Journal of Asian Scientific Research
ISSN(e): 2223-1331
ISSN(p): 2226-5724
DOI: 10.55493/5003.v15i3.5601
Vol. 15, No. 3, 591-607.

URL: www.aessweb.com

Dynamic spillovers between G7 stock markets and precious metals: A time-varying analysis of gold and silver

Nadia Belkhir[1+]
Wafa Kammoun Masmoudi[2]

[1]*Imam Mohammad Ibn Saud Islamic University, Riyadh, Saudi Arabia.*
[1]*Email: nabelkhir@imamu.edu.sa*
[2]*University of Carthage, Institute of Higher Commercial Studies of Carthage, Tunisia.*
[2]*Email: wafa.kammoun@ihec.ucar.tn*

(+ *Corresponding author*)

Article History
Received: 23 June 2025
Revised: 29 August 2025
Accepted: 4 September 2025
Published: 19 September 2025

Keywords
G7 markets
Gold
Quantile VAR
Silver
Time frequency
Uncertainty.

ABSTRACT

The purpose of this study is to examine the dynamic spillover effects and interconnectedness among major global equity markets (G7 indices), precious metals (gold and silver), and the Volatility Index (VIX). The analysis aims to identify how shocks are transmitted across these markets under varying conditions and horizons, with particular attention to the roles of safe-haven assets and volatility measures. Employing a quantile VAR framework combined with time-frequency connectedness techniques, the analysis captures both distributional asymmetries and temporal variations in market linkages, providing a comprehensive perspective on risk transmission across different regimes and horizons. This methodological integration allows for a richer understanding of risk transmission compared to conventional approaches. The findings reveal a substantial degree of interconnectedness across the examined markets. European indices such as DAX 40, CAC 40, and FTSE MIB act as dominant transmitters of shocks, highlighting their central role in global contagion. In contrast, gold and silver exhibit strong shock-absorbing capacity, reinforcing their safe-haven properties during periods of financial turbulence. The VIX emerges as a key transmitter of volatility, particularly under extreme market conditions, underscoring its role as a reliable proxy for systemic risk. Meanwhile, indices such as NASDAQ and S&P/TSX show more neutral or bidirectional spillover patterns. These results have important implications for investors, risk managers, and policymakers concerned with portfolio diversification, systemic risk monitoring, and financial stability in interconnected markets.

Contribution/ Originality: This study contributes to the existing literature by examining dynamic spillovers among G7 equity markets, precious metals, and the VIX. It employs a quantile VAR combined with a time-frequency connectedness methodology. The primary contribution of the paper is the finding that shocks from equity markets spill over to precious metals, highlighting their safe-haven properties.

1. INTRODUCTION

In recent years, economic and financial instability has been caused by events, including the COVID-19 pandemic, the Russia-Ukraine conflict, and the Israel-Palestine conflict. Commodity market uncertainty has profound implications for global financial systems, leading investors to rebalance portfolios toward safer assets. Precious metals, particularly gold, are known as classic safe havens and have become popular for their ability to preserve value in turbulent markets [1-4]. Silver, another major precious metal, is an industrial commodity and investment asset. In general, its safe-haven status has long been less glamorous than that of gold, but current volatility has led to a re-evaluation of its role as an alternative asset. Given uncertain times, can silver serve as an effective hedge similar to gold during periods of financial turmoil? Gold's connection to equity markets is well-known, but the evolution of its interaction with systemic uncertainty in the G7 financial markets, particularly in comparison to silver, is not well-defined. This study analyzes the dynamic spillover effects and interconnections between G7 financial markets and gold and silver returns in the context of economic uncertainty. By examining each G7 market individually for gold and silver, this study recognizes that the strength of spillovers and safe-haven effects might vary by country. National factors, such as differences in monetary policy, investor base, or currency movements, can modulate how strongly a country's stock market is linked with precious metals. A comprehensive analysis across all G7 nations will shed light on whether gold and silver consistently provide a shield across different developed markets or if their protective power is country-specific.

Our study makes several important contributions to portfolio management. First, this is the primary study to employ newly updated uncertainty indices (VIX) to capture economic uncertainty more precisely in the G7 context. Second, this study examines the impact of two major war events (the Russia-Ukraine conflict and the Israel-Palestine conflict) on volatility connectedness across key global markets. Third, the study presents empirical evidence showing that during periods of heightened uncertainty, such as geopolitical conflicts, stress in G7 equity markets spills over to measurable aspects of gold and silver. Gold, as a safe haven, acts as a reliable shock absorber against uncertainty, whereas silver, despite being a precious metal, plays a limited protective role. To the best of my knowledge, no previous study has conducted an in-depth examination of the impact of two significant concurrent wars on financial and commodity markets. Moreover, in terms of methodological contributions, this study uses a comprehensive suite of approaches, including dynamic connectedness, quantile connectedness, and time-frequency connectedness analyses, to capture the evolving, nonlinear, and frequency-dependent spillover dynamics among assets.

The structure of the paper is arranged as follows: Section 2 addresses the literature review, Section 3 outlines the data sources and methodology, Section 4 examines the empirical outcomes, and Section 5 delivers the concluding insights.

2. LITERATURE REVIEW

The intricate interplay between economic uncertainty, G7 markets, and precious metals such as gold and silver has been extensively researched by financial investigators, particularly because of the repeated crises faced by global markets and the changing risks. The established behavior of gold and silver as hedging instruments and safe havens against market turbulence is often an aspect of research. For example, Baur and McDermott [5] laid out one of several sources of international evidence that suggests gold behaves as a safe haven for the major G7 stock markets. This type of research is abundant, including that of Dutta [6], who specifically investigated the volatility spillover between gold and silver, which further confirms the intrinsic relationship. In recent years, Shahzad et al. [7] and Kayral et al. [8] have proposed a comparison of gold performance with more recent safe havens to G7 investors, including Bitcoin, but concluded that gold often displays superior safe-haven qualities, particularly throughout turbulent periods like the COVID-19 pandemic and the Russia-Ukraine conflict. Abdullah et al. [9] investigated gold as a zero-beta asset in US asset pricing procedures and showed how this improves the performance of their routine models followed by their focus on risk during global crises for Fakhfekh et al. [10] and Antonakakis et al. [11] concentrated on implied volatilities with gold and silver. Mensi et al. [12] examined a larger category of precious metals and their relationship with G7 currencies under different scenarios using multi-scale research methods.

Economic uncertainty, typically represented by other indices (such as the Volatility Index, Economic Policy Uncertainty, and geopolitical risk), is a strong force behind market fluctuations and safe assets. After all, G7 market changes have a significant influence on precious metal prices, and as such, uncertainty is a prime factor in investment in metals such as gold and silver. During instances of financial uncertainty, the price of gold tends to see increased demand when the G7 markets rise, naturally driving price increases. Mokni et al. [13] revisited uncertainty in precious metal connectedness through EPU and deployed a Quantile-VAR method, and determined that metals were always considered gold-dominated safe-haven roles, irrespective of their variation with silver and other metals, especially during COVID-19. Troster et al. [14] measured flight-to-safety behavior through implied volatilities and established relationships with uncertainty, providing substantiation for gold and silver prices. Tansuchat et al. [15] supported these suggestions in their GARCH-MIDAS analysis of precious metal prices, in which their analysis indicated that data driven by EPU had a stronger influence in times of crises such as COVID-19, providing further legitimacy. A consistent selection of approaches and methods was used in confirming presumptive relationships through a Markov-switching model to analyze EPU and precious metal returns; however, Thongkairat et al. [16] also noted that different distribution characteristics exist in periods of high and low uncertainty. According to Bossman et al. [17], all commodities are impacted by any market's uncertainty. However, Bossman et al. [17] specify that asymmetric effects exist in commodity markets. With regard to uncertainty from global factors, Mensi et al. [18] titled their work Effects of global factors and their transfer to G7 stock markets and commodity uncertainty (oil and gold) about uncertainty, which describes conditions in commodities precisely, an example demonstration of Positionality on Humanity. The study and its comparison with geopolitical risk demonstrate aspects of uncertainty that have evolved around risk and its relationship with safe-haven assets. Understanding the dynamic connectedness and spillover effects between G7 markets, precious metals, and other asset classes is essential for effective portfolio management. The VIX Index, which estimates market volatility, demonstrates considerable spillover effects on precious metals, with Chaudhry and Bhargava [19] highlighting the asymmetrical influences of silver and platinum. Kang et al. [20] examined dynamic spillovers among various markets, such as commodities and the VIX, whereas Alomari et al. [21] concentrated on higher moments and jumps. Ghorbel et al. [22] focused on the relationships between cryptocurrencies, gold, and stock markets during the COVID-19 pandemic. Clear evidence from Alam et al. [23] outlined the fluctuating interconnectedness between commodities (such as gold and silver) and the G7/BRIC markets during the Russia-Ukraine invasion, revealing significant interconnectedness and pinpointing major shock transmitters and shock receivers. Furthermore, Naeem et al. [24] investigated the time-frequency relationship of fear between stock markets and alternative assets such as gold, emphasizing the significance of various VIX metrics. Although evidence typically supports the idea that economic uncertainty boosts precious metal prices, some contend that this link may not be consistent, especially during stable economic times when the demand for safe havens decreases. Kayral et al. [8], Fakhfekh et al. [10], and Alam et al. [23] discussed the COVID-19 pandemic and/or Russia-Ukraine conflict, generally affirming the significant role of gold as a safe-haven asset. Mokni et al. [13] explicitly examined the COVID-19 period and discovered that it notably changed the connectedness of precious metals and their association with EPU, highlighting that spillover effects heightened during this health emergency. This is consistent with research indicating that the COVID-19 pandemic has affected the performance of precious metals across various market situations [25]. The literature shows a distinct advancement towards more advanced econometric methods to analyze these intricate dynamics. While previous research may have utilized simpler regression or GARCH models, contemporary studies increasingly adopt quantile-based approaches [12, 14] to analyze tail behavior, Dynamic Conditional Correlation GARCH models and their extensions [8, 11, 26] Time-Varying Parameter Vector Autoregressive models [23] for assessing dynamic connectedness, wavelet analysis [24] for frequency analysis, and regime-switching models [16, 27, 28] to address structural breaks and varying market conditions. The GARCH-MIDAS method employed by Tansuchat et al. [15] also illustrates this shift towards capturing interactions in mixed-frequency data. This methodological advancement enables a deeper understanding of how economic uncertainty influences the relationships between G7 markets and precious metals, shifting from static or average interactions to reflect their dynamic, state-dependent, and frequency-changing characteristics.

Despite the extensive literature on the safe-haven properties of precious metals and their interactions with equity markets during periods of heightened uncertainty, there remains limited evidence on the time-varying, quantile-dependent, and frequency-specific nature of these relationships particularly involving the VIX and G7 markets. Prior studies often overlook the joint role of economic uncertainty and market regimes across different crisis periods. This study addresses this gap by applying a combined quantile VAR and time-frequency connectedness approach to capture the dynamic spillovers and interdependencies between G7 equity indices, gold, silver, and the VIX. By doing so, it contributes a deeper, more granular understanding of market behavior during episodes of systemic uncertainty, such as the COVID-19 pandemic and the Russia–Ukraine conflict.

3. DATA AND METHODOLOGY

3.1. Data

The sample comprises daily closing prices of major stock market indices from G7 countries, alongside two key precious metals, such as gold and silver, and the Volatility Index (VIX), over the period from January 1, 2017, to March 30, 2025. The selection of these indices is intended to capture the dynamics of advanced economies under extreme market conditions, particularly during the COVID-19 pandemic and the Russia–Ukraine war. Each selected index reflects the economic and financial structure of its respective country. The selected variables reflect a broad spectrum of global financial markets and asset classes. The VIX index is included as a widely used proxy for market uncertainty and investor fear. Gold and silver both represent traditional safe-haven assets, with gold often acting as a store of value during periods of market turbulence. The Nasdaq Composite captures the performance of growth-oriented technology stocks in the U.S., while the FTSE 100, DAX 40, CAC 40, FTSE MIB, and S&P/TSX represent leading equity markets in the UK, Germany, France, Italy, and Canada, respectively. The Nikkei 225 reflects Japan's equity market dynamics, offering insight into Asia's economic exposure.

Table 1 summarizes the selected indices and their corresponding abbreviations, while Table 2 reports the descriptive statistics and stochastic properties of the return series. Among the variables, the VIX and FTSE 100 exhibited the highest levels of volatility. Normality tests indicate that the return series are asymmetric and fat-tailed, as shown by skewness and excess kurtosis values. Moreover, the Jarque–Bera test strongly rejects the null hypothesis of normality at the 1% significance level for all return series, justifying the use of a quantile-based analytical approach in the subsequent empirical analysis.

Table 1. Description of indices.

Index	Abbr.	Description	Source
Volatility index	VIX	Measures implied volatility in the S&P 500; a proxy for global market uncertainty.	DataStream
Gold	Gold	Represents gold prices; widely considered a safe-haven asset.	DataStream
Silver	Silver	Represents silver prices; it combines industrial and safe-haven characteristics.	DataStream
Nasdaq Composite	Nasdaq	The US stock index, focused on technology and growth-oriented firms.	DataStream
FTSE 100	FTSE 100	The UK stock index of the 100 largest firms listed on the London Stock Exchange.	DataStream
Nikkei 225	Nikkei 225	The major Japanese stock market index represents large firms in Japan.	DataStream
DAX 40	DAX 40	The leading stock index represents the top 40 companies in Germany.	DataStream
CAC 40	CAC 40	Benchmark French stock market index.	DataStream
FTSE MIB	FTSE MIB	The Italian stock index covers 40 major companies.	DataStream
S&P/TSX Composite	S&P/TSX	Canada's main stock market index.	DataStream

Table 2. Descriptive statistics.

Indices / Descriptive statistics	VIX	Gold	Nasdaq	FTSE	Nikkei	DAX.40	CAC.40	FTSE.MIB	S.P.TSX	Silver
Mean	0.000	0.000***	0.001**	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.929)	(0.008)	(0.044)	(0.924)	(0.322)	(0.209)	(0.397)	(0.414)	(0.182)	(0.319)
Variance	0.006	0	0	0.005	0	0	0	0	0	0
Skewness	1.373***	-0.249***	-0.371***	-0.281***	-0.450***	-0.717***	-1.000***	-1.853***	-1.670***	-0.510***
Ex. Kurtosis	9.067***	3.018***	8.456***	1146.852***	11.138***	12.739***	13.288***	22.129***	42.605***	5.714***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	8970.43***	935.29***	7202.23***	131472065.16***	12481.38***	16427.11***	18049.24***	50322.34***	182561.20***	3367.98***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-21.378	-7.333	-22.265	-29.021	-22.044	-20.480	-15.529	-17.676	-19.726	-6.629
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q(20)	29.821***	8.033	126.282***	577.644***	22.817***	27.443***	19.965**	24.816***	174.145***	27.276***
	(0.000)	(0.722)	(0.000)	(0.000)	(0.005)	(0.001)	(0.018)	(0.002)	(0.000)	(0.001)
Q2(20)	147.04***	197.74***	1392.87***	599.40***	577.17***	651.42***	808.44***	343.98***	2384.65***	308.81***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: ***, ** shows that the relevant coefficient is significant at a 1%, 5% level, respectively.

Table 3. Kendall correlation:

Variables	VIX	Gold	Nasdaq	FTSE	Nikkei	DAX.40	CAC.40	FTSE.MIB	S.P.TSX	Silver
VIX	1.000***	0.002	-0.510***	-0.209***	-0.042***	-0.287***	-0.283***	-0.261***	-0.411***	-0.059***
Gold	0.002	1.000***	0.009	0.001	-0.013	-0.020	-0.022	-0.017	0.101***	0.476***
Nasdaq	-0.510***	0.009	1.000***	0.189***	0.067***	0.295***	0.275***	0.245***	0.430***	0.073***
FTSE	-0.209***	0.001	0.189***	1.000***	0.131***	0.479***	0.518***	0.433***	0.323***	0.087***
Nikkei	-0.042***	-0.013	0.067***	0.131***	1.000***	0.151***	0.141***	0.116***	0.101***	0.007
DAX.40	-0.287***	-0.020	0.295***	0.479***	0.151***	1.000***	0.721***	0.623***	0.361***	0.078***
CAC.40	-0.283***	-0.022	0.275***	0.518***	0.141***	0.721***	1.000***	0.640***	0.376***	0.074***
FTSE.MIB	-0.261***	-0.017	0.245***	0.433***	0.116***	0.623***	0.640***	1.000***	0.349***	0.076***
S.P.TSX	-0.411***	0.101***	0.430***	0.323***	0.101***	0.361***	0.376***	0.349***	1.000***	0.165***
Silver	-0.059***	0.476***	0.073***	0.087***	0.007	0.078***	0.074***	0.076***	0.165***	1.000***

Note: *** indicates the significance level at 1%.

In Table 3, the Kendall correlation results demonstrate significant relationships among the indices, reflecting the interconnectedness in global markets. Notably, DAX 40 shows the strongest positive correlation with CAC 40 (0.721***), indicating a strong link between Germany's benchmark stock market index and the French stock market index. Additionally, FTSE MIB exhibited high correlations with CAC 40 (0.640***) and DAX 40 (0.623***). The VIX acts as a counter-cyclical risk indicator and is inversely correlated with every stock index. Gold is highly independent of equity markets, affirming its safe-haven status. Similarly, Silver follows gold but with a slightly higher equity bias. In fact, the European markets (DAX, CAC, and FTSE MIB) reflect high intra-regional correlations. The least integrated is Nikkei, perhaps because of its geography and economics.

3.2. Methodology

To explore the quantile spillover mechanism across diverse financial markets, we employ the novel quantile and frequency connectedness approach, which allows for the investigation of propagation mechanisms, as estimated via a quantile and frequency-modeling framework. Recently applied by Ando et al. [29], Bouri et al. [30], and Chatziantoniou et al. [31], initially developed the quantile-connectedness methodology. We begin by estimating the overall connectedness measure through the construction of a quantile vector autoregression (QVAR(p)) model in the following form:

$$\mathbf{x}_t = \boldsymbol{\mu}_t(\tau) + \Phi_1(\tau)\mathbf{x}_{t-1} + \Phi_2(\tau)\mathbf{x}_{t-2} + \dots + \Phi_p(\tau)\mathbf{x}_{t-p} + \boldsymbol{u}_t(\tau) \quad (1)$$

Here: $\boldsymbol{x}_t$ and $\boldsymbol{x}_{t-j}$ are vectors for endogenous variables of dimensions $N \times 1$.

The parameter τ represents a closed interval within the interval range [0, 1].

p stands for the QVAR model lag length.

(τ) is an $N \times 1$ dimensional vector that depicts the conditional mean.

$\boldsymbol{\Phi j}$ (τ) is an $N \times N$ QVAR coefficients' dimensional matrix.

Next, to calculate the forward M-step generalized forecast error variance decomposition (GFEVD), we transform Equation 1 into the form of QVMA(∞) by implementing Wold's theorem, as shown in Equation 2:

$$\mathrm{x}_t = \boldsymbol{\mu}(\tau) + \sum_{j=1}^{p} \Phi_j(\tau)\mathbf{x}_{t-j} + \boldsymbol{u}_t(\tau) \quad (2)$$

We then compute the generalized forecast-error variance decomposition (GFEVD) for forecast horizon H as a critical part of the connectedness approach [32, 33]. This approach refers to the effect of series j on variable i concerning the forecast-error variances as follows:

$$\theta_{ij}(\mathrm{H}) = \frac{(\Sigma(\tau))_{jj}^{-1} \sum_{\mathrm{h}=0}^{\mathrm{H}-1}\left((\Psi_h(\tau)\Sigma(\tau))_{ij}\right)^2}{\sum_{\mathrm{h}=0}^{\mathrm{H}}\left(\Psi_h(\tau)\Sigma(\tau)\Psi_h'(\tau)\right)_{ii}} \quad (3)$$

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

Where:

- $\theta_{ij}(\mathrm{H})$:Proportion of forecast error variance in variable i due to shocks in variable j over horizon H.
- $\Psi_h(\tau)$ is the matrix of impulse response coefficients at lag h and quantile τ.
- $\Sigma(\tau)$ is the covariance matrix of error terms at quantile τ.
- $\Psi_h'(\tau)$ is the transpose of $\Psi_h(\tau)$.

Since the rows of θ_{ij} (H) were not summed to one, we had to normalize them by the row sum, culminating in $\tilde{\tilde{\theta}}_{ij}$. Through the normalization process, the row sum was equal to one, thereby representing how a shock in series i affects the series itself and the entirety of the other series. Thus, the following identities were reached:

$$\sum_{\mathrm{i}=1}^{\mathrm{N}} \theta_{\tilde{\mathrm{ij}}}(\mathrm{H}) = 1 \text{ and } \sum_{j=1}^{N}\sum_{i=1}^{N}\tilde{\tilde{\theta}}_{ij}(H) = N$$

Hence, all connection measures were calculated. Initially, we determined the net pairwise connectivity as follows:

$$NPDC_{ij}(\mathrm{H}) = \tilde{\theta}_{ij}(\mathrm{H}) - \tilde{\theta}_{ji}(\mathrm{H}) \quad (4)$$

If $NPDC_{ij}(\mathrm{H}) > 0$ $(NPDC_{ij}(\mathrm{H}) < 0)$, then series j demonstrates a higher (lower) influence on series i than vice versa.

Thus, the overall trend of connectedness regarding others highlights the extent to which an impact in series i could affect the entirety of series j.

$$TO_i(H) = \sum_{i=1, i\neq j}^{N} \tilde{\tilde{\theta}}_{ji}(\mathrm{H}). \quad (5)$$

Therefore, the total directional connectedness from the others helps quantify the degree of impact on series i resulting from shocks incurred by all the other series j.

$$FROM_i(\mathrm{H}) = \sum_{i=1, i\neq j}^{N} \tilde{\theta}_{ij}(\mathrm{H}). \quad (6)$$

The general net total directional connectedness enables us to estimate the difference between the total directional connectedness directed toward and emanating from others. This discrepancy can be referred to as the net impact of series i on the predefined network, wherein:

$$NET_i(H) = TO_i(\mathrm{H}) - FROM_i(\mathrm{H}) \quad (7)$$

If NETi >0 (NETi < 0), then series i tends to demonstrate a higher (lower) impact on the entirety of the other series j relative to the extent of the impact it receives from them; therefore, it is considered a net transmitter (receiver) of shocks. Thus, computing the total connectedness index (TCI) should enable us to estimate the overall degree of interconnectedness within the network. A higher TCI value denotes the persistence of increased market risk, while a lower value implies the opposite.

$$TCI(H) = N^{-1}\sum_{i=1}^{N} TO_i(H) = N^{-1}\sum_{i=1}^{N} FROM_i(H) \quad (8)$$

At this level, determining the temporal domain-associated connectedness entails estimating connectivity within the frequency domain using Stiassny [34] spectral decomposition technique. To this end, we initiate by estimating the following frequency response function, $\boldsymbol{\Psi}(e^{-i\omega}) = \sum_{\mathrm{h}=0}^{\infty} e^{-iwh}\,\Psi_{\mathrm{h}}$, wherein $i = \sqrt{-1}$ and ω denotes the frequency. We then proceed with determining the spectral density of x_t at a specific frequency ω, which can only be attained through the implementation of a Fourier transformation on the *QVMA(∞)*, as follows:

$$\boldsymbol{S}_x(\omega) = \sum_{h=-\infty}^{\infty} E(x_t x'_{t-h})\, e^{-iwh} = \boldsymbol{\Psi}(e^{-i\omega h}) \sum_t \boldsymbol{\Psi}'(e^{+i\omega h}) \quad (9)$$

Similarly, because the frequency-based GFEVD is merely the fusion of spectral density and GFEVD, the GFEVD can be normalized in the frequency domain in the same manner required for normalizing its time domain.

$$\theta_{ij}(\omega) = \frac{(\Sigma(\tau))_{jj}^{-1}\left|\sum_{h=0}^{\infty}\left(\boldsymbol{\Psi}(\tau)(e^{-iwh})\Sigma(\tau)\right)_{ij}\right|^2}{\sum_{h=0}^{\infty}\left(\boldsymbol{\Psi}(e^{-iwh})\Sigma(\tau)\boldsymbol{\Psi}(\tau)(e^{iwh})\right)_{ii}} \quad (10)$$

$$\tilde{\theta}_{ij}(\omega) = \frac{\theta_{ij}(\omega)}{\sum_{k=1}^{N}\theta_{ij}(\omega)} \quad (11)$$

The expression $\theta \tilde{i}j\ (\omega)$ refers to the i^{th} series spectrum fraction at a given frequency ω that can be attributed to an effect on the j^{th} series. This measure is widely recognized as an intrafrequency indicator; thus, for connectedness across both the short-term and long-term time frames to be effectively evaluated (and rather than focusing on a single frequency), we considered aggregating the entirety of frequencies within a specified range, denoted as $d = (a, b)$: a, $b \in (-\pi, \pi)$, $a < b$, such as:

$$\theta_{\tilde{ij}}(\mathrm{d}) = \int_{\mathrm{a}}^{\mathrm{b}} \theta_{\tilde{ij}}(\mathrm{w})\mathrm{dw}. \quad (12)$$

Thus, we calculated similar connectedness measurements, as already stated, and evaluated them following the same procedure. At this level, such measures are recognized as frequency connectedness measures, allowing us to depict the transmission of impacts within specified frequency ranges (denoted d), similarly interpretable as:

$$NPDC_{ij}(d) = \tilde{\tilde{\theta}}_{ij}(d) - \tilde{\tilde{\theta}}_{ji}(d) \quad (13)$$

$$TO_i(d) = \sum_{i=1, i\neq j}^{N} \tilde{\tilde{\theta}}_{ji}(d) \quad (14)$$

$$FROM_i(d) = \sum_{i=1, i\neq j}^{N} \tilde{\tilde{\theta}}_{ij}(d) \quad (15)$$

$$NET_i(d) = TO_i(d) - FROM_i(d) \quad (16)$$

$$TCI(d) = N^{-1}\sum_{i=1}^{N} TO_i(d) = N^{-1}\sum_{i=1}^{N} FROM_i(d) \quad (17)$$

In this study, we defined two frequency intervals to analyze dynamics over different time horizons. The first interval, $d1 = (\pi/5, \pi)$, captures short-term effects spanning one to five days, while the second, $d2 = (0, \pi/5]$, represents long-term effects from six days onward. Corresponding measures NPDCij (d1), $TO_i(d1)$, $FROM_i(d1)$,

$NET_i(d1)$, and $TCI(d1)$ are computed separately for these intervals to reflect short- and long-term directional connectedness and total connectedness indices. Moreover, we explored linking these frequency-based metrics, as developed by Baruník and Křehlík [35], with established time-domain connectedness measures from Diebold and Yılmaz [36], Diebold and Yılmaz [37], and Diebold and Yılmaz [38].

Hence

$$NPDC_{ij}(H) =\cdot \sum_d NPDC_{ij}(d) \quad (18)$$

$$TO_i(H) = \sum_d (\mathrm{d}) \cdot TO_i(d) \quad (19)$$

$$FROM_i(d) = \sum_d (\mathrm{d}) \cdot FROM_i(d) \quad (20)$$

$$NET_i(H) = \sum_d (\mathrm{d}) \cdot NET_i(d) \quad (21)$$

$$TCI(H) = \sum_d (\mathrm{d}) \cdot TCI(d) \quad (22)$$

The total connectedness measures can be derived by aggregating the entire frequency connectedness measures, computed using a specified quantile denoted as $\tau.2$.

4. RESULT ANALYSIS AND DISCUSSION

4.1. Dynamic Connectedness Analysis

Table 4 displays the findings related to the interconnections observed among all indices within the network. In this table, revealing the relative roles that assets play as transmitters or receivers of systemic risk through "To" and "From" indicators enhances our understanding of how shocks propagate across markets. The TO values, representing how much each asset contributes to shocks to the rest of the system, show that CAC.40 (90.55%) and DAX.40 (88.54%) act as the primary shock transmitters. Conversely, silver (39.01%) and Nikkei (18.71%) serve as the least influential in spreading shocks, indicating their relative detachment. Regarding the FROM values, which measure the extent of shocks received from others, CAC.40 (73.94%) and DAX.40 (73.47%) are the most susceptible, while gold (48.76%) and silver (48.04%) display greater resilience, highlighting their more independent roles within the network.

Net connectedness (NET) values indicate whether an asset is a net transmitter or receiver of shocks. CAC.40 (16.61%), DAX.40 (15.07%), FTSE MIB (7.74%), and VIX (4.34%) are net transmitters, so they actively propagate shocks to others. Conversely, Gold (−6.93%), silver (−9.02%), and Nikkei (−36.35%) are net recipients, so they are more influenced by others than by others. In contrast, S.P. TSX (6.63%) and NASDAQ (3.00%) play dual roles, functioning as both moderate transmitters and recipients of shocks, thereby displaying a more balanced status within the interconnected system. The total connectedness index (TCI) stands at 62.38%, reflecting a substantial degree of interdependence among the assets and notable spillover effects throughout the network. In terms of net transmission power (NPT), CAC.40 (ranked 9) and DAX.40 (ranked 8) emerge as the strongest shock transmitters, with FTSE.MIB following closely, while Nikkei and Silver hold the lowest positions in transmission strength.

Table 4. Average dynamic connectedness.

	VIX	Gold	Nasdaq	FTSE	Nikkei	DAX.40	CAC.40	FTSE.MIB	S.P.TSX	Silver	FROM
VIX	36.50	1.92	17.85	5.18	1.81	7.69	7.45	6.96	13.25	1.39	63.50
Gold	2.94	51.24	3.11	2.57	1.81	3.70	3.62	3.23	4.08	23.70	48.76
Nasdaq	18.08	2.16	37.20	4.83	2.00	7.59	6.84	5.79	13.81	1.72	62.80
FTSE	5.62	1.65	4.81	39.12	2.56	12.35	13.88	10.82	7.42	1.77	60.88
Nikkei	7.68	3.12	7.73	5.12	44.94	7.86	7.54	6.56	7.24	2.22	55.06
DAX.40	6.58	2.03	6.46	10.43	2.43	26.53	19.81	16.50	7.50	1.73	73.47
CAC.40	6.38	1.86	5.69	11.66	2.42	19.47	26.06	16.82	7.91	1.73	73.94
FTSE.MIB	6.04	1.87	5.03	9.87	2.04	17.82	18.55	29.31	7.58	1.89	70.69
S.P.TSX	12.04	2.70	12.40	7.57	2.06	8.89	9.54	8.55	33.39	2.87	66.61
Silver	2.50	24.52	2.72	2.58	1.58	3.18	3.33	3.20	4.44	51.96	48.04
TO	67.84	41.83	65.80	59.80	18.71	88.54	90.55	78.44	73.24	39.01	623.77
Inc.Own	104.34	93.07	103.00	98.92	63.65	115.07	116.61	107.74	106.63	90.98	cTCI/TCI
NET	4.34	-6.93	3.00	-1.08	-36.35	15.07	16.61	7.74	6.63	-9.02	69.31/62.38
NPT	5.00	2.00	3.00	5.00	0.00	8.00	9.00	7.00	5.00	1.00	

The dynamic total connectedness index (TCI) covering the period from 2017 to 2025 is illustrated in Figure 1. The COVID-19 pandemic in 2020 and the Ukraine war in early 2022 pushed the index well above 80%, representing the highest connectedness levels. During these episodes, a shock in one market propagated quickly to others, yielding a tightly knit network of volatility. The markets were relatively placid in early 2018, allowing the TCI to dip. Except for one, a sudden volatility spike in February 2018 briefly shook markets, and the VIX volatility index spiked by a record amount, indicating a short-lived surge in cross-market stress. By December 2018, U.S. stocks had been on track for their worst December since 1931, with broad-based declines. This late-2018 turbulence pushed the TCI upward. By 2019, the conditions had stabilized. TCI surged in March 2020, indicating that shocks in one market rapidly infected others. Stock markets worldwide crashed together, and the VIX hit record highs, illustrating how tightly coupled markets became under pandemic panic. During 2021, the TCI declined, revealing periods of relatively calm and divergent market paths, indicating that markets were not as tightly bound as during the acute phase of the pandemic. In February 2022, Russia's invasion of Ukraine caused serious geopolitical and commodity shocks. The connectedness index rose sharply again because of these developments. When the war broke out in early 2022, global markets once again moved in a highly correlated, risk-off manner; volatility indicators jumped, energy and commodity prices surged, and stock indices fell in tandem. The TCI remained elevated until 2022, with only minor dips during brief rally periods. In 2023, markets experienced a mix of calm and intermittent bouts of market turmoil as the impact of global shocks faded. The TCI stabilized at a lower level. However, the VIX rose above 30 in mid-March 2023, as this shock was relatively limited and short-lived. In mid-to-late 2023, connectedness dropped to moderate levels. Rekindled geopolitical tensions in late 2023 caused another small shock. Global conditions were comparatively stable as 2024 approached. TCI exhibited another increase by the end of 2024 and the beginning of 2025. Re-tightening correlations may be caused by persistent geopolitical risks or policy and economic uncertainties (such as U.S. elections or changes in monetary policy stance). This implies that markets will still be widely interconnected by 2025, and that any new shock or change in sentiment will have an increasing ability to spread across assets.

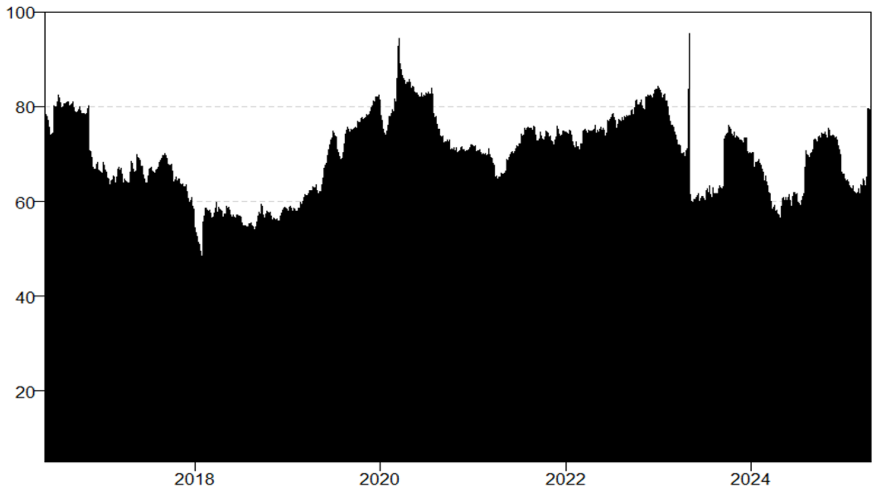


Figure 1. Dynamic total connectedness.

Figure 2 illustrates dynamic net total connectedness, assessing whether an index primarily transmits or receives shocks within this network of indices and offering insights into their evolving roles over time. VIX, S.P.TSK, Nasdaq, FTSE, and FTSE.MIB fluctuate throughout the period, oscillating among net transmitters and receivers of shocks. Conversely, the Gold and Silver indices consistently show negative net connectedness, indicating that they primarily act as net receivers of shocks in this network.

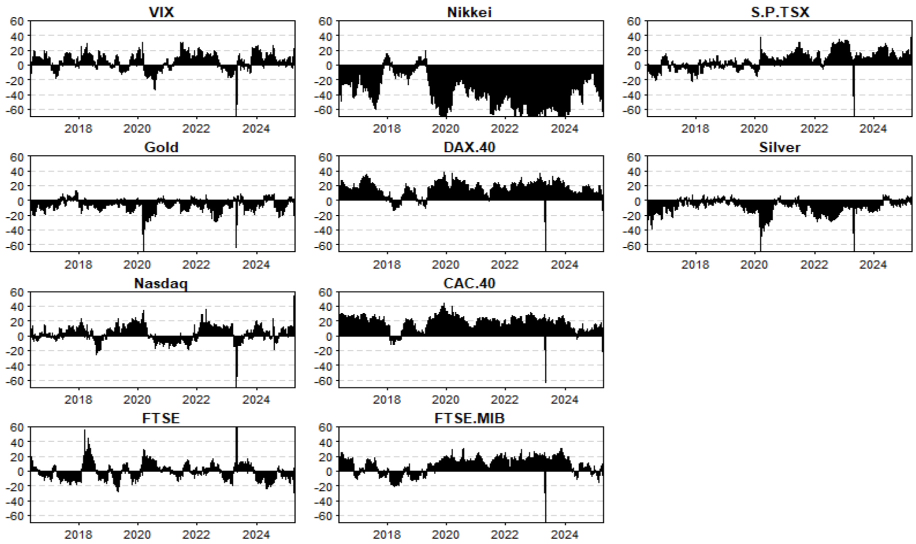


Figure 2. Dynamic net total connectedness.

Figure 3 illustrates net-pairwise directional connectedness among G7 equity indices and two major precious metals, gold and silver, from 2010 to 2025. The major G7 equity indices (DAX 40, CAC 40, FTSE MIB, S&P/TSX, and Nasdaq) and the VIX emerge as key transmitters of shocks within the network, influencing other markets. These markets transmit more volatility and shocks to others than they receive. By contrast, Nikkei and precious metals (gold and silver) are consistently net receivers, showing greater susceptibility to external shocks. They absorb more shocks from markets than they impart. The Nikkei index shows the strongest connection within the network, as evidenced by the thickness of the arrows. It is one of the largest net receivers of shocks among G7 indices. Similarly, gold and silver are primarily driven by incoming shocks from other assets. This aligns with their traditional safe haven role. These results were consistent with those reported by Kayral et al. [8]. This vision highlights that the strongest connections are from major stock markets and the VIX outward to Japan's market and precious metals, providing insights into each index's role in the broader network under varying market conditions.

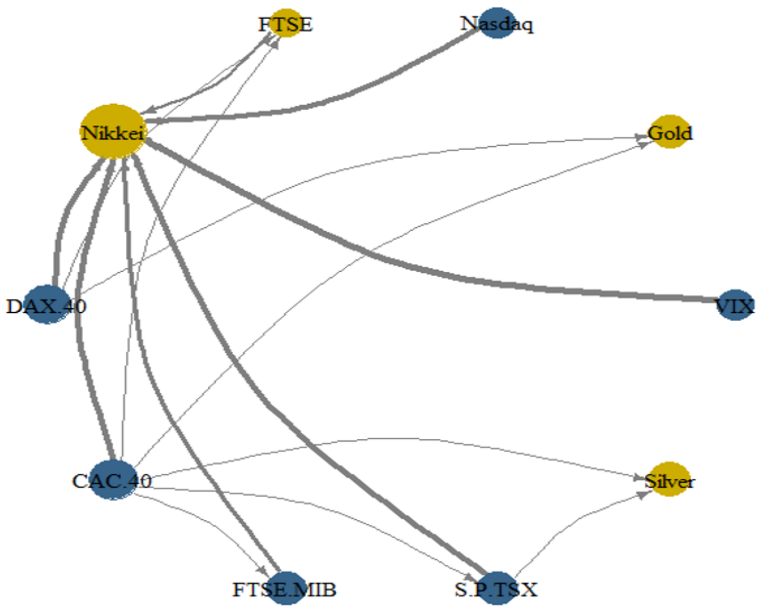
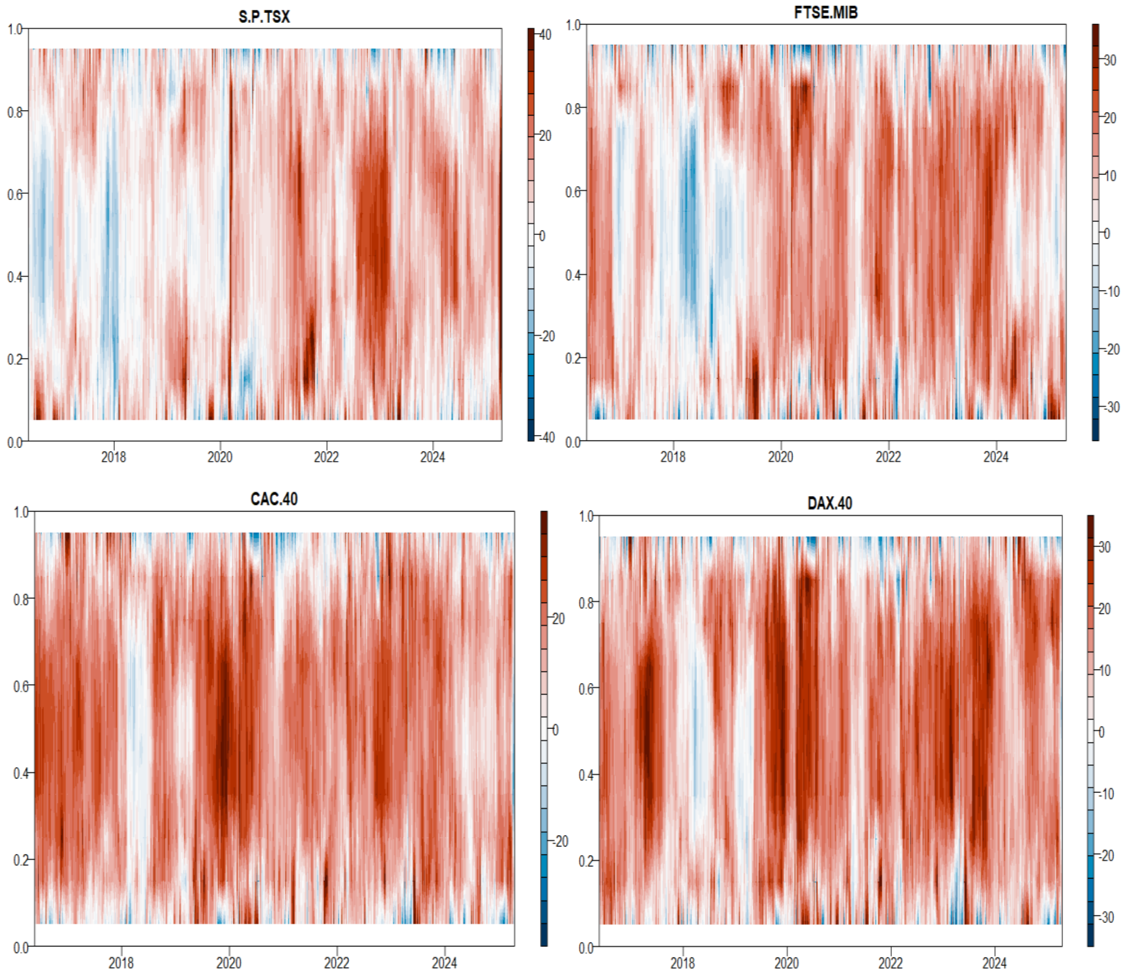


Figure 3. Net-pairwise directional connectedness.

Notes: Nodes colored in blue (yellow) indicate net sources (receivers) of shocks. The thickness of the edges corresponds to the average net directional connectedness between pairs, while the size of each node represents its weighted average net total directional connectedness. This network visualization is based on a TVP-VAR model with one lag (selected via BIC) and uses a 10-step-ahead generalized forecast error variance decomposition.

4.2. Dynamic Quantile Connectedness Analysis

For a thorough understanding of market dynamics processes, a detailed depiction of the indices' net directional connectedness correlations in the time quantile space is displayed in Figure 4. Analyzing dynamic quantile connectedness reveals varying degrees of connectedness across quantiles at different points in time. The CAC.40 index is consistently a strong transmitter across both quantiles and in absolute amounts, highlighting its significant impact under diverse market conditions. The DAX 40 index is also a strong overall transmitter of shocks but is slightly more volatile than the CAC 40 and consistently leads to many of the percentage levels and time periods being analyzed, aligned with Germany's economic strength in Europe. A comparable transmission pattern is noted in the FTSE.MIB index, as it is also a strong net transmitter at the mean and across extreme quantiles. In contrast, S&P/TSX and Nasdaq, while both perform as net receivers at extreme quantiles and mean, both veer toward transmitting shocks in high-volatility regimes, indicating their varying environments conditional on current market conditions. This dynamic pattern illustrates that these indices are not definable as shock transmitters or receivers, as they will also be distinctive shock transmitters or receivers based on the conditions of the market. Finally, indices such as Nikkei and VIX generally appear to be net receivers over time and across quantiles. This finding may indicate that the Japanese market can absorb shocks from global sources rather than echo them into the economy. This notion is also potentially an indication of Japan's safe-haven region during uncertainty, and given that volatility can be either selective, relative, or reactive, volatility may generally just be a conditional environment, over and about a market state, increasing particularly during market stress.



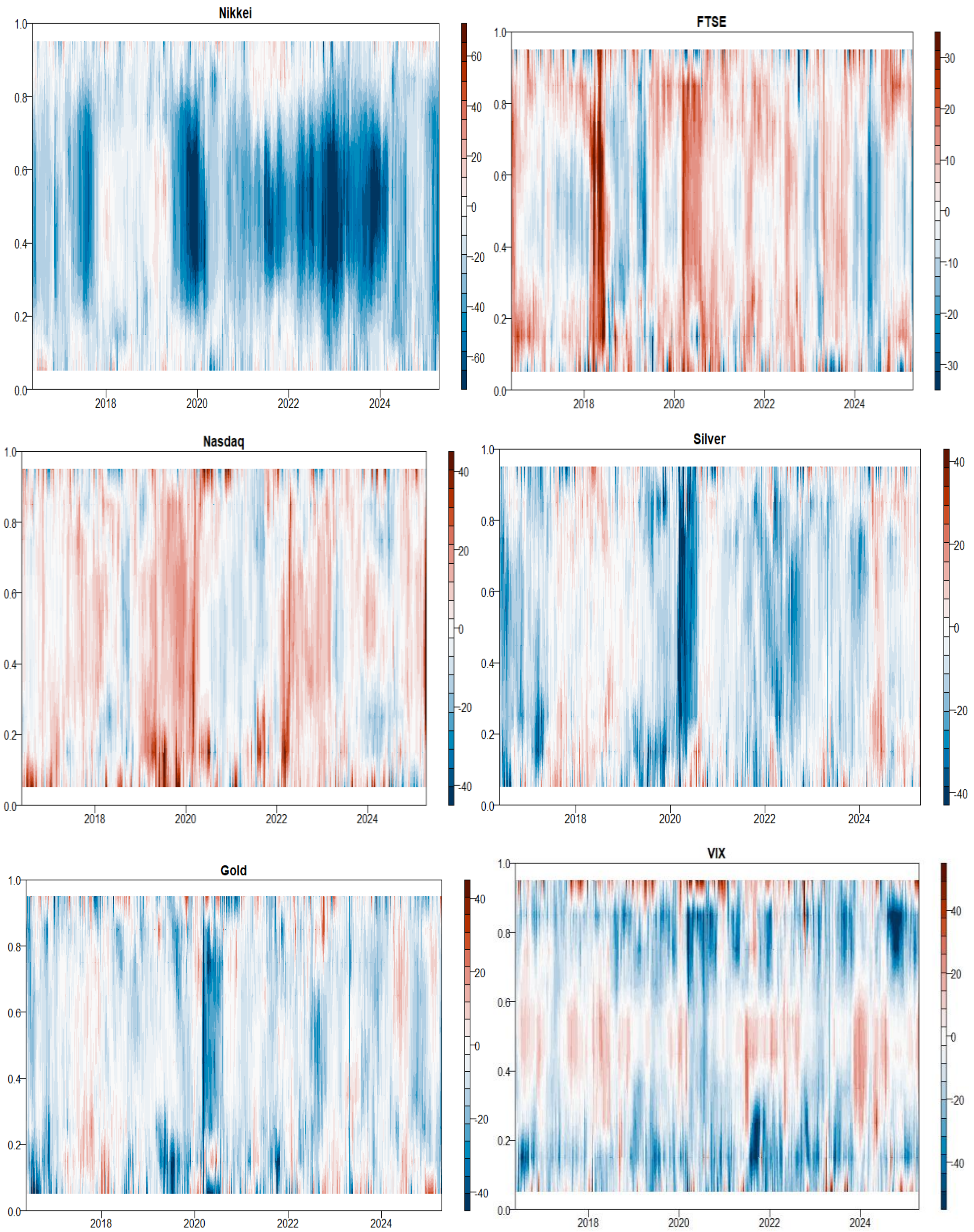


Figure 4. Net dynamic connectedness across quantiles.

4.3. Time Frequency Connectedness Analysis

Figure 5 illustrates a time-varying total connectedness index (TCI), which peaked around 2020 and again around 2023, exhibiting times when there is a higher chance of market co-movement or contagion. This could be driven by global events such as the COVID-19 pandemic or tensions from geopolitical events. The strong prevalence of the red region in the figure signifies that most of the interdependency among assets is located in short-term extreme left-tail events, which implies greater susceptibility to contagion during crisis times. The green space represents spillovers that occur when the market is stable or bullish. These periods often align with investments over a longer horizon and positive long-term macroeconomic factors. It reflects interdependencies that are longer-lasting and slower to develop, such as those stemming from structural economic linkages, global trade, or similar policy styles.

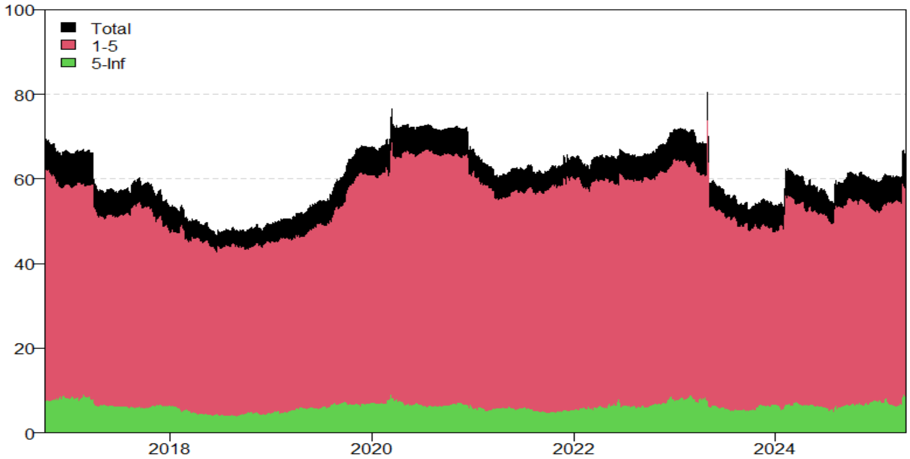


Figure 5. Total connectedness across frequencies.

Note: The figure illustrates the breakdown of total volatility spillovers into short-term (up to one week, d = π/5 to π), shown in red, and long-term (over one week, d = 0 to π/5), shown in green, representing the respective frequency bands of market fluctuations.

Examining the quantile net connectedness of various indices, as shown in Figure 6, provides valuable insights into their interrelationships during crisis periods. The analysis indicates that Nikkei, along with Gold and Silver, tends to receive shocks from the market, especially during crises. This behavior reflects Nikkei's vulnerability and passive response to external turbulence. Similarly, Gold and Silver predominantly act as net receivers of shocks, exhibiting less volatility in their net connectedness than Nikkei. This confirms Gold and Silver's status as long-term safe-haven assets, with further reduced spillover transmission ability at higher risk levels. In contrast, S&P/TSX displays mixed behavior, both transmitting and receiving shocks, with notably more shock transmission, particularly early in 2023 across the connectedness continuum, resulting in increased total connectedness.

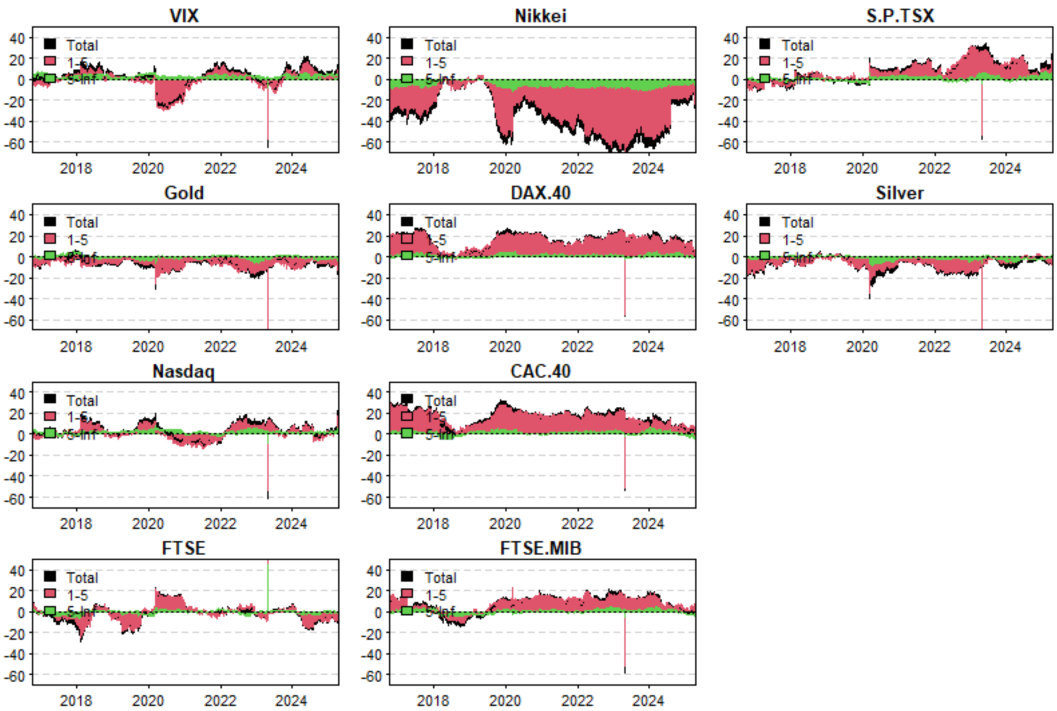


Figure 6. Total net connectedness across frequencies.

FTSE and FTSE MIB demonstrated limited influence, implying relatively low roles in systemic shock transmission. The VIX frequently acts as a strong net transmitter of shocks under both normal and extreme market conditions. Conversely, NASDAQ presents a moderately volatile net connectedness, indicating a more balanced role in shock transmission and reception. Finally, DAX 40 and CAC 40 exhibit notable spikes in net total connectedness at the end of 2020 and around mid-2023, emphasizing their elevated roles as shock transmitters. These markets serve as key transmission channels under stress. These findings are consistent with those reported by Mensi et al. [18].

5. CONCLUSION

Understanding market interconnectedness under conditions of uncertainty is essential for informed investment and policy decisions. This study contributes to the literature by investigating the dynamic spillovers among G7 equity markets, precious metals (gold and silver), and the VIX using a TVP-VAR framework. The findings reveal a moderately high Total Connectedness Index (TCI) of approximately 62%, underscoring the significant degree of interaction among these markets. European stock indices, particularly DAX 40, CAC 40, and FTSE MIB, emerge as primary transmitters of shocks within the network, while gold and silver tend to serve as safe havens by absorbing volatility during turbulent periods. The VIX also plays a pivotal role in both normal and crisis episodes, acting as a barometer of global market stress.

Beyond empirical outcomes, these results offer several broader insights. First, the dominant influence of European markets suggests that regional shocks in Europe can have disproportionate global consequences, highlighting the need for coordinated regulatory and macroprudential responses. Second, the safe-haven role of precious metals is reaffirmed, emphasizing their utility in hedging strategies during heightened uncertainty. Third, moderate but dynamic spillovers from North American indices like NASDAQ and S&P/TSX reflect their dual roles as both transmitters and absorbers of shocks, offering nuanced diversification benefits.

In practical terms, investors can use these findings to optimize international portfolio allocations by factoring in the directional and time-varying nature of spillovers. Policymakers may also leverage such insights to monitor systemic risk more effectively, especially during periods of geopolitical or macroeconomic stress.

Nevertheless, this study has certain limitations. It focuses primarily on daily data and excludes other relevant asset classes such as bonds, currencies, or energy commodities. Structural breaks, model specification choices, and the exclusion of macroeconomic variables may also affect the robustness of the results. Future research could explore high-frequency connectedness, the role of macroeconomic uncertainty, or compare the performance of alternative modeling frameworks such as copulas, regime-switching models, or tail-based approaches.

5.1. Policy Implications

The findings of this study have several important policy implications. First, the strong spillover effects identified among G7 stock markets and between these markets and precious metals highlight the need for enhanced international coordination in financial supervision, particularly during periods of elevated uncertainty. Policymakers should monitor these cross-market dynamics to anticipate systemic risks and prevent contagion effects.

Second, the demonstrated safe-haven behavior of gold and silver during times of market stress reaffirms their relevance in strategic asset allocation and central bank reserve management. These metals can be leveraged as effective tools for financial stability, especially when equity markets are highly volatile.

Third, the role of VIX as a prominent transmitter of volatility suggests that policymakers and regulators should integrate market-based uncertainty indices into their early warning systems and macroprudential frameworks. This can support better timing of policy interventions and more effective stabilization measures.

Lastly, the asymmetry and time-varying nature of the connectedness patterns across quantiles and frequencies underscore the importance of dynamic and flexible policy responses. Static, one-size-fits-all approaches may be insufficient in mitigating the risks associated with increasingly interconnected global financial markets.

Funding: This work was supported and funded by the Deanship of Scientific Research at Imam Mohammad Ibn Saud Islamic University (IMSIU) (Grant number IMSIU-DDRSP2504).
Institutional Review Board Statement: Not applicable.
Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: Both authors contributed equally to the conception and design of the study. Both authors have read and agreed to the published version of the manuscript.

REFERENCES

[1] M. N. Khan, "Assessing the impact of geopolitical crises on global financial markets: Insights from the novel TVP-VAR model," *Journal of Economic Integration*, vol. 40, no. 1, pp. 29-52, 2025. https://doi.org/10.11130/jei.2024037

[2] N. Belkhir, "Dynamic interconnectedness and portfolio implications of bitcoin, gold, currencies, and TASI: A TVP-VAR approach," *Zhongguo Kuangye Daxue Xuebao*, vol. 30, no. 1, pp. 224-237, 2025.

[3] N. Belkhir and O. E. Aoun, "Dynamic connectedness between cryptocurrencies and currencies: Analyzing the impact of CHF and JPY on bitcoin and Ethereum," *International Journal of Innovative Research and Scientific Studies*, vol. 8, no. 2, pp. 2285–2295, 2025. https://doi.org/10.53894/ijirss.v8i2.5681

[4] M. Liu and C. C. Lee, "Is gold a long-run hedge, diversifier, or safe haven for oil? Empirical evidence based on DCC-MIDAS," *Resources Policy*, vol. 76, p. 102703, 2022. https://doi.org/10.1016/j.resourpol.2022.102703

[5] D. G. Baur and T. K. McDermott, "Is gold a safe haven? International evidence," *Journal of Banking & Finance*, vol. 34, no. 8, pp. 1886-1898, 2010. https://doi.org/10.1016/j.jbankfin.2009.12.008

[6] A. Dutta, "A note on the implied volatility spillovers between gold and silver markets," *Resources Policy*, vol. 55, pp. 192-195, 2018. https://doi.org/10.1016/j.resourpol.2017.11.017

[7] S. J. H. Shahzad, E. Bouri, D. Roubaud, and L. Kristoufek, "Safe haven, hedge and diversification for G7 stock markets: Gold versus bitcoin," *Economic Modelling*, vol. 87, pp. 212-224, 2020. https://doi.org/10.1016/j.econmod.2019.07.023

[8] I. E. Kayral, A. Jeribi, and S. Loukil, "Are bitcoin and gold a safe haven during COVID-19 and the 2022 Russia–Ukraine war?," *Journal of Risk and Financial Management*, vol. 16, no. 4, p. 222, 2023. https://doi.org/10.3390/jrfm16040222

[9] M. Abdullah, H. A. Abdou, C. Godfrey, A. A. Elamer, and Y. Ahmed, "Assessing the use of gold as a zero-beta asset in empirical asset pricing: Application to the US equity market," *Journal of Risk and Financial Management*, vol. 16, no. 3, p. 204, 2023. https://doi.org/10.3390/jrfm16030204

[10] M. Fakhfekh, Y. S. Manzli, A. Béjaoui, and A. Jeribi, "Can cryptocurrencies be a safe haven during the 2022 Ukraine crisis? Implications for G7 investors," *Global Business Review*, 2023. https://doi.org/10.1177/09721509231164808

[11] N. Antonakakis, J. Cunado, G. Filis, D. Gabauer, and F. P. De Gracia, "Oil and asset classes implied volatilities: Investment strategies and hedging effectiveness," *Energy Economics*, vol. 91, p. 104762, 2020. https://doi.org/10.1016/j.eneco.2020.104762

[12] W. Mensi, S. Hammoudeh, and A. K. Tiwari, "New evidence on hedges and safe havens for Gulf stock markets using the wavelet-based quantile," *Emerging Markets Review*, vol. 28, pp. 155-183, 2016. https://doi.org/10.1016/j.ememar.2016.08.003

[13] K. Mokni, M. Al-Shboul, and A. Assaf, "Economic policy uncertainty and dynamic spillover among precious metals under market conditions: Does COVID-19 have any effects?," *Resources Policy*, vol. 74, p. 102275, 2021.

[14] V. Troster, E. Bouri, and D. Roubaud, "A quantile regression analysis of flights-to-safety with implied volatilities," *Resources Policy*, vol. 62, pp. 482-495, 2019. https://doi.org/10.1016/j.resourpol.2018.10.004

[15] R. Tansuchat, P. Tarkhamtham, W. Puntoon, and R. Phadkantha, "Forecasting precious metals prices volatility with the global economic policy uncertainty index: The GARCH-MIDAS technique for different frequency data sets. In V. N. Huynh, B. Le, K. Honda, M. Inuiguchi, & Y. Kohda (Eds.), Integrated uncertainty in knowledge modelling and decision making (IUKM 2023) (Lecture Notes in Computer Science," vol. 14375. Cham: Springer. https://doi.org/10.1007/978-3-031-46775-2_14, pp. 208–220, 2023.

[16] S. Thongkairat, W. Yamaka, and S. Sriboonchitta, "Economic policy uncertainty effect on precious metal markets: A Markov-switching model with mixture distribution regimes," *Thai Journal of Mathematics*, vol. 17, pp. 77-92, 2019.

[17] A. Bossman, M. Gubareva, and T. Teplova, "Asymmetric effects of market uncertainties on agricultural commodities," *Energy Economics*, vol. 127, p. 107080, 2023. https://doi.org/10.1016/j.eneco.2023.107080

[18] W. Mensi, S. A. Ziadat, X. V. Vo, and S. H. Kang, "Spillovers and portfolio management between the uncertainty indices of oil and gold and G7 stock markets," *Computational Economics*, vol. 64, no. 4, pp. 2233-2262, 2024. https://doi.org/10.1007/s10614-023-10488-y

[19] M. K. Chaudhry and V. Bhargava, "Volatility spillover effects: VIX and precious metals," *The Journal of Wealth Management*, vol. 23, no. 3, pp. 99-111, 2020. https://doi.org/10.3905/JWM.2020.1.115

[20] S. H. Kang, J. Arreola Hernandez, M. U. Rehman, S. J. H. Shahzad, and S.-M. Yoon, "Spillovers and hedging between US equity sectors and gold, oil, islamic stocks and implied volatilities," *Resources Policy*, vol. 81, p. 103286, 2023. https://doi.org/10.1016/j.resourpol.2022.103286

[21] M. Alomari, R. Selmi, W. Mensi, H. U. Ko, and S. H. Kang, "Dynamic spillovers in higher moments and jumps across ETFs and economic and financial uncertainty factors in the context of successive shocks," *The Quarterly Review of Economics and Finance*, vol. 93, pp. 210-228, 2024. https://doi.org/10.1016/j.qref.2023.12.009

[22] A. Ghorbel, S. Loukil, and W. Bahloul, "Connectedness between cryptocurrencies, gold and stock markets in the presence of the COVID-19 pandemic," *European Journal of Management and Business Economics*, vol. 33, no. 4, pp. 466-487, 2024. https://doi.org/10.1108/EJMBE-10-2021-0281

[23] M. K. Alam, M. I. Tabash, M. Billah, S. Kumar, and S. Anagreh, "The impacts of the Russia–Ukraine invasion on global markets and commodities: A dynamic connectedness among G7 and BRIC markets," *Journal of Risk and Financial Management*, vol. 15, no. 8, p. 352, 2022. https://doi.org/10.3390/jrfm15080352

[24] M. A. Naeem, M. Hasan, A. Agyemang, M. I. H. Chowdhury, and F. Balli, "Time-frequency dynamics between fear connectedness of stocks and alternative assets," *International Journal of Finance & Economics*, vol. 28, no. 2, pp. 2188-2201, 2023. https://doi.org/10.1002/ijfe.2532

[25] O. B. Adekoya and J. A. Oliyide, "How COVID-19 drives connectedness among commodity and financial markets: Evidence from TVP-VAR and causality-in-quantiles techniques," *Resources Policy*, vol. 70, p. 101898, 2021. https://doi.org/10.1016/j.resourpol.2020.101898

[26] S. A. Basher and P. Sadorsky, "Hedging emerging market stock prices with oil, gold, VIX, and bonds: A comparison between DCC, ADCC and GO-GARCH," *Energy Economics*, vol. 54, pp. 235-247, 2016. https://doi.org/10.1016/j.eneco.2015.11.022

[27] N. Apergis, A. Cooray, N. Khraief, and I. Apergis, "Do gold prices respond to real interest rates? Evidence from the Bayesian Markov switching VECM model," *Journal of International Financial Markets, Institutions and Money*, vol. 60, pp. 134-148, 2019. https://doi.org/10.1016/j.intfin.2018.12.014

[28] M. Balcilar, R. Demirer, R. Gupta, and M. E. Wohar, "The effect of global and regional stock market shocks on safe haven assets," *Structural Change and Economic Dynamics*, vol. 54, pp. 297-308, 2020. https://doi.org/10.1016/j.strueco.2020.04.004

[29] T. Ando, J. Bai, L. Lu, and C. M. Vojtech, "Scenario-based quantile connectedness of the U.S. interbank liquidity risk network," Federal Reserve Bank of Boston Supervisory Research and Analysis Working Paper, No. 2402, 2024.

[30] E. Bouri, R. Gupta, and D. Roubaud, "Quantile connectedness in the cryptocurrency market," *International Review of Financial Analysis*, vol. 71, p. 101536, 2021.

[31] I. Chatziantoniou, D. Gabauer, and A. Stenfors, "Interest rate swaps and the transmission mechanism of monetary policy: A quantile connectedness approach," *Economics Letters*, vol. 204, p. 109891, 2021. https://doi.org/10.1016/j.econlet.2021.109891

[32] M. H. Pesaran and Y. Shin, "Generalized impulse response analysis in linear multivariate models," *Economics Letters*, vol. 58, no. 1, pp. 17–29, 1998. https://doi.org/10.1016/S0165-1765(97)00214-0

[33] G. Koop, M. H. Pesaran, and S. M. Potter, "Impulse response analysis in nonlinear multivariate models," *Journal of Econometrics*, vol. 74, no. 1, pp. 11 9–147, 1996. https://doi.org/10.1016/0304-4076(95)01753-4

[34] A. Stiassny, "Spectral decomposition of variance in multivariate time series," *Journal of Time Series Analysis*, vol. 17, no. 2, pp. 123–137, 1996.

[35] J. Baruník and T. Křehlík, "Measuring the frequency dynamics of financial connectedness and systemic risk," *Journal of Financial Econometrics*, vol. 16, no. 2, pp. 271–296, 2018. https://doi.org/10.1093/jjfinec/nby001

[36] F. X. Diebold and K. Yılmaz, "Measuring financial asset return and volatility spillovers, with application to global equity markets," *Economic Journal*, vol. 119, no. 534, pp. 158–171, 2009. https://doi.org/10.1111/j.1468-0297.2008.02208.x

[37] F. X. Diebold and K. Yılmaz, "Better to give than to receive: Predictive directional measurement of volatility spillovers," *International Journal of Forecasting*, vol. 28, no. 1, pp. 57–66, 2012. https://doi.org/10.1016/j.ijforecast.2011.02.006

[38] F. X. Diebold and K. Yılmaz, "On the network topology of variance decompositions: Measuring the connectedness of financial firms," *Journal of Econometrics*, vol. 182, no. 1, pp. 119–134, 2014. https://doi.org/10.1016/j.jeconom.2014.04.012