factors affect voter assessments. For this purpose, the analysis is subdivided into two types: first, heterogeneous effects are assessed using stock variables. Basically, the objective is to understand how public infrastructure and forest cover, key variables in defining local vulnerability, can affect voter behavior. Next, the goal is to understand the possible mechanisms of transmission of accountability political to incumbents using flow variables and, therefore, how response and prevention expenditures affect electoral results by analyzing expenditures under mayors' control.

[33] As Bardhan (2016) indicates, municipal elections have a more local agenda than elections for governor or president and therefore electoral sanctions due to disasters may be expected to occur more at the municipal level. In Brazil, the three levels of the Executive Branch - Federal, State and Municipal Governments - have distributed and well-defined Civil Defense responsibilities. The responsibility of municipalities is to identify risks and provide the first response when a disaster occurs.

[34] The sample with the 1-km buffer comprises 5.1 census tracts, while the sample with the 5-km buffer comprises 5.9 census tracts on average.

## 5.1 Heterogeneous effects and possible mechanisms

The results outlined in Table 3 indicate the need to understand how the heterogeneity of characteristics of census tracts can affect voter responses. Moreover, the response of those in power as well as prevention measures undertaken by the incumbent may, as well, be relevant determinants of voter behavior. It should be noted that Table 2 shows that census tracts hit by natural disasters have, on average, the worst provision of public services and are located in municipalities with higher expenses related to natural disasters.

To assess heterogeneous effects, we use reduced form estimates because it is more interesting to understand the effects of public infrastructure given an extreme weather event, which, in our case, is linked to rainfall. The variables related to public infrastructure, as detailed in the section describing the data, are from the 2010 Census. In turn, the forest cover and health coverage variables are from 2012. Thus, they are all observable variables only at one point in time.

Therefore, we estimated the following reduced-form equation:

$$Incumbent\ Share_{it} = \gamma_0 + \gamma_1 Extreme\ Rainfall_{it} + \gamma_2 Extreme\ Rainfall_{it} * X_i + \alpha_t + \lambda_i + \epsilon_{it} \quad (4)$$

where $X_i$ is a vector with the variables of interest: sewage and garbage collection, forest cover, urban drainage and presence of primary care units and of substandard urban settlements. The other variables are the same as those presented in the empirical strategy section. This estimation allows us to capture heterogeneities in voters' responses to extreme rainfall conditioned by public policy variables. The results outlined in the tables of this section refer to the benchmark distance buffer of 5 km.

The results for heterogeneous effects, considering some characteristics of the census tracts (and their surroundings) relative to public infrastructure and land use are outlined in Table 4.[35] Column (1) presents results for the effects from extreme rainfall and its interaction with the percentage of households that dump garbage in empty lots. Column (2) shows the effects of the interaction with the variable relating to open sewage disposal. Column (3) shows the heterogeneous effects of the variable relating to the absence of urban drainage. These first three variables refer to measures of provision of public services. Columns (4) and (5), which show the effects of the area occupied by substandard urban settlements

[35] It is worth noting that the variables in point are defined by the weighted mean of the area or total households of each census tract belonging to the area defined by the 5-km radius.

and by forests, respectively, refer to land use. In column (6), the effects of the presence of primary care units are shown. Finally, column (7) outlines the results when all variables are considered together.

Table 4: Heterogeneous effects: Reduced Form

| VARIABLES | (1) RF | (2) RF | (3) RF | (4) RF | (5) RF | (6) RF | (7) RF |
|---|---|---|---|---|---|---|---|
| Extreme Rainfall | -2.105** | -2.337** | -3.083*** | -1.878* | -1.917* | -1.997** | -3.051*** |
| | (0.954) | (0.962) | (1.113) | (1.000) | (0.989) | (0.968) | (1.105) |
| Extreme Rainfall X Garbage | 0.099*** | | | | | | 0.026 |
| | (0.025) | | | | | | (0.045) |
| Extreme Rainfall X Open Sewage | | 0.046*** | | | | | 0.017 |
| | | (0.015) | | | | | (0.011) |
| Extreme Rainfall X Lack of Drainage | | | 0.026** | | | | 0.027** |
| | | | (0.011) | | | | (0.013) |
| Extreme Rainfall X Subnormal Settlement | | | | -0.018 | | | -0.025 |
| | | | | (0.016) | | | (0.019) |
| Extreme Rain X Forest Cover | | | | | -0.024 | | -0.038* |
| | | | | | (0.021) | | (0.021) |
| Extreme Rain X Health | | | | | | 0.001 | 0.000 |
| | | | | | | (0.005) | (0.004) |
| Observations | 3,888 | 3,888 | 3,888 | 3,888 | 3,888 | 3,888 | 3,888 |
| Number of Census Tract | 1,657 | 1,657 | 1,657 | 1,657 | 1,657 | 1,657 | 1,657 |
| Census Tract FE | Y | Y | Y | Y | Y | Y | Y |
| Period FE | Y | Y | Y | Y | Y | Y | Y |
| Number of clusters | 70 | 70 | 70 | 70 | 70 | 70 | 70 |
| Cluster | Rainfall Station | Rainfall Station | Rainfall Station | Rainfall Station | Rainfall Station | Rainfall Station | Rainfall Station |

Note: sample include election years 2008, 2012 and 2016. All regressions include period and census tract fixed effects. Instrumental variable: Extreme Rainfall and its interactions. Robust standard errors are clustered by rainfall station. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Overall, results point to significant effects from extreme rainfall. An extra day of rainfall above 100 mm/day implies a loss between 1.8 and 3.0 percentage points. The results outlined in columns (1), (2) and (3) show that the poor provision of public services attenuates the electoral sanction. Localities with poor garbage collection, open sewage and lack of drainage are associated to less punishment to incumbents when extreme rainfall events strike. Respectively, one standard deviation in each of these variables is associated to more 0.23, 0.50 and 0.80 p.p., when one more day of extreme weather event occurs. This effect, although it may seem paradoxical, because those locations are precisely the most vulnerable, may be related to the fact that "communities with inadequate levels [of public services] tend to develop a certain political resignation and discouragement" (Kerstenetzky, 2012, p.274). Thus, where vulnerability is higher and the occurrence of natural disasters more common, this problem becomes less salient from the standpoint of the local electorate (Pavao, 2015). Though not statistically significant, the coefficient of the interaction with forest cover goes in the same direction: localities with less suppression of trees tend to punish more the incumbents.

Although the heterogeneous effects of extreme rainfall when considering substandard settlements and on locations with a higher level of coverage of primary care units are non-significant, they have the opposite direction to that discussed above: higher punishment in places with a greater share of substandard settlements and more votes for the incumbent in locations with better health coverage. The results outlined in Column (7), considering all the interactions, corroborate the previous analysis: it seems to have an 'political resignation effect that is more sound in places with insufficient drainage and forest cover.

The heterogeneity results refer to stock variables, measured at a specific point in time. Therefore, they result from public investments and policies that may have been conducted also by mayors prior to the incumbent. Thus, a more accurate discussion of retrospective voting mechanisms after a natural disaster requires an analysis of variables directly under incumbent control.

Accordingly, the results regarding the effects of expenditures on disaster prevention and response are outlined in Table 5. As discussed in the section describing the data, these expenditures originate from federal government transfers and are only available for the first two electoral cycles, that is, 2005-2008 and 2009-2012.[36] Unlike the interaction variables in Table 4, the data on expenditures vary in time but are aggregated at the municipality and not at the census tract level.

As before, we focus our attention on reduced-form estimates that permit an interpretation of the politician's reactions to a possible salient event: extreme rainfall. Estimates regress extreme rainfall and its interaction with the variables related to disaster response and prevention expenditures in the share of votes held by the incumbent. Thus, the reduced-form equatio is defined as:

$$Incumbent\ Share_{ijt} = \beta_0 + \beta_1 Extreme\ Rainfall_{ijt} + \beta_2 Extreme\ Rainfall_{ijt} * X'_{jt} + \beta_3 X_{jt} + \alpha_t + \lambda_i + \epsilon_{ijt} \quad (7)$$

where $X_{jt}$ is a vector with the variables of interest at the municipal level. The other variables are presented in the empirical strategy section. In this case, the other variables are indexed in census tract $i$ of municipality $j$ in election year $t$.

[36]For this reason, the census tracts coverage and, consequently, the number of clusters is smaller in this table in relation to the other tables presented throughout the article.

Table 5: Expenditures as mechanisms: Reduced Form

| VARIABLES | (1) RF | (2) RF | (3) RF |
|---|---|---|---|
| Extreme Rainfall | -4.465** | -2.783 | -4.586** |
| | (1.969) | (1.857) | (1.981) |
| Extreme Rainfall X Prevention | 3.324*** | | 3.214*** |
| | (0.508) | | (0.554) |
| Prevention | -27.970*** | | -26.869*** |
| | (4.791) | | (5.370) |
| Extreme Rainfall X Response | | 4.669*** | 3.730 |
| | | (1.470) | (2.393) |
| Response | | -5.286** | -3.918 |
| | | (2.589) | (4.420) |
| Observations | 1,918 | 1,918 | 1,918 |
| Number of census tract | 959 | 959 | 959 |
| Census Tract FE | Y | Y | Y |
| Period FE | Y | Y | Y |
| Number of clusters | 48 | 48 | 48 |
| Cluster | Rainfall Station | Rainfall Station | Rainfall Station |

Note: sample include election years 2008, 2012. All regressions include period and census tract fixed effects. Instrumental variable: Extreme Rainfall and its interactions shown in Panel B. Robust standard errors are clustered by rainfall station. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 5 shows the results from the reduced-form estimation. Column (1) outlines the effects of prevention expenditures – by level and its interaction with extreme rainfall – on electoral performance. Overall, results show a negative effect of extreme rainfall on the vote share. The size of the coefficient of the level of expenditure on prevention signs that at the municipality level, this kind of expenditure is not valuable to the voter. However, when one looks at the coefficient of the interaction, it seems that voters that are affected by extreme rainfall do recognize prevention efforts. This is an interesting result that sheds light on the importance of having a accurate focus on where to expend the public budget, at least when it comes to get prepared to extreme weather. Column (2) shows similar results for expenditures with response to natural disasters.The same pattern is repeated in Column (3), which considers both types of expense, albeit non significant to response expenditures, both in level and in interaction. These findings do not corroborate Healy and Malhotra (2009) that find, in Presidential elections at the USA, a positive association between expenditures on response and votes to the incumbent, but not on prevention.

The results outlined in Tables 4 and 5 indicate that voters (i) respond negatively to the occurrence of extreme rainfall; (ii) where infrastructure is chronically deficient, voters perceive the problem as more recurrent and, therefore, the punishment is smaller; (iii) voters recognize efforts to prevent new episodes.

### 5.2 Political participation and electoral competition

In addition to the effects that natural disasters may have on the predisposition to vote for the incumbent politician, natural disasters may also affect the political participation of the electorate. Accordingly, similar to Fair et al. (2017), this study will examine how natural disasters affect turnout. Furthermore, the fact that natural disasters decrease the incumbent's share of votes does not necessarily mean more votes for the opponents. Thus, analyzing the effects on the share of invalid votes and turnout will make it possible to outline a general scenario of what also occurs in terms of electoral competition and political participation.

Table 6 outlines the effects of natural disasters on turnout and on the share of invalid votes. Similar to Table 3, both OLS and 2SLS estimation results are shown.

Table 6: Turnout and Share of Invalid Votes

| VARIABLES | (1)<br>Turnout<br>OLS | (2)<br>Turnout<br>2SLS | (3)<br>Invalid Share<br>OLS | (4)<br>Invalid Share<br>2SLS |
|---|---|---|---|---|
| (Dummy of) Disaster | -0.395*** | -1.844** | 0.376 | -2.985 |
| | (0.119) | (0.875) | (0.293) | (1.999) |
| Observations | 3,888 | 3,888 | 3,888 | 3,888 |
| Census Tract FE | Y | Y | Y | Y |
| Period FE | Y | Y | Y | Y |
| Number of Census Tract | 1,657 | 1,657 | 1,657 | 1,657 |
| SW first stage F | | 20.11 | | 20.11 |
| Number of clusters | | 70 | | 70 |
| Cluster | | Rainfall Station | | Rainfall Station |

Note: sample include election years 2008, 2012. All regressions include period and census tract fixed effects. Instrumental variable: Extreme Rainfall. Robust standard errors are clustered by rainfall station. Significance: *** p<0.01, ** p<0.05, * p<0.1.

The results indicate that census tracts hit by disasters in their surroundings (considering the 5-km buffer) showed a decrease in turnout of 1.8 percentage points (Column (2)). The results of the share of invalid votes indicate no effect different from zero. Accordingly and also considering the previous results, the occurrence of disasters leads to (i) a lower level of political participation and (ii) stronger punishment of incumbent politicians.

## 5.3 Robustness

To test the robustness of the results, two tests are performed. First, two additional disaster measures are introduced. These variables are the unweighted sum of natural disasters occurring over the electoral cycle per census tract - *Unweighted Disaster* - and the weighted sum of natural disasters, where events closest to elections have a greater weight than events more distant in time - *Weighted Disaster*. The benchmark measurement of natural disasters records only occurrences of at least one disaster per electoral cycle, whereas the weighted and unweighted sum measures allow for capturing the effects of the recurrence of natural disasters at a specific location. As shown in Table 1, some tracts were hit by up to three natural disasters in the same electoral cycle. The results of the estimations with these variables are outlined in Table 7. Next, a placebo test is performed, which assesses the impacts of natural disasters that occurred in other electoral cycles (in *t-1* and *t+1*) on electoral performance variables.

Table 7 outlines the results for alternative variables of natural disasters. The results of OLS estimations, with Conley correction for spatial correlation, are shown in Panel A, whereas the results of instrumental variable estimations are shown in Panel B. The results of the unweighted sum of natural disasters are outlined in columns (1) to (3). The columns show results for the three dependent variables previously used: *Incumbent Share, Turnout and Invalid Share*, respectively. The results of the weighted sum are shown in columns (4) to (6).

The results show that the *Unweighted Disaster* coefficients – the sum of natural disasters during the incumbent's term – are quite similar to the main variable – *Disaster* –, particularly in instrumental variable estimations. The results in columns (4) to (6), particularly the results of the instrumental variable estimations, have higher values. The comparison between the pairs of coefficients (1) and (4), (2) and (5) and (3) and (6), in addition to those outlined in Tables 3 and 6, show that the occurrence of natural disasters closer to elections result in stronger punishment of incumbents and lower political participation because the *Weighted Disaster* coefficients are more than double the coefficients of the variables *Unweighted Disaster* and *Disaster*. However, the *Weighted Disaster* results, shown in panel B, fail the strength test of their instrumental variable. As shown by the Sanderson-

Windmeijer F-statistic for the first stage, the low result (F<10) indicates that the instrument is weak. Thus, the results for *Weighted Disaster* in the instrumental variable estimation should be interpreted with caution.

Table 7: Alternative measures for disasters

| VARIABLES | (1) Incumbent Share | (2) Turnout | (3) Invalid Shares | (4) Incumbent Share | (5) Turnout | (6) Invalid Share |
|---|---|---|---|---|---|---|
| | *Panel A: OLS* | | | | | |
| Unweighted Disaster | -2.441 | -0.240** | 0.503** | | | |
| | (1.853) | (0.093) | (0.199) | | | |
| Weighted Disaster | | | | -5.519* | -0.377** | 1.343*** |
| | | | | (3.281) | (0.169) | (0.336) |
| | *Panel B: Second Stage* | | | | | |
| Unweighted Disaster | -17.323* | -1.849* | -2.994 | | | |
| | (9.130) | (0.989) | (2.260) | | | |
| Weighted Disaster | | | | -40.808* | -4.357* | -7.052 |
| | | | | (23.359) | (2.579) | (5.880) |
| Observations | 3,888 | 3,888 | 3,888 | 3,888 | 3,888 | 3,888 |
| Number of census tract | 1,657 | 1,657 | 1,657 | 1,657 | 1,657 | 1,657 |
| Census Tract FE | Y | Y | Y | Y | Y | Y |
| Period FE | Y | Y | Y | Y | Y | Y |
| SW first stage F | 11.42 | 11.42 | 11.42 | 6.320 | 6.320 | 6.320 |
| Number of clusters | 70 | 70 | 70 | 70 | 70 | 70 |
| Cluster | Rainfall Station | Rainfall Station | Rainfall Station | Rainfall Station | Rainfall Station | Rainfall Station |

Note: sample include election years 2008, 2012 and 2016. All regressions include period and census tract fixed effects. Instrumental variable: Extreme Rainfall. Robust standard errors are clustered by rainfall station. Significance: *** p<0.01, ** p<0.05, * p<0.1.

The effects of the variable *Disaster* lagged and led by one electoral cycle are outlined in Table 8. The purpose is to conduct a placebo test because future disasters, by definition, cannot affect elections in the current electoral cycle. In addition, disasters in an earlier electoral cycle should affect earlier but not current elections. As shown, the effects are only contemporaneous. The results outlined in column (1), with lagged disasters, indicate that the current findings do not stem from pre-existing trends.

Table 8: Effects from lagged and forward disasters

| VARIABLES | (1)<br>IV | (2)<br>IV | (3)<br>IV |
|---|---|---|---|
| (Dummy of) $Disaster_{t-1}$ | 1.821 | | |
| | (13.979) | | |
| (Dummy of) $Disaster_{t}$ | | -17.275* | |
| | | (9.253) | |
| (Dummy of) $Disaster_{t+1}$ | | | -11.137 |
| | | | (11.752) |
| Observations | 1,148 | 3,888 | 1,148 |
| Number of Census Tract | 574 | 1,657 | 574 |
| Census Tract FE | Y | Y | Y |
| Period FE | Y | Y | Y |
| Sanderson-Windmeijer first stage F | 9.578 | 20.11 | 5.228 |
| Number of clusters | 38 | 70 | 38 |
| Cluster | Rainfall Station | Rainfall Station | Rainfall Station |

Note: sample include election years 2008, 2012 and 216. All regressions include period and census tract fixed effects. Instrumental variable: Extreme Rainfall. Robust standard errors are clustered by rainfall station. Significance: *** p<0.01, ** p<0.05, * p<0.1.

# 6 Conclusion

This article examines the role of natural disasters on electoral accountability in municipal elections. The main findings show, in response to the occurrence of natural disasters, (i) decreased turnout; (ii) decreased votes for the incumbent; (iii) no increase in invalid votes and, therefore, increased votes for the incumbent's opponents.

In addition, when using spatial heterogeneity in land use and in the provision of public services, voters from more vulnerable locations punish incumbents less in response to natural disasters because, under those circumstances, these events partly lose their salience. That is, as highlighted by Bordalo et al. (2012), natural disasters no longer attract the attention of voters because they do not bring new information to the set relevant to the voting decision (Ashworth et al., 2016; Pavao, 2015).

Finally, the results of the analysis of possible retrospective voting mechanisms show that prevention spending is rewarded at the polls, whereas disaster response spending is not. These results refute the hypotheses of other studies indicating voter myopia and patronage

(Healy and Malhotra, 2009; Gallego, 2012).

This study allows furthering the understanding of how highly visible events, such as natural disasters, affect the population's perception and the accountability it attributes to the political class. In addition, as noted above, most studies regard disasters as natural and therefore exogenous events. However, disasters and the extent of their damage arguably depend on the state's ability to prevent and to respond, in order to minimize the effects of extreme weather events. Accordingly, natural disasters, when raising electoral questions among the population, may induce institutional improvement that enables the adoption of more adequate policies for adaptation to climate change.

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