Beyond the Storm: Analysis of the Economic Impacts of Cyclone Bomb Events in the Southern Region of Brazil in 2020.

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Extended Version

Special Area: S07 Navigating the Storm: Exploring the Socio-Economic and Behavioural Impacts of Natural Disasters on Communities
or
Special Area: S15 Flood Risk and Natural Hazard in the Built Environment - From Economic Impact to Regional Resilience

1 Introduction

In recent years, there has been a significant increase in the frequency and intensity of natural disasters worldwide, which has had profound effects on communities and economies. In Brazil, the southern region of the country is particularly vulnerable to such events due to its location in a corridor that is conducive to the formation of tornadoes and cyclones. The region has experienced a series of catastrophic weather events that have had a profound impact on its socioeconomic fabric.

An example is the Cyclone Bomb that hit the region in 2020. This event is characterized by rapid intensification, commonly known as bombogenesis. According to reports from the Civil Defense, this Cyclone Bomb stands as the most severe wind-related natural disaster ever recorded in history of Brazil South region, surpassing even the previous catastrophe of Hurricane Catarina in 2004 (GaúchaZH (2020) and Battistella (2020)). The damage and disruption it caused left an indelible mark, claiming at least 12 lives, including nine in Santa Catarina (SC), one in Rio Grande do Sul (RS), and two in Paraná (PR), and affecting more than a million people. The estimated cost of the cyclone's damage is expected to reach billions of Brazilian reais.

The Cyclone Bomb occurred in late June 2020, causing extensive damage through strong winds, heavy rainfall, and even sporadic snowfall in some areas. Wind speeds reached up to 116 kilometers per hour (approximately 72 miles per hour) in various locations, resulting in power outages, deforestation, structural damage to buildings and transportation disruptions. It had economic impacts beyond the affected areas, affecting businesses, agriculture, infrastructure, and the overall quality of life of the population, demonstrating the region's inherent economic and social integration.

The effects of the Cyclone Bomb were felt in several sectors, especially in agriculture, where crops suffered significant damage, and in the broader economy where commercial entities and infrastructure were disrupted. It should be noted that infrastructure damage in Santa Catarina alone exceeded 20 million euros. Flash floods and mudslides caused by the cyclone resulted in crop losses of up to 30 million euros. In response to the crisis, the Brazilian government implemented financial aid and directed investments towards fortifying infrastructure to mitigate future calamities.

In Brazil, municipalities affected by natural disasters, such as floods or strong winds, are legally entitled to declare a state of emergency or a state of public calamity. Once these declarations have been validated, they confer a number of significant benefits that facilitate disaster response and recovery. However, municipalities that have not been approved in these states, even if they experience secondary effects from the disaster, do not enjoy the same advantages. Municipalities that declare a state of emergency or calamity have prioritized access to financial resources from federal and state governments. Administrative and contractual flexibility is another critical benefit for municipalities that declare a state of emergency or calamity. They can expedite the procurement of goods and services without undergoing the usual bidding processes required by public procurement laws. This ability significantly accelerates the implementation of urgent measures. Furthermore, municipalities under a state of emergency or calamity can suspend or extend administrative and legal deadlines, providing essential leeway to manage the crisis effectively.

Despite these efforts, a comprehensive recovery trajectory is expected to last several years. As a precautionary measure, the government has worked hard to improve meteorological forecasting, strengthen emergency response protocols, and educate residents about disaster preparedness. The Cyclone Bomb event demonstrated the southern region's susceptibility to meteorological extremes and confirmed concerns about the rising frequency and intensity of such events in the context of global climate change.

Globally, the economic costs of extreme weather events have been shown to increase over time. Climate change is expected to exacerbate these trends. In 2020, according to the Global Natural Disaster Assessment Report, natural disasters worldwide resulted in significant human and economic losses. A staggering 15,082 lives were lost, with storms affecting nearly half of the 98.9667 million people affected worldwide. Direct economic losses amounted to $173.133 billion dollars, with storms accounting for more than half of this total, underscoring the significant impact of these events on both human lives and economies (IFRC (2021)).

Storms exerted a significant contribution to economic losses, amounting to US$ 93.2 billion in 2020, representing a 64% increase over historical levels. In comparison with the average of the last 30 years, direct economic losses in 2020 were 29% higher, thereby underscoring the impact of natural disasters in this domain(IFRC (2021)).

Newman and Noy (2023) estimates that climate change is responsible for $143 billion per year of the global cost of extreme weather events. This highlights the importance of the findings from southern Brazil in the broader context of increasing economic vulnerability to extreme weather events.

Despite acknowledging that the most significant tragedies are associated with human losses, the focus of this work centers on the economic effects of natural disasters.

A comprehensive understanding of the effects of natural disasters on the regional economy is crucial to formulating effective mitigation and adaptation policies that promote sustainable development and economic resilience. Improving understanding of the intricate interplay between natural disasters and the regional economy will equip Brazil's southern region to confront imminent climate challenges with greater efficacy.

This article aims to analyze the economic impact of one of such economic disasters, namely the Cyclone Bomb. Effects on agricultural and extraction, industry, commerce and service variables of employment and production will be estimated. Furthermore, the analysis will go beyond the immediate direct effects to uncover the complex chain reaction of impacts and their resulting spatial spillovers on various aspects of society. It is a challenging task because it requires, on one hand, analyzing the events over time and, on the other hand, understanding the spatial dynamics of these phenomena. The complexity is further enhanced when considering the interconnections among these climatic events across different geographic domains.

The methodology used in this paper is based on the studies conducted by Delgado and Florax (2015) and Bardaka et al. (2019). These researchers combine spatial econometrics in DiD models to analyze the direct, indirect (spillover) and total effects recurring to Spatial Lag X (SLX) models. In fact, Delgado and Florax (2015) emphasize the importance of realising that with spatial data, the traditional SUTVA assumption is questionable due to the existence of local spatial interactions in treatment responses. They deal with that situation introducing a given spatially lagged term in the DiD estimation allowing to determine the average direct effect of treatment and the average indirect effect which takes into account the proportion of neighbours that are affected by treatment.

In addition to this introduction, the article comprises five more chapters. Chapter 2 provides a literature review on natural disasters and their economic impacts, while Chapter 3 outlines the data and methods employed. The results are presented in Chapter 4, followed by the concluding remarks in Chapter 5.

2 Literature Review

Natural disasters encompass a broad range of environmental phenomena, including hurricanes, cyclones, floods, earthquakes, tsunamis, and droughts. Each type of disaster presents unique challenges and economic implications, from immediate physical damage to long-term disruptions in economic activities and social systems. These events, which are often sudden and devastating, can have multifaceted impacts on the economy, affecting infrastructure, human capital, and overall productivity. A clear understanding of the mechanisms through which natural disasters influence economic growth is essential for the design of effective mitigation and adaptation strategies.

Natural disasters and economic growth: There are several theoretical models that examine the relationship between natural disasters and economic growth. Typically, these models conceptualize disasters as sudden losses of factors of production that cause the economic system to adjust, either returning to the pre-disaster equilibrium or shifting to a new one (Botzen et al. (2019)).

In Botzen et al. (2019) there is an extensive literature review of models such as those based on Social Accounting Matrices (which use input-output and computable general equilibrium frameworks to predict how damage in one sector affects trade and output throughout the economy), Neoclassical Growth Theory Models (which predict a gradual return to steady state after shocks to capital or labor supply), Endogenous Growth Models (such as and AK models, which consider the role of investment in driving technological change and productivity growth), Regional Models (which explicitly consider that geography is crucial in bridging the gap between macro-level indirect impacts and micro-level direct damages), and Computational Models for Simulating the Impacts of Disasters (with computational models to simulate the impact of hypothetical or historical natural disasters).

Despite all the advancements in the conceptual framework, the economic impacts of natural disasters are still not a consensus and may depend on short-term or long-term analyses. Various heterogeneous effects can occur depending on the type of natural disaster phenomenon, the region of occurrence, and the form of reconstruction. Both positive and negative short, medium, and long-term outcomes have been found in the literature. In this context, the work of Okuyama (2003), Okuyama and Chang (2004) and more recently Okuyama (2022) continues to be a significant reference in the field of natural disasters and economic growth and provide important guidance for future studies.

Recently, Akao and Sakamoto (2018) proposed a unified approach applied to an endogenous growth model to consider the influence of disasters on long-term equilibrium and the transition phase. The results indicate that while disasters may decrease the average growth rate of affected countries, there are various channels through which the risk of disasters and long-term economic performance are positively correlated. This finding reconciles apparently contradictory evidence in recent empirical studies.

A thorough and in-depth examination of recent research can be found in Skidmore (2022) handbook, which delves into advancements in the field of natural disaster economics. The volume covers a wide array of topics, including: (1) theoretical frameworks for modeling impacts and decision-making processes, (2) methodologies and practical applications for assessing the impacts of disasters, and (3) strategies for evaluating and bolstering risk management, resilience, and adaptability. Skidmore (2022) explores the intricate link between natural disasters and economic growth, offering fresh perspectives and insights into this multifaceted relationship.

International empirical studies:With regard to empirical studies assessing the economic impacts of natural disasters, the impacts of extreme weather phenomena have been extensively studied worldwide. The following articles provide a small sample illustrating the state of the art in empirical studies estimating the economic impacts of natural disasters.

Loayza et al. (2012) investigates the repercussions of natural disasters on economic growth, recognizing the divergent conclusions within the current body of literature. Employing a dynamic generalized method of moments panel estimator on data encompassing the years 1961 to 2005 across various nations, the authors discern that natural disasters indeed influence economic growth, albeit with nuances contingent upon the type of disaster and economic sector. While moderate disasters may yield positive growth effects in selected sectors, severe disasters exhibit negligible benefits. Moreover, the study underscores that natural disasters exert a more pronounced impact on economic growth in developing countries relative to developed ones, affecting a broader spectrum of sectors and yielding more significant economic ramifications.

Fomby et al. (2013) analyzed the impact of natural disasters on economic growth, considering the differential effects between developed and developing countries, as well as among natural disasters of varying magnitudes. The study examines 84 countries from various regions of the world over the period from 1960 to 2007. The principal findings underscore that the impact of natural disasters varies between developed and developing countries, being more pronounced in less developed countries. The study separates the analyses into agriculture and non-agriculture sectors, recognizing that the results may differ across sectors, with the most significant impact observed in agricultural sectors. The study also suggests that moderate-magnitude natural disasters may have positive effects on economic growth, while severe disasters tend to have more detrimental effects and the results may differ according to the types of natural disasters, such as droughts, floods, earthquakes, and storms.

Wu et al. (2019) examined the impacts of tropical cyclones on employment, specifically focusing on the quantity of labor employed and employee compensation. The study investigates data from various sources and periods to comprehend these effects. The method employed is meta-regression analysis, which combines results from previous studies to draw more comprehensive conclusions. The main findings indicate that tropical cyclones have a significant short-term impact on employment quantity, but this impact diminishes over time. These results suggest that, while there are immediate negative impacts, economic recovery following cyclones may lead to long-term positive effects on employment and employee compensation. In the conclusions and discussions, the authors deliberate on post-disaster reconstruction and the creation of employment opportunities in reconstruction sectors such as industrial, commercial, residential, and infrastructure areas. They emphasize that post-disaster reconstruction activities can generate numerous job opportunities due to the demand for labor in the rebuilding and rehabilitation of areas affected by tropical cyclones.

Panwar and Sen (2019) examines the economic impact of natural disasters, focusing on short and medium-term effects across different sectors and levels of development. Its primary objectives include investigating how natural disasters affect economic growth, identifying the types of disasters considered, and evaluating their consequences in both developed and developing countries. The study covers the period from 1981 to 2015 and utilizes a sample of 102 countries, comprising 29 OECD and 73 non-OECD countries. The methodology employed includes panel analyses and growth regressions, incorporating control variables and proxies for external shocks. The results highlight that natural disasters have varied economic impacts, with more pronounced effects observed in developing countries.

Bănică et al. (2020) investigate the spatial dynamics of natural disasters and their effects on various regions. The study encompasses European countries, Japan, and the United States, analyzing data from 1990 to 2019. Methodologically, they employ data from the Emergency Events Database (EM-DAT) alongside case studies from diverse regions. The key findings challenge conventional wisdom by suggesting that natural disasters might contribute, albeit to some extent, to economic resilience and socioeconomic development, contrary to the prevailing notion of their purely detrimental impact. Moreover, the study underscores the importance of understanding the intricate interplay between natural disasters and spatial systems, shedding light on the potential positive feedback loops that can emerge in the aftermath of such disturbances.

Furthermore, Bănică et al. (2020) delve into the spatial aspects of natural disasters and their ramifications on affected areas. They underscore the significance of integrating spatial and economic resilience strategies in response to natural disasters, emphasizing the intricate relationship between spatial and economic systems. The analysis delves into the interconnectedness of geography and economics, highlighting how the level of spatial aggregation can influence spatial dynamics during times of upheaval.

Kuhla et al. (2021) examine the effects of interactions between extreme weather events and their repercussions, emphasizing the significance of ripple effects along supply chains. The study shows that climate-induced heat stress, river floods, and tropical cyclones cause economic losses to increase on average 21% due to the resonance of economic shockwaves. The authors utilize simulations to model the global supply network's response to extreme weather eventswith daily time series by integrating this data with economic ripple effect modeling. They examine over 7000 regional economic sectors and 1.8 million trade relationships, considering the temporal evolution of trade relationships between economic sectors. The spatial effects identified in the study on the economic ripple effects caused by extreme weather events can be related to regional vulnerability and adaptation issues. The variation in intensity and effects of economic ripple effects across different regions underscores the importance of considering geography and specific locality characteristics when planning adaptation and mitigation measures.

Brazilian empirical studies: In the Brazilian context, an array of studies has intricately examined the interplay between natural disasters and their economic repercussions.

Monte et al. (2021) offers a comprehensive literature review on natural disasters and their links with resilience, adaptation, risk, hazard, vulnerability, and capabilities. The author examines the evolution and application of terms related to disasters caused by natural hazards, providing holistic definitions and approaches for their use, with a specific focus on Brazil. The article aims to clarify and enhance the understanding of the terms used in disaster risk management, particularly within a specific regional context like Brazil.The author analyzes and synthesizes a variety of studies, definitions, origins, and applications of key terms like risk, hazard, vulnerability, adaptation, and resilience, aiming to elucidate and enhance the understanding of these concepts.

Wink Junior et al. (2023) estimated the impact of the 2008 flood in the Brazilian state of Santa Catarina on poverty levels, aiming to assist in the formulation of public policies capable of mitigating the identified negative effects. The analysis period spanned from 2001 to 2015, excluding the year 2010 due to the demographic census conducted in that year. The region under scrutiny was the state of Santa Catarina, Brazil, which experienced an increase in poverty levels following the event, while other regions of Brazil either maintained their levels or experienced decreases. The methodology employed involved the application of a Differences-in-Differences method, exploiting exogenous variation in the location and timing of the event, along with proposing mechanisms to explain the findings. The main findings indicated that the natural disaster increased the likelihood of an individual being below the extreme poverty line by 2 percentage points in the first year after the event (2009), with this effect increasing over the analyzed years, reaching up to 6 percentage points in 2014.

Using a different approach Lima and Barbosa (2018) investigates the presence of spatial spillovers from natural disasters in geographically linked areas, using as a case study a flash flood that occurred in Santa Catarina, Brazil, in 2008. The analysis period covers the year of the flood and the three subsequent years. The methodology employed was a Differences-in-Differences model that explicitly allows for the existence of spatial interactions within affected and unaffected regions (SLX model expanded for multiple periods). Additionally, the authors considered disaggregated data at the municipal level to assess how each of the three economic sectors - agriculture, industry, and services - responded to the flood. The main results of the study showed that municipalities directly affected by the flood experienced a 7.6% decrease in GDP per capita in the year following the disaster. Three years after the flood, GDP per capita recovered to pre-disaster levels in all sectors except the agricultural sector, which experienced a significant decrease of about 19.2% in the first year after the shock and a statistically significant decrease of about 9.5% three years after the flood. The spatial estimates revealed the existence of spillovers and their economic relevance. Specifically, the indirect impact of the flash flood ranged from -0.543% to -1.384%.

de Oliveira (2019) examines how natural disasters affect the GDP growth rate of municipal economies in the state of Ceará, located in Northeast Brazil. The analysis period covers historical data from the past 30 years, focusing on the state of Ceará in Northeast Brazil. The study employs an econometric growth model approach using Generalized Method of Moments (GMM). The key findings indicate that damages caused by natural disasters have a negative impact on the economic growth of municipalities in Ceará. The agricultural sector is adversely affected by both droughts and floods, while the service sector is primarily impacted by floods. Conversely, the industrial sector does not appear to be sensitive to natural disasters. Specifically, an increase of one standard deviation in direct damage caused by natural disasters results in a reduction of approximately 3.1% in the GDP growth rate. Additionally, the specific impact of droughts and floods on economic sectors is quantified. For instance, a similar increase in direct damage caused by droughts leads to a decrease of approximately 2.4% in the GDP growth rate and about 6.5% in the agricultural sector.

Alongside natural disasters, human-made disasters, or technological disasters, exist within the same spectrum of concern. One such example is elucidated in the research conducted by Niquito et al. (2021) that examined the short-term economic impacts of the technological disaster related to the collapse of the Fundão mining waste dam, known as the "Mariana Tragedy," located in the Brazilian states of Minas Gerais and Espírito Santo, classified as a man-made disaster. The analysis period covered the years 2006 to 2017, focusing on the consequences of the disaster on economic activities in the agriculture, industry, and services sectors. The methodology employed was the estimation of spatial difference-in-differences models, considering spatial effects à la Delgado and Florax (2015). The main results indicated a direct negative impact on total GDP (-6.81%), gross value added in agriculture (-12.12%), and industry (-15.57%). Regarding indirect effects, a positive impact on total GDP (+2.69%) was observed in some specifications, with a robust effect. No effects of the disaster were found in the services sector. These findings contribute to the discussion on how man-made disasters affect developing economies and may provide support for the formulation of public policies for disaster prevention, mitigation, and remediation.

Regarding the 2020 Cyclone Bomb, Giehl et al. (2020) has been produced a technical report, providing descriptive information on the socioeconomic effects caused by the phenomenon, with a special focus on losses incurred in agricultural and fishing establishments in the affected municipalities of Santa Catarina. Permanent crops accounted for 48.64% of the total value of losses in the state. Following were damages to improvements in agricultural establishments, reforestation, and pastures, which accounted for 19.29% and 16.03% of the total losses, respectively. Losses in temporary crops representing 3.54% of the value of losses resulting from the extratropical cyclone.

Spatial econometrics and natural disasters: Okubo and Strobl (2021) investigates the impact of the 1959 Ise Bay Typhoon on firm survival probability and performance in Nagoya, Japan. The analysis period spans both the years immediately before and several years after the typhoon. They used spatial DiD (SLX) to allowed for a direct effect of the typhoon through the location of the firm in its own geographic area, as well as weighted spatial spillovers from other areas. This was justified by the fact that firms may obtain material inputs and labor from other geographic areas, and shocks in these areas can propagate through space. Additionally, firms may spatially compete in product markets with each other, so shocks in production in one region can affect nearby regions. The main results include the identification of persistent impacts of the typhoon on firms, with heterogeneity in effects across sectors. It was observed that location in flooded areas had no significant effect on firms' sales, employment, and labor productivity. Furthermore, the study highlights the importance of disaster risk reduction policies in post-disaster recovery and suggests that the absence of these policies can amplify the negative effects of extreme weather events.

Barth et al. (2024) examines the direct and indirect impacts of natural disasters on deposit rates of bank branches in the United States. The study focuses on the United States, with the analysis period spanning from October 2008 to December 2017. The methodology employed includes a triple difference model to capture post-disaster effects, differences between affected and unaffected counties, and the distinction between branches setting their own rates and those adopting them. Additionally, the study utilizes a spatial difference-in-differences (DID) framework (SAR and SDM model) to decompose the impact of natural disasters on changes in deposit rates of bank branches into direct and indirect effects. The main findings of the study include the analysis of local competition among bank branches being affected by advancements in information technology, with online banks showing a greater response to natural disasters in neighboring counties. Online-oriented banks demonstrate an information advantage following natural disasters, adjusting their deposit rates more significantly. The failure to consider spatial spillover effects may substantially underestimate the impact of shocks on local markets on bank deposit rates. These results contribute to a better understanding of the role of spatial competition among branches in setting interest rates in markets affected by natural disasters.

Fischer (2021) examined the relationship between natural disasters and economic growth in Iran, employing a spatial panel Durbin model spanning from 2010 to 2016, focusing on 29 provinces. The methodology entailed the application of a spatial panel Durbin model, with maximum likelihood estimation. The SDM model was selected as the most suitable for this study due to its capacity to capture spatial contagion effects and its superior fit to the data compared to other spatial models. The effects vary depending on the type of natural disaster and the considered time period. For instance, the incidence of a flooding event is associated with an average increase in GDP per capita ranging between 4.3% and 4.9%. The authors suggest that these positive effects could be attributed to the reconstruction and replacement of necessary services and industries in the affected provinces, as well as to the increased economic activity related to these processes. However, it is important to highlight that these positive effects tend to be short-term and do not persist for long periods, especially for neighboring provinces, which may revert to their pre-disaster development path after the completion of reconstruction efforts.

Patrascu and Mostafavi (2024) examine the relationship between population activity recovery in the aftermath of Hurricane Harvey in 2017 in Harris County, Texas. The study categorizes recovery into four segments associated with physical vulnerability, access, exposure, impact of the disaster, protective actions, and population characteristics. It seeks to identify factors linked to faster or slower recovery post-disaster, enabling proactive monitoring of the process across different neighborhoods. The methodology employed was the Spatial Durbin Model to fit and evaluating the direct, indirect, and total effects of the characteristics on population activity recovery. This analytical approach considers both global and local spatial interactions, emphasizing the neighbor interactions across diverse spatial scales. Moreover, the authors show an array of models, ranging from non-spatial to local and global spatial frameworks and they expound that while global models encompass broader-scale neighbor-to-neighbor interactions, local models exclusively focus on the direct influences of immediate neighbors. The results indicated that the extent of physical vulnerability, measured by road network density, prolongs the duration of population activity recovery through direct and spillover effects. Additionally, the extent of access to essential facilities, measured based on the number of points-of-interest (POIs), shortens the duration of population activity recovery. The ability to predictively monitor population activity recovery can significantly enhance the recovery resource allocation process.

Wang and Chen (2021) examined the emergency response capacity to rain-flood disasters in provinces within the Yangtze River Economic Belt (YREB) in China, focusing on the interplay between economic-social factors (ESF) and environmental-natural factors (ENF) subsystems from 2013 to 2017. Employing the Spatial Durbin Model (SDM), the study delved into the influencing mechanism of the ESF and ENF subsystems' developmental levels and their coupling on the emergency response capacity to rain-flood disasters across provinces. The SDM facilitated a comprehensive analysis of the relationship and contagion effect among relevant spatial variables, offering insights into emergency response capacities across different regions. Moreover, the study observed Spatial Spillover and Diffusion Effects showing that he development of economic-social and environmental-natural subsystems generated spatial spillover and diffusion effects in neighboring areas. This suggests that actions taken in a particular location can positively influence emergency capacities in nearby regions.

The literature on natural disasters reveals their significant and multifaceted impacts on economies. These events, ranging from hurricanes and earthquakes to floods and droughts, pose immediate and long-term challenges to economic activities and social systems. Theoretical models suggest that natural disasters disrupt production factors, compelling economies to either recover or adapt to new equilibriums. Despite advancements in understanding these impacts, consensus remains elusive, as outcomes vary by disaster type, region, and recovery efforts. Empirical studies worldwide highlight the heterogeneity of these effects, with developing countries often experiencing more pronounced negative consequences. Notably, the research underscores the complex interplay between disaster types, economic sectors, and regional characteristics, demonstrating both adverse impacts and, in some cases, positive long-term growth through reconstruction efforts. This body of work also emphasizes the importance of integrate spatial and economic resilience strategies to mitigate and adapt to these events effectively.

This study aims to build upon existing knowledge by examining the nuanced economic impacts of the 2020 Cyclone Bomb that struck southern Brazil. Leveraging advanced spatial econometrics techniques, the research seeks to provide a detailed analysis of the direct and indirect effects of this natural disaster on local and regional economies.

3 Methodology

3.1 Data

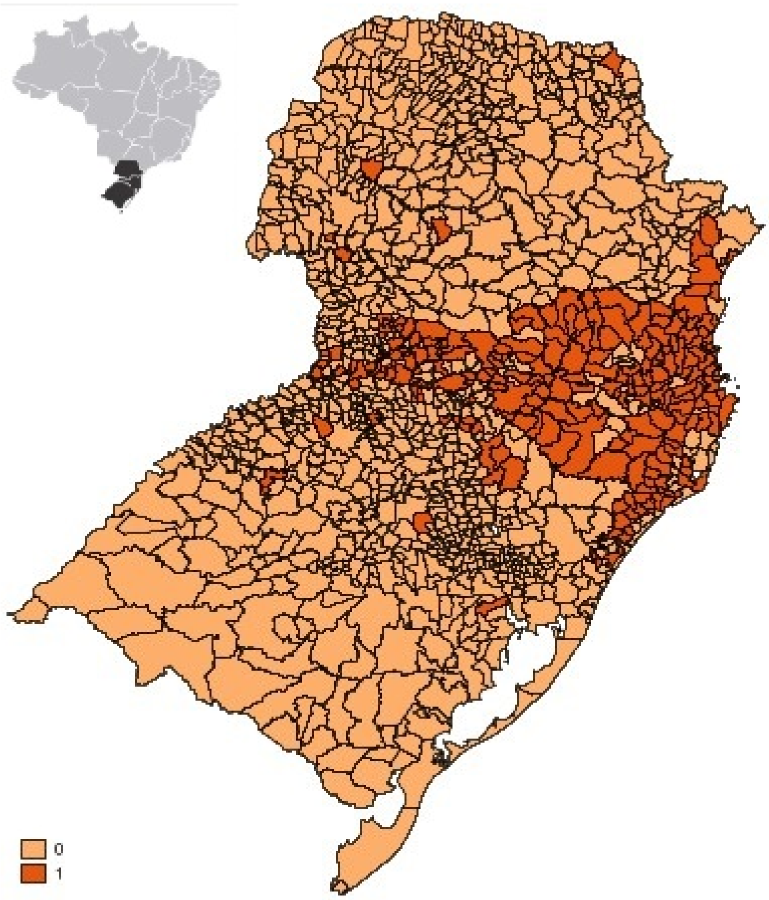
This study uses publicly available panel data to examine the economic impact of Cyclone Bomb events in Brazil in 2020 covering all municipalities in the southern region of Brazil (Paraná - PR, Santa Catarina - SC and Rio Grande do Sul - RS) for the years 2019 and 2021. The outcomes of interest will be municipal production (measured by its added value) and also labor market indicators[1] (measured by the number of jobs, wage mass, average salary) in each major sector of the economy (agriculture and extraction, manufacturing industry, trade and services). The production and employment data are available online annually on the websites of the Brazilian Institute of Geography and Statistics (IBGE) and the Annual Social Information Report (RAIS), respectively.

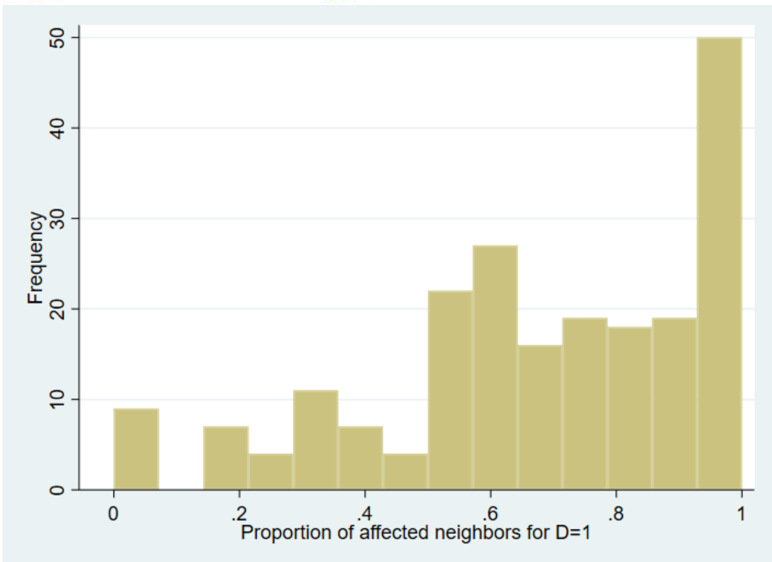
To identify the municipalities affected by the Cyclone Bomb, information from the Civil Defense, through the Ministry of Integration and Regional Development, will be used regarding the declaration of emergency and/or public calamity due to the natural disaster at the end of June and beginning of July 2020 that had the status of "Recognized" by the Civil Defense within the class "Local/Convective Storm - Windstorm". The data are public and available online annually. In this study, the municipalities that had the emergency and/or public calamity decree recognized receive the value 1 and zero otherwise. This is therefore a dummy variable to capture municipalities affected by the Cyclone (this dummy is generically called “Treatment” in the DiD literature).

The figure 1 displays the municipalities of the southern region, highlighting those affected by the Cyclone Bomb of June/July 2020. A total of 1188 municipalities from the southern region of Brazil were included in the sample, of which 213 municipalities experienced situations of emergency or public calamity recognized by civil defense due to the Cyclone Bomb. A significant portion of the affected municipalities is located in the state of Santa Catarina, in the central region of the map. The histogram illustrates the frequency distribution of municipalities directly affected (D=1) based on the proportion of affected neighbors (wd). It is noteworthy that 50 municipalities, representing nearly 25% of the total affected, experienced a scenario where 100% of their neighboring municipalities were also affected. On average, each directly affected municipality had approximately 67% of its neighbors also affected.

[1] This study delimits its investigation to the formal employments within legal entities categorized as 'Business Entities.' Individuals employed on 'Public Administration,' 'Nonprofit Organizations,' 'Individual Entities,' and 'International Organizations and Other Extraterritorial Institutions' are excluded from the sample.

Figure 1: Map and histogram with the municipalities affected by the Cyclone Bomb of 2020





Source: Author's calculations based on Civil Defense database. Note: D=1 if affected; D=0 otherwise)

Table 1 presents the main descriptive statistics of these variables for the analysis period. The group of unaffected municipalities comprises 975, while the group of affected municipalities comprises 213. It is noticeable that between 2019 and 2021, the average values of wage mass and employment decreased across all sectors for both affected and unaffected municipalities. For instance, the average agricultural wage mass for the unaffected municipalities decreased from $0.72 million to $0.22 million, while for the affected municipalities, it decreased from $1.06 million to $0.30 million. These results are understandable as they pertain to the period following the COVID-19 pandemic, which had a widespread impact on all municipalities in the southern region. The COVID-19 pandemic significantly reduced employment and production due to a sharp drop in offer and demand, business closures, and activity restrictions. Mobility restrictions further disrupted operations and caused job losses. Logistical disruptions impacted supply chains, leading to production delays and increased costs, particularly in sectors dependent on timely goods movement. However, it is interesting to note that the municipalities affected by the Cyclone Bomb already had higher average values than the unaffected municipalities before the event for all employment variables and maintained this characteristic in the post-event period.

In comparing the production variables, the behavior between the municipalities before and after the Cyclone Bomb is similar. Both groups increased production in agriculture and industry over time and decreased in services. Interestingly, the affected municipalities already exhibited a lower average production performance in agriculture and higher in industry and services.

Following the recommendations of the literature, additional control variables will be included in the model to isolate effects that may contaminate the analysis. The Firjan Fiscal Management Index (I-FIRJAN) is included as an additional control measure. This index evaluates the quality of fiscal management in Brazilian municipalities taking into account factors such as expenditure, investment, and debt. Its inclusion ensures a more comprehensive control of the post-reconstruction period by accounting for the impact of municipal fiscal management on performance (Noy and Nualsri (2011), Cevik and Huang (2018), Deryugina (2022)). The data source for this index is the Federation of Industries of the State of Rio de Janeiro (Firjan).

The Brazilian Electoral Justice provides control variables related to voting behavior and political orientation. These covariates focus on electoral participation and political party alignment between local and state governments, serving as a proxy for local institutional quality. The first reflects civic engagement and the second may indicate that local government may obtain resources easier from state governments and recent literature suggests its impact on local growth (Barone and Mocetti (2014); Lima and Barbosa (2018); Asher and Novosad (2017); Niquito et al. (2021)). The resident population variable is also included as an additional control in the model. This variable helps capture demographic dynamics associated with economic growth and also serves to control for the size of the affected cities. The data for resident population is also available on IBGE website.

3.2 Empirical Strategy

Natural disasters associated with wind phenomena bear some resemblance to random or quasi-random events, as they often exhibit unpredictable and seemingly arbitrary patterns of occurrence. Although not a perfect comparison, it is possible to argue that these unpredictable and seemingly random climatic events share some conceptual similarities with randomization processes (Nasution et al. (2019); Judt et al. (2015); Makridakis and Bakas (2016)).

The unpredictability and apparent randomness in the geographical distribution of dam-

Table 1: Descriptive statistics

Variable	Unaffected				Affected			
	Before		After		Before		After	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Agricultural wage mass (in R$ millions)	0.72	2.06	0.22	0.67	1.06	2.46	0.30	0.69
Industrial wage mass (in R$ millions)	16.88	77.07	4.82	21.77	32.64	87.45	9.46	25.23
Commerce and services wage mass (in R$ millions)	28.21	224.78	7.58	57.98	43.52	154.72	12.39	42.33
Total agricultural employed	339.65	917.86	94.24	272.36	446.52	966.96	118.25	270.51
Total industrial employed	6704.53	24018.99	1785.79	6402.21	13333.05	31751.18	3568.39	8447.08
Total commerce and services employed	12307.52	84415.08	3088.54	20310.54	19254.95	64110.95	5123.28	16600.75
Average hourly wage contracted agricultural	36.54	21.87	41.96	25.50	44.89	28.13	48.45	33.63
Average hourly wage contracted industrial	46.32	25.04	53.11	54.02	50.01	15.69	53.39	14.74
Average hourly wage contracted commerce and services	47.48	9.63	50.78	10.42	48.75	7.74	52.35	8.98
Value added in agriculture	42204.76	43222.12	67985.67	76152.57	33078.88	32087.64	44870.59	44941.48
Value added in industry	119911.50	502174.30	127818.70	517805.70	167421.50	450189.70	185813.30	499030.40
Value added in commerce and services	69753.31	249521.70	63672.63	218059.70	88915.06	204201.50	83751.89	189513.00
Number of observations	975				213			

Source: Author's calculations based on data processing ages caused by tornadoes and cyclones resemble the concept of randomization, where the random assignment of groups is crucial to ensure equivalence between them. The lack of human control over the occurrence and trajectory of these phenomena is comparable to the absence of control in randomization.

In contrast, water events such as floods and inundations are often associated with predefined climatic patterns and may occur more frequently and predictably in certain geographical areas (with rivers or lakes nearby). While water events may follow predictable patterns and affect specific areas with greater regularity, wind phenomena can impact one city but not the neighboring one, in an apparent random sequence.

However, it is important to acknowledge limitations in this analogy. Factors such as the specific trajectory of the cyclone, geographical characteristics of the affected areas, and emergency responses may influence results in a non-random manner. These factors introduce complexities that must be considered when interpreting results from studies employing this analogy (Nasution et al. (2019); Judt et al. (2015); Makridakis and Bakas (2016)).

Therefore, to address the above mentioned limitations and mitigate potential biases, quasi-experimental techniques such as spatial differences-in-differences can be employed to contribute to a better understanding of the effects of natural disasters and informing more effective policy responses. One basic premise is that, in the absence of treatment, the (conditional) difference in the trajectories of the outcome variables of interest between the treated and untreated groups remains constant, assuming the existence of (conditional) parallel trends. Furthermore, it is also necessary to ensure that the impact of treatment on the treated group has no effect on the results of the untreated group, the well-known SUTVA assumption (Angrist et al. (1996); Delgado and Florax (2015)).

When dealing with spatial data, such as observations at the municipal level, it is highly unlikely that municipal economies do not exert influence on neighboring areas. The channels through which economic outcomes are transmitted between regions are diverse, with trade, the integration of production chains, the mobility of factors of production, transportation, and communication networks as examples, among others as documented by Anselin and Bera (1998), LeSage and Fischer (2008), and Elhorst (2014).

In this context, spatial econometrics provide useful tools useful to incorporate the spatial dimension into models, taking into account interdependencies and neighborhood effects between geographic units (Anselin (2003); LeSage and Pace (2009); Elhorst (2017) and Elhorst (2021)). This tools allows for the decomposition of the impact of exogenous variables into direct, indirect and total effects.

With spatial data the omission of spatial elements in DiD models can lead to bias and inconsistency in the estimated treatment effects. In addition to this bias, the omission of spatial lags can also lead to the control group not being correctly specified, violating the Stable Unit Treatment Value Assumption (SUTVA). This can happen because observations that are indirectly affected by the treatment may be included in the control group.

To overcome the above mentioned problems, the SLX DiD model for two time periods was introduced by Delgado and Florax (2015). This model is an extension of a typical SLX model, inserting spatial lags in the treatment variable allowing for the spatial interaction between treated and untreated locations.

Following closely Delgado and Florax (2015) and Bardaka et al. (2019), letting W_N be an (NxN) proximity matrix based on contiguity, spatial interaction in the treatment response is modeled via $(I + \delta W)D \circ T_t$, where I is the identity matrix, δ is a spatial parameter that captures the indirect effects of treatment, $W = bdiag(W_N)$ is the $N\tau \times N\tau$ block diagonal over time of all cross-sectional contiguity matrices. Considering that each unit i is observed in two time periods $(\tau = 2)$ and the treatment occurs in the second period, let $T \in \{0, 1\}$ be a time period indicator such that $T = 1$ for each unit i in the second time period, the spatial DID regression model for local spatial interaction is:

$$\begin{aligned} Y &= \alpha_0 l + \alpha_1 D + \alpha_2 T + \alpha_3 (I + \delta W) D \circ T + \phi' X + u \\ &= \alpha_0 l + \alpha_1 D + \alpha_2 T + \alpha_3 D \circ T + \alpha_3 \delta W D \circ T + \phi' X + u \end{aligned} \tag{1}$$

where Y is the NTx1 outcome variable, l is a NTx1 vector of ones, D is the dummy variable that indicates unit treatment (D=0 if units are not treated, D=1 if units are treated); T is the dummy variable that indicates period of treatment (T=0 pre-treatment , T=1 post-treatment); the interaction between $D \circ T$ is the Hadamard product between D and T and represents the treated group in the second period, with is the effect of the treatment; X represents the set of covariates used in the estimation to control observable characteristics and u is the usual error term. The α_j represent the differential coefficient of groups and time and ϕ are the parameters of the control variables.

Similarly to Delgado and Florax (2015) and Bardaka et al. (2019), we employ W_N as a row-standardized matrix and, in this case, the $WD \circ T$ interaction shows the proportion of neighbors treated for each unit i, regardless of whether i is treated or not. Thus, treated and untreated units may be affected by indirect treatment effects of their neighbors $(wd \in WD_i)$ for $(0 < wd \leq 1)$. The individuals in the control group must be those that were not directly affected $(D = 0)$ and did not experience indirect effects from their neighbors$(WD = 0)$.

In the he SLX model, proposed by Delgado and Florax (2015), the average effect of treatment for an individual who switches from nontreated to treated and from zero treated neighbors to wd share of treated neighbors is:

$$\begin{aligned} ATE_{wd_i} = [E(Y|X, D = 1, T = 1, WD = wd_i) - E(Y|X, D = 1, T = 0, WD = wd_i)] - \\ [E(Y|X, D = 0, T = 1, WD = 0) - E(Y|X, D = 0, T = 0, WD = 0)] \\ = \alpha_3 + \alpha_3 \delta wd_i \end{aligned} \tag{2}$$

and

$$ATE = (1/n) \sum_{i=1}^{n} ATE_{wd_i} \tag{3}$$

where α_3 captures the average direct effect of treatment (that is, the average effect of the treatment of i on unit i) and $\alpha_3 \delta wd_i$ captures the average indirect effect of treatment given a particular level of $wd \in WD$ (the average effect on unit i of the treatment of $i's$ neighbors) (Bardaka et al. (2019)).

In the case when $\delta = 0$ the spatial-DiD reverse to the standart non-spatial DiD with:

$$Y = \alpha_0 l + \alpha_1 D + \alpha_2 T + \phi' X + u \tag{4}$$

and the ATE reverse to:

$$\begin{aligned} ATE = [E(Y|X, D = 1, T = 1) - E(Y|X, D = 1, T = 0)] - \\ [E(Y|X, D = 0, T = 1) - E(Y|X, D = 0, T = 0)] \\ = \alpha_3 \end{aligned} \tag{5}$$

Additionally, this study extends the Spatial Lag of X (SLX) model by incorporating spatially lagged terms in the dependent variable (Y), thereby adopting the Spatial Durbin Model (SDM) to account for spatial global effects. It also includes spatial lag in the error term (u), following the Spatial Durbin Error Model (SDEM), to adjust for potential autocorrelations in the error. For the SDM model, the equation became:

$$Y = \alpha_0 l + \alpha_1 D + \alpha_2 T + \alpha_3 D \circ T + \alpha_3 \delta W D \circ T + \phi' X + \rho W Y + u \tag{6}$$

And the ATE_{wd_i} will be as follows:

$$\begin{aligned} ATE_{wd_i} = [E(Y|X, D=1, T=1, WD=wd_i) - E(Y|X, D=1, T=0, WD=wd_i)] - \\ [E(Y|X, D=0, T=1, WD=0) - E(Y|X, D=0, T=0, WD=0)] \\ = (I-\rho W)^{-1}[\alpha_3 + \alpha_3 \delta wd_i] \end{aligned} \tag{7}$$

Unlike (2), in (7) there is no easy explicit form for the direct, indirect e total effect. The average of row sums from the matrix is the Average Total Impact to an observation. An average of the diagonal of the matrix provides a summary measure of the Average Direct Impact and a scalar summary of the Average Indirect Impact is by definition the difference between the Average Total Impact and Average Direct Impact LeSage and Pace (2009).

The inclusion of the spatial lag error in the model does not affect the ATE results.

This extension is important for obtaining a detailed understanding of the spatial dynamics under investigation, as it not only captures the spatial interdependencies among the independent variables, but also addresses potential lagged effects in the dependent variable and error term. The analysis, straddling local and global spatial models, delves into the distinct nuances of spatial dynamics. While nonspatial models disregard spatial effects altogether, local spatial models (spatial lag on X) incorporate only direct neighbor spatial influence, whereas global spatial models (spatial lag on Y) encompass neighbor-to-neighbor interactions (Halleck Vega and Elhorst (2015), Elhorst (2014)). The analysis aims to verify the robustness of the findings and enhance the investigation's overall depth and breadth by incorporating these refinements.

The SDM and SDEM models were estimated using Two-Way Fixed Effects Spatial (S2WFE) quasi-maximum likelihood (QML) estimator as proposed by Lee and Yu (2010) to accommodate the model's specifications. To avoid potential endogeneity issues, the models are estimated via pseudo-maximum likelihood in their reduced form when incorporating spatial autoregressive elements. This approach mitigates endogeneity bias between the spatial autoregressive term and the (spatial) error.

4 Results

The STATA17 software was used to estimate the models through the spxtregress command (StataCorp (2021)) and the full results of the estimations can be viewed in Appendix.

Considering that a large proportion of the affected municipalities also had 100% of their neighbors affected, Table 2 summarizes the main effects when comparing the extreme observed effects (comparing $D = 0$, $wd = 0$ against $D = 1$, $wd = 1$). The statistical results for the models SDM and SDEM presented in Table 2 support significant findings from a quantitative analysis, particularly within the agricultural and extractive industries. The estimations showed a significant decrease in wage mass, total employed personnel, and value added, with statistical significance. These outcomes appear to be related to the destructive aftermath of the cyclone, which included crop devastation, harvest losses, and infrastructure impairments.

It is interesting to note that the results of the SDM (global) and SDEM (local) models are very similar, indicating that the indirect effects appear to have a more local rather than global reach. In some cases, the difference is only noticeable at the fourth or fifth decimal place. Therefore, the primary analysis will be based on the effects of the SDEM model. It is noteworthy, however, that the SDM model follows a similar pattern, with very few deviations.

The impact of the cyclone is evident in the significant decrease in wage mass and total occupied personnel, indicating immediate consequences on operational capacities. The

Table 2: Full Average treatment effects ($wd = 1$) on several outcomes

	Agricultural and Extractive			Manufacturing Industry			Commerce and Services		
	Direct	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
SDM Model									
Wage Mass (ln)	-0.437*	-0.088	-0.525*	-0.149	0.173	0.024	0.009	0.058**	0.067***
Total Occupied Personnel (ln)	-0.221**	0.064	-0.156	-0.092**	0.104*	0.012	0.010	0.036	0.046***
Average Hourly Wage (ln)	-0.111	-0.078	-0.189**	-0.065	0.052	-0.012	-0.001	0.007	0.006
Value Added (ln)	-0.017	-0.142***	-0.159***	-0.018	0.077	0.058	0.000	0.018***	0.018***
SDEM Model									
Wage Mass (ln)	-0.443*	-0.064	-0.507***	-0.148	0.172	0.024	0.011	0.056**	0.066***
Total Occupied Personnel (ln)	-0.218**	0.069	-0.149	-0.091**	0.102*	0.011	0.012	0.034	0.046***
Average Hourly Wage (ln)	-0.113	-0.074	-0.187**	-0.065	0.053	-0.012	-0.001	0.007	0.006
Value Added (ln)	-0.028	-0.111***	-0.139***	-0.018	0.076	0.058*	0.001	0.018***	0.019***

Source: Author's calculations based on data processing. Note: The models SLX, SDM and SDEM were estimated with fixed effects for individuals and time, and controlled for political variables, management quality, and population. Statistical significance at 1% (***), 5% (**) and 10% (*)

spillover effects, while less pronounced than the direct effects, also have a negative contribution, reflecting the broader economic disruptions caused by the cyclone. The negative total effects of the Cyclone Bomb highlights the vulnerability of the sector to natural disasters.

In contrast, the manufacturing sector produced ambiguous results. This sector depicted only significant effects in employment and value added. For the former, a direct negative effects was registered offset by a positive direct effect while for the later positive indirect effects contributed to a total positive effect, indicating a resilience in certain areas despite the cyclone's challenges. In some cases, positive indirect effects suggest that the sector may have benefited from spillover economic activities, possibly due to increased demand for manufacturing goods in reconstruction efforts.

In contrast, the commerce and services sectors showed a paradoxical benefit from the cyclone event, possibly by an increase in demand for services related to repair, construction, and trade activities that are integral to post-disaster reconstruction efforts. This resulted in a statistically significant increase in wage mass, employment and value added, indicating a stimulating effect on economic activity and the creation of temporary employment opportunities.

This is likely due to the increased demand for reconstruction services. The positive spillovers further amplify the sector's growth, indicating an overall economic stimulus driven by the need for recovery and rebuilding. The combined direct and indirect effects culminate in a robust enhancement of the sector's economic indicators, reflecting its critical role in post-disaster recovery.

The analysis of the bomb cyclone's effects provides a comprehensive understanding of its impact on different sectors. It emphasizes the need for sector-specific policy interventions, particularly in the agricultural and extractive sectors, which require immediate attention and support to mitigate the direct and spillover effects of such disasters. In contrast, the growth trajectory of the commerce and services sector should be utilized to enhance overall economic recovery.

These policies should cover reconstruction initiatives, economic support, and infrastructure reinforcement against extreme weather events. Strengthening social protection measures is considered crucial to ensuring food security and maintaining income for families in vulnerable situations, particularly in the most affected sectors.

The empirical findings from the analysis of the 2020 bomb cyclone's impact on Southern Brazil's economic sectors resonate with broader patterns observed in similar studies conducted both within Brazil and internationally. The differentiated effects across sectors align with the findings from the study of a flash flood in Santa Catarina, Brazil of Wink Junior et al. (2023) and also in other studies for different disasters in Brazil as presented in Lima and Barbosa (2018) and de Oliveira (2019). International evidence, as shown in Fomby et al. (2013), Loayza et al. (2012), Panwar and Sen (2019), Bănică et al. (2020) and Okubo and Strobl (2021) also point to the fact that the effects of natural disasters can vary significantly depending on the sector under analysis.

The results obtained in this study, especially those related to the impact on the agricultural sector, align as well with the findings of Panwar and Sen (2019). The latter argue that certain natural disasters, such as Storms can have a negative impact on GDP growth and agricultural growth in developing countries, but floods can have positive effects on the reconstruction sector by potentially boosting GDP growth, particularly in agriculture-based economies.

This perspective highlights the complexity of disaster impacts, emphasizing both negative consequences and growth opportunities in recovery sectors. It emphasizes that natural disasters can create growth opportunities in the reconstruction and recovery sectors, particularly in certain economies, despite their significant negative impacts.

Additionally, post-disaster reconstruction and recovery efforts may involve reallocating resources and labor from affected sectors to less affected ones. For example, investing in infrastructure reconstruction can generate employment in the construction sector and related services, temporarily redirecting labor from affected sectors to these areas. These migration and job reallocation dynamics between sectors can be observed in response to the impacts of natural disasters and are part of the adaptation and economic recovery processes following such events (Wu et al. (2019); Loayza et al. (2012)).

The analysis of our work is also in line with studies such as Kuhla et al. (2021), which demonstrate how economic losses amplify or mitigate the economic impact caused by individual events in a globally connected economy. This phenomenon of 'economic ripple resonance' is particularly relevant to Southern Brazil. At an inter-regional level, local production shocks induced by extreme events can result in losses or gains in production, wages, or consumption, depending on the sector of the economic activity.

For comparison, following the example of Bardaka et al. (2019), direct, indirect, and total effects can be evaluated considering any specific proportion of affected neighbors (wd). In line with Bardaka et al. (2019), given the highly clustered nature of affected municipalities, it is feasible to define wd as the average of the proportion of neighbors that are treated directly for the units that are directly treated. On average, each directly affected municipality had approximately 67% of its neighbors also affected. Table 3 presents the direct, indirect, and total effects for the SDEM model considering this proportion.

Table 3: Average treatment effects ($wd = 0.67$) on several outcomes

Sector	**Direct**	**Indirect**	**Total**
Agricultural and Extractive			
Wage Mass (ln)	-0.443*	-0.043	-0.486***
Total Occupied Personnel (ln)	-0.218**	0.046	-0.172
Average Hourly Wage (ln)	-0.113	-0.049	-0.162**
Value Added (ln)	-0.028	-0.075***	-0.102***
Manufacturing Industry			
Wage Mass (ln)	-0.148	0.116	-0.033
Total Occupied Personnel (ln)	-0.091**	0.069*	-0.022
Average Hourly Wage (ln)	-0.065	0.035	-0.030
Value Added (ln)	-0.018	0.051	0.033*
Commerce and Services			
Wage Mass (ln)	0.011	0.037**	0.048***
Total Occupied Personnel (ln)	0.012	0.023	0.035***
Average Hourly Wage (ln)	-0.001	0.004	0.004
Value Added (ln)	0.001	0.012***	0.013***

Source: Author's calculations based on data processing. Statistical significance at 1% (***), 5% (**) and 10% (*)

5 Final remarks

Unfortunately, evaluating the economic impacts of natural disasters has become an increasingly frequent task. This study analyzes the significant short-term impacts brought about by the 2020 cyclone bomb in the southern region of Brazil. The investigation covers the years 2019 and 2021 and uses several spatial differences-in-differences model of the Spatial Lag (SLX, SDM and SDEM) type applied to a set of municipalities in the states of Paraná (PR), Santa Catarina (SC), and Rio Grande do Sul (RS).

The empirical investigation into the economic impact of the 2020 bomb cyclone on Southern Brazil's economic sectors sheds light on the nuanced dynamics of natural disasters' repercussions on regional economies. The findings underscore the multifaceted nature of these impacts, highlighting both direct and indirect effects across different sectors.

The study revealed the significant and heterogeneous impact of the cyclone on different economic sectors in southern Brazil. Specifically, the agricultural and extractive industries experienced significant reductions in wage mass, total occupied personnel, and value added, indicating the immediate consequences of the destructive aftermath of the cyclone. The destructive force of the cyclone exacerbated vulnerabilities in certain sectors, such as crop devastation, harvest losses, and infrastructural impairments.

The response of the manufacturing sector was more ambiguous, showing divergent outcomes across different models regarding indirect effects, although the conclusions remained similar for total effects.

In contrast, the commercial and service sectors benefited from the cyclone, experiencing an increase in demand for services related to repair, construction, and trade activities that are essential for post-disaster reconstruction. This sector demonstrated resilience, as evidenced by statistically significant increases in wage mass, employment and value added. These increases reflect the sector's critical role in driving economic recovery efforts.

The study highlights the significance of examining both direct and indirect effects, along with spatial spillovers, to fully understand the economic impacts of natural disasters. Spatial econometrics models were used to capture the complex interplay between the direct effects of the cyclone and its wider repercussions on neighboring regions and economic sectors.

These findings have significant implications for policymakers and stakeholders involved in disaster management and regional economic development. Tailored public policies are essential to address the specific needs of sectors most severely impacted by natural disasters, such as agriculture and extraction. Initiatives that focus on reconstruction, economic sustenance, infrastructural fortification are crucial for mitigating the adverse effects of such events and facilitating long-term economic recovery.

The study's alignment with broader patterns observed in similar studies conducted both within Brazil and internationally underscores its relevance in the context of global climate change. As extreme weather events become more frequent and intense, it is increasingly vital to understand their economic implications for informed decision-making and policy formulation.

In conclusion, the analysis of the 2020 bomb cyclone's impact on Southern Brazil's economic sectors provides some insights into the complex dynamics of natural disasters' repercussions on regional economies. The study contributes to the ongoing discourse on disaster risk management and sustainable development by highlighting sector-specific vulnerabilities and resilience. It emphasizes the importance of proactive measures to improve economic resilience and mitigate the adverse effects of future events.

The results support the importance of regional reconstruction policies that provide support to cities and regions, even if they are not directly affected by a disaster but experiencing indirect effects stemming from overflow effects. Economic integration results in the transmission of these effects to neighboring areas, subsequently rebounding through negative externalities related to the loss of regional competitiveness.

References

AKAO, K.-I., AND SAKAMOTO, H. A theory of disasters and long-run growth. *Journal of Economic Dynamics and Control*, 95:89–109, 2018. ISSN 0165-1889. doi: https://doi.org/10.1016/j.jedc.2018.08.006. URL https://www.sciencedirect.com/science/article/pii/S0165188918302549.

ANGRIST, J. D., IMBENS, G. W., AND RUBIN, D. B. Identification of causal effects using instrumental variables. *Journal of the American Statistical Association*, 91(444):444–455, 1996. URL https://doi.org/10.1080/01621459.1996.10476902.

ANSELIN, L. Spatial econometrics. In BALTAGI, B. H., editor, *A Companion to Theoretical Econometrics*, pages 310–330. Blackwell Publishing Ltd, 2003. URL https://doi.org/10.1002/9780470996249.ch15.

ANSELIN, L., AND BERA, A. K. Spatial dependence in linear regression models. In ULLAH, A., AND GILES, D. E. A., editors, *Handbook of applied economic statistics*, pages 275–306. Marcel Dekker, 1998. URL https://doi.org/10.1201/9781482269901-36.

ASHER, S., AND NOVOSAD, P. Politics and local economic growth: evidence from india. *American Economic Journal: Applied Economics*, 9(1):229–273, 2017.

BARDAKA, E., DELGADO, M. S., AND FLORAX, R. J. G. M. A spatial multiple treatment/multiple outcome difference-in-differences model with an application to urban rail infrastructure and gentrification. *Regional Science and Urban Economics*, 79:325–345, 2019. URL https://doi.org/10.1016/j.tra.2019.01.028.

BARONE, G., AND MOCETTI, S. Natural disasters, growth and institutions: a tale of two earthquakes. *Journal of Urban Economics*, 84:52–66, 2014.

BARTH, J. R., HU, Q., SICKLES, R., SUN, Y., AND YU, X. Direct and indirect impacts of natural disasters on banks: A spatial framework. *Journal of Financial Stability*, 70: 101194, 2024. ISSN 1572-3089. doi: https://doi.org/10.1016/j.jfs.2023.101194. URL https://www.sciencedirect.com/science/article/pii/S1572308923000943.

BATTISTELLA, C. Ciclone de terça-feira supera furacão catarina e é o pior desastre com ventos da história de sc. *NSC Total*, 2020. URL https://shorturl.at/FR079.

BOTZEN, W. J. W., DESCHENES, O., AND SANDERS, M. The economic impacts of natural disasters: A review of models and empirical studies. *Review of Environmental Economics and Policy*, 13(2):191–215, 2019. URL https://doi.org/10.1093/reep/rez004.

BĂNICĂ, A., KOURTIT, K., AND NIJKAMP, P. Natural disasters as a development opportunity: a spatial economic resilience interpretation. *Review of Regional Research*, 40:223–249, 2020. URL https://doi.org/10.1007/s10037-020-00141-8.

CEVIK, M. S., AND HUANG, G. *How to manage the fiscal costs of natural disasters*. International Monetary Fund, 2018.

DE OLIVEIRA, V. Natural disasters and economic growth in northeast brazil: evidence from municipal economies of the ceará state. *Environment and Development Economics*, 24 (3):271–293, 2019. URL https://doi.org/10.1017/S1355770X18000517.

DELGADO, M. S., AND FLORAX, R. J. G. M. Difference-in-differences techniques for spatial data: Local autocorrelation and spatial interaction. *Economics Letters*, 137:123–126, 2015. URL https://doi.org/10.1016/j.econlet.2015.10.035.

DERYUGINA, T. The fiscal consequences of natural disasters. In SKIDMORE, M., editor, *Handbook on the Economics of Disasters*, chapter 11, pages 208–228. Edward Elgar Publishing, Cheltenham, UK and Northampton, MA, USA, October 18 2022. ISBN 9781839103728. doi: 10.4337/9781839103735.00019.

ELHORST, P. *Spatial econometrics: From spatial autocorrelation to spatial panel data models*. Springer, 2014. URL https://doi.org/10.1007/978-3-642-40340-8.

ELHORST, P. Spatial panel data analysis. In SHEKHAR, S., XIONG, H., AND ZHOU, X., editors, *Encyclopedia of GIS*, volume 2, pages 2050–2058. Springer International Publishing, Cham, Switzerland, 2017. URL https://doi.org/10.1007/978-3-319-17885-1_1641.

ELHORST, P. Spatial panel models and common factors. In FISCHER, M., AND NIJKAMP, P., editors, *Handbook of regional science*, volume 2, pages 2141–2159. Springer Berlin / Heidelberg, 2021. URL https://doi.org/10.1007/978-3-662-60723-7_86.

FISCHER, S. Post-disaster spillovers: Evidence from iranian provinces. *Journal of Risk and Financial Management*, 14:193, 2021. doi: 10.3390/jrfm14050193. URL https://doi.org/10.3390/jrfm14050193.

FOMBY, T., IKEDA, Y., AND LOAYZA, N. V. The growth aftermath of natural disasters. *Journal of Applied Econometrics*, 28(3):412–434, 2013. URL https://doi.org/10.1002/jae.1273.

GAÚCHAZH. Ciclone -bomba foi o pior desastre com ventos da história de santa catarina, segundo defesa civil. *Gaúcha Zero Hora-GZH*, 2020. URL https://shorturl.at/rsRX7.

GIEHL, A., LUCA, F. D., PADRÃO, G. D. A., ELIAS, H., ALVES, J., GUGEL, J., MONDARDO, M., GOULART JÚNIOR, R., AND MARCONDES, T. Efeitos socioeconômicos causados pelo ciclone extratropical no estado de santa catarina em 2020. Documentos 318, Epagri, Florianópolis, 2020.

HALLECK VEGA, S., AND ELHORST, J. P. The SLX model. *Journal of Regional Science*, 55(3):339–363, 2015. doi: doi.org/10.1111/jors.12188. URL https://doi.org/10.1111/jors.12188.

IFRC. 2020 global natural disaster assessment report. Technical report, International Federation of Red Cross and Red Crescent Societies, 2021. URL https://www.preventionweb.net/publication/2020-global-natural-disaster-assessment-report.

JUDT, F., CHEN, S. S., AND BERNER, J. Predictability of tropical cyclone intensity: scale-dependent forecast error growth in high-resolution stochastic kinetic-energy backscatter ensembles. *Quarterly Journal of the Royal Meteorological Society*, 141(692):2342–2351, 2015. URL https://doi.org/10.1002/qj.2626.

KUHLA, K., WILLNER, S. N., OTTO, C., GEIGER, T., AND LEVERMANN, A. Ripple resonance amplifies economic welfare loss from weather extremes. *Environmental Research Letters*, 16(11):114010, 2021. URL https://doi.org/10.1088/1748-9326/ac2932.

LEE, L.-F., AND YU, J. Estimation of spatial autoregressive panel data models with fixed effects. *Journal of Econometrics*, 154:165–185, 2010. doi: 10.1016/j.jeconom.2009.08.001. URL https://doi.org/10.1016/j.jeconom.2009.08.001.

LESAGE, J. P., AND FISCHER, M. M. Spatial growth regressions: Model specification, estimation and interpretation. *Spatial Economic Analysis*, 3(3):275–304, 2008. URL ttps://doi.org/10.1080/17421770802353758.

LESAGE, J. P., AND PACE, R. K. *Introduction to Spatial Econometrics*. Chapman and Hall/CRC, 2009. URL https://doi.org/10.1201/9781420064254.

LIMA, R., AND BARBOSA, A. Natural disasters, economic growth and spatial spillovers: Evidence from a flash flood in brazil. *Papers in Regional Science*, pages 1–20, 2018.

LOAYZA, N. V., OLABERRÍA, E., RIGOLINI, J., AND CHRISTIAENSEN, L. Natural disasters and growth: Going beyond the averages. *World Development*, 40(7):1317–1336, 2012. URL https://doi.org/10.1016/j.worlddev.2012.03.002.

MAKRIDAKIS, S., AND BAKAS, N. Forecasting and uncertainty: A survey. *Risk and Decision Analysis*, 6(1):37–64, January 2016. ISSN 1569-7371. URL https://doi.org/10.3233/RDA-150114.

MONTE, B. E. O., GOLDENFUM, J. A., MICHEL, G. P., AND DE ALBUQUERQUE CAVALCANTI, J. R. Terminology of natural hazards and disasters: A review and the case of brazil. *International Journal of Disaster Risk Reduction*, 52:101970, 2021. URL https://doi.org/10.1016/j.ijdrr.2020.101970.

NASUTION, B. B., SEMBIRING, R. W., SYAHRUDDIN, M., MUSTARI, N., DALIMUNTHE, A. R., BAHRI, N., BR GINTING, B., AND LUBIS, Z. Real-time tornado forecasting using slhgn. In MURAYAMA, Y., VELEV, D., AND ZLATEVA, P., editors, *Information Technology in Disaster Risk Reduction*, pages 97–119, Cham, 2019. Springer International Publishing. ISBN 978-3-030-32169-7. URL https://doi.org/10.1007/978-3-030-32169-7_8.

NEWMAN, R., AND NOY, I. The global costs of extreme weather that are attributable to climate change. *Nature Communications*, 14:6103, 2023. URL https://doi.org/10.1038/s41467-023-41888-1.

NIQUITO, T. W., POZZOBON, F., HALMENSCHLAGER, V., AND RIBEIRO, F. G. Human-made disasters and economic impact for a developing economy: evidence from brazil. *Natural Hazards*, 2021. URL https://doi.org/10.1007/s11069-021-04921-4.

NOY, I., AND NUALSRI, A. Fiscal storms: public spending and revenues in the aftermath of natural disasters. *Environment and Development Economics*, 16(1):113–128, 2011. doi: 10.1017/S1355770X1000046X.

OKUBO, T., AND STROBL, E. Natural disasters, firm survival, and growth: evidence from the Ise Bay Typhoon, Japan. *Journal of Regional Science*, 61(5):944–970, 2021. URL https://doi.org/10.1111/jors.12523.

OKUYAMA, Y. Economics of natural disasters: A critical review. Digital Commons Citation, 2003. Regional Research Institute Working Papers. 131. https://researchrepository.wvu.edu/rri_pubs/131.

OKUYAMA, Y. A few good models for economic analysis of disasters: Can your model handle the truth? In SKIDMORE, M., editor, *Handbook on the Economics of Disasters*, chapter 3, pages 30–49. Edward Elgar Publishing, 2022.

OKUYAMA, Y., AND CHANG, S. E., editors. *Modeling Spatial and Economic Impacts of Disasters*. Springer, Advances in Spatial Science, 2004. ISBN 978-3-540-24787-6. Currently edited by Manfred Fischer, Jean Claude Thill, Jouke van Dijk, and Hans Westlund.

PANWAR, V., AND SEN, S. Economic impact of natural disasters: An empirical re-examination. *Margin: The Journal of Applied Economic Research*, 13(1):109–139, 2019. URL https://doi.org/10.1177/0973801018800087.

PATRASCU, F. I., AND MOSTAFAVI, A. Spatial model for predictive recovery monitoring based on hazard, built environment, and population features and their spillover effects. *Environment and Planning B: Urban Analytics and City Science*, 51(1):39–56, 2024. doi: 10.1177/23998083231167433. URL https://doi.org/10.1177/23998083231167433.

SKIDMORE, M., editor. *Handbook on the Economics of Disasters*. Edward Elgar Publishing, October 2022. ISBN 9781839103728. URL https://doi.org/10.4337/9781839103735.

STATACORP. *Stata 17 Base Reference Manual*. College Station, TX, 2021.

WANG, Q., AND CHEN, J. Spatio-temporal evaluation of the emergency capacity of the cross-regional rain-flood disaster in the yangtze river economic belt in china. *Sci Rep*, 11:2580, 2021. doi: 10.1038/s41598-021-82347-5. URL https://doi.org/10.1038/s41598-021-82347-5.

WINK JUNIOR, M., DOS SANTOS, L., AND RIBEIRO, F. Natural disasters and poverty: evidence from a flash flood in brazil. *Environmental Development and Sustainability*, 2023. URL https://doi.org/10.1007/s10668-023-03623-0.

WU, X., XU, Z., LIU, H., GUO, J., AND ZHOU, L. What are the impacts of tropical cyclones on employment? an analysis based on meta-regression. *Weather Clim. Soc.*, 11:259–275, 2019.

A Appendix

Table 4: SDM Results

	Massa Salarial			Total de Pessoal Ocupado			Média de Salário Hora		
	Agropecuário e Extrativo	**Indústria de Transformação**	**Comércio e Serviços**	**Agropecuário e Extrativo**	**Indústria de Transformação**	**Comércio e Serviços**	**Agropecuário e Extrativo**	**Indústria de Transformação**	**Comércio e Serviços**
I-FIRJAN	−0.419	0.495*	0.023	−0.040	0.188*	0.036	−0.182	0.161	−0.005
Elect._part	1.639***	0.446	0.217**	3.182***	0.778***	0.287***	0.592	−0.112	−0.058
Alin.	−0.145	−0.020	−0.006	−0.019	−0.009	−0.004	−0.041	−0.021	−0.002
ln(Pop)	−1.034	−0.249	0.415*	−0.931	−0.306	0.533**	−0.261	−0.088	−0.050
T	−0.721***	−1.256***	−1.092***	−0.815***	−1.209***	−1.236***	0.174***	0.077***	0.061***
DT	−0.436*	−0.148	0.007	−0.223**	−0.093**	0.010	−0.111	−0.065	−0.001
delta	−0.029	0.172	0.050**	0.101	0.104*	0.033	−0.067	0.053	0.007
ro	0.116**	−0.011	0.145***	0.223***	0.067	0.077	0.063	0.026	0.059
sigma_e	1.641***	0.781***	0.119***	0.570***	0.294***	0.111***	0.633***	0.311***	0.072***
Obs	2376	2376	2376	2376	2376	2376	2376	2376	2376

Source: Author's calculations based on data processing. Statistical significance at 1% (***), 5% (**), and 10% (*).

Table 5: SDEM Results

	Massa Salarial			Total de Pessoal Ocupado			Média de Salário Hora		
	Agropecuário e Extrativo	Indústria de Transformação	Comércio e Serviços	Agropecuário e Extrativo	Indústria de Transformação	Comércio e Serviços	Agropecuário e Extrativo	Indústria de Transformação	Comércio e Serviços
I-FIRJAN	−0.352	0.496*	0.021	−0.004	0.186*	0.034	−0.170	0.161	−0.004
Elect._part.	1.873***	0.445	0.243**	3.408***	0.804***	0.317***	0.628	−0.114	−0.065
Alin.	−0.149	−0.021	−0.005	−0.019	−0.008	−0.004	−0.041	−0.021	−0.002
ln(Pop)	−1.240	−0.253	0.476*	−1.223	−0.304	0.569**	−0.275	−0.087	−0.046
T	−0.832***	−1.243***	−1.275***	−1.054***	−1.293***	−1.338***	0.182***	0.079***	0.065***
DT	−0.443*	−0.148	0.011	−0.218**	−0.091**	0.012	−0.113	−0.065	−0.001
delta	−0.064	0.172	0.056**	0.069	0.102*	0.034	−0.074	0.053	0.007
gamma	0.120**	−0.012	0.149***	0.232***	0.066	0.092*	0.064	0.027	0.062
sigma_e	1.641***	0.781***	0.119***	0.570***	0.294***	0.111***	0.633***	0.311***	0.072***
Obs	2376	2376	2376	2376	2376	2376	2376	2376	2376

Source: Author's calculations based on data processing. Statistical significance at 1% (***), 5% (**), and 10% (*).