IJSES
International Journal of Scientific Engineering and Science
Volume 10, Issue 1, pp. 30-39, 2026. ISSN (Online): 2456-7361

Time-varying Volatility Spillovers Among G7 and E7 Stock Markets

Jinpeng Feng
School of Statistics and Mathematics, Shandong University of Finance and Economics, Jinan, Shandong, 250014

Abstract**—***This investigation explores a TVP-VAR model to examine the dynamic connectedness between the Chinese stock market and those of the G7 and E7 countries. The study reveals that the E7 markets predominantly act as receivers of volatility spillovers emanating from the G7 markets. Evidence indicates an incremental surge in volatility spillovers of China over time, with a considerable portion of this risk emanating from the G7 markets. Further analysis presents notable geographical characteristics in Chinese risk dissemination to other regions. The research also explores the dynamics of volatility spillover connectedness during extreme events. Findings reveal that during these periods, both the transmission and reception of risk intensify significantly, and there are marked differences in the spillover structures across various extreme events.*

Keywords**—***Volatility spillovers; Stock markets; TVP-VAR; China; G7 and E7 countries*

I. Introduction

The progression of global economic integration has enhanced the interconnectivity of international financial markets, thereby accentuating the transmission of stock market volatility risks across nations. As key participants in the global economic framework, the analysis of the interplay between the stock markets of the developed (G7) and emerging (E7) economies gains paramount importance. This importance is underscored by the implications for the stability of the financial markets of individual nations as well as the robust functioning of the global financial system.

Previous studies have extensively examined the volatility spillover effects within stock markets across different countries, documenting considerable inter-country volatility and return spillovers (Al-Hajieh, 2023; Irfana et al., 2021; Kakran et al., 2023; Sevinç, 2022; Yadav et al., 2022). Particularly during shifts in the global economic landscape or during significant events, these transmission effects are significantly magnified (Agyei, 2023; Chopra and Mehta, 2022; Feng et al., 2023). Initial investigations focused on the volatility spillovers across developed countries' stock markets, identifying substantial spillovers within these markets (Habiba et al., 2020; Nguyen and Le, 2018; Vo and Tran, 2020). The US, being central to the global financial markets, frequently exerts a substantial influence on other developed markets (Ji et al., 2020; Su, 2020). As emerging economies rise and their global sway augments, inquiries into the volatility spillovers in E7 countries' stock markets have seen a steady increase. These inquiries indicate that the markets of emerging economies are often more sensitive to the shifts in international markets (Zhang et al., 2020; Samadder, 2021; Ziaur Rehman et al., 2023). China, as the world's second-largest economy, has garnered significant academic interest in examining the spillover effects of its stock market (Lin and Chen, 2021; Pan et al., 2022; Vuong et al., 2022; Zhong and Liu, 2021), with the impacts of its volatility on financial markets becoming increasingly evident (Fang et al., 2021; Hung, 2020; Wang and Xiao, 2023). Nonetheless, a consensus on the spillover relationship between Chinese stock market and those of the G7 and E7 countries remains elusive. Moreover, existing literature has predominantly concentrated on single-market studies or relatively short-term analyses, leading to a significant gap in research on long-term, dynamic correlations.

Our research distinguishes itself from prior studies in several key respects. Firstly, we examine the volatility spillover effects of stock markets between China and the G7 and E7 countries, a scope not commonly addressed in earlier works that typically centered on either G7 or E7 markets individually (Agyei et al., 2022; Zhang et al., 2021; Irshad et al., 2021). Secondly, our adoption of the TVP-VAR methodology sets our analysis apart from the static approaches prevalent in past research on G7 and E7 market volatility spillovers (Kirkulak Uludag and Khurshid, 2019; Tabash et al., 2024). The TVP-VAR model enables us to track and assess the dynamic shifts in risk spillover effects over time. This offers a more intricate picture of the interlinkages among these markets.

Our study yields several insights. Firstly, as globalization deepens, G7 countries emerge predominantly as transmitters of financial risk, whereas E7 nations more often act as receivers. Secondly, data suggest a steady rise in volatility spillovers of China over time, and a significant share of its risk sources from the G7 markets. Additionally, these transmissions demonstrate distinct regional characteristics, with China exerting a substantial impact on adjacent economies. Thirdly, in periods of market turbulence, our observations point to a significant amplification in both risk transmission and reception across countries. Notably, our analysis identifies diverse transmission dynamics during varying types of extreme events. The structure of this paper is organized as follows: Section 2 outlines the methodology adopted; Section 3 details the data utilized; Section 4 discusses empirical findings from the TVP-VAR model; and Section 5 provides concluding observations of the study.

II. Methodology

In this study, we use the Time-Varying Parameter Vector Autoregressive (TVP-VAR) approach in conjunction with risk spillover indices based on the Generalized Forecast Error Variance Decomposition (GFEVD) to construct a network of

Volume 10, Issue 1, pp. 30-39, 2026.
ISSN (Online): 2456-7361

risk spillover for the G7 and E7 stock markets (Antonakakis et al., 2020; Diebold and Yilmaz, 2012). The TVP-VAR model is proficient in handling time-varying characteristics, offering intuitive interpretations of parameters, and describing the evolution of economic structures via stochastic processes. The mathematical representation of the TVP-VAR(p) model is as follows:

$$y_t = A_t z_{t-1} + \varepsilon_t,\ \ \varepsilon_t|\Omega_{t-1} \sim N(0, \Sigma_t) \tag{1}$$

$$vec(A_t) = vec(A_{t-1}) + \xi_t,\ \ \xi_t|\Omega_{t-1} \sim N(0, \Xi_t) \tag{2}$$

where $z_{t-1} = (y_{t-1}, y_{t-2}, \dots, y_{t-p})^T$, $A_t = (A_{1t}, A_{2t}, \dots, A_{pt})^T$. Ω_{t-1} incorporate all available information up to moment $t-1$, y_t and z_{t-1} represent the $m \times 1$ and $mp \times 1$ dimensional vectors, A_t and A_{it} are $m \times mp$ and $m \times m$ dimensional matrices, ε_t and ξ_t are $m \times 1$ and $m^2 p \times 1$ dimensional vectors. Moreover, the time-varying covariance-covariance matrices Σ_t and Ξ_t are the $m \times m$ and $m^2 p \times m^2 p$ dimensional matrices, respectively. Similarly, $vec(A_t)$ is a vectorisation of A_t, $vec(A_t)$ is an $m^2 p \times 1$ dimensional vector.

We estimate the TVP-VAR using a Kalman filter following the procedure proposed by (Del Negro and Primiceri, 2015; Primiceri, 2005) and set the initial values as the estimates from the preceding 300 days. Following (Koop and Korobilis, 2014), we set the forgetting factors of the Kalman filter to $\kappa_1 = 0.99$ and $\kappa_2 = 0.96$.

The TVP-VAR model can be transformed into a Time-Varying Parameter Vector Moving Average (TVP-VMA) as follow:

$$y_t = \sum_{j=0}^{\infty} B_{jt} \varepsilon_{t-j} \tag{3}$$

where B_{jt} is an $m \times m$ dimensional matrices.

The elements of the H-step-ahead GFEVD matrix, denoted as $\tilde{\Phi}_{ij,t}(H)$, is computed in the following manner:

$$\tilde{\Phi}_{ij,t}(H) = \frac{\sum_{t=1}^{H-1} \Psi_{ij,t}^2}{\sum_{j=1}^{m} \sum_{t=1}^{H-1} \Psi_{ij,t}^2} \tag{4}$$

where $\sum_{j=1}^{m} \tilde{\Phi}_{ij,t}(H) = 1$ and $\sum_{i,j=1}^{m} \tilde{\Phi}_{ij,t}(H) = m$, $\Psi_{ij,t}^2$ represents the Generalized Impulse Response Function (GIRF).

Firstly, we delineate the volatility transmission from market i to other markets in the system (TO) alongside the volatility reception by market i from these markets (FROM).

$$TO_{i\to\cdot,t}(H) = \frac{\sum_{j=1,i\neq j}^{m} \tilde{\Phi}_{ji,t}(H)}{\sum_{j=1}^{m} \tilde{\Phi}_{ji,t}(H)} \times 100 \tag{5}$$

$$FROM_{\cdot\leftarrow j,t}(H) = \frac{\sum_{j=1,i\neq j}^{m} \tilde{\Phi}_{ij,t}(H)}{\sum_{j=1}^{m} \tilde{\Phi}_{ij,t}(H)} \times 100 \tag{6}$$

Secondly, we introduce the Total Connectedness Index (TCI), quantifying the extent of volatility spillover effects among the G7 and E7 stock markets.

$$TCI_t(H) = \frac{\sum_{i,j=1,i\neq j}^{m} \tilde{\Phi}_{ij,t}(H)}{\sum_{i,j=1}^{m} \tilde{\Phi}_{ij,t}(H)} \times 100 \tag{7}$$

Thirdly, the Net Total Directional Connectedness (NET) quantifies the aggregate level of spillover effects by the ith stock market to others.

$$NET_{i,t}(H) = TO_{i\to j,t}(H) - FROM_{i\leftarrow j,t}(H) \tag{8}$$

If $NET > 0$ (< 0), it indicates that the impact of market i on other markets is greater than (less than) the impact of other markets on i, making it a risk transmitter (receiver).

Finally, we establish the Net Pairwise Directional Connectedness (NPDC) to scrutinize the net total directional connectedness and elucidate bidirectional relationships.

$$NPDC_{ij,t(H)} = (\tilde{\Phi}_{ij,t}(H) - \tilde{\Phi}_{ji,t}(H)) \times 100 \tag{9}$$

If $NPDC > 0$ (< 0), it indicates that stock market i dominates (is dominated by) stock market j.

III. DATA

Subsequent reforms have augmented the interconnectivity of the Chinese stock market with global stock markets post 2006 (Wang and Li, 2020). Consequently, we extracted daily data for the G7 and E7 stock markets from investing.com, spanning from January 10, 2006, to January 25, 2024. Additionally, major stock index data for G7 and E7 countries were obtained based on the study by (Tarchella et al., 2024; Kirkulak Uludag and Khurshid, 2019), including key indices such as the (S&P 500-US, FTSE 100-UK, Nikkei 225-Japan, DAX-Germany, CAC 40-France, S&P TAX-Canada, FTSE MIB-Italy, BSE Sensex 30-India, BVSP-Brazil, JKSE-Indonesia, MXX-Mexico, RTSI-Russia, BIST 100-Tuekey, SSE-China). Following (Korkusuz et al., 2023), data misaligned with the trading hours of each stock market were excluded, and we end up with 3152 samples. Then we computed the low-frequency volatility of the stock indices (Feng et al., 2023):

$$RV_{i,t} = 0.511\left(H_{i,t} - L_{i,t}\right)^2 - 0.019[(C_{i,t} - O_{i,t})(H_{i,t} + L_{i,t} - 2O_{i,t}) - 2(H_{i,t} - O_{i,t})(L_{i,t} - O_{i,t})] - 0.383 (C_{i,t} - O_{i,t})^2 \tag{10}$$

where H (L) represents the logarithm of the maximum (minimum) price of the day, and C (O) represents the logarithm of the closing (opening) price of the day. Subsequently, we compute the annualized volatility $\sigma = 100 \times \sqrt{RV_{i,t} \times 252}$ to reflect market volatility.

Fig. 1 illustrates stock and volatilities price trends within G7 and E7 countries. In the G7, the US, Germany, Japan, and Canada demonstrated significant price growth. In contrast, the UK and France experienced considerable declines during the 2008 financial crisis before a swift rebound, while Italy showed a slower recuperation. In the E7, India, Brazil, Indonesia, Mexico, and Turkey experienced upward price movements, however, Russia and China experiencing significant volatility and post crisis recovery challenges. Volatility for both G7 and E7 stock indices significantly increased during global crises, with the G7 showing lower levels of volatility, underscoring developed economies' higher risk absorption capacity. Table 1 conveys descriptive statistics of stock market volatility, with G7 markets demonstrating lower mean and variance than E7, suggesting the comparative immaturity and fragility of emerging economies. Fig. 2 identifies a substantial positive correlation between G7 and E7 volatilities, offering key insights for advancing research into their volatility interconnections.

IV. EMPIRICAL RESULTS

This section presents an empirical study on the volatility spillover effects of stock markets between China and G7 and E7 countries. Firstly, we focus on utilizing the TVP-VAR model to obtain time varying spillover indices, analyzing the

International Journal of Scientific Engineering and Science
Volume 10, Issue 1, pp. 30-39, 2026. ISSN (Online): 2456-7361

changing trends in volatility spillover levels across different countries at various time points. Secondly, we establish a volatility spillover network, informed by six perspectives of extreme events, to scrutinize the propagation paths and intensities within the network across various phases.

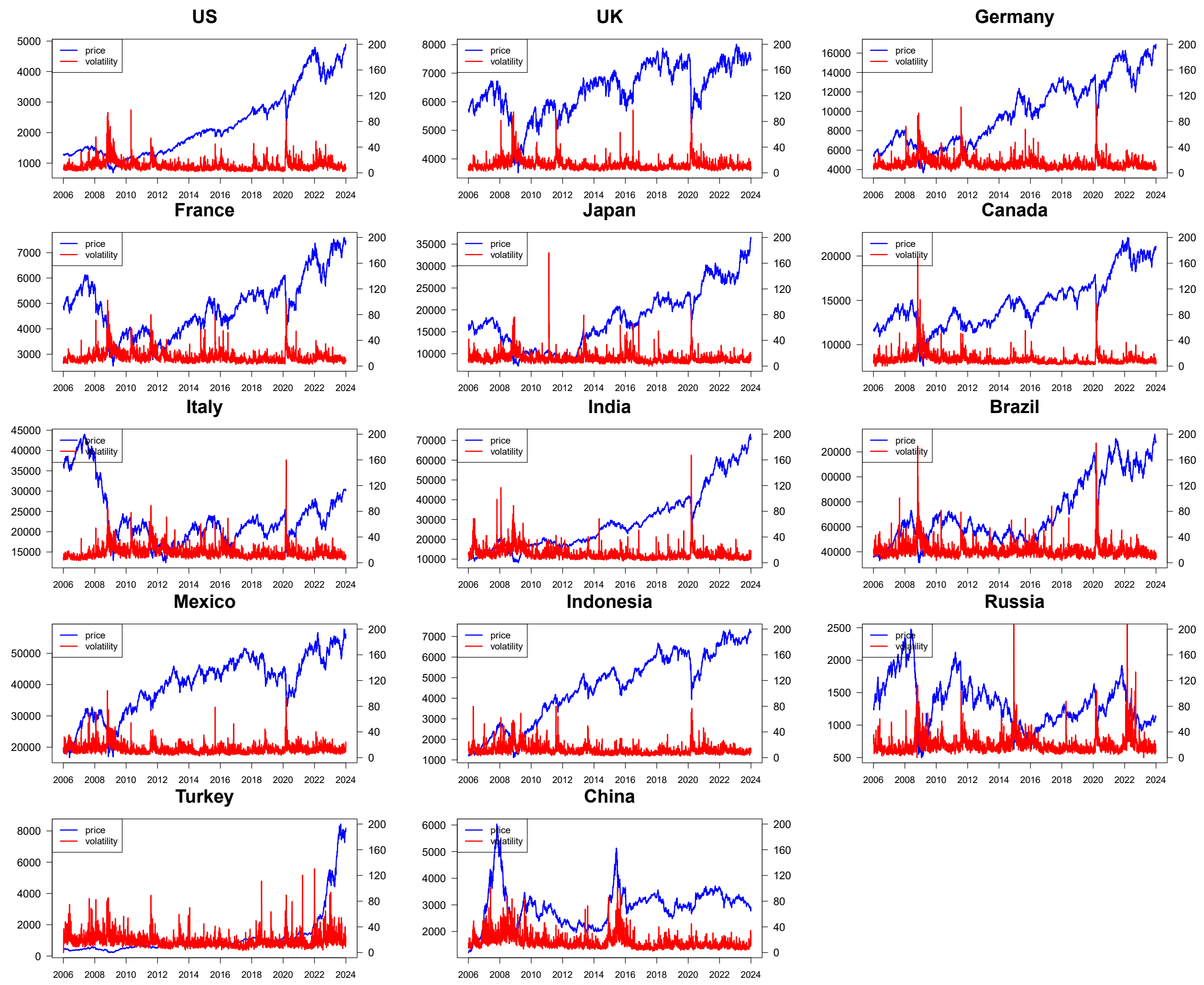


Fig. 1. The price and volatility trends of the G7 and E7 stock markets.

TABLE 1. Descriptive Statistics of stock markets volatility

	Country	Stock index	Mean	Variance	Skewness	Kurtosis	JB	ERS	Q(10)	Q2(10)
	US	S&P 500	11.439	80.99	3.304***	17.656***	46678.065***	-7.715***	6225.092***	4256.910***
	UK	FTSE 100	12.425	71.192	3.399***	19.939***	58286.290***	-6.717***	5326.664***	2848.908***
	Germany	DAX	14.254	87.878	2.988***	15.808***	37510.475***	-7.764***	5563.898***	3894.140***
G7	France	CAC 40	13.959	83.186	2.972***	15.249***	35178.977***	-7.029***	5381.265***	3585.318***
	Japan	Nikkei 225	11.674	66.372	5.371***	67.133***	607051.107***	-13.43***	2688.999***	397.860***
	Canada	S&P TAX	10.741	88.363	5.158***	49.987***	342139.865***	-9.278***	6428.741***	2750.437***
	Italy	FTSE MIB	16.181	100.686	3.003***	20.937***	62310.457***	-7.188***	4800.488***	2172.439***
	India	BSE Sensex	13.583	96.04	4.085***	34.061***	161127.569***	-9.909***	5105.431***	1641.303***
	Brazil	BVSP	18.99	141.863	4.742***	42.182***	245500.006***	-11.231***	4288.942***	2769.427***
	Indonesia	JKSE	11.709	61.537	2.941***	13.881***	29848.079***	-12.304***	3596.335***	2073.452***
E7	Mexico	MXX	13.365	63.6	3.322***	20.248***	59642.751***	-11.956***	3410.094***	2418.298***
	Russia	RTSI	20.088	289.591	10.458***	243.167***	7823239.49***	-12.497***	3056.277***	143.146***
	Turkey	BIST 100	18.962	129.425	2.946***	15.388***	35659.572***	-6.188***	2589.773***	1360.795***
	China	SSE	16.109	124.335	2.499***	9.522***	15187.279***	-10.223***	5230.920***	2974.903***

Notes: ERS test (Elliott et al., 1992) is applied with null hypothesis shows that series is non-stationary, JB is normality test by (Jarque and Bera, 1980) with null hypothesis shows the series is normally distributed. ***, ** and * indicate significance levels of 1%, 5 %and 10 %.

A. Analysis of dynamic volatility spillover

Based on the Bayesian Information Criterion (BIC) output, we have selected a lag order of p=2 for TVP-VAR model and have set the forecast horizon at H=10. The TCI as shown in Table 2 stands at 64.1%. Within the G7, Canada (109.73%) records the highest spillover effect, followed by the US (97.11%), France (90.65%), Germany (87.95%), Italy

International Journal of Scientific Engineering and Science
Volume 10, Issue 1, pp. 30-39, 2026. ISSN (Online): 2456-7361

(81.85%), and the UK (79.28%), with Japan (32.38%) registering the lowest.

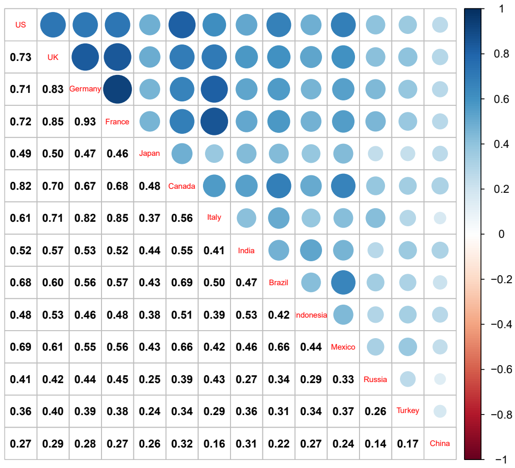


Fig. 2. Correlations of G7 and E7 stock markets volatility.

For the E7 countries, Mexico (62.90%) leads with the highest spillover effect to others, trailed by Brazil (60.17%), Russia (49.96%), India (42.09%), Turkey (38.00%), and Indonesia (34.45%), with China (30.86%) showing the smallest effect. It is evident that the volatility spillover effects from G7 countries are significantly more considerable than those from E7 countries. Moreover, all G7 countries, except for Japan (-24.95%), display positive NET, indicating their role as primary transmitters of volatility information. In contrast, within the E7, only Mexico (1.24%) and Brazil (0.37%) record positive NET values, while all others are negative, underscoring that developed markets in Europe and America are predominant sources of risk transmission. Fig. 3 delineates the dynamic NET among G7 and E7 countries, revealing that the US, Germany, France, and Canada have been consistent risk transmitters throughout the observed period. In contrast, Turkey, Russia, Japan, Indonesia, India, and China have been consistent receivers. On the other hand, the UK, Mexico, Italy, and Brazil have oscillated between being net transmitters and receivers of risk within the timeframe of the study.

TABLE 2. Dynamic Connectedness based on TVP-VAR model

					G7							E7				FROM
		US	UK	Germany	France	Japan	Canada	Italy	India	Brazil	Indonesia	Mexico	Russia	Turkey	China	
	US	29.62	6.95	6.93	6.9	2.4	15.26	6.04	2.89	6.42	2.35	7.02	3.13	2.22	1.88	70.38
	UK	9.42	24.22	11	11.83	2.35	9.52	8.5	3.09	4.31	2.25	4.44	4.44	2.64	1.99	75.78
	Germany	7.69	10.23	23.61	16.75	2.09	7.78	12.4	2.66	3.05	1.82	3.4	4.07	2.52	1.92	76.39
G7	France	7.7	10.88	16.39	22.33	2.05	8.26	13.68	2.67	3.13	1.86	3.15	4	2.3	1.61	77.67
	Japan	6.87	4.04	4.26	4.09	42.67	7.58	4.56	3.66	4.75	3.17	5.15	3.47	2.82	2.91	57.33
	Canada	13.42	6.51	6.09	6.23	2.55	31.19	5.7	3.32	6.31	2.86	6.35	3.83	2.8	2.85	68.81
	Italy	6.09	8.1	14.01	16.09	1.98	6.51	28.79	2.56	3.06	1.77	2.79	4.28	2.3	1.65	71.21
	India	6.8	4.83	4.2	3.69	3.18	8.52	3.92	40.3	4.34	4.24	4.85	3.9	4.3	2.94	59.7
	Brazil	8.81	5.12	3.88	4.09	2.68	8.97	4.75	2.64	40.2	2.05	7.88	3.72	2.58	2.62	59.8
	Indonesia	6.08	4.72	3.38	3.63	2.82	7.83	3.59	5.66	4.59	41.95	5.34	3.89	3.49	3.03	58.05
E7	Mexico	9.48	4.83	4.24	4.22	2.51	9.07	4.08	3.23	8	2.9	38.34	3.23	3.33	2.53	61.66
	Russia	5.78	5.42	5.51	5.27	2.18	8.61	6.03	3.25	4.92	2.91	3.91	40.85	3.19	2.17	59.15
	Turkey	5.18	4.89	4.81	4.92	2.43	5.36	4.83	3.19	3.95	2.82	5.32	4.67	44.89	2.74	55.11
	China	3.78	2.75	3.26	2.95	3.17	6.47	3.77	3.27	3.35	3.46	3.28	3.33	3.5	53.66	46.34
TO		97.11	79.28	87.95	90.65	32.38	109.73	81.85	42.09	60.17	34.45	62.9	49.96	38	30.86	897.37
Inc.Own		126.73	103.5	111.57	112.99	75.05	140.92	110.64	82.39	100.37	76.39	101.24	90.81	82.89	84.51	TCI
NET		26.73	3.5	11.57	12.99	-24.95	40.92	10.64	-17.61	0.37	-23.61	1.24	-9.19	-17.11	-15.49	64.10
TORank		2	6	4	3	13	1	5	10	8	12	7	9	11	14	
FROMRank		5	3	2	1	12	6	4	9	8	11	7	10	13	14	
NETRank		2	6	4	3	14	1	5	12	8	13	7	9	11	10	

Notes: This table reports the results of volatility. "TORank" stands for transmitter index rank, "FROMRank" stands for receiver index rank, and "NETRank" stands for Net spillover index rank.

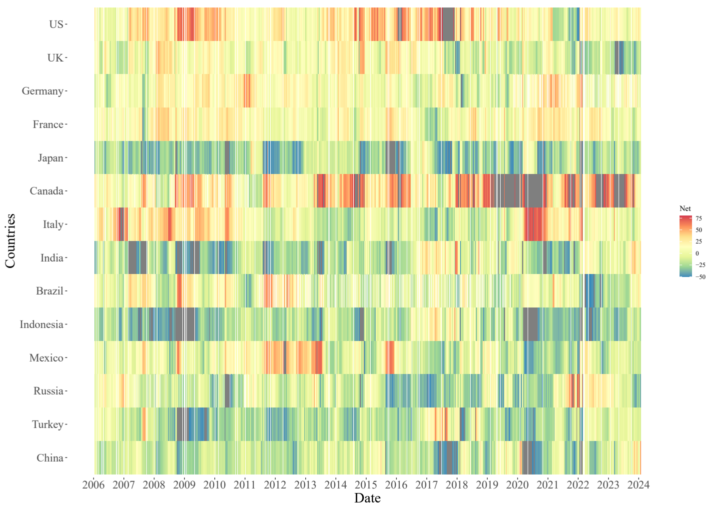
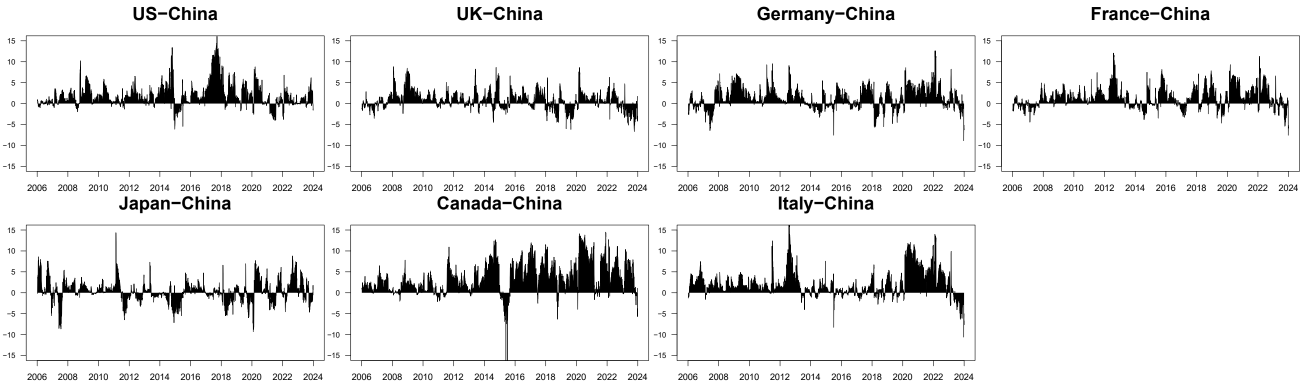
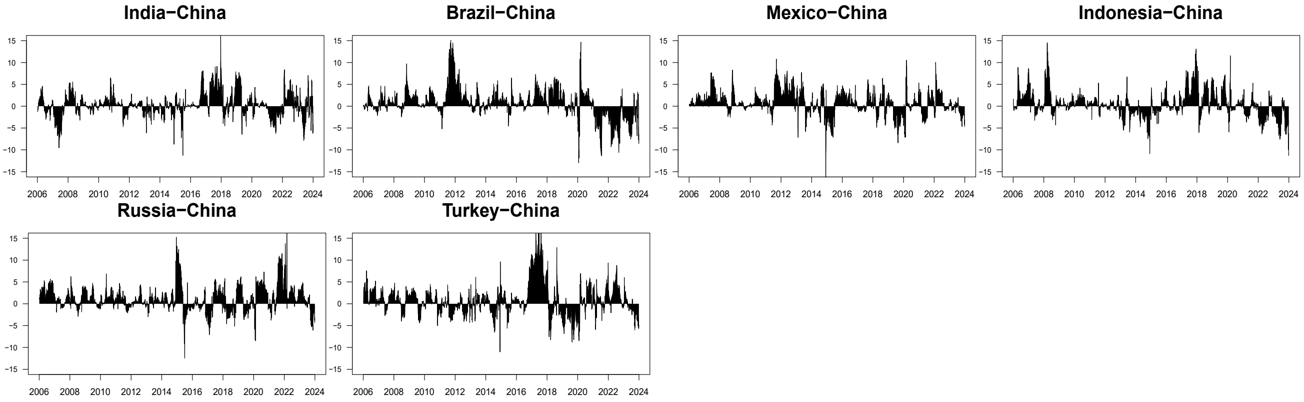


Fig. 3. NET volatility spillover results with TVP-VAR of G7 and E7 stock markets

International Journal of Scientific Engineering and Science
Volume 10, Issue 1, pp. 30-39, 2026.
ISSN (Online): 2456-7361



Panel A: NPDC of G7 countries to China



Panel B: NPDC of E7 countries to China

Fig. 4. NPDC results of China with other countries

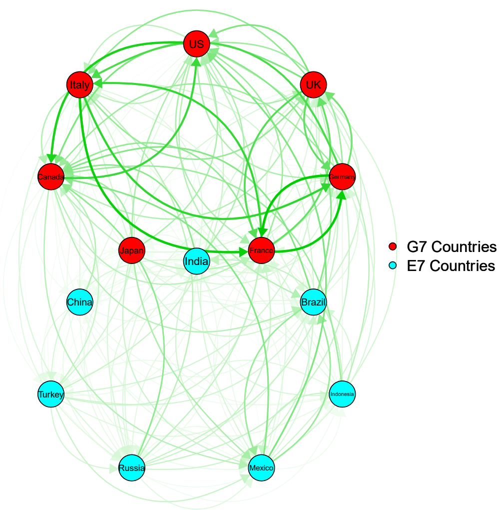


Fig. 5. Network spillovers of G7 and E7 stock markets

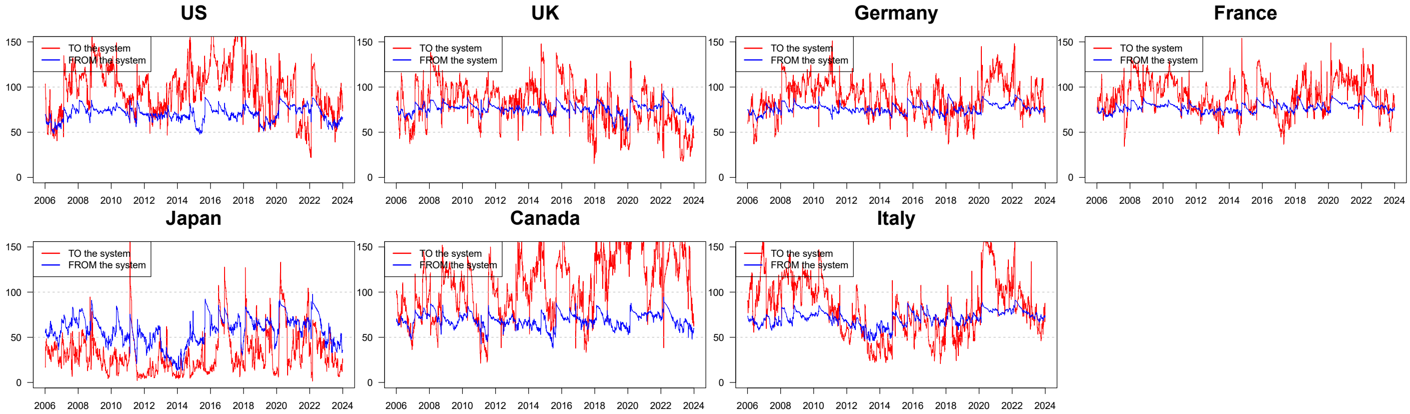
Further analysis of the data in Table 2 has uncovered distinct geographical characteristics of volatility spillovers among countries. Significantly, China demonstrates an intensified volatility spillover effect to its neighboring countries, including Japan, India, and Indonesia. Similarly, European countries such as the UK, Germany, France, and Italy, along with the Americas, including the US, Canada, Mexico, and Brazil, also demonstrate distinct geographical characteristics. Fig. 4 illustrates Chinese NPDC with other countries, indicating that Chinese risk reception is mainly attributed to G7 countries, with only marginal risk transmission to these countries. Additionally, Chinese NPDC with E7 countries indicates that China alternates between being a risk transmitter and receiver over different periods. Fig. 5 depicts the volatility spillover network for the entire sample period, showing that volatility spillover effects among G7 countries is significantly more considerable than that among E7 countries, with the volatility spillover effects from China to other countries being relatively muted. However, the analysis Panel B of Fig. 6 reveals a notable increase over time in Chinese volatility spillover effects to other countries and a growing influx from them, suggesting an increasing connectivity of stock markets between China and G7 and E7 countries over time.

B. Volatility spillover from extreme risk

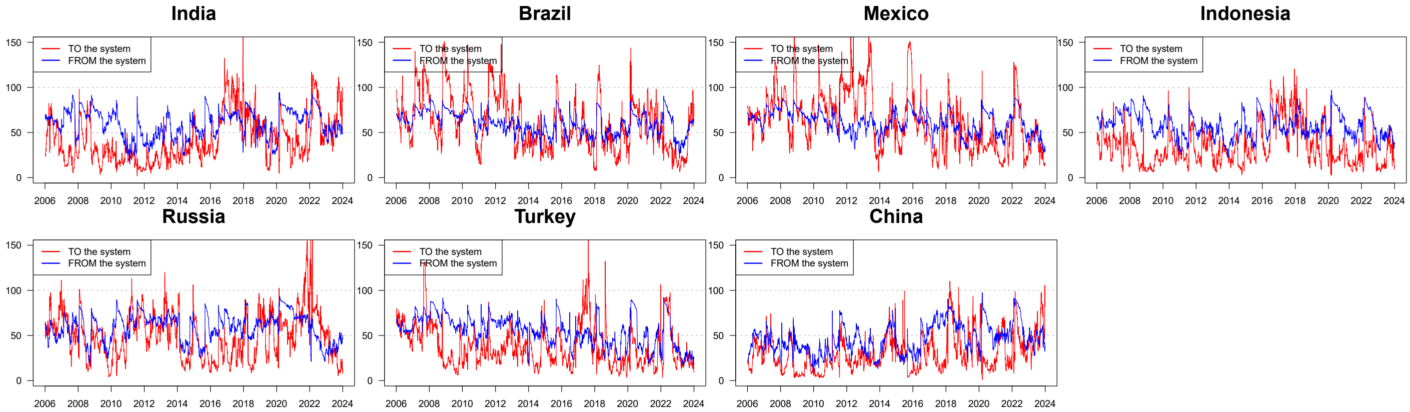
Fig. 7 displays the dynamic changes in the TCI. Notably, during certain periods, the TCI exhibited significant spikes, each with an overflow level exceeding 20%, followed by a rapid decline. Further investigation revealed that these spikes occurred during extreme events, which had a profound impact on global stock market risk levels, characterized by suddenness, complexity, and significant cross-contagion effects. To study the volatility spillover structure during extreme events, we constructed volatility spillover effects for G7 and E7 stock markets based on six extreme events. Following (Horta et al., 2015; Mohti et al., 2019; Wang and Hui, 2018; Huang et al.,

International Journal of Scientific Engineering and Science
Volume 10, Issue 1, pp. 30-39, 2026. ISSN (Online): 2456-7361

2023; Urom et al., 2023; Gheorghe and Panazan, 2023) , these extreme events are defined as follows: the Subprime Crisis (August 1, 2007 to December 7, 2009; 409 samples); the European Debt Crisis (December 8, 2009 to April 27, 2012; 412samples); the Global Stock Market Crash (June 15, 2015 to February 29, 2016; 126 samples); the US-China Trade War (March 22, 2018 to January 9, 2019; 138 samples); the COVID-19 Pandemic (January 1, 2020 to April 29, 2021; 234 samples); and the Russo-Ukrainian War (January 1, 2022 to December 31, 2022; 163 samples.



Panel A: Volatility spillover transmitted TO (received FROM) the system (G7)



Panel B: Volatility spillover transmitted TO (received FROM) the system (E7)

Fig. 6 Dynamic result of volatility spillover transmitted TO the system and received FROM system of each stock market using red and blue, respectively.

Panel A of Table 3, it was observed that during the Subprime Mortgage Crisis, the TCI reached 76.25%, significantly higher than the average of 64.10% for the full sample period. Notably, European countries and the US emerged as the primary transmitters of risk. During the European Debt Crisis, the TCI rose to 77.48%, surpassing the level observed during the Subprime Mortgage Crisis. This period saw significant changes in the risk spillover structure among various countries' stock markets, particularly with an increase in volatility spillovers in European markets, notably affecting Germany, the UK, and France. Throughout the Global Stock Market Crash, the TCI remained at 77.03%, comparable to that during the European Debt Crisis. However, there were significant changes in the spillover structure, with the E7 countries demonstrating significantly higher spillover levels compared to the European Debt Crisis. In Panel B of Table 3, during the US-China Trade War, the TCI decreased to 70.44%, significantly lower than during other extreme events. Nonetheless, China, as a major participant, demonstrated notably higher spillover indices during this period compared to others. During the COVID-19 pandemic, the TCI reached 85.48%, representing a significant global crisis. The US and European countries still maintained relatively high spillover indices. Moreover, during this period, Chinese spillover index significantly increased to 78.22%, reflecting its status as the first country to encounter the COVID-19 outbreak. During the Russia-Ukraine War, the TCI decreased to 78.45%, with Russia, as the principal participant, displaying a spillover level of 76.52%, notably higher than during other periods. The TCI during these extreme events is ranked as follows: COVID-19 pandemic > Russia-Ukraine War > European Debt Crisis > Global Stock Market Crash > Subprime Mortgage Crisis > US-China Trade War.

Fig. 8 displays the volatility spillover networks within G7 and E7 stock markets during six extreme events. It was observed that, except for the US-China trade war, spillover effects during the other five periods were more pronounced than those observed over the entire sample period. Additionally, the spillover effects within the G7 countries consistently exceeded those within the E7 countries. Further analysis revealed distinct variations in the spillover structures across different crisis periods, indicating shifts in the sources of risk and the primary transmitters and receivers of risk.

IJSES
International Journal of Scientific Engineering and Science
Volume 10, Issue 1, pp. 30-39, 2026. ISSN (Online): 2456-7361

V. CONCLUSIONS

In the context of today's increasingly interconnected global markets, economic ties between nations are closer than ever. Our study provides TVP-VAR model to analyze the volatility spillover effects of stock markets between China and G7 and other E7 countries from 2006 to 2024. Firstly, we find that G7 (E7) countries predominantly act as risk transmitters (receivers), aligning with most recent studies (Khurshid et al., 2023; Irshad et al., 2021; Kakran et al., 2023; Feng et al., 2023; Tabash et al., 2024). Specifically, the US, Germany, France, and Canada consistently serve as risk transmitters throughout the study period, while Turkey, Russia, Japan, Indonesia, India, and China persistently receive risk. Additionally, the roles of the UK, Mexico, Italy, and Brazil fluctuate between risk transmitters and receivers. Secondly, data suggest a steady rise in volatility spillovers from China, and a significant share of this risk sources from the G7 markets. Further analysis presents notable volatility spillovers from China to other countries demonstrate regional characteristics, with notably increased transmissions to neighboring countries align with (Khurshid et al., 2023; Irshad et al., 2021). Thirdly, during extreme events, there is a significant increase in volatility spillover effects, and the risk structures among countries vary depending on the sources of risk associated with these events (Agyei, 2023; Chopra and Mehta, 2022; Vlasova and Luo, 2022). These results provide valuable insights for policymakers in formulating regulations to foster the healthy development of capital markets and offer practical guidance for investors engaged in cross-market investments and risk forecasting.

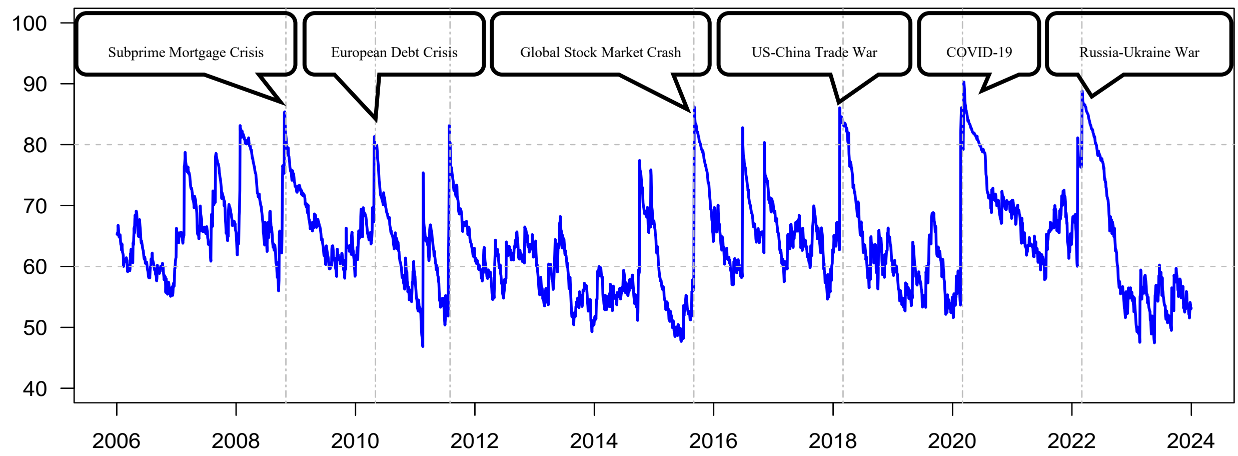


Fig. 7 Total Connectedness Index

TABLE 3. Dynamic Connectedness based on TVP-VAR model in extreme events

Panel A: Dynamic Connectedness based on TVP-VAR model in Subprime Mortgage Crisis, European Debt Crisis and Global Stock Market Crash periods

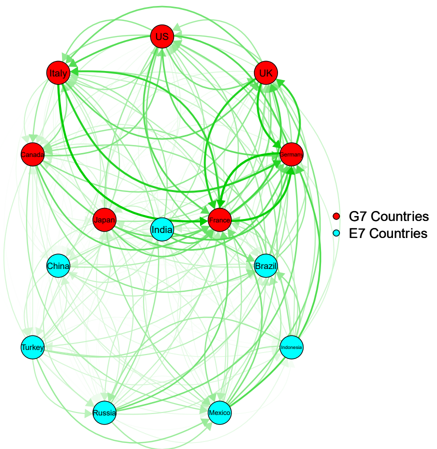
		Subprime Mortgage Crisis			European Debt Crisis			Global Stock Market Crash		
		TO	FROM	NET	TO	FROM	NET	TO	FROM	NET
	US	121.74	81.89	39.86	89.06	83.21	5.84	105.85	80.49	25.36
	UK	98.14	80.64	17.49	116.85	81.60	35.25	105.52	80.27	25.25
	Germany	105.98	80.77	25.20	143.51	78.26	65.25	85.80	80.04	5.77
G7	France	111.70	80.84	30.86	144.40	80.09	64.31	111.84	76.95	34.90
	Japan	40.26	78.33	-38.07	50.45	65.18	-14.74	37.77	84.20	-46.43
	Canada	96.10	77.97	18.13	71.16	85.75	-14.59	88.38	75.13	13.25
	Italy	84.56	79.62	4.94	107.85	82.19	25.65	90.19	81.81	8.38
	India	35.20	65.40	-30.19	45.25	79.95	-34.69	49.92	67.34	-17.43
	Brazil	85.13	79.22	5.91	73.00	80.87	-7.87	91.29	80.20	11.09
	Indonesia	27.16	67.81	-40.65	37.05	74.28	-37.23	43.54	73.28	-29.74
E7	Mexico	96.22	81.06	15.16	74.18	80.75	-6.56	96.63	77.21	19.42
	Russia	71.71	70.19	1.52	50.02	81.30	-31.28	51.26	73.66	-22.39
	Turkey	74.49	78.98	-4.49	38.47	69.59	-31.11	57.85	66.78	-8.92
	China	19.17	64.84	-45.67	43,47	61.69	-18.22	62.62	81.10	-18.48
			TCI	76.25		TCI	77.48		TCI	77.03

Panel B: Dynamic Connectedness based on TVP-VAR model in US-China Trade War, COVID-19 Pandemic and Russia-Ukraine War periods

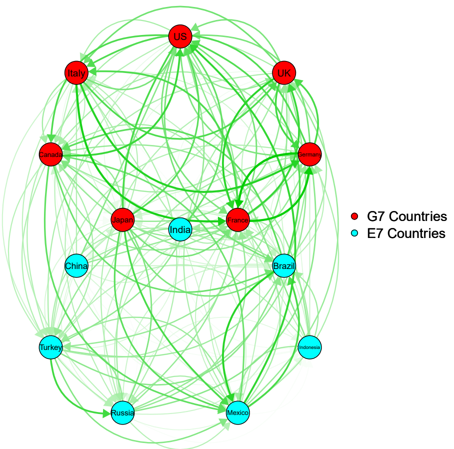
		US-China Trade War			COVID-19 Pandemic			Russia-Ukraine War		
		TO	FROM	NET	TO	FROM	NET	TO	FROM	NET
	US	71.49	84.07	-12.58	160.74	85.44	75.30	112.18	81.57	30.60
	UK	77.34	80.29	-2.95	74.86	91.32	-16.46	88.90	79.62	9.28
	Germany	87.84	78.16	9.68	109.76	89.66	20.10	99.40	84.18	15.23
G7	France	98.78	76.32	22.46	116.58	89.28	27.30	111.03	85.34	25.69
	Japan	64.65	69.76	-5.10	38.62	83.48	-44.86	35.39	61.61	-26.22
	Canada	88.00	79.30	8.70	187.39	81.40	105.99	109.73	77.07	32.66
	Italy	61.90	56.09	5.81	111.64	88.93	22.72	98.38	84.26	14.12
E7	India	42.49	58.81	-16.32	29.27	82.26	-52.99	68.66	81.45	-12.97

International Journal of Scientific Engineering and Science
Volume 10, Issue 1, pp. 30-39, 2026. ISSN (Online): 2456-7361

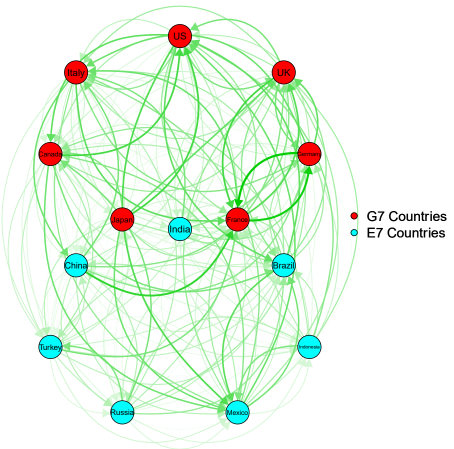
Brazil	101.07	67.37	33.69	98.62	88.72	9.89	43.57	77.22	-33.64
Indonesia	42.16	68.18	-26.02	58.18	87.97	-29.79	54.87	71.07	-16.20
Mexico	45.21	67.58	-22.37	53.82	86.19	-32.36	73.20	81.65	-8.45
Russia	70.36	76.60	-6.24	53.57	92.35	-38.78	76.52	80.48	-3.96
Turkey	42.01	63.57	-21.55	25.44	62.39	-36.96	71.83	80.09	-8.26
China	92.83	60.03	32.81	78.22	87.33	-9.11	54.68	72.73	-18.06
		TCI	70.44		TCI	85.48		TCI	78.45



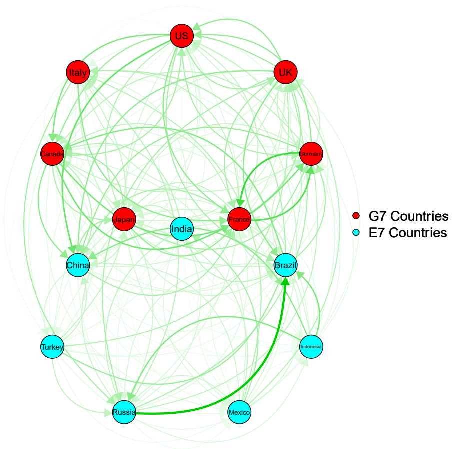
Panel A: Subprime mortgage crisis



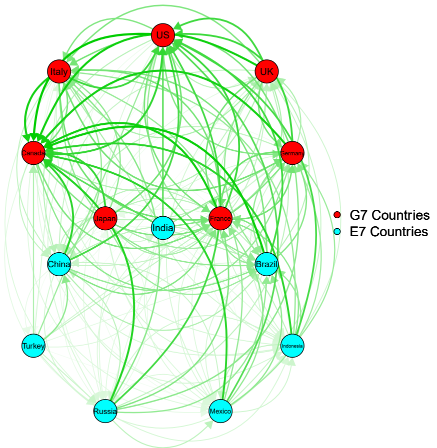
Panel B: European debt crisis



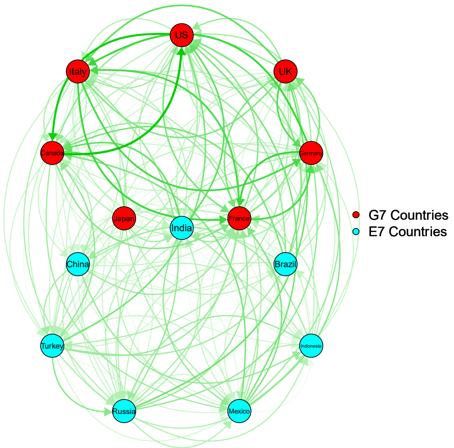
Panel C: Global Stock Market Crash



Panel D: US-China Trade War



Panel E: COVID-19



Panel F: Russia-Ukraine War

Fig. 8. Network spillovers of G7 and E7 stock markets during extreme events

Notes: This figure showcases the network spillovers between G7 and E7 stock markets using a TVP-VAR model during extreme events, where the thicker the line, the stronger the spillover effect.

REFERENCES

[1] Al-Hajieh, H. 2023. Predictive directional measurement volatility spillovers between the US and selected Asian Pacific countries. Cogent Economics & Finance, 11.https://doi.org/10.1080/23322039.2023.2173124

[2] Irfana, M., Hasan, M. M., Ahmedc, E. & Shaikhd, Z. H. 2021. Stock Market Volatility: A Pre-Post Covid19 Analysis of Emerging Markets. Accounting and Financial Sciences Conferences, 01.https://doi.org/10.46988/icaf.01.12.2021.002

[3] Kakran, S., Sidhu, A., Bajaj, P. K. & Dagar, V. 2023. Novel evidence from APEC countries on stock market integration and volatility spillover: A Diebold and Yilmaz approach. Cogent Economics & Finance, 11.https://doi.org/10.1080/23322039.2023.2254560

[4] Sevinç, D. 2022. Volatility spillovers among MIST stock markets. Data Science in Finance and Economics, 2, 80-95.https://doi.org/10.3934/dsfe.2022004

[5] Yadav, M. P., Sharma, S., Aggarwal, V. & Bhardwaj, I. 2022. Correlations and volatility spillover from China to Asian and Latin American Countries: Identifying diversification and hedging opportunities. Cogent Economics & Finance, 10.https://doi.org/10.1080/23322039.2022.2132634

[6] Agyei, S. K. 2023. Emerging markets equities' response to geopolitical risk: Time-frequency evidence from the Russian-Ukrainian conflict era. Heliyon, 9, e13319.https://doi.org/10.1016/j.heliyon.2023.e13319

[7] Chopra, M. & Mehta, C. 2022. Is the COVID-19 pandemic more contagious for the Asian stock markets? A comparison with the Asian financial, the US subprime and the Eurozone debt crisis. J Asian Econ, 79, 101450.https://doi.org/10.1016/j.asieco.2022.101450

[8] Feng, Z., Liu, X. & Yao, Y. 2023. Impact of geopolitical risk on the volatility spillovers among G7 and BRICS stock markets. Procedia Computer Science, 221, 878-884

[9] Habiba, U. E., Peilong, S., Zhang, W. & Hamid, K. 2020. International stock markets Integration and dynamics of volatility spillover between the USA and South Asian markets: evidence from Global financial crisis. Journal of Asia Business Studies, 14, 779-794.https://doi.org/10.1108/jabs-03-2019-0071

[10] Nguyen, M. K. & Le, D. N. 2018. Return Spillover from the US and Japanese Stock Markets to the Vietnamese Stock Market: A Frequency-Domain Approach. Emerging Markets Finance and Trade, 57, 47-58.https://doi.org/10.1080/1540496x.2018.1525357

[11] Vo, X. V. & Tran, T. T. A. 2020. Modelling volatility spillovers from the US equity market to ASEAN stock markets. Pacific-Basin Finance Journal, 59.https://doi.org/10.1016/j.pacfin.2019.101246

[12] Ji, Q., Liu, B.-Y., Cunado, J. & Gupta, R. 2020. Risk spillover between the US and the remaining G7 stock markets using time-varying copulas with Markov switching: Evidence from over a century of data. The North American Journal of Economics and Finance, 51.https://doi.org/10.1016/j.najef.2018.09.004

[13] Su, X. 2020. Dynamic behaviors and contributing factors of volatility spillovers across G7 stock markets. The North American Journal of Economics and Finance, 53.https://doi.org/10.1016/j.najef.2020.101218

[14] Zhang, W., Zhuang, X., Lu, Y. & Wang, J. 2020. Spatial linkage of volatility spillovers and its explanation across G20 stock markets: A network framework. International Review of Financial Analysis, 71, 101454

[15] Samadder, S. 2021. A comparative study on nonlinearity, volatility, chaos and causal relationship between prime stock exchanges of E7 countries in last two decades. Adv. Dyn. Syst. Appl, 16, 1725

[16] Ziaur Rehman, M., Kumar Tiwari, A. & Prasad Samontaray, D. 2023. Analyzing Markov dependence-switching between E7 stock markets. Economic research-Ekonomska istraživanja, 36

[17] Lin, S. & Chen, S. 2021. Dynamic connectedness of major financial markets in China and America. International Review of Economics & Finance, 75, 646-656.https://doi.org/10.1016/j.iref.2021.04.033

[18] Pan, Q., Mei, X. & Gao, T. 2022. Modeling dynamic conditional correlations with leverage effects and volatility spillover effects: Evidence from the Chinese and US stock markets affected by the recent trade friction. The North American Journal of Economics and Finance, 59.https://doi.org/10.1016/j.najef.2021.101591

[19] Vuong, G. T. H., Nguyen, M. H. & Huynh, A. N. Q. 2022. Volatility spillovers from the Chinese stock market to the U.S. stock market: The role of the COVID-19 pandemic. J Econ Asymmetries, 26, e00276.https://doi.org/10.1016/j.jeca.2022.e00276

[20] Zhong, Y. & Liu, J. 2021. Correlations and volatility spillovers between China and Southeast Asian stock markets. The Quarterly Review of Economics and Finance, 81, 57-69.https://doi.org/10.1016/j.qref.2021.04.001

[21] Fang, Y., Jing, Z., Shi, Y. & Zhao, Y. 2021. Financial spillovers and spillbacks: New evidence from China and G7 countries. Economic Modelling, 94, 184-200.https://doi.org/10.1016/j.econmod.2020.09.022

[22] Hung, N. T. 2020. Regional Statistics, Vol. 10. No. 2. 2020: 63–82; DOI: 10.15196/RS100203 Volatility spillovers and time-frequency correlations between Chinese and African stock markets. Regional Statistics, 10, 63-82.https://doi.org/10.15196/rs100203

[23] Wang, B. & Xiao, Y. 2023. Risk spillovers from China's and the US stock markets during high-volatility periods: Evidence from East Asianstock markets. International Review of Financial Analysis, 86.https://doi.org/10.1016/j.irfa.2023.102538

[24] Agyei, S. K., Owusu Junior, P., Bossman, A., Asafo-Adjei, E., Asiamah, O. & Adam, A. M. 2022. Spillovers and contagion between BRIC and G7 markets: New evidence from time-frequency analysis. PLoS One, 17, e0271088.https://doi.org/10.1371/journal.pone.0271088

[25] Vlasova, E. & Luo, D. 2022. Volatility spillover between the Russia–India–China triad and the United States: A multivariate generalized autoregressive conditional heteroscedasticity analysis. Journal of the New Economic Association., 2, 111-128

[26] Zhang, P., Sha, Y. & Xu, Y. 2021. Stock Market Volatility Spillovers in G7 and BRIC. Emerging Markets Finance and Trade, 57, 2107-2119.https://doi.org/10.1080/1540496x.2021.1908256

[27] Khurshid, M., Azeem, M. & Ahmad, N. 2023. VOLATILITY SPILLOVERS FROM THE JAPANESE STOCK MARKET TO EMERGING STOCK MARKETS. Bulletin of Business and Economics (BBE), 12, 118-125

[28] Irshad, S., Khurshid, M., Badshah, W. & Bulut, M. 2021. Volatility spillovers from US to Emerging seven stock markets: Pre & post analysis of gfc. International Journal of Contemporary Economics and Administrative Sciences, 11

[29] Kirkulak Uludag, B. & Khurshid, M. 2019. Volatility spillover from the Chinese stock market to E7 and G7 stock markets. Journal of Economic Studies, 46, 90-105.https://doi.org/10.1108/jes-01-2017-0014

[30] Tabash, M. I., Chalissery, N., Nishad, T. M. & Al-Absy, M. S. M. 2024. Market Shocks and Stock Volatility: Evidence from Emerging and Developed Markets. International Journal of Financial Studies, 12.https://doi.org/10.3390/ijfs12010002

[31] 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.https://doi.org/10.3390/jrfm13040084

[32] Diebold, F. X. & Yilmaz, K. 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. International Journal of forecasting, 28, 57-66

[33] Del Negro, M. & Primiceri, G. E. 2015. Time varying structural vector autoregressions and monetary policy: a corrigendum. The review of economic studies, 82, 1342-1345

[34] Primiceri, G. E. 2005. Time varying structural vector autoregressions and monetary policy. The Review of Economic Studies, 72, 821-852

[35] Koop, G. & Korobilis, D. 2014. A new index of financial conditions. European Economic Review, 71, 101-116

[36] Wang, R. & Li, L. 2020. Dynamic relationship between the stock market and macroeconomy in China (1995–2018): new evidence from the continuous wavelet analysis. Economic Research-Ekonomska Istraživanja, 33, 521-539.https://doi.org/10.1080/1331677x.2020.1716264

[37] Tarchella, S., Khalfaoui, R. & Hammoudeh, S. 2024. The safe haven, hedging, and diversification properties of oil, gold, and cryptocurrency

Volume 10, Issue 1, pp. 30-39, 2026. ISSN (Online): 2456-7361

for the G7 equity markets: Evidence from the pre- and post-COVID-19 periods. Research in International Business and Finance, 67.https://doi.org/10.1016/j.ribaf.2023.102125

[38] Korkusuz, B., Kambouroudis, D. & Mcmillan, D. G. 2023. Do extreme range estimators improve realized volatility forecasts? Evidence from G7 Stock Markets. Finance Research Letters, 55.https://doi.org/10.1016/j.frl.2023.103992

[39] Elliott, G., Rothenberg, T. J. & Stock, J. H. 1992. Efficient tests for an autoregressive unit root. National Bureau of Economic Research Cambridge, Mass., USA.

[40] Jarque, C. M. & Bera, A. K. 1980. Efficient tests for normality, homoscedasticity and serial independence of regression residuals. Economics letters, 6, 255-259

[41] Horta, P., Lagoa, S. & Martins, L. 2015. Unveiling investor-induced channels of financial contagion in the 2008 financial crisis using copulas. Quantitative Finance, 16, 625-637.https://doi.org/10.1080/14697688.2015.1033447

[42] Mohti, W., Dionísio, A., Vieira, I. & Ferreira, P. 2019. Financial contagion analysis in frontier markets: Evidence from the US subprime and the Eurozone debt crises. Physica A: Statistical Mechanics and its Applications, 525, 1388-1398.https://doi.org/10.1016/j.physa.2019.03.094

[43] Wang, X. & Hui, X. 2018. Cross-Sectoral Information Transfer in the Chinese Stock Market around Its Crash in 2015. Entropy (Basel), 20.https://doi.org/10.3390/e20090663

[44] Huang, Y., Lin, C., Liu, S. & Tang, H. 2023. Trade networks and firm value: Evidence from the U.S.-China trade war. Journal of International Economics, 145.https://doi.org/10.1016/j.jinteco.2023.103811

[45] Urom, C., Ndubuisi, G., Del Lo, G. & Yuni, D. 2023. Global commodity and equity markets spillovers to Africa during the COVID-19 pandemic. Emerging Markets Review, 55.https://doi.org/10.1016/j.ememar.2022.100948

[46] Gheorghe, C. & Panazan, O. 2023. Effects of information related to the Russia-Ukraine conflict on stock volatility: An EGARCH approach. Cogent Economics & Finance, 11.https://doi.org/10.1080/23322039.2023.2241205