MASTERARBEIT | MASTER'S THESIS

Titel | Title

Financial Interconnectedness and Volatility Spillovers Between BRICS, European, and U.S. Stock Markets

verfasst von | submitted by

Anastasiya Balukova BSc

angestrebter akademischer Grad | in partial fulfilment of the requirements for the degree of

Master of Science (MSc)

Wien | Vienna, 2025

Studienkennzahl lt. Studienblatt | Degree programme code as it appears on the student record sheet:	UA 066 974
Studienrichtung lt. Studienblatt | Degree programme as it appears on the student record sheet:	Masterstudium Banking and Finance
Betreut von | Supervisor:	Univ.-Prof. Mag. Günter Strobl PhD

Acknowledgements

I would like to express my sincere gratitude to my supervisor, Univ.-Prof. Mag. Günther Strobl, for his invaluable guidance, constructive feedback, and continuous support throughout the course of this thesis. His expertise, critical insights, and patience played a key role in shaping the direction and quality of this work.

I also wish to thank the Faculty of Business, Economics and Statistics and teaching staff of the Department of Finance at the University of Vienna, whose teaching and academic resources provided a solid foundation for my research. I am especially grateful to Prof. Dr. Wieland Müller for the insightful comments and feedback offered during my thesis presentation, which helped improve the clarity and structure of my work.

Lastly, I would like to thank my family and friends for their unwavering support, patience, and understanding throughout this academic journey.

Zusammenfassung

Diese Studie untersucht die Dynamik der finanziellen Verbindung und Spillovers der Volatilität zwischen den Aktienmärkten der BRICS-Staaten, der USA und Europas von 2005 bis 2025. Die Interaktionen von Renditen und Volatilitäten über mehrere Krisen und krisenfreie Zeiträume werden unter Verwendung des Diebold-Yilmaz-Spillover-Index analysiert, der auf einem vektorautoregressiven Modell mit generalisierter Prognosefehler-Varianzzerlegung basiert. Die Ergebnisse zeigen erhebliche zeitlich variierende Spillovers, wobei eine stärkere Verflechtung sowohl während globaler als auch regionaler Krisen zu beobachten ist, darunter die COVID-19-Pandemie, die globale Finanzkrise, der chinesische Börsencrash und der Konflikt zwischen Russland und der Ukraine. Während die entwickelten Märkte die Übertragung von Spillovers bestimmen, weisen die BRICS-Märkte ein heterogenes Verhalten auf. Außerdem scheint der chinesische Markt von anderen Märkten isoliert zu sein, während Brasilien und Südafrika zunehmend an der globalen Übertragung von Rendite und Volatilität teilnehmen. Diese Studie füllt wesentliche Wissenslücken und liefert wertvolle Kenntnisse für Investoren und politische Entscheidungsträger, indem sie die wichtigen entwickelten Aktienmärkte untersucht und ihre Dynamik mit der der wichtigsten Schwellenmärkte vergleicht.

Abstract

This study explores the dynamics of financial connectedness and volatility spillovers across stock markets of BRICS, the U.S., and Europe from 2005 to 2025. Return and volatility interactions during the number of crisis and non-crisis periods are analyzed using the Diebold-Yilmaz spillover index that is based on a Vector Autoregression model and Generalized Forecast Error Variance Decomposition. The results show substantial time-varying spillovers, with enhanced connections observed during both global and regional crises, such as COVID-19 and Global Financial Crisis, Chinese stock market crash and the Russian-Ukrainian conflict. While developed markets dominate the spillover transmission, BRICS markets exhibit heterogeneous behavior. Furthermore, the Chinese market appears to be the most isolated from other stock markets, whereas Brazil and South Africa increasingly participate in the global transmission of returns and volatilities. This study fills important research gaps and provides valuable insights for investors and policymakers by examining key developed stock markets and comparing their dynamics with those of major emerging markets.

Contents

1 Introduction

Stock market interconnectedness can be highly dependent on region and country characteristics such as macroeconomic indicators, market openness, and investor sentiment. While some stock markets tend to be more isolated, other markets are interconnected and react strongly to global shocks. Market interconnection is driven by the exchange of information between them, and the development of digital technologies and modern communication networks increases the speed of this exchange every day. Due to increased cross-border sharing of information, financial shocks spread almost instantaneously now, transforming local disturbance into global events. The accelerated speed of information distribution has transformed recent crises such as the Global Financial Crisis, the COVID-19 pandemic, and geopolitical tensions in Eastern Europe and the Middle East into clear signals of the strength of financial interdependencies. In addition to causing excess volatility, these crises have also revealed the interdependence among world stock markets, which can offer benefits in terms of superior access to funding, enhanced investment opportunities, and risk sharing, but can also have a disadvantage as market volatility originated in one place has an immediate effect on the other markets. Furthermore, despite being part of a shared global network, markets react differently based on their unique characteristics, and there can be substantial variation in terms of the strength and duration of their reactions to financial stress. Crisis reactions are immediate, synchronized, or limited to particular regions depending on the severity of the crisis, structural vulnerabilities of affected economies, policy response, and investor exposure. Such mixed behavior patterns raise questions regarding the development of market relationships, particularly between emerging and developed markets.

The connections between emerging and developed markets are evolving considerably, but remain complex. In recent years, emerging economies have been financially integrated into global systems through macroeconomic reforms, increased trade with other economies, and market access for foreign investors. Nevertheless, there is no established pattern of their connections to developed economies. Several articles have shown increasing levels of connectedness between emerging and developed markets in times of crises (Bekaert et al., 2005; Wang and Moore, 2008). The findings of these papers indicate that co-movements of the emerging and developed markets may temporarily alter due to uncertainty and/or investor behavior. In contrast, another research finds that the degree of integration during turbulent periods is higher for emerging markets, while developed markets become more segmented (Lehkonen, 2015). Overall, the papers show that the levels of integration of emerging and developed markets change over time. These mixed results suggest that market connections are dynamic and subject to change based on regional dynamics, market-specific factors, and global conditions. Understanding how these dynamics change over time is essential for evaluating systemic risk, enhancing market resilience to crises, and guiding investment strategy and policy response in an increasingly linked financial environment.

Most of the previous research on financial integration between emerging and developed markets has focused on the major crises experienced by emerging markets in the last decades of the twentieth century, particularly the Latin American crises in the 1980s and 1990s and the Asian crisis of 1997 (S. G. Calvo and Reinhart, 1996; Masson, 1998; Bekaert et al., 2005). The papers have also examined shock transmission from emerging to developed markets during a period of financial stress using data from markets located in the crisis-affected regions. The Global Financial Crisis in 2008 exposed weaknesses in global financial systems, thereby broadening the focus of research and emphasizing increased co-movements between markets. Since then, shocks experienced in the financial environment have become more pronounced, with recent crises such as COVID-19 that considerably disrupted global markets. Thus, greater prominence has been placed on the financial behavior of larger emerging economies, especially the BRICS countries (Brazil, Russia, India, China, and South Africa). With the economies representing a large share of the world's GDP, trade, and population, BRICS countries also shape the trends of global finance and economy. BRICS economies are classified as emerging; however, they differ dramatically in terms of regulatory framework, macroeconomic policies, and market openness. These factors not only shape their relationships with developed markets, but also define how they react to financial stress. As a result, the relevance of the analysis of BRICS responses to external shocks has increased as countries become more and more integrated in the global system. Although several studies have explored aspects of the market behavior of the BRICS countries, only a small number have looked at their financial connections with developed markets over a long period and during several significant disruptions in the financial system. Moreover, the European market is often neglected in existing research despite its close trade, investment, and financial links to emerging economies, while the United States is frequently used as the main reference for advanced markets. As a result, there is a lack of understanding of global financial interdependence and the evolving role of BRICS economies.

This study aims to fill the existing research gaps by examining the dynamics of spillovers between BRICS and developed stock markets over the last twenty years and by including European market in the analysis. Spillovers are defined as the transmission of sudden changes in returns in volatility, i.e., shocks, from one market to another. The transmitted shocks may originate in different regions under the influence of many factors, which allow them to travel across markets in different directions and reveal deeper interdependencies in capital flows, trade relationships, and investor behavior. One method that is appropriate for the investigation of this dynamic and which is used in this study is the Diebold-Yilmaz spillover index, introduced by F. Diebold and K. Yilmaz in 2009. This method is based on the Vector Autoregression model and forecast error variance decomposition and provides a broad picture of relationships between markets by quantifying spillover magnitude and direction. In addition, this index is applied in a rolling window framework, which enables the assessment of dynamics of market behavior during stable and turbulent periods. The dataset covers multiple global crises, such as the Global Financial Crisis, and the COVID-19 pandemic, as well as several local crises, which helps to compare market reactions to various events. The analysis presented here contributes to a better understanding of return and volatility shock transmission across key emerging and developed markets and highlights the growing integration of BRICS economies into the global financial system, by evaluating the spillover behavior in different scenarios.

The results identify substantial time-varying return and volatility spillovers, with considerable increases in spillover indices during periods of global crises. Return spillovers tend to evolve more gradually and are more persistent, while volatility exhibits sharp but short-term reactions to changes in risk perception. Developed markets remain the leaders in return and volatility transmission, whereas BRICS markets mostly act as shock absorbers. Nevertheless, Brazil and South Africa demonstrate growing integration into the global market system by alternating between the roles of net shock transmitters and receivers. The other BRICS markets show a lower degree of influence on other markets, while China remains the most isolated market throughout the sample period. These findings highlight the asymmetric nature of financial interconnectedness and the significance of global and local events in shaping spillover patterns.

The remainder of the thesis is organized as follows. Section 2 reviews the relevant literature on market integration and financial spillovers. Section 3 discusses the methodology and explains the construction of the Diebold-Yilmaz index. Section 4 outlines the data. Section 5 presents the empirical results. Section 6 discusses possible transmission mechanisms and prospects for future research. Section 7 concludes the study.

2 Literature Review

Recently, the degree of international financial integration has been steadily increasing. The globalization of trade and periodic financial crises have made it necessary to understand how financial markets are linked and how these linkages change over time. The interconnectedness of markets increases the likelihood that shocks to a market in one asset class or a country can be rapidly transmitted to other markets, increasing volatility, and potentially threatening the stability of the international financial system. The topic of financial spillovers has been gaining considerable attention in light of the increasing degree of cross-border financial linkages between developed economies and large emerging markets. The BRICS economies stand out from other emerging economies with their significant participation in international trade and investment, but the trend toward increasing linkages across their financial systems with those in the U.S. and Europe indicates the more mutual nature of market interconnections. This area needs more research that explores the transmission of volatility across BRICS and advanced economies in both stable and crisis situations.

Financial market spillovers are generally referred to as the transfer of shocks or volatility from one market to another. The spillover processes between foreign markets were examined in the early empirical work by Engle et al. (1990), adopting the phenomena of "meteor showers", where volatility from a single market is transmitted to other markets, and "heat waves", where volatility persists in the same market. Their results provided important foundations for later research on dynamic connectivity and market interdependence by demonstrating that the volatility in the foreign exchange markets can spread throughout the globe across time zones based on new information.

Different factors, such as trade and economic relations and investor behavior, affect the emergence of financial spillovers. Dornbusch et al. (2000) and Masson (1998) distinguish between fundamentals-based and non-fundamental spillovers, where the former appear due to shift in economic fundamentals and the latter are caused by information asymmetry or changes in investor sentiment. Forbes and Rigobon (2002) further differentiate between interdependence and contagion. According to their study, interdependence refers to reaction of markets to intensifying financial linkages, whereas contagion implies increased market co-movements during periods of financial distress, beyond what can be explained by existing interdependence. The authors study contagion during crises using a heteroskedasticity-consistent correlation estimator to evaluate behavior of several financial markets. They conclude that there was no significant increase in cross-market correlations during turbulent times, once controlling for volatility, and that co-movements can be explained by stronger general interdependence rather than contagion. On the other hand, Corsetti et al. (2005) criticize the findings of Forbes and Rigobon (2002). The authors state that the findings can be biased towards interdependence, since the correction for heteroskedasticity imposed too many restrictions and unrealistic assumptions on shock variance. In contrast, their study utilizes correlation analysis within a factor model framework, which enables more flexibility for variance structures and better identification of transmission mechanisms. This method allowed the authors to find the evidence of contagion during the 1997 Hong Kong stock market crisis by identifying at least five markets where correlations with the Hong Kong market increased during the crisis, exceeding the explanation provided by interdependence alone. The study provides a more dynamic approach rather than a correlation-based analysis by allowing for time-varying changes in transmission mechanisms. Additionally, the findings confirm the presence of contagion in emerging markets during times of crises, when the sensitivity of several markets to regional or global factors increases substantially. The paper underscores the importance of flexible methods for capturing changes in transmission channels.

Early studies of financial interconnectivity focused mainly on correlation-based models (King and Wadhwani, 1990; Karolyi and Stulz, 1996; Forbes and Rigobon, 2002). Such models do not allow to identify time-varying directional relationships and do not incorporate volatility clustering. In order to capture the dynamics and direction of financial spillovers more accurately and correct limitations of the approaches, later studies use more advanced econometric models, such as the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model introduced by Bollerslev (1986). The model, especially its extensions such as DCC-GARCH (Engle, 2002) and BEKK (Engle and Kroner, 1995), allow for testing time-varying relations and the impact of shocks in a particular market on another. Consequently, Li and Glies (2015) utilize an asymmetric GARCH-BEKK to examine U.S.-Asian stock market spillovers with the outcome of realizing significant spillover effects between and from developed markets. Similarly, Chiang et al. (2007) tested contagion effects within the Asian crisis using the DCC-GARCH model.

GARCH models, while practical for analyzing volatility clustering and time-varying shock transmission, have significant drawbacks for assessing interconnectedness across markets. These disadvantages include the complexity of each model estimation, the interpretation of a system of multiple markets, and most importantly, the lack of clear directionality of spillover effects. A common solution to the issues came in the form of Vector Autoregressive (VAR) models which could be run in relatively less complicated ways and allow straightforward interpretation of results. Importantly, the application of methods such as impulse response functions and forecast error variance decomposition (FEVD) enabled the modeling of linear interdependencies and evaluation of the shock direction in VAR-style frameworks. Studies such as Galesi and Sgherri (2009) and Wen et al. (2019) employ VAR-based frameworks to detect spillover effects and transmission channels across different financial markets and find significant transmission through asset prices.

Although conventional VAR approaches are helpful, they are limited in identifying spillover direction and magnitude in systems with many variables. Moreover, standard forecast error variance decomposition relies on Cholesky decomposition, which is sensitive to variable ordering, reducing the robustness of the results. In order to eliminate these disadvantages, Diebold and Yilmaz (2009, 2012) proposed an improved approach that uses generalized forecast error variance decomposition to extend the VAR model. A significant advantage of this method is the ability to quantify directional spillovers, differentiating between shocks that a market transmits and receives within a market system. An understanding of this directional perspective is crucial for research contexts, such as the present study, which attempts to evaluate the changing impact between BRICS and developed economies. Due to these characteristics, the Diebold-Yilmaz spillover index has become a widely adopted tool in the literature on financial market interconnectedness. It is particularly suitable for studies that aim to track and compare dynamic transmission mechanisms across several financial markets and can be applied to different asset classes. For instance, Zhang and Broadstock (2020) examine the evolution of connectedness of major commodity markets and find that price co-movements become significantly intense in the aftermath of the Global Financial Crisis.

The Diebold-Yilmaz index has also gained popularity as a tool in the analysis of stock market interconnectedness. Baruník et al. (2016) utilize the modified index framework to examine asymmetric volatility spillovers from major sectors of the U.S. stock market. While their study focuses primarily on asymmetry of volatility transmission, their findings also demonstrated evidence that total market connectedness is highest during times of financial stress, which was also indicated by the spillover literature. Costa et al. (2022) also use the Diebold-Yilmaz approach to assess the effect of the recent COVID-19 pandemic on volatility spillovers in the U.S. stock market. The results show that the measures of total connectedness among sectors of the market increase significantly at the onset of the pandemic, demonstrating the effect of the crisis on sectoral dependence. Strong connectedness has also been identified in studies focused solely on spillovers between developed stock markets, particularly in financial sectors. In their study of the connectedness of stock return volatility of major U.S. and European financial institutions, Diebold and Yilmaz (2015) find that spillovers increase and become more bidirectional as the Global Financial Crisis intensifies. The studies provide evidence of the usefulness of the Diebold-Yilmaz framework for observing volatility spillover in periods of elevated uncertainty in the market.

The literature on the development of emerging markets has also considered the concept of spillovers and contagion during crisis events. For instance, S. G. Calvo and Reinhart (1996) claim that disturbances in one country can have a comprehensive effect on investor behavior in all neighboring countries, even if they are not directly economically linked. Their study examined the economies of Latin America and suggested that while investor sentiment, portfolio reallocation, and liquidity shocks play a crucial role in transmitting financial instability, these factors are also helpful for understanding market-wide volatility spillovers. In addition, the paper states that financial connectivity is shaped by regional and global events and that small economies are more exposed to spillovers from big countries. Another study by Yarovaya et al. (2016) finds that developed markets appear to transmit more spillovers than emerging economies, particularly during economic turmoil. Their findings are also supported by a broad body of literature on stock market spillovers, which analyzes the behavior of emerging and developed markets – especially the U.S., Japan, and main European economies – across different periods of time (e.g. Beirne et al., 2013; Kenourgios et al., 2011; Chiang et al., 2007).

Due to the large economy size, growing influence on the global stage, and intensifying integration with global financial markets, BRICS countries stand out among emerging markets and receive increasing attention in the literature, which investigates their function as sources and transmitters of financial shocks. Furthermore, financial integration within BRIC markets (i.e., Brazil, Russia, India, China) and their connectedness with developed markets were analyzed by Chittedi (2010). The study finds a long-term and short-term cointegration of BRIC with developed economies, suggesting the presence of persistent trends in integration and responsiveness of BRIC markets to immediate shocks. In a majority of studies, BRICS markets are studied as receivers of volatility shocks from developed markets (e.g., Mensi et al., 2014; Syriopoulos et al., 2015; Mensi et al., 2016), demonstrating their vulnerability to external shocks originating in developed markets. Nevertheless, recent research demonstrates stronger financial connections within the BRICS group and enhanced transmission of shocks to Western countries, especially from commodity-linked economies such as Russia and South Africa. For instance, Panda et al. (2020) state that all BRICS economies, except for Brazil, may potentially act as sources of volatility spillovers, indicating the need for further research into the dynamics of BRICS connectedness with global market system, particularly in the context of recent economic disruptions.

Although there is a growing body of research on financial interconnectedness between emerging and developed markets, several gaps remain. While different studies investigate the connections between emerging and developed markets during individual crises, such as the Global Financial Crisis or the Asian Financial Crisis, there is a lack of literature that describes the dynamic of long-term interconnectedness between these markets across several major events. Furthermore, while analyzing the connections between emerging markets, in particular the BRICS group, to developed markets, most research focuses on the United States as an advanced market (Mensi et al., 2016; Aloui et al., 2011), excluding the European market, which is also a significant player on the global market stage. This gap is notable as Europe has strong financial connections with some of the BRICS countries, especially through trade, investment, and banking, making it crucial to include the European market in the research. Moreover, BRICS countries are gaining more influence in global capital flows, indicating the necessity of research on their interaction with several developed economies.

This research addresses these gaps by analyzing return and volatility spillovers between BRICS and developed stock markets, including both the U.S. and European markets, over a time period from 2005 to 2025 and covering multiple global financial disruptions, including the Global Financial Crisis, the COVID-19 pandemic, and the Russia-Ukraine war. With the Diebold-Yilmaz spillover index applied both to return and volatility, the study provides new insights into the direction, magnitude, and evolution of global financial market interconnectedness. It contributes to the literature by providing a dynamic and comparative insight into the differences between emerging and developed markets and by employing a methodologically robust volatility measure that improves the precision of spillover estimation.

3 Methodology

The existing papers use different methods of market connectivity analysis. Many of them exploit GARCH models and their modifications to study volatility transmission (Beirne et al., 2013; McIver and Kang, 2020). A more recent approach to measure the interconnection between different markets is the Diebold-Yilmaz spillover index, which was developed by Diebold and Yilmaz (2009, 2012). This method is often used for the analysis of the interconnections between different financial markets, assets, and their classes. Unlike standard correlation measures and prominent GARCH models, the index is able to capture the direction and magnitude of shock transmission, providing a more detailed understanding of market interdependence. In addition to providing information on overall spillovers, the Diebold-Yilmaz framework makes it possible to determine markets that are net transmitters and net receivers of shocks. This is essential for identifying market vulnerabilities, interpreting financial contagion dynamics, and evaluating the interconnection between markets in the sample. In contrast, multivariate GARCH models emphasize volatility within and between series without identifying directionality. Furthermore, unlike traditional VAR approaches, the index is based on Generalized Forecast Error Variance Decomposition (GFEVD), which is invariant to the ordering of variables in the VAR model. As a result, the method becomes more robust and interpretable when dealing with multiple interconnected markets. Additionally, the index can be utilized in a rolling window framework, which allows to track the dynamics of stock market behavior. Overall, the Diebold-Yilmaz index provides a complete picture of how and to what degree markets affect each other over time.

This study employs the spillover index methodology to measure interconnectedness in terms of return and volatility spillovers between BRICS and developed stock markets over the last 20 years. Return-based spillovers reflect how price movements in one market influence returns of other markets and are associated with investor expectations about future cashflows, while volatility-based spillovers show how risk and uncertainty caused by investor sentiment spread across the markets in the financial system. Since the Diebold-Yilmaz index is a static measure of connectedness, using it in a rolling window framework will enable the analysis of different periods and shifts in financial linkages by observing spillover changes over time.

The index is constructed based on the following VAR(p) model:

$$X_t = \sum_{i=1}^{p} \Phi_i X_{t-i} + \varepsilon_t, \tag{1}$$

where X_t is a vector of daily index returns or daily volatilities, Φ_i - coefficient matrix, ε_t - vector of i.i.d. shocks. The model estimates how much of the future variance in returns or volatilities comes from its own past shocks and shocks from other variables. The lag order p is determined using the Bayesian Information Criterion (BIC), as it penalizes the complexity of a model, which is particularly useful when data consists of large time series. The model is then transformed into a moving average process:

$$X_t = \sum_{h=0}^{\infty} A_h \varepsilon_{t-h}, \tag{2}$$

where A_h are obtained from recursion:

$$A_h = \Phi_1 A_{h-1} + \Phi_2 A_{h-2} + \cdots + \Phi_p A_{h-p} \tag{3}$$

and represent shock dispersion over time. The coefficients from the moving average representation are further used for variance decomposition.

The original spillover index from Diebold and Yilmaz (2009) relies on Cholesky decomposition, which requires variable ordering. Different orderings may result in different variance decompositions, which may bias the overall results. In addition, Cholesky decomposition makes the calculation of the spillover index relatively complicated. To address this issue, Diebold and Yilmaz (2012) improve index calculations by utilizing the General Forecast Error Variance Decomposition proposed by Koop et al. (1996) and Pesaran and Shin (1998). This method is more robust for spillover analysis since it is invariant to variable ordering.

The variance decomposition enables splitting the variance into contributions from own past movements and shocks from other markets, i.e., how much of a market's variance is explained by preceding shocks in this market and how much of it can be attributed to fluctuations in external markets. The shock transmission is captured over the H-step forecast horizon, which defines how far ahead its effects are observed. In Diebold and Yilmaz (2012), spillovers are defined as fractions of H-step-ahead error variances in forecasting X_i due to shocks to X_j for $i, j = 1, 2, \dots, N$ such that $i \neq j$, and variance decompositions are defined as:

$$\theta_{ij}(H) = \frac{\sigma_{ii}^{-1} \left(\sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j) \right)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)} \tag{4}$$

where σ_{ii} – the standard deviation of i^{th} error term, e_i and e_j - selection vectors for i^{th} and j^{th} variables, Σ - variance matrix for ε, A_h - coefficients from the moving average representation. The term $\theta_{ij}(H)$ refers to the fraction of total error variance of market i explained by variance of market j, while $\theta_{ii}(H)$ represents volatility contributions from own prior shocks. The larger the term $\theta_{ij}(H)$, the stronger the effect of movements of market j on the volatility in market i. This indicates severe impact of markets on each other, meaning that they are highly interdependent. Conversely, a larger term $\theta_{ii}(H)$ demonstrates that a large proportion of the volatility of market i is due to its own past movements, or that markets are quite isolated from each other. Economically, $\theta_{ij}(H)$ captures how much market j influences the behavior of market i, making it possible to identify the vulnerability of markets to external shocks.

Since GFEVD does not require shocks to be orthogonalized, the sum of contributions is not necessarily equal to 1. To derive correct values of spillover index, each element $\theta_{ij}(H)$

is normalized as:

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N} \theta_{ij}(H)} \tag{5}$$

Diebold and Yilmaz (2012) define four spillover indices:

1. Total spillover index:

$$S_T = \frac{\sum_{i,j=1;i\neq j}^{N} \tilde{\theta}_{ij}(H)}{N} \tag{6}$$

   This index measures the fraction of the total variance in the financial system that comes from fluctuations across different markets and is bounded between 0% and 100%. In extreme case of complete independence, the shocks are not transmitted between the markets, and the index equals to 0%. At the other extreme, perfect connectedness implies that the variance of the market system is fully explained by shocks transmitted across markets, resulting in index approaching 100%. Real-world spillover values typically fluctuate between these bounds, indicating a varying degree of connection between different markets.

2. Directional spillover indices:

   (a) Directional spillover received by i from j (Directional FROM):

$$S_{i\cdot} = \frac{\sum_{j=1;j\neq i}^{N} \tilde{\theta}_{ij}(H)}{\sum_{j=1}^{N} \tilde{\theta}_{ij}(H)} \tag{7}$$

   The index determines the fraction of volatility of market i caused by fluctuations in market j. Directional indices are also expressed as a percentage, ranging from 0% to 100%. The low value of 0% would indicate that market transmits no shocks and plays a more passive role, whereas higher values of the index imply that the market becomes a major source of shocks that affect others.

   (b) Directional spillover transmitted by i to j (Directional TO):

$$S_{\cdot i} = \frac{\sum_{j=1;j\neq i}^{N} \tilde{\theta}_{ji}(H)}{\sum_{j=1}^{N} \tilde{\theta}_{ji}(H)} \tag{8}$$

   This index calculates the amount of volatility of market i that is contributed to volatility in market j. The value of 0% would imply that the market is fully self-driven and isolated from the dynamics of other markets. In contrast, another extreme of 100% would suggest that the variance in the market is entirely determined by external shocks. By assessing the strength and direction of influence of markets on each other, both indexes allow to determine more influential and more dependent markets. Combined with the rolling window approach explained further, we can analyze the development of linkages between markets over time.

3. Net spillover index:

$$S_{net} = S_{\cdot i} - S_{i\cdot} \tag{9}$$

   The index indicates whether the market i is a net transmitter or receiver of shocks. When market i sends more shocks to other markets than it receives from them, the net spillover index is positive. Thus, market i is a net transmitter of volatility. On the contrary, a negative index defines a market as a net receiver that receives more shocks than it transmits.

To illustrate the Diebold-Yilmaz index mechanics, two market systems are considered. The first system consists of the S&P 500 index, which represents the U.S. market, and the STOXX 600 index, which represents the broad European market. Strong historical ties between European and American economies, excessive trade, and substantial global influence allow to consider these markets as highly integrated. The second system includes the American and Chinese markets, which are represented by the S&P 500 and the Shanghai Composite Index. These markets may be considered less integrated due to limited capital flow and strict regulatory restrictions in the Chinese market. The comparison of these systems provides an insight into how the Diebold-Yilmaz framework quantifies financial interconnectedness under varying levels of market integration. The simplified example helps to illustrate how Diebold-Yilmaz framework translates variance decomposition results into economically meaningful measures of connectedness between financial markets or assets.

The detailed calculation steps, including VAR estimation, GFEVD derivations, and normalization of contributions are provided in Appendix B. The return of each market is modeled using VAR model, which captures how current values are affected by both the market's own past behavior and past behavior of other markets in the system. The Generalized Forecast Error Variance Decomposition is then applied to decompose the forecast error variance of each market into components attributable to its own shocks and those from other markets.

The results of decomposition are presented in Table 1 and indicate that 75.3% of the forecast error variance of the S&P 500 comes from its own past shocks, whereas 24.7% of its variance comes from the shocks in the European market. 64.6% of the forecast error variance of STOXX 600 is explained by past fluctuations in the European market itself, and 35.4% are attributed to spillovers from the S&P 500. These values indicate a moderate level of market integration in the system. The American market appears to be more self-driven since a substantial share of its shock variance comes from its past movements, while the European market is more sensitive to the external shocks due to the fact that 35% of its forecast error variance is explained by fluctuations in the U.S. market. This asymmetry confirms the financial dominance of the U.S. and its strong influence on other developed markets.

	Shock from S&P 500	Shock from STOXX 600
Variance in S&P 500	75.3%	24.7%
Variance in STOXX 600	35.4%	64.6%

Table 1: The results of GFEVD for the U.S.-Europe system

The GFEVD results for the second system are presented in Table 2. In contrast to the first market system, own shocks of the U.S. market explain 98.3% of its forecast variance in the second system, with only 1.7% attributable to the Chinese market. The results for the Shanghai Composite index are similar, with the own contribution about 99.1% and a minimal spillover of 0.85% from the American market. This pattern illustrates a minimal degree of interconnectedness between these two markets, which is consistent with the tightly controlled and policy-driven Chinese market environment.

	Shock from S&P 500	Shock from Shanghai Composite
Variance in S&P 500	98.3%	1.7%
Variance in Shanghai Composite	0.85%	99.15%

Table 2: The results of GFEVD for the U.S.-China system

Based on the contribution values, the spillover indices can be computed and evaluated in the context of the underlying financial relationships between markets. For the first market system, the Total Spillover index is calculated as: $S_T = \frac{24.7\%+35.4\%}{2} = 30.1\%$. This number suggests that 30.1% of the total forecast error variance in the entire market system is attributed to cross-market spillovers, while the remaining 69.9% is caused by the effect of markets' prior movements on the current values. Approximately one-third of the volatility of the market system comes from the influences of both markets on each other, suggesting a moderate degree of interdependence. This result reflects the existence of stable economic linkages between the United States and Europe, including exposure to global financial cycles and coordinated responses to changes in macroeconomic conditions. From an investor perspective, this reduces the diversification benefits of holding assets from both markets in one portfolio, particularly during turbulent times.

Directional spillovers allow to measure the influence and exposure of each individual market. The spillovers received by the S&P 500 and transmitted to the STOXX 600 are: $S_{S\&P\cdot} = \frac{24.7\%}{24.7\%+75.3\%} = 24.7\%; S_{\cdot S\&P} = \frac{35.4\%}{64.6\%+35.4\%} = 35.4\%$ This shows that the S&P 500 receives 24.7% of its forecast error variance from the STOXX 600 and transmits 35.4% of its forecast error variance to the STOXX 600. These values imply that the U.S. market is moderately affected by fluctuations of the European market, however, it plays a more influential role as a shock transmitter by transmitting more spillovers than it receives. The U.S. market appears to be less exposed to shocks from the European market, likely due to its size and the significance of U.S. monetary and financial policy.

Likewise, for STOXX 600: $S_{STOXX\cdot} = \frac{35.4\%}{64.6\%+35.4\%} = 35.4\%; S_{\cdot STOXX} = \frac{24.7\%}{24.7\%+75.3\%} = 24.7\%$. The indices show that STOXX 600 sends 24.7% of variance to S&P 500 and receives 35.4% of its variance from the American index, reflecting the sensitivity of the European market to global spillovers. This is consistent with a more reactive role of the European market in comparison to the leading position of the U.S. market.

Finally, the net spillover index is calculated as the difference between transmitted and received spillovers: $S_{net,S\&P} = 35.4\% - 24.7\% = 10.7\%; S_{net,STOXX} = 24.7\% - 35.4\% = -10.7\%$. The positive net spillover index of S&P 500 confirms its role as a dominant transmitter in this relationship, whereas STOXX 600 with a negative index value acts as a net receiver in the market system. U.S. financial markets are large, liquid, and followed by investors around the world, which makes them sources of return and volatility spillovers. Conversely, Europe receives shocks originating in the U.S., indicating its vulnerability to the events that occur in the U.S., particularly during periods of financial stress.

In contrast, the contributions from the U.S. – China market system allow to calculate the following Total Spillover index: $S_T = \frac{1.7\%+0.85\%}{2} = 1.275\%$. This extremely low value suggests that markets are strongly isolated from each other, as over 98% of the return variation in each market is explained by its own shocks, while cross-market influences contribute only a small portion of 1.275% to the system volatility. Although China is a significant player in global trade and production, its capital markets remain strongly isolated from the rest of the world, with the price discovery driven by sentiment of domestic investors and state interventions rather than by global dynamics. The fluctuations of the Chinese stock market have very limited impact on the American market, although China is one of the key trading partners of the U.S. The asset prices in the Chinese equity market are shaped by domestic factors, which reduces their value for U.S. investors. The U.S. market is more open and connected with other open markets, which makes it less sensitive to developments of isolated markets, despite strong trade links. As a result, short-term volatility shocks in China do not trigger significant reactions in the U.S. market. On the other side, regulatory restrictions also limit the influence of the U.S. market on Chinese equities, leading to minimal cross-market transmission of shocks and low value of spillover index.

The directional spillover indices support this conclusion. The spillovers received by the S&P 500 and transmitted to the Shanghai Composite are: $S_{S\&P\cdot} = 1.7\%; S_{\cdot S\&P} = 0.85\%$, showing that the S&P 500 receives just 1.7% of its variance from the Shanghai Composite and transmits only 0.85% of shocks to the Chinese market. For the Shanghai Composite, the directional indices are: $S_{SC\cdot} = 0.85\%; S_{\cdot SC} = 1.7\%$. The indices show that Shanghai Composite sends 1.7% of variance to S&P 500 and receives 0.85% of its variance from the American index. The low values of directional spillover indices indicate that a negligible portion of volatility is exchanged between markets, and developments in both markets are driven by domestic factors.

The net spillover indices for the S&P 500 and Shanghai Composite are $S_{net,S\&P} = -0.85\%, S_{net,SC} = 0.85\%$. While the Shanghai Composite acts as a net transmitter, the S&P 500 plays a minor role as a receiver. Although this suggests the influence of China on the U.S., the magnitudes are extremely small, confirming that these markets are highly independent and there is no meaningful contagion between them.

In terms of return spillovers, the U.S. and Chinese stock markets function largely in isolation from each other, as evidenced by low values of all spillover indices. These values reflect the extreme case of market independence, highlighting the absence of meaningful financial linkages between these markets. In contrast, higher spillover indices for the U.S. – European system reflect a higher level of shock transmission and deeper financial integration. This interconnectedness stems from strong institutional linkages, close trade relationships, and shared policy environments. As a result, shocks from the U.S. may be swiftly transmitted to European market, making them more vulnerable to external fluctuations and more reflective of global financial cycles. These results highlight the usefulness of the Diebold-Yilmaz framework for distinguishing between highly integrated and independent markets.

The indices provide a clear and understandable measure that allows to analyze all connections between BRICS, U.S., and European markets, their strengths and directions, and how their interrelations evolve over time in response to different events. However, since indices are static, their calculation is not sufficient to capture the dynamics of financial markets. To address this limitation, I use the rolling window approach, which allows to track connection changes over time. In this method, the calculation of each index is repeated within a 200-day moving window. The VAR model and variance decomposition are calculated at each stage, and the window is then shifted forward by one day, adding the most recent observation and removing the oldest. The received dynamics are then easily represented on the graph, which provides a dynamic view of changing market connections.

4 Data

For the analysis of the interconnectedness daily prices of the following stock indices of BRICS countries were used: Bovespa (short BVSP; Brazil), MOEX (Russia), Nifty 500 (India), Shanghai Composite (China), and FTSE/JSE All Shares (South Africa). These indices are considered the main indices of these stock markets and can be used for their representation. Developed markets are represented by the main indices of two major developed stock markets analyzed in this study. These indices are STOXX 600 (Europe), and S&P 500 (USA). The data cover a 20-year period from the beginning of 2005 till the end of 2024. This time span captures major global crises like Global Financial Crisis or COVID-19 pandemic, and regional events, which include the U.S. - China trade war and the Russia-Ukraine conflict. The analysis of both global and local crises will provide a better understanding of volatility sources and transmission dynamics.

The analysis is based on daily log returns and annualized intraday volatilities of stock index prices. Intraday volatility was measured using the Garman-Klass volatility estimator, derived by Garman and Klass (1980), which belongs to range-based volatility estimators. This class of estimators relies on high-frequency information such as open, close, high, and low prices instead of using closing prices alone. Due to this advantage, the Garman-Klass estimator is widely used to determine daily volatility. The daily variance of index i on day t is calculated as follows:

$$\sigma_{it} = \sqrt{\frac{1}{2}(ln\frac{P_{high,it}}{P_{low,it}})^2 - (2ln2-1)(ln\frac{P_{close,it}}{P_{open,it}})^2} \tag{10}$$

This term is annualized by multiplying it by $\sqrt{252}$ and multiplied by 100 to express daily volatility as a percentage. The intraday price ranges contain more information about price variability during the trading day, which results in a substantial reduction of the estimation error, especially when markets are volatile. Under the assumption of zero drift, this approach is up to seven times more efficient than close-to-close estimator (Garman and Klass, 1980) and also improves forecasting performance (Hung et al., 2012). In this research, the estimator is calculated on a daily basis using price values for each trading day under the assumption that the intraday drift is negligible due to the short time horizon of a single trading day. This approach is consistent with the initial Garman-Klass approach, which assumes that drift over a day will not have any material impact on estimator accuracy since intraday motions are short-term in nature. Furthermore, even though intraday data may be more accurate, its usage is often limited by availability and may generate ambiguity because of market microstructure noise, data quality, and differences between trading platforms. In this regard, the Garman-Klass estimator offers a reliable alternative, providing a good approximation of true volatility while using only open, close, high, and low daily prices, which are more available and less prone to noise.

Tables 3 and 4 present summary statistics of daily log returns and volatilities for all indices based on 5105 observations. Stationarity assumption is extremely crucial to the validity of the VAR model, so the Augmented Dickey-Fuller test is performed to check stationarity of the time series. The results of the test are reported in Tables 3 and 4 and indicate that the series are stationary and may be analyzed under the Diebold-Yilmaz framework. The results indicate that emerging markets, including Brazilian, Russian, and Chinese markets, are more volatile than developed markets in terms of returns and intraday volatilities. The Russian stock index is the most volatile with the highest mean and standard deviation of the volatility measure, while the Indian and South African indices are the most stable among the five emerging markets. Furthermore, the Russian market also has the highest standard deviation of returns, indicating strong fluctuations of daily returns.

Index	Observations	Mean	Standard Deviation	Minimum	Median	Maximum	Skewness	Kurtosis	ADF
BVSP	5105	0.0003	0.0165	-0.1599	0.00	0.1368	-0.4136	9.7343	-16.062***
MOEX	5105	0.0003	0.019	-0.4047	0.0002	0.2523	-1.9861	61.0052	-17.412***
Nifty 500	5105	0.0005	0.0128	-0.1371	0.0008	0.1503	-0.6182	12.7855	-15.088***
Shanghai Composite	5105	0.0002	0.0148	-0.0926	0.00	0.0903	-0.5095	5.918	-15.599***
JSE	5105	0.0004	0.0119	-0.1023	0.0004	0.0905	-0.2701	5.9145	-18.043***
S&P 500	5105	0.0003	0.0124	-0.1277	0.0005	0.1096	-0.4424	14.4431	-17.425***
STOXX 600	5105	0.0001	0.0114	-0.1219	0.0005	0.0941	-0.491	9.6553	-17.439***

Table 3: Daily log returns summary statistics. The last column represents Augmented Dickey-Fuller test statistics for unit root testing. Significance levels are denoted by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Rejection of null hypothesis implies stationarity of the time series.

Index	Observations	Mean	Standard Deviation	Minimum	Median	Maximum	Skewness	Kurtosis	ADF
BVSP	5105	18.475	11.451	0.00	16.159	186.528	4.325	36.587	-8.425***
MOEX	5105	19.034	17.937	0.00	14.481	470.762	6.697	101.454	-7.073***
Nifty 500	5105	12.432	9.341	0.00	9.982	161.202	4.450	39.527	-8.494***
Shanghai Composite	5105	15.739	10.696	2.543	12.517	101.745	2.532	9.999	-7.748***
JSE	5105	12.692	7.396	0.00	10.897	107.453	2.736	16.107	-6.982***
S&P 500	5105	11.118	8.699	1.453	8.802	122.169	3.661	23.481	-7.778***
STOXX 600	5105	11.054	8.089	0.00	8.940	123.278	3.635	25.167	-8.678***

Table 4: Daily volatility summary statistics. The last column represents Augmented Dickey-Fuller test statistics for unit root testing. Significance levels are denoted by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Rejection of null hypothesis implies stationarity of the time series.

5 Results

This section discusses empirical findings on return and volatility spillovers across BRICS and developed markets, based on the Diebold-Yilmaz spillover index framework. The results are based on a VAR model with a lag order of 1 for return spillovers and a lag order of 4 for volatility spillovers, as determined by the BIC criterion. The forecast error variance decomposition is calculated for a 30-day forecast horizon to capture medium-term volatility effects. At first, the study presents the results for static spillover indices, which reflect the average contributions of all markets examined. By applying the index methodology in the rolling window framework, the dynamic behavior of return and volatility spillovers is then analyzed over the whole sample period. Static spillovers provide a comprehensive overview of general state of market interconnectedness for the last two decades, while dynamic approach allows to explore shock transmission in more detail and to detect time-varying trends, particularly during times of increased uncertainty.

5.1 Static Spillover Indices

The results for Diebold-Yilmaz return-based spillover indices are presented in Table A1 in the Appendix A. The diagonal elements of the spillover table represent the own variance share, i.e., the fraction of error variance explained by the market's own past movements. The off-diagonal terms indicate directional spillovers, i.e., variance contributions from one index to another. The row TO and the column FROM represent total directional FROM and TO spillover indices for each market, demonstrating how much overall volatility was received from and transmitted to other markets. The last row represents the contribution of the market to all other markets, including itself. It displays each market's overall impact on the entire system, including its own dynamics, which is important for assessing the role of the market in shock transmission. The last column displays net spillover indices, showing which market is, on average, a net transmitter and which is a net receiver. It is calculated by subtracting the directional FROM index from the directional TO index. Finally, the total spillover index is presented in the bottom right corner of the spillover table and indicates the average forecast error variance share coming from cross-market influences.

The spillover table demonstrates that the BRICS markets are generally more influenced by developed markets than by one another. Their low directional spillover indices suggest weaker intra-group connectedness and stronger relation to advanced economies. Among all indices, the STOXX 600 is both the most impacted and the most influential market. While the market itself transfers 77.75% of its volatility to other markets, external shocks account for 61.70% of its return volatility.

Another finding is that over the last 20 years, the Chinese market has been the most isolated, possibly due to strict market regulations and capital controls. The own variance share of 80.88% is the highest among all indices, whereas the variance transmission from each of the other markets does not exceed 4%. It also does not transmit much of its return volatility to other markets, which is shown by an overall directional TO index of 7.18%.

Among BRICS stock markets, Brazil and South Africa are the most connected with other global markets through return transmission, since more than half of their price fluctuations can be attributed to external shocks from other markets. According to the table, the Brazilian market receives 17.20% of return volatility from S&P 500, which indicates strong influence of the American market on Brazil. In contrast, the South African market is heavily influenced by the European stock market, from which it receives 18.68% of variance. Notably, these emerging markets also transmit a significant portion of the shocks to the market system, which is shown by the directional TO indices of 57.24% for Brazil and 59.78% for South Africa. These countries demonstrate their financial openness; however, they are also sensitive to global investor sentiment and capital flows from larger economies.

Finally, the estimated total spillover index of 47.49% indicates that cross-market interactions were, on average, responsible for almost half of the return fluctuations across the market system during the last 20 years. It indicates considerable interdependence among the BRICS, U.S., and European markets, and the existence of strong transmission mechanisms.

Similar to Table A1, Table A2 presents the results for volatility spillovers. The findings show that the BRICS markets have relatively low influence on each other compared to their greater exposure to developed markets, which was also the case for return transmission. Among them, the Chinese market remains the most isolated from external uncertainty shocks. The lowest transmission values of the Shanghai Composite highlight the independence of China from international markets. In contrast, the Brazilian and South African markets continue to be strongly affected not only by return but also by volatility movements in other markets, as demonstrated by their FROM indices of 43.51% for Bovespa and 50.87% for JSE. JSE, however, receives more volatility from other markets than it transmits to them, highlighting its role as a net volatility receiver. Thus, this market does not have enough influence on other markets in terms of volatility transmission. Additionally, the S&P 500 transmits 79.52% of its forecast error variance to other markets, which confirms its role as the dominant transmitter of volatility spillovers. This finding is consistent with the swift reaction of other global stock markets to uncertainty and turbulence originated in the U.S. market. The total spillover index of 43.72% indicates that the volatility of the whole market network is less affected by volatility transmission between markets. However, it still suggests that markets are strongly interconnected, emphasizing that shocks transmitted between them account for a considerable amount of volatility in the whole system.

Overall, the results confirm that all markets have a substantial impact on each other, with stronger connections through price reactions than through risk transmission. According to the findings, developed markets drive return and volatility spillovers, while emerging markets remain the recipients of external shocks. With the exception of China, the BRICS markets were highly dependent on global investment patterns and movements of the U.S. and European markets, which occurred during the last 20 years, although they became more integrated into the global market network.

5.2 Dynamic Total Spillovers

This section provides the analysis of spillover dynamics over the last 20 years. The Diebold-Yilmaz index is calculated over a 200-day rolling window and plotted on a graph. Figure 1 presents the total return spillover index for the market system from 2005 till 2025. The graph of return transmission dynamics clearly demonstrates several increases and declines in market interconnectedness. The growth of the spillover index is likely caused by market response to major global events. For instance, the graph illustrates a strong increase in spillover index around 2008-2009, which then persists over approximately 5 years. The index peaks above 60% in 2009, suggesting strong cross-market return transmission due to collapse of financial markets during the Global Financial Crisis. This trend persisted until 2011, when a minor decline occurred and then built up again as the European debt crisis created uncertainty in global markets.

Another notable increase in the return spillover index occurred around 2016, when it surged to approximately 55% and then declined to 35% in 2017, remaining low until the COVID-19 pandemic. This spike may be caused by different factors and events that took place in this period. These include the oil price collapse in 2014, the Chinese stock market crash in 2015, or increased uncertainty around the U.S. presidential elections. The substantial uncertainty and turbulence triggered by these events likely resulted in synchronization of market reactions and increased return spillovers between international markets.

This peak of market interconnectedness was followed by a relatively calm period, when the total spillover index was fluctuating around 35%, until the outbreak of the COVID-19 pandemic triggered an unprecedented spike in return spillovers, reflecting the simultaneous impact on developed and emerging markets. The disruptions of the global economic network and herding investor behavior led to simultaneous asset repricing and sell-offs across all financial markets, which resulted in a sharp surge of return spillovers. The shock transmission remained high for the entire year 2020, while markets strove to adapt to new healthcare and economic policies and regulations.

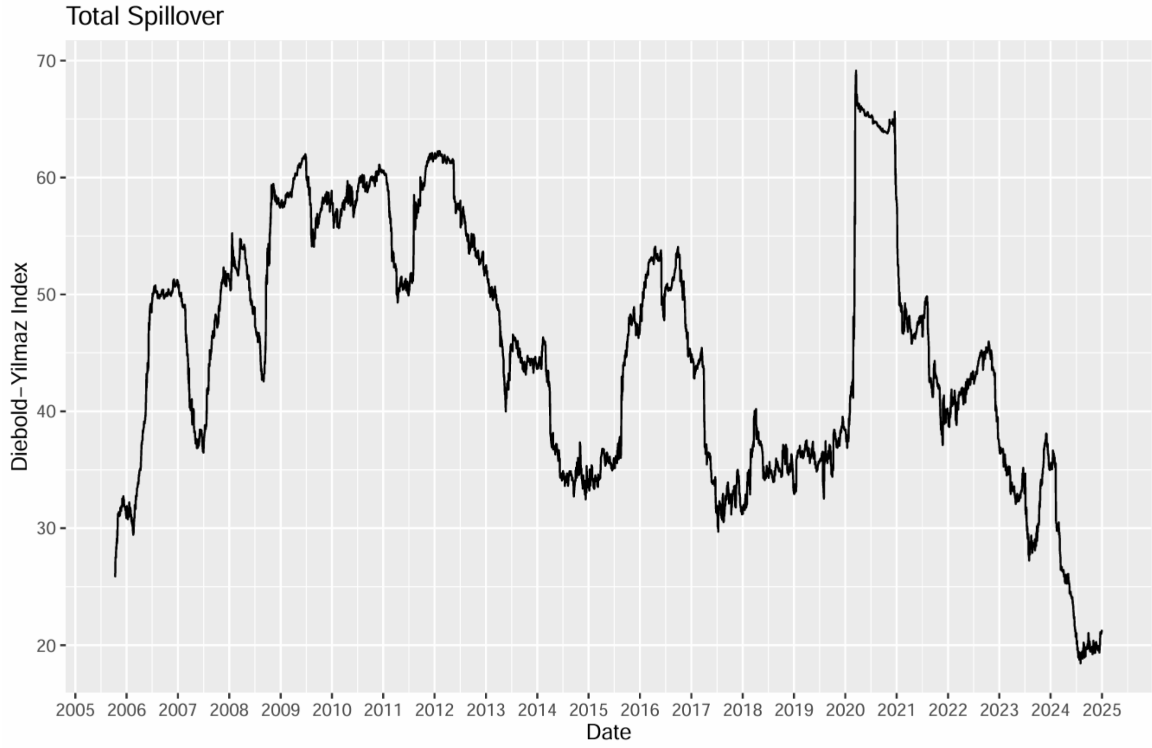

Figure 1: Dynamic total return spillover

The total spillover index began to decline gradually after 2020, reflecting weakening market synchronization. However, some temporary spillover increases took place in 2022. The increase may be associated with geopolitical tensions caused by the onset of the Russian-Ukrainian conflict in 2022. Since Russia is part of the BRICS and a large emerging market, the imposed sanctions strongly hit its economy, causing the transmission of return volatility, particularly across emerging markets. Although this event had a significant effect on the world economy, it was more regional in nature and was not directly related to any macroeconomic changes. Therefore, it did not affect all markets simultaneously and resulted in a spike that was less pronounced than the spillover surge in 2020.

Following these episodes, the total spillover index fell significantly to the lowest value of 20% for the entire sample period. This reduction indicates decrease in shock transmission and growing market segmentation, where return dynamics became more localized. Furthermore, it may reflect more divergent monetary policies or structural shifts in international capital flows and investment behavior.

Figure 2 illustrates the graph of the dynamics of the Diebold-Yilmaz index based on volatility spillovers. The overall dynamic of the volatility spillover index is similar to that of the return-based index, although some considerable differences can be observed. The volatility spillover index ranges from values below 20% to peaks above 80% over the sample period. In contrast to the return-based index, volatility transmission fluctuates substantially and sharply, indicating that it is more sensitive to changes in systemic risk and policy, investor sentiment, and geopolitical risks. Unlike return spillovers, which develop gradually, volatility reacts quickly to new information but does not persist for a long time, suggesting swift market reactions to risk even in the presence of relatively steady prices.

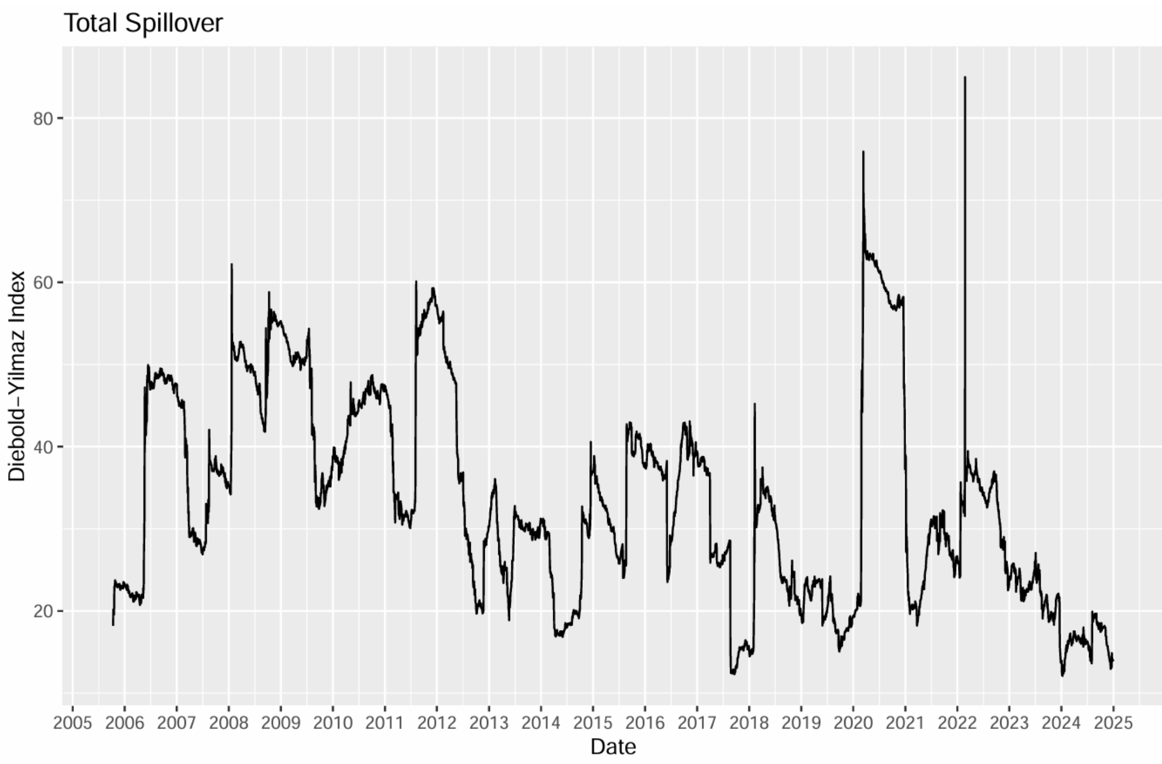

Figure 2: Dynamic total volatility spillover

The graph illustrates periodic spikes that occur roughly every 1-2 years and may be caused by global or regional turmoil. Similar to return spillovers, volatility spillovers also experience a sharp increase during significant crises, such as the Global Financial Crisis, the Eurozone debt crisis, or the COVID-19 pandemic. However, the most pronounced spike occurred in 2022, when the total spillover index achieved values above 80%. This surge was triggered by the outbreak of the Russian-Ukrainian conflict, which led to commodity price shocks, inflation fears, and increased geopolitical risks around the world. Nevertheless, the high level of volatility transmission did not persist for a long time and decreased swiftly after markets recovered from the shock and adapted to new political and economic measures. As the graph illustrates, the index gradually declined after 2022, indicating possible market isolation and localization of volatility dynamics due to new sanctions or regulations.

5.3 Directional Spillovers

So far, the total spillover index has shown the shock transmission across the markets. However, it does not tell anything about the role and share of each market in this transmission. The directional spillover index allows to determine which markets have been influenced by others and which markets transmitted shocks the most.

Figures A1 and A2 in Appendix A illustrate directional return spillovers FROM and TO seven stock markets based on the Diebold-Yilmaz framework. Each index shows time-varying spillovers, with noticeable increases around the Global Financial Crisis and Eurozone crisis in the early years of the sample and during the COVID-19 pandemic. In most markets, return volatility is transmitted and received in a different way, indicating the different roles each market plays within the global network.

The indices show largely similar spillover dynamics, except for China, which indicates their strong interconnectedness. Developed market indices S&P 500 and STOXX 600 act as primary sources of return volatility, with consistently high levels of spillovers from and to other markets. As can be seen in the graph, both their Directional FROM and TO indices remain high throughout the sample period, reflecting their important role in global transmission mechanisms. The S&P 500 exhibits more pronounced spikes, especially during periods of large crises and increased geopolitical risks. For instance, a large spike was observed in 2018, which can be attributed to the escalation of the trade war between the U.S. and China. This period is also associated with a moderate increase in the Chinese spillover index. Another reason could be the tightening policy of the Federal Reserve, which caused shifts in global asset allocation. Similarly, the STOXX 600 demonstrates strong inbound and outbound return spillovers, particularly during the Eurozone debt crisis, the COVID-19 pandemic, and the period of energy crisis caused by the Russian-Ukrainian conflict. The substantial declines in the Directional FROM index occur in 2018 and 2024, caused by the Brexit referendum, parliamentary and presidential elections in several European countries, and the U.S. presidential elections in 2024. The STOXX 600 represents diverse European economies, which have different dynamics. As a result, mixed behavior of European countries may lead to lower overall volatility. The dynamic of the broad European market is robust and remains relatively stable throughout the observed period, indicating that European shocks have significant transmission effects, although the strength of its volatility spillovers is lower than that of its developed competitor.

BRICS markets demonstrate mixed behavior, which reflects differences in their financial development, growth, and global integration. The results show how spillover intensity, and reactions to crises varies among these markets and throughout the examined period. Nevertheless, markets tend to receive more than they transmit, emphasizing their role as shock receivers in the system.

It can be clearly seen that the Chinese market is the most isolated among the indices examined, with the Directional FROM index consistently below 5% and the Directional TO index that averages about 5-7%. While the Directional FROM index shows modest increases around 2013, 2016, and 2018-2020, they remain quite low compared to the dynamics of other markets. These increases are associated with periods of financial stress, including concerns over economic slowdown, stock market crash, the U.S.-China trade war, and the COVID-19 crisis. Nevertheless, China does not transmit any considerable amount of return shocks even during these significant events. The Directional TO index is higher than the Directional FROM index, which indicates that the Chinese market receives more return volatility than it transmits to other markets. It can be concluded that China is only partially integrated into the global system in terms of return transmission, despite the rapid growth of its economy and market that becomes more available to foreign investors.

Among BRICS markets, South Africa and Brazil are the most interconnected markets, which significantly transmit and receive return volatility. Their FROM indices often exceed 10%, while TO indices demonstrate dynamics similar to those of developed markets. Both of these countries show similar patterns in spillover index dynamics, reflecting a strong dependence of their economies on the common factor - global commodity prices. During the 2000s, the Brazilian and South African markets experienced a strong increase in exports and a stock market swing, driven by commodity-linked companies. Due to their strong economic and geopolitical positions as large commodity exporters, Brazil and South Africa gained significant influence on global transmission mechanisms. As a result, their spillover indices remained relatively high during the commodity boom period. The end of the supercycle around 2014 led to lower commodity prices, which probably caused investors to reallocate their capital towards more profitable assets. Thus, the transmission of return spillovers from commodity-dependent markets such as Brazil and South Africa decreased, reflecting decreased investor interest in commodities and leading to reduced influence of these markets after the supercycle. Directional indices increased around 2016 and 2020, indicating the adherence to global market trends. These patterns were then followed by a notable decline that may be caused by growing segmentation and possible influence from the U.S. market. As a commodity-linked market, Russia exhibited dynamics similar to Brazil and South Africa at the beginning of the observed period, suggesting that country's reliance on commodities may be responsible for the amount of shocks transmitted and absorbed. Although previous research does not find a consistently strong connection between commodity and stock markets (Diebold and Yilmaz, 2012; Yoon et al., 2019), a large presence of commodity-linked companies in stock market indices may still affect return and volatility spillovers. However, Russia's spillover patterns differ slightly from those of Brazil and South Africa. Although Russia initially acted as an active return transmitter, the year 2022 has broken this trend. A clear reduction in return spillovers can be attributed to the beginning of the Russia-Ukraine conflict and the introduction of sanctions, which led to the financial isolation of not only the Russian stock market but its whole economy. In contrast to other BRICS countries, India demonstrates the most stable behavior, with return transmission averaging at 5%-7%, indicating a moderately integrated market. With the exception of a noticeable spike during the COVID-19 epidemic and a decline around 2023, India's spillovers remain largely limited.

The dynamics of volatility spillovers presented in Figures A3 and A4 in Appendix A reveal differences in risk transmission between emerging and developed markets. As can be observed, BRICS markets act mostly as volatility receivers from developed markets, with relatively low and stable Directional FROM index dynamics. As shown in Figure A3, Brazil is an exception among the BRICS markets, acting as a shock transmitter, especially during the COVID-19 pandemic when the Directional FROM index achieved the highest levels of almost 30%. Russian and South African markets also acted as relatively active volatility transmitters during the period surrounding the Global Financial Crisis; however, in subsequent years, their Directional FROM indices remained below 10%, except for moderate increases during the COVID-19 pandemic and the onset of the Russia-Ukraine conflict. Indian and Chinese markets show the most moderate transmitter dynamics. The Indian market was quite active during the Global Financial Crisis, but then the shock transmission faded over time, stabilizing at lower levels. The Chinese market remains isolated, with the Directional FROM index staying close to zero for the whole period and the most noticeable spike around 2018 during the trade war with the U.S. At the same time, the spillover index of the U.S. market also experienced a substantial increase, indicating the reinforcement of connections between these two markets. Interestingly, China did not transmit any considerable amount of volatility in early 2020, although it was the center of the COVID-19 outbreak. This finding suggests that the most risk transmitted globally originated in other markets, while turbulence that originated in China was contained within the domestic market. In contrast, the higher levels of uncertainty transmission from developed markets reveal their role as primary sources of volatility.

The dynamics of Directional TO indices are considerably fluctuating with higher and more frequent spikes. This illustrates how global markets are interconnected and how shocks that start in one market can spread quickly to others. Notably, the TO index patterns of Brazil and South Africa both repeat the dynamics of developed markets, suggesting strong connections at the global level. The Chinese index demonstrates limited volatility transmission once again, further highlighting low levels of its integration into global volatility networks, even during the COVID-19 pandemic. Furthermore, Russia transmitted a significant amount of risk caused by the Russian-Ukrainian conflict to other markets in

2022, which can be seen from the significant spike in the Directional TO index on the graph. This uncertainty was received by all the markets explored, suggesting the vulnerability of the markets to local geopolitical events.

In general, the return spillovers, which reflect the asset repricing across the markets in response to new information, are more stable and moderate over time. In contrast, volatility spillovers, which capture the transmission of risk caused by fear perception in one market, are more frequent and sensitive to global shocks, especially during periods of systemic stress. During times of high uncertainty, volatility can surge even without strong return movements, reflecting increased risk aversion and financial contagion. Across the sample, emerging markets show lower transmission dynamics, both in return and volatility spillovers; however, they show their high exposure to shocks coming from developed markets. As a result, they tend to absorb volatility emerging in developed markets without transmitting shocks back to the financial system.

5.4 Net Spillovers

This section discusses the dynamics of net spillovers of BRICS and developed markets. Net spillovers correspond to the difference between the Directional FROM and the Directional TO indices discussed earlier and provide a simple and direct representation of markets' net influence within the global financial system.

The net return spillovers are presented in Figure A5 in Appendix A section. It is evident that developed markets consistently act as strong return transmitters, as indicated by their positive Diebold-Yilmaz net indices. In comparison with other markets, the U.S. market displays the highest levels of shock transmission, while the European market remains relatively moderate. Among BRICS markets, Russia, India and China are the main net receivers of return shocks. Whereas Russia occasionally becomes a net transmitter for some short periods, China and India remain in the negative area for the whole sample period, with only a few short-lived and small positive spikes. The net spillovers of India do not fall below -5%, indicating that differences between return volatility transmitted and received are relatively small. This minimal fluctuation suggests a moderate degree of integration of the

Indian stock market into the global system, which prevents it from being a highly exposed receiver of return volatility. Similarly, the net spillover index of China shows negative values close to zero, with one notable dip below -5% in 2020, when the Chinese market absorbed increased return volatility from other markets, although the country was the primary source of the virus. Strong capital controls, government policies, and interventions in China provided relatively stable domestic market conditions during this crisis. In contrast, Brazil and South Africa cannot be clearly labeled as net transmitters and net receivers, as their role has been changing over time. Brazil was acting as a net transmitter before 2015, which was made possible by its economic growth, driven by the commodity supercycle. After 2015, however, the spillover values became moderate, fluctuating around zero and pointing to the decreased role of Brazil as a transmitter due to recession and lower commodity prices. South Africa, despite being one of the most developed African economies, has a more passive role and limited integration in global return transmission, as shown by its neutral and slightly negative return spillover values. Its net return spillovers fluctuate around zero, suggesting that the market switches between receiving and transmitting return shocks without persistent dominance in either direction. Such dynamic reflects the exposure to both domestic economic events and global investor sentiment, as well as the moderate level of financial integration of the country.

The dynamic of net volatility spillovers is captured in Figure A6. The graph of the S&P 500 demonstrates positive values of the spillover index for most of the sample period, highlighting the role of the U.S. market as the main volatility transmitter and driver of global risk sentiment. However, a large negative spike in 2022 also indicates a possibility of the U.S. economy to absorb shocks even from localized events, in this case from the conflict in Eastern Europe. The European market, despite being significantly influential, does not show significant volatility dynamics, although there is a significant risk transmission around the COVID-19 outbreak and increased received volatility in early 2022, likely caused by the Russian-Ukrainian conflict, energy market disruptions, and economic sanctions. Net volatility spillovers are generally moderate and stable for all emerging markets, with notable movements only in 2020 and 2022, which are associated with major crises. In addition, there was a substantial volatility transmission from the Russian market shortly after the Global Financial Crisis. In 2008, oil prices declined, and the Russian market responded aggressively, adjusting to these price changes. As a result, these adjustments caused uncertainty that spread into the global system and was absorbed mainly by other BRICS countries. However, the function of important volatility transmitters among BRICS countries changed in the following years. In 2020, Brazil showed up as a significant net volatility transmitter, reflecting market sensitivity to global turbulence and strong reaction to price and capital flow shocks. In contrast, other BRICS markets, namely China, Russia, and India, absorbed this volatility while transmitting low amounts of shocks. The Indian market reached one of its lowest spillover values in 2020, indicating the vulnerability of the Indian market to this major crisis. Another major trigger of a widespread volatility shock was the onset of the Russian–Ukrainian conflict in 2022. During the early phase of the conflict, Russia acted as a net transmitter of volatility. However, the subsequent financial isolation and sanctions limited its global financial interactions. Despite the local nature of the conflict, other markets absorbed this volatility, underscoring how turmoil and growing risk in a major emerging economy can spread across the financial system even if the source becomes isolated.

6 Discussion

The analysis of return and volatility spillovers presented in this thesis identifies differences in transmission patterns between BRICS and developed markets. Developed markets still have lead positions in shock transmission, while emerging markets like India, China, and Russia primarily function as shock absorbers. Brazil and South Africa, in turn, demonstrate mixed dynamics. Their dynamic positions change over time between net transmitters and net receivers, indicating their increasing contribution to global spillover transmission. During the COVID-19 pandemic, Brazil was exceptionally dominant in volatility transmission, as its spillover index values were even larger than those of developed markets, indicating its active participation in risk transmission. In contrast, the Chinese stock market's cross-border shock transmissions are very limited, which can be observed from its consistently low return and volatility spillover indices. Thus, this is the most financially isolated and least integrated market in the system involved. Such isolation is probably caused by capital controls, barriers to regulation, and a financial system that remains partially closed to foreigners.

Both return and volatility spillovers become more pronounced during periods of financial stress. For instance, events like the COVID-19 pandemic or the Russian-Ukrainian conflict led to extreme values of spillover transmission. However, the dynamic of return transmission is considerably different from the transmission of volatility. Return spillovers are more stable, with gradual changes and constant presence, and reflect market responses to fundamental changes. In contrast, volatility spillovers react rapidly and sharply to any changes in risk perception, panic-driven behavior, or asset repricing, describing them as a more sensitive measure of shock transmission. For example, the onset of the Russian-Ukrainian conflict caused a huge spike in volatility propagation. On the other hand, the shock to returns was less pronounced, suggesting gradual adjustments of prices and market expectations. This implies that return spillovers represent long-term integration and response to shifts in fundamentals, while volatility spillovers can be used as an indicator for levels of systemic risk and investor sentiment.

One key limitation of the method used in this thesis is that, while the Diebold-Yilmaz methodology enables the analysis of the intensity and direction of return and volatility shock transmission, it does not identify causality or distinguish between underlying transmission channels. The existing literature attributes spillovers to several important transmission mechanisms. The first mechanism is based on the distribution of information around the world. This mechanism is present when markets react to the latest financial, macroeconomic, or geopolitical announcements and consequently transmit return or volatility shocks, as traders and investors process this information. Examples of such information include Federal Reserve announcements, regulatory changes, and even news about geopolitical events, such as the onset of the Russia-Ukraine conflict, which caused significant transmission of risk and uncertainty. The idea of an information-based transmission mechanism is examined by the early study by Engle et al. (1990). The authors demonstrate that volatility transmission is primarily caused by public news that spreads from one foreign exchange market to another as they open during the day. Further, King and Wadhwani (1990) suggest that price movements in one market can serve as informational signals to traders in other markets. The traders and investors can then overreact or misinterpret the information received, leading to volatility transmission across borders. These studies highlight the important role played by information in dynamics of financial spillovers, contributing to an understanding of transmission mechanisms.

The second mechanism of shock transmission is based on liquidity. When investors, in particular global funds, face funding distress or risk pressure in one market, they may pursue portfolio rebalancing to manage their risks across markets. Through their rebalancing process, investors might sell assets in one market to reduce their exposure in another. Forced selling or selling under pressure can originate from liquidity events or funding constraints, sometimes creating a contagion of volatility across markets, particularly when credit access is limited, asset prices are declining, and investors are forced to divest assets or hold onto cash when they can no longer access credit. Kyle and Xiong (2001) documented this process by demonstrating how losses in one market trigger fire sales in other, unrelated markets as investors attempt to raise funds. This process leads to increased return volatility transmission, even in the absence of new information. Kodres and Pritsker (2002) arrived at even more nuanced conclusions that not only do shocks transmit temporally and contemporaneously but also in much the same way through portfolio rebalancing to control overall risk exposure, when investors experiencing shocks in one market revise their holdings in related or other markets. While this channel is not directly observable, the volatility transmission patterns observed during the Global Financial Crisis, during which regional market constraints forced investors to reallocate their asset holdings through regions as the U.S. credit market was disrupted, give credence to liquidity-based spillover patterns. This behavior likely contributed to the high volatility transmission observed during the crisis and its aftermath.

The investor behavior channel is another important way of transmission, through which shocks spread because of herding behavior or changes in global investor sentiment rather than fundamentals. It should be noted that this mechanism is also relevant during crisis periods when panic or fear exists, and markets move together rather than respond to fundamentals. G. A. Calvo and Mendoza (2005) illustrate that investors may choose to herd when there are trading constraints and the cost of obtaining new information is expensive, allowing contagion to develop endogenously in globalized and securitized markets. Such scenarios might arise at the beginning of the COVID-19 crisis when investors began to sell risky assets across all markets regardless of local fundamentals. Rather than analyzing firm-specific or country-specific information, investors were reacting to broad risk signals such as global health data, suggesting that decisions were made based on fear. Exceedingly extreme volatility across all markets was caused by a reaction to risk in all markets, even in the countries with low infection rates, such as South Africa and Brazil.

Finally, there is a macroeconomic transmission mechanism where global capital flows may change with movements in observable variables, e.g., interest rates, inflation expectations, and the monetary policy of key global economies. The existing literature has documented the inherent volatility and capital flight of emerging markets when U.S. interest rates climb (Ehrmann and Fratzscher, 2009; Rey, 2015). The greatest example of this channel also occurs during the initial months of the COVID-19 pandemic, when U.S. monetary easing caused a sharp but persistent increase in return spillovers. At the same time, liquidity pressures and the extreme reaction of investors led to massive sell offs and asset repricing that occurred in all markets, causing massive and systemic cross-border transmission of volatility and return movements. Such dynamics illustrate how the channels of transmission may not be distinct but operate in conjunction with each other, particularly in periods of financial stress.

Although this thesis does not go into detail about these channels, future empirical work may seek to distinguish them in more targeted ways. For example, event studies conducted around macroeconomic announcements could detect information-based spillovers and allow for the investigation of rapid cross-market adjustments, while accounting for liquidity measures such as TED spread or bid-ask spreads in spillover models would allow for testing liquidity-based spillovers. Text-based sentiment analysis techniques, including natural language processing technologies to analyze news articles or social media, may enable the capture of sentiment-based spillovers. Future research could also explore how macroeconomic transmission mechanisms cause spillovers, for example, using structural VARs to help isolate shocks to economic variables and track secondary effects. Alternatively, implementing spillover regressions with macroeconomic controls would establish whether the variation in spillovers is explained by macroeconomic conditions, such as changes in monetary policy and shifts in inflation expectations. A potential avenue for future investigation includes the multi-asset or sectoral level of spillover dynamics, as investigating these relationships may uncover more nuanced mechanisms and also deliver a more holistic understanding of the function of financial system. Finally, in light of the emergence of digital finance and automated trading in financial markets, it is essential to investigate whether newer sources of spillovers can be revealed.

7 Conclusion

This research has explored return and volatility spillovers across U.S., European, and BRICS markets over the past twenty years. The Diebold-Yilmaz framework, which is based on Generalized Forecast Error Variance Decomposition and the VAR model, allowed to examine both the static and dynamic interconnectedness between markets and recognize distinctions in the direction of return and volatility spillovers over time. This study confirms the role of developed markets as the generally dominant net transmitters of return and volatility shocks. Comparatively, several other BRICS markets, specifically Russia, India, and China, appeared to be net receivers over the examined period. However, Brazil and South Africa show different dynamics, with periods where they assumed the role of a net transmitter to periods of being a net receiver, suggesting they are more integrated in the global stock market system. The spillover intensity fluctuates over the entire sample period and spikes sharply at times of financial market stress. Moreover, there are substantial differences in the return and volatility spillover dynamics, as volatility spillovers react quickly to uncertainty shocks and risk sentiment, which leads to a more turbulent dynamic than that of return spillovers, which develop gradually and tend to be persistent.

The Diebold-Yilmaz spillover indices used for the analysis provide meaningful insights about the magnitude and direction of stock market connectedness. However, they do not describe the underlying mechanisms of transmission. The literature has proposed several mechanisms, which have been discussed in this thesis, including information-based and liquidity-based spillovers, effects related to investor behavior, and macroeconomic transmission mechanisms. Empirical patterns suggest that these mechanisms might interact during times of crisis, when multiple stressors are intensifying simultaneously.

By examining the strength and direction of return and volatility spillover transmission between emerging and developed markets, this research improves our understanding of the role and dynamics of the BRICS markets in the global financial system. The results may be of great significance to policymakers and international investors who are concerned with market stability, and risk transmission to other economies. Global financial connections continue to develop, fostered by monetary policy shifts, geopolitical events and technological advancements. As these developments continue to evolve, the monitoring and understanding of spillover effects become more important. This thesis suggests a solid framework for these efforts, while recognizing the need for additional research to fully explore the complexity of the underlying mechanisms and cross-market dimensions that determine global financial connectedness.

8 References

Aloui, R., Aïssa, M. S. B., & Nguyen, D. K. (2011). Global financial crisis, extreme interdependences, and contagion effects: The role of economic structure? *Journal of Banking Finance*, *35*(1), 130–141. https://doi.org/10.1016/j.jbankfin.2010.07.021

Baruník, J., Kočenda, E., & Vácha, L. (2016). Asymmetric connectedness on the us stock market: Bad and good volatility spillovers. *Journal of Financial Markets*, *27*, 55–78. https://doi.org/10.1016/j.finmar.2015.09.003

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), 1060–1075. https://doi.org/10.1111/roie.12091

Bekaert, G., Harvey, C. R., & Ng, A. (2005). Market integration and contagion. *The Journal of Business*, *78*(1), 39–69. https://doi.org/10.1086/426519

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*(3), 307–327. https://doi.org/10.1016/0304-4076(86)90063-1

Calvo, G. A., & Mendoza, E. G. (2005). Rational contagion and the globalization of securities markets. *Journal of International Economics*, *51*(1), 79–113. https://doi.org/10.1016/S0022-1996(99)00038-0

Calvo, S. G., & Reinhart, C. (1996). *Capital flows to latin america: Is there evidence of contagion effects?* (Policy Research Working Paper Series No. 1619). The World Bank. https://ssrn.com/abstract=636120

Chiang, T. C., Jeon, B. N., & Li, H. (2007). Dynamic correlation analysis of financial contagion: Evidence from asian markets. *Journal of International Money and Finance*, *26*(7), 1206–1228. https://doi.org/10.1016/j.jimonfin.2007.06.005

Chittedi, K. R. (2010). Global stock markets development and integration: With special reference to bric countries. *International Review of Applied Financial Issues and Economics*, *1*, 18–36. https://mpra.ub.uni-muenchen.de/18602/

Corsetti, G., Pericoli, M., & Sbracia, M. (2005). 'some contagion, some interdependence': More pitfalls in tests of financial contagion. *Journal of International Money and Finance*, *24*(8), 1177–1199. https://doi.org/10.1016/j.jimonfin.2005.08.012

Costa, A. C., Matos, P., & Silva, C. (2022). Sectoral connectedness: New evidence from us stock market during covid-19 pandemics. *Finance Research Letters*, *45*, 102–124. https://doi.org/10.1016/j.frl.2021.102124

Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, *119*(534), 158–171. https://doi.org/10.1111/j.1468-0297.2008.02208.x

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, *28*(1), 57–66. https://doi.org/10.1016/j.ijforecast.2011.02.006

Diebold, F. X., & Yilmaz, K. (2015). Trans-atlantic equity volatility connectedness: Us and european financial institutions, 2004–2014. *Journal of Financial Econometrics*, *14*(1), 81–127. https://doi.org/10.1093/jjfinec/nbv021

Dornbusch, R., Park, Y. C., & Claessens, S. (2000). Contagion: Understanding how it spreads. *The World Bank Research Observer*, *15*(2), 177–197. https://doi.org/10.1093/wbro/15.2.177

Ehrmann, M., & Fratzscher, M. (2009). Global financial transmission of monetary policy shocks. *Oxford Bulletin of Economics and Statistics*, *71*(6), 739–759. https://doi.org/10.1111/j.1468-0084.2009.00561.x

Engle, R. F. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business Economic Statistics*, *20*(3), 339–350. https://doi.org/10.1198/073500102288618487

Engle, R. F., Ito, T., & Lin, W.-L. (1990). Meteor showers or heat waves? heteroskedastic intra-daily volatility in the foreign exchange market. *Econometrica*, *58*(3), 525–542.

Engle, R. F., & Kroner, K. F. (1995). Multivariate simultaneous generalized arch. *Econometric Theory*, *11*(1), 122–150. https://doi.org/10.1017/S0266466600009063

Forbes, K., & Rigobon, R. (2002). No contagion, only interdependence: Measuring stock market comovements. *The Journal of Finance*, *57*(5), 2223–2261. https://doi.org/10.1111/0022-1082.00494

Galesi, M., & Sgherri, S. (2009). *Regional financial spillovers across europe: A global var analysis.* (IMF Working Paper No. 09/23). International Monetary Fund. https://doi.org/10.5089/9781451871708.001

Garman, M. B., & Klass, M. J. (1980). On the estimation of security price volatilities from historical data. *The Journal of Business*, 67–78. https://doi.org/10.1086/296072

Hung, J.-C., Lou, T.-W., Wang, Y.-H., & Lee, J.-D. (2012). Evaluating and improving garch-based volatility forecasts with range-based estimators. *Applied Economics*, *45*(28), 4041–4049. https://doi.org/10.1080/00036846.2012.748179

Karolyi, G. A., & Stulz, R. M. (1996). Why do markets move together? an investigation of us-japan stock return comovements. *The Journal of Finance*, *51*(3), 951–986. https://doi.org/10.1111/j.1540-6261.1996.tb02713.x

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. https://doi.org/10.1016/j.intfin.2010.08.005

King, M. A., & Wadhwani, S. (1990). Transmission of volatility between stock markets. *The Review of Financial Studies*, *3*(1), 5–33. https://doi.org/10.1093/rfs/3.1.5

Kodres, L. E., & Pritsker, M. (2002). A rational expectations model of financial contagion. *The Journal of Finance*, *57*(2), 769–799. https://doi.org/10.1111/1540-6261.00441

Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, *74*(1), 119–147. https://doi.org/10.1016/0304-4076(95)01753-4

Kyle, A. S., & Xiong, W. (2001). Contagion as a wealth effect. *The Journal of Finance*, *56*(4), 1401–1440. https://doi.org/10.1111/0022-1082.00373

Lehkonen, H. (2015). Stock market integration and the global financial crisis. *Review of Finance*, *19*(5), 2039–2094. https://doi.org/10.1093/rof/rfu039

Li, Y., & Glies, D. E. (2015). Modelling volatility spillover effects between developed stock markets and asian emerging stock markets. *International Journal of Finance Economics*, *20*(2), 155–177. https://doi.org/10.1002/ijfe.1506

Masson, P. R. (1998). *Contagion: Monsoonal effects, spillovers, and jumps between multiple equilibria.* (IMF Working Papers No. 98/142). International Monetary Fund. https://doi.org/10.5089/9781451856224.001

McIver, R. P., & Kang, S. H. (2020). Financial crises and the dynamics of the spillovers between the us and brics stock markets. *Research in International Business and Finance*, *54*, 101276. https://doi.org/10.1016/j.ribaf.2020.101276

Mensi, W., Hammoudeh, S., Nguyen, D. K., & Kang, S. H. (2016). Global financial crisis and spillover effects among the us and brics stock markets. *International Review of Economics Finance*, *42*, 257–276. https://doi.org/10.1016/j.iref.2015.11.005

Mensi, W., Hammoudeh, S., Reboredo, J. C., & Nguyen, D. K. (2014). Do global factors impact brics stock markets? a quantile regression approach. *Emerging Markets Review*, *19*, 1–17. https://doi.org/10.1016/j.ememar.2014.04.002

Panda, P., Vasudevan, S., & Panda, B. (2020). Dynamic connectedness among brics and major countries stock markets. *Journal of Public Affairs*, *21*(3), e2265. https://doi.org/10.1002/pa.2265

Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics letters*, *58*(1), 17–29. https://doi.org/10.1016/S0165-1765(97)00214-0

Rey, H. (2015). *Dilemma not trilemma: The global financial cycle and monetary policy independence.* (NBER Working Paper No. 21162). National Bureau of Economic Research. https://doi.org/10.3386/w21162

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. https://doi.org/10.1016/j.irfa.2015.01.015

Wang, P., & Moore, T. (2008). Stock market integration for the transition economies: Time-varying conditional correlation approach. *The Manchester School*, *76*, 116–133. https://doi.org/10.1111/j.1467-9957.2008.01083.x

Wen, D., Wang, G.-J., Ma, C., & Wang, Y. (2019). Risk spillovers between oil and stock markets: A var for var analysis. *Energy Economics*, *80*, 524–535. https://doi.org/10.1016/j.eneco.2019.02.005

Yarovaya, L., Brzeszczyński, J., & Lau, C. K. M. (2016). Intra- and inter-regional return and volatility spillovers across emerging and developed markets: Evidence from stock indices and stock index futures. *International Review of Financial Analysis*, *43*, 96–114. https://doi.org/10.1016/j.irfa.2015.09.004

Yoon, S.-M., Al Mamun, M., Uddin, G. S., & Kang, S. H. (2019). Network connectedness and net spillover between financial and commodity markets. *The North American Journal of Economics and Finance*, *48*, 801–818. https://doi.org/10.1016/j.najef.2018.08.012

Zhang, D., & Broadstock, D. C. (2020). Global financial crisis and rising connectedness in the international commodity markets. *International Review of Financial Analysis*, *68*, 101239. https://doi.org/10.1016/j.irfa.2018.08.003

Appendix A: Tables and Figures

Index	BVSP	MOEX	Nifty 500	Shanghai Composite	JSE	S&P 500	STOXX 600	FROM	Net
BVSP	48.66%	5.75%	4.57%	1.15%	9.64%	17.20%	13.03%	51.34%	5.90%
MOEX	8.07%	54.68%	5.09%	0.91%	11.46%	6.69%	13.10%	45.32%	-9.75%
Nifty 500	7.73%	5.59%	56.40%	2.18%	9.06%	8.38%	10.66%	43.60%	-13.41%
Shanghai Composite	3.33%	2.08%	3.44%	80.88%	3.79%	3.08%	3.40%	19.12%	-11.94%
JSE	10.53%	8.93%	6.43%	1.58%	42.46%	11.39%	18.68%	57.54%	2.24%
S&P 500	16.40%	4.17%	4.34%	0.55%	9.48%	46.19%	18.87%	53.81%	10.90%
STOXX 600	11.19%	9.04%	6.32%	0.81%	16.35%	17.98%	38.30%	61.70%	16.05%
TO	57.24%	35.57%	30.19%	7.18%	59.78%	64.71%	77.75%	332.42%	
TO (incl. own)	105.9%	90.2%	86.6%	88.1%	102.2%	110.9%	116.1%	700.0%	
							Total spillover index	**47.49%**	

Table A1: Return spillover table

Index	BVSP	MOEX	Nifty 500	Shanghai Composite	JSE	S&P 500	STOXX 600	FROM	Net
BVSP	58.21%	3.69%	3.44%	0.78%	6.98%	17.09%	9.80%	43.51%	19.29%
MOEX	8.20%	60.68%	3.72%	1.10%	6.28%	10.29%	9.74%	39.91%	-4.90%
Nifty 500	12.75%	5.76%	55.74%	1.96%	6.96%	10.12%	6.71%	45.66%	-25.88%
Shanghai Composite	2.58%	3.27%	2.38%	84.50%	2.40%	2.49%	2.37%	17.01%	-10.22%
JSE	10.74%	6.08%	4.41%	0.65%	49.80%	16.47%	11.85%	50.87%	-7.31%
S&P 500	15.04%	7.07%	3.19%	0.76%	9.53%	48.33%	16.09%	52.62%	26.90%
STOXX 600	12.61%	6.95%	3.86%	1.29%	9.55%	21.73%	44.01%	56.44%	2.12%
TO	62.80%	35.02%	19.78%	6.79%	43.56%	79.52%	58.55%	306.01%	
TO (incl. own)	119.29%	95.10%	74.12%	89.78%	92.69%	126.90%	102.12%	700.0%	
							Total spillover index	**43.72%**	

Table A2: Volatility spillover table

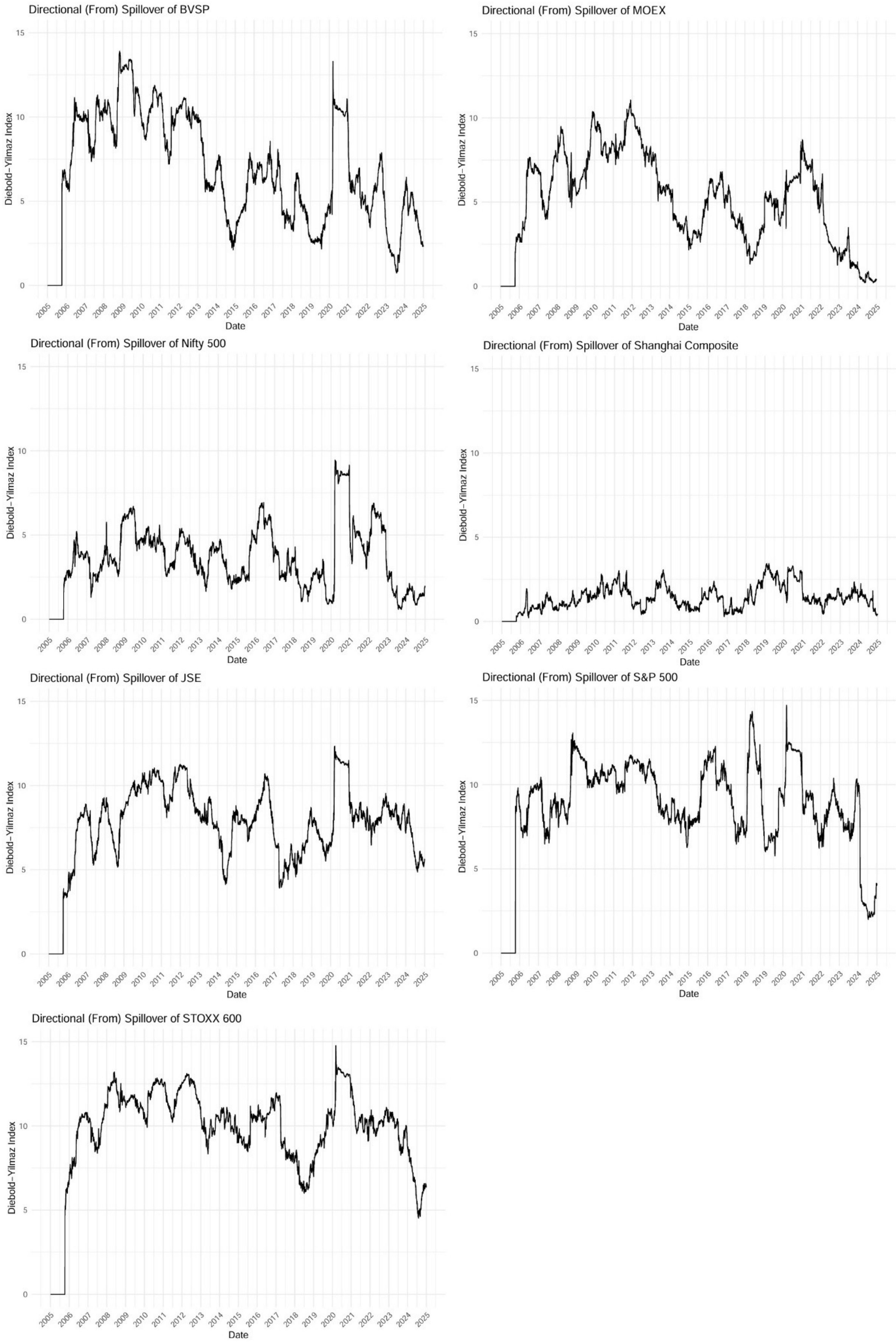

Figure A1: Directional (FROM) return spillovers

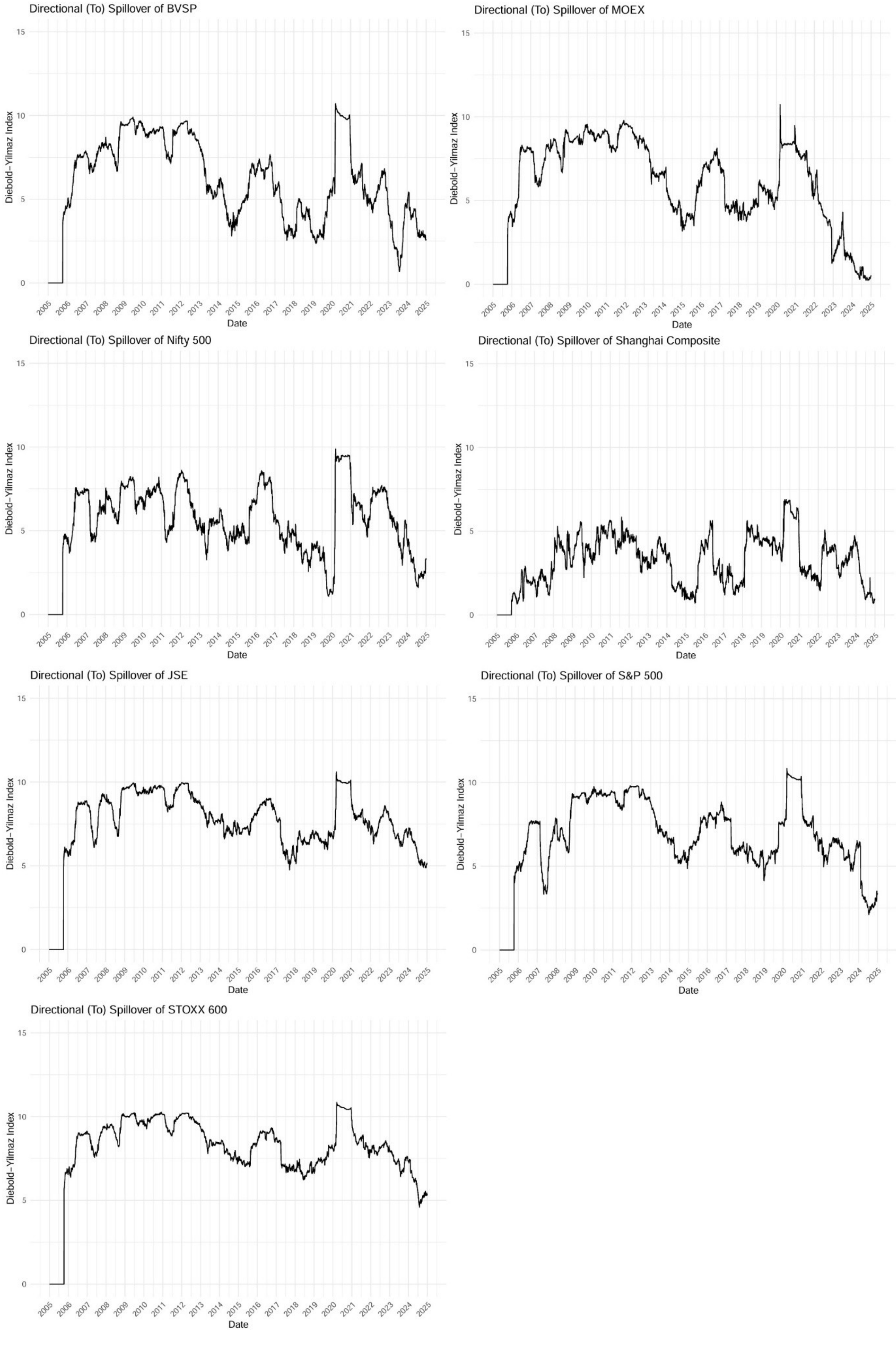

Figure A2: Directional (TO) return spillovers

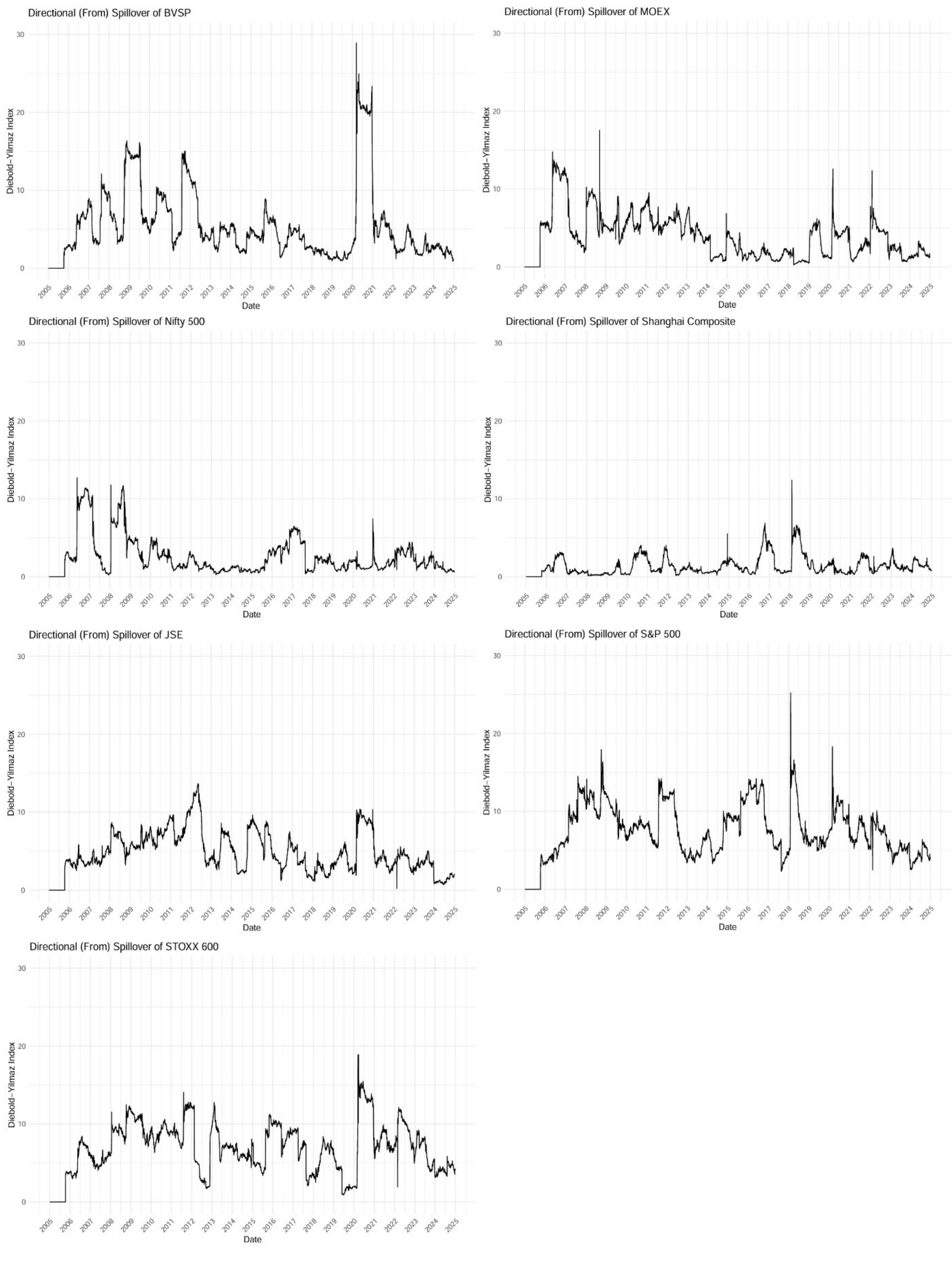

Figure A3: Directional (FROM) volatility spillovers

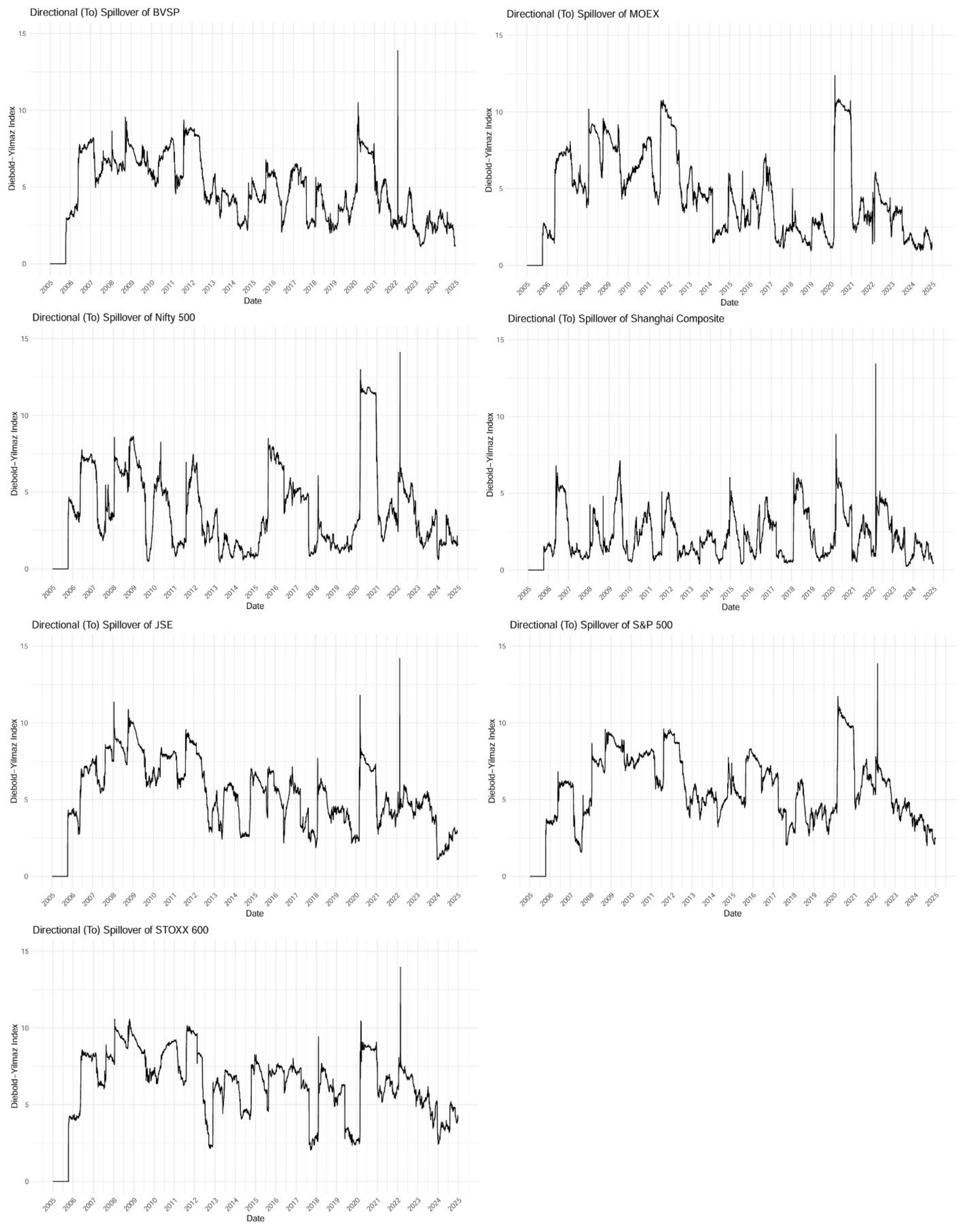

Figure A4: Directional (TO) volatility spillovers

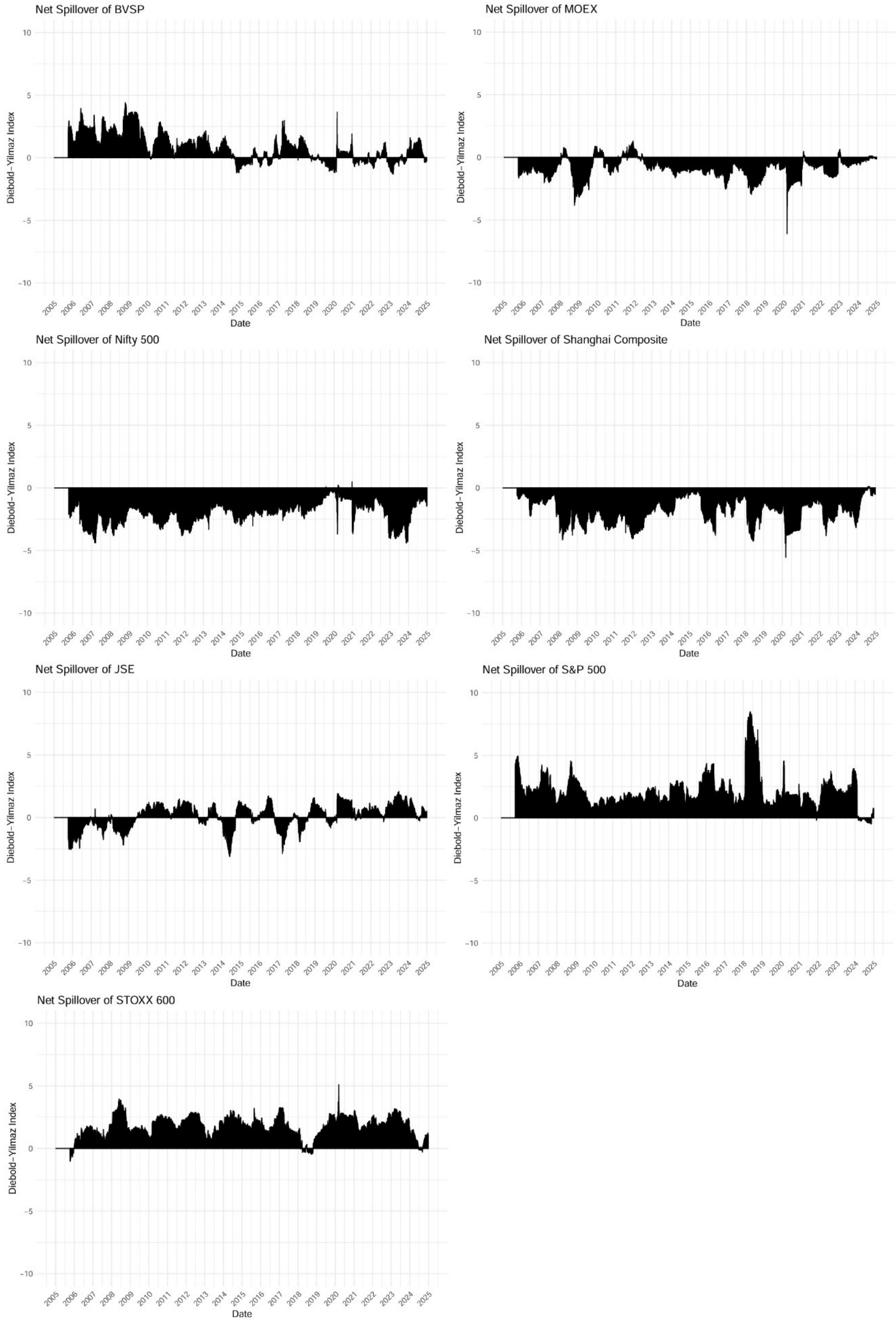

Figure A5: Net return spillovers

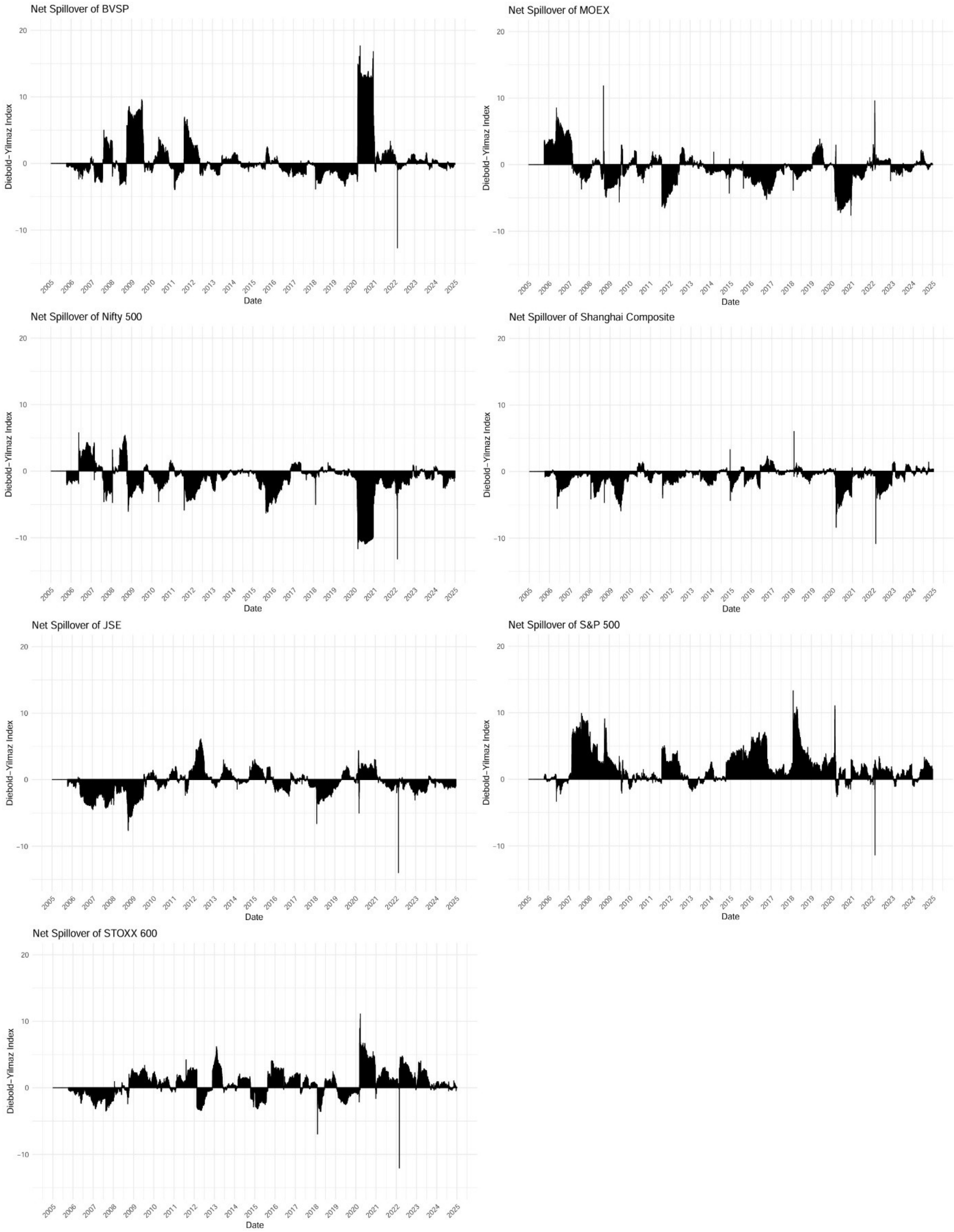

Figure A6: Net volatility spillovers

Appendix B: Calculation of VAR Model and GFEVD

This appendix provides detailed calculations of spillover indices introduced in the methodology section. A Vector Autoregression (VAR) model of order 1 is estimated for two market systems, and a forecast horizon of two steps is used to calculate the GFEVD. The VAR(1) model and a short forecast horizon are taken for illustrative purposes to keep the example brief and computationally transparent. The numbers are taken from real-world return data for the S&P 500 and Shanghai Composite index for the period from 2005 to 2025.

The VAR model for both market systems is given as follows:

$$X_t = \begin{bmatrix} R_{1,t} \\ R_{2,t} \end{bmatrix} = \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix},$$

where $\Phi = \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix}$ - coefficient matrix, X_t – vector of log returns at time t for markets 1 and 2. For simplicity, market 1 is considered to be the U.S. market, while market 2 represents either European or Chinese market, depending on the system under consideration.

The moving average representation is obtained as:

$$X_t = \sum_{h=0}^{\infty} \Phi^h \varepsilon_{t-h} = \sum_{h=0}^{\infty} A_h \varepsilon_{t-h},$$

where $A_h = \Phi^h$.

The estimated coefficient matrix for the first market system is

$$\Phi = \begin{bmatrix} 0.0269 & 0.00036 \\ -0.1996 & 0.000066 \end{bmatrix},$$

for h = 0,1, the coefficients A_h are:

$$A_0 = I = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, A_1 = \Phi = \begin{bmatrix} 0.0269 & 0.00036 \\ -0.1996 & 0.000066 \end{bmatrix}$$

The estimated variance matrix of shocks is

$$\Sigma = \begin{bmatrix} 0.00015 & 0.000086 \\ 0.000086 & 0.000119 \end{bmatrix}.$$

The diagonal elements of the matrix represent the variance of shocks within American and European markets: 0.00015 for the S&P 500, and 0.000119 for the STOXX 600. The off-diagonal elements define the covariance between shocks to S&P 500 and STOXX 600, which is 0.000086.

The coefficient and covariance matrices for the second market system are estimated as

$$\Phi = \begin{bmatrix} 0.000577 & 0.000356 \\ -0.00486 & 0.000136 \end{bmatrix}, \Sigma = \begin{bmatrix} 0.00015 & 0.0000196 \\ 0.0000196 & 0.0002125 \end{bmatrix}.$$

The covariance between shocks to S&P 500 and Shanghai Composite index is equal to 0.0000196. The variance of shocks within the Chinese market is 0.0002125, while the variance within the American market remains the same for both market systems.

The General Forecast Error Variance Decomposition, applied to the U.S. - Europe system, yields the own contributions of S&P 500 and STOXX 600 and the contributions of these indices to each other. The contributions of the S&P 500 are given as follows:

Own shock contribution $\theta_{11}(2)) = \frac{0.00015^{-1}((e_1^{'}A_0\Sigma e_1)^2+(e_1^{'}A_1\Sigma e_1)^2)}{(e_1^{'}A_0\Sigma A_0^{'}e_1)+(e_1^{'}A_1\Sigma A_1^{'}e_1)}$.

Computing the following numerator components:

$$e_1^{'}A_0\Sigma e_1 = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 0.00015 & 0.000086 \\ 0.000086 & 0.000119 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} = 0.00015$$

$$e_1^{'}A_1\Sigma e_1 = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} 0.0269 & 0.00036 \\ -0.1996 & 0.000066 \end{bmatrix} \begin{bmatrix} 0.00015 & 0.000086 \\ 0.000086 & 0.000119 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} = 0.0000041$$

Then the numerator is: $0.00015^{-1} * (0.00015^2 + 0.0000041^2) = 0.00015$

Computing the following denominator components:

$$e_1^{'}A_0\Sigma A_0^{'}e_1 = \begin{bmatrix}1 & 0\end{bmatrix}\begin{bmatrix}0.00015 & 0.000086\\ 0.000086 & 0.000119\end{bmatrix}\begin{bmatrix}1\\ 0\end{bmatrix} = 0.00015$$

$$\begin{aligned}e_1^{'}A_1\Sigma A_1^{'}e_1 = &\begin{bmatrix}1 & 0\end{bmatrix}\begin{bmatrix}0.0269 & 0.00036\\ -0.1996 & 0.000066\end{bmatrix}\begin{bmatrix}0.00015 & 0.000086\\ 0.000086 & 0.000119\end{bmatrix}\\ &\times\begin{bmatrix}0.0269 & 0.00036\\ -0.1996 & 0.000066\end{bmatrix}\begin{bmatrix}1\\ 0\end{bmatrix}\\ &= -0.00000037\end{aligned}$$

The denominator is: 0.00015-0.00000037=0.00014963

Thus, the own shock contribution of the S&P 500 is $\theta_{12}(2) = \frac{0.00015}{0.00014963} = 1.0025$

The spillover from STOXX 600 to S&P 500 is defined similarly as:

$$\theta_{12}(2) = \frac{0.00015^{-1}((e_1^{'}A_0\Sigma e_2)^2 + (e_1^{'}A_1\Sigma e_2)^2)}{(e_1^{'}A_0\Sigma A_0^{'}e_1) + (e_1^{'}A_1\Sigma A_1^{'}e_1)}$$

Following the same calculation procedure, the value of numerator is equal to 0.0000493, while the denominator remains equal to 0.00014963. The spillover from the STOXX 600 is then $\theta_{12}(2) = \frac{0.0000493}{0.00014963} = 0.32978$

Following the same process, the own contribution of STOXX 600 and the spillover from S&P 500 to STOXX 600 are computed as:

$$\theta_{22}(2) = \frac{0.00015^{-1}((e_2^{'}A_0\Sigma e_2)^2 + (e_2^{'}A_1\Sigma e_2)^2)}{(e_2^{'}A_0\Sigma A_0^{'}e_2) + (e_2^{'}A_1\Sigma A_1^{'}e_2)} = 0.798$$

$$\theta_{21}(2) = \frac{0.00015^{-1}((e_2^{'}A_0\Sigma e_1)^2 + (e_2^{'}A_1\Sigma e_1)^2)}{(e_2^{'}A_0\Sigma A_0^{'}e_2) + (e_2^{'}A_1\Sigma A_1^{'}e_2)} = 0.437$$

Since GFEVD does not require orthogonalization, the terms do not sum up to 1 and should be normalized across each row to calculate the percentage of forecast error variance.

For S&P 500 normalized contributions are:

$$\tilde{\theta}_{11}(2) = \frac{1.0025}{1.0025 + 0.32978} = 0.753, \tilde{\theta}_{12}(2) = \frac{0.32978}{1.0025 + 0.32978} = 0.247$$

Normalized contributions for STOXX 600 are:

$$\tilde{\theta}_{22}(2) = \frac{0.798}{0.798 + 0.437} = 0.646, \tilde{\theta}_{21}(2) = \frac{0.437}{0.798 + 0.437} = 0.354$$

For the second market system, the same procedure is applied. The GFEVD calculations yield the following contributions for S&P 500 and Shanghai Composite:

$$\theta_{11}(2) = 1.0000025, \theta_{12}(2) = 0.01707, \theta_{21}(2) = 0.0121, \theta_{22}(2) = 1.4167.$$

Normalized contributions are equal to:

$$\tilde{\theta}_{11}(2) = 0.983, \tilde{\theta}_{12}(2) = 0.017, \tilde{\theta}_{21}(2) = 0.0085, \tilde{\theta}_{22}(2) = 0.9915.$$