BORRADORES DE ECONOMÍA

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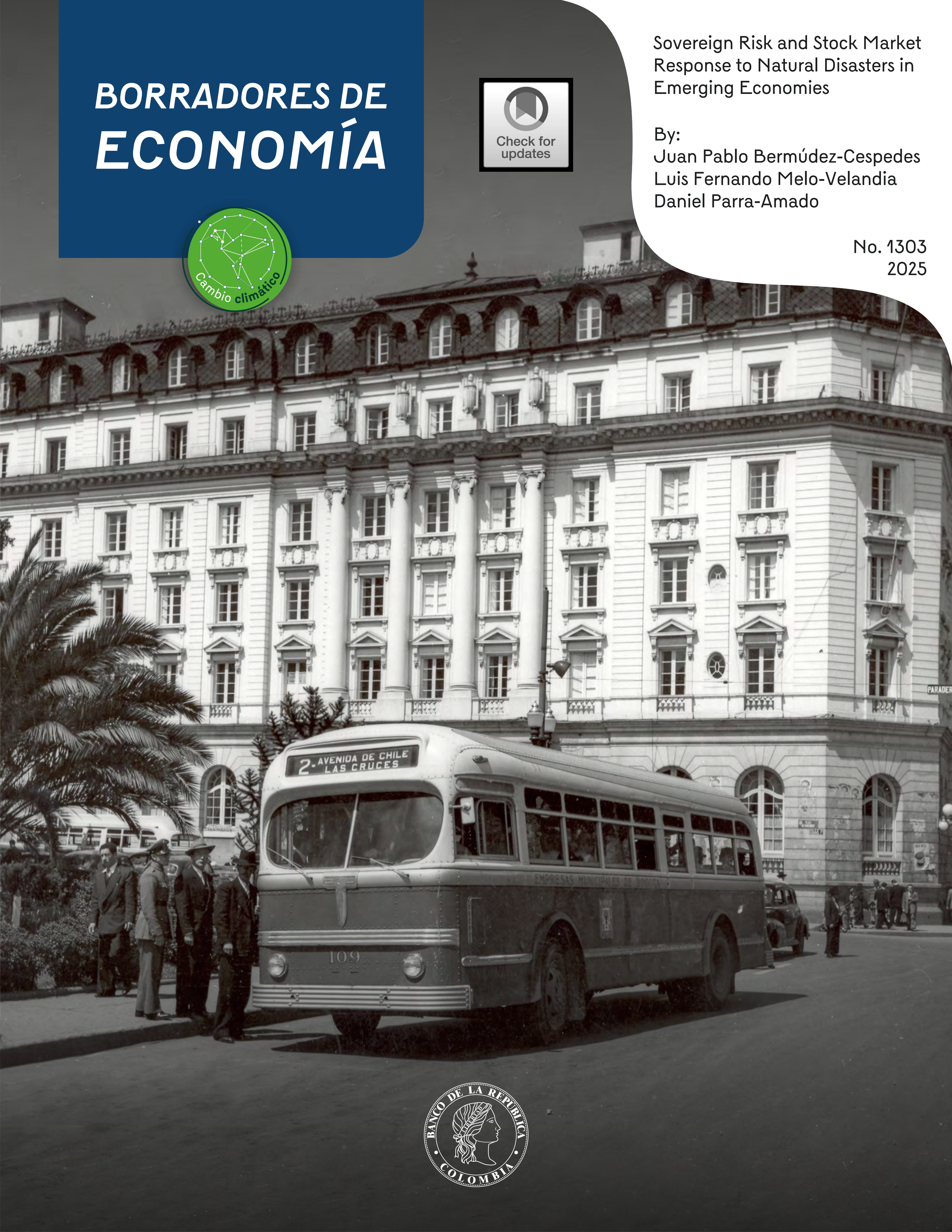
By:
Juan Pablo Bermúdez-Cespedes
Luis Fernando Melo-Velandia
Daniel Parra-Amado

No. 1303
2025



BANCO DE LA REPUBLICA COLOMBIA

Sovereign Risk and Stock Market Response to Natural Disasters in Emerging Economies

Juan Pablo Bermúdez-Cespedes [*] Luis Fernando Melo-Velandia[†]
Daniel Parra-Amado[‡]

Abstract

This study examines how natural disasters affect sovereign risk premiums (CDS) and stock returns in emerging economies. Using an event study approach from October 2004 to August 2022, we analyze 1,400 natural disasters across 11 countries, assessing market responses both in aggregate and by disaster type. The analysis also reveals notable country-specific disparities. Results show that: i) while stock returns (mean) are largely unaffected, volatility (variance) increases significantly; ii) sovereign risk premiums respond in both their mean and variance; iii) contagion effects are stronger in volatility than in the mean, with sovereign risk premiums exhibiting greater contagion than stock market dynamics; and iv) Latin American countries are particularly sensitive to contagion, not only from neighboring disasters but also from events in regions like Asia. These findings highlight the differentiated impacts of natural disasters on emerging financial markets, with volatility and sovereign risk exhibiting the most pronounced responses.

JEL codes: C58, C4, H63, D53

keywords: Natural disasters, Stock returns, Sovereign risk premium (CDS), GARCH, Event study

[*]Economist in the Financial Stability Department at the Banco de la República de Colombia.
E-mail: jbermuce@banrep.gov.co

[†] Senior econometrician in the Econometric Unit at the Banco de la República de Colombia.
E-mail: lmelovel@banrep.gov.co

[‡] Researcher in the Macroeconomic Models Department at the Banco de la República de Colombia.
E-mail: dparraam@banrep.gov.co.

Respuesta de las primas de riesgo soberano y los mercados accionarios a desastres naturales en economías emergentes

Juan Pablo Bermúdez-Cespedes [1] Luis Fernando Melo-Velandia[2]
Daniel Parra-Amado[3]

Resumen

Este estudio examina cómo los desastres naturales afectan las primas de riesgo soberano (CDS) y los retornos accionarios en economías emergentes. Utilizando un enfoque de estudio de eventos desde octubre de 2004 hasta agosto de 2022, se analizan 1.400 desastres naturales en 11 países, evaluando las respuestas del mercado tanto de forma agregada como por tipo de desastre. El análisis también revela notables disparidades a nivel de país. Los resultados muestran que: i) aunque los retornos accionarios (media) no se ven significativamente afectados, la volatilidad (varianza) aumenta considerablemente; ii) las primas de riesgo soberano responden tanto en su nivel (media) como en su varianza; iii) los efectos de contagio son más fuertes en la volatilidad que en la media, con una mayor incidencia en las primas de riesgo soberano que en la dinámica de los mercados bursátiles; y iv) los países de América Latina son particularmente sensibles al contagio, tanto por desastres ocurridos en países vecinos como en regiones como Asia. Estos hallazgos resaltan los impactos diferenciados de los desastres naturales en los mercados financieros emergentes, con respuestas más pronunciadas en la volatilidad y el riesgo soberano.

Clasificación JEL: C58, C4, H63, D53

Palabras clave: Desastres naturales, Rendimientos bursátiles, Primas de riesgo soberano (CDS), GARCH, Estudio de eventos

[1] Economista del Departamento de Estabilidad Financiera del Banco de la República Colombia. E-mail: jbermuce@banrep.gov.co.
[2] Econometrista Principal de la Unidad de Investigaciones del Banco de la República Colombia. E-mail: lmelovel@banrep.gov.co.
[3] Investigador del Departamento de Modelos Macroeconómicos del Banco de la República Colombia. Email: dparraam@banrep.gov.co

1 Introduction

Over the past few decades, there has been a notable increase in the economic losses and the financial impacts of natural disasters, resulting from both the rising occurrence rate of these events and the worsening of their intensity (Hoeppe (2016), Zhang and Managi (2020)). According to the National Oceanic and Atmospheric Administration (NOAA), since 1980, the United States has experienced 378 weather and climate disasters causing damages or costs surpassing one billion, and these events collectively have incurred a total cost exceeding \$2.690 trillion.[1] As a matter of fact, 2023 stands as the historical record with the highest occurrence of disasters, totaling 28 events that incurred costs of 93.7 billions. In the case of the European Union, the European Environment Agency estimates an economic loss of around 650 billion euros between 1980 and 2022, of which 112 billion occurred in the last two years.[2].

While there is no consolidated calculation for regions with developing countries, the consensus among the academic community suggests that these countries are more exposed to such shocks.[3] Therefore, we have focused our attention on a specific set of these countries, and this study examines the question whether natural disasters affect the mean and volatility of sovereign credit default swap (CDS) spreads and stock market returns in emerging economies? It seeks to provide clarity on the short-term financial repercussions of such events across various disaster types and geographic regions. Understanding this relationship is crucial, particularly as emerging economies face heightened vulnerability to natural disasters due to limited resources and infrastructure. Disruptions in financial markets triggered by these events can undermine economic stability, affecting investor confidence and sovereign borrowing costs (Klomp (2015), Di Tommaso et al. (2023)). Moreover, such insights can inform risk management strategies and policymaking in disaster-prone regions (Mnasri and Nechi (2016)).

Although the majority of literature deals with estimating the impacts of losses in the banking (Cortés and Strahan (2017), Brei et al. (2019) and Chen and Chang (2021)) and insurance sector (Born and Viscusi (2006), Benali and Feki (2017) and Tesselaar et al. (2022)),[4] other topics have also gained relevance, such as the effects of natural disasters on stock markets (Wang and Kutan (2013), Bourdeau-Brien and Kryzanowski (2017) and Massa and Zhang (2021)) and sovereign risk premiums(Worthington and Valadkhani (2004), Klomp (2015), Di Tommaso et al. (2023) and Başkaya

[1] https://www.ncei.noaa.gov/access/billions/

[2] https://www.eea.europa.eu/en/analysis/indicators/economic-losses-from-climate-related

[3] According to Noy (2009), show that developing countries endure markedly more pronounced declines in output compared to developed counterparts when they confronted with disasters of equivalent relative magnitudes. Klomp and Valckx (2014) indicate that climatic disasters have the most substantial negative impacts on economic growth in developing nations. Wang and Kutan (2013) and Pagnottoni et al. (2022) emphasize that emerging markets exhibit different financial responses to disasters compared to developed economies, particularly in terms of volatility.

[4] Other studies also assess the effects on real activity like Hallegatte and Ghil (2008), Fomby et al. (2013), Klomp and Valckx (2014) and Shabnam (2014) for economic growth and Belasen and Polachek (2013) and Berlemann and Steinhardt (2017) for migration issues.

et al. (2024)). Our research falls within the scope of the last branch of literature where natural disasters tend to increase both stock market volatility and the volatility of sovereign risk perception in the short term due to the uncertainty they generate. Investors react to the potential impact on the economy, the affected sectors, and the government's response capacity. Our methodology is based in an event study that covers 1,400 natural disasters from 11 emerging economies between 2004 and 2022. By focusing on short-term effects, the study captures immediate market reactions, such as volatility spikes and changes in risk perceptions. Similar approaches have been adopted in the literature to evaluate disaster effects on financial markets (Scholtens and Voorhorst (2013), Bourdeau-Brien and Kryzanowski (2017)).

The novelty of this article lies in its examination of both the mean and volatility effects of natural disasters on financial markets in emerging economies. Unlike prior studies, this research integrates a granular, event-specific approach to analyze diverse disaster types and their differential impacts on sovereign CDS spreads and stock market indices. In addition, it introduces a contagion analysis between countries, providing insights into how natural disasters in one region may influence the dynamics of the financial market in others. This approach enriches the existing literature by extending the analysis beyond developed economies and offering a broader analysis of disaster-driven financial market volatility. It extends the findings of earlier works (Klomp (2015) and Di Tommaso et al. (2023)) by exploring the short-term volatility effects.

The structure of the paper is as follows: After this introductory section, Section 2 offers an extensive literature review on the influence of natural disasters on stock prices and risk premiums. Subsequently, Section 3 outlines the data and methodology employed. Section 4 show the main findings of this research. Finally, Section 5 wraps up the article by discussing its limitations and offering recommendations for future research.

2 Literature review

2.1 Effects on stock markets

The empirical evidence on the effects of natural disasters on stock markets is mixed, depending on the economic structure, the type of shock, and its duration. On one hand, some studies show evidence the significant and negative effects of natural disaster on stock markets. Scholtens and Voorhorst (2013) find that stock market values decrease by 6-12% following earthquakes, the initial impact on the first day outweighs that of the following two days, indicating an initial market overreaction. The authors include more than on hundred earthquakes with fatalities by employing an event study model for twenty-one countries. Their results suggest no distinction in responses between the most severe and least severe earthquakes, or between earthquakes in high-income and low-income countries. Pagnottoni et al. (2022) examined the effects of natural disasters on 27 stock market indices from 2001 to 2019. Employing event study methodology, the authors discovered diverse impacts of natural hazard shocks on stock markets. Climatological and biological calamities seem the disaster types which, overall, induce the most extreme reactions of international financial markets. While the former have a negative effect, the latter affect positively financial markets. Chen et al. (2023) show that financial firms' market responses differ depending on the type of natural disaster and the type of financial firm. Security companies are most sensitive, experiencing significant negative abnormal returns to all disasters. Banks react only to earthquakes, while insurance companies generally show insignificant abnormal returns to earthquakes, storms, and floods. Seetharam (2017) show that the adverse impact of natural disaster exposure on stock returns ranges from 0.3 to 0.7 percentage points across different event-day windows, where the largest negative impact is concentrated around 6 days prior and 20 days post the event.

On the other hand, several studies suggest that there are no short-term impacts of natural events on stock prices, at least in terms of returns. However, volatility tends to rise under these circumstances. For instance, Bourdeau-Brien and Kryzanowski (2017) show evidence that disasters do not affect stock markets in the very short term (1 to 5 days). However, over a two-to-three month period, only around 6% to 7% of disasters significantly affect stock returns. Therefore, by extending the event window beyond three months, the proportion of impactful disasters is reduced. Additionally, local firms' stocks react more strongly to natural catastrophes than those of firms in nearby states. While hurricanes, floods, severe winter weather, or extreme temperature episodes are linked to significant increase of impacts on the second moments of returns for the average local firm, tornadoes, hailstorms, thunderstorms, and other storm-like events have a neutral effect on volatility. Ferreira and Karali (2015) analyze the effect of major earthquakes on the returns and volatility of aggregate stock market indices across thirty-five financial markets. The results indicate that global financial markets exhibit resilience to shocks caused by earthquakes, even when they occur domestically (5-day window). Although earthquakes did elevate stock market volatility in Japan, other markets did not experience the same short-term impact. Worthington (2008) examine the impact of natural disasters on the Australian capital market from 1982 to 2002. Employing intervention analysis methodology, the authors demonstrate how shocks from natural disasters have no significantly influence on Australian market stock returns.

2.2 Effects on sovereign risk

Disasters usually result in significant immediate financial obligations for governments. These may include increased spending on goods and services, expanded transfers to address humanitarian and welfare needs, particularly for vulnerable populations, financial aid to businesses and financial institutions. This increases debt servicing if additional resources are needed to respond to the catastrophe, and the current debt becomes riskier, causing risk premiums to rise. Gupta et al. (2019) examine the theoretical assertion that rare disaster risks impact government bond market movements. They show that rare disaster risks influenced only the volatility, not the returns, of long-term (10-year) government bonds in the United States, the United Kingdom, and South Africa. Climate vulnerability increases cost of debt directly by 0.63% and indirectly through its impact on restricting access to finance by 0.05% from 1999 to 2017. Beirne et al. (2021) confirm that climate vulnerability has significant implications for sovereign borrowing costs, and that the direct effects of climate change matter substantially more than climate risk resilience. The effect on bond yields is stronger for countries deemed highly vulnerable to climate change. Kling et al. (2018) find that countries with higher climate vulnerability exhibit 1.174 percent higher cost of debt on average.

There are few studies that investigate these effects on sovereign risk premiums. For instance, Klomp (2015) highlight a substantial rise in the sovereign default premium paid by bondholders after natural disasters. Thus, bondholders perceive these occurrences as destabilizing factors for government debt sustainability, potentially leading to defaults. Notably, geophysical and meteorological disasters have a persistent impact on the credit default risk, affecting both short-term and long-term perspectives, while hydrological disasters show only a temporary effect. Di Tommaso et al. (2023) examine how natural disasters impact the sovereign CDS spread in Europe. Their results indicate a positive reaction in the sovereign CDS market, signifying that natural disasters elevate a country's risk. Moreover, the response varies across regions, and a contagion effect is observed. Natural disasters can exacerbate regional inequality due to increased credit costs for sovereigns and limited flexibility in public finances.

3 Data and methodology

Many authors have explored various typologies of disaster impacts which can impact the economy both physically and through expectations, the former encompass the direct and indirect economic consequences of natural hazards while the latter pertains to changes in disaster risk perception and uncertainty regarding future profitability and investment returns resulting from a disaster occurrence (Cochrane (2004), Hallegatte and Przyluski (2010) and Zhou et al. (2023)). Direct losses entail the immediate consequences of the disaster's physical manifestations: inundation, hurricane, winds. Indirect losses encompass all losses not directly caused by the disaster itself but by its aftermath. Our research focuses on short run impacts of natural disasters on financial stock markets and sovereign risk by using an event study approach, therefore we focus on more direct effects.[5]

A limitation of statistical methods in assessing natural disaster risks is their reliance on adequate loss records at the local level, which may be lacking for disasters with low probabilities of occurrence in specific areas (Botzen et al. (2019)).[6]Considering these factors, and recognizing the

[5]For this reason, we do not assess climatic events, as many of them persist beyond the event evaluation windows.

[6]Catastrophe models are frequently utilized to evaluate natural hazard risks for insurance purposes (Grossi et al.

challenge of event repetition in the same location and the consistency of events over time, we use event study methodology across eleven emerging countries for this investigation. This help to identify which events have a large and widespread effect on stock markets and country's sovereign risk for different regions. Our approach involves initially presenting the results in an aggregated format, followed by an analysis of event effects based on the type of natural disaster, namely geophysical, hydrological, and meteorological, and finally, provide a breakdown by individual country.

3.1 Data

3.1.1 Financial data

We collected data from multiple sources like Bloomberg, datastream and yahoo finance. Specifically, we use the daily 5-year sovereign risk premium by using the measure of the Credit Default Swap (CDS) for the following countries: Brazil, Chile, China, Colombia, Indonesia, South Korea, Malaysia, Mexico, Peru, South Africa, and Turkey. The sample spans from October 10, 2004, to August 10, 2022. Table 1 presents the descriptive statistics for the first differences of all CDS series, with the original data expressed in basis points. The results indicate that extreme events are more frequent in the right tail, reflecting positive skewness and high kurtosis. This pattern suggests that greater risk exposure is associated with higher sovereign risk premiums.

Table 1: Descriptive Statistics sovereign risk premium (CDS)

Country	Minimum	Maximum	Mean	Std. Dev.	Skewness	Kurtosis
Brazil	-124.91	186.53	-0.03	8.45	2.01	81.53
Chile	-64.27	63.11	0.02	3.71	0.66	67.48
China	-58.91	67.47	0.01	3.52	0.63	73.61
Colombia	-126.52	180.59	-0.02	8.20	1.38	83.91
Indonesia	-223.81	324.52	-0.06	13.30	3.12	170.85
South Korea	-168.55	133.28	0.00	5.72	2.92	266.79
Malaysia	-101.34	119.40	0.01	5.22	1.71	128.90
Mexico	-132.96	197.20	0.01	7.31	3.82	168.49
Peru	-126.10	161.39	-0.04	6.72	1.82	120.92
South Africa	-82.36	146.45	0.03	7.99	2.25	58.39
Turkey	-131.91	166.47	0.08	10.72	1.57	48.01
Emerging market (EM)	-11.46	20.19	0.01	1.33	3.17	50.01

The descriptive statistics are computed by using the first difference of each country sovereign risk premium (CDS) which can be regarded as basic points.

(2005)), macroeconomic risks with regional and spatial dimension in a computable general equilibrium framework (Rose and Liao (2005) and Carrera et al. (2015)) and input–output (I-O) models (Hallegatte (2008) and Okuyama and Santos (2014)).

We also assessed the impact of natural disasters on major stock indices across those countries: Bovespa (Brazil), S&P CLXIPSA (Chile), ChinaA50 (China), COLCAP (Colombia), JSX (Indonesia), KOSPI (South Korea), KLCI (Malaysia), S&P BMVIPC (Mexico), IGBVL (Peru), South Africa Top 40 (South Africa), and BIST100 (Turkey). Table 2 presents the descriptive statistics for the returns of these stock index series, covering the same sample period as the CDS data, from October 10, 2004, to August 10, 2022. Consistent with the stylized facts of financial assets, the stock index returns exhibit a mean close to zero, with extreme events more frequent in the left tail. This indicates negative skewness and high kurtosis, reflecting that extreme losses tend to exceed extreme gains.

Table 2: Descriptive Statistics Stock Indexes

Stock Index	Min.	Max.	Mean	Std. Dev.	Skewness	Kurtosis
BIST100	-11.06	12.13	0.05	1.59	-0.53	7.53
Bovespa	-15.99	13.68	0.03	1.69	-0.43	12.70
ChinaA50	-9.86	9.20	0.03	1.61	-0.24	7.58
JSX	-10.95	7.62	0.05	1.22	-0.62	10.41
KOSPI	-11.17	11.28	0.02	1.19	-0.47	12.38
S&P BMVIPC	-7.27	10.44	0.03	1.17	0.00	9.66
S&P CLXIPSA	-15.22	11.80	0.02	1.12	-0.80	23.80
SouthAfricaTop40	-10.45	9.11	0.04	1.29	-0.20	8.76
IGBVL	-13.29	12.82	0.04	1.42	-0.52	14.11
KLCI	-9.98	6.63	0.01	0.72	-0.88	17.31
COLCAP	-16.29	14.69	0.03	1.25	-0.80	26.72
Emerging market (EM)	-9.99	10.07	0.02	1.22	-0.53	11.29

The descriptive statistics are computed by using the log-returns of each country stock index which can be regarded as percentage.

3.1.2 Disaster Database: Data characterization and cleaning

We use the internationally recognized Emergency Events Database (EM-DAT), published by the Centre for Research on the Epidemiology of Disasters (CRED),[7] to gather data on natural disasters. The dataset covers events occurring between October 10, 2004, and August 10, 2022, across the selected countries. According to the Peril Classification and Hazard Glossary by the Integrated Research on Disaster Risk (IRDR), disaster types are classified as follows: i) *Geophysical* disasters originate from solid Earth processes, ii) *Hydrological* disasters are linked to the occurrence, movement, and distribution of surface and subsurface freshwater and saltwater, iii) *Meteorological* disasters result from short-term extreme weather events, iv) *Climatological* disasters are driven by long-term atmospheric processes and v) *Biological* disasters, caused by exposure to living organisms, their toxic substances, or related diseases. Table 8 provides a breakdown of disasters by type, as recorded in the original database (1.400 events).

[7] This database can be accesed in the next link https://www.emdat.be/

To prepare the dataset, a rigorous cleaning procedure was applied. Disasters were first categorized as either short- or long-duration events. The first three categories (geophysical, hydrological, and meteorological) are considered short-lived phenomena, while climatological and biological disasters typically persist longer. Given this study's focus on the short-term financial market impacts, long-duration events were excluded. [8] Additionally, events with unclear start or end dates were excluded.[9] Then, events were filtered to include only those with over 1,000 fatalities, 1,000 injuries, 10,000 affected individuals, or damages exceeding 1 billion USD as in Gassebner et al. (2010). After applying these filters, the number of events was reduced from 1.400 to 670, as summarized in Table 9.

In line with the estimation procedure detailed in the next section, we excluded events that did not align with the definitions of the *estimation window* and *event window*.[10] Additionally, disasters with overlapping periods were removed. To address this, a 50-day period was defined, ensuring that, for each country, only one event was included within each 50-day window. The selected event was the one affecting the highest number of people during that period. After applying this criterion, the effective sample was reduced to 213 disasters (Table 3). Hydrological disasters, primarily floods, dominate the sample, accounting for 61.03% of events. Earthquakes represent 16.42%, while storms account for 13.15%, making these the most common disaster types in the final sample.

[8]Following Cavallo et al. (2022), the climatological category was excluded from the analysis. This decision was based on the observation that such disasters are typically less fatal and significantly longer in duration than other event types.

[9]By doing this, the number of biological disasters was reduced from 20 to 5, so we decided to drop this category from our analysis.

[10]The estimation window is used to estimate a model for expected returns, while the event window assesses abnormal returns following each disaster.

Table 3: Proportion of each disaster type after cleaning original database.

Disaster Type	Disaster Subtype	Count	Proportion
Geophysical	Earthquake	42	19.72%
	Volcanic Activity	5	2.35%
	Subtotal	**47**	**22.07%**
Hydrological	Flood	130	61.03%
	Landslide	2	0.94%
	Subtotal	**132**	**61.97%**
Meteorological	Storm	28	13.15%
	Extreme temperature	6	2.82%
	Subtotal	**34**	**15.96%**
Total		213	100%

The table presents the count and proportion of each disaster type in the database after cleaning process.

3.2 Methodology

We apply the Event Study Methodology (ESM) to quantify the impact of natural disasters on financial markets, specifically on stock indices and sovereign risk premiums. This approach requires an initial estimation period preceding the event, allowing for the calculation of abnormal returns—defined as the difference between the observed return and the model's forecasted return—within a specified event window. Figure 1 illustrates the basic structure of the event study framework, where t_0 represents the event date, t_1 marks the start of the event window, t_2 its end. Also, $t_0 - k$ is the beginning of the estimation window while $t_0 - 1$ its end.

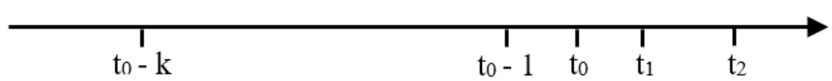


Figure 1: Event Study Framework

The figure shows that the estimation window is defined as $[(t_0 - k), (t_0 - 1)]$ and the event window is defined by $[t_1, t_2]$. Since the analysis examines the effects on both the mean and the volatility of the series, the event window differs between the two cases. Specifically, for the mean, t_1 corresponds to the day after the natural disaster, while for the volatility, t_1 is the day of the natural disaster. In both cases, the event window length, $t_2 - t_1 + 1$ is 15 days, and k is the parameter determining the length of the estimation window ($k = 500$). Following Demirer and Kutan (2010), we estimated the next econometric model during the estimation window for each natural disaster:

$$R_{i,t} = \alpha + \sum_{k=1}^{p} \theta_k R_{i,t-k} + \beta_i R_t^* + \delta_i X_{i,t} + \varepsilon_{i,t} \tag{1}$$

$$\eta_{i,t} = \frac{\varepsilon_{i,t}}{\sqrt{h_{i,t}}} \sim N(0,1) \tag{2}$$

$$h_{i,t} = \gamma_0 + \gamma_1 h_{i,t-1} + \gamma_2 \varepsilon_{i,t-1}^2 \tag{3}$$

where $R_{i,t}$ is either the stock's return or the first difference of the CDS for each country associated to the i-th disaster. We include some controls like R_t^* which is the market return[11] and $X_{i,t}$ which is a matrix of exogenous variables[12]. $\varepsilon_{i,t}$ is the error, whilst $\eta_{i,t}$ is the standardized error which is is corrected by $h_{i,t}$ (the conditional variance).

Once equations 1, 2, and 3 have been estimated, the Event Study Methodology is employed to examine the impact of disasters on the mean returns. The abnormal return is defined as $AR_{i,t} = R_{i,t} - E[R_{i,t}]$, where t is a specific day of the event window and $E[R_{i,t}]$ is the expected return based on the estimation window ending at $t_0 - 1$. Abnormal returns are aggregated over the event window ($T = t_1, ..., t_2$) to obtain the Cumulative Abnormal Return (CAR) for each i disaster event ($CAR_i = \sum_{t=t_1}^{t_2} AR_{i,t}$). To generalize across disasters, we calculate the Cumulative Average Abnormal Return (CAAR), $CAAR = \frac{1}{N}\sum_{i=1}^{N} CAR_i$ where N represents the final sample size of 213 disasters (after filtering). Following Savickas (2003) and Demirer and Kutan (2010), we use the following statistics to evaluate the null hypothesis $H_0 : CAAR \geq 0$ against the alternative $H_1 : CAAR < 0$ for the stock indexes, or $H_0 : CAAR \leq 0$ against the alternative $H_1 : CAAR > 0$ for CDS:

$$\text{TGarch} = \sum_{i=1}^{N} \frac{S_{i,T}}{N} / \sqrt{\frac{1}{N(N-1)} \cdot \sum_{i=1}^{N} \left(S_{i,T} - \sum_{j=1}^{N} S_{j,T}/N \right)^2} \tag{4}$$

where N is the number of events and $S_{i,T}$ is defined as:

$$S_{i,T} = \frac{\sum_{t=t_1}^{t_2} AR_{i,t}/(t_2 - t_1 + 1)}{\sqrt{\sum_{t=t_1}^{t_2} \hat{h}_{i,t}/(t_2 - t_1 + 1)}} \tag{5}$$

where $\hat{h}_{i,t}$ is the estimated variance by the GARCH model for i-th event on time t, based on information up to $t_0 - 1$.

On the other hand, regarding the volatility, we follow the methodology proposed by Mnasri and Nechi (2016), who argue that the variance of the residuals $\varepsilon_{i,t}$ is $M_t * E[h_{i,t}|\Omega_{t^*}]$ during the event

[11]Similar to a CAPM model, R_t^* is a variable that indicates a reference for the market value. Emerging market (EM) as MSCI Emerging Makets index for the stock markets and Moving Average of the 11 countries of sample for soverign risk premium market.

[12]VIX index, Financial development index, and daily activity index

window; where $E[h_{i,t}|\Omega_{t^*}]$ is the conditional variance forecasted by the GARCH model,[13] and M_t is a multiplicative effect. According to the these authors, the estimation of M_t is:

$$\widehat{M_t} = \frac{1}{N-1} \sum_{i=1}^{N} \frac{\left(N \times \hat{\varepsilon}_{i,t} - \sum_j^N \hat{\varepsilon}_{j,t}\right)^2}{N \times (N-2) \times E\left[h_{i,t}|\Omega_{t^*}\right] + \sum_{j=1}^N E\left[h_{j,t} \mid \Omega_{t^*}\right]}, \tag{6}$$

where N is the number of events, $\hat{\varepsilon}_{i,t}$ are the residuals during the event window, $E\left[h_{j,t} \mid \Omega_{t^*}\right]$ are the forecasts of the conditional variance with information up to $t_0 - 1$. In this test, the null hypothesis states that for a specific day $t > t^*$ the volatility does not increase, i.e, $M_t = 1$ vs. $M_t > 1$. Then, under the null hypothesis:

$$CAV\left(t_1, t_2\right) \equiv \left(\sum_{t=t_1}^{t_2} \widehat{M_t}\right) - \left(t_2 - t_1 + 1\right) = 0. \tag{7}$$

where $CAV(t_1, t_2)$ is known as Cumulative Abnormal Volatility. Finally, to calculate the significance this indicator we follow the same bootstrapping algorithm described in Mnasri and Nechi (2016).

4 Results

4.1 Natural disasters effect on the mean.

Table 4 indicates that, on the whole, there is no discernible impact on the average performance of stock indices and Sovereign risk premium when disaggregating the data by type of disaster. Therefore, we can assert that the statistical evidence suggests that, overall, the occurrence of natural disasters does not impact the means of stock returns or sovereign risk premiums. This is encouraging as it implies that governments do not see their access to credit affected to respond to the crisis triggered by the event in short term, and private investors also do not see their incomes affected by such a shock. However, geophysical disasters exhibit a notable and statistically significant positive effect on the CDS levels. This result can be explained due to the greater harmful impact on infrastructure and other physical damages compared to other types of disasters, as also found in the studies by Klomp (2015) and Di Tommaso et al. (2023).

[13] With Ω_{t^*} defined as an information set up to $t^* = t_0 - 1$.

Table 4: Event study results in mean: Reaction of CDS and Stock Indexes' mean to natural disasters.

Type of disaster \Series	CDS	Stock Index
Geophysical	**2.4984**	-
BMP test (p-value)	(0.0195)**	
Hydrological	-	-
Meteorological	**0.5892**	-
BMP test (p-value)	(0.0916)*	
All	-	-

The table reports the CAARs of CDS and stock indices in response to geophysical, hydrological and meteorological disasters.

Significance is tested using two tests: a GARCH-based test, and a Wilcoxon test. We report the p-value for the two tests in parenthesis.

***, **, * indicate statistical significance at 1%, 5% and 10%.

- indicates that the test was not significant.

Tables 14 and 15 of the Appendix C provide a breakdown both by country and by type of disaster. Regarding CDS, a significant effect of geophysical events is observed in Chile and Turkey, while for hydrological events, only Colombia shows a significant effect. Finally, a significant effect is identified in Mexico for meteorological events. In the case of stock indices, fewer effects on the mean are observed. Geophysical events affected only Indonesia, while hydrological events had an impact on Brazil. Lastly, no effect of meteorological events was recorded on the stock index of any country.

4.2 Natural disasters effect on the variance.

Extending the event analysis to assess the impact on the second moment (variance) of financial assets, we observe significant and positive impacts of natural disasters on the volatility of both stock markets and sovereign risk premiums in the selected emerging economies (Table 5).

Table 5: Reaction of CDS and Stock Indexes' variance to natural disasters.

Type of disaster \Series	CDS	Stock Index
Geophysical	11.504 *	3.088 **
Hydrological	17.077 ***	1.078 *
Meteorological	4.898 **	7.020 ***
All	19.179 ***	2.352 ***

The table reports the CAV of CDS and stock indices in response to geophysical, hydrological and meteorological disasters.
Significance is tested using bootstrap.
***, **, * indicate statistical significance at 1%, 5% and 10%.

Tables 16 and 17 of the Appendix C provide a breakdown of variance effects by country and disaster type. For CDS, geophysical events have a significant impact mainly in Chile and China, while hydrological events show significant effects in Chile, Colombia, Indonesia and Mexico. Meteorological events, however, exhibit a significant impact only in China. In contrast, the impact on stock indices is more limited. Geophysical events influence variance only in China, while hydrological events significantly affect Brazil and Mexico. Meteorological events, meanwhile, produce measurable effects in Mexico and China.

In Figure 2 and 3, we present the cumulative abnormal volatility relative to the disaster date for both CDS and stock indices. For both analyzed assets, it is observed that the impact of natural disasters on volatility is significant and positive for windows of 0 to 14 days relative to the day of the disaster event. It is important to note that this impact is more pronounced and relevant in the case of CDS. In Figure 2 the null hypothesis for each hypothesis test is shaded with the respective color for the type of disaster. Since all lines are in the rejection zone, we conclude that abnormal volatility occurred for all types of disasters. Similarly, in Figure 3 the null hypothesis is shaded with the respective color for the type of disaster, and as can be seen all lines are very close to the non rejection zone, we can conclude that while for some types of disasters, cumulative abnormal volatility is significant, the effect is not as strong as for CDS.

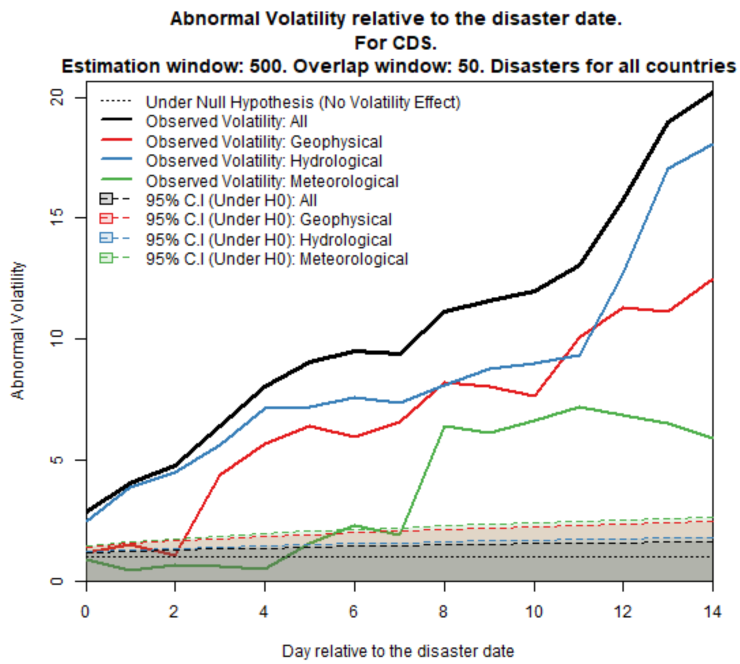


Figure 2: Cumulative Abnormal Volatility (CAV) relative to the disaster date for CDS.

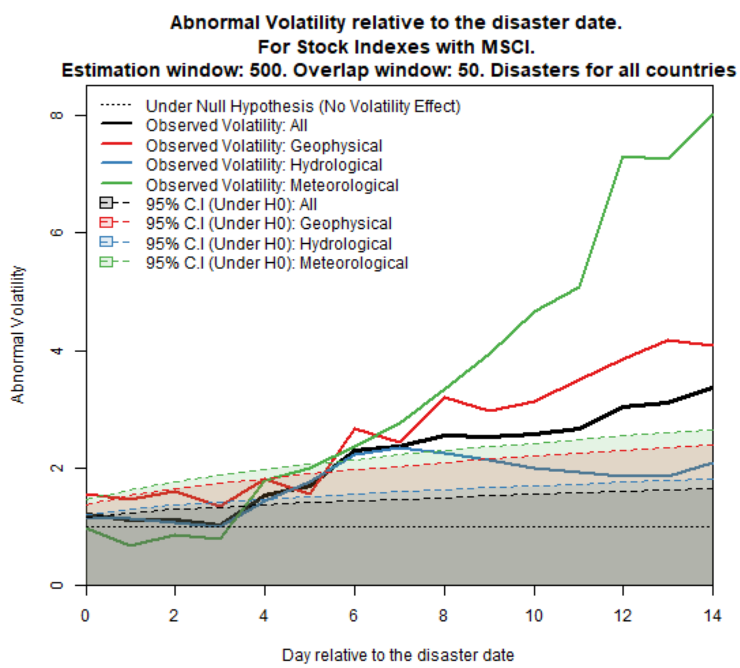


Figure 3: Cumulative Abnormal Volatility (CAV) relative to the disaster date for Stock Indexes.

4.3 Contagion effect of natural disasters

The analysis is further extended to test for the contagion effect in the sovereign CDS market and Stock market of countries that were not directly impacted by natural disasters. To measure this contagion and its propagation, a second event study evaluates how an event in country A propagates within its region and to other regions. To ensure clean identification, overlapping events within a five-day window across countries were excluded. The same regression model specification from the previous subsection was applied, but this time the focus is on the response of the variables of interest for all countries within a region, excluding the country where the natural disaster occurred. As shown in Tables 6 and 7, the findings are consistent with the earlier analysis. While the occurrence of a natural disaster does not significantly affect the mean returns of stock indices or sovereign risk premiums, it does produce significant contagion effects by increasing the volatility of financial markets across regions.

Table 6: Contagion effect of a natural disaster on CDS.

	LAC - LAC	LAC - ASIA	ASIA - LAC	ASIA - ASIA
Test in Mean	**2.5908**	**1.963**	**-1.000**	**1.001**
BMP test (p-value)	(0.0052)***	(0.0253)**	(0.8408)	(0.8411)
Test in Variance	**1.920**	**5.191**	**5.449**	**31.929**
Bootstrap	(0.0476)**	(0)***	(0.0144)**	(0)***

The label LAC-ASIA indicates the effect observed in the Latin American region in response to a natural disaster occurring in the Asian region. The same applies to the rest of the labels.
The table reports the CAARs and CAVs of CDS in response to natural disasters that occured in specific regions.
P-values in parenthesis.
***, **, * indicate statistical significance at 1%, 5% and 10%.

Table 7: Contagion effect of a natural disaster on stock indexes.

	LAC - LAC	LAC - ASIA	ASIA - LAC	ASIA - ASIA
Mean	**1.6379**	**-1.409**	**0.677**	**-0.786**
BMP test (p-value)	(0.9485)	(0.0799)*	(0.7505)	(0.2163)
Variance	**0.744**	**2.183**	**0.829**	**2.228**
Bootstrap	(0.1282)	(0.0001)***	(0.0808)*	(0.0004)***

The label LAC-ASIA indicates the effect observed in the Latin American region in response to a natural disaster occurring in the Asian region. The same applies to the rest of the labels.
The table reports the CAARs and CAVs of Stock indexes in response to natural disasters that occured in specific regions.
P-values in parenthesis
***, **, * indicate statistical significance at 1%, 5% and 10%.

5 Final remarks

The relationship between natural disasters and stock markets or sovereign CDS is multifaceted, encompassing short-term volatility, industry-specific impacts, insurance and rebuilding efforts, government response and policy measures, and long-term economic effects. Immediately following a natural disaster, markets often experience heightened volatility as investors react to uncertainty and potential economic ramifications, leading to short-term declines in stock prices, particularly in industries directly affected by the disaster. Government response and policy measures, such as emergency spending and interest rate adjustments, further influence market dynamics. In the long term, the economic impact of natural disasters on affected regions can shape GDP growth, employment, consumer spending, and investor confidence, thereby impacting stock market performance over time.

In this study, we have investigated the relationship between natural disasters and the fluctuations of sovereign CDS spreads and stock returns across a selection of emerging economies. Our analysis aimed to discern whether such natural events exert an influence on both the mean and the volatility of these financial markets. Utilizing an event study methodology spanning from October 2004 to August 2022 and drawing from a comprehensive database detailing 1400 natural disasters across 11 emerging economies, we examined the responses of sovereign CDS and stock markets to these events both in aggregate and by the type of disaster.

Although there has been increasing interest in recent years in evaluating the impacts of natural disasters on financial markets, the evidence remains scarce and there is no consensus on the findings. For example, in the case of stock markets, while some studies find that natural disasters significantly affect stock returns (Worthington and Valadkhani (2004)), other studies argue that such returns are not affected by those events (Wang and Kutan (2013)). On the other hand, the study of these events on sovereign risk premiums is very limited (Di Tommaso et al. (2023)). Thus, our study contributes to this particular branch of literature because it evaluates not only the impacts on the first moment (mean) but also on the second moment (variance) of the data-generating process of these financial assets. Furthermore, it provides empirical evidence on emerging economies, as most studies use information from developed economies. We find that natural disasters have mixed impacts on the mean of sovereign risk premiums and positive and statistically significant effects of such events on volatility. Regarding the stock market, we find only effects on volatility.

By establishing a clearer link between natural disasters and financial market dynamics, this research challenges traditional views of sovereign and market resilience, suggesting that volatility, rather than returns, may be the more critical indicator of market vulnerability. These findings advocate for the development of proactive measures to mitigate the financial repercussions of natural disasters, thereby fostering economic resilience in vulnerable economies.

It is important to note that this has implications in terms of financial risk assessment, which is not directly studied in the present article, but opens up space to generate a future research agenda. In addtition, looking forward, this serves as the beginning of a research agenda on identifying the most exposed regions and assessing mitigation policies aimed at reducing the risk of contagion among emerging countries. Additionally, future research could explore medium- or long-term impacts, which are likely associated with disasters that have a more lasting effect, such as the destruction of physical infrastructure and significant loss of life. These factors create greater pressures on fiscal positions and sovereign risk premiums while also impacting stock markets due to the deterioration of household wealth. This dynamic also influences portfolio reallocation and global capital flows, making it important to identify why the impact on volatility is more pronounced than the effects observed on the mean of financial markets.

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A Data for CDS and Stock Index by country: Original and transformation data for modeling.

A.1 Sovereing risk premium (CDS)

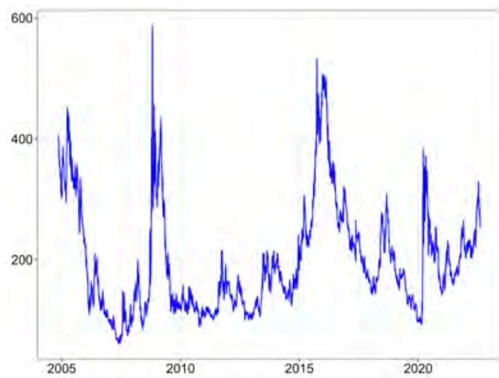


Figure 4: CDS Brazil

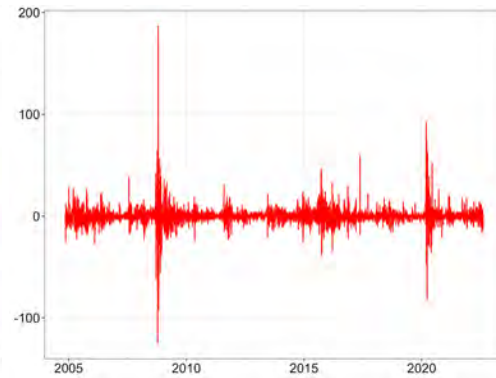


Figure 5: Δ CDS Brazil

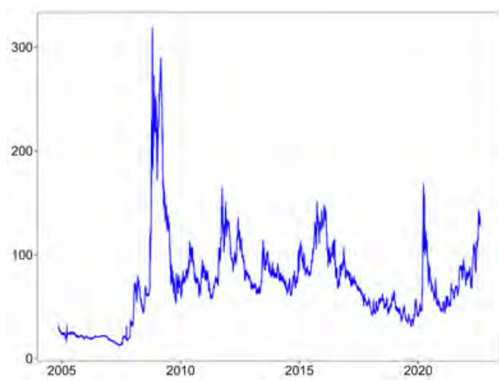


Figure 6: CDS Chile

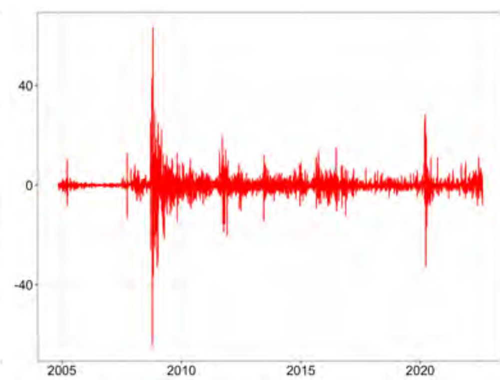


Figure 7: Δ CDS Chile

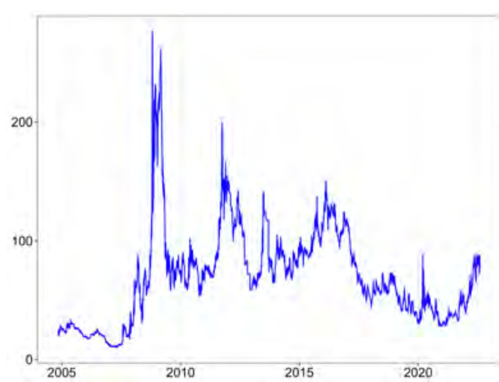


Figure 8: CDS China

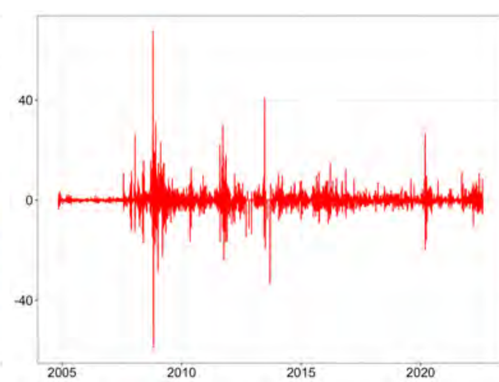


Figure 9: Δ CDS China

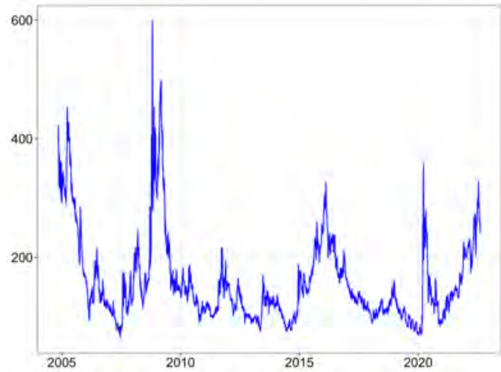


Figure 10: CDS Colombia

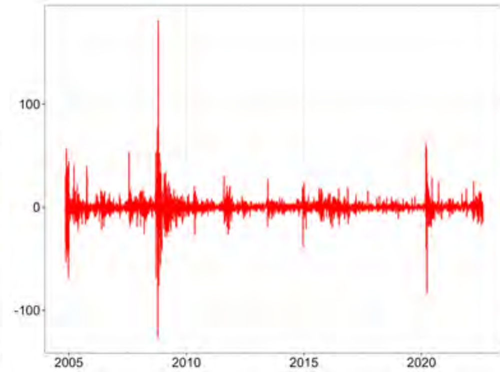


Figure 11: Δ CDS Colombia

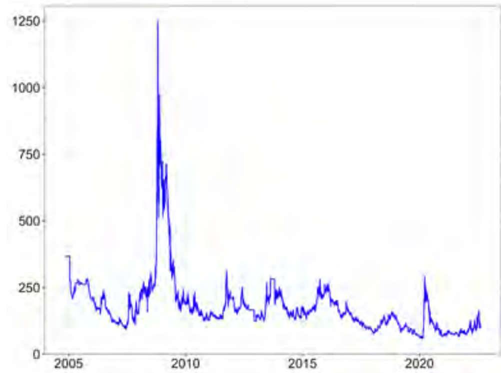


Figure 12: CDS Indonesia

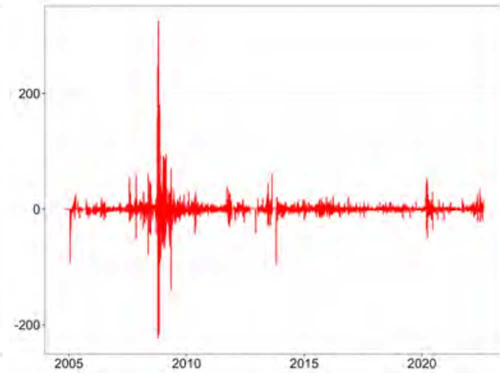


Figure 13: Δ CDS Indonesia

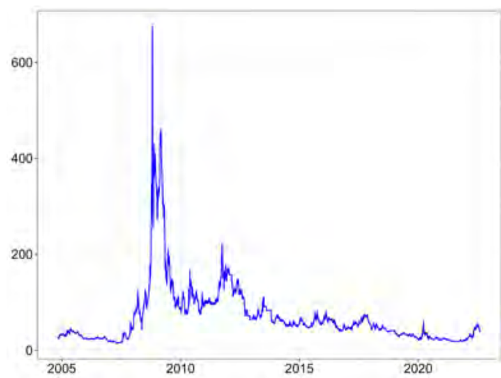


Figure 14: CDS Korea

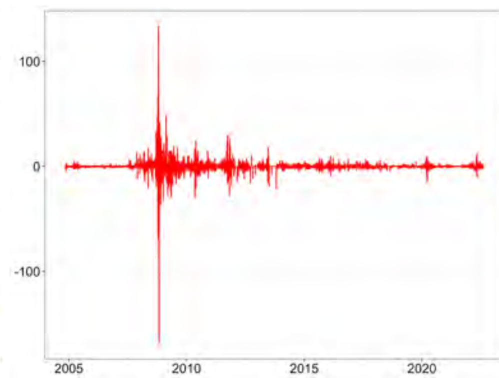
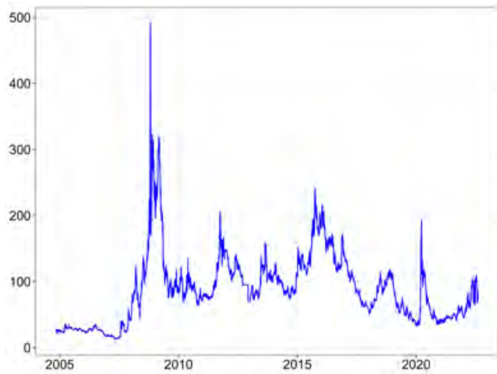


Figure 15: Δ CDS Korea



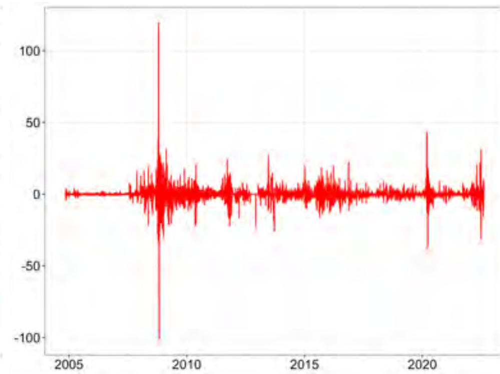
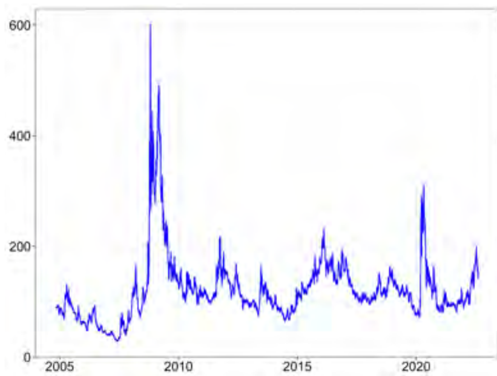


Figure 16: CDS Malaysia

Figure 17: Δ CDS Malaysia



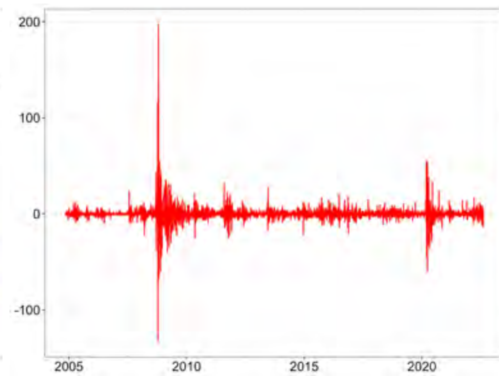
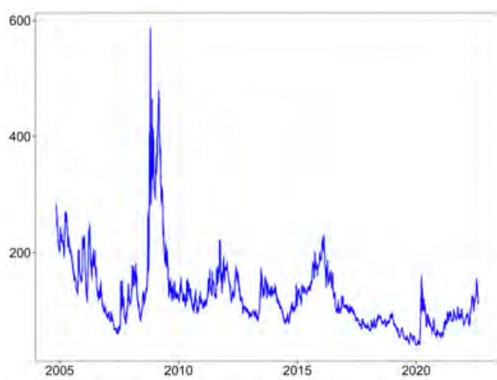


Figure 18: CDS Mexico

Figure 19: Δ CDS Mexico



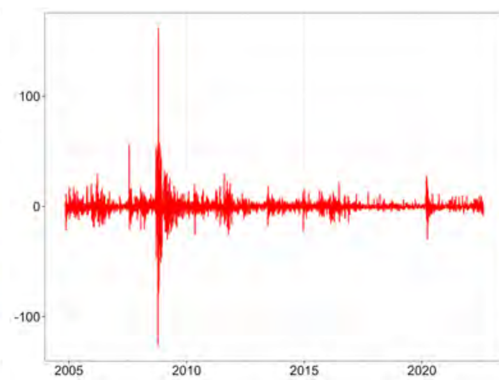


Figure 20: CDS Peru

Figure 21: Δ CDS Peru

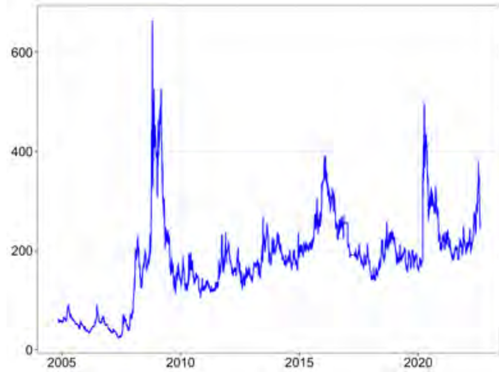


Figure 22: CDS South Africa

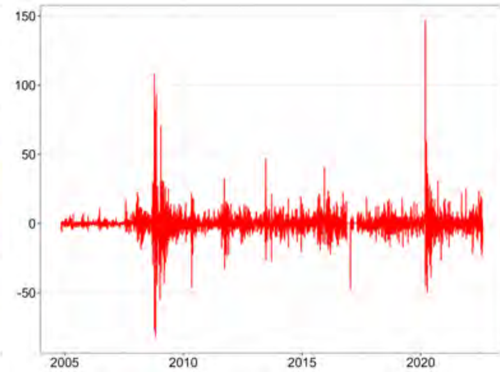


Figure 23: Δ CDS South Africa

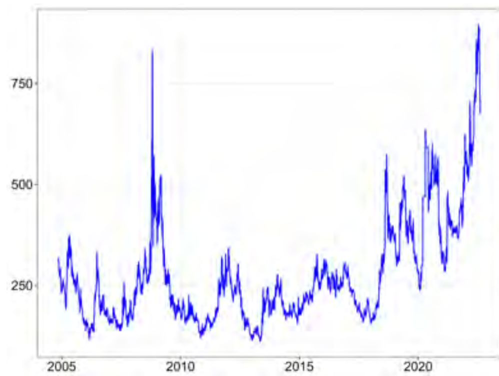


Figure 24: CDS Turkey

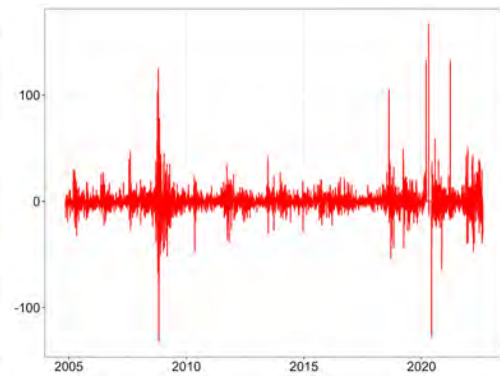


Figure 25: Δ CDS Turkey

A.2 Stock indexes

Figure 26: BIST 100 series

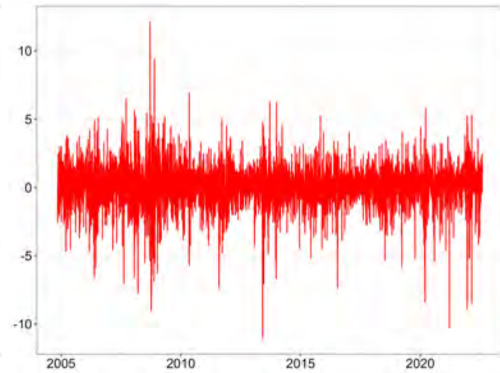


Figure 27: BIST 100 logreturns

Figure 28: Bovespa series

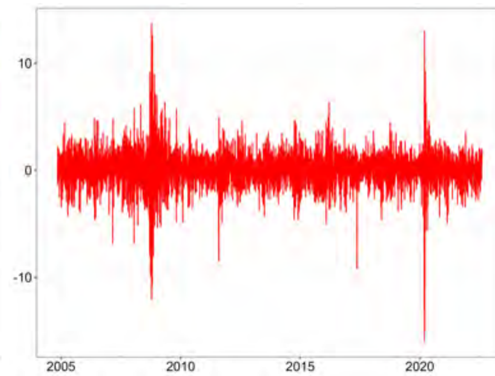


Figure 29: Bovespa logreturns

Figure 30: China A50 series

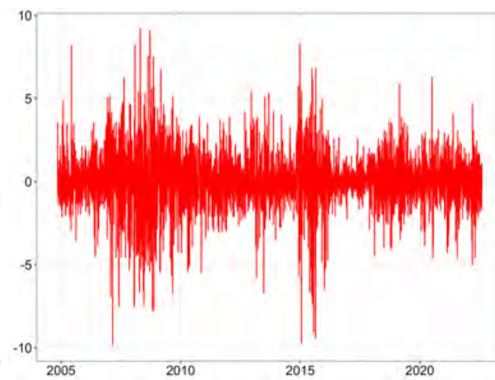


Figure 31: ChinaA50 logreturns

Figure 32: COLCAP series

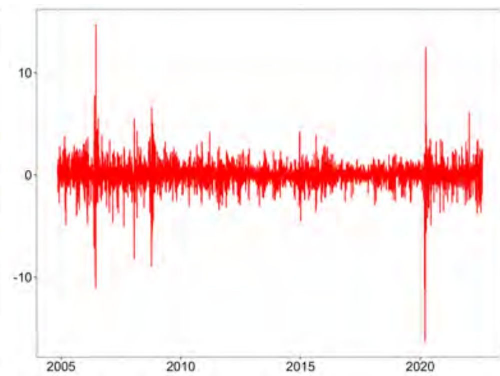


Figure 33: COLCAP logreturns

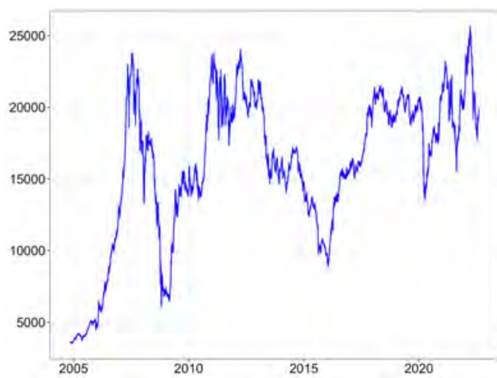


Figure 34: IGBVL series

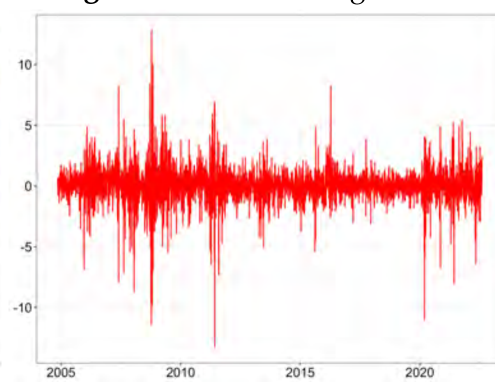


Figure 35: IGBVL logreturns

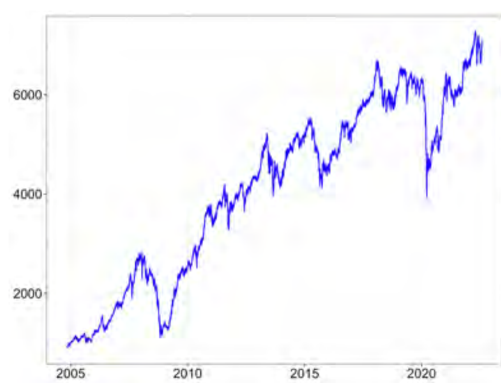


Figure 36: JSX series

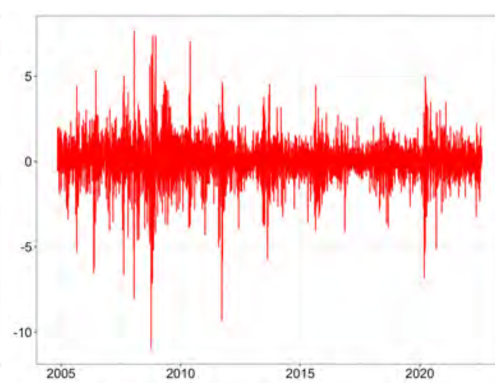


Figure 37: JSX logreturns

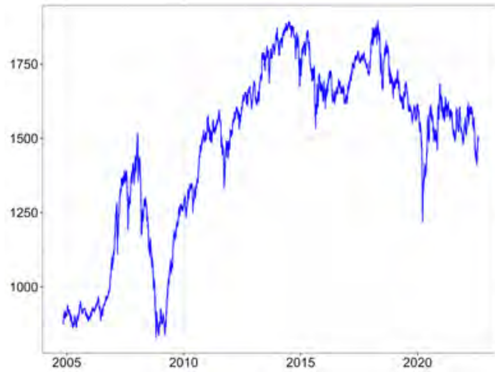


Figure 38: KLCI series

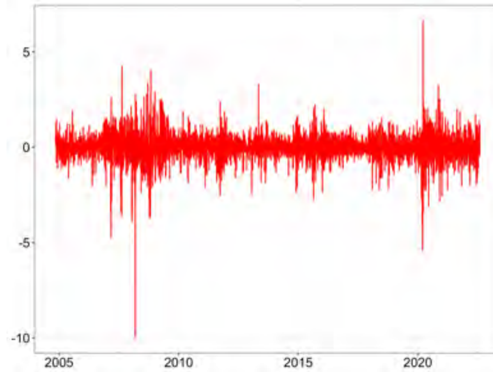


Figure 39: KLCI logreturns

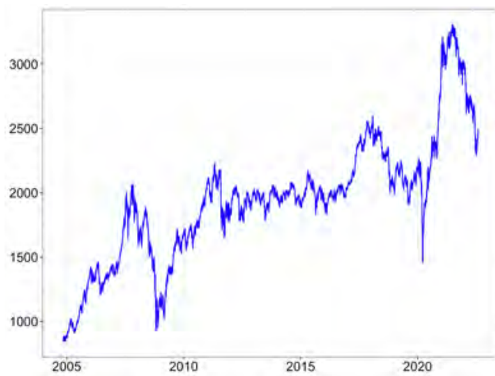


Figure 40: KOSPI series

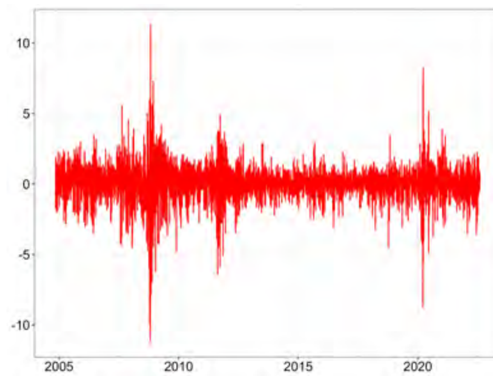


Figure 41: KOSPI logreturns

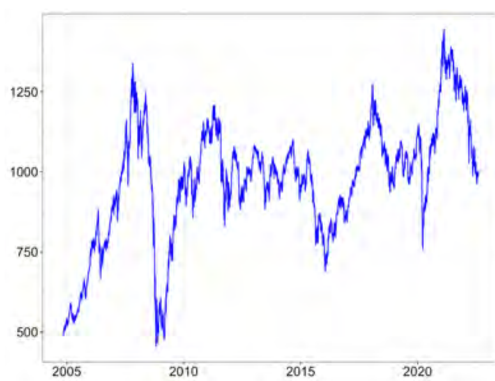


Figure 42: MSCI Emerging Markets series

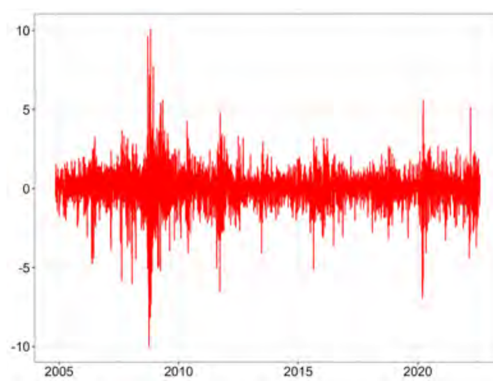


Figure 43: MSCI Emerging Markets logreturns

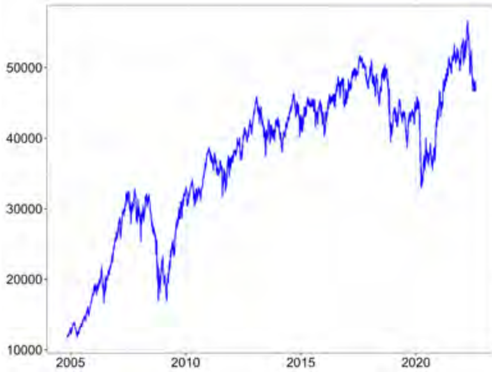


Figure 44: S&P BMVIPC series

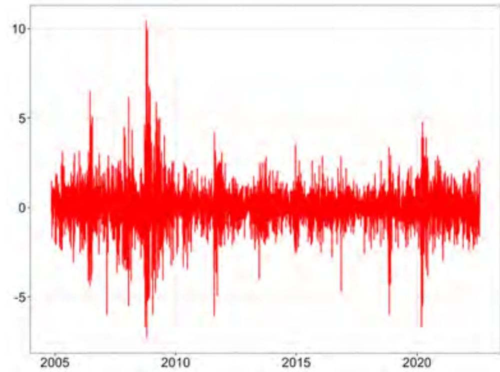


Figure 45: S&P BMV IPC logreturns

Figure 46: S&P CLX IPSA series

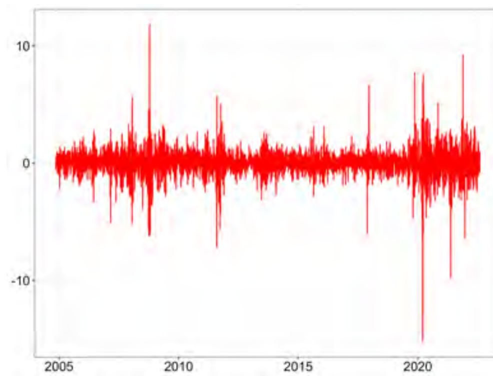


Figure 47: S&P CLX IPSA logreturns

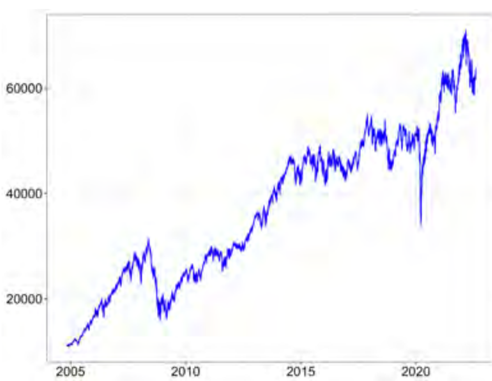


Figure 48: South Africa Top 40 series

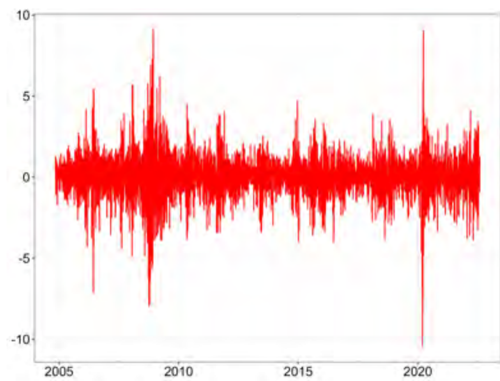


Figure 49: South Africa Top 40 logreturns

B Disasters Database

B.1 Original database

Disaster Type	Disaster Subtype	Count	Proportion
Biological	Epidemic	23	1.43%
	Subtotal	**23**	**1.43%**
Climatological	Drought	33	2.36%
	Wildfire	28	2.00%
	Subtotal	**61**	**4.36%**
Geophysical	Earthquake	195	13.96%
	Volcanic Activity	35	2.51%
	Mass Movement	4	0.29%
	Subtotal	**234**	**16.76%**
Hydrological	Flood	654	46.81%
	Landslide	115	8.23%
	Subtotal	**769**	**55.04%**
Meteorological	Storm	283	20.26%
	Extreme temperature	30	2.15%
	Subtotal	**313**	**22.41%**
Total		1400	100%

Table 8: Count and proportion of each disaster type (Original database)

B.2 Pre-cleaning database

Table 9: Proportion of each disaster type.

Disaster Type	Disaster Subtype	Count	Proportion
Geophysical	Earthquake	110	16.42%
	Volcanic Activity	16	2.39%
	Subtotal	**126**	**18.81%**
Hydrological	Flood	366	54.63%
	Landslide	9	1.34%
	Subtotal	**375**	**55.97%**
Meteorological	Storm	160	23.88%
	Extreme temperature	9	1.34%
	Subtotal	**169**	**25.22%**
Total		670	100%

The table presents the count and proportion of each disaster type in the database after pre-cleaning process.

Table 10: Count of each disaster type per country.

Country	Geophysical	Hydrological	Meteorological	Total
Brazil	0	43	3	46
Chile	6	5	2	13
China	56	142	122	320
Colombia	3	27	2	32
Indonesia	42	102	2	146
Korea	1	3	4	8
Malaysia	0	16	1	17
Mexico	9	15	31	55
Peru	4	11	2	17
South Africa	0	7	0	7
Turkey	5	4	0	9
Total	126	375	169	670

The table presents the count of each disaster type per country after pre-cleaning process.

Table 11: Count of each disaster type per continent.

Country	Geophysical	Hydrological	Meteorological	Total
Latin America	22	101	40	163
Asia	104	267	129	500

The table presents the count of each disaster type per country after pre-cleaning process.
South Africa was excluded for the contagion analysis.

B.3 Cleaning database avoid overlapping among disasters during event window and estimation window

Table 12: Count of each disaster type per country.

Country	Geophysical	Hydrological	Meteorological	Total
Brazil	0	26	2	28
Chile	5	4	1	10
China	15	20	12	47
Colombia	3	18	1	22
Indonesia	10	30	2	42
Korea	1	1	2	4
Malaysia	0	10	0	10
Mexico	5	6	12	23
Peru	4	9	2	15
South Africa	0	5	0	5
Turkey	4	3	0	7
Total	47	132	34	213

The table presents the effective count of each disaster type per country which are used in the empirical exercises. Cleaning database avoid overlap among disasters during event window.

Table 13: Count of each disaster type per continent.

Country	Geophysical	Hydrological	Meteorological	Total
Latin America	17	63	18	98
Asia	30	64	16	110

The table presents the effective count of each disaster type per country which are used in the empirical exercises. Cleaning database avoid overlap among disasters during event window.
South Africa was excluded for the contagion analysis.

C Other results

Table 14: Event study results in mean: Reaction of CDS's mean by country to natural disasters.

Country \Type of disaster	Geophysical	Hydrological	Meteorological	All
Brazil	-	-	-	-
Chile	12.59 **	-	-	-
China	-	-	-	-
Colombia	-	4.65 *	-	-
Indonesia	-	-	-	-
Korea	-	-	-	-
Malaysia	-	3.28 *	-	3.28 *
Mexico	11.55 **	-	6.20 **	7.40 ***
Peru	-	-	-	-
South Africa	-	-	-	-
Turkey	16.35 **	-	-	-
All	2.50 **	-	0.59 *	-

The table reports the CAARs of CDS in response to geophysical, hydrological and meteorological disasters.
***, **, * indicate statistical significance at 1%, 5% and 10%. - indicates that the test was not significant.

Table 15: Event study results in mean: Reaction of Stock indexes' mean by country to natural disasters.

Country \Type of Disaster	Geophysical	Hydrological	Meteorological	All
Brazil	-	- 1.29 **	-	- 1.02 **
Chile	- 2.44 *	-	-	-2.11 *
China	-	-	-	-
Colombia	-	-	-	-
Indonesia	- 1.19 **	-	-	- 0.78 *
Korea	-	-	-	-
Malaysia	-	-	-	-
Mexico	-	-	-	-
Peru	-	-	-	-
South Africa	-	-	-	-
Turkey	-	-	-	-
All	-	-	-	-

The table reports the CAARs of Stock indexes in response to geophysical, hydrological and meteorological disasters.
***, **, * indicate statistical significance at 1%, 5% and 10%. - indicates that the test was not significant.

Table 16: Event study results in variance: Reaction of CDS's volatility by country to natural disasters.

Country \Type of disaster	Geophysical	Hydrological	Meteorological	All
Brazil	-	-	-	-
Chile	25.96 **	165.36 ***	-	116.26 ***
China	46.05 **	-	10.90 **	17.98 ***
Colombia	-	12.56 ***	-	9.16 ***
Indonesia	-	11.42 *	-	-
Korea	-	-	-	12.45 *
Malaysia	-	-	-	-
Mexico	-	16.05 **	-	6.19 **
Peru	-	-	-	-
South Africa	-	-	-	-
Turkey	-	-	-	-
All	11.50 *	17.08 ***	4.90 **	19.18 ***

The table reports the CAVs of CDS in response to geophysical, hydrological and meteorological disasters.
Significance is tested using bootstrap.
***, **, * indicate statistical significance at 1%, 5% and 10%. - indicates that the test was not significant.

Table 17: Event study results in variance: Reaction of Stock indexes' volatility by country to natural disasters.

Country \Type of disaster	Geophysical	Hydrological	Meteorological	All
Brazil	-	5.77 ***	-	4.96 ***
Chile	-	-	-	6.06 *
China	10.86 ***	-	5.48 *	4.15 ***
Colombia	-	-	-	-
Indonesia	-	-	-	-
Korea	-	-	-	28.98 ***
Malaysia	-	-	-	-
Mexico	-	17.43 ***	16.30 ***	10.1 ***
Peru	-	-	-	-
South Africa	-	-	-	-
Turkey	-	-	-	-
All	3.09 **	1.08 *	7.02 ***	2.35 ***

The table reports the CAVs of Stock indexes in response to geophysical, hydrological and meteorological disasters.
Significance is tested using bootstrap.
***, **, * indicate statistical significance at 1%, 5% and 10%. - indicates that the test was not significant.