Master

Mathematical Finance

Master's Final Work

Dissertation

Volatility Spillovers among BRICS and Developed Stock Markets: Impact of Recent Global Shocks

Ana Sofia Pires Alexandre

October - 2024

Master

Mathematical Finance

Master's Final Work

Dissertation

Volatility Spillovers among BRICS and Developed Stock Markets: Impact of Recent Global Shocks

Ana Sofia Pires Alexandre

Supervision:
Prof. Nuno Ricardo Martins Sobreira

DOCUMENT SPECIFICALLY CREATED FOR OBTAINING A MASTER'S DEGREE

October - 2024

GLOSSARY

ADF – Augmented Dickey-Fuller.

AIC – Akaike Information Criterion.

BRA – Brazil.

BRICS – Brazil, Russia, India, China, and South Africa.

CH – China.

DY – Diebold-Yilmaz.

FPE – Final Prediction Error.

G7 – Group of Seven.

GARCH – Generalized Autoregressive Conditional Heteroskedasticity.

GER – Germany.

GDP – Gross Domestic Product.

GFC – Global Financial Crisis.

HQ – Hannan-Quinn Criterion.

IND – India.

JPN – Japan.

KPPS – Koop, Pesaran, Potter, and Shin.

MA – Moving Average.

RUS – Russia.

SC – Bayesian Criterion.

UK – United Kingdom.

USA – United States of America.

VAR – Vector Autoregressive.

ABSTRACT

This study analyses volatility spillovers amongst four developed financial markets and four BRICS markets, using the Diebold and Yilmaz (2012) methodology, based on generalized variance decompositions within a VAR framework. The study covers a period from March 2013 to December 2023, focusing on contemporaneous global events, from financial markets turbulences to geopolitical conflicts.

The results show evidence that a substantial share of total forecast error variance in volatility is attributable to spillovers. It was found that spillovers primarily occur within developed markets, particularly amongst the USA, UK, and Germany. Spillovers from developed markets to BRICS are also significant, while spillovers from BRICS markets display more isolated levels.

Major financial upheavals have profoundly influenced spillover dynamics, increasing volatility transmission to extreme levels. BRICS markets displayed more erratic responses to global shocks, particularly during the COVID-19 pandemic and the onset of the Russia-Ukraine war, reflecting heightened vulnerability.

The study also finds that developed markets predominantly acted as net transmitters throughout the period, while BRICS markets acted as net receivers. However, during periods of turmoil, this dynamic shifted, with BRICS markets performing as net transmitters of volatility.

KEYWORDS: Stock Markets; Volatility Spillovers; Diebold-Yilmaz; Forecast Error Variance Decomposition; BRICS; Developed markets.

JEL CODES: C32; C58; G01; G10; G15; F65.

Resumo

Este estudo efetua uma análise da transmissão de volatilidade (*spillovers*), entre os mercados financeiros de quatro países desenvolvidos e quatro mercados emergentes integrados no grupo dos BRICS, usando a metodologia proposta por Diebold e Yilmaz (2012), assente na decomposição da variância generalizada a partir de um modelo vetor autorregressivo (VAR). O estudo abrange o período de março de 2013 a dezembro de 2023, focando-se em eventos que ocorreram nesse intervalo, com impacto a uma escala global, desde turbulências nos mercados financeiros a conflitos geopolíticos.

Os resultados demonstram que os *spillovers* ocorrem principalmente entre mercados financeiros de países desenvolvidos, especialmente entre os EUA, Reino Unido e Alemanha. Os *spillovers* dos mercados desenvolvidos para os BRICS também são significativos, enquanto os *spillovers* originários dos BRICS apresentam níveis mais isolados.

Os resultados revelam ainda que as perturbações significativas nos mercados financeiros influenciaram profundamente a dinâmica dos *spillovers*, resultando em níveis extremos de transmissão da volatilidade. Os mercados dos BRICS exibiram respostas mais erráticas face a choques globais, nomeadamente no período do COVID-19 e no início da guerra entre a Rússia e a Ucrânia, refletindo uma maior vulnerabilidade.

O estudo conclui ainda que os mercados financeiros mais desenvolvidos foram transmissores líquidos durante o período em análise, enquanto os mercados dos BRICS foram recetores líquidos. No entanto, durante períodos de turbulência, esta dinâmica mudou, com os mercados dos BRICS a surgirem como transmissores líquidos de volatilidade.

Palavras-Chave: Mercados de Ações; Transmissão de Volatilidade; Diebold-Yilmaz; Decomposição da Variância do Erro de Previsão; BRICS; Mercados Desenvolvidos.

Códigos JEL: C32; C58; G01; G10; G15; F65.

TABLE OF CONTENTS

LIST OF FIGURES

List of Tables

Acknowledgments

First, I would like to express my sincere gratitude to my supervisor, Professor Nuno Sobreira, for his contributions and guidance throughout this journey.

I would also like to thank the coordinator of my master's course, Maria Grossinho, for her support and encouragement at the beginning of this journey, which helped me get started on the right path.

Lastly, I am deeply grateful to my boyfriend and my family for always being by my side, offering their patience and unwavering support as I pursued this work.

1. INTRODUCTION

In today's increasingly interconnected global economy, the linkages between financial markets are strengthening at a staggering pace. This growing interconnectedness – the degree to which financial markets across various regions are connected and influence each other – has become a key focus in modern finance theory and empirical research. A major area of study within this framework is the concept of volatility spillovers, which explore how fluctuations in one market are transmitted to others. Understanding these spillovers is crucial to grasp the complex dynamics of contemporary financial markets as global economic conditions evolve over time.

The past few decades have been marked by a series of significant global shocks that have challenged the resilience of financial systems and increased volatility in stock markets. The World Economy has faced financial downturns, including the 2008 Global Financial Crisis (GFC), geopolitical uncertainties arising from conflicts like the USA-China trade tensions and the Russia-Ukraine war, and unprecedented economic and health crises caused by the COVID-19 pandemic. Although each of these shocks is distinct in nature, they have all had profound and far-reaching impacts on financial markets worldwide. In this context of escalating global uncertainty, it is imperative to understand how these shocks are transmitted across borders and how they affect both developed and emerging markets.

Emerging markets, particularly those within the BRICS group (Brazil, Russia, India, China, and South Africa), have demonstrated rapid economic growth, overlooking the G7 nations (USA, UK, Germany, France, Italy, Japan, and Canada) in their share of the world's total gross domestic product (GDP) in terms of purchasing power parity in 2018. By 2024, the gap between BRICS and the G7 had widened further, with the BRICS holding 35 percent of the world's GDP compared to the G7 countries' share of 30 percent (Statista, 2024). Given their impressive growth, numerous studies have analysed the integration of BRICS markets into the global economy and their influence on advanced economies. Furthermore, these emerging markets are often characterized by higher volatility and greater susceptibility to external shocks, making it essential to understand their role within the global financial landscape.

To this extent, this work focuses on studying volatility spillovers across major developed and emerging markets amongst the G7 and BRICS groups. The countries under analysis from developed markets include the United States of America (USA), the United Kingdom (UK), Germany, and Japan, while those from emerging markets are Brazil, Russia, India, and China. The goal is to understand how market interconnectedness amongst these eight stock markets has evolved over the past decade, from March 2013 to December 2023, particularly during periods of significant uncertainty and turmoil. The study aims to determine the magnitude and direction of volatility spillovers, identifying which markets act as primary transmitters or receivers of shocks and uncovering any distinct patterns in spillover effects between developed and emerging markets.

The literature on volatility spillovers between financial stock markets has attracted significant academic interest since the 1980s, particularly in the wake of major financial crises. Early studies focused on understanding how financial shocks spread across established markets, with many studies identifying the USA as a key driver of volatility transmission, such as Hamao et al. (1990), and Theodossiou and Lee (1993). Following the currency crises that impacted emerging economies during the 1990s, the research has expanded to include these markets in spillover analyses. Researchers such as Edwards (1998) and Park and Song (1999) examined the extent of contagion from emerging markets. Subsequent studies by Bekaert et al. (2005) and Beirne et al. (2013) analysed how regional and global markets influenced volatility spillovers in emerging economies and vice versa. Bhar and Nikolova (2009) and Kenourgios et al. (2011) investigated the integration of BRICS economies with developed markets and assessed their vulnerability to financial shocks.

After the 2007-2008 Global Financial Crisis (GFC), research on volatility spillovers surged, with a heightened focus on the BRICS economies as researchers sought to understand how shocks from developed markets, particularly the USA, impacted emerging markets during this period of global financial turmoil. Studies such as those by Zhang et al. (2013) and Singh and Singh (2017) have highlighted the far-reaching spillover effects of the US subprime crisis on BRICS economies.

The GARCH framework and its multivariate extensions have been widely adopted for analysing volatility spillovers, often in combination with Volatility Impulse Response

Functions and Copula models. A key development in the literature arose with the works of Diebold and Yilmaz (2009, 2012). Diebold and Yilmaz proposed the DY spillover index which is based on forecast error variance decomposition within a Vector Autoregressive (VAR) framework. The DY spillover index provides an indicator of the magnitude of cross-market volatility spillovers and identifies directional transmission patterns, allowing for a better understanding of financial market interconnections. Following this development, the DY spillover index has been widely applied in empirical studies. Recent examples include Prasad (2018), Panda and Thiripalraju (2018), and Su (2020a), which explore the dynamics of volatility spillovers across global financial markets.

More recently, new economic shocks – such as the Eurozone debt crisis, the COVID-19 pandemic, and ongoing geopolitical tensions – and corresponding influence on global volatility patterns, highlight the need for more research about the dynamics of financial spillovers. Studies by Zhang et al. (2021), Shi (2021), and Agyei et al. (2022) have applied the Diebold-Yilmaz (DY) framework, concluding that recent major events significantly shape spillover dynamics. Zhang et al. (2021) found that G7 countries primarily act as net transmitters of risk, while BRICS nations are net recipients. Agyei et al. (2022) and Shi (2021) focused on time-frequency spillovers, capturing transmission effects across different frequency scales. Agyei's research concluded that developed markets are the main sources of shocks in both the short and long term, while Shi (2021) analysed volatility connectedness amongst BRICS markets, finding that China and Russia’s stock markets were likely influential sources of spillovers.

Building on the Diebold-Yilmaz (2012) framework, this study aims to contribute to the literature by providing insights into the evolving dynamics of volatility spillovers between BRICS and developed markets, while also analysing their responses to contemporary financial shocks.

As financial markets become more integrated, understanding these spillover effects is crucial for policymakers, investors, and regulators to manage risk and formulate effective strategies. Additionally, by extending the existing research to cover more recent periods, this study offers valuable insights into the changing role of BRICS economies in the global financial landscape, helping to inform decisions in an increasingly volatile and interconnected world.

The results show that spillovers primarily occur within developed markets, especially amongst the USA, UK, and Germany, followed by spillovers from developed to BRICS markets, while spillovers from BRICS display lower values.

Major financial upheavals have profoundly influenced spillover dynamics, increasing volatility transmission to extreme levels. I found that BRICS markets exhibited more erratic responses to global shocks, particularly during the COVID-19 pandemic and the onset of the Russia-Ukraine war, reflecting their heightened vulnerability compared to developed markets.

The study also finds that, in general, developed markets predominantly acted as net transmitters throughout the period, while BRICS markets acted as net receivers. However, during periods of turmoil, this dynamic shifted, with BRICS markets performing as net transmitters of volatility.

The remainder of this work is structured as follows. Section 2 summarises existing studies related to volatility spillovers amongst developed and emerging markets. This is followed by an explanatory data analysis in section 3. Section 4 details the methodology and section 5 reports the study's findings. Finally, the conclusion is drawn in the last section.

2. Literature Review

This work is closely related to the main strand of literature on volatility spillovers across financial stock markets, which focuses on understanding how financial shocks propagate across markets and how market interconnectedness has evolved over time.

The academic literature on volatility spillovers is extensive, tracing its roots back to the 1980s, particularly following the October 1987 stock market crash in the USA. This event spurred research into the transmission of shocks across established financial markets, with many studies identifying the USA as a key driver of volatility transmission. Noteworthy examples include the work of Hamao et al. (1990), who examined volatility spillovers amongst the USA, UK, and Japanese stock markets, and Theodossiou and Lee (1993), who expanded the analysis to include Canada and Germany.

Subsequent research in this literature was boosted by the emerging market crises of the 1990s, in particular the currency crises in Mexico (1994), Asia (1997), and Russia (1998). This body of research has expanded to explore how financial shocks in major economies affect emerging markets, and vice versa, in terms of volatility spillovers. For instance, Edwards (1998) and Park and Song (1999) investigated whether these crises triggered contagion from emerging markets during the Mexican crisis and the Asian crisis, respectively. Bekaert and Harvey (1997), Ng (2000), Bekaert et al. (2005), Bhar and Nikolova (2009), and Beirne et al. (2013) have analysed how volatility spillovers in emerging markets are affected by regional and global markets, often considering the USA as a key driver on the global level. Bhar and Nikolova (2009) explored the level of integration of BRICS countries with their regions and the global market, from 1995 to 2004, using a bivariate EGARCH model and time-varying correlations. Their findings indicated that India has the highest level of integration, followed by Brazil, Russia, and lastly by China. Kenourgios et al. (2011) used the AG-DCC approach and a Multivariate Regime-Switching Copula model to explore financial contagion between the USA, the UK, and BRICS markets during five financial crises. Their results highlighted significant contagion effects, emphasizing the BRICS markets' vulnerability to financial shocks.

This study contributes to the growing body of literature on volatility spillovers amongst BRICS and developed markets, a topic that has gained significant traction since the 2007-2008 Global Financial Crisis (GFC). In the aftermath of this crisis, researchers have increasingly focused on understanding how shocks from developed markets, particularly the USA, impacted emerging markets during this period of global financial turmoil. Zhang et al. (2013) concluded that the GFC has led to a significant structural change in correlation dynamics amongst developed and BRICS stock markets, by employing a DCC model. Their findings reveal that since the crisis, about 70% of BRICS stock markets have shown an increasing long-term trend in their conditional correlations with developed markets. Utilizing a multivariate DCC-GARCH model, Singh and Singh (2017) observed contagion effects from the US subprime crisis to India and Russia, as well as heightened interdependence between the USA and Brazil. Their results were consistent with Zhang et al. (2013), who found that the equity relationship between the USA and China showed lower levels of interdependence compared to other BRICS countries. Other studies, including those by Gilenko (2014), Syriopoulos et al. (2015), and Panda and Thiripalraju (2018), using GARCH frameworks, have also identified significant volatility transmission dynamics between BRICS stock markets and the rest of the world.

Researchers have employed various methodologies to study volatility spillovers, with the GARCH framework (Engle, 1982; Bollerslev, 1986) and its multivariate extension (Engle and Kroner, 1995) being the most widely adopted. Advanced models, such as MGARCH-BEKK, EGARCH, DCC-GARCH, and ADCC-GARCH have also been extensively used, often in combination with Volatility Impulse Response Functions (Jin and An 2016), and Copula models (Kenourgios 2011). A key contribution to this field arises from Diebold and Yilmaz (2009), who introduced the DY spillover index to measure return and volatility spillovers amongst Asia-Pacific stock markets. This novel metric is based on forecast error variance decomposition within a Vector Autoregressive (VAR) framework, which decomposes variability into components attributable to various shocks, providing deeper insights into market interconnectedness. Diebold and Yilmaz (2012) expanded on their earlier work by enhancing the DY spillover index to more accurately capture the dynamic nature of financial market interconnections and to allow for the measurement of directional spillovers, identifying not just the presence of spillovers but also which markets act as transmitters or receivers of shocks. The enhanced method employs a generalized VAR framework, drawing on the work of Koop et al. (1996) and Pesaran and Shin (1998), which ensures invariance to variable ordering and effectively manages correlated shocks.

The new approach of Diebold and Yilmaz (2009, 2012) has been widely adopted in the literature to examine volatility spillover and transmission effects in financial markets. Yilmaz (2010) examines the extent of contagion and interdependence across the East Asian equity markets. Similarly, Zhou et al. (2012) measured directional volatility spillovers between the Chinese and global equity markets. Liena et al. (2018) compared the volatility spillovers between the USA and East Asian stock markets during the US subprime crisis and the Asian currency crisis. Prasad (2018) found that spillovers surged significantly during the GFC and the subsequent European sovereign debt crisis, with advanced Western economies, especially the USA, dominating transmission to other markets. Prasad (2018) also observed that although emerging markets like China, India, and Brazil initially remained relatively isolated, their contributions to global volatility spillovers have increased significantly since 2006.

Additional contributions to the literature can be found in more recent studies. Panda et. al (2021) examined volatility spillovers between the G7 and BRICS stock markets during the GFC. They found that Brazil, Hong Kong, Germany, and Japan were net receivers of volatility, while South Africa, London, and the USA were identified as net transmitters. Su (2020a) applied the DY methodology with a quantile regression analysis to study extreme risk spillovers over a broader period from 1998 to 2017. The study revealed that the USA, Germany, France, and Canada acted as net transmitters of risk, while the UK, Japan, Italy, and the BRICS nations were predominantly net receivers throughout most of the sample period.

More efforts can be found in the literature addressing how recent events, such as the Eurozone debt crisis, Brexit, the USA-China trade war, the COVID-19 pandemic, and the ongoing geopolitical tensions involving Russia and Ukraine, have reshaped spillover patterns amongst developed and BRICS nations. Zhang et al. (2021), Agyei et al. (2022), and Shi (2021) concluded that these systemic risk events significantly influence spillover dynamics. Zhang et al. (2021) combined Directed Acyclic Graphs (DAG) with the DY spillover index, identifying the G7 as a net exporter of risk and the BRICS as net receivers. Agyei (2022) and Shi (2021) explored time-frequency spillovers using the Baruník and Křehlík index (Baruník et. al, 2016), which extends the Diebold-Yilmaz Spillover Index to capture spillovers at specific frequencies. Agyei's findings reveal that developed markets acted as the primary shock providers in both the short and long run. Additionally, Shi (2021) analysed volatility connectedness amongst BRICS markets, finding that China and Russia’s stock markets likely acted as significant sources of volatility spillover within BRICS.

Other methodologies, such as Wavelet Analysis and Multivariate Regime-Switching Copula models, have also been used to analyse volatility spillovers in more recent studies. For example, Gurgiev (2021) and Hanif et al. (2021) employed these techniques to explore contemporary spillover dynamics.

This research contributes to previous literature by applying the Diebold-Yilmaz 2012 methodology to analyse volatility spillovers between BRICS and developed markets, covering the last decade, from 2013 to 2023. While much of the existing literature has concentrated on the crises of the 1990s and the GFC, my work aims to address more recent developments. Specifically, I aim to provide a detailed analysis of how recent economic shocks have affected both the magnitude and direction of volatility spillovers in developed and emerging markets.

3. The Dataset and Exploratory Analysis

Following the review of existing literature on volatility spillovers, this section presents an in-depth exploratory analysis of the price stock indices and their volatility. The analysis aims to provide a detailed understanding of the dataset, uncovering key statistical features and patterns, which should be addressed before conducting an accurate analysis of volatility spillovers.

3.1. Stock Indices

The underlying data for this study are daily nominal local-currency stock indices from developed and BRICS markets, taken from Yahoo Finance. The analysis focuses on four developed markets within the G7 – United States of America (USA), United Kingdom (UK), Germany, and Japan – and four BRICS markets – Brazil, Russia, India, and China. The selected representative stock market indices were the S&P 500 (USA), FTSE 100 (UK), DAX 40 (Germany), Nikkei 225 (Japan), Shanghai Composite Index (China), Ibovespa Index (Brazil), MOEX Russia Index (Russia) and BSE SENSEX Index (India). Table I presents the key information for each index under study.

TABLE I – LIST OF STOCK INDICES

Symbol	Country	Stock Indices	Currency	Quote in Yahoo Finance
USA	United States of America	S&P 500 Index	USD	^GSPC
UK	United Kingdom	FTSE 100 Index	GBP	^FTSE
GER	Germany	DAX 40 Index	EUR	^GDAXI
JPN	Japan	Nikkei-225 Index	JPY	^N225
BRA	Brazil	Ibovespa Index	BRL	^BVSP
CH	China	Shanghai Composite Index	CNY	000001.SS
RUS	Russia	MOEX Russia Index	RUB	IMOEX.ME
IND	India	BSE SENSEX Index	INR	^BSESN

The daily time series sample covers the period from March 5, 2013, to December 28, 2023, comprising 2,091 daily observations. Due to the unavailability of earlier data, the dataset only begins in March 2013. To maintain the integrity of the analysis, days with missing values for any specific indices were excluded.

This dataset spans a period marked by several major shocks, including crises in BRICS economies at the start of 2014, the 2014 Brazil economic crisis, and the 2014-2016 Russia financial crisis, along with various global economic, health, and political events. Amongst the significant occurrences captured in the dataset is the 2015-2016 Stock Market Selloff, which was a series of global selloffs that took place over the course of a year, beginning in June 2015. This event included the 2015-2016 Chinese stock market turbulence, the decline in oil prices, the effects of the end of quantitative easing in the USA in October 2014, a sharp rise in bond yields in early 2016, and the 2016 UK-EU membership referendum, during which Brexit was voted upon. Additionally, the dataset covers significant geopolitical conflicts, including the USA-China trade war from 2018 to 2019, and the onset of the Russia-Ukraine war in 2022, along with the unprecedented economic and health crisis caused by the COVID-19 pandemic in 2020. Figure 1 provides an initial overview of how global stock markets have reacted to these various shocks over the analysed timeframe, highlighting the vulnerability of global markets to major economic and geopolitical disturbances.

Over the analysed period, all indices display similar patterns, particularly a sustained upward trajectory that reflects global economic growth and market expansion. However, despite this positive trend, periods of heightened turmoil led to extreme price movements, resulting in increased volatility.

China's market, as illustrated in the upper right panel in Figure 1, exhibited notable volatility in 2015, with stock prices surging by 115% within a year, from June 2014 to June 2015, before experiencing a sharp decline of around 47% over the following six months. This sharp decline marked the burst of a market bubble and highlighted the turbulence within the Chinese stock market.

Between 2015 and 2016, the effects of the 2015-2016 Stock Market Selloff were evident across all markets, with developed economies experiencing the most significant impact. During this period, indices saw sharp declines in stock prices, driven by rising global uncertainty and deteriorating investor confidence, which stemmed from a series of interconnected factors.

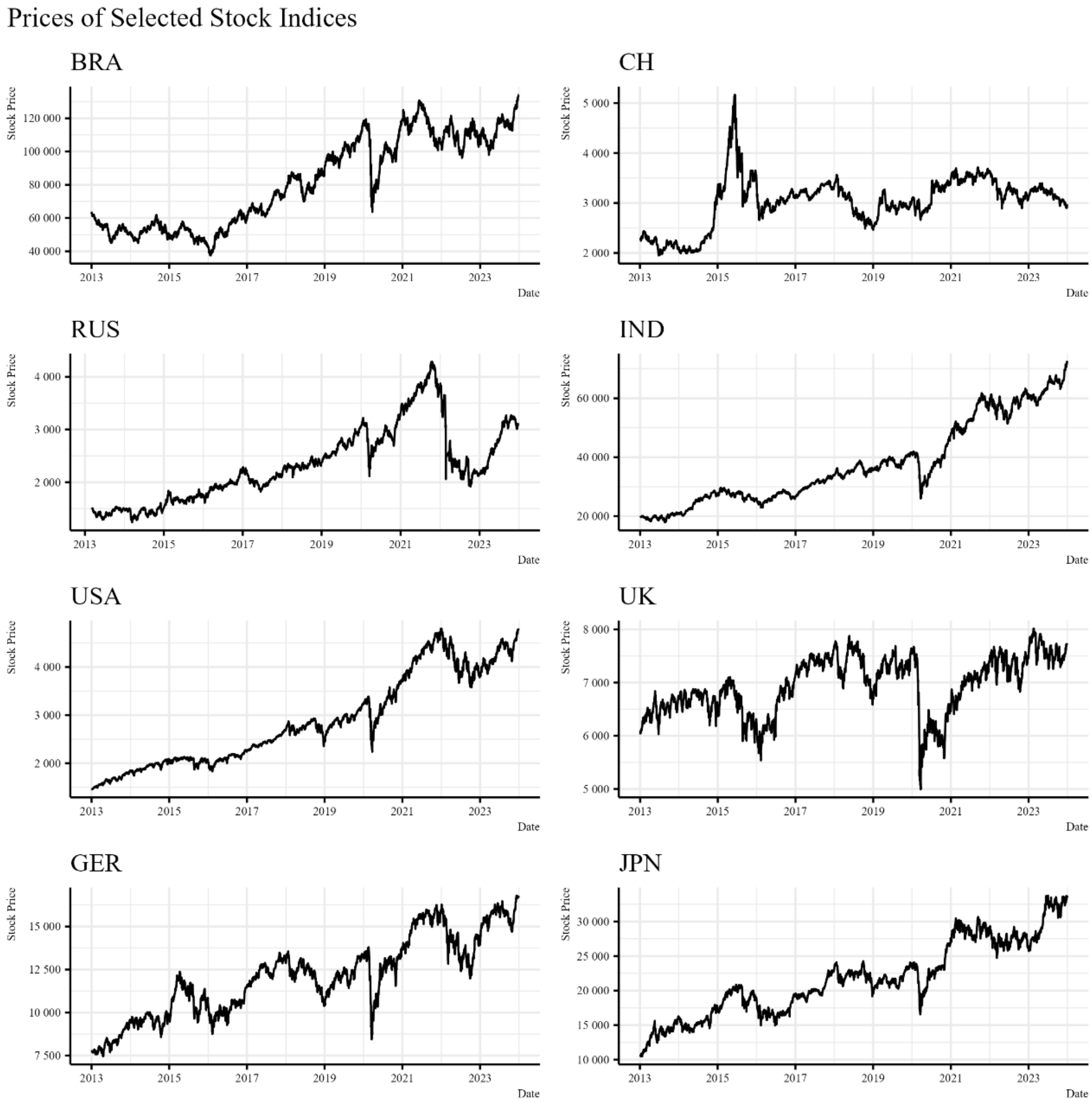

FIGURE 1 – Dynamics of daily stock price (in local-currency) in each market.

Amidst the USA-China trade tensions in 2018, characterized by the imposition of additional tariffs and trade barriers between the world’s two largest economies, a clear downward trend is evident in China’s stock price indices throughout 2018 and in the USA, particularly in early 2018.

All indices experienced a significant decline in 2020, driven by the onset of the COVID-19 pandemic, emphasizing its severe impact on global financial markets as they faced unprecedented uncertainty and economic disruption. In March, Brazil and India experienced the steepest declines, with drops of approximately 33% and 26%, respectively, while China saw a more moderate decrease of around 11%. Despite these sharp downturns, all indices demonstrated strong recoveries, with sustained price increases in the following months.

Lastly, as illustrated in Figure 1, the Russian stock index experienced a sharp decline in late 2021 and early 2022, dropping by approximately 51% over the four-month period from November 1 to February 24. This significant decrease coincided with the onset of the Russia-Ukraine conflict, which led to heightened geopolitical tensions and disruptions in global energy supplies. A particularly steep drop of round 33% occurred between February 22 and February 24, the day Russia first invaded Ukraine. Similar downward trends are evident in the USA and German indices, as shown in the graph, reflecting increased global market volatility during this period.

3.2. Stock Volatility

To explore and analyse volatility spillover effects across the financial markets under analysis, stock volatility was estimated using a daily range-based volatility estimator, following Garman and Klass (1980), Alizadeh et al. (2002), and Diebold Yilmaz's (2009) work. The estimator utilized employs the differences between the natural logarithms of the daily high, low, opening, and closing prices, as follows:

$$\sigma_t^2 = 0.511(h_t - l_t)^2 - 0.019[(c_t - o_t)(h_t + l_t - 2o_t) - 2(h_t - o_t)(l_t - o_t)] - 0.383(c_t - o_t)^2, \quad (1)$$

where h_t, l_t, o_t and c_t are, respectively, the natural logarithms of daily high, low, opening, and closing prices on day *t*.

Figure 2 illustrates the estimated volatility over time for each index, revealing significant clusters and sudden spikes that align with previously discussed periods of market stress. These volatility surges clearly reflect the sensitivity of the indices to global economic events and their interconnectedness with other major economies. However, the effects of global events differ across various indices, with the same event influencing each index in unique ways (Wael Dammak, 2024).

In early 2014, Russia experienced a significant surge in volatility, increasing by approximately 107% from February 26 to February 28. By mid to late 2014, heightened volatility also became particularly evident in Brazil and China. During this period, Brazil and Russia faced severe economic and financial crises, which likely had a profound impact on their stock prices.

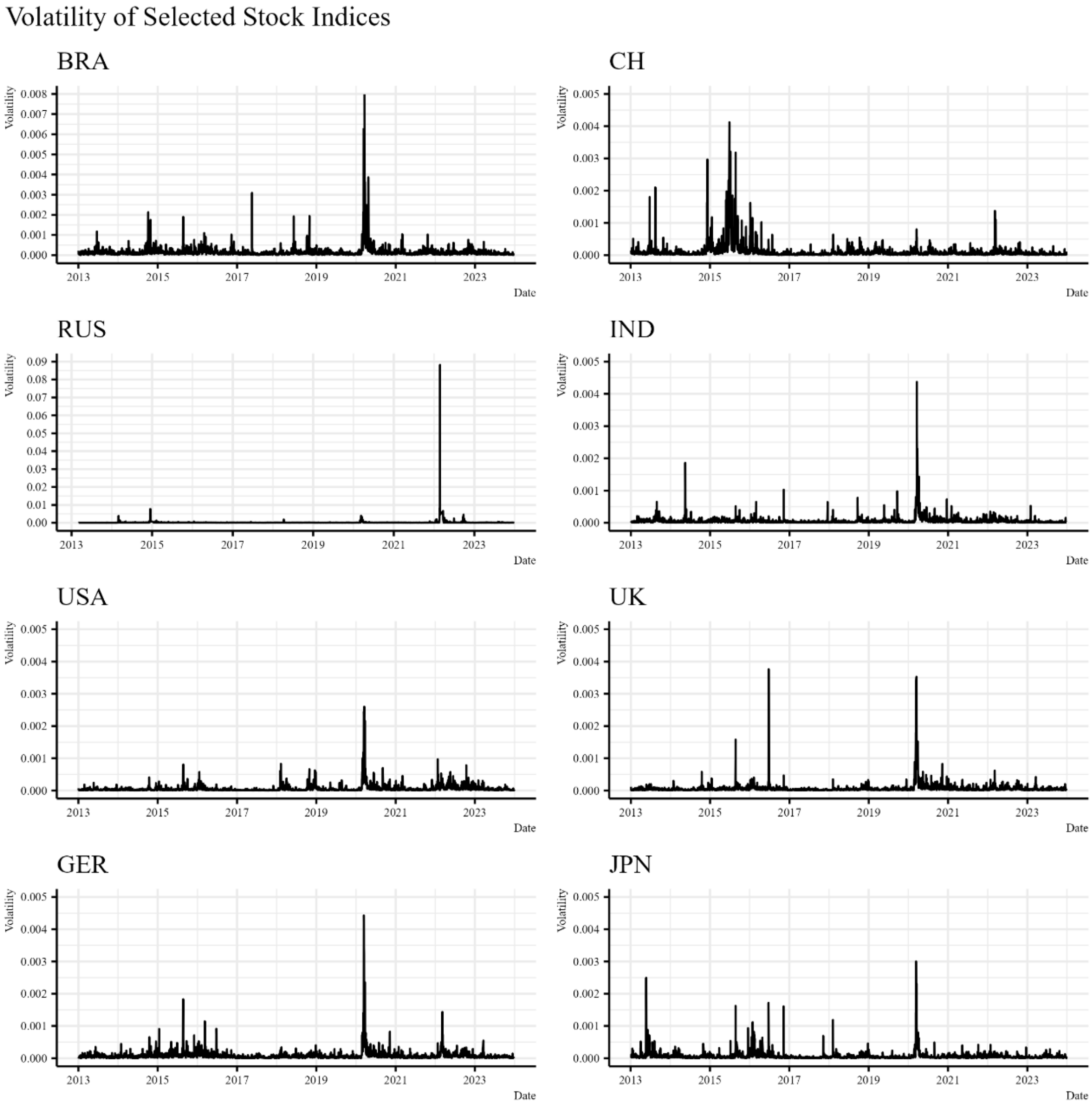

FIGURE 2 – Dynamics of daily volatility in each market.

During 2015 and 2016, a significant rise in volatility was observed across all indices, particularly amongst developed markets, reflecting the global impacts of the events that culminated in the 2015-2016 Stock Market Selloff. China experienced extreme fluctuations in 2015 due to its market turbulence, with its index surging by approximately 5,145% in just two months, from the end of April to the end of June. Additionally, the UK index saw a dramatic spike in volatility of approximately 3,011% from June 23 to

June 24, 2016, attributed to the uncertainty and market reactions surrounding the Brexit referendum held on June 23.

The USA-China trade war from 2018 to 2019 contributed to some volatility in China and the USA, though its influence was less impactful on volatility compared to other shocks.

The shock induced by the COVID-19 pandemic led to unprecedented disruptions in all financial markets, resulting in sharp increases in volatility across all indices in 2020. For most indices, except those of Russia, China, and the UK, the highest volatility spike occurred in 2020. The UK experienced a volatility spike during COVID-19 that was very close to the peak observed in 2016 (Brexit). China's most significant spike occurred in mid-2015, during its market turbulence, while Russia experienced its highest volatility level in late February 2022, during the onset of the Ukraine-Russia war, with a surge of approximately 1,343% from February 22 to February 24.

The uncertainties arising from the Russia-Ukraine war, particularly its impact on energy and food prices, have differentially impacted markets, resulting in notable increases in volatility in the USA, China, and Germany.

3.3. Descriptive Analysis of Stock Volatility

Table II and Table III present a summary of key statistical measures of the stock volatility estimates of the eight stock market indices: S&P 500 (USA), FTSE 100 (UK), DAX 40 (GER), Nikkei 225 (JPN), Shanghai Composite Index (CH), Ibovespa Index (BRA), MOEX Russia Index (RUS) and BSE SENSEX Index (IND).

Russia’s index has the largest standard deviation and the highest volatility spike, indicating a greater level of market instability, greater dispersion of price movements, and an overall higher risk. Following Russia, Brazil's index has the second highest standard deviation, with India's index ranking third and China’s index fourth.

All indices have a mean volatility higher than the median, suggesting the presence of extreme values or outliers that drive up the average volatility. For Russia and China, the mean is approximately 1.58 and 1.13 times the third quartile, respectively, suggesting that although overall volatility is generally moderate, there are significant spikes during periods of crisis. This observation is supported by the positively high skewness values for all indices. Furthermore, kurtosis values are extremely high across all indices, confirming that the distributions are heavily tailed. The evidence of leptokurtosis indicates more extreme deviations from the volatility mean than would be expected in a normal distribution, highlighting the presence of outliers and periods of heightened market stress. The Jarque-Bera test was conducted to assess normality, confirming evidence of non-normal distributions. This evidence is supported by the high kurtosis and positive skewness values.

TABLE II – VOLATILITY SUMMARY STATISTICS, BRICS' STOCK INDICES

	BRA	**CH**	**RUS**	**IND**
Min	0.0000033	0.0000026	0.000000	0.0000034
1st Qu.	0.0000560	0.0000236	0.000028	0.0000202
Median	0.0000997	0.0000466	0.000055	0.0000343
Mean	0.0001718	0.0001071	0.000167	0.0000700
3rd Qu.	0.0001720	0.0000944	0.000106	0.0000640
Max	0.0137523	0.0041217	0.088180	0.0111144
Std. Dev.	0.0004805	0.0002540	0.001962	0.0002884
Kurtosis	396.81333	95.919581	1936.6442	1056.27429
Skewness	17.335280	8.3106016	43.248678	29.2111585
JB-Stat	13616853***	776311***	326410477***	96952691***
ADF-Stat	-18.6475***	-16.1372***	-27.914***	-23.3615***

*, ** and *** indicates significance level at 10%, 5% and 1%, respectively.

TABLE III – VOLATILITY SUMMARY STATISTICS, DEVELOPED MARKETS' STOCK INDICES

	USA	**UK**	**GER**	**JPN**
Min	0.00000084	0.0000015	0.00000095	0.000000
1st Qu.	0.00001130	0.0000186	0.00002322	0.000017
Median	0.00002513	0.0000335	0.00004632	0.000032
Mean	0.00006096	0.0000658	0.00008486	0.000066
3rd Qu.	0.00005542	0.0000635	0.00009250	0.000064
Max	0.00260155	0.0037617	0.00442989	0.003002
Std. Dev.	0.00014940	0.0001727	0.00018819	0.000153
Kurtosis	134.578521	256.00917	244.036676	150.0858
Skewness	9.87778548	13.988531	13.3264695	10.44164
JB-Stat	1542390***	5645383***	5123739***	1922879***
ADF-Stat	-13.3086***	-17.6223***	-16.1436***	-20.2602***

*, ** and *** indicates significance level at 10%, 5% and 1%, respectively.

The Augmented Dickey-Fuller (ADF) test, with both drift and trend components, was used to assess the stationarity of the volatility series for each index. The results confirm that all volatility series are stationary, indicating no unit root and suggesting that the series are mean reverting, as expected in financial markets.

3.4. Correlogram of Stock Volatilities

To gain an initial overview of the co-movement of stock volatility, I plotted the full-sample contemporaneous correlation matrix (Pearson correlation matrix) in Figure 3. High correlations amongst Germany, the UK, and the USA's volatility reflect strong economic ties amongst developed markets and similar market responses to global events. Germany and the UK's volatility exhibit the highest correlation (0.82), suggesting a significant economic and financial linkage. Japan's volatility also shows moderate correlations with these three countries. China and Russia's low correlations with other markets indicate their relatively independent and distinct volatility behaviour. In contrast, Brazil and India, as emerging markets, show some correlation with other markets' volatility, reflecting their partial integration into the global financial system.

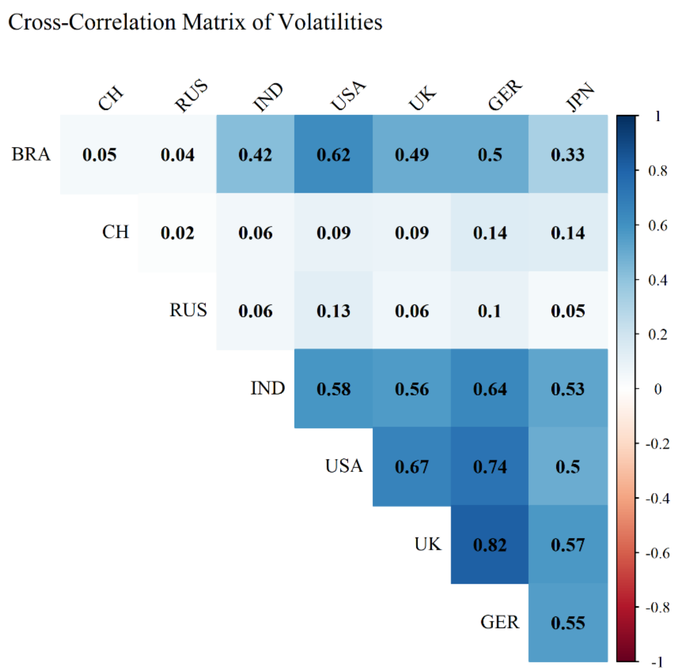

FIGURE 3 – Cross-correlations matrix of volatilities.

4. METHODOLOGY

This section describes the Diebold-Yilmaz (2012) methodology that I use to identify and quantify volatility spillovers across the stock markets of the developed and BRICS countries under study.

Diebold-Yilmaz proposed the DY-2012 spillover index that simplifies complex market interactions into a single, comprehensive metric, providing clearer insights into the dynamics and interconnectedness of cross-market volatility spillovers. The DY-2012 spillover index is based on the forecast error variance decomposition of a Vector Autoregressive (VAR) model, which allows breaking down the forecast error variances of each variable into components attributable to various system shocks.

I began by estimating an appropriate VAR model for an 8-dimensional vector composed of eight variables corresponding to the volatility indices of the following markets: USA, UK, Germany, Japan, China, Brazil, Russia, and India. To determine the optimal lag order for the VAR model, I analysed the following information criteria: Akaike Information Criterion (AIC), Hannan-Quinn Criterion (HQ), Schwarz Bayesian Criterion (SC), and Final Prediction Error (FPE). According to the AIC and FPE criteria the optimal lag length to be used and which minimizes their values is 14. However, I considered using a VAR model with lag 14 inaccurate due to excessive complexity and risk of overfitting. The HQ and SC criteria suggested more reasonable lag lengths of 7 and 5, respectively. Therefore, I opted to use a VAR model with a lag length of 5 for calculating the DY-2012 spillover index, although similar results could be achieved with a lag length of 7.

The 8-dimensional VAR model of order 5 is formulated as:

$$x_t = \sum_{j=1}^{5} \Phi_j \, x_{t-j} + \varepsilon_t \tag{2}$$

where Φ_j denote (8×8) parameter matrices and $\varepsilon \sim (0, \Sigma)$ represents a vector of independently and identically distributed disturbances with a mean of zero and covariance matrix Σ.

The VAR model can be rewritten into a moving average (MA) representation, which expresses x_t as a linear combination of present and past shocks. The MA representation is given by $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$ where A_i are (8×8) matrices of coefficients that map shocks to responses over time. These matrices are defined recursively as $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{i-p}$, for $i \geq 1$. The coefficient matrix A_0 is the (8×8) identity matrix, representing the contemporaneous impact of shocks, while $A_i = 0$ for $i < 0$, ensuring causality. This representation captures how current and past shocks influence x_t with A_i describing the system's dynamic responses at each lag.

Following Diebold and Yilmaz (2012), the shocks were decomposed using a generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998), hereafter KPPS, ensuring that the forecast-error variance decompositions are invariant to the ordering of the variables. The predictive horizon for the variance decomposition was set as 10 days.

The own variance shares are defined as the fractions of the 10-step-ahead error variances in forecasting x_i that are due to shocks to x_i , for $i = 1, 2, \dots, 8$, whereas cross variance shares, or spillovers, as the fractions of the 10-step-ahead error variances in forecasting x_i that are due to shocks to x_j , for $i, j = 1, 2, \dots, 8$, such that $i \neq j$. The KPPS 10-step-ahead (H=10) generalized forecast error variance decompositions can be defined as follows:

(3) $$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A'_h e_i)} \text{ for i, j } = 1, 2, \dots, 8$$

where Σ is the variance matrix for the error vector ε, σ_{jj} is the standard deviation of the error term for the *j*th equation, and e_i is the selection vector with one at the *i*th position and zeros elsewhere.

Diebold and Yilmaz (2009, 2012) employed normalized forecast error variance decomposition $\tilde{\theta}_{ij}^{g}(H)$, defined in equation (4), to ensure that the sum of the variance decomposition contributions for each variable equal 1. This approach allows for the calculation of the total spillover index, directional spillover index, and net spillover index.

(4) $$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{8} \theta_{ij}^{g}(H)}$$

The total spillover index is calculated as the proportion of forecast error variance in all variables attributable to cross-market spillovers, measuring the overall degree of volatility transmission across markets, as follows:

(5) $$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{8} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{8} \tilde{\theta}_{ij}^{g}(H)} \cdot 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{8} \tilde{\theta}_{ij}^{g}(H)}{8} \cdot 100$$

The directional spillovers provide a detailed breakdown of the total spillovers, capturing the shocks received by market *i* from all other markets and transmitter by market *i* to all other markets. The directional spillovers transmitted by market *i* to all other markets *j* ("From" directional spillover index) is calculated as:

(6) $$S_{\cdot i}^{g}(H) = \frac{\sum_{\substack{j=1 \\ i \neq j}}^{8} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{8} \tilde{\theta}_{ji}^{g}(H)} \cdot 100 = \frac{\sum_{\substack{j=1 \\ i \neq j}}^{8} \tilde{\theta}_{ji}^{g}(H)}{8} \cdot 100$$

Conversely, the spillovers received by market *i* from all other markets *j* ("To" directional spillover index) is given by:

(7) $$S_{i \cdot}^{g}(H) = \frac{\sum_{\substack{j=1 \\ i \neq j}}^{8} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{8} \tilde{\theta}_{ij}^{g}(H)} \cdot 100 = \frac{\sum_{\substack{j=1 \\ i \neq j}}^{8} \tilde{\theta}_{ij}^{g}(H)}{8} \cdot 100$$

Net spillovers are simply the difference between the gross volatility shocks transmitted to others ("To" directional spillover index) and those received from all other markets ("From" directional spillover index). It indicates whether a market is a net transmitter or a net receiver of volatility. The net volatility spillover from market *i* to all other markets *j* is obtained as:

(8) $$S_{i}^{g}(H) = S_{\cdot i}^{g}(H) - S_{i \cdot}^{g}(H)$$

Net pairwise spillovers provide a bilateral perspective, showing the net effect of volatility transmission between two specific markets *i* and *j*. The net pairwise volatility spillover between markets *i* and *j* is simply the difference between the gross volatility shocks transmitted from market *i* to market *j* and those transmitted from *j* to *i*:

(9) $$S_{ij}^{g}(H) = \left(\frac{\tilde{\theta}_{ji}^{g}(H)}{\sum_{i,k=1}^{8} \tilde{\theta}_{ik}^{g}(H)} - \frac{\tilde{\theta}_{ij}^{g}(H)}{\sum_{j,k=1}^{8} \tilde{\theta}_{jk}^{g}(H)} \right) \cdot 100 = \left(\frac{\tilde{\theta}_{ji}^{g}(H) - \tilde{\theta}_{ij}^{g}(H)}{8} \right) \cdot 100$$

I began by using a static approach, following the work of Diebold and Yilmaz (2012), by building a full-sample spillover table to summarize the average behaviour. However, as Diebold and Yilmaz (2012) emphasize, a single fixed-parameter model may not adequately reflect the varying conditions across the entire sample period, potentially overlooking key secular and cyclical fluctuations in spillovers. Financial markets have experienced both periods of growth and stability, with rising prices, as well as episodes of turbulence and uncertainty, marked by sharp declines and heightened volatility. To better capture these dynamics, I employed a rolling-sample approach, using a 200-day rolling window width, to identify the time-varying nature of spillovers and provide a dynamic view of how spillover indices evolve over time.

Finally, I used the R programming language and environment for statistical computing (R Core Team 2024; R version 4.4.0), along with the newly developed "Spillover" package (Urbina 2023), to apply the DY-2012 methodology and generate all the results presented in this study. The "Spillover" package offers a comprehensive set of functions for implementing the models and plots detailed in Diebold and Yilmaz (2009, 2012).[1]

5. Empirical Results

This section presents and describes the results of the DY spillover index derived from both static and dynamic analyses for the period from March 2013 to December 2023. First, the static analysis offers a broad understanding of volatility spillovers across the entire sample, providing insights into overall market interconnectedness. Subsequently, the rolling-sample analysis is explored, revealing how spillover effects have evolved over time, particularly in response to changing economic conditions and significant periods of turmoil.

5.1 Static Volatility Spillover Analysis

Table IV, referred to as the Volatility Spillover Table, presents all spillover indices, expressed in percentage, obtained using the entire sample. The *ij*th entry represents the estimated contribution to the forecast error variance of market *i* resulting from innovations to market *j*. In other words, it quantifies the portion of volatility forecast error variance of market *i* attributable to shocks from market *j*. The diagonal elements indicate the contribution of own-market volatility (self-spillovers), whereas the off-diagonal elements capture the cross-market volatility spillovers. The column sums labelled “To others” indicate the total spillover effect that a particular market (column) has on all other markets. Conversely, the row sums labelled “From others” reflect the total spillover effect that all other markets have on a particular market (row). Notice that the column sums labelled “To other (including own)” include its own self-spillovers. Finally, the total

[1] The code used to generate the results of this work is available upon request to the author.

spillover index is presented in the lower right corner, measuring the overall level of interconnectedness between the markets. Additionally, the table presents both the total spillovers within the BRICS and G7 groups of countries, as well as spillovers between the BRICS and G7, offering a detailed decomposition of the total spillover index.

The total volatility spillover index stands at 44.92%, revealing a high overall level of interconnectedness amongst the analysed stock markets, as nearly 45% of the forecast error variance across all stock indices is attributable to spillovers.

This value can be decomposed into spillovers transmitted by BRICS countries (24.23%) and by developed countries (20.69%), showing a relatively small discrepancy between the two. However, when considering the decomposition of total spillover based on spillover recipients, developed markets are significantly more affected, receiving a significantly higher portion of 31.28%, whereas BRICS countries receive 13.64%.

The total spillover can also be broken down into within-group spillovers – 7.00% within BRICS and 14.05% within G7 – and cross-group spillovers – 17.23% from BRICS to G7 countries and 6.64% from G7 to BRICS countries. Thereby, spillovers from BRICS to developed markets, along with those within developed markets, are the largest contributors to overall total volatility spillover.

Brazil stands out as the strongest transmitter of volatility to other markets, contributing 168.35% to the forecast error variance of spillovers. Developed markets are the primary recipients, absorbing 119.29% of Brazil's spillovers, with Germany (38.88%), the USA (33.90%), and the UK (28.83%) being the main receivers. Within the BRICS group, Brazil's spillovers are predominantly directed toward India, accounting for 47.91%.

After Brazil, India is the second-largest BRICS market contributing to spillovers, with 23.37%, including 16.99% to developed markets. However, India also stands out as the largest recipient of spillovers within the BRICS group, receiving 68.2%, with 20.07% coming from developed markets.

China and Russia have the smallest spillover indices amongst all the selected markets in both directions, contributing only about 1% to others while receiving approximately 9% and 5%, respectively, mainly from developed markets. Both China and Russia's indices reveal relatively isolated market behaviour.

TABLE IV – VOLATILITY SPILLOVER TABLE, EIGHT STOCK MARKETS

	FROM										
TO	BRA	CH	RUS	IND	USA	UK	GER	JPN	FROM BRICS	FROM G7	**FROM OTHERS**
BRA	72.93	0.13	0.04	5.76	7.69	7.32	5.49	0.64	5.93	21.14	**27.07**
CH	1.01	90.98	0.05	0.19	0.75	0.8	5.53	0.7	1.25	7.78	**9.02**
RUS	0.19	0.08	95.17	0.42	2.4	0.39	1.28	0.07	0.69	4.14	**4.83**
IND	47.91	0.14	0.08	31.8	5.31	5.28	6.5	2.98	48.13	20.07	**68.2**
USA	33.29	0.09	0.39	2.45	37.55	11.62	13.37	1.23	36.22	26.22	**62.45**
UK	28.83	0.13	0.07	3.69	9.53	37.21	16.15	4.38	32.72	30.06	**62.79**
GER	38.88	0.1	0.4	5.06	12.04	15.06	26.91	1.56	44.44	28.66	**73.09**
JPN	18.24	0.39	0.03	5.79	7.2	12.47	7.79	48.09	24.45	27.46	**51.91**
TO BRICS	49.11	0.35	0.17	6.37	16.15	13.79	18.8	4.39	7.00	6.64	**13.64**
TO G7	119.24	0.71	0.89	16.99	28.77	39.15	37.31	7.17	17.23	14.05	**31.28**
TO OTHERS	**168.35**	**1.05**	**1.06**	**23.37**	**44.93**	**52.93**	**56.12**	**11.56**	**24.23**	**20.69**	**44.92**
TO OTHERS (INCLUDING OWN)	241.27	92.03	96.23	55.17	82.48	90.14	83.03	59.65	484.71	315.29	800

Amongst developed markets, Germany, followed by the UK and the USA, are the main transmitters of volatility, contributing 56.12%, 52.93%, and 44.93% respectively to the forecast error variance of other markets. Spillovers from other markets to these markets are also substantial, with Germany receiving 73.09% of its volatility from other markets, while the UK and the USA each receive approximately 63%. The spillovers for these three markets are largely driven by their interconnectedness, with significant portions of their volatility coming from each other. This highlights the strong links amongst these markets and their collective impact on overall market volatility.

Japan emerges as the developed market contributing the least to spillovers, with only 11.56%. It primarily acts as a net receiver, absorbing around 52% of volatility from other markets – 24.45% from BRICS and 27.46% from developed markets.

5.2. Dynamic Volatility Spillover Analysis

The Static Analysis provides a snapshot of market interconnectedness, which may overlook the dynamic nature of interactions, failing to capture how spillover effects can shift over time in response to changing economic conditions. To address this gap, this section focuses on the findings from the rolling sample analysis, focusing on the time-varying characteristics of volatility spillovers. I discuss the Spillover Plots, providing insights into total, directional, and net spillovers across financial markets, thereby highlighting the importance of a dynamic approach in understanding volatility spillovers.

5.2.1. Total Volatility Spillover

Figure 4 presents the Dynamic Total Spillover Index, revealing spillovers ranging from approximately 25% to over 80% of the forecast error variance across all stock indices. The fluctuations in volatility spillovers highlight the dynamic nature of market interdependencies and the significant influence of global economic events. Compared with Figure 2, the total spillover is highly consistent with the world's risk events as they tend to rise in tandem with underlying market volatility, with periods of heightened uncertainty leading to sharp increases in spillover effects.

The plot reveals at least six significant peaks of high volatility spillovers, which can be associated with key shocks. The first outstanding spike occurs in late 2014, surpassing 60%. This peak is likely connected to the unsustainable rise in Chinese stock prices in late 2014 and the onset of turbulence in its market. A period of sustained high volatility spillovers followed from mid-2015 to mid-2016, aligning with the 2015-2016 Stock Market Selloff. During this period, spillover values exceeded 60% and peaked at nearly 70% during two spikes at the beginning and end of this interval. The peak in mid-2016 can be attributed to the market reactions surrounding the Brexit referendum in June 2016.

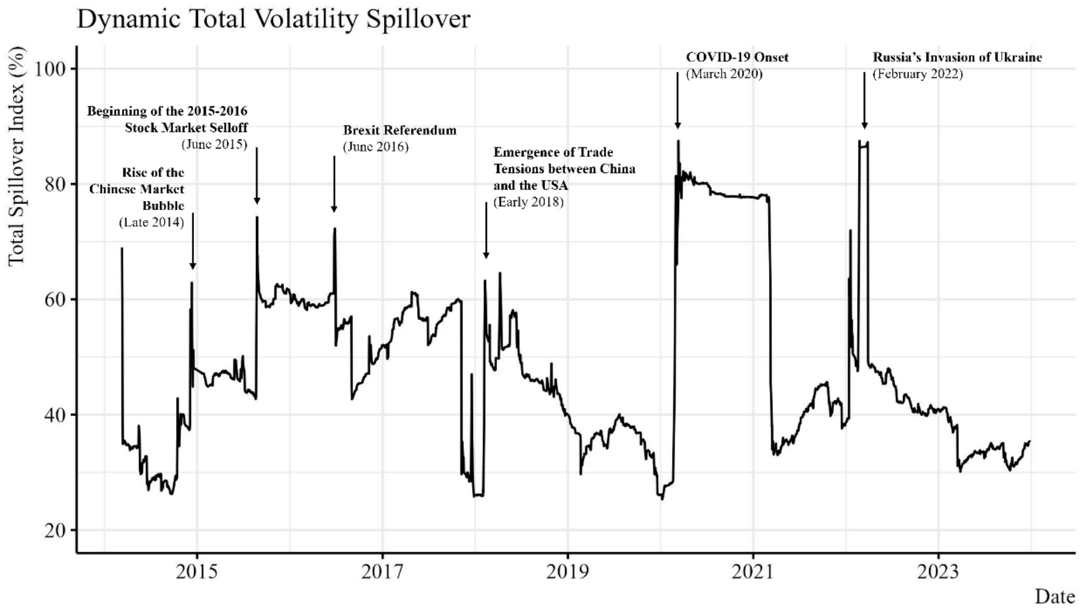

FIGURE 4 – Total volatility spillovers.

In 2017, volatility spillovers showed an upward trend, followed by a sudden drop to below 20% in late 2017. However, they surged rapidly again in early 2018, with two notable peaks observed during that period. This surge is likely linked to the emergence of trade tensions between China and the USA in 2018.

From mid-2018, volatility spillovers decreased until a prominent and persistent peak emerged during the COVID-19 pandemic in 2020. The index spiked above 80% and remained at this elevated level for nearly a year, indicating an exceptionally high degree of global market interconnectedness and volatility transmission.

In early 2022, there was also a significant peak in volatility, exceeding 80%, likely driven by the crash in the Russian stock market following Russia's invasion of Ukraine.

In summary, major financial turbulences, such as the Global Stock Market Selloff, global health emergencies as the COVID-19 pandemic, and geopolitical conflicts such as the trade tensions between China and the USA, and the Russia-Ukraine war, have profoundly influenced the dynamics of volatility spillovers, driving them to extremely high levels. These occurrences illustrate the strong connection between external shocks and the increased volatility transmission across global markets.

5.2.2. Directional Volatility Spillover

5.2.2.a. At Group Level

This section presents three distinct time-varying overviews of the decomposition of the total spillover index, as illustrated in Figure 5, Figure 6 and Figure 7. This analysis focuses on the directional volatility spillovers between the two groups of countries, emerging markets within BRICS and developed markets within the G7. It identifies the main transmitters and receivers of volatility throughout the study period, revealing which group has been more affected by each phase of turmoil outlined in the previous section.

Figure 5 shows the trend of directional volatility spillovers from BRICS and from developed markets to other markets. Throughout most of the observed period, developed markets consistently show higher spillover transmission levels than BRICS. Typically, spillovers from developed markets range from 20% to 40%, excluding periods of volatility spikes, while BRICS markets usually transmit spillovers in the lower range of 10% to 20%.

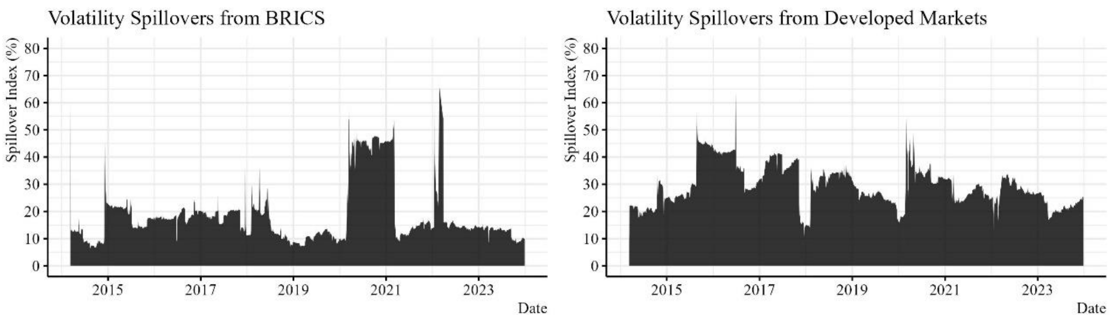

FIGURE 5 – Directional volatility spillovers:
FROM BRICS to other markets vs FROM developed to other markets.

Both groups generally follow similar trends over time. However, substantial shifts in the directional dynamics of the spillover trends occur during periods of heightened turmoil. For example, during the Chinese stock market boom in late 2014 and the onset of the Russia-Ukraine war in early 2022, spillovers from the BRICS countries significantly surpassed those from the G7 nations, reaching peaks of 45% and over 60%, respectively.

During the global upheaval caused by the COVID-19 pandemic in early 2020, both groups experienced a drastic surge in spillover transmission, reaching nearly 60%, indicating that this event significantly impacted both groups of countries. However, throughout the rest of 2020, spillovers from BRICS remained elevated at around 45%, while those from developed markets showed a gradual downtrend. Similarly, in early 2018, the escalation of trade tensions led both groups to exhibit spikes in spillover transmission.

During the 2015-2016 Stock Market Selloff, the primary spillover transmitters were developed markets, which experienced a notable increase in spillover transmission, marked by two distinct spikes at the beginning and end of this period.

To sum up, besides both groups of countries experiencing extreme surges in spillovers during key events, emerging markets demonstrated the most significant and drastic spikes in volatility transmission, highlighting the heightened susceptibility of BRICS countries to transmit volatility in the face of major global financial shocks.

Figure 6 presents the dynamics of volatility spillovers received by BRICS and developed markets. In addition to being the group that transmits more spillovers over time, developed markets also consistently receive a larger share of spillovers. In general, excluding periods of volatility spikes, the spillovers to developed countries range from approximately 15% to 35%, whereas BRICS markets receive between 10% and 25%.

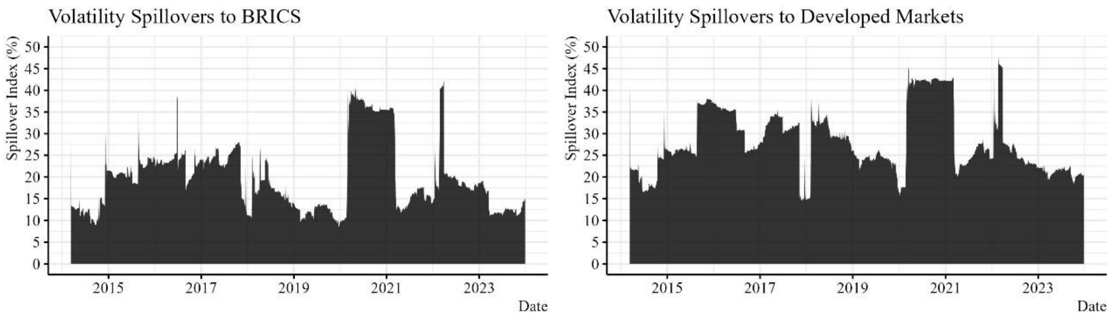

FIGURE 6 – Directional volatility spillovers:
from other markets TO BRICS vs from other markets TO developed markets.

Even during periods of significant turmoil, spillovers to developed markets dominate, highlighting their greater exposure and integration in global volatility transmission networks.

Lastly, Figure 7 offers a more detailed view of how volatility spillovers move through the system, illustrating the flow of volatility between the two groups. It illustrates the decomposition of total spillovers into within-group spillovers – both within BRICS and within developed markets – and cross-group spillovers, which include spillovers from BRICS to developed markets and from developed markets to BRICS.

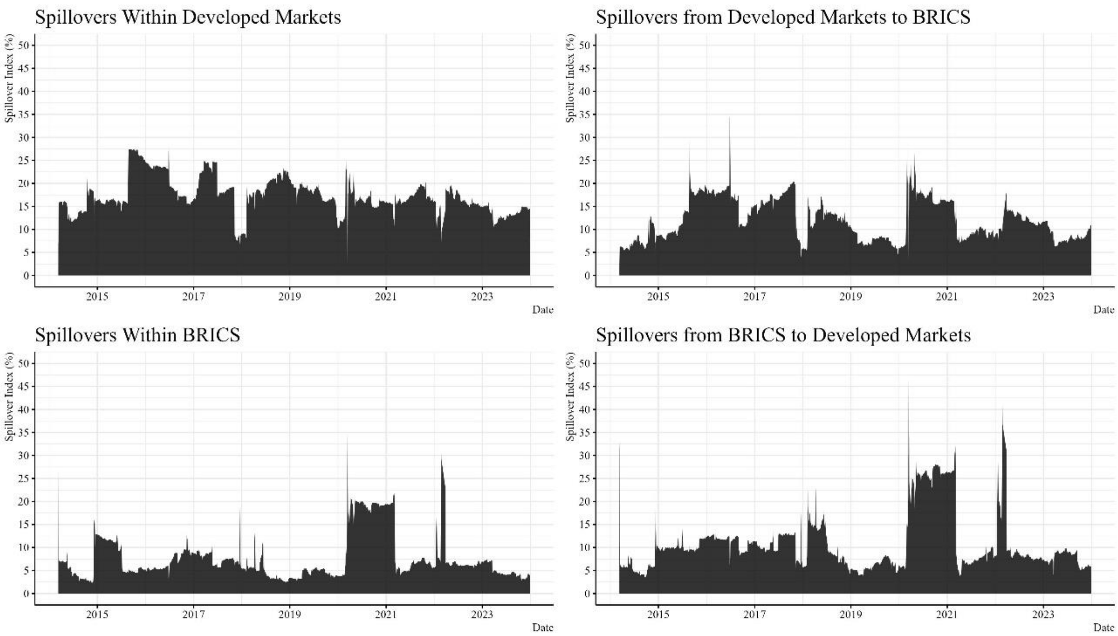

FIGURE 7 – Directional volatility spillovers: within-group and cross-group.

In line with Figure 5 and Figure 6, which identify developed markets as the primary transmitters and receivers of volatility over the observed period, the highest spillovers were consistently observed within developed markets, reflecting a relatively high degree of integration amongst these advanced economies.

Spillovers within developed markets are closely followed by spillovers from developed markets to BRICS, underscoring the influence that advanced economies exert on emerging markets. This influence is particularly evident during critical events such as the onset of the 2015-2016 Stock Market Selloff and the Brexit referendum in June 2016. During these episodes, the volatility originating from developed markets not only impacted their own economies but also had substantial repercussions for BRICS.

In mid-2015, spillovers within developed markets surged to 27.5%, while spillovers from developed markets to BRICS reached 30%. Similarly, in mid-2016, coinciding with the Brexit referendum, another peak emerged, with intra-developed market spillovers again reaching 27.5% and spillovers from developed markets to BRICS hitting their highest point at 35%.

As previously evidenced in Figure 5, spillovers from BRICS are generally lower throughout most periods. In contrast, during major global upheavals, these emerging markets often become the primary transmitters of volatility, significantly impacting developed markets during such times.

For instance, during the emergence of the Chinese market bubble, spillovers within BRICS surged, exceeding 25%, followed closely by spillovers from BRICS to developed markets. In early 2018, there was also a sudden increase in spillovers from BRICS to developed markets.

At the onset of the COVID-19 pandemic, all groups experienced substantial increases in spillover transmission, with spillovers from BRICS to developed markets dominating, peaking at over 45%. Spillovers within BRICS also rose significantly, reaching around 35%, while spillovers from developed markets to BRICS increased to 30%. Throughout the remainder of 2020, spillovers from BRICS to developed markets remained elevated, hovering around 25%, followed by spillovers within BRICS.

Similarly, during the onset of the Russia-Ukraine war, spillovers from BRICS to developed markets reached a high level of approximately 40%, while spillovers within BRICS also escalated, attaining an elevated level of 30%.

All in all, while spillovers predominantly occur within developed markets during most periods, significant shifts in the directional spillover dynamics are observed during times of heightened turmoil. During events such as the onset of the Stock Market Selloff and the Brexit referendum, spillovers from developed markets to emerging markets surged, reflecting the influence that advanced economies have on these emerging markets. Furthermore, despite their relatively isolated interactions during the overall period, BRICS countries emerge as significant transmitters of volatility during the Chinese market turbulence, the COVID-19 pandemic, and the onset of the Russia-Ukraine war, primarily affecting developed markets.

5.2.2.b. At Individual Market Level

In this section, I assess the directional volatility spillovers at the individual market level, identifying the key countries that drive spillovers within each group and highlighting which indices act as the primary transmitters or receivers of volatility, particularly after the shocks previously identified.

Figure 8 illustrates the directional spillovers transmitted by each index to other markets, while Figure 9 shows the spillovers received by each index from other markets.

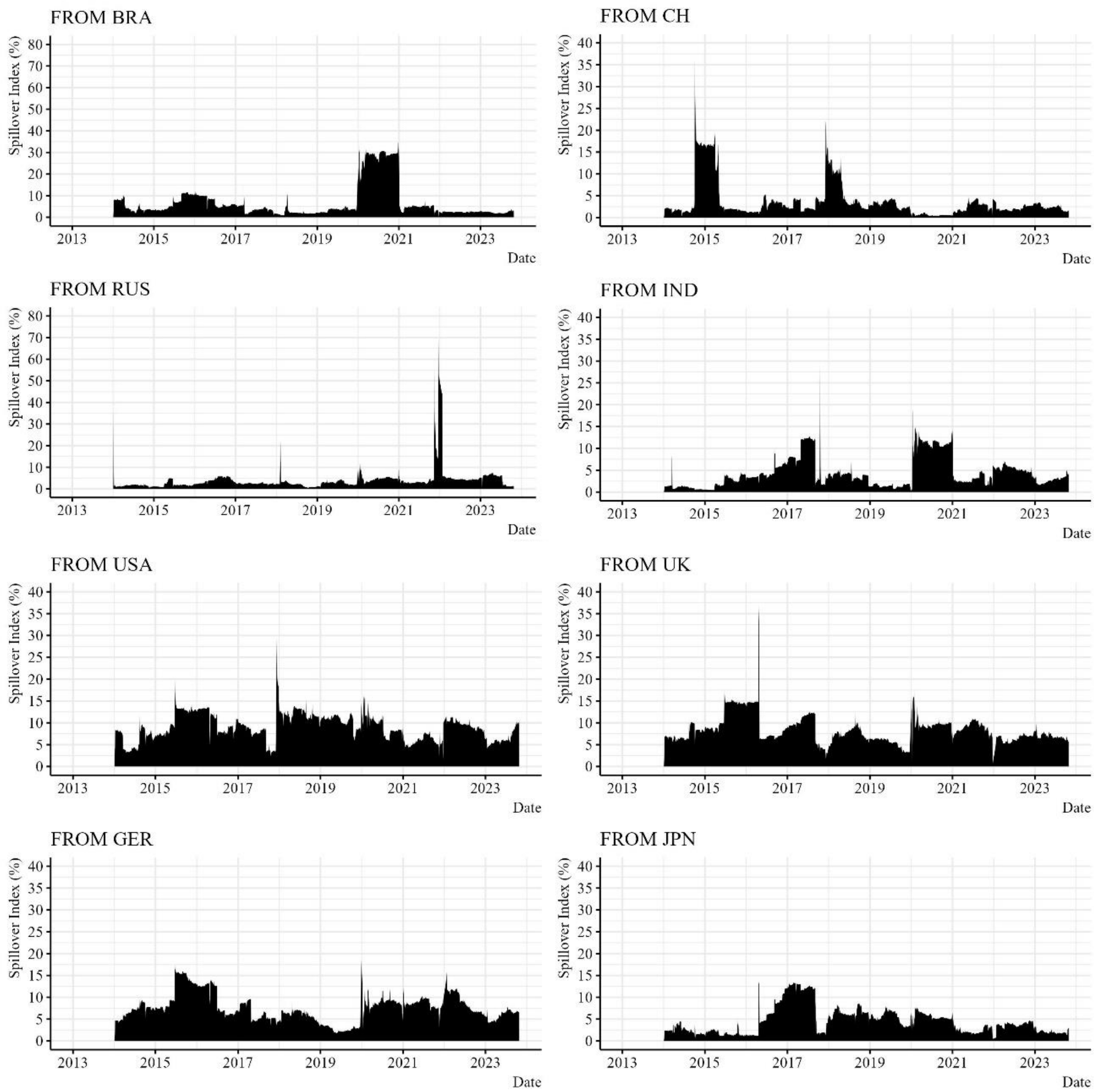

FIGURE 8 – Directional volatility spillovers: FROM each index to other markets.

From Figure 8, several key conclusions can be drawn. Overall, it can be observed that developed markets, particularly the USA, UK, and Germany, consistently maintain elevated spillover levels of around 5% to 10%. In contrast, emerging markets have spillovers below 5% for most of the time.

During major events and crises, sharp increases in volatility are observed across all countries, with emerging markets exhibiting the most extreme spikes.

In late 2014, China emerged as a key contributor to volatility transmission, with its market experiencing a significant spike in the volatility spillover index, reaching nearly 35% during the onset of turbulence in the Chinese market. China continued to exhibit elevated spillover transmission, hovering above 15% until early 2015.

During the onset of the 2015-2016 Stock Market Selloff, there was a notable increase in spillovers from the USA, UK, and Germany, with values rising from around 10% to 15%. These spillovers remained elevated throughout the period, culminating in a significant spike of nearly 35% in the UK market during the Brexit referendum, positioning the UK as the primary transmitter of volatility amongst developed markets at that time.

Another significant peak, nearing 30%, was evident in the Indian market around late 2017, after an upward trend in its spillover transmission. The Russian market also saw a peak of approximately 20% around April 2018, likely linked to USA sanctions imposed on Russian oligarchs, officials, and companies on April 6, 2018. Additionally, two peaks were observed in the China market and one in the USA, each reaching around 20% to nearly 30%, likely linked to trade tensions between these two countries.

At the onset of the COVID-19 pandemic, there were clear peaks in volatility transmission amongst various markets, including both BRICS and developed markets. Specifically, Brazil emerged as a major transmitter of volatility during the early stages of the pandemic in early 2020, with spillovers exceeding 70% and remaining elevated around 30% throughout the year.

Finally, the spike in volatility transmission during the onset of the Russia-Ukraine war was clearly driven by spillovers originating from Russia.

In Figure 9, regarding the share of spillovers received by each market, all plots display similar trends over time, with significant peaks in volatility reception during all major events covered in the analysis. It is evident that developed markets consistently receive more volatility than BRICS markets, as already uncovered in Figure 6. Developed markets regularly exhibit spillovers exceeding 5%, whereas BRICS markets more commonly experience spillovers ranging from less than 2.5% to 5%.

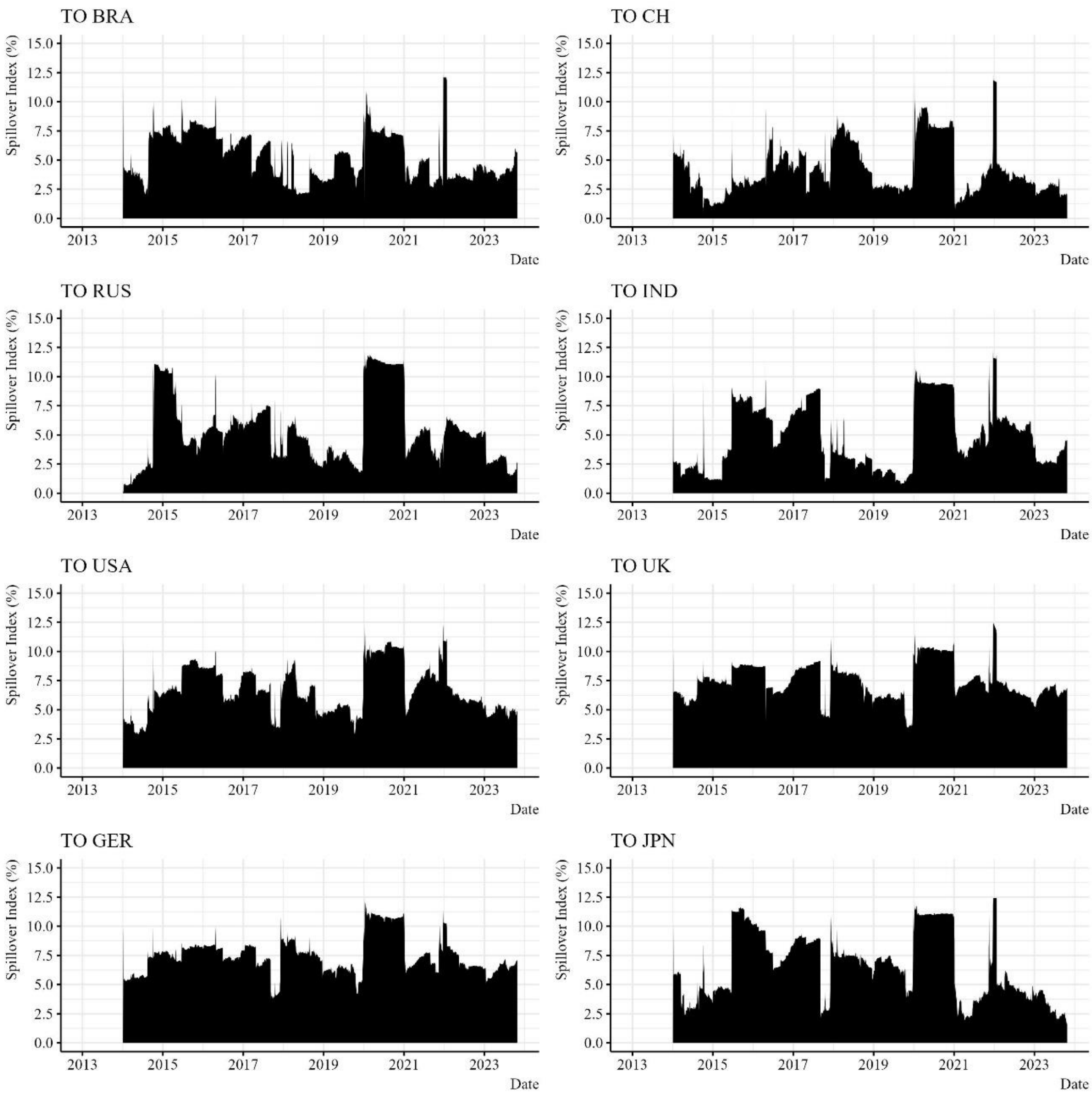

FIGURE 9 – Directional volatility spillovers: from other markets TO each index.

5.2.3. Net Volatility Spillover

This section complements the analysis by exploring the net spillovers for each index, calculated as the difference between volatility transmitted to other markets and volatility received from them. The aim is to identify whether the indices act as net transmitters or net receivers of volatility throughout the study period, thereby reinforcing the findings from the previous sections.

Figure 10 presents the net spillovers, where positive values indicate that the index is a net transmitter of volatility, meaning it transmits more than it receives, while negative values indicate that the index is a net receiver, indicating the opposite.

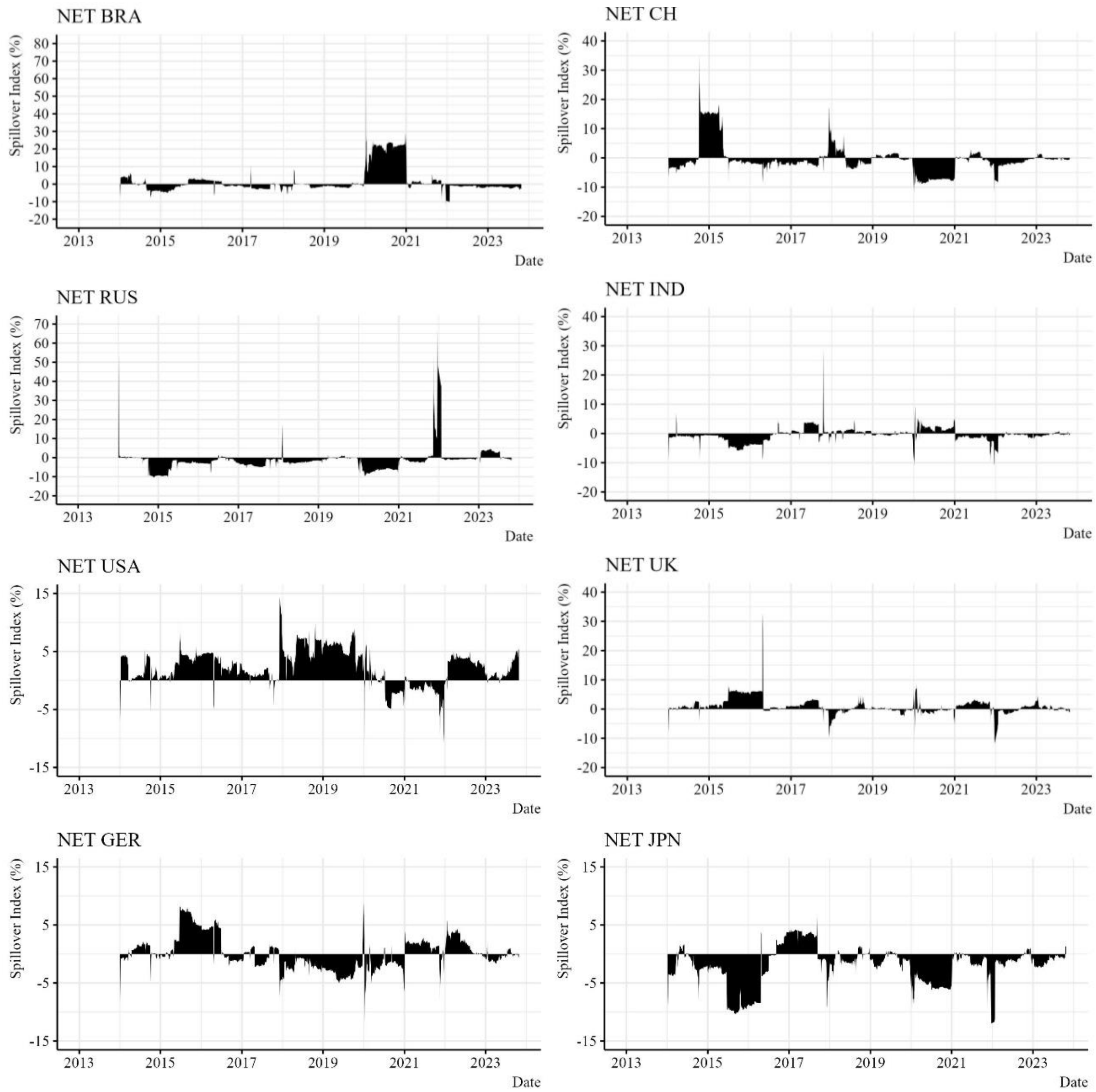

FIGURE 10 – Net volatility spillovers.

Amongst developed markets, the USA consistently emerged as the major net transmitter of volatility to other markets throughout most of the period, except during the COVID-19 pandemic, when this trend temporarily shifted. The USA's highest volatility transmission peak occurred during the trade tensions with China, reaching over 20%.

During the Stock Market Selloff from mid-2015 to mid-2016, Germany, the UK, and the USA acted as main net transmitters of volatility, with spillover values ranging from nearly 5% to 10%. Moreover, there was a dramatic surge in volatility spillovers from the

UK index, which escalated from approximately 6% to over 30%, likely attributable to the Brexit referendum. In contrast, Japan and the BRICS markets were predominantly net receivers during the Stock Market Selloff, with Japan exhibiting the highest spillover reception, reaching 10%. Japan remained a net receiver of volatility for most of the period, briefly acting as a net transmitter from mid-2016 to mid-2017.

During the COVID-19 pandemic, both the UK and Germany displayed significant spikes in volatility transmission in early 2020, reflecting the heightened uncertainty and interconnectedness of global markets during this crisis.

Amongst emerging markets, all indices consistently acted as net receivers of spillovers, with spillover values remaining relatively low and hovering around zero, except during periods of significant shocks when spillover dynamics change dramatically.

The upper right panel of Figure 10 reveals that China emerged as a significant net transmitter of volatility during two key periods: from late 2014 to mid-2015, coinciding with its market turbulence, and again in early 2018, during the onset of tensions between the USA and China.

During the COVID-19 pandemic, between 2020 and 2021, Brazil stood out as the most significant and persistent net transmitter of volatility to other markets. Its spillover values peaked at over 70% in March 2020 and remained elevated above 20% for the remainder of the year, reflecting its heightened sensitivity to this global turmoil.

India also displayed evidence of net spillovers during the pandemic, though to a lesser extent. Additionally, India experienced a significant spike in volatility transmission in December 2017, reaching nearly 30%.

By early 2022, Russia emerged as a key net transmitter of volatility, with its volatility transmission index peaking at over 50%, emphasizing the impact of geopolitical developments on market dynamics.

5.2.4. Pairwise Net Volatility Spillover

This section discusses Figure 11, Figure 12 and Figure 13, which provide a more detailed view of net spillovers, illustrating pairwise net spillovers within the same group and across different groups. The insights drawn from these graphs further reinforce the conclusions established in previous analyses.

From the analysis of Figure 11, several patterns emerge from the spillovers between BRICS and developed countries. Generally, BRICS countries acted as net receivers of volatility, while developed markets predominantly acted as net transmitters. However, there are notable exceptions during the periods of turmoil.

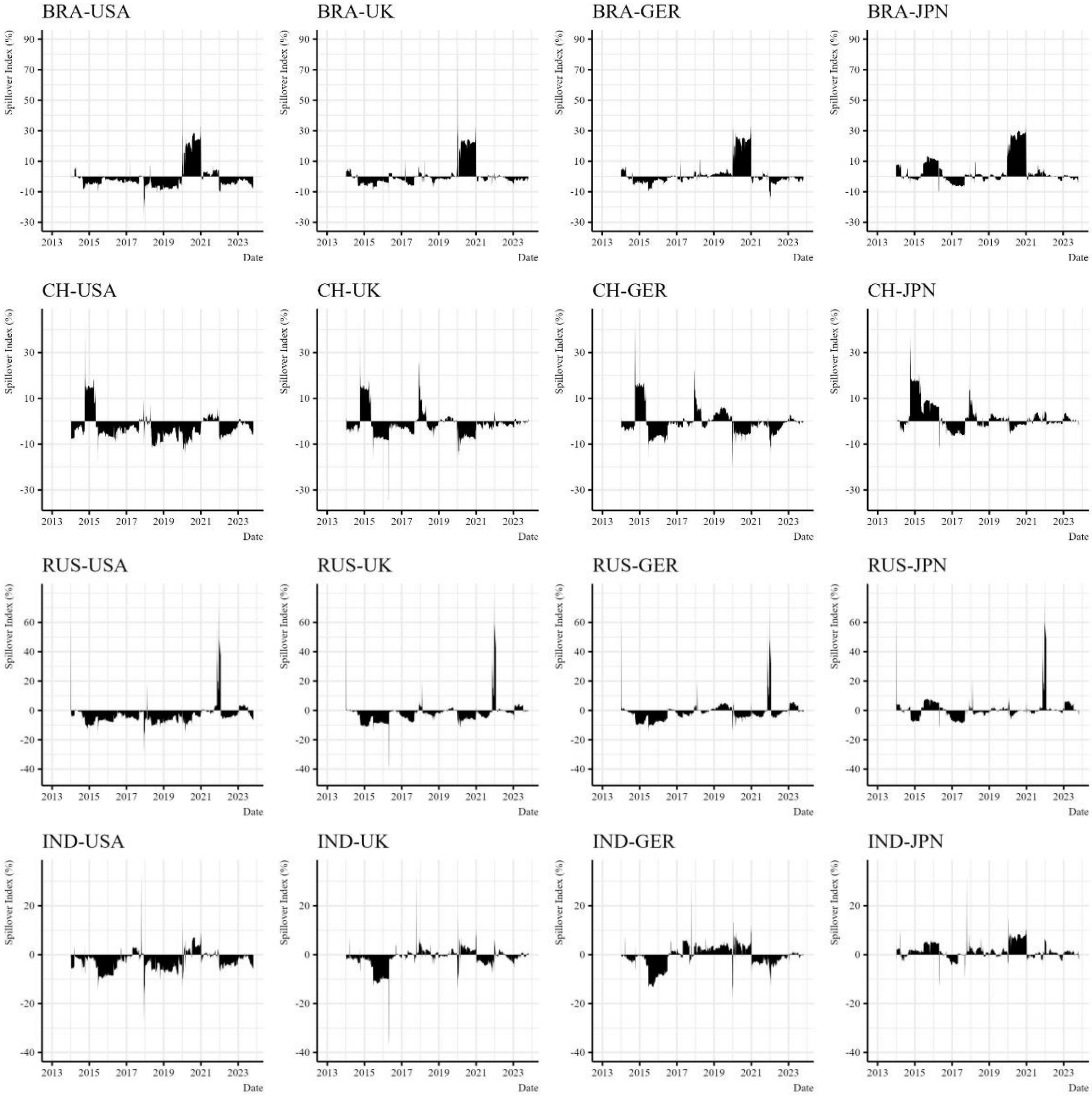

FIGURE 11 – Pairwise net volatility spillovers between BRICS and developed markets.

During the Chinese stock market boom in early 2014, China emerged as a net transmitter of volatility to all developed markets. China also played a key role during the onset of the USA-China trade war in early 2018, although the spillovers between the two countries during this period were relatively smaller, as the USA itself was transmitting a larger share of volatility.

From 2017 until the onset of the COVID-19 pandemic, India demonstrated significant spillovers, particularly towards Germany, the UK, and Japan, highlighting India's growing influence on global market volatility.

During the COVID-19 pandemic, Brazil and India became prominent net transmitters of volatility, affecting all the developed markets under analysis. Russia also emerged as a key net transmitter, particularly during the onset of the Russia-Ukraine war and in early 2018, transmitting substantial volatility to all markets.

Net spillovers within the BRICS group, as shown in Figure 12, remained relatively low, hovering close to zero for most of the period. However, after major global shocks, spillovers between these countries surged significantly, aligning with previously identified patterns of heightened volatility transmission during turbulent periods.

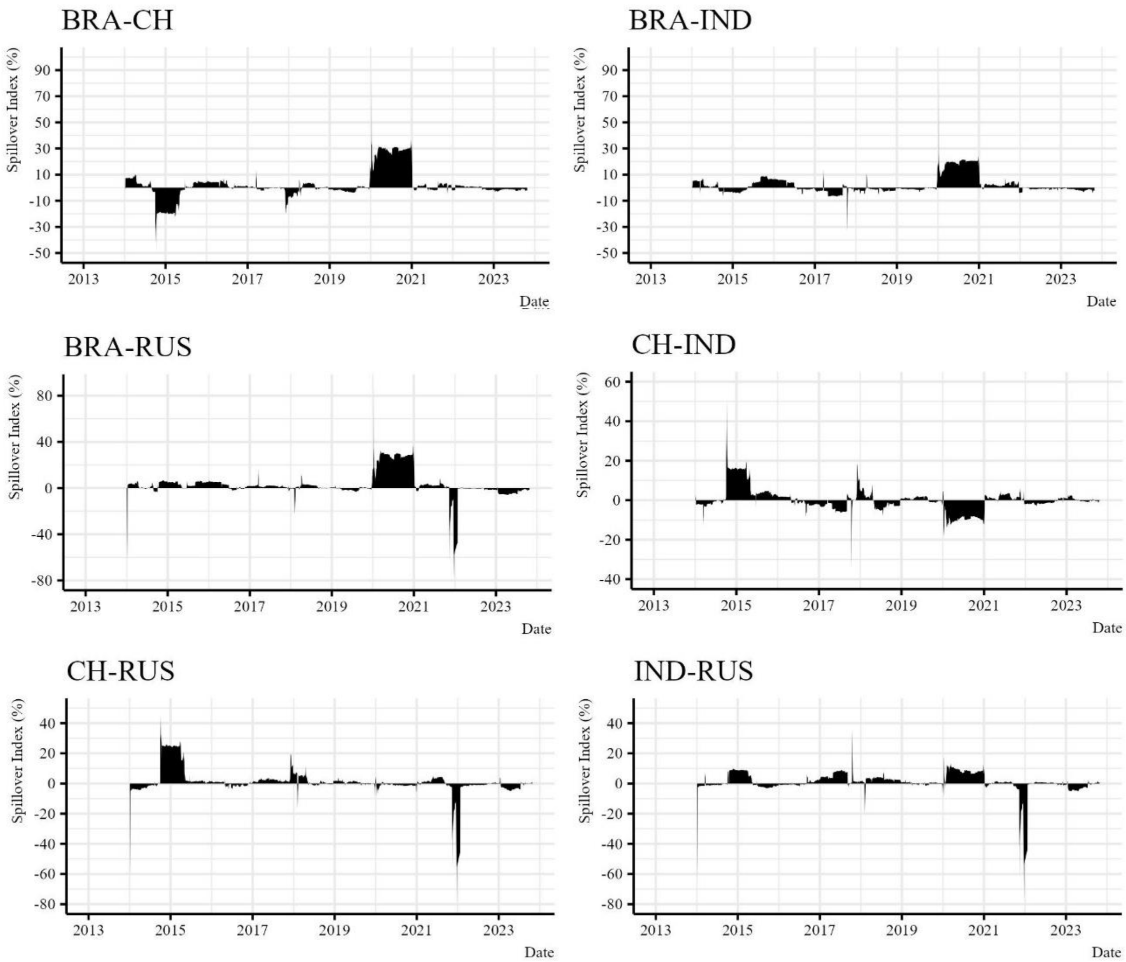

FIGURE 12 – Pairwise net volatility spillovers within BRICS markets.

In contrast, Figure 13 revealed that spillovers within developed markets remained consistently elevated over time, with occasional spikes of heightened volatility, such as in early 2018 for the USA and mid-2016 for the UK. Notably, the USA consistently acted as a primary net transmitter of volatility within developed markets. On the other hand, Japan stood out as a significant net receiver, particularly during the 2015-2016 Stock Market Selloff, receiving substantial spillovers from the USA, UK, and Germany during that period.

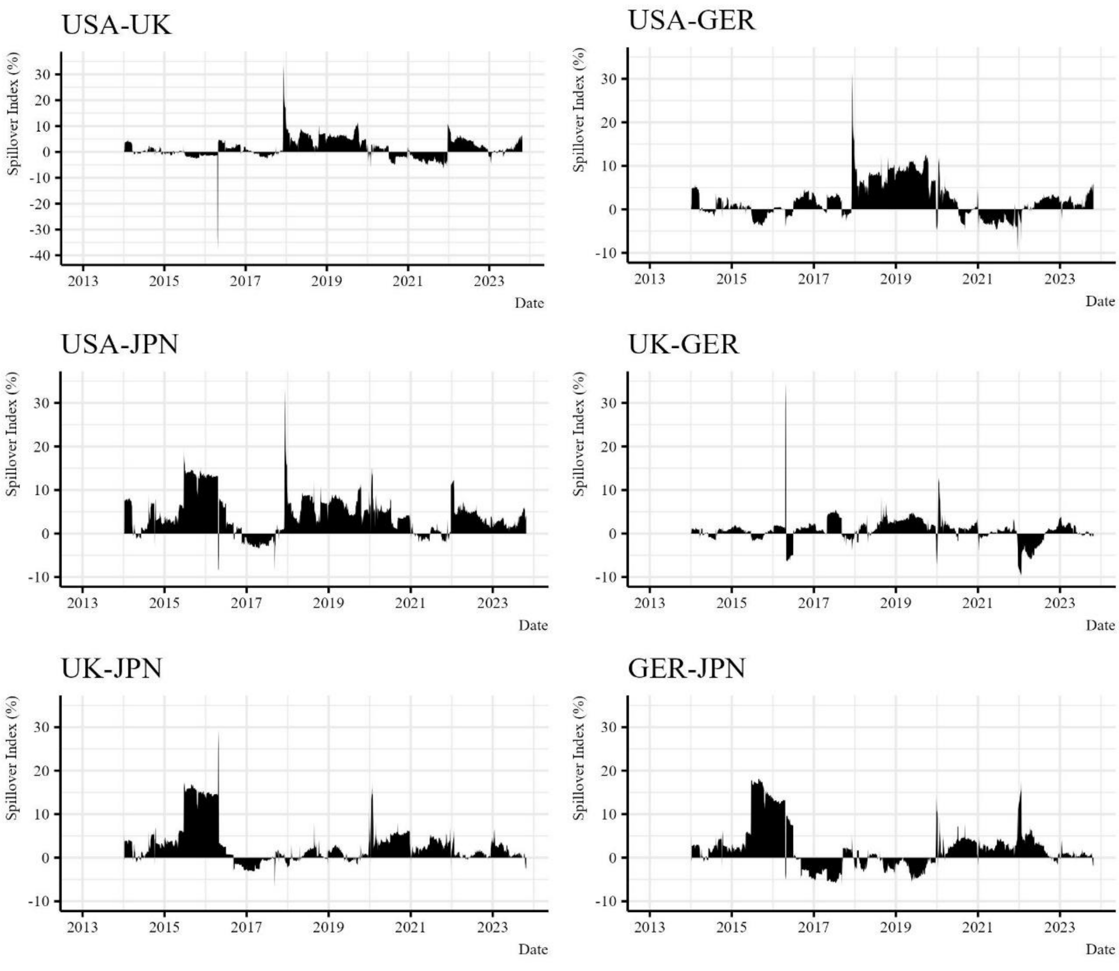

FIGURE 13 – Pairwise net volatility spillovers within developed markets.

6. CONCLUSION

This work studies the volatility spillovers in developed and emerging financial markets. I applied the Diebold and Yilmaz (2012) methodology, which uses generalized variance decompositions within the VAR framework, to measure total, directional, and net volatility spillovers across a sample of eight major stock markets. I used the stock market indices from the USA, UK, Germany, and Japan to characterize the financial market dynamics of developed countries, and the indices from Brazil, Russia, India, and China to represent the BRICS markets. The analysis spans the period from March 2013 to December 2023, capturing key events that contributed more to uncertainty about the World Economy. These events include the Chinese market turbulence (mid-2014 to mid-2015), the Global Stock Market Selloff (mid-2015 to mid-2016), the Brexit referendum (June 2016), the USA-China trade war (2018-2019), the COVID-19 pandemic (2020), and the Russia-Ukraine war (2022).

My findings reveal that a significant share of market volatility is driven by the interconnectedness amongst the indices, with an average of 45% of the total forecast error variance attributed to spillovers.

Throughout most of the period, developed markets were the primary source of spillovers, which aligns with existing findings in the literature. Spillovers within developed markets contributed the most to the overall total spillover, highlighting the strong degree of integration amongst these markets, particularly amongst the USA, the UK, and Germany. Spillovers from developed markets to BRICS were the second most prominent, revealing the significant influence that developed markets have on BRICS volatility. Conversely, I found that spillovers from BRICS markets remained relatively isolated for most of the period, exhibiting the lowest values overall.

Major financial upheavals, such as financial downturns, geopolitical conflicts, and the unprecedented economic and health crises caused by the COVID-19 pandemic, have significantly influenced the directional dynamics of volatility spillovers, and increased spillover indices to exceptionally high levels. For instance, during the onset of the COVID-19 pandemic, spillovers increased by approximately 60%, with spillovers from BRICS surpassing those from developed markets. These occurrences highlight the strong link between global shocks and increased volatility transmission across global markets, a finding also supported by existing literature.

At the individual market level, China emerged as the primary transmitter of volatility during its market turbulence in late 2014. Developed markets like the USA, UK, and Germany were the main transmitters during the 2015-2016 Stock Market Selloff, with the UK becoming a key transmitter around the Brexit referendum in June 2016. Both the

USA and China strongly transmitted during the onset of the USA-China trade war in early 2018. Lastly, Brazil dominated volatility transmission during the COVID-19 pandemic, and Russia became the main transmitter during the onset of the Russia-Ukraine war in early 2022.

The study also finds that BRICS markets had more erratic responses to global events, with spillovers surging drastically and affecting all other markets, particularly developed markets. For instance, spillovers from Brazil's index increased drastically during the COVID-19 pandemic by more than 60%, and spillovers from Russia's index surged significantly following its stock market crash after Russia invaded Ukraine. These sharp increases in volatility transmission likely reflect the susceptibility of emerging markets in the face of major global financial shocks, highlighting their growing importance to global market participants. On the other hand, I found that developed markets demonstrated greater resilience to strong global shocks, with spillovers being less extreme compared to BRICS markets.

Lastly, I observed that, in general, developed markets consistently transmitted more volatility to other markets than they received between 2014 and 2023, with the USA standing out as the most consistent net transmitter of volatility which is not surprising given its size and influence over the global economy. However, during periods of significant turmoil previously mentioned, this trend reversed for BRICS, as spillovers from these markets soared to extreme levels, positioning BRICS as the main net transmitters of volatility.

Hence, despite the impressive economic growth of the BRICS nations, developed markets remain the most integrated and exposed to spillover dynamics, both transmitting and receiving a larger share of volatility. While both groups are susceptible to external shocks during times of turmoil, BRICS markets demonstrate a greater degree of vulnerability, often acting as substantial sources of spillovers in these periods. This disparity underscores the challenges that BRICS economies face in achieving stability amidst global uncertainties, as they strive for growth and deeper integration into the World Economy.

To gain a more comprehensive understanding of global volatility spillovers, future research could extend the analysis by incorporating different frequency scales, as demonstrated by Agyei et al. (2022) and Shi (2021), and by employing different methodologies to estimate volatility. It would also be valuable to include a broader range of countries, capturing a more diverse set of economies to reflect the wider impact of volatility spillovers. Another promising direction would involve expanding the study to examine the key factors driving these spillovers, as seen in Su's work (2020b). Additionally, investigating spillover effects between stock markets and uncertainty indices could provide further insights into how market sentiment and economic uncertainty interact with volatility.

REFERENCES

Agyei, S. K., Owusu Junior, P., Bossman, A., Asafo-Adjei, E., Asiamah, O., & Adam, A.M. (2022). *Spillovers and contagion between BRIC and G7 markets: New evidence from time-frequency analysis*. PLOS ONE, 17 (7).

Alizadeh, S., Brandt, M. W., & Diebold, F. X. (2002). *Range-based estimation of stochastic volatility models*. Journal of Finance, 57, 1047-1092

Baruník, J., Kočenda, E., & Vácha, L. (2016). *Asymmetric connectedness on the U.S. stock market: Bad and good volatility spillovers*. Journal of Financial Markets, 27, 55-78.

Beirne, J., Caporale, G.-M., Schulze-Ghattas, M., & Spagnolo, N. (2013). *Volatility Spillovers and Contagion from Mature to Emerging Stock Markets*. Review of International Economics, 21 (5), 1060-75.

Bhar, R., & Nikolova, B. (2009). *Return, volatility spillovers and dynamic correlation in the BRIC equity markets: An analysis using a bivariate EGARCH framework*. Global Finance Journal, 19 (3), 203-218.

Bekaert, G., & Harvey, C. R. (1997). *Emerging equity market volatility*. Journal of Financial Economics, 43 (1), 29-77.

Bekaert, G., Harvey, C. R., & Ng, A. (2005). *Market Integration and Contagion.* The Journal of Business, 78 (1), 39-69.

Bollerslev, T. (1986). *Generalized autoregressive conditional heteroskedasticity.* Journal of Econometrics, 31(3), 307-327.

Dammak, W., Gökgöz, H., & Jeribi, A. (2024). *Time-frequency connectedness in global banking: Volatility and return dynamics of BRICS and G7 banks*. Preprint (Version 1) available at Research Square.

Diebold, F. X., & Yilmaz, K. (2009). *Measuring financial asset return and volatility spillovers, with application to global equity markets*. Economic Journal, 119, 158-171.

Diebold, F. X., & Yilmaz, K., (2012). *Better to give than to receive: predictive directional measurement of volatility spillovers*. International Journal of Forecasting, 28, 57-66.

Edwards, S. (1998). *Interest rate volatility, capital controls, and contagion*. NBER Working Paper 6756.

Engle, R. F. (1982). *Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation*. Econometrica, 50 (4), 987-1007.

Engle, R. & Kroner, K. (1995) *Multivariate Simultaneous GARCH*. Econometric Theory, 11, 122-150.

Garman, M., & Klass, M. (1980). *On the estimation of security price volatilities from historical data*. Journal of Business, 53, 67-78.

Gilenko, E., & E. Fedorova. (2014). *Internal and external spillover effects for the BRIC countries: Multivariate GARCH-in-mean approach*. Research in International Business and Finance, 31 (31), 32-45.

Gurdgiev, C., & O'Riordan, C. (2021). *A Wavelet Perspective of Crisis Contagion between Advanced Economies and the BRIC Markets*. Journal of Risk and Financial Management, 14, 503.

Hamao, Y., Masulis, R. W., & Ng, V. (1990). *Correlations in price changes and volatility across international stock markets*. The Review of Financial Studies, 3 (2), 281-307.

Hanif, W., Mensi, W., & Vo, X. V. (2021). *Impacts of COVID-19 outbreak on the spillovers between US and Chinese stock sectors.* Finance Research Letters, 40.

Jin, X., & An, X. (2015). *Global financial crisis and emerging stock market contagion: A volatility impulse response function approach*. Research in International Business and Finance, 36, 179-195.

Kenourgios, D., Samitas, A., & Paltalidis, N. (2011). *Financial crises and stock market contagion in a multivariate time-varying asymmetric framework*. Journal of International Financial Markets, Institutions and Money, 21 (1), 92-106.

Koop, G., Pesaran, M. H., & Potter, S. M. (1996). *Impulse response analysis in non-linear multivariate models*. Journal of Econometrics, 74, 119-147.

Lien, D., Lee, G., Yang, L., & Zhang, Y. (2018). *Volatility spillovers among the U.S. and Asian stock markets: A comparison between the periods of Asian currency crisis and* *subprime credit crisis.* The North American Journal of Economics and Finance, 46, 187-201.

Ng, A. (2000). *Volatility spillover effects from Japan and the US to the Pacific–Basin*. Journal of International Money and Finance, 19 (2), 207-233.

Panda, P., & Thiripalraju, M. (2018). *Return and volatility spillovers among stock markets: BRICS countries experience*. Afro-Asian Journal of Finance and Accounting, 8 (2), 148-166.

Panda, P., Vasudevan, S., & Panda, B. (2021). *Dynamic Connectedness among BRICS and Major Countries Stock Markets*. J Public Affairs. 21, e2265.

Park, Y. C., & Song, C.-Y. (1999). *The East Asian Financial Crisis: A Year Later*. IDS Bulletin, 30 (1), 93-107.

Pesaran, M. H., & Shin, Y. (1998). *Generalized impulse response analysis in linear multivariate models*. Economics Letters, 58, 17-29.

Prasad, N., Grant, A., & Kim, S.-J. (2018). *Time varying volatility indices and their determinants: Evidence from developed and emerging stock markets.* International Review of Financial Analysis, 60, 115-126.

Shi, K. (2021). *Spillovers of Stock Markets among the BRICS: New Evidence in Time and Frequency Domains before the Outbreak of COVID-19 Pandemic*. Journal of Risk and Financial Management, 14 (3), 112.

Singh, A., & Singh, M. (2017). *A revisit to stock market contagion and portfolio hedging strategies: BRIC equity markets and financial crisis*. International Journal of Law and Management, 59, 618-35.

Statista Research Department. (2024). *BRICS and G7 countries' share of the world's GDP in PPP 2000-2024.* Available from: https://www.statista.com/statistics/1412425/gdp-ppp-share-world-gdp-g7-brics/

Su, X. (2020a). *Measuring extreme risk spillovers across international stock markets: A quantile variance decomposition analysis*. The North American Journal of Economics and Finance, 51.

Su, X. (2020b). *Dynamic behaviors and contributing factors of volatility spillovers across G7 stock markets*. The North American Journal of Economics and Finance, 53.

Syriopoulos, T., Makram, B., & Boubaker, A. (2015). *Stock market volatility spillovers and portfolio hedging: BRICS and the financial crisis*. International Review of Financial Analysis, 39, 7-18.

Theodossiou, P., & Lee, U. (1993). *Mean and volatility spillovers across major national stock markets: Further empirical evidence*. Journal of Financial Research, 16 (4), 337-350.

Urbina, J. (2023). *Spillover: Spillover/Connectedness Index Based on VAR Modelling. R package version 0.1.0.3*. Available for download from: https: //CRAN.R-project.org/package=Spillover

Yilmaz, K. (2010). *Return and volatility spillovers among the East Asian equity markets*. Journal of Asian Economics, 21 (3), 304-313.

Zhang, B., Li, X., & Yu, H. (2013). *Has recent financial crisis permanently the correlations between BRICS and developed stock markets?* The North American Journal of Economics and Finance, 26, 725-38.

Zhang, P., Sha, Y., & Xu, Y. (2021). *Stock market volatility spillovers in G7 and BRIC*. Emerging Market Finance and Trade, 57, 2107-2119.

Zhou, X., Zhang, W., & Zhang, J. (2012). *Volatility spillovers between the Chinese and world equity markets*. Pacific-Basin Finance Journal, 20 (2), 247-270.