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Instituto de Economia e Relações Internacionais – Universidade Federal de Uberlândia

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Economic Impacts of Natural Disasters in Brazilian Municipalities and the Focus of the BNDES PER Program

Impactos Econômicos de Desastres Naturais nos Municípios Brasileiros e a Focalização do Programa BNDES PER

Ricardo Agostini Martini[1]
Maria Eduarda Campello Gallo[2]

Abstract: The aim of this study is to evaluate the targeting of the BNDES Emergency Program for the Reconstruction of Municipalities Affected by Natural Disasters (BNDES PER) in Brazilian municipalities. The impact of natural disasters on economic activity in the municipalities was estimated using the synthetic control methodology. The program's targeting was estimated using logistic regression and fixed effects methods, taking the estimated impact as the regressor. Looking at data from 2008 to 2017, it was found that natural disasters had a negative impact on the GDP per capita of most of the affected municipalities, with effects lasting up to three years after the events. On the other hand, the BNDES PER was able to reach the most intensely impacted municipalities in terms of GDP per capita and value added by services per capita.

Keywords: Impact Evaluation; Natural Disasters; Synthetic Control Methods.
JEL Classification: C23, Q54, R51

Resumo: O presente trabalho tem o objetivo de avaliar a focalização do Programa BNDES Emergencial de Reconstrução de Municípios Afetados por Desastres Naturais (BNDES PER) nos municípios brasileiros. O impacto dos desastres naturais sobre a atividade econômica nos municípios foi estimado com o uso da metodologia do controle sintético. A focalização do programa foi estimada via métodos de regressão logística e de efeitos fixos, tomando o impacto estimado como regressor. Observando dados de 2008 a 2017, verificou-se que os desastres naturais impactaram negativamente o PIB per capita da maior parte dos municípios afetados, com efeitos prolongados em até três anos após os eventos. Por outro lado, o BNDES PER foi capaz de atingir os municípios mais intensamente impactados em termos de PIB per capita e valor adicionado pelos serviços per capita.

Palavras-chave: Desastres Naturais; Avaliação de Impacto; Controle Sintético.
Classificação JEL: C23, Q54, R51

[1] Economist at the National Bank for Economic and Social Development, (BNDES), Rio de Janeiro, RJ, Brasil. E-mail: ricardo.martini@bndes.gov.br. ORCID: https://orcid.org/0009-0002-1859-9528.
[2] Master in Statistics from the Federal University of Rio de Janeiro (UFRJ), Rio de Janeiro, RJ, Brasil. E-mail: dudacgallo@gmail.com. ORCID: https://orcid.org/0009-0008-3819-3780.

1. Introduction

Natural disasters are events caused by natural phenomena, such as climate or geology, which disrupt the functioning of an economic system, with a significant impact on its production, income, jobs and consumption (HALLEGATTE and PRZYLUSKI, 2010). In recent decades, a growing international literature has been investigating this topic, both from a theoretical and empirical point of view (KOUSKY, 2013). Among the evidence obtained so far, it has been found that less developed economies are more vulnerable (TOYA and SKIDMORE, 2005; NOY, 2007; LOYAZA et al., 2009; MARIN et al., 2021). On the other hand, there is a relevant role for financial aid flows as an effort to mitigate the adverse impacts of disasters, especially in less developed economies (YANG, 2008).

In Brazil, the literature invariably indicates that natural disasters have a negative impact on the affected economies (HADDAD and TEIXEIRA, 2014; RIBEIRO et al., 2014; OLIVEIRA, 2017; SIMONATO, 2017; HALMENSCHLAGER et al., 2018; CASTRO and ALMEIDA, 2019). However, all these studies focus on specific cases of disasters. In other words, there is a lack of a study that focuses on the impacts of all natural disasters in the country, as well as the role of efforts to mitigate them. The aim of this study is to fill this gap. To do so, it sought to evaluate the targeting of the BNDES Emergency Program for the Reconstruction of Municipalities Affected by Natural Disasters (BNDES PER). This study used the synthetic control methodology to estimate the impact of natural disasters, restricted to events such as floods, rains, floods or torrents, on the economic activity of Brazilian municipalities. Based on these estimates, the paper sought to estimate the probability of a municipality benefiting from the program using logistic regression and fixed effects methods, taking the estimated impact as the regressor. The aim is to verify the hypothesis that the BNDES PER affects the municipalities most affected by disasters. The variables observed were the total municipal GDP per capita, broken down by the agricultural, industrial and services sectors.

The study carried out here used a municipal database with information from the Brazilian Institute of Geography and Statistics (IBGE), which contains information on the gross domestic product per capita of municipalities in the period between 2002 and 2017. Information on the declaration of a state of calamity was also obtained from the Ministry of Regional Development's Integrated Disaster Information System. This database was cross-referenced with information on BNDES PER operations aggregated by municipality and year. The analysis found that natural disasters had a negative impact on the GDP per capita of most of the affected municipalities, with effects lasting up to three years after the events and with a total estimated loss of R$30.8 billion in these municipalities. In sectoral terms, agriculture and industry were hit harder than services. On the other hand, the BNDES PER was able to reach the municipalities that were intensely impacted in terms of GDP per capita and value added by services per capita.

The paper is organized as follows: this introduction is followed by a theoretical and empirical literature review on the economics of natural disasters, surveying not only international evidence, but also specific cases in Brazil. After that, the BNDES PER program is presented. Next, the database and analysis methodology are presented, i.e. the synthetic control and the logistic regression and fixed effects methods. The results of the two stages of analysis follow. Finally, the final considerations of the work and possible future developments in the line of research are presented.

2. The Economics of Natural Disasters

The most common definition of what a natural disaster is in the international literature is given by the CRED (Center for Research on the Epidemology of Disasters) of the Catholic University of Louvain in Belgium[3]. According to this definition, a natural disaster is an event of nature that meets at least one of the following four criteria: i) ten or more people have died as a result of the phenomenon; ii) at least a hundred people have been affected by it; iii) the phenomenon caused the authorities to declare a state of emergency or public calamity; iv) there was a request for international assistance. From an economic point of view, a natural disaster can be understood as a natural event that causes a disturbance in the functioning of an economic system, with a significant impact on assets, factors of production, income, production, employment or consumption (HALLEGATTE and PRZYLUSKI, 2010).

The impacts of natural disasters are generally negative for the performance of the affected economy. This is because disasters cause two economic costs: direct costs and indirect costs (CAVALLO and NOY, 2010; HALLEGATTE and PRZYLUSKI, 2010; KOUSKY, 2013).

Direct costs arise from the instantaneous effects of the phenomenon, including tangible and intangible costs (HALLEGATTE and PRZYLUSKI, 2010; KOUSKY, 2013). It includes the costs of physical destruction caused by damage to homes, businesses, productive structures and infrastructure. For the agricultural sector, this includes damage to crops, livestock and farm equipment. For the public sector, this includes the costs of emergency actions, such as evacuations and rescues, as well as cleaning up debris. It also includes the impact of the disaster on the growth of morbidity and mortality for those affected. Finally, it includes losses from environmental degradation and damage to the historical and cultural heritage of the affected region.

Indirect costs, on the other hand, do not arise directly from the natural disaster, but from its consequences. They spread over a longer period, a larger spatial scale and a greater diversity of sectors of the economy than the initial disaster (HALLEGATTE and PRZYLUSKI, 2010; KOUSKY, 2013). Examples of indirect costs are business interruption losses for companies not directly affected by the disaster, including those caused by the loss of their suppliers and the reduced availability of labor. It also includes the multiplier effects of supply and demand contractions in the markets. Another significant indirect cost is the cost of companies and families adapting to the destruction of infrastructure. It also includes the opportunity cost of reconstruction activities and the use of inferior means of production and distribution by companies (CAVALLO and NOY, 2010). Finally,

[3] More details can be found at https://www.cred.be/.

phenomena indirectly related to the natural disaster can affect people's well-being, health conditions and the environment, such as pollution and sanitation problems.

The empirical evidence observed in the studies surveyed indicates that, in general, the effects tend to be negative in the short term and dissipate over a few years, although the channels through which the economic cost of these events manifests itself are unclear (CAVALLO and NOY, 2010). On the other hand, empirical studies have identified a series of stylized facts about the relationship between natural disasters and the performance of the affected economies (KOUSKY, 2013). Firstly, the effects depend on the type of natural disaster that has occurred (POPP, 2006; LOAYZA et al., 2009, PLENNINGER, 2022). The most common events that have the greatest impact on people around the world are hydro-meteorological disasters, such as those caused by floods and storms. The magnitude of the impacts varies between sectors of the economy. The sectors most directly affected concentrate negative impacts, such as agriculture (MARIN et al., 2021), while there may be positive effects in the sectors involved in reconstruction activities. Economies tend to be resilient, especially for smaller-scale disasters and in economies with higher incomes, better institutions and better educational levels (TOYA and SKIDMORE, 2005; NOY, 2007; LOYAZA et al., 2009; MARIN et al., 2021). Similarly, a better-developed banking system can have a moderating effect on impacts (CHEN et al., 2022). The developed economies most exposed to disaster risk tend to be even more resilient (SCHUMACHER and STROBL, 2008). There is evidence of persistent long-term effects of disasters on income, related to more severe cases with greater catastrophic potential (NOY, 2007; LOYAZA et al., 2009; JOSEPH, 2022), as well as repeated events (HSIANG and JINA, 2014, PLENNINGER, 2022). Serious events are relatively rarer and may even be related to disruptive political disorders (CAVALLO et al., 2010). The effects on income distribution are uncertain and may affect middle-income earners, who take on more risk associated with owning small and medium-sized businesses (PLENNINGER, 2022). The negative impacts are more noticeable on a small scale than in countries as a whole (JOSEPH, 2022). Finally, foreign aid, social safety nets and counter-cyclical fiscal policy can soften negative economic impacts.

One notable study is that of Yang (2008), who sought to examine the impact of hurricanes on international financial flows to developing countries. It was observed that, for all countries, disasters led to an increase in official development assistance, so this is evidence that this type of capital flow plays a relevant role in mitigating the effects of natural disasters.

In Brazil, there are studies that focus on the effects of specific cases of natural disasters - or technological disasters with environmental implications - that have occurred in the country. The focus of these studies is sub-national, i.e. aimed at measuring the impacts on the states and municipalities directly affected by the disasters. The effects estimated in all the studies are negative for the affected economies.

Two studies were found that used the computable general equilibrium methodology. Haddad and Teixeira (2013) sought to verify the effects of flooding in the municipality of São Paulo in 2008. Simonato (2017) sought to capture the regional economic impacts of the Mariana mining disaster in 2015.

Two other studies used regressions with panel data techniques. Oliveira (2017) sought to observe the impact of climate disasters such as droughts and floods on the economic growth of municipalities in the state of Ceará. Sant'Anna (2018) sought to observe the effects of public policies on the probability of occurrence of natural disasters related to high volumes of rainfall in the state of Rio de Janeiro from 2005 to 2015. The study concluded that the federal government's transfers are focused on the municipalities most at risk from disasters. In addition, the lack of urban infrastructure is linked to greater risks.

Finally, there were three studies that used the synthetic control methodology. Ribeiro et al. (2014) addressed the case of the rains in Santa Catarina in 2009. The article calculated that, thanks to the rains, Santa Catarina's industrial production was on average 5.13% lower than in the counterfactual scenario in the two years following the event. According to the authors' calculations, this reduction in industrial activity was associated with a loss of 33,100 jobs and a reduction in income of between 1.5 and 1.7%.

Halmenschlager et al. (2018) applied synthetic control to assess the impact of rains and landslides on the GDP of municipalities in the Serrana region of the state of Rio de Janeiro in 2011. The article found that the impact was negative and growing in the affected municipalities until the third year after the event, with an average peak of -8% in that reference year. After this period, there was a trend towards a rapprochement between the trajectory of treaties and controls.

Castro and Almeida (2019) sought to assess the impact of the Mariana disaster on industrial production in the states of Minas Gerais and Espírito Santo. It was found that the negative effect of the disaster reached -18% in relation to its synthetic control in the latter case.

3. The BNDES PER Program

The BNDES Emergency Program for the Reconstruction of Municipalities Affected by Natural Disasters (BNDES PER) was originally created in July 2010, specifically to support municipalities affected by floods in the states of Alagoas and Pernambuco in June of the same year. In January 2011, a similar program was created to support municipalities in the Serra Fluminense region affected by floods and torrents[4].

The program was consolidated at the BNDES as of October 2011, supported by Provisional Measure 546 of September 29 of that year (later converted into Law nº. 12,597 of March 21, 2012). This Provisional Measure authorized the Federal Government to grant an economic subsidy to the BNDES, in the form of interest rate equalization, in financing

[4] Both programs had identical conditions to the later BNDES PER program. The only difference was the financing limit per CNPJ/CPF. While in the case of the Northeast, the limit was R$1 million, in the case of Rio de Janeiro the limit was R$2 million.

operations aimed at working capital and investments by companies, individual entrepreneurs and individuals or legal entities characterized as rural producers, located in municipalities hit by natural disasters that have had a state of emergency or a state of public calamity recognized by the Federal Executive Branch. Therefore, BNDES PER aims to support the resumption of economic activity in locations affected by events causing emergencies or calamities.

BNDES PER funds were disbursed through indirect operations, i.e. through the network of financial agents accredited to the BNDES. Its initial conditions included an equalized interest rate fixed at 5.5% per year. The level of BNDES participation was up to 100% of the items that could be financed. The financing limit per beneficiary (CNPJ/CPF) was R$1 million, with up to R$500,000 for financing an investment project and up to R$500,000 for working capital or agricultural funding.

Over the years, the BNDES PER conditions have changed. The interest rate became variable and the financing limit was increased to a total of R$5 million, of which R$2.5 million was for investment projects and R$2.5 million for working capital. In January 2017, the program was discontinued and replaced by a line without equalized interest rates. The total amount of credit released by the program was R$2.4 billion between 2010 and 2017.

4. Databases

This work was based on cross-referencing information from 6 databases. The Ministry of Regional Development's Integrated Disaster Information System has provided information on the municipalities that have entered a state of public calamity or emergency[5]. The number of decrees for each municipality (emergency or calamity) and the event that caused each decree were identified. From the BNDES, we obtained the number of BNDES PER operations and their total amount disbursed per municipality and year. From Estban, the Central Bank of Brazil, we obtained the number of bank branches per municipality. The number of deaths due to exposure to forces of nature was obtained from Datasus, considering ICD-10 categories X30 to X39. From table 5938 of the IBGE's Sidra system, we obtained the municipalities' GDP in nominal values, both in total terms and broken down by major economic sectors (agriculture, industry and services). The population by municipality and year was obtained from the same source. Finally, the amount transferred from the Federal Government for disaster response purposes by municipality and year, in nominal values, was obtained from the National Treasury. Since international empirical evidence shows that the effects of disasters can be different for different economic sectors (KOUSKY, 2013), four indicators of interest were chosen: the

[5] A state of emergency is characterized by imminent damage to health and public services. A state of public calamity is decreed when these situations arise. It is up to the mayor to assess the situation and declare an emergency or calamity, in which case it is easier to obtain federal and state funds. The state of calamity, since it is declared after events that cause damage, is more associated with economic impacts. It will therefore be the focus of this evaluation.

municipality's GDP per capita and its breakdown into the major sectors (agriculture, industry and services).

The data was consolidated into a panel with information on the municipalities that declared a state of public calamity in the period 2002-2017. From 2008 to 2016, the period covered by the Public Defense data, a total of 142 municipalities declared a state of calamity, as shown in Table 1. The total number of disaster declarations in the period was 172. The period with the most disasters was between 2010 and 2011, which coincides with the flood disasters in Pernambuco, Alagoas and Serra Fluminense.

A total of 528 municipalities received support from BNDES PER during this period, 59% of which declared a state of calamity. The total amount released was R$2.4 billion, with a peak of R$620 million in 2011, although it has reached a greater number of municipalities since 2014. The federal government transferred around R$4.9 billion to municipalities in response to natural disasters during this period. Finally, 2,964 people died as a result of exposure to the forces of nature in Brazil, most notably in 2011, when the flooding tragedy occurred in the Serra Fluminense region.

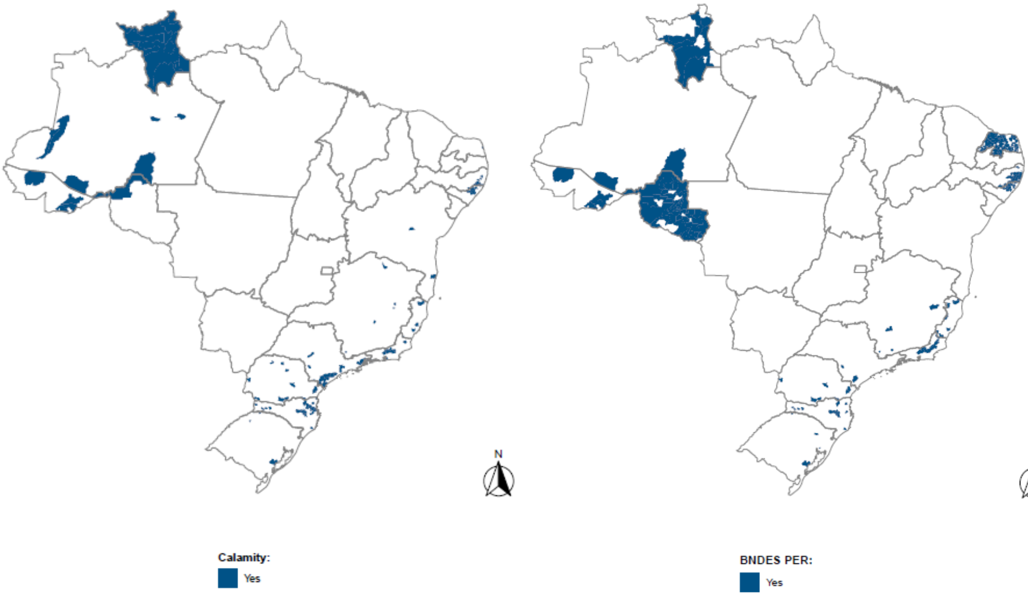
Table 1: Count of Municipalities, Amount Released and Deaths per Year.

Year	Municipalities with Calamities	BNDES PER operations	Amount released BNDES PER (R$ thousand)	Transfers from the Federal Administration (R$ thousand)	Deaths
2008	0	0	0	79.307	304
2009	17	0	0	216.464	196
2010	44	56	141.312	708.679	476
2011	49	87	620.661	201.548	1.042
2012	5	41	567.878	458.699	173
2013	7	38	392.204	601.846	210
2014	19	94	426.994	871.995	137
2015	14	124	164.740	517.872	161
2016	7	87	89.892	751.575	145
2017	-	1	600	538.251	120
TOTAL	142	528	2.404.281	4.946.235	2.964

Source: Own elaboration based on data from the Integrated Disaster Information System, the BNDES, the Federal Government and DATASUS. Data from the Integrated Disaster Information System is available up to 2016.

The following maps show the geographical distribution of the incidence of disasters in Brazilian municipalities, as well as the amount released by BNDES PER.

Graph 1: Municipalities that Declared Calamity (2008-2016) and Received BNDES PER Disbursements (2010-2017, R$ Million)



Source: Own elaboration based on data from the Integrated Disaster Information System and the BNDES.

Disasters were concentrated in Santa Catarina (37 municipalities), Pernambuco (31 municipalities), São Paulo (17 municipalities), Alagoas and Roraima (15 municipalities each). The region with the highest number of municipalities declaring a disaster was the South, with 54 cases. BNDES PER had more releases in Rio de Janeiro (R$ 832 million), Santa Catarina (R$ 541 million), Pernambuco (R$ 287 million), Acre (R$ 235 million), Rondônia[6] (R$ 165 million), Rio Grande do Norte (R$ 115 million) and Roraima (R$ 63 million). Operations are concentrated in municipalities in the regions affected by the disasters that led to the creation of the program, such as the municipalities of Alagoas and Pernambuco, the Serra Fluminense and the north of Santa Catarina. It is important to note that the BNDES PER was also made available to municipalities that declared an emergency, which explains the coverage in places that did not declare a calamity. The municipality that received the most funds was Petrópolis-RJ (R$ 338 million), followed by Nova Friburgo-RJ (R$ 264 million), Rio Branco-AC (R$ 209 million), Brusque-SC (R$ 176 million), Rio do Sul-SC (R$ 160 million) and Teresópolis-RJ (R$ 140 million).

[6] It is important to note that Rondônia was the only case of a state of public calamity declared by the state government (2014) in the entire analysis.

In general, the most common events associated with disasters in Brazilian municipalities are torrents, rain, floods and flash floods. Therefore, the identification strategy adopted to define the treated units is the declaration of the municipality's state of public calamity due to events related to these phenomena in the period of analysis (2008 to 2016), which represents a total of 133 treated municipalities. A total of 9 municipalities declared calamity for other reasons (such as droughts, dry spells and erosion) and were discarded as contaminated samples. This procedure is justified by the observation of previous work that different types of natural disasters can have different effects on the economy (POPP, 2006; LOAYZA et al., 2009). The group of potential controls (donor pool) included all Brazilian municipalities that did not enter a state of calamity during this period. The following table shows the descriptive statistics for treated and controls. Although the data covers the period between 2002 and 2017, we chose to focus on the first year in which there is information in the Public Defense database (2008).

Table 2: Descriptive Statistics by Treatment Status (2008)

Variable	Average of treatments	Average *Donor Pool*	t	Pvalue
Population	130.232,4	31.718,0	1,19	0,237
GDP (R$)	3.337.696.774,4	490.865.297,7	1,07	0,287
Part. Agriculture in GDP (%)	17,5	22,8	-4,16	0,000
Part. Industry in GDP (%)	16,3	13,4	2,24	0,027
Part. Services in GDP (%)	31,2	29,8	1,02	0,309
GDP per capita (R$)	10.645,5	10.299,6	0,54	0,592
V. A. from agriculture per capita (R$)	1.394,6	2.144,9	-6,05	0,000
V. A. of industry per capita (R$)	2.134,8	2.206,2	-0,25	0,803
V. A. of services per capita (R$)	3.403,7	2.937,8	1,56	0,122
Bank branches	21,8	3,0	1,08	0,282
South Region (*dummy*)	34,6%	21,0%	3,25	0,002
Northern Region (*dummy*)	18,8%	7,8%	3,21	0,002

Northeast Region (*dummy*)	22,6%	32,5%	-2,68	0,008
Southeast Region (*dummy*)	24,1%	30,1%	-1,61	0,110
Central-West Region (*dummy*)	0,0%	8,6%	-22,58	0,000
Federal Administration transfers to disasters (R$)	19.698,7	64.404,2	-2,52	0,012
Deaths due to exposure to forces of nature	3,0	0,2	2,40	0,022
Total number of municipalities	133	5.437		

Source: IBGE, Finbra and Datasus.

Table 2 shows that, at the beginning of the analysis period, there are significant differences between the municipalities of the two statuses in the share of agriculture in GDP (higher for the donor pool), in the share of industry in GDP (higher for the treaties) and in the value added by agriculture per capita (higher for the donor pool). There are significant regional variations in treatment. There is a higher probability of being in the treatment group for municipalities in the South and North, and a lower probability for those located in the Northeast and Center-West. In addition, the test found significant differences for federal transfers to municipalities for disaster response, with the opposite sign to that expected, possibly due to the time lag between the disaster and federal aid, and for the number of deaths due to exposure to the forces of nature.

5. Methodology

As mentioned above, the aim of this study is to evaluate the targeting of the BNDES PER program. To do this, it sought to estimate the likelihood of a municipality being supported based on the magnitude of the impact of the natural disaster suffered. The aim was to verify the hypothesis that the BNDES PER program was focused on the municipalities that suffered the greatest economic losses due to public disasters. This procedure was based on previous work verifying the importance of financial aid flows in mitigating the effects of natural disasters (YANG, 2008; SANT'ANNA, 2018).

In order to carry out this evaluation, it was necessary to estimate the impact of events associated with public disasters, restricted to phenomena such as floods, torrents, rains and inundations, on the economic indicators of Brazilian municipalities. However, this estimation is hampered by the fact that the occurrence of a natural disaster depends on random factors related to climatic issues, it occurs in non-random geographical regions. In other words, its impact on socio-economic variables is related to environmental issues, urbanization and the existence of risk areas in each place. In other words, there is a selection bias in the municipalities that suffer natural disasters, so that econometric models that do not deal with this problem tend to arrive at correlation inferences without causality. Therefore, for each municipality that has been granted treaty status, according to the criteria described above, it is necessary to compare the observed performance with the performance that this municipality would have had if it had not been affected by the disaster. This hypothetical comparison scenario is called a counterfactual scenario. This scenario is not observable in the data, so it needs to be estimated using methodological procedures.

5.1. Synthetic control

The methodology adopted in this work to estimate the counterfactual of natural disasters is synthetic control (ABADIE and GARDEAZABAL, 2003; ABADIE et al., 2010, 2015). This methodology has already been used in previous studies with a similar objective (CAVALLO et al., 2010; RIBEIRO et al., 2014; HALMENSCHLAGER et al., 2018; CASTRO and ALMEIDA, 2019). Its aim is to build an artificial control unit for each treated municipality, which simulates, using data from untreated municipalities, what the trajectory of the variable of interest would be in a scenario in which the municipality in question had not been treated. As this simulated trajectory is not affected by the effects of the treatment, it can be taken as a counterfactual scenario. The value of the impact, therefore, will be the difference between the trajectories of the two units after the moment of treatment. This methodology is suitable for the proposed exercise, since it allows for the construction of a counterfactual scenario that reflects the trajectory of each affected municipality in the absence of the event. In addition, as the direct and indirect costs of environmental disasters vary from event to event, synthetic control makes it possible to verify the impact at an individual level for each municipality affected. Finally, the synthetic control makes it possible to check the dynamics of the effects over time, so that not only the direct costs of disasters can be analyzed, but also the indirect costs, as discussed in section 2 of this paper.

The logic of a synthetic control evaluation can be formalized as follows[7]. It is assumed that the population of Brazilian municipalities with observed data is equal to $J+1$. The municipality $j=1$ is the municipality affected by a natural disaster event. The remaining J Brazilian municipalities form a group of municipalities not treated by the event in question. They serve as potential units of comparison with the treated municipality (donor pool)[8]. It is assumed that the sample includes a positive number of pre-disaster

[7] The formalization of the synthetic control model presented here is based on the work of Martini et al. (2018).

[8] It is important to note that the effect of natural disasters can be spatially broad, impacting municipalities in the donor pool. This is especially likely when estimating its indirect costs, which involve economic flows between directly affected and unaffected municipalities. In addition, the donor pool can include municipalities affected by natural disasters, but which have not declared a disaster. These situations can weaken the estimation of the counterfactual scenario. However, since

periods T_0, as well as post-disaster periods T_1, so that $T = T_0 + T_1$. The treatment that will be evaluated consists of the exposure of municipality $j = 1$ to the natural disaster during periods $t = T_0 + 1, \ldots, T$, considering that it has no effects during the pre-treatment period $t = 1, \ldots, T_0$. Finally, let Y_{jt} be the Variable of interest for municipality j at time t (for example, GDP per capita). Given these hypotheses, the aim of the impact analysis is to measure the effect of the disaster on the treated municipality $j = 1$ on na indicator of interest Y_{it} in the post-treatment period T_1.

A central hypothesis assumed by the synthetic control methodology is that the trajectory of Y in the pre-treatment period of the treated municipality is better approximated by a combination of data from the untreated municipalities than by any of these untreated municipalities taken in isolation. In this way, the synthetic control can be understood as a weighted average of the municipalities in the donor pool that will be compared with the treated municipality. The synthetic control is represented by a vector $(J\ X\ 1)$ of weights $W = (w_2, \ldots, w_{j+1})$, such that $0 \le w_j \le 1$ for $j = 2, \ldots, J$ and $w_2 + \cdots + w_{J+1} = 1$. In this way, choosing any particular value of W is equivalent to choosing a synthetic control. However, the methodology seeks to identify the vector of weights that makes the weighted average of the municipalities in the donor pool as similar as possible to the municipality being treated.

Let K be a set of variables associated with the characteristics of the municipalities in the pre-treatment period, including the trajectory of the variable of interest Y and not being affected by the treatment in this period. Let X_1 be a vector $(K\ X\ 1)$ containing the values of the pre-treatment variables of the treated municipality, which we want to approximate as closely as possible. X_0, in turn, is a matrix $(K\ X\ J)$ containing the values of the same variables for the donor pool. In this study, the K set consists of the same variables of interest, i.e. municipal GDP per capita and its sectoral breakdowns (agriculture, industry and services).

The vector $X_1 - X_0W$ represents the difference between the characteristics of the treated municipality and the donor pool. Therefore, the aim of the synthetic control methodology applied here is to choose the vector of weights W^* which minimizes this distance. This vector is obtained through a conditional optimization exercise. For $m = 1, \ldots, K$, seja X_{1m} the value of the variable m for the treated municipality and X_{0m} a vector $1\ X\ J$ which contains the values of the variable m for the donor pool municipalities, you must choose the W^* which minimizes:

$$min_{w \in W} \sum_{m=1}^{K} v_m (X_{1m} - X_{0m} W)^2 \tag{1}$$

This optimization is conditional on the assumptions that the sum of the weights w is equal to unity and that no municipality in the donor pool has a weight lower than zero or higher than 1. In this equation, the v matrix is obtained through an optimization process

these cases are difficult to verify, and municipal governments have incentives to declare calamity and thus have access to federal funds, this study disregarded their effects.

that seeks to generate the set of weights that best match the information from the treated municipality with that from the donor pool. Therefore, v_m is a weight that reflects the relative importance attributed to the variable m when measuring the discrepancy between X_1 and X_0W.

Once you have obtained the W^* by the process described above, the value of the variable of interest Y for the synthetic unit is the weighted average of the value of this variable for each unit in the donor pool by its respective estimated optimal weight. Let Y_1 be a vector $(T_1 X\ 1)$ of the post-disaster values of the variable of interest for the treated municipality, so that $Y_1 = (Y_{1T_0+1}, \dots, Y_{1T})'$. Y_0 is a matrix $(T_1\ X\ J)$ where column j contains the post-treatment values of the variable of interest for the municipality $j+1$. Therefore, the synthetic control variable of interest is $Y_1^* = Y_0 W^*$. With this variable, the synthetic control estimator can be calculated for the impact of the disaster on the treated municipality. The impact is equal to the difference between the values of the variable of interest for the treated municipality and the synthetic control municipality in the post-treatment period:

$$\delta = Y_1 - Y_1^* \tag{2}$$

$$\delta = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt} \tag{3}$$

This work includes 133 municipalities. In this case, the synthetic control is applied to each individual case and the individual estimates are compiled to obtain the aggregate effects (ASSUNÇÃO et al., 2016). Formally, a set of G treated municipalities is considered, which are indexed by $g = 1, 2, \dots, G$. Let T_{0g} be the year in which the treatment took place in each municipality treated. To better compare treatment in different years, these are normalized in $\tau = t - T_{0g}$, where $\tau = 0$ is the year of treatment for each municipality in G.

After time normalization, be $\hat{\delta}_{j\tau g} = y_{j\tau g} - \hat{y}^*_{j\tau g}$ the estimated effect of the public disaster on the municipality $g \in G$. Therefore, the average impact of G treatments in each municipality g and each year t will be:

$$\bar{\delta}_t = \frac{\sum_{g=1}^{G} \delta^*_{g1\tau}}{G} = \frac{\sum_{g=1}^{G} \left(y_{g1\tau} - y^*_{g1\tau}\right)}{G} \tag{4}$$

As it is common for there to be a high degree of heterogeneity in the effects between the municipalities treated, the average impact can be distorted. Therefore, the individual results can be compiled using other statistics that are better able to deal with heterogeneity, such as the median, as well as the 0.25 and 0.75 percentiles for each case:

$$Px(\delta_\tau) = Px(\delta^*_{g1\tau}) \tag{5}$$

In this formula, Px equals the chosen impact statistic for each treatment τ.

It is important to bear in mind that there are a number of problems that can jeopardize conclusions in terms of inference regarding the individual effects compiled. For example, the consistency of the synthetic control estimator is greater the greater the number of pre-treatment periods present in the database, since this factor helps to reduce the role of unobserved variables in determining the pre-treatment trajectory of the variable of interest. Furthermore, the trajectory of the variable of interest in a treated municipality may have been detached from its synthetic control since before the time of the disaster. This situation characterizes a bias in the estimation, so that it becomes difficult to associate the difference between the trajectories with the treatment. Another problem is the possibility that a treated municipality receives random shocks to its variable of interest with a variance different from its synthetic control. These shocks can underestimate or overestimate the calculated impact.

To verify the existence of these problems in the estimation, it is necessary to have a measure to measure the quality of the adjustment of the synthetic control municipality in comparison with the treated municipality. The most common measure in the literature, and the one adopted in this study, is the pre-treatment Root Mean Squared Prediction Error (RMSPE). This indicator is equivalent to the square root of the mean square error, understood as the ratio between the square deviations of the trajectory of the variable of interest between the reference municipality and its corresponding synthetic control before the point of treatment. The closer it is to zero, the smaller the distance between the trajectories and the better the fit.

$$RMSPE = \left(\frac{1}{T_0} \sum_{t=1}^{T_0} \left(Y_1 t - \sum_{j=2}^{J+1} w_j^* Y_{jt} \right)^2 \right)^{1/2} \tag{6}$$

Estimation problems, as described above, are detected in the empirical exercise by a poor pre-treatment fit of the variable of interest, and this can be tested in the form of a high pre-treatment RMSPE. For this reason, a simple way of controlling the influence of these cases in the estimation of the compiled effect of the interventions is to eliminate the treated municipalities with a pre-treatment MSPR level above a chosen threshold.

5.2. Logit Regression and Fixed Effects Panel

One advantage of working with the synthetic control method is that it allows the impact of a series of events to be obtained individually for the units treated and for the reference years at the time of treatment. This allows the calculated impact of the treatment for each municipality to be transformed into a continuous variable, defined as the economic effect of the disaster (for each estimated variable, i.e. GDP per capita and values added per capita for agriculture, industry and services) by municipality and year. Thus, the impacts calculated by the synthetic control were stacked in a panel of reference years, from t (the year in which the municipality declared a state of public calamity due to rains, downpours, floods and flash floods for the first time in the period analyzed) to t + 3 (three years after this event). By cross-referencing this panel with the original database, the targeting of the BNDES PER program, both in terms of access and the volume of funds released, can be estimated.

Therefore, two blocks of regressions were estimated from this panel. In the first block, access to BNDES PER support is the explained variable, specified as a dummy variable equal to 1 from the first year in which the municipality receives some amount released by the bank, and 0 in other cases. In the second block, the explained variable is the cumulative value of BNDES PER releases in each municipality in each reference year. The estimated model shows access to the program as a function of the economic impact of the natural disaster (measured by the result of the synthetic control for the four estimated variables and validated by the RMSPE test), a control variable related to the event (number of deaths due to exposure to nature, included as a proxy for the intensity of the disaster in physical terms), control variables related to the characteristics of the municipality (logarithm of GDP, % of agriculture in GDP, % of industry in GDP, % of services in GDP and region dummies) and annual fixed effects controls, taking the first year of the series as a reference. As BNDES PER is disbursed through accredited financial agents, the logarithm of the number of bank branches in the municipality was included in the models as a proxy for the capacity of the local credit market. To make variables with different units of measurement compatible, they were all normalized by their scales. The regression methods adopted are different for each block[9]. The first block used logit regression, which follows a binomial probability distribution and is suitable for models with binary dependent variables. In the second block, a model based on fixed effects within units (within estimator) was adopted.

In a binary dependent variable model, the endogenous variable y takes on one of two possible values, equal to one (success), or equal to zero (failure). The aim of working with this type of empirical model is to estimate, or predict, the probability of success and failure, conditional on a given vector x of explanatory variables. Logistic regression models, or regression for limited dependent variables, therefore, consist of a series of mathematical transformations to restrict the estimated probability vector to the interval [0, 1], which is important for interpreting its parameters. Demonstrating mathematically, given the probability of an event occurring:

$$P(Y=1|x)=\frac{e^{\beta_0+\beta_1x_1+...+\beta_px_p}}{1+e^{\beta_0+\beta_1x_1+...+\beta_px_p}} \tag{7}$$

The odds are the chance of the event occurring:

[9] This section is based on the work of Cameron and Trivedi (2005).

$$odds = \frac{P(Y=1)}{P(Y=0)} = \frac{p}{1-p}$$

(8)

The odds can vary from zero to infinity. If *odds* = 1, the probability of success is equal to the probability of failure. If *odds* < 1, the probability of success is lower than the probability of failure. If *odds* > 1, the probability of success is greater than the probability of failure. To represent this model in linear format, a logital transformation is performed on it, i.e:

$$\log it(pi) = \ln\left(\frac{p_i}{1-p_i}\right) = \ln\left[\frac{P(Y=1\,|\,x)}{P(Y=0\,|\,x)}\right]$$

(9)

$$G(x) = \ln\left[\frac{P(Y=1\,|\,x)}{P(Y=0\,|\,x)}\right] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p = G(\beta_0 + x\beta) = \eta_i$$

(10)

Panel data econometric models track the behavior of the same observation units over periods of time. However, it is known that, in most cases, observations are not always independently distributed over time. In other words, there are unobserved factors specific to each unit that can cause heterogeneity bias in the estimates. The fixed effects model is a way of eliminating the individual heterogeneity term fixed in time (α). In short, this model allows each cross-section unit in the sample to have a different intercept, although the slopes of the parameters are the same for all. Given the model:

$$Y_{it} = \alpha_i + X_{it}'\beta + u_{it} \qquad i = 1, ..., N \qquad t = 1, \ldots, T$$

(11) For each observation *i*, we calculate the average of the equation over time. By subtracting the equation from its average, we have:

$$(Y_{it} - \bar{Y}_i) = \alpha_i - \alpha_i + (X_{it} - \bar{X}_i)'\beta + (u_{it} - \bar{u}_i)$$

(12)

$$\ddot{Y}_{it} = \ddot{X}_{it}'\beta + \ddot{u}_{it}$$

(13)

This procedure ended up eliminating the term α_i, which is constant over time. The fixed effects transformation is an internal transformation, i.e. it is considered a within estimator, since it depends on the variations. It doesn't matter the raw magnitude of the value of the variables for each individual, but how it varies over time.

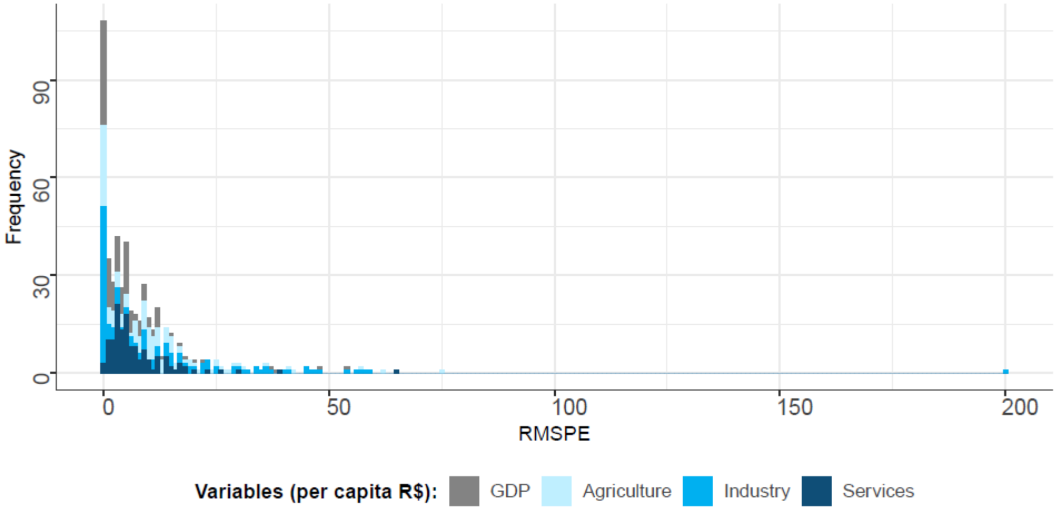
6. Results

6.1. Synthetic control

The synthetic control method was applied individually to compare each municipality treated with its counterfactual. This methodology was applied to a panel of data from 2002 to 2017. After this, the results were computed so that an aggregate analysis could be made of all the municipalities that had declared a state of calamity due to rain, torrents, floods and flash floods.

The first exercise is a general analysis of the quality of the synthetic control settings. As already mentioned, any adjustment problems are detected in the empirical exercise in the form of a high pre-treatment Root Mean Squared Prediction Error (RMSPE). In accordance with the literature on the synthetic control method, it was decided to exclude evaluations with RMSPE above 20[10]. The following graph shows that most of the synthetic control estimates were well adjusted, with a total of 88.5% validation in the 524 exercises carried out. By variable, validation was 96.2% for GDP per capita and value added by services per capita, 87% for value added by agriculture per capita and 74.8% for value added by industry per capita.

Graph 2: Mean Square Error Pre-Treatment of the Synthetic Control Adjustments.



Source: Elaborated by the author.

The next analysis based on the results consisted of a comparison of the proportion of cases in which each variable of interest in the treated municipalities outperformed the values observed for their respective synthetic controls. Intuitively, assuming that the method is not biased for the definition of controls, we should observe that, if the calamities

[10] The literature presents other tests for the adequacy of synthetic control results, such as the placebo in time, placebo in space and leave one out tests (ABADIE and GARDEAZABAL, 2003; ABADIE et al., 2010, 2015). However, due to the large number of units treated, such tests are not possible in this exercise. On the other hand, the statistical procedures adopted to analyze the results deal with possible distortions from outlier values.

had no impact on the locations, this proportion should circulate around 50% over time, just as occurs with the proportion of "heads" results obtained after n tosses of an unbiased coin.

To judge whether these values are statistically significant, a confidence interval was constructed based on a Bernoulli distribution, assuming a *p* parameter of 50%. Thus, the null hypothesis assumes that, in the absence of the impact of disasters, there is a 50% chance that a treated municipality will be worse off than its control at each point in time. If the observed proportion falls below the lower limit of the confidence intervals, this can be interpreted as evidence of a negative impact of the event.

Below is a table with the results of the analysis. According to the table, the economic effects of the disasters were generally dispersed. There was a detachment in the proportion of negative effects in relation to the confidence interval only for the per capita value added from agriculture variable, from the second year after treatment.

Table 3: Proportion of Positive Effects and Confidence Interval for each Reference Year.

Variable	Year	Positive Cases	Negative cases	Proportion of Positive Cases	Lower limit	Upper limit
GDP per capita	t	65	61	0,516	0,414	0,586
	t+1	55	71	0,437	0,414	0,586
	t+2	52	67	0,437	0,412	0,588
	t+3	49	62	0,441	0,409	0,591
V.A. Agriculture per capita	t	58	56	0,509	0,410	0,590
	t+1	52	62	0,456	0,410	0,590
	t+2	37	71	0,343	0,407	0,593
	t+3	40	60	0,400	0,404	0,596
V.A. Industry per capita	t	55	43	0,561	0,403	0,597
	t+1	46	52	0,469	0,403	0,597
	t+2	40	52	0,435	0,400	0,600
	t+3	37	49	0,430	0,397	0,603
V.A. Services per capita	t	66	60	0,524	0,414	0,586
	t+1	66	60	0,524	0,414	0,586
	t+2	64	55	0,538	0,412	0,588
	t+3	57	55	0,509	0,409	0,591

Source: Elaborated by the author.

The next step in the work seeks to analyze the magnitude of the estimated impacts of the treated municipalities in relation to their control groups. The following table shows the statistics of the estimated synthetic control results for each variable and reference year, where t is the treatment year for each case. All values are in percentage terms and indicate the difference in the performance of the treated units compared to their respective synthetic controls.

Table 4: Compared results: Statistics (%)

Variable	Year	Average	DP	P25	Median	P75	Minimum	Maximum
GDP per capita	t	1,85	16,11	-6,83	0,57	6,96	-30,24	92,91
	t+1	-0,71	15,53	-9,44	-2,43	6,46	-57,57	47,38
	t+2	-0,41	20,79	-12,46	-3,96	9,17	-46,66	78,29
	t+3	-2,35	20,20	-15,04	-4,41	10,13	-58,09	54,90
V.A. Agriculture per capita	t	5,11	38,96	-20,89	1,95	15,92	-54,54	219,15
	t+1	-4,03	30,53	-20,10	-3,03	12,77	-74,93	101,05
	t+2	-5,88	42,31	-26,85	-13,55	14,46	-98,20	168,33
	t+3	-7,80	40,52	-32,33	-6,30	14,27	-98,01	162,12
V.A. Industry per capita	t	4,33	35,72	-16,90	1,24	15,90	-63,71	195,84
	t+1	9,17	49,54	-15,49	-3,67	26,83	-65,91	320,99
	t+2	10,25	73,28	-21,59	-3,90	21,42	-87,27	511,59
	t+3	3,37	51,36	-30,29	-7,90	27,57	-91,35	215,87
V.A. Services per capita	t	1,11	16,34	-6,92	0,37	7,63	-54,35	61,92
	t+1	2,55	25,96	-9,39	0,75	10,52	-81,87	188,44
	t+2	3,38	27,80	-10,69	1,29	11,17	-81,94	138,52
	t+3	3,47	29,44	-12,23	0,22	13,74	-81,62	144,71

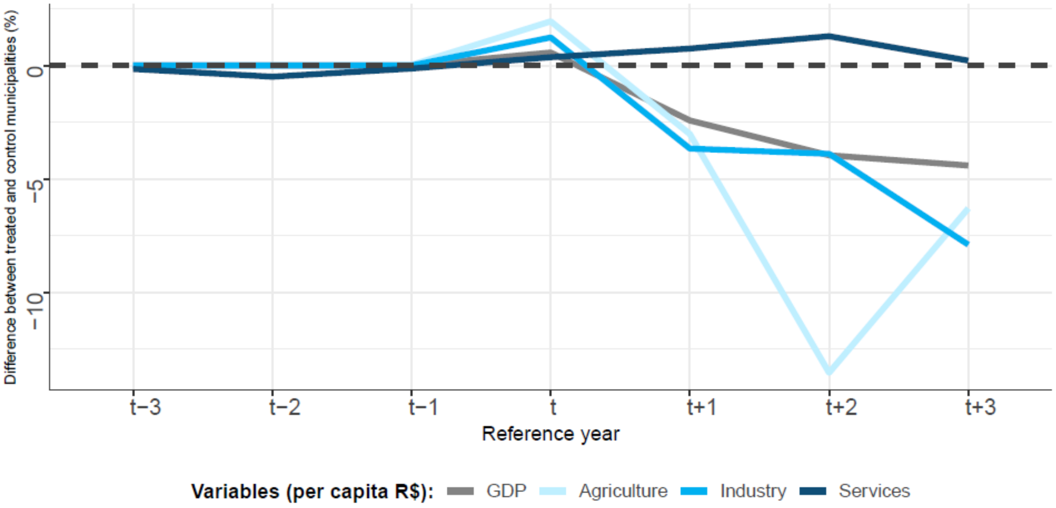
Source: Elaborated by the author.

The main results are summarized in the graph below. The graph shows the behavior of the median percentage effect of the differences in the variable of interest between treated and controls over time, where t is the year of treatment for each case. The advantage of working with the median of the effects is that this statistic is less sensitive to extreme values, unlike the average (ASSUNÇÃO et al., 2016). Trajectories close to zero are observed in the pre-treatment period, which shows good synthetic control settings for all variables. After treatment, on the other hand, there was a negative detachment of the curves relating to the variables GDP per capita and added value of agriculture and industry per capita. In general, the effects of climate disasters are negative for the economic indicators considered, in agreement with the literature surveyed for Brazil (RIBEIRO et al., 2014; HALMENSCHLAGER et al., 2018; CASTRO and ALMEIDA, 2019).

More specifically, from the first year after treatment, the three variables mentioned begin to shift, while the curve relating to the value added of services per capita remains relatively horizontal. While the shifts in GDP per capita and value added by industry per capita increase over the years, the shift in value added by agriculture loses momentum in the third year after treatment. The effect on GDP per capita and on the added value of industry peaks at -4.4% and -7.9% respectively in the third year after treatment. The effect on the value added by agriculture per capita peaks at -13.5% in the second year after treatment.

Finally, the total monetary value lost as a result of the disasters was calculated. That is, for each estimated variable, the loss of value in monetary terms per capita per municipality was calculated, multiplied by its population in the reference year and the loss from t to t+3 was added up. The total loss of GDP was around R$30.8 billion. In the sectors, the losses amounted to R$12.4 billion in the values added by industry and services, and R$1.9 billion in the value added by agriculture. In other words, even though the median impact on GDP per capita of the services sector in the municipalities is nil, the total value lost was high, since this sector has great weight in the municipal economies.

Graph 3: Median Percentage Differences of each Treated Unit in Relation to its Synthetic Control



Source: Elaborated by the author.

6.2. Regressions

As mentioned above, based on the results calculated by the synthetic control for each municipality evaluated, validated by the RMSPE test, we sought to identify whether the BNDES PER program is more likely to reach those municipalities that have been most affected by natural disasters, with a greater volume of resources. To do this, a panel was set up with data on the results by municipality - restricted to those that declared a state of calamity due to hydro-meteorological phenomena between 2008 and 2016 - and reference year (4 in total, from t to t + 3), and this information was crossed with data from the BNDES and the control variables, including annual fixed effects.

The results, as shown in the table below, show a negative correlation between the program's support for municipalities and the synthetic control results for GDP per capita and value added by services per capita. This means that the BNDES may be focusing more on the most serious situations. It is important to note that BNDES PER is a program aimed at micro and small companies, which are concentrated in the service sector.

In addition, there was a positive correlation with the share of agriculture and services in GDP and with municipalities located in the Northeast, North and South regions (the model took the Southeast region as a baseline). This regional correlation may also explain the result for industry, whose share of GDP is higher in the municipalities of the Southeast than in the Northeast and North of Brazil. Similarly, the results of the regressions by sector may be related to greater access to BNDES PER in municipalities whose productive structure is more concentrated in the services sector than in industry.

In the case of the amount released accumulated by BNDES PER, the results showed a negative correlation with the results of the synthetic control for GDP per capita and value added by services per capita. These results corroborate the evidence raised by the previous estimations. In addition, higher disbursements by the BNDES PER are correlated with municipalities with higher GDP.

It should be noted that these results corroborate previous empirical studies, such as Yang (2008) and Sant'Anna (2018), which found evidence that financial aid flows play an important role in economies' efforts to mitigate the adverse impacts of natural disasters.

Table 5: Estimates of Access to BNDES PER (logit).

	Dependent Variable:			
	Access to BNDES PER			
	GDP per capita	V. A. Agriculture per capita	V. A. Industry per capita	V. A. Services per capita
Synthetic Control Result	-0,480***	0,072	0,209	-0,605***
	(0,141)	(0,165)	(0,175)	(0,135)
Deaths	0,467	0,249	0,367*	0,332
	(0,290)	(0,177)	(0,218)	(0,225)
Bank Agencies (log)	-0,246	0,074	-0,693	-0,373
	(0,340)	(0,368)	(0,448)	(0,363)
GDP (log)	0,210	0,271	0,496	0,413
	(0,403)	(0,381)	(0,490)	(0,395)
% Agriculture in GDP	1,066***	0,808***	0,571**	0,852***
	(0,228)	(0,227)	(0,248)	(0,220)
% Industry in GDP	0,567**	0,205	0,325	0,579***
	(0,208)	(0,217)	(0,272)	(0,224)
% Services in GDP	1,072***	0,726**	0,932***	0,862***
	(0,297)	(0,282)	(0,327)	(0,295)
Northeast Region	5,875***	5,860***	5,964***	5,161***
	(0,710)	(0,730)	(0,762)	(0,581)
Northern Region	2,241***	1,612***	2,383***	2,232***
	(0,579)	(0,580)	(0,683)	(0,587)
Southern Region	0,766**	0,837**	1,080**	0,771**
	(0,372)	(0,388)	(0,429)	(0,323)
Constant	-1,982***	-1,717***	-2,066***	-2,009***
	(0,457)	(0,492)	(0,505)	(0,457)

Annual checks	Yes	Yes	Yes	Yes
Observations	482	436	374	483
Pseudo-R2	0,496	0,477	0,486	0,432
LR Chi2	221,047***	189,439***	167,953***	187,165***

Note: *p-value<0.1; ** p-value<0.05; *** p-value<0.01
Source: Elaborated by the author.

Table 6: Estimates of BNDES PER releases (fixed effects)

	Dependent Variable: Amount released by BNDES PER (logarithm)			
	GDP per capita	V. A. Agriculture per capita	V. A. Industry per capita	V. A. Services per capita
Synthetic Control Result	-0,180***	0,007	0,0005	-0,240***
	(0,043)	(0,041)	(0,039)	(0,047)
Deaths	0,022	0,020	0,018	0,020
	(0,019)	(0,020)	(0,021)	(0,019)
Bank Agencies (log)	-0,052	-0,043	-0,004	-0,051
	(0,194)	(0,176)	(0,235)	(0,197)
GDP (log)	1,432***	0,926***	1,275***	1,276***
	(0,309)	(0,281)	(0,354)	(0,294)
% Agriculture in GDP	0,240**	0,046	-0,074	0,161
	(0,110)	(0,113)	(0,106)	(0,102)
% Industry in GDP	-0,144	-0,311**	-0,481**	-0,101
	(0,128)	(0,124)	(0,186)	(0,126)
% Services in GDP	-0,010	-0,117	-0,225	0,263
	(0,163)	(0,148)	(0,163)	(0,173)
Annual checks	Yes	Yes	Yes	Yes
Observations	482	436	374	483
R2	0,209	0,183	0,121	0,222
R2 Adjusted	-0,112	-0,154	-0,218	-0,093
F-statistics	6,472***	4,923***	5,267***	6,985***

Note: * p-value<0.1; ** p-value<0.05; *** p-value<0.01
Source: Elaborated by the author.

7. Final considerations

This study carried out 524 synthetic control exercises to verify the effects of natural disasters such as rains, floods and flash floods on the GDP per capita of the Brazilian municipalities affected, both in aggregate and broken down by major sectors (agriculture, industry and services). Of these exercises, 88.5% were validated according to the RMSPE test, with the adjustments being slightly worse for industry. For GDP per capita and its breakdowns related to agriculture and industry, there were negative effects, with different dynamics for each case. In agriculture, the effect is more intense, but loses strength in the third year after treatment. For GDP per capita and its breakdown into industry, the effect is relatively moderate, but growing over time. There was no evidence of a return to the previous trend in these variables, which is evidence that the indirect costs of disasters play a significant role. The estimated total loss from disasters in the municipalities was R$30.8 billion in the three years following each event.

An analysis based on regressions showed that access to the program was more likely in the municipalities most affected by the disasters in terms of GDP per capita and value added by services per capita. Therefore, the results observed robustly verified that the program reached the municipalities with the greatest losses in the face of events such as rains, downpours, floods and flash floods.

To assess the effectiveness of this program, i.e. whether it has in fact been able to mitigate the adverse impacts of disasters on municipalities, some factors need to be taken into account. Firstly, as the BNDES PER was only made available in municipalities that have experienced emergencies or public calamities, there is a situation of endogeneity in relation to any estimates of its impact on the economies of these municipalities. Secondly, the direct beneficiaries of the program are companies or individual entrepreneurs, so these are the most appropriate units of observation to measure the effect of the program. Thirdly, even in an analysis carried out at company level, BNDES PER funds were only made available to companies that survived the disasters, so there is a risk of overestimating their effects. Therefore, any inference about the possible effects of this program, based on the evidence presented here, should be made with caution.

Finally, it should be noted that this work was the first effort to calculate the impact of natural disasters on Brazilian municipalities in a systematic way. The results are promising, as negative impacts on GDP per capita were identified with no tendency to return to the trajectory within three years of the event, even with a lot of dispersion. Furthermore, in sectoral terms, it was observed that agriculture and industry are more intensely affected than services. The future research agenda on this topic involves, firstly, identifying the determinants of the magnitudes of the impacts, with an emphasis on the different types of disasters, their intensities and the role of institutions, perceived risks, levels of local development and education related to the municipalities. Secondly, it is important to identify the transmission mechanisms, both short-term and long-term. Finally, in terms of public policies, it is worth exploring the targeting of other public financial flows of assistance to municipalities hit by disasters, as a way of comparing the results of the BNDES PER, as well as highlighting the initiatives considered most successful.

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