International Journal of Economic Practices and Theories (IJEPT)
ISSN: 2247-7225
Volume 2026, Issue 1

Volatility Transmission Across Developed and Emerging Equity Markets: Evidence from Diebold–Yilmaz TVP-VAR Spillover Analysis of Volatility Indices

[1]Tuhin Mukherjee, [2]Subhrajyoti Mandal

[1]Associate Professor Department of Business Administration University of Kalyani, West Bengal, India

[2]Senior Research Scholar Department of Business Administration University of Kalyani, West Bengal, India

Abstract

Volatility indices have emerged as important forward-looking indicators of market uncertainty and investor sentiment. Understanding the transmission of volatility across global financial markets has become crucial in an increasingly interconnected financial system. This study examines the dynamic spillover effects among major global volatility indices and their corresponding stock markets across developed and emerging economies. The analysis covers twelve major markets—United States, United Kingdom, Germany, Hong Kong, Japan, Australia, South Korea, China, Taiwan, South Africa, India, and Brazil—over the period 2015–2025.

To capture the time-varying nature of volatility transmission, the study employs the **Time-Varying Parameter Vector Autoregression (TVP-VAR)** model combined with the **Diebold–Yilmaz spillover framework** based on generalized forecast error variance decomposition (FEVD). This methodology enables the measurement of total, directional, and net volatility spillovers across markets without imposing restrictive assumptions about variable ordering. The empirical results reveal substantial cross-market volatility transmission, confirming the presence of strong global financial linkages. The United States emerges as the dominant net transmitter of volatility shocks, highlighting the central role of the U.S. financial market in driving global risk dynamics. In contrast, emerging markets such as India, Brazil, South Africa, and Taiwan are identified as major net receivers of volatility shocks, indicating their higher susceptibility to external market disturbances.

Furthermore, the results show that volatility spillovers are strongly time-varying and intensify during periods of global financial stress, particularly during the COVID-19 pandemic and recent geopolitical tensions. These findings provide important implications for international investors, policymakers, and risk managers in understanding global financial contagion and portfolio diversification strategies. Overall, the study contributes to the literature by providing comprehensive evidence on the dynamics of volatility spillovers between global volatility indices and stock markets using a TVP-VAR spillover framework.

Keywords: Volatility Spillovers; Volatility Indices; TVP-VAR; Diebold–Yilmaz Spillover Framework; Global Equity Markets; Financial Connectedness.

JEL Classification: C32, C58, G12, G15, G17.

1. Introduction

Financial markets across the world have become increasingly interconnected due to globalization, technological advancement, and rapid cross-border capital flows. As a result, shocks originating in one market are often transmitted rapidly to other markets, creating significant volatility spillovers across global financial systems. Understanding the transmission of volatility across international equity markets has therefore become an important area of research for investors, policymakers, and financial regulators. In this context, volatility indices have gained considerable attention as forward-looking indicators of market uncertainty and investor sentiment.

Volatility indices, commonly referred to as “fear gauges,” measure the market’s expectation of future volatility derived from option prices. The Chicago Board Options Exchange Volatility Index (VIX) is the most widely recognized measure of expected market volatility and has often been used as a benchmark indicator of global risk perception. Over time, several countries have developed their own volatility indices corresponding to major stock market indices. These include the volatility indices for markets such as the United Kingdom, Germany, Japan, Hong Kong, Australia, South Korea, China, India, and Brazil. These indices reflect investors’ expectations regarding future uncertainty in their respective markets and serve as important tools for risk management and portfolio allocation.

Given the growing integration of global financial markets, volatility shocks in one market can quickly propagate to other markets through various transmission channels. Such spillovers may arise from international portfolio rebalancing, global macroeconomic shocks, financial contagion during crises, and shifts in investor sentiment. Previous studies have documented significant volatility transmission across financial markets, particularly during periods of economic stress. Events such as the Global Financial Crisis, the European debt crisis, the COVID-19 pandemic, and geopolitical tensions have demonstrated that volatility spillovers intensify during turbulent periods.

While a substantial body of literature has examined volatility spillovers across stock markets, relatively fewer studies have focused on the role of **volatility indices themselves as transmitters and receivers of global financial uncertainty**. Moreover, traditional econometric approaches such as static Vector Autoregression (VAR) models assume constant parameters over time, which may not adequately capture the evolving nature of financial market linkages. Financial markets are inherently dynamic, and the strength of volatility transmission can change significantly over time due to structural shifts, economic shocks, and changes in market sentiment.

To address these limitations, this study employs the **Time-Varying Parameter Vector Autoregression (TVP-VAR)** model combined with the **Diebold–Yilmaz spillover framework** based on generalized forecast error variance decomposition (FEVD). The TVP-VAR approach allows model parameters to evolve over time, enabling a more flexible representation of dynamic interrelationships among financial markets. The Diebold–Yilmaz methodology further provides measures of total spillover, directional spillovers, and net spillovers, allowing a comprehensive analysis of volatility transmission across markets.

The present study investigates the dynamic volatility spillovers among major global volatility indices and their corresponding stock markets across twelve economies, including both developed and emerging markets. The sample consists of the United States, United Kingdom, Germany, Hong Kong, Japan, Australia, South Korea, China, Taiwan, South Africa, India, and Brazil. The study covers the period from **2015 to 2025**, which includes several significant global economic events such as the COVID-19 pandemic and heightened geopolitical uncertainties. By examining both developed and emerging markets, the study aims to understand the asymmetric transmission of volatility across different levels of market development.

The empirical results provide important insights into the structure of global volatility transmission. In particular, the findings highlight the dominant role of developed markets, especially the United States, as major transmitters of volatility shocks to other markets. In contrast, emerging markets tend to be more vulnerable to external volatility shocks, acting primarily as net receivers of risk transmission. Additionally, the analysis reveals that volatility spillovers are highly time-varying and tend to increase significantly during periods of global financial turmoil.

This study contributes to the existing literature in several ways. First, it provides a comprehensive analysis of volatility spillovers using a large set of global volatility indices representing both developed and emerging markets. Second, it employs the TVP-VAR spillover framework, which captures the time-varying dynamics of volatility transmission more effectively than traditional static models. Third, the study offers updated empirical evidence covering recent global economic events, including the COVID-19 pandemic and recent geopolitical shocks.

The findings of this study have important implications for international investors, policymakers, and financial market participants. A better understanding of volatility transmission mechanisms can assist investors in improving portfolio diversification strategies and risk management practices. For policymakers and regulators, insights into global volatility linkages are valuable in designing appropriate financial stability policies and monitoring systemic risk in increasingly interconnected financial markets.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature on volatility spillovers and volatility indices followd by research gap in the next section. Section 4 describes the data and methodology, including the TVP-VAR model and the Diebold–Yilmaz spillover framework. Section 5 presents the empirical results and discussion. Section 6 concludes with policy implications and suggestions for future research is depicted in the final section.

2. Literature Review

The transmission of volatility across financial markets has been widely studied in financial economics due to the increasing integration of global capital markets. Volatility spillovers occur when shocks or uncertainty originating in one market influence the volatility dynamics of other markets through financial, informational, or behavioral channels. The literature on volatility spillovers has evolved significantly over the past four decades, with methodological advancements allowing researchers to better capture the complex interdependencies among financial markets.

2.1 Early Studies on Volatility Modelling

The empirical analysis of financial market volatility gained momentum with the introduction of the **Autoregressive Conditional Heteroskedasticity (ARCH)** model by Engle (1982), which allowed conditional variance to change over time. This framework was extended by Bollerslev (1986) through the **Generalized ARCH (GARCH)** model, which became one of the most widely used tools for modeling volatility clustering in financial markets.

Subsequent extensions such as **EGARCH (Nelson, 1991)**, **TGARCH (Zakoian, 1994)**, and **GJR-GARCH (Glosten, Jagannathan, & Runkle, 1993)** further improved the ability to capture asymmetric volatility effects and leverage effects in financial markets. These models provided important insights into volatility dynamics but were primarily designed for single-market analysis.

To examine volatility transmission across multiple markets, researchers introduced **multivariate volatility models** such as the **VECH model (Bollerslev, Engle, & Wooldridge, 1988)** and the **BEKK model (Engle & Kroner, 1995)**. Later developments such as the **Dynamic Conditional Correlation (DCC-GARCH) model proposed by Engle (2002)** allowed the estimation of time-varying correlations among multiple financial assets.

Although these multivariate GARCH frameworks significantly improved the understanding of volatility interdependence, they often suffer from high dimensionality and computational complexity when applied to large financial systems.

2.2 Volatility Spillovers and Financial Contagion

The concept of volatility spillovers is closely related to the literature on **financial contagion and market interdependence**. Early empirical studies by **King and Wadhwani (1990)** and **Hamao, Masulis, and Ng (1990)** documented significant volatility transmission across major stock markets such as the United States, Japan, and the United Kingdom. Similarly, **Karolyi (1995)** provided evidence of volatility spillovers between the U.S. and Canadian equity markets.

During the late 1990s and early 2000s, research increasingly focused on volatility spillovers during periods of financial crises. Studies such as **Kaminsky and Reinhart (1998)** and **Forbes and Rigobon (2002)** examined how financial crises propagate across countries through contagion effects. These studies highlighted the role of financial integration, investor behavior, and macroeconomic linkages in transmitting volatility shocks across markets.

Later research expanded the analysis of volatility spillovers across asset classes including commodities, foreign exchange markets, and financial institutions. For instance, **Balcilar, Demirer, and Hammoudeh (2015)** documented significant volatility spillovers across international stock markets, particularly during crisis periods. Similarly, research on crude oil markets has found strong volatility transmission across regional oil benchmarks, emphasizing the importance of spillover effects for risk management and asset allocation.

2.3 Diebold–Yilmaz Spillover Framework

A major methodological advancement in the study of financial spillovers was introduced by **Diebold and Yilmaz (2009)**, who developed a spillover index based on **forecast error variance decomposition (FEVD)** from vector autoregression (VAR) models. Their framework allows the quantification of total spillovers as well as directional spillovers across markets.The methodology was further refined in **Diebold and Yilmaz (2012)** through the use of

generalized variance decomposition, which eliminates the dependence on variable ordering. The framework was later extended by **Diebold and Yilmaz (2014)** to analyze the network topology of financial connectedness.

The Diebold–Yilmaz spillover index has since become one of the most widely used methods for analyzing volatility transmission across financial markets. The framework provides measures of **total spillovers, directional spillovers, and net spillovers**, enabling researchers to identify major transmitters and receivers of financial volatility.

Subsequent studies have applied the Diebold–Yilmaz methodology to various financial markets including equity markets, commodities, banking systems, and cryptocurrencies. The framework has also been extended using **network analysis, regime-switching models, and frequency-domain approaches** to capture more complex spillover structures.

2.4 Time-Varying Spillover Models

While the Diebold–Yilmaz spillover framework provides valuable insights into financial interconnectedness, the traditional VAR approach assumes constant parameters over time. However, financial market relationships often evolve due to structural changes, economic shocks, and policy interventions.

To address this limitation, researchers have increasingly adopted **Time-Varying Parameter Vector Autoregression (TVP-VAR)** models. The TVP-VAR approach, originally developed by **Primiceri (2005)**, allows the parameters of the VAR model to evolve over time, thereby capturing dynamic changes in financial relationships.

More recently, **Antonakakis, Chatziantoniou, and Gabauer (2020)** proposed a refined **TVP-VAR spillover framework** that eliminates the need for rolling-window estimation and avoids the loss of observations associated with traditional rolling-window methods. This approach allows for a more efficient estimation of time-varying connectedness across financial markets.

Recent empirical studies have applied TVP-VAR spillover models to examine volatility transmission across global financial markets. For example, research analyzing volatility spillovers among **G20 stock markets** finds that spillover intensity increases significantly during global crises such as the Global Financial Crisis, the European sovereign debt crisis, and the COVID-19 pandemic.

2.5 Volatility Indices and Investor Sentiment

Another important strand of literature focuses on **volatility indices as indicators of market uncertainty**. The **CBOE Volatility Index (VIX)** is widely regarded as a forward-looking measure of expected stock market volatility and is often referred to as the “investor fear gauge.”

Whaley (2000) demonstrated that the VIX captures investor sentiment and expected market risk derived from option prices. Subsequent studies have found that volatility indices provide valuable information about market expectations and play a significant role in transmitting financial uncertainty across global markets.

Empirical research examining international volatility indices suggests that volatility shocks originating in major financial centers often propagate to other markets. Studies such as **Sarwar (2012)** found that the VIX significantly influences equity markets in emerging economies. Similarly, several studies have documented strong volatility spillovers between volatility indices and stock markets across developed and emerging economies.

Overall, the existing literature highlights that global financial markets are highly interconnected and that volatility shocks can propagate rapidly across borders. However, the magnitude and direction of these spillovers vary across markets and over time.

3. Research Gap and Contributions

Although a substantial number of studies have investigated volatility spillovers across financial markets, several gaps remain in the existing literature.

First, many previous studies focus primarily on stock market volatility rather than volatility indices themselves. Volatility indices represent forward-looking measures of market uncertainty derived from option prices and therefore provide more direct insights into investors' expectations of future market risk. However, empirical research examining the interactions among multiple global volatility indices remains relatively limited.

Second, a large portion of the existing literature concentrates mainly on developed financial markets such as the United States and Europe. Comparatively fewer studies incorporate a comprehensive set of both developed and emerging markets. Emerging markets play an increasingly important role in the global financial system, yet they may exhibit different volatility transmission dynamics due to differences in market maturity, liquidity, and regulatory environments.

Third, many earlier studies employ static econometric models such as standard VAR or multivariate GARCH frameworks. While these models are useful for capturing volatility relationships, they assume constant parameters over time and may fail to capture the evolving nature of global financial linkages. Financial markets are subject to structural changes and crisis events, which can significantly alter the pattern of volatility spillovers.

Fourth, there is limited empirical evidence covering recent global economic events such as the **COVID-19 pandemic and subsequent geopolitical tensions**, which have significantly affected global financial markets. An updated analysis incorporating these events can provide valuable insights into the time-varying nature of volatility transmission.

To address these gaps, the present study makes several important contributions to the literature. First, it examines volatility spillovers among a broad set of global volatility indices and their corresponding stock markets across twelve economies, including both developed and emerging markets. Second, the study employs the **Time-Varying Parameter Vector Autoregression (TVP-VAR)** model combined with the **Diebold–Yilmaz spillover framework**, which allows for a dynamic analysis of volatility transmission over time. Third, the study provides updated empirical evidence covering the period **2015–2025**, which includes several major global economic shocks.

By providing a comprehensive analysis of global volatility spillovers using a time-varying econometric framework, the study offers important insights into the structure and dynamics of international financial market interdependence.

4. Data and Methodology

4.1 Data Description

This study examines volatility spillovers across global financial markets using a set of **twelve volatility indices and their corresponding stock market indices** representing both developed and emerging economies. The dataset covers the period **January 2015 to December 2025**, capturing several important global events including the COVID-19 pandemic and recent geopolitical tensions. Table 1 describes the countries considered.

Table 1: Indices of selected countries and their volatility Indices

	Volatility Index	VIX Current Value -2025	Country / Region	Underlying Stock Index	Index Current Value -2025	Development Status
1	CBOE Volatility Index	19.55	United States	S&P 500	6,890.07	Developed
2	VFTSE	10.96	United Kingdom	FTSE 100	10,680.59	Developed
3	VDAX-NEW	18.56	Germany	DAX	24,986.25	Developed
4	VHSI	23.09	Hong Kong	Hang Seng Index	26,767.81	Developed

5	VXJ	26.76	Japan	Nikkei 225	58,583.12	Developed
6	AVIX	11.69	Australia	S&P/ASX 200	9,128.30	Developed
7	VKOSPI	47.61	South Korea	KOSPI 200	6,083.86	Developed
8	China iVIX	33.49	China	CSI 300	4,735.89	Developing (Emerging)
9	TAIEX Volatility Index (VIXTWN)	26.29	Taiwan	TAIEX	35,413.07	Developing (Emerging)
10	SAVI (South African Volatility Index)	18.75	South Africa	FTSE/JSE Top 40	########	Developing (Emerging)
11	India VIX (IVIX)	13.45	India	Nifty 50	25,473.30	Developing (Emerging)
12	VXBR	20.71	Brazil	Ibovespa	########	Developing (Emerging)

Daily closing prices are used to compute logarithmic returns as follows:

$$r_t = \ln(P_t) - \ln(P_{t-1})$$

where

- Pt= price (or index value) at time t
- r_t = continuously compounded return

The return series are used to estimate the volatility spillover dynamics across markets.

4.2 Time-Varying Parameter Vector Autoregression (TVP-VAR)

To capture the evolving relationships among financial markets, this study employs the **Time-Varying Parameter Vector Autoregression (TVP-VAR)** model. Unlike the traditional VAR model with constant parameters, the TVP-VAR allows coefficients to vary over time.

The TVP-VAR model of order p is expressed as:

$$y_t = A_{1,t}y_{t-1} + A_{2,t}y_{t-2} + \cdots + A_{p,t}y_{t-p} + \varepsilon_t$$

where

- yt = N×1N \times 1N×1 vector of endogenous variables
- Ai,t= N×N time-varying coefficient matrices
- p= lag length
- εt = vector of error terms

The error term follows:

$$\varepsilon_t \sim N(0, \Sigma_t)$$

where Σt is the **time-varying variance-covariance matrix**.

The time evolution of coefficients follows a random walk process:

$$A_t = A_{t-1} + u_t$$

where

- At = vectorized coefficient matrix
- ut= disturbance term

This structure allows the relationships among variables to evolve over time, which is particularly useful in financial markets characterized by structural changes and crisis periods.

4.3 Moving Average Representation

The TVP-VAR model can be rewritten in its **moving average representation**:

$$y_t = \sum_{h=0}^{\infty} \Phi_{h,t} \varepsilon_{t-h}$$

Where

$$\Phi_{0,t} = I$$

and Φh,t represents the **time-varying impulse response coefficients**.

This representation is necessary for computing **forecast error variance decomposition**.

4.4 Generalized Forecast Error Variance Decomposition (FEVD)

The **Generalized Forecast Error Variance Decomposition (GFEVD)** proposed by Koop et al. (1996) and Pesaran and Shin (1998) is used to measure the contribution of shocks from one market to the forecast error variance of another market.

The **H-step-ahead FEVD** is defined as:

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

where

- θij(H) = contribution of shocks from variable jjj to variable iii
- Σ = variance-covariance matrix
- ei = selection vector
- H = forecast horizon

To ensure rows sum to unity, the normalized FEVD is calculated as:

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

4.5 Total Spillover Index

The **Total Spillover Index** measures the overall level of volatility transmission across markets.

$$S^{(H)} = \frac{\sum_{i=1}^{N} \sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ij}^{(H)}}{N} \times 100$$

where

- N = number of markets

A higher value indicates stronger global volatility spillovers.

4.6 Directional Spillovers

Directional spillovers measure the transmission of shocks **to and from individual markets**.

Spillovers FROM others to market i

$$S_i^{\leftarrow} = \sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ij}^{(H)} \times 100$$

This indicates how much volatility market i receives from other markets.

Spillovers FROM market i to others

$$S_i^{\rightarrow} = \sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ji}^{(H)} \times 100$$

This measures how much volatility market iii transmits to other markets.

4.7 Net Spillover

Net spillover identifies whether a market is a **net transmitter or receiver of volatility**.

$$NS_i = S_i^{\rightarrow} - S_i^{\leftarrow}$$

where

- NSi>0 → Net transmitter
- NSi<0 → Net receiver

4.8 Rolling Window Spillover Analysis

To examine the **time-varying dynamics of spillovers**, the spillover index is estimated using a rolling window approach. This allows the spillover measures to evolve over time and capture changes during major economic events.

Let the window size be W. The model is re-estimated sequentially for:

$$t = W, W + 1, \ldots, T$$

This produces a time series of spillover indices, enabling the identification of periods of heightened financial contagion.

5. Empirical Results and Discussion

This section presents the empirical findings of the study based on the **TVP-VAR based generalized forecast error variance decomposition (FEVD)** within the **Diebold–Yilmaz spillover framework**.

5.1 Volatility Spillover Matrix

Table 2 presents the **volatility spillover matrix** derived from the TVP-VAR model for the period 2015–2025. Each element of the matrix represents the percentage contribution of shocks originating from one market to the forecast error variance of another market. The diagonal elements represent own-market effects, while the off-diagonal elements capture cross-market volatility spillovers.

For instance, the United States market exhibits an own variance contribution of approximately **57.7 percent**, indicating that a large portion of volatility in the U.S. market originates from domestic shocks. Similar patterns are observed in other developed markets such as the United Kingdom (45.8%), Germany (43.2%), and Australia (48.4%).

However, the off-diagonal elements reveal substantial cross-market spillovers, confirming strong financial interdependence across global markets. Among the markets analyzed, the United States exerts considerable influence on other markets. Volatility shocks originating from the U.S. market contribute significantly to the volatility of both developed and emerging markets. This finding highlights the dominant role of the U.S. financial system in shaping global risk dynamics.

Emerging markets, including India, Brazil, and South Africa, display comparatively lower own variance contributions and higher exposure to external shocks. This suggests that these markets are more sensitive to volatility originating from other international financial markets.

Table 2: Volatility Spillover Matrix Based on TVP-VAR FEVD (2015–2025)

(All values in %, rows = shock transmitters, columns = shock receivers)

From \ To	US	UK	GER	HK	JPN	AUS	KOR	CHN	TWN	SA	IND	BRA	From Others
US	57.7	4.6208	4.8691	4.2003	4.351	2.9923	4.051	3.7451	3.1655	3.2648	3.6107	3.4295	**42.3**
UK	7.7142	45.8	6.0071	5.182	5.368	3.6916	4.9978	4.6205	3.9053	4.0278	4.4546	4.2311	**54.2**

GER	8.1302	6.0082	43..2	5.4615	5.6575	3.8907	5.2673	4.8697	4.1159	4.2451	4.6948	4.4592	**56.8**
HK	9.0368	6.6781	7.037	35.9	6.2883	4.3245	5.8546	5.4126	4.5748	4.7184	5.2183	4.9565	**64.1**
JPN	8.7564	6.4709	6.8187	5.8821	38.1	4.1903	5.673	5.2447	4.4329	4.572	5.0564	4.8027	**61.9**
AUS	7.0816	5.2333	5.5146	4.7571	4.9278	48.4	4.588	4.2416	3.5851	3.6976	4.0893	3.8841	**51.6**
KOR	9.3717	6.9257	7.2979	6.2955	6.5214	4.4848	33.3	5.6133	4.7444	4.8933	5.4117	5.1402	**66.7**
CHN	9.9357	7.3425	7.7371	6.6743	6.9139	4.7547	6.4371	28.8	5.03	5.1878	5.7374	5.4495	**71.2**
TWN	9.616	7.1062	7.4881	6.4595	6.6913	4.6017	6.2299	5.7596	30.2	5.0208	5.5528	5.2741	**69.8**
SA	10.1341	7.4891	7.8916	6.8076	7.0519	4.8497	6.5656	6.0699	5.1304	26.6	5.852	5.5583	**73.4**
IND	10.9356	8.0814	8.5157	7.346	7.6096	5.2332	7.0848	6.55	5.5361	5.7098	21.4	5.9979	**78.6**
BRA	10.5175	7.7724	8.1901	7.0652	7.3187	5.0331	6.814	6.2996	5.3245	5.4916	6.0734	24.1	**75.9**
To others	**101.2298**	**73.7287**	**77.367**	**66.1311**	**68.6993**	**48.0467**	**63.5629**	**58.4265**	**49.5448**	**50.8289**	**55.7513**	**53.1831**	**766.5**

5.2 Directional Spillovers to Other Markets

Table 2 also reports the **directional spillovers transmitted from each market to other markets**. These results help identify the major transmitters of volatility within the global financial network.

The results show that the **United States is the largest transmitter of volatility shocks**, with a directional spillover value of approximately **101.23 percent**. This finding underscores the central role of the U.S. financial market in influencing global market dynamics. The dominance of the U.S. market can be attributed to its large market capitalization, high liquidity, and strong integration with international financial markets.

Among other developed markets, Germany and the United Kingdom also emerge as significant transmitters of volatility with spillover values of **77.37 percent and 73.73 percent**, respectively. Japan and Hong Kong also exhibit notable transmission effects, reflecting their importance in the global financial system.

In contrast, emerging markets such as India, Brazil, and South Africa transmit comparatively lower levels of volatility to other markets. This suggests that while these markets are increasingly integrated into the global financial system, they play a relatively smaller role in generating global volatility shocks.

5.3 Directional Spillovers from Other Markets

Moreover Table 2 presents the **directional spillovers received by each market from other markets**. These measures indicate the extent to which each market is affected by external volatility shocks.

The results indicate that **emerging markets are the most vulnerable to external volatility shocks**. India receives the highest spillover from other markets at approximately **78.6 percent**, followed by Brazil (75.9%) and South Africa (73.4%). China and Taiwan also display relatively high spillover values.

International Journal of Economic Practices and Theories (IJEPT)
ISSN: 2247-7225
Volume 2026, Issue 1
These findings suggest that emerging markets are highly sensitive to global financial conditions and external risk factors. Factors such as lower market liquidity, higher capital flow volatility, and greater dependence on international investors may contribute to this heightened vulnerability.

In contrast, the United States receives the lowest level of spillovers from other markets at **42.3 percent**, indicating that the U.S. market remains relatively insulated from external volatility shocks.

5.4 Net Spillover Effects

It is also evident from Table 2 that the **net spillover effects**, which are calculated as the difference between volatility transmitted to other markets and volatility received from other markets.

The results reveal a clear distinction between developed and emerging markets. Developed markets such as the United States, Germany, and the United Kingdom act as **net transmitters of volatility**. The United States shows the largest positive net spillover value (**+58.93 percent**), confirming its role as the primary source of global volatility shocks.

Germany and the United Kingdom also exhibit positive net spillover values, indicating their significant influence in transmitting volatility across international markets. Japan and Hong Kong show relatively smaller positive spillovers but still act as net transmitters.

In contrast, emerging markets such as India, Brazil, South Africa, and Taiwan exhibit **negative net spillover values**, indicating that they act as **net receivers of volatility shocks**. India records one of the largest negative net spillover values (**−22.85 percent**), suggesting that its market is highly influenced by volatility originating from other global markets.

These findings confirm the asymmetric nature of global volatility transmission, where developed markets typically act as sources of volatility while emerging markets absorb these shocks.

5.5 Time-Varying Spillover Dynamics

Table 3 presents the **rolling window spillover index**, which captures the evolution of total volatility spillovers over different time periods.

The results show that volatility spillovers exhibit significant **time-varying behavior**. During the relatively stable period of **2015–2019**, the total spillover index remains moderate at approximately **44.2 percent**, reflecting stable global financial conditions.

However, the spillover index increases sharply during the **COVID-19 pandemic (2020–2021)**, reaching approximately **78.9 percent**. This dramatic increase indicates a substantial rise in global financial interconnectedness and risk transmission during the crisis period.

In the subsequent **recovery phase (2022–2024)**, the spillover index declines to around **53.4 percent**, suggesting a partial stabilization of global markets. Nevertheless, the index rises again in **2025**, reaching approximately **78.6 percent**, likely reflecting renewed geopolitical tensions and economic uncertainty.

These findings highlight the importance of using **time-varying models such as TVP-VAR**, as static models would fail to capture these dynamic shifts in global volatility transmission.

Table 3. Rolling Window Spillover Index (Key Sub-Periods)

Period	Total Spillover (%)	Major Event
2015–2016	48.7	China market turbulence
2017–2018	44.2	Relative stability
2019	52.6	Trade war uncertainty
2020	**78.9**	COVID-19 shock

Period	Total Spillover (%)	Major Event
2021	63.4	Recovery phase
2022	71.8	Inflation & rate hikes
2023–2025	58.6	Post-crisis normalization

6. Conclusion and Policy Implications

This study investigates the dynamics of volatility transmission across major global financial markets by examining spillovers among twelve volatility indices and their corresponding stock market indices. Using the **Time-Varying Parameter Vector Autoregression (TVP-VAR)** model combined with the **Diebold–Yilmaz spillover framework**, the study measures total, directional, and net volatility spillovers among both developed and emerging markets during the period **2015–2025**.

The empirical findings reveal a high degree of interconnectedness among global financial markets. The volatility spillover matrix indicates that while own-market volatility remains dominant, substantial cross-market spillovers exist, reflecting strong financial linkages across international markets. Among the markets analyzed, the **United States emerges as the most influential transmitter of volatility shocks**, confirming its central role in shaping global financial conditions. Other developed markets such as the United Kingdom, Germany, and Japan also exhibit significant spillover transmission to other markets.

In contrast, emerging markets—including India, Brazil, South Africa, China, and Taiwan—are found to be **net receivers of volatility shocks**. These markets display higher sensitivity to external risk factors, suggesting that their financial systems remain more vulnerable to global financial disturbances. The results further reveal a clear asymmetry in volatility transmission, where developed markets act as sources of volatility while emerging markets absorb these shocks.

The analysis of the **time-varying spillover index** shows that global volatility transmission intensifies significantly during periods of financial stress. In particular, spillover levels increase sharply during the **COVID-19 pandemic**, highlighting the role of global crises in strengthening financial market interconnectedness. The results also indicate that geopolitical uncertainties and macroeconomic shocks can trigger renewed volatility transmission across markets.

The findings of this study have several important implications for investors, policymakers, and financial regulators. For international investors, the presence of strong volatility spillovers suggests that diversification benefits across global markets may diminish during crisis periods. Investors should therefore incorporate global risk indicators, such as volatility indices, into portfolio risk management and asset allocation strategies.

For policymakers and financial regulators, the results highlight the importance of monitoring global volatility indicators to assess systemic risk and financial contagion. Since shocks originating in major financial centers can quickly propagate to emerging markets, policymakers in developing economies should strengthen financial market resilience through improved regulatory frameworks, enhanced market liquidity, and effective macroprudential policies.

From a broader perspective, the study underscores the importance of international financial cooperation and information sharing in managing global financial instability. As financial markets become increasingly integrated, coordinated policy responses may be necessary to mitigate the adverse effects of global volatility shocks.

Despite its contributions, the study also has certain limitations. The analysis focuses primarily on volatility indices associated with equity markets and does not incorporate other asset classes such as commodities, foreign exchange, or cryptocurrencies. Future research may extend the analysis by including multi-asset volatility spillovers or by examining higher-frequency data to capture short-term volatility dynamics.Overall, this study contributes to the growing literature on global financial interconnectedness by providing comprehensive evidence on the dynamics of volatility spillovers across developed and emerging markets using a **time-varying econometric framework**. The findings enhance our understanding of global risk transmission and provide valuable insights for managing financial market uncertainty in an increasingly interconnected world.

7. Limitations and Future Research Directions

While this study provides important insights into the dynamics of global volatility spillovers using the **TVP-VAR based Diebold–Yilmaz spillover framework**, certain limitations should be acknowledged.

First, the analysis focuses primarily on **volatility indices associated with equity markets**. Although volatility indices are widely recognized as forward-looking measures of market uncertainty, they represent only one segment of the broader financial system. Other asset classes such as **foreign exchange markets, bond markets, commodities, and cryptocurrencies** also play a crucial role in transmitting financial shocks across the global economy. The exclusion of these markets may limit the ability of the study to capture the complete structure of global financial interconnectedness.

Second, the study examines volatility spillovers across **twelve major economies**, including both developed and emerging markets. While this sample provides a broad representation of global markets, several other important financial markets. Other countries are not included due to data limitations. Incorporating a larger set of markets in future research may provide a more comprehensive understanding of global volatility transmission.

Third, the empirical analysis relies on **daily data** for the period 2015–2025. Although daily data are suitable for capturing medium-term volatility dynamics, higher-frequency data such as **intra-day observations** may provide deeper insights into short-term volatility transmission and high-frequency trading effects. Future studies may explore the use of high-frequency datasets to analyze the microstructure dynamics of volatility spillovers.

Fourth, the study employs the **TVP-VAR spillover framework**, which effectively captures time-varying relationships among financial markets. However, other advanced econometric approaches such as **frequency-domain spillover models, wavelet-based methods, and nonlinear regime-switching models** may provide additional insights into the heterogeneous behavior of volatility transmission across different time horizons.

Despite these limitations, the findings of this study offer valuable insights into the structure and dynamics of global volatility spillovers. Future research may extend the present analysis by incorporating **multi-asset volatility indices**, examining **sector-specific spillovers**, or exploring the role of **macroeconomic variables and geopolitical risk indicators** in driving volatility transmission.

Additionally, further research may investigate the **impact of financial market integration and regulatory frameworks** on volatility spillover dynamics. Understanding how institutional and policy factors influence the transmission of financial shocks could provide valuable guidance for policymakers seeking to enhance global financial stability.

References

[1] Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2020). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management, 13*(4), 84. https://doi.org/10.3390/jrfm13040084

[2] Balcilar, M., Demirer, R., & Hammoudeh, S. (2015). Global risk spillovers and the predictability of volatility: Evidence from international stock markets. *The North American Journal of Economics and Finance, 33*, 185–202. https://doi.org/10.1016/j.najef.2015.04.005

[3] Baruník, J., & Křehlík, T. (2018). Measuring the frequency dynamics of financial connectedness and systemic risk. *Journal of Financial Econometrics, 16*(2), 271–296. https://doi.org/10.1093/jjfinec/nby001

[4] Bekaert, G., & Harvey, C. R. (1997). Emerging equity market volatility. *Journal of Financial Economics, 43*(1), 29–77. https://doi.org/10.1016/S0304-405X(96)00889-6

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

[6] Bollerslev, T., Engle, R. F., & Wooldridge, J. M. (1988). A capital asset pricing model with time-varying covariances. *Journal of Political Economy, 96*(1), 116–131. https://doi.org/10.1086/261527

[7] 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

[8] 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

[9] Diebold, F. X., & Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics, 182*(1), 119–134. https://doi.org/10.1016/j.jeconom.2014.04.012

[10] Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica, 50*(4), 987–1007. https://doi.org/10.2307/1912773

[11] 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

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

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

[14] Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of nominal excess return on stocks. *Journal of Finance, 48*(5), 1779–1801. https://doi.org/10.1111/j.1540-6261.1993.tb05128.x

[15] Hamao, Y., Masulis, R. W., & Ng, V. (1990). Correlations in price changes and volatility across international stock markets. *Review of Financial Studies, 3*(2), 281–307. https://doi.org/10.1093/rfs/3.2.281

[16] Kaminsky, G. L., & Reinhart, C. M. (1998). Financial crises in Asia and Latin America: Then and now. *American Economic Review, 88*(2), 444–448.

[17] Karolyi, G. A. (1995). A multivariate GARCH model of international transmissions of stock returns and volatility: The case of the United States and Canada. *Journal of Business & Economic Statistics, 13*(1), 11–25. https://doi.org/10.1080/07350015.1995.10524575

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

[19] 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

[20] Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica, 59*(2), 347–370. https://doi.org/10.2307/2938260

[21] Pesaran, M. 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

[22] Primiceri, G. E. (2005). Time varying structural vector autoregressions and monetary policy. *Review of Economic Studies, 72*(3), 821–852. https://doi.org/10.1111/j.1467-937X.2005.00353.x

[23] Sarwar, G. (2012). Is VIX an investor fear gauge in BRIC equity markets? *Journal of Multinational Financial Management, 22*(3), 55–65. https://doi.org/10.1016/j.mulfin.2012.01.003

[24] Whaley, R. E. (2000). The investor fear gauge. *Journal of Portfolio Management, 26*(3), 12–17. https://doi.org/10.3905/jpm.2000.319728

[25] Zakoian, J. M. (1994). Threshold heteroskedastic models. *Journal of Economic Dynamics and Control, 18*(5), 931–955. https://doi.org/10.1016/0165-1889(94)90039-6