Economics

Impact of External Shocks on Global Major Stock Market Interdependence: Insights from Vine-Copula Modeling

--Manuscript Draft--

Manuscript Number:	ECONJOURNAL-D-25-00046
Full Title:	Impact of External Shocks on Global Major Stock Market Interdependence: Insights from Vine-Copula Modeling
Article Type:	Research Article
Keywords:	Vine-Copula; dynamic interdependence; tail dependence; global sudden events
Manuscript Region of Origin:	ROMANIA
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Manuscript Classifications:	3.3: Mathematical Methods; 6.6: International Finance; 7.4.6: International Financial Markets

Impact of External Shocks on Global Major Stock Market Interdependence: Insights from Vine-Copula Modeling

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Abstract

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JEL Classification: F36, G15, C58

1. Introduction

Amidst the gradual subsidence of the COVID-19 pandemic, coupled with the resurgence of global terrorism, heightened tensions in Europe, and the rise of China, the world is witnessing a shift towards a multipolar world order. With the advent of economic globalization and financial integration, risks have evolved from individual institutional risks to global risks (Freixas et al., 2015), driven by the complex interconnections among financial institutions and markets. Simultaneously, the increasingly frequent occurrence of global sudden events has brought significant uncertainty, triggering panic among investors and impacting the financial stability of various countries. Financial risks, stemming from sudden events, have been characterized by their rapid transmission, broad scope, and high destructiveness (Silva, 2017, Babaei, 2023). Furthermore, these events can lead to reductions in consumption and investment as well as disruptions in trade and supply chains (Yigit, 2023), resulting in substantial fluctuations and contagion effects in stock markets.

The rapid pace of economic globalization and financial integration has significantly increased the interdependence among international stock markets. In recent years, unprecedented shocks—ranging from the COVID-19 pandemic to geopolitical conflicts such as the Russia-Ukraine war—have profoundly reshaped market dynamics, leading to pronounced volatility spillovers across regions. These crises expose the limitations of traditional linear models and underscore the necessity for more sophisticated frameworks that can capture the complex, nonlinear, and high-dimensional dependency structures that characterize modern financial systems.

Extant literature has demonstrated significant volatility spillovers in stock markets (Forbes, 2002, Quinn, 2008 and Balli, 2021), and public health incidents can even precipitate regional financial crises (Bennet et al., 2015). Following the outbreak of COVID-19 in 2020, relevant studies have consistently shown the intensification of volatility spillover effects (Mazur et al., 2021, Zhang, 2023), leading to a significant increase in risk levels (Albulescu 2021). During the pandemic, investor herd behavior further intensified (Chang, 2020, Xing, 2024). Amidst the economic recovery from COVID-19, the Russia-Ukraine military conflict broke out in 2022. Previous research into similar conflicts has revealed that geopolitical crises and localized conflicts heighten market uncertainty and risk aversion (Hudson et al., 2010, Guidolin et al., 2015). The Israel-Palestine conflict negatively affected stock market transactions in the short term (Hassouneh et al., 2018) and intensified spillover effects in financial markets (Cui et al., 2024). The Russia-Ukraine conflict has drawn significant scholarly attention due to its profound impact on the EU. Research indicates that developed markets experienced more significant negative impacts compared to emerging markets (Boubaker et al., 2022). Furthermore, markets closer to the Russia-Ukraine conflict zone and those with lower market efficiency were more adversely affected by the conflict (Kumari et al., 2023). Other types of sudden events such as air disasters triggered investor panic, affecting stock prices (Kaplanski and Levy, 2010), while natural disasters, such as China's Wenchuan earthquake, exhibit short-term negative impacts on the stock market (Humphrey and Carter, 2016).

There are two main methods to measure volatility spillover effects: The first is the traditional single model, such as the Granger causality test (Granger, 1987), Vector Autoregressive model (VAR, Sims 1980), and Generalized Autoregressive Conditional Heteroscedasticity model (GARCH, Bollerslev 1986). While single models are straightforward to comprehend and interpret, they often exhibit poor fitting performance with nonlinear relationships. The second approach, the composite model, overcomes these limitations by combining multiple single models. Composite models are widely used in the financial domain due to their flexibility, multidimensionality, and scalability. For instance, Jondeau and Rockinger (2006) developed the Copula-GARCH approach, and Karmakar (2019) utilized the CGARCH-EVT-Copula model to predict the value at risk (VaR) of the returns. CoVaR, which is based on VaR (Adrian and Brunnermeier, 2016), is widely combined with other models to gauge the strength of volatility spillovers (Karimalis & Nomikos, 2018, Yan et al., 2022). Copula models, including pair-copula (Sklar, 1959), Time-varying copula (Patton, 2002), and Vine copula models (Aas, 2009), are utilized to capture nonlinear and heavy-tailed risk correlations, demonstrating excellent performance with high-frequency financial data.

In this context, our study further investigates the impact of recent major events on dependency structure and strength of financially important stock markets, particularly concerning the application of measure dependency for high-dimensional, high-frequency data. We extend the existing literature by examining volatility spillover effects among stock markets in Europe (France, Germany, Netherlands, Russia, Switzerland and the UK), the US, and Asia (China, Japan and South Korea). These countries have largest and most active stock market, accounting for over 75% of the global stock market capitalization. The stability and developmental trends of these stock markets play a crucial role in the global economy and financial markets. Furthermore, we employ the latest data, time spanning from 2016 to 2024, this study utilizes the structurally flexible Vine copula to investigate the dependency structures, and also employs dynamic SJC copula for robustness tests and research on dependency strength.

Our empirical findings demonstrate that major events have varying impacts on the interdependencies across different regions. The COVID-19 pandemic shifted the symmetric dependence structure of European stock markets to an asymmetric structure that is more sensitive to negative news. While it significantly increased the dependence strength of Asian markets, moving from tail asymmetric to symmetric dependence. The US and European markets experienced a decrease in dependence strength, while China’s stock market exhibited a declining trend in dependence with other markets. Tail dependence analysis shows that stock markets exhibit stronger co-movement during downturns than upturns, potentially leading to herd behavior during crises. We also find that the R-Vine model outperforms D-Vine and C-Vine models in modeling volatility due to its flexibility in high-dimensional data analysis.

Our research has both theoretical and practical significance. Theoretically, it reveals how global events differently affect stock market interdependencies and market behavior, offering insights into the latest developments and trends of financial markets. Practically, the insights from this research are invaluable for investors and regulators, highlighting the need for region-specific risk strategies, particularly in managing the stronger co-movement in markets during downturns. The proven efficacy of the R-Vine model in high-dimensional volatility analysis offers a practical tool for more accurate market risk assessments.

The remainder of the paper is organized as follows: Section 2 proposes hypotheses based on the existing literature. Section 3 describes the methodology. Section 4 introduces the sample and the data. Section 5 presents the empirical results. Finally, Section 6 concludes.

2. Literature Review and Hypotheses

The interconnectedness of global stock markets has long been a critical area of study in financial economics, with implications for portfolio diversification, risk management, and the transmission of financial shocks. Numerous studies have demonstrated that the interconnectedness of stock markets is not randomly distributed, but exhibits a clear regional clustering. This phenomenon of spatial regional clustering can be attributed primarily to the increased frequency of information exchange between countries that are geographically proximate, resulting in the strengthening of their economic and cultural ties. Tobler's first law of geography states that things that are geographically close are more related (Tobler, 1979), and this principle is reflected in financial markets. Geographical proximity fosters market linkages through a variety of mechanisms. It has been demonstrated that geographical proximity can serve to reduce transaction costs, accelerate the dissemination of information, and enhance the efficiency of capital markets (Li et al., 2022). Moreover, empirical evidence suggests a correlation between geographical proximity and technological similarity, as well as stronger economic ties among countries (Haddad et al., 2024). Furthermore, the phenomenon of geographical proximity is frequently accompanied by a reduction in cultural distances. This cultural affinity, in turn, fosters market linkages by impacting investor behavior and market sentiment (Lucey & Zhang, 2010).

Some scholars used spatial econometric methods to provide empirical evidence for regional agglomeration. The research found that a country's economic (especially bilateral trade) and geographical relationships significantly affect the co-movement of its stock markets (Asgharian et al., 2013), and shocks can be transmitted between different markets through foreign direct investment (FDI), trade channels and geographical proximity (Djemo & Eita, 2024). Although some studies have pointed out that financial linkages measured by FDI may be able to explain market volatility better than purely geographical distance (Fernández-Avilés et al., 2012), and that the sensitivity of stock return correlations to geographical distance may be limited to shorter distances (Eckel et al., 2011), or that economic factors may be more sensitive than geographical factors in some cases (e.g. spillover of investor sentiment) (Jiang & Jin, 2021), but spatial dependence itself remains pervasive.

Regional clustering is further reinforced by region-specific studies. Asian financial markets, especially East Asia, exhibit significant interconnectedness, and these links have strengthened during crises (Tam, 2014; Kim et al., 2015). Research on G20 financial networks also reveals clear regional clustering characteristics, such as the Asia-Pacific, European and American regions, and finds that emerging markets are increasingly becoming key nodes in the network (Zhang et al., 2019). Dynamic spatial model analysis shows that the global stock market's connectivity has evolved over time, and the connectivity within different regions (e.g., Europe) may be stronger than that across regions (Heil et al., 2022), and regional markets are simultaneously affected by global and intraregional factors (Sugimoto & Matsuki, 2019). Information factors such as media sentiment divergence can also have significant negative spatial spillover effects, affecting geographically adjacent markets (Zhang & Chen, 2025). In summary, the interconnectedness of the stock market is not only driven by geographical proximity, but also by non-geographical factors such as economics, technology, culture, and sentiment. Despite the complex and diverse driving factors, the interconnectedness of the stock market does exhibit obvious regional agglomeration characteristics.

The spillover effects of volatility between stock markets are more pronounced during market downturns, i.e., negative news spreads more quickly and strongly, intensifying market panic. Research confirms this phenomenon, pointing out that markets usually react more strongly to downside risks (negative shocks) than to upside risks (positive shocks) (Maneejuk et al., 2025; Mensi et al., 2024). Market sentiment, particularly panic, has been identified as a pivotal factor in this regard. For instance, an increase in the VIX (fear index) is frequently accompanied by an increase in cross-market risk spillovers (Huang et al., 2023). Empirical evidence further confirms this, spillover effects from the Chinese market to the US stock market increased significantly during the outbreak of the COVID-19 pandemic (Vuong et al., 2022). In particular, in energy and agricultural markets, which are closely linked to the real economy, negative news is more likely to trigger concerns about economic recession, exacerbating investor panic and overreaction (Maneejuk et al., 2025). The spillover effects of extreme market conditions are stronger than those in stable periods, and the sensitivity to negative news is particularly prominent (Khalfaoui et al., 2023; Mensi et al., 2024). The phenomenon of "bad news travels fast" is not only reflected in the stock market's sensitivity to negative news significantly outweighing its sensitivity to positive news (Baek et al., 2020), but also in the speed of price adjustment. For example, the short selling mechanism can accelerate how quickly stock prices incorporate bad news (Gao & Ding, 2019). Even in other markets such as real estate, market network connectivity also significantly increases during periods of negative shocks (market downturns), and information spreads faster. This phenomenon is attributed to the amplifying effects of information dissemination efficiency and herd behavior in such negative environments (Xu et al., 2024).

Building on the above theoretical and empirical findings, our paper proposes the following two research hypotheses:

Hypothesis 1: Stock market linkages exhibit regional clustering.

Hypothesis 2: Volatility spillover effects are more pronounced during market downturns.

3. Methodology

3.1 Copula

Copula functions establish a connection between marginal and joint distributions and are used to describe the dependence relationships among random variables. Copula functions effectively characterize the dependencies between random variables, encompassing not only linear and nonlinear correlations but also symmetric and asymmetric correlations, as well as upper and lower tail dependencies.

The concept of Copula functions stems from Sklar's theorem (1959): For a p-dimensional random variable $x = (x_1, x_2, \cdots, x_p)^T$, where F represents the marginal distributions $F_1(x_1), F_2(x_2), \cdots, F_p(x_p)$, there exists a Copula function $C(\cdot)$ such that:

$$F(x_1, x_2, \cdots, x_p) = C\left(F_1(x_1), F_2(x_2), \cdots, F_p(x_p)\right) \tag{1}$$

$$f(x_1, x_2, \cdots, x_p) = C\left(F_1(x_1), F_2(x_2), \cdots, F_p(x_p)\right) \times \prod_{k=1}^{p} f_k(x_k) \tag{2}$$

$C(F_1(x_1), F_2(x_2), \cdots, F_p(x_p))$ represents the probability density function of the Copula function, where $f_k(x_k)$ denotes the probability density function of the marginal distribution of the variable $x_k (k = 1,2, \cdots, p)$. The Vine-Copula model is an extension of the Copula function model.

3.2 Vine-Copula

To better handle asymmetric and nonlinear dependence relationships, scholars Aas, Czado, Frigessi, and Bakken (2009) proposed the Pair-Copula model. The Pair-Copula model decomposes the multidimensional Copula function into a product of several bivariate Copula functions. The Vine-Copula model, developed based on the Pair-Copula model and graph theory, adopts a tree structure to combine multiple bivariate Copula functions. The tree structure created by Vine-Copula, known as the "Vine graph," was introduced by Bedford (2002). The Vine structure includes nodes, branches, and trees. Each node signifies a variable, each branch represents the Copula function between variables, and each tree consists of branches connecting two nodes. The Vine-Copula model is a method used to model the joint distribution of multivariate random variables, to describe the dependencies between variables. This model provides improved flexibility and interpretability, offering a clearer depiction of dependencies among multidimensional random variables.

Assuming $X = (X_1, X_2, \dots X_d)$ is a d-dimensional random vector with marginal distribution functions $F_1, F_1, \dots F_d$, $C(u_1, u_2, \dots, u_d)$ is its Copula function. The Vine-Copula model represents the Copula function using the product form conditional probability distributions in a tree-like structure, given by:

$$C(u_1, \dots, u_d) = \prod_{i=1}^{d} \prod_{j=i+1}^{d} C_{i,j|p_{i,j}}(u_i, u_j) \tag{3}$$

Here $C_{i,j|p_{i,j}}$ represents the conditional Copula function between X_i and X_j on the tree structure, where $p_{i,j}$ indicates their parent node on the tree. In the tree structure, nodes represent variables, edges represent dependencies between variables, and each node's edge represents its dependency on the parent node. The Vine-Copula model can accurately describe the dependency relationships among multidimensional random variables due to the flexibility and interpretability of the tree structure.

Vine structures are commonly categorized into three types: C-Vine, D-Vine, and R-Vine.

a. C-Vine Copula

In a C-Vine structure, each tree has only one central node, exhibiting a star-like characteristic. The joint probability density function of the C-Vine Copula is given by:

$$f(x_1, x_2, \cdots, x_d) = \left[\prod_{k=1}^{d} f_k(x_k)\right] \times \left\{\prod_{j=1}^{d-1} \prod_{i=1}^{d-j} C_{j,j+i|i,\cdots,j-1}\left[F\left(x_j \mid x_{1,\cdots,j-1}\right), F\left(x_{j+i} \mid x_{1,\cdots,j-1}\right)\right]\right\} \tag{4}$$

Here, the tree is indexed by $j = 1, 2, \cdots, n-2$, and each edge in the tree is represented by i, $f_k(x_k)$is the marginal density function of the *k*-th variable.

b. D-Vine Copula

In the D-Vine structure, each node has at most two branches, exhibiting a chain-like characteristic. The joint probability density function of the D-Vine Copula is given by:

$$f(x_1, x_2, \cdots, x_d) = \left[\prod_{k=1}^{d} f_k(x_k)\right] \times \left\{\prod_{j=1}^{d-1} \prod_{i=1}^{d-j} C_{i,i+j|i+1,\cdots,i+j-1}\left[F\left(x_i \mid x_{i+1,\cdots,i+j-1}\right), F\left(x_{i+j} \mid x_{i+1,\cdots,i+j-1}\right)\right]\right\} \tag{5}$$

c. R-Vine Copula

The R-Vine structure is flexible, allowing for multiple nodes. The joint probability density function of the R-Vine Copula is:

$$f(x_1, x_2, \cdots, x_d) = \left[\prod_{k=1}^{d} f_k(x_k)\right] \times$$

$$\left\{\prod_{j=1}^{d-1} \prod_{e \in E_I} \boldsymbol{C}_j(e), k(e) \mid D(e) \left[F\left(x_{j(e)} \mid x_{D(e)}\right), F\left(x_{k(e)} \mid x_{D(e)}\right)\right]\right\} \quad (6)$$

The Vine-Copula model employs Kendall's rank correlation coefficient as weights and estimates the related parameters using maximum likelihood estimation. Kendall's rank correlation coefficient is a non-parametric statistical method used to measure the degree of correlation between two random variables. It examines the consistency of the trend in changes between pairs of variables. If the trend is consistent, it indicates a positive correlation; otherwise, it suggests a negative correlation. A value of -1 represents a perfect negative correlation, 0 indicates no correlation, and 1 signifies a perfect positive correlation.

Let (X_1, Y_1) and (X_2, Y_2) be independently and identically distributed random variables. The definition of Kendall's rank correlation coefficient τ is given by:

$$\tau = P[(X_1 - X_2)(Y_1 - Y_2) > 0] - P[(X_1 - X_2)(Y_1 - Y_2) < 0] \quad (7)$$

Here, τ represents Kendall's rank correlation coefficient. If $\tau > 0$, it indicates a consistent trend between *X* and *Y*, implying a positive correlation. If $\tau < 0$, it suggests an inconsistent trend, indicating a negative correlation. If $\tau = 0$, it implies that it is not possible to determine whether *X* and *Y* correlated.

3.3 Tail dependence

The tail dependence coefficient refers to the probability of occurrence of extreme values in one or more random variables when another or other random variables are in extreme states within a multivariate random variable setting. In other words, tail dependence explores the degree of correlation among different assets when extreme losses or extreme gains occur simultaneously. This study employs the limit form of conditional probabilities to measure tail dependence, with specific definitions for the upper tail dependence coefficient τ^U and the lower tail dependence coefficient τ^L as follows:

$$\tau^U = \lim_{u \to 1^-} P\left(Y > G^{-1}(u) \mid X > F^{-1}(v)\right) = \lim_{u \to 1^-} \frac{C(1-u, 1-v)}{1-v} \quad (8)$$

$$\tau^L = \lim_{v \to 0^+} P\left(Y \le G^{-1}(u) \mid X \le F^{-1}(v)\right) = \lim_{v \to 0^+} \frac{C(u, v)}{v} \quad (9)$$

Where *X* and *Y* are two random variables, and $F(X), G(Y)$ are the distribution functions of *X* and *Y*.

The time-varying Copula function modifies the static Copula function by replacing the constant correlation coefficient τ with a time–varying correlation coefficient τ_t. This modification is used to measure the dynamic upper and lower tail dependence between two variables. τ_t^U represents the upper tail correlation coefficient, and τ_t^L represents the lower tail correlation coefficient. The parameter evolution equations are given by:

$$\begin{cases} \tau_t^U = \Lambda\left(\omega^U + \beta^U \tau_{t-1}^U + \frac{\alpha^U}{q}\sum_{i=1}^{q}|u_{t-i} - v_{t-i}|\right) \\ \tau_t^L = \Lambda\left(\omega^L + \beta^L \tau_{t-1}^L + \frac{\alpha^L}{q}\sum_{i=1}^{q}|u_{t-i} - v_{t-i}|\right) \end{cases} \tag{10}$$

In equation (10), $\Lambda(x) = \frac{1}{1+e^{-x}}$ is the modified logistic function, and u and v are from SJC-Copula model. The SJC-Copula model is an extension of the Joe-Clayton Copula model, the time-varying expression for the Joe-Clayton Copula given by:

$$C_{JC}(u, v; \tau_t^U, \tau_t^L) = 1 - \left\{1 - \{[1-(1-u)^\kappa]^{-\gamma} + [1-(1-v)^K]^{-\gamma} - 1\}^{-\frac{1}{\gamma}}\right\}^{\frac{1}{\kappa}} \tag{11}$$

In equation (11), $\kappa = \frac{1}{\log_2(2-\tau_t^U)}$, $\gamma = -\frac{1}{\log_2 \tau_t^L}$;

The expression for the time-varying SJC Copula model is:

$$C_{SJC}(u, v; \tau_t^U, \tau_t^L) = \frac{1}{2}\left[C_{JC}(u, v; \tau_t^U, \tau_t^L) + C_{JC}(1-u, 1-v; \tau_t^U, \tau_t^L) + u + v - 1\right] \tag{12}$$

4. DATA

Our analysis is conducted within a time window starting from January 2016 to February 2024. We divide the timeline into three stages based on two major events (as shown in Figure 1). The World Health Organization announced the COVID-19 epidemic as a Public Health Emergency of International Concern on January 30th, 2020; therefore, we define the first division point as January 30, 2020. Russia initiated a special military operation against Ukraine on February 24th, 2022, marking the start of a major conflict in Europe. This date serves as our second division point: February 24, 2022. The first period represents a relatively stable phase; the second corresponds to the peak COVID-19 period; and the third encompasses the Russia-Ukraine conflict alongside the lingering impact of COVID-19. Our study compares the changes in the interdependence of stock markets across these three periods to analyze the impact of major exogenous shocks on financial markets.

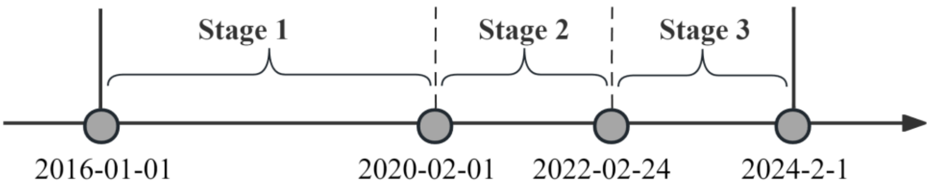

Figure 1. Timeline stage division

We selected representative stock indices from ten major global economies based on their financial significance, guided by Statista's 'Leading Financial Centers Worldwide 2023' report (as delineated in Table 1). The selection of representative stock indices for each country is based on previous literature and the World Financial Annual Report of 2023 by Guotai Junan Securities. These chosen stock indices exhibit broad market coverage, strong representativeness, high accuracy, and sustained continuity. Data on the daily closing prices of each country's stock index were retrieved from the website: cn.investing.com.

Table 1. Representative stock indices from 10 countries

	Country	Country Abbreviation	Stock Index	Stock Index Abbreviation
1	China	CN	Shenzhen Component Index	SZI
2	France	FR	CAC40 Index	CAC
3	Germany	DE	DAX30 Index	DAX
4	Japan	JP	Nikkei 225 Index	N225
5	Netherlands	NL	AEX Index	AEX
6	Russia	RU	MOEX Russia Index	MOEX
7	South Korea	SKR	KOSPI Index	KOSPI
8	Switzerland	CH	SWI20 Index	SWI
9	United Kingdom	UK	FTSE 100 Index	FTSE
10	United States	US	S&P 500 Index	SPX

We adjust the daily closing price data collected for each stock index for extreme and missing values. Considering variations in trading schedules and market closure days across nations, trading days with three or more missing values were excluded. We fill the remaining missing values using a binomial moving average method. The resulting preprocessed data were visualized in Figure 2. By observing the line charts revealed similarities in trends among stock indices, this phenomenon, known as volatility contagion, is driven by both global factors (such as changes in the global economic environment) and local factors (such as political and economic changes). Major exogenous events, such as the onset of the COVID-19 pandemic and the Russia-Ukraine conflict, led to significant downturns in stock indices across various countries.

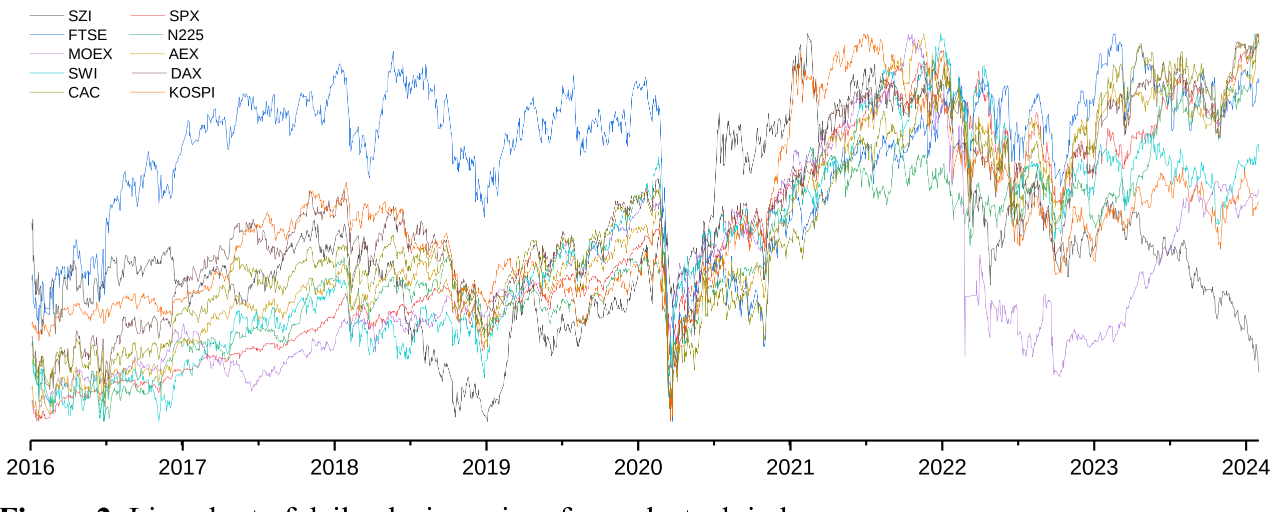

Figure 2. Line chart of daily closing prices for each stock index

Due to the non-stationarity of the original daily closing price data, we apply a logarithmic difference transformation and use the resulting series as returns for modeling. Table 2 presents descriptive statistics for the return series of ten stock market indices across three distinct periods. Our findings reveal that during the COVID-19 pandemic period, not all stock indices exhibited a uniform trend in mean returns. For instance, the mean returns of the China SZI, Netherlands AEX, and Korea KOSPI increased compared to the first period. Conversely, the mean returns of other indices decreased. Specifically, the volatility, as measured by the standard deviation of returns, increased for all ten indices during the crisis period. The returns of most stock indices exhibit negative skewness (skewness < 0) and leptokurtosis (kurtosis > 3). During the pandemic, kurtosis values reached high values but subsequently fell back to lower levels later. This may be attributable to widespread quantitative easing policies adopted by most countries, which temporarily boosted stock market liquidity and activity. During the Russia-Ukraine conflict period, the MOEX index's returns exhibited positive skewness and leptokurtosis. The uncertainty and negative effects accompanying the war likely contributed to stock market declines, influencing these return characteristics.

Table 2. Descriptive statistical for the return series

	Stage	SZI	CAC	DAX	N225	AEX	MOEX	KOSPI	SWI	FTSE	SPX
Mean	1	-0.0001	0.0003	0.0003	0.0003	0.0003	0.0006	0.0002	0.0002	0.0002	0.0005
	2	0.0007	0.0003	0.0002	0.0002	0.0004	-0.0004	0.0005	0.0002	0.0000	0.0005
	3	-0.0010	0.0003	0.0004	0.0007	0.0003	0.0010	-0.0001	-0.0001	0.0001	0.0003
Std.D	1	0.0145	0.0097	0.0099	0.0114	0.0087	0.0091	0.0078	0.0081	0.0082	0.0081
	2	0.0244	0.0163	0.0164	0.0143	0.0145	0.0178	0.0147	0.0120	0.0145	0.0167
	3	0.0126	0.0115	0.0116	0.0110	0.0108	0.0169	0.0104	0.0086	0.0087	0.0117
Skew-ness	1	-0.716	-0.958	-0.718	-0.595	-0.718	-0.639	-0.842	-0.472	-0.335	-0.918
	2	-0.472	-1.208	-0.810	0.120	-1.030	-2.993	-0.103	-1.384	-1.123	-0.989
	3	-0.163	0.050	0.240	-0.025	-0.164	1.912	0.194	0.079	-0.414	-0.127
Kurt-osis	1	4.331	8.045	4.448	6.586	4.607	7.222	3.302	2.431	3.165	4.694
	2	1.441	12.572	13.865	4.489	11.930	26.446	6.669	14.627	12.636	14.318
	3	1.780	3.693	4.676	0.398	2.369	32.195	1.890	1.835	2.903	1.487

Note: This table presents descriptive statistics for the return series of ten stock market indices across three stages. Specifically, cells with a white background denote the first stage, representing a stable period. Cells with a light gray background indicate the second stage, corresponding to the COVID-19 pandemic period. Cells with a dark gray background signify the third stage, identified as the Russia-Ukraine war period.

5. Results

5.1 Results of Fitting Marginal Distributions

To capture the volatility clustering and asymmetry in the returns, we employ the ARMA-GARCH framework to fit the marginal distributions. We utilize the ARMA model to determine the optimal lag order for the conditional mean equation. Then, we compare the results of standard residual distributions with normal distribution, skewed normal distribution, T-distribution, skewed T-distribution, GED distribution, and skewed GED distribution. The ARMA(p,q)-GARCH(1,1)-skewed Student's t-distribution for the residuals is selected as the optimal model based on parameter significance and the minimum AIC principle. We use R Studio to fit the marginal distributions of stock index returns in different stages, the model parameters are estimated and summarized in Table 3.

The marginal distribution model parameters reveal that the ARCH(α) and GARCH(β) values for each series are statistically significant and generally satisfy the stationarity constraint $\alpha+\beta < 1$. The estimated β values across all return series exceed 0.5, signifying substantial historical influence on their yield rates and suggesting volatility clustering phenomena, which is particularly noteworthy for the SPX index. Through diagnostic tests on the standardized residuals, including the Ljung-Box test for autocorrelation in residuals and squared residuals, and the ARCH-LM test, no significant autocorrelation or remaining ARCH effects (heteroscedasticity) were observed. Combining these diagnostic results with the AIC values and likelihood estimates, we conclude that the GARCH(1,1)-

Skewed Student's t model provides a good fit for the return series.

Table 3. Estimated parameters for the marginal distributions at each stage

	Stage	SZI	CAC	DAX	N225	AEX	MOEX	KOSPI	SWI	FTSE	SPX
α	1	0.0341	0.2662	0.0496	0.1079	0.2352	0.0762	0.0416	0.1386	0.1612	0.2521
	2	0.0708	0.1674	0.1550	0.9224	0.1520	0.1163	0.1639	0.2022	0.1615	0.3934
	3	0.0494	0.1218	0.1270	0.0160	0.0926	0.2885	0.0654	0.1233	0.2806	0.0615
β	1	0.9649	0.6744	0.9481	0.8644	0.6463	0.8572	0.9028	0.8060	0.7331	0.7453
	2	0.8973	0.8107	0.8440	0.5224	0.8296	0.8500	0.7779	0.7620	0.8313	0.6056
	3	0.9422	0.8518	0.8654	0.9830	0.9064	0.7105	0.8944	0.8437	0.5831	0.9375
skew	1	0.9672	1.0888	0.9744	1.0350	0.9937	1.0537	0.9159	1.0648	1.0085	1.0627
	2	0.9278	0.9697	1.0150	1.1617	0.9816	0.8971	1.0071	0.9719	0.9928	1.0725
	3	1.1114	1.0098	0.9849	0.9374	0.9965	1.0214	1.0388	1.0697	0.9722	1.0565
shape	1	4.45	4.41	4.49	3.70	5.52	8.57	4.85	8.64	4.89	3.55
	2	8.37	3.82	3.30	5.25	5.00	4.69	6.19	4.79	4.23	8.30
	3	12.99	6.82	6.16	12.46	4.73	2.70	7.13	10.62	3.53	9.89
LogLik	1	2878	3266	3194	3120	3347	3247	3421	3379	3390	3497
	2	1426	1485	1489	1468	1513	1474	1493	1632	1537	1551
	3	1403	1457	1467	1438	1490	1422	1476	1576	1593	1444
AIC	1	-5.91	-6.71	-6.57	-6.41	-6.87	-6.68	-7.02	-6.94	-6.96	-7.19
	2	-5.74	-5.98	-5.99	-5.91	-6.09	-5.92	-6.00	-6.57	-6.18	-6.23
	3	-6.01	-6.25	-6.30	-6.17	-6.40	-6.10	-6.34	-6.77	-6.84	-6.20
LB(4)	1	0.3964	0.3391	0.1612	0.5597	0.9524	0.4456	0.9992	0.8423	0.3549	0.3904
	2	0.9294	0.3858	0.3154	0.5415	0.1738	0.9580	0.5157	0.1615	0.0902	0.7177
	3	0.9991	0.9515	0.9102	0.8453	0.9863	0.9999	0.9898	0.9950	0.9295	0.9801
LB2(4)	1	0.6420	0.6368	0.2402	0.6958	0.9074	0.2677	0.7919	0.7236	0.7742	0.8380
	2	0.1503	0.6987	0.3083	0.6275	0.3945	0.3524	0.7164	0.8823	0.4612	0.6233
	3	0.0828	0.6954	0.3733	0.5273	0.7348	1.0000	0.4929	0.5329	0.3636	0.9556
ARCH-LM(20)	1	0.9899	0.8464	0.0770	0.7946	0.9579	0.3830	0.5798	0.7220	0.7934	0.9313
	2	0.4690	0.9615	0.9224	0.6368	0.8554	0.9615	0.6357	0.9573	0.3923	0.8548
	3	0.8066	0.4374	0.1084	0.2961	0.5322	1.0000	0.2512	0.3684	0.2641	0.7258

Note: This table represents Estimated parameters for the marginal distributions at each stage. α is the coefficient of the ARCH term; β is the coefficient of the GARCH term; skew and shape are parameters of the skewed-t distribution; LogLik stands for the log-likelihood value; LB and LB2 represent the Ljung-Box statistics for testing autocorrelation in the residuals and squared residuals, respectively. Specifically, Cells with a white background denote the first stage, representing a stable period. Cells with a light gray background indicate the second stage, corresponding to the COVID-19 pandemic period. Cells with a dark gray background signify the third stage, identified as the Russia-Ukraine war period.

5.2 Vine-Copula Estimation Results

We employ the Vine-Copula methods described in section 2 to analyze the dependence structure among stock markets by fitting probability integral transformed residuals. Kendall's rank correlation coefficient serves as the measure of pairwise dependence, and we utilize the maximum spanning tree (MST) algorithm to construct Vine-Copula model (specifically, the first tree, T1). The copula parameters are estimated using the maximum likelihood method. Subsequently, we identify the optimal R-Vine structure and select the best-fitting pair-copula families based on the minimum AIC criterion. Table 4 presents the parameters and selected pair-copula families of the first tree for each stage. The results indicate that while some countries exhibit consistent interdependence, there is also considerable variability in the chosen pair-copula families, the strength of dependence, and implied tail dependence.

Table 4. The parameters of the first Copula tree for each stage

Stage	edge	Copula	par1	par2	tau	utd	ltd
1	5,10	T-Copula	0.58 (0.02)	9.28 (2.95)	0.39	0.13	0.13
	2,3	T-Copula	0.89 (0.01)	8.64 (2.24)	0.70	0.47	0.47
	2,8	T-Copula	0.78 (0.02)	7.32(1.57)	0.57	0.34	0.34
	5,2	T-Copula	0.89 (0.01)	4.11 (0.59)	0.70	0.62	0.62
	5,9	T-Copula	0.78 (0.01)	8.55(1.95)	0.57	0.30	0.30
	5,6	T-Copula	0.41 (0.03)	10.00(2.40)	0.27	0.06	0.06
	7,1	SG-Copula	1.26 (0.03)	-	0.21	-	0.27
	7,4	SG-Copula	1.58 (0.05)		0.37	-	0.45
	7,5	SG-Copula	0.91 (0.01)	-	0.23	-	0.29
2	5,10	Normal-Copula	0.51 (0.04)	-	0.34	-	-
	5,8	SG-Copula	2.25 (0.11)	-	0.56	-	0.64
	2,9	SG-Copula	2.72 (0.14)	-	0.63	-	0.71
	3,2	T-Copula	0.89 (0.01)	2.70(0.50)	0.70	0.67	0.67
	5,3	SG-Copula	2.90 (0.15)	-	0.65	-	0.73
	5,6	SG-Copula	1.65 (0.07)	-	0.39	-	0.48
	4,5	Normal-Copula	0.41 (0.04)	-	0.27	-	-
	7,1	Normal-Copula	0.37 (0.04)	-	0.24	-	-
	7,4	T-Copula	0.61 (0.03)	7.06(2.60)	0.42	0.20	0.20
3	10,6	Normal -Copula	0.12 (0.05)	-	0.08	-	-
	2,3	SG-Copula	3.82 (0.21)	-	0.74	-	0.80
	5,10	T-Copula	0.57 (0.03)	8.08(2.86)	0.39	0.15	0.15
	2,8	T-Copula	0.76 (0.02)	7.46(1.96)	0.55	0.31	0.31
	2,9	T-Copula	0.79 (0.02)	5.06(1.41)	0.58	0.43	0.43
	7,1	F-Copula	2.20 (0.29)	-	0.23	-	-
	5,2	SG-Copula	2.95 (0.17)	-	0.66	-	0.74
	7,4	SG-Copula	1.61 (0.07)	-	0.38	-	0.46
	7,5	F-Copula	1.83 (0.30)	-	0.20	-	-

Note: This table presents the parameters of the first Copula tree for each stage. The term "edge" refers to a connecting branch within the tree structure. Copula functions include T-copula, SG-Copula, Normal Copula, F Copula, etc. SG-Copula (Survival Gumbel Copula) is a 180-degree rotation of the Gumbel Copula, characterized by tail symmetry. While the T-Copula, Normal-Copula, and F-Copula exhibit tail asymmetry. Parameters Par1 and Par2 represent the first and second parameters of the Copula function, respectively. Tau (τ) is the Kendall rank correlation coefficient, utd is the upper tail dependence coefficient, ltd is the lower tail dependence coefficient, and the values in parentheses denote the standard errors of Copula model parameter estimates. The structural tree is derived from equations. Cells with a white background denote the first stage, representing a stable period. Cells with a light gray background indicate the second stage, corresponding to the COVID-19 pandemic period. Cells with a dark gray background signify the third stage, identified as the Russia-Ukraine war period.

We utilize the graphical representation of the R-Vine structure (Vine trees) to provide a more intuitive visualization of the dependency structure, including the dependence strength (τ) and the selected pair-copula families, across the three stages, as illustrated in Figure 3.

The overall structure exhibits a star-chain configuration, wherein the Netherlands emerges as the pivotal nexus of stock market volatility transmission. It serves as a conduit linking European, US, and Asian markets. This structural pattern reveals pronounced regional clustering; specifically, the interconnectedness between European and U.S. markets is notably tighter compared to their connection with Asian markets. The Kendall rank correlation within the EU stock markets exceeded 0.55 throughout all observed periods, initially presenting a star configuration with symmetrical tail dependencies. This evolved into an asymmetric chain structure in the second stage. Despite the UK's secession from the EU, its dependency remained significant, with an asymmetric structure. In the third stage, with the pandemic's attenuation and ensuing economic revival, the EU’s central node shifted to Switzerland, presenting a star-shaped structure with enhanced dependencies. The interdependence between the US and European equities generally maintained a symmetrical dynamic. In the second stage, the US stock market experienced a series of trading halts, and average interconnectedness with European markets decreased by approximately 12.8% compared to the first stage. According to investor behavior theory, global crises elevate market uncertainty, prompting investors to seek refuge in safe-haven assets like gold. This behavior diminishes market liquidity and amplifies volatility, thereby reinforcing the volatility contagion effect. This dependency rebounded towards pre-crisis levels in the third stage.

Prior to the Russo-Ukrainian conflict, Russia maintained a moderate level of dependency with European markets, and the pandemic heightened this dependency. However, subsequent political factors and the onset of hostilities led to the severance of economic ties between Russia and Europe, resulting in Russia maintaining only a weaker dependency with the US in the third stage.

Asian markets sustained a stable dependency with European markets, with an uptick during recent years. The profound military and political linkages between South Korea, Japan and the US, alongside their capitalist frameworks, have cemented their integration with Western markets. Inter-market connectivity between South Korea and Japan approximately doubled amid the pandemic, likely influenced by geographic proximity and pandemic-related lockdowns. Conversely, the dependency between China and other countries transitioned from asymmetric to symmetric, exhibiting a weakening trend in dependence strength.

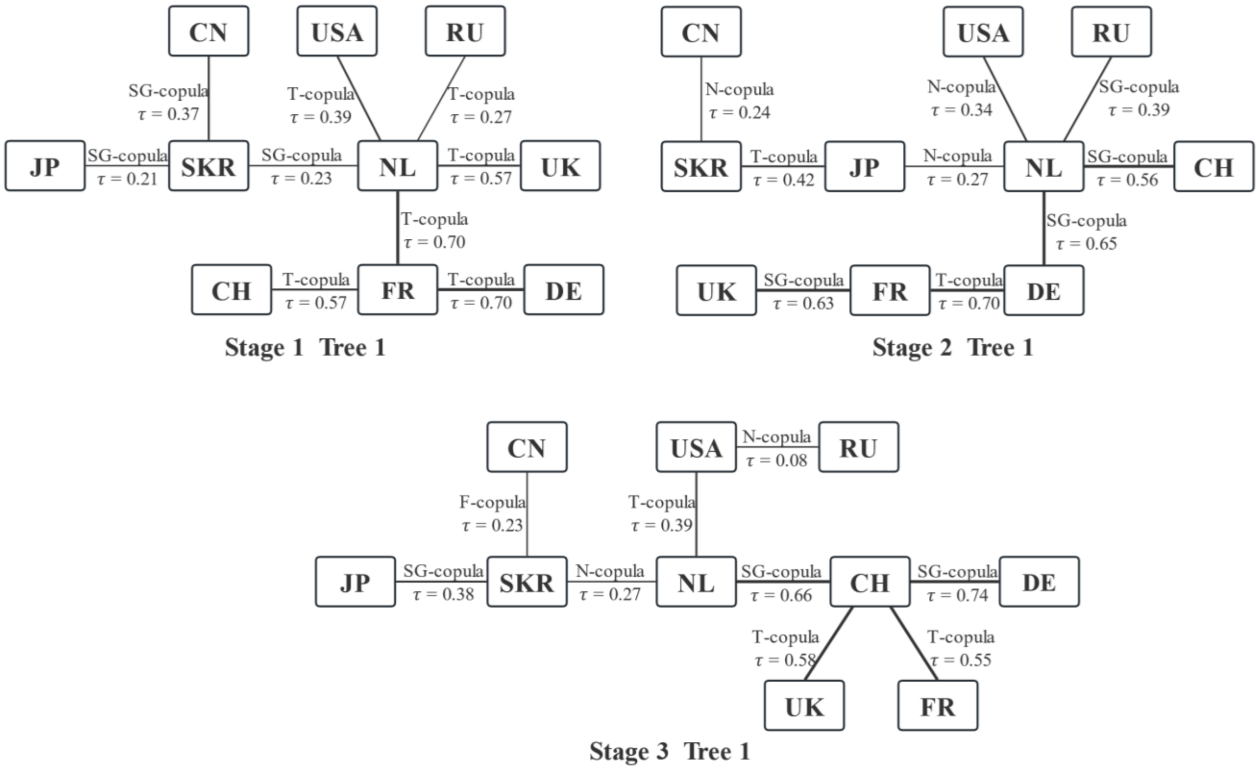

Figure 3. The first tree structure of the Vine-Copula for each stage

Note: This figure illustrates the Vine-Copula tree structures for three distinct stages. On each edge (connecting branch), the Kendall rank correlation coefficient (τ) and the Copula type are presented. Each node represents a country's stock market. Stage 1: Stable Period; Stage 2: COVID-19 Pandemic Period; Stage 3: Russia-Ukraine War Period.

5.3 Robust Check

We further examine the robustness of our findings by analyzing both static and dynamic tail dependencies within Copula frameworks across stock markets, alongside exploring variations in transmission strength. We compute static and dynamic tail dependence coefficients for ten pairs of interrelated stock indices, with Table 5 presenting the static lower and upper tail dependence coefficients for these pairs.

European stock markets exhibit pronounced high level of dependence. Notably, the pair between the German DAX and French CAC indices demonstrates the highest upper (0.7564) and lower (0.8183) tail dependence coefficients, indicating strong mutual influences in both market upswings and downturns. The US demonstrates a moderate dependency with European markets, with minimal difference between its upper and lower tail dependence coefficients, suggesting predominantly symmetric volatility spillovers. Interdependencies between Asian and European markets are less pronounced than those between the US and Europe. Within Asia, South Korea and Japan exhibit the highest level of co-movement, while China's market interdependence with other markets is markedly low. Overall, our analysis reveals that the lower tail dependence among stock market pairs generally exceeds the upper tail dependence. This implies that markets are more correlated during downturns (bear markets) than during upturns (bull markets), suggesting that negative news spreads faster, inciting market panic and leading to steeper declines in stock prices.

Table 5. The static tail dependence coefficients of stock index returns

	Upper tail	Lower tail
US&NL	0.4011	0.4014
US&UK	0.2990	0.3076
RU&NL	0.2022	0.2783
RU&US	0.0861	0.1604
FR&DE	0.7564	0.8183
NL&UK	0.5865	0.6893
NL&DE	0.6749	0.7592
JP&SKR	0.3258	0.4362
SKR&NL	0.1338	0.2507
CN&JP	0.0680	0.1433

To model dynamic dependence, we approximate the Copula distribution from among Normal, Clayton, Frank, Gumbel, T, and SJC types using the kernel density estimation method. The optimal dynamic copula model was selected based on the minimum Akaike Information Criterion (AIC) value, which identifies the time-varying SJC Copula as the optimal specification for our analysis.

Subsequently, we calculate the dynamic upper and lower tail dependence coefficients for the ten pairs of dependent stock indices under study. The results are visualized through line plots, as depicted in Figures 4 to 7.

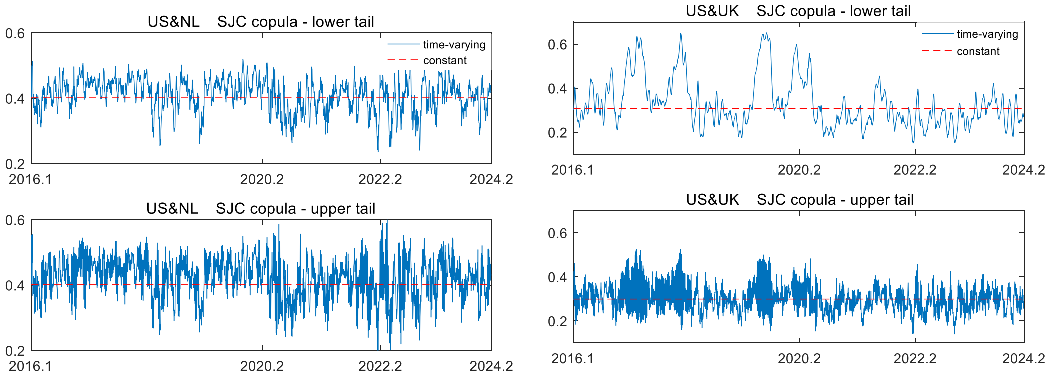

Figure 4. The dynamic tail dependence of US stock index returns

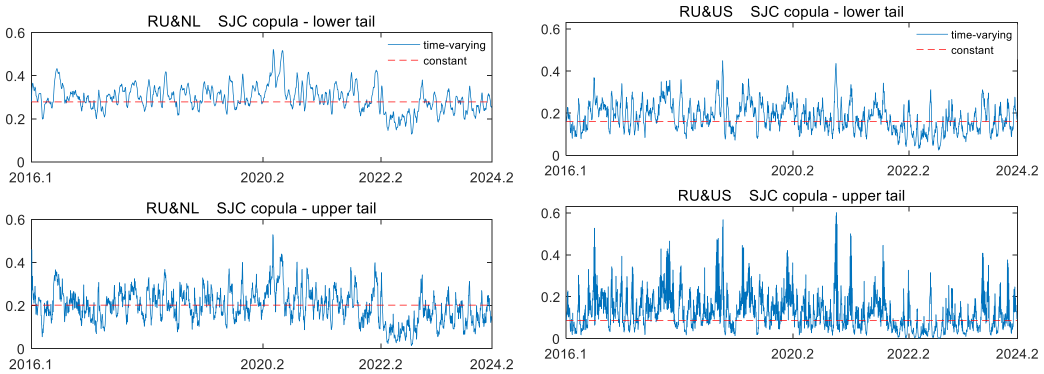

Figure 5. The dynamic tail dependence of Russian stock index returns

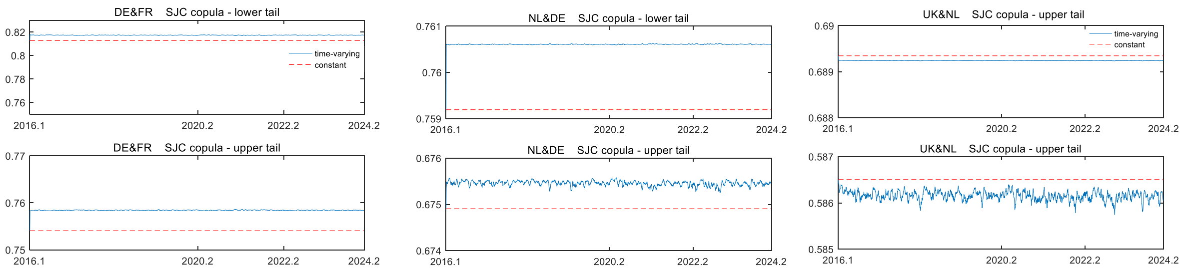

Figure 6. The dynamic tail dependence of European stock index returns

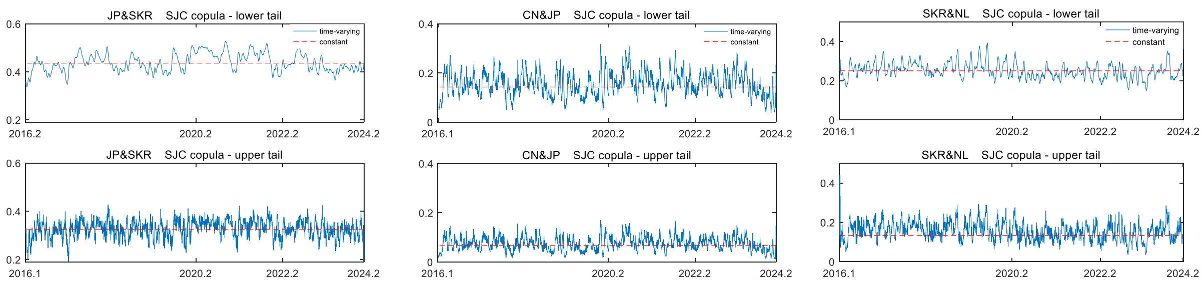

Figure 7. The dynamic tail dependence of Asian stock index returns

Figure 4 illustrates the dynamic dependence changes between the stock markets of US and Europe, revealing that the frequency of fluctuations in lower tail dependence is higher than that in upper tail dependence. A sharp decrease in dependency is observed at the start of the second stage, followed by a gradual recovery.

Figure 5 displays the dynamic dependency fluctuations between the Russian market and other stock markets. At the onset of the Russo-Ukrainian War, its dependency with European markets sharply decreased, maintaining levels below the average throughout the third stage. The dependency between Russia and the US, though initially reduced, swiftly reverted to its historical average level.

Figure 6 demonstrates the dynamic dependency changes within European stock markets. The dependency among these markets remains high, with minimal fluctuation over time. Similarly, the pandemic and the Russo-Ukrainian conflict did not appear to significantly disrupt the internal dependency structure within Europe. The Brexit event in 2020 did not significantly impact the dependency between the UK and other European stock markets.

Figure 7 presents the dynamic dependency between Asian stock markets and others. Within Asia, Japan and South Korea exhibit the highest dependency, which significantly increased during the pandemic. China's dependency with other markets is the lowest and shows a downward trend in recent years. South Korea serves as a link between Asian and European markets, with its dependency being not high but stable, and less affected by major events. These observations align with the results from Vine-copula analysis.

6. Conclusion & Discussion

This paper, against the backdrop of recent major global shocks (including public health crises and regional conflicts in Europe), explores dynamic changes in interdependence and volatility spillover effects among ten financially important stock markets. Asia, America, and Europe are pivotal arenas for financial and capital activity, playing crucial roles in the development and stability of the global financial system.

Our analysis, using the Vine copula model, demonstrates distinct regional clustering characteristics across different regions, with a sequential dependence strength ranking being Europe > Europe-US > Asia. This finding is consistent with the research results of Khoo et al. (2023) and León et al. (2017), their studies also indicated the presence of geographically dominant regional clusters in global stock markets. Moreover, major sudden events have varied impacts on different regions. For COVID-19, it did not affect the high interdependency of European stock markets; instead, it shifted their symmetric dependence towards an asymmetric dependence structure more sensitive to negative news. Conversely, for Asian stock markets, COVID-19 significantly increased the dependence strength, transitioning from tail asymmetric dependence to symmetric. The symmetric dependence structure between the US and Europe remained largely unaffected; however, due to multiple circuit breaker events in the US stock market and during the pandemic, the overall strength of dependence decreased. Notably, the interdependence between China's stock market and others is low, showing a declining trend in recent years. China's stock market, established later and relatively more closed compared to Western markets, is influenced significantly by domestic policies. The Russia-Ukraine conflict had minimal direct spillover impact on the interdependence structure of stock markets beside Russia itself, according to our model.

Our examination of dynamic copula tail dependence across markets reveals a significant asymmetry: lower tail dependence is generally higher than upper tail dependence, indicating stronger co-movement during market downturns. This asymmetry suggests that during market downturns, the co-movement between stock markets strengthens, while during market upswings, the co-movement weakens. Consistent with this, Yin et al. (2017) and Bhattacharjee et al. (2019) demonstrated that global stock market linkages become more pronounced during periods of financial turmoil. This sensitivity to negative information is further evidenced by the disproportionate increase in lower tail dependence compared to upper tail dependence when sudden global events occur. This amplified lower tail dependence during crises indicates a heightened susceptibility to investor panic and the subsequent emergence of herd behavior.

We also find that the structurally rich R-Vine model is more suitable for describing the transmission structure of volatility contagion effects in stock markets compared to the D-Vine and C-Vine structures. The R-Vine structure excels in handling high-dimensional data, allowing for the flexible selection of different marginal distributions and copula functions.

In sum, our analysis sheds light on the latest dependency trends in financially important stock markets and the effects of major events on volatility spillover. This paper contributes to the literature by examining the structure and strength of interdependence, providing empirical evidence of regional clustering and dependence dynamics in global stock markets, analyzing the distinct impacts of recent global events, confirming asymmetric tail dependence and its behavioral implications, and demonstrating the suitability of the R-Vine model for more accurate and flexible modeling of volatility spillovers. From the theoretical and practical perspectives, the findings offer insights for investors, policymakers, and regulators, emphasizing the need for region-specific risk management strategies, particularly to address the stronger market co-movement during downturns. Understanding the dynamics of interdependence and volatility spillover effects is essential for designing effective regulatory and policy responses to mitigate systemic risks, especially during times of global uncertainty.

CRediT authorship contribution statement

Wenjing Jiang: Conceptualization, Methodology, Software, Validation, Writing – original draft, Data curation, Writing – review & editing. Yue Hu: Formal analysis, Supervision, Funding acquisition, Methodology. Yicheng Xu: Visualization, Validation, Writing – review & editing. Hanyu Miao: Conceptualization, Writing – review & editing.

Declaration of competing interest

We declare we have no competing interests.

Data availability

Data will be made available on request.

Acknowledgement

This work is supported by the National Natural Science Foundation of China (No. 11901524).

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