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Dynamic Return and Volatility Connectedness across Global Markets: A Time - Frequency Analysis

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Abstract

This paper examines return and volatility connectedness across eight global markets (Brent crude oil, gold, Bitcoin, the S&P 500, MSCI World, MSCI Emerging Markets, the US dollar index, and the US 10-year Treasury yield), using daily data from January 2016 to March 2026. A VAR-based connectedness framework is complemented by rolling-window estimation, frequency-domain decomposition, and a time-varying parameter VAR to capture the dynamics of cross-market spillovers. The equity subsystem is also analysed to identify intra-group transmission patterns.

Average return connectedness reaches 38.22% in the static model and approximately 44% in rolling estimations, peaking near 60% during periods of market stress. Equity markets, particularly MSCI World and the S&P 500, act as the main shock transmitters, while Bitcoin, crude oil, the US dollar index, and Treasury yields primarily absorb shocks. Frequency decomposition indicates that short-term spillovers (21.3%) exceed long-term spillovers (17.0%), highlighting the importance of investor sentiment and rapid repricing. Volatility connectedness is higher, at 44.33% in the static estimation, rising to a rolling-window average of 40.28% (range: 27.43%–87.47%). Frequency decomposition shows the opposite pattern to returns: volatility spillovers are predominantly long-term (35.77% versus 8.67% short-term). Bitcoin is predominantly a net receiver in both return and volatility spillovers. Within the equity subsystem, connectedness rises to 58.86%, suggesting limited diversification benefits during turbulent periods. Overall, the findings identify equity markets as the central channel of global financial

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spillovers and underline the diverging, horizon-specific nature of cross-market risk transmission across the return and volatility channels.

Keywords: financial connectedness, time-frequency analysis, Bitcoin, volatility spillovers, safe-haven assets, systemic risk.

JEL Classification: G15; C32; G01; F30.

Introduction

Global financial markets have grown increasingly interconnected over the past two decades, creating conditions in which shocks originating in one market propagate rapidly across asset classes and geographies. This interconnectedness carries significant consequences for portfolio diversification, systemic risk monitoring, and macroprudential policy. The COVID-19 pandemic offered a stark illustration: cross-market spillovers intensified sharply precisely when diversification was most needed, compressing the risk-reducing benefits that investors typically expect from holding heterogeneous assets.

Understanding the structure and dynamics of financial connectedness has therefore become a central concern in empirical finance. A growing literature documents that spillovers are neither static nor uniform; they vary over time, respond to macroeconomic conditions, and differ across investment horizons. Yet despite these advances, several gaps persist.

First, most existing studies examine either return spillovers or volatility spillovers in isolation. Since return and volatility transmission may reflect distinct economic mechanisms, treating them separately limits the comprehensiveness of any assessment of global market integration. Second, asset coverage in the connectedness literature remains relatively narrow, with fewer attempts to jointly model a system spanning commodities, equities, currencies, fixed income, and cryptocurrencies simultaneously. Third, while frequency-domain decompositions have gained methodological prominence following Baruník & Křehlík (2018), their application to broad and heterogeneous asset sets remains limited, leaving the horizon-specific nature of spillovers insufficiently characterised.

This research paper addresses these gaps by examining dynamic return and volatility connectedness across eight major global markets: Brent crude oil, gold, Bitcoin, the S&P 500, MSCI World, MSCI Emerging Markets, the US dollar index, and the US 10-year Treasury yield. Daily data spanning January 2016 to March 2026 are analysed using a VAR-based connectedness framework augmented with rolling-window estimation and frequency-domain decomposition, allowing assessment of average connectedness levels, their evolution through tranquil and turbulent periods, and the distribution of spillovers across short- and long-run horizons.

The present study makes three main contributions. First, it provides a unified analysis of return and volatility connectedness across a comprehensive and economically diverse asset set, capturing interactions across traditional and alternative markets within a single framework. Second, frequency decomposition reveals an asymmetry between the two transmission channels: return spillovers are predominantly short-term, driven by sentiment and rapid information transmission, whereas volatility spillovers are predominantly long-term, consistent with the persistence typically documented in volatility clustering. Third, the analysis evaluates Bitcoin's role within the global spillover network relative to conventional safe-haven assets such as gold, finding that Bitcoin behaves predominantly as a net receiver of shocks, a result with direct implications for its hedging and diversification properties.

1. Literature Review

The measurement of financial connectedness gained systematic traction with Diebold & Yilmaz (2009, 2012), who proposed a spillover index derived from forecast error variance decompositions of vector autoregressions. This framework offered a tractable and replicable approach to quantifying cross-market shock transmission and rapidly became a benchmark in the empirical finance literature. Subsequent refinements addressed the network topology of variance decompositions and extended the framework to macro-financial monitoring (Diebold & Yilmaz, 2014, 2015).

A prominent strand of this literature emphasises the time-varying nature of connectedness. Rolling-window and time-varying parameter specifications consistently show that spillovers respond to shifting economic conditions, rising sharply during episodes of financial stress and receding during tranquil periods (Antonakakis et al., 2013, 2018; Koop & Korobilis, 2014; Primiceri, 2005). Demirer et al. (2017) document this pattern specifically for global bank networks, while Korobilis & Yilmaz (2018) demonstrate its relevance in large-scale Bayesian VAR settings. The procyclical nature of financial linkages (strengthening during downturns and weakening during expansions) is now well established across both developed and emerging market contexts, most recently confirmed by Mateus et al. (2024) for East and Southeast Asian equity markets using a structural-break-augmented connectedness framework.

An important methodological advancement is provided by Baruník & Křehlík (2018), who decompose connectedness across frequency bands, distinguishing between short-horizon spillovers associated with sentiment and rapid market adjustments, and long-horizon spillovers tied to macroeconomic fundamentals. This frequency-domain perspective reveals heterogeneity in transmission mechanisms that aggregate measures obscure. Dew-Becker & Giglio (2016) provide complementary theoretical grounding, showing that asset pricing dynamics differ meaningfully across frequencies.

Commodity markets have received considerable attention within this framework. Oil price shocks are well documented as sources of cross-market spillovers, particularly during periods of geopolitical uncertainty and macroeconomic stress (Kang et al., 2017; Mensi et al., 2014; Antonakakis et al., 2014). Gold, in contrast, has traditionally been associated with safe-haven behaviour, exhibiting lower correlations with risk assets during market downturns and serving as a benchmark for evaluating the hedging properties of alternative assets (Bouri et al., 2017). Exchange rates and interest rates reflect broader global financial conditions, influencing capital flows and asset valuations across both developed and emerging economies (Rey, 2015; Miranda-Agrippino & Rey, 2020).

The integration of cryptocurrencies into the connectedness literature has generated substantial debate. Bitcoin has been examined as a potential hedge, diversifier, and safe haven, with Baur et al. (2018) and Dyhrberg (2016) documenting relatively low average correlations with traditional assets. However, Corbet et al. (2018) and Bouri et al. (2017, 2020) find that these relationships are unstable, particularly during stress periods, limiting Bitcoin's effectiveness as a safe haven.

More recently, Iyer & Popescu (2023) show that crypto assets predominantly transmit spillovers to broader financial markets, with these linkages intensifying further during periods of financial stress. The broader evidence thus suggests that Bitcoin's role within the global financial system is highly context-dependent and warrants careful empirical evaluation.

Parallel contributions emphasise volatility dynamics and systemic risk. Multivariate GARCH models document the persistence and clustering of volatility across markets (Engle, 1982; Bollerslev, 1986; Bauwens et al., 2006; Engle & Kroner, 1995), while network-based approaches highlight the role of interconnectedness in amplifying systemic risk (Billio et al., 2012; Acemoglu et al., 2015; Adrian & Brunnermeier, 2016). More recent applications extend this network-based approach to alternative asset classes, with Alamaren et al. (2026) documenting substantial volatility connectedness among renewable energy, green bond, and cryptocurrency markets.

Against this backdrop, three gaps motivate the present study. First, return and volatility spillovers are rarely examined jointly within a unified framework, limiting the comprehensiveness of existing assessments. Second, most studies focus on narrow asset sets, leaving the dynamics of a system spanning commodities, equities, currencies, fixed income, and cryptocurrencies underexplored. Third, frequency-domain approaches have seen limited application to broad and heterogeneous asset universes. This article addresses all three gaps, contributing new evidence on the structure, dynamics, and horizon-specific nature of global financial connectedness across traditional and alternative markets.

2. Data and Methodology

Data

The analysis draws on daily closing prices for eight financial assets: Brent crude oil, gold, Bitcoin, the S&P 500, MSCI World, MSCI Emerging Markets, the US dollar index (DXY), and the US 10-year Treasury yield (TNX). All series are sourced from Yahoo Finance and span January 2016 to March 2026, yielding approximately 2,600 daily observations per series. Missing values arising from non-synchronous trading calendars are removed prior to estimation, leaving a balanced panel of clean daily observations. All data handling and estimation are conducted in R.

The selection of these eight assets reflects the objective of capturing connectedness across the major segments of the global financial system. Brent crude oil serves as the benchmark global energy commodity and a key driver of inflation expectations and macroeconomic conditions, with well-documented spillover effects to equity, currency, and bond markets (Kang et al., 2017; Mensi et al., 2014). Gold is included for its established safe-haven role, providing a conventional benchmark against which the hedging properties of alternative assets can be assessed (Bouri et al., 2017).

Bitcoin represents the cryptocurrency market, where ongoing debate surrounds its classification as a speculative asset, diversifier, or safe haven (Baur et al., 2018; Dyhrberg, 2016). The S&P 500 proxies the US equity market, which remains the dominant driver of global financial conditions and international capital allocation. The MSCI World and MSCI Emerging Markets indices extend equity coverage to developed and emerging economies respectively, allowing the analysis to distinguish spillover dynamics across these two groups.

The DXY captures global currency market conditions and international liquidity, given the US dollar's central role in trade, investment, and reserve management (Rey, 2015). Finally, TNX serves as a benchmark for global fixed income conditions, with Treasury yields influencing discount rates, borrowing costs, and cross-border portfolio flows (Adrian et al., 2013).

Let $X_t = (x_{1t}, x_{2t}, \dots, x_{Nt})'$ denote an $N \times 1$ vector of asset prices, where x_{it} is the price of asset *i* at time *t*. We transform prices into continuously compounded returns:

$$r_{it} = \ln P_{it} - \ln P_{i,t-1} \tag{1}$$

where P_{it} is the price of asset *i* at time *t*. Log returns are symmetric, approximately normally distributed for small changes, and directly interpretable as continuously compounded percentage changes. They also eliminate the upward drift in price levels that would otherwise violate the stationarity conditions underlying the VAR.

Volatility is proxied by squared returns:

$$v_{it} = {r_{it}}^2 \tag{2}$$

While realised variance estimators or GARCH-based approaches capture dynamics with greater precision, squared returns have a long track record in connectedness studies and facilitate replication across the literature.

The system dynamics are characterised by a p^{th}-order vector autoregression (Sims, 1980):

$$X_t = \sum_{k=1}^{p} A_k X_{t-k} + \varepsilon_t \tag{3}$$

where Ak (k = 1, …, p) are N × N coefficient matrices and εt ~ (0, Σ).

The equivalent moving average representation is:

$$X_t = \sum_{h=0}^{\infty} \Phi_h \varepsilon_{t-h} \tag{4}$$

where Φh is the impulse response matrix at horizon h, recovered from Φh = Σ^{e}k=1 AkΦh−k, with Φ0 = IN and Φh = 0 for h < 0. The connectedness measures are derived from the forecast error variance decompositions of this MA representation.

Following Diebold & Yilmaz (2012), connectedness measures are constructed from the generalised forecast error variance decomposition (GFEVD) of Pesaran & Shin (1998), which is invariant to variable ordering. The H-step-ahead GFEVD is:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e'i\, \Phi_h\, \Sigma\, e_j)^2}{\sum_{h=0}^{H-1} (e'i\, \Phi_h\, \Sigma\, {\Phi_h}' e_i)} \tag{5}$$

where σ_{jj} is the j^{th} diagonal element of Σ and e_i is a selection vector with unity in position *i*. Since rows of θg(H) need not sum to unity under generalised identification, normalisation is applied:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{6}$$

ensuring that contributions to the forecast error variance of variable *i* sum to one.

The Total Connectedness Index (TCI) measures the average share of forecast error variance attributable to cross-market shocks:

$$TCI = \frac{1}{N} \sum_{i \neq j} \tilde{\theta}_{ij}^{g}(H) \times 100 \tag{7}$$

Directional spillovers received by market *i* from all others, and transmitted from market *i* to all others, are:

$$C_{i\leftarrow} = \sum_{j \neq i} \tilde{\theta}_{ij}^{g}(H) \tag{8}$$

$$C_{i\rightarrow} = \sum_{j \neq i} \tilde{\theta}_{ji}^{g}(H) \tag{9}$$

Net connectedness is:

$$C_i^{net} = C_{i\rightarrow} - C_{i\leftarrow} \tag{10}$$

A positive net measure identifies market i as a net transmitter of shocks; a negative value identifies it as a net receiver.

To track the evolution of spillovers, the model is estimated over a rolling window of 200 trading days. At each point *t*, parameters are estimated over [*t* − 199 + 1, *t*], yielding a time series of connectedness indices $\{TCI_t\}$. The window-specific VAR is:

$$X_t = \sum_{k=1}^{p} A_k^{(w)} X_{t-k} + \varepsilon_t^{(w)} \tag{11}$$

where superscript (w) denotes window-specific estimation.

This allows coefficients, and consequently connectedness measures, to vary over time, enabling identification of periods of heightened spillovers and structural shifts in shock transmission.

Following Baruník & Křehlík (2018), spillovers are decomposed across frequency bands $d \subset (-\pi, \pi)$. The frequency-specific variance decomposition is:

$$\theta_{ij}(d) = \frac{1}{2\pi} \int_{\omega \in d} \Gamma_{ij}(\omega)\, d\omega \tag{12}$$

where $\Gamma_{ij(\omega)}$ is the frequency response function capturing the contribution of variable *j* to variable *i* at frequency *ω*.

This decomposition separates high-frequency (short-horizon) spillovers, driven by sentiment and rapid market adjustments, from low-frequency (long-horizon) spillovers tied to macroeconomic fundamentals. Connectedness indices are constructed from equations (6) – (10), replacing $\tilde{\theta}gij(H)$ with the normalised version of $\theta ij(d)$.

To quantify risk transmission, the framework is applied to volatility proxies. Let $V_t = (v_{1t}, v_{2t}, \ldots, v_{Nt})'$ be the N × 1 vector of squared returns. Volatility dynamics are modelled as:

$$V_t = \sum_{k=1}^{p} B_k V_{t-k} + u_t \tag{13}$$

where Bk (k = 1, …, p) are N × N coefficient matrices and u_t is a vector of innovations.

The GFEVD is applied to this system, yielding volatility spillover indices directly comparable to their return counterparts.

To examine intra-group dynamics within the dominant transmitter bloc identified in the full-system analysis, connectedness is additionally estimated for the equity subsystem, comprising the S&P 500, MSCI World, and MSCI Emerging Markets. This subsystem is analysed using the same VAR-based connectedness framework applied to the full system, allowing a direct comparison between intra-equity transmission and full-system transmission.

Several checks verify that the findings are not artefacts of model specification. First, the VAR is re-estimated under alternative lag orders (p = 1, 2, 3). Second, the rolling window length is varied to distinguish genuine time-variation from sensitivity to window choice. Third, subsample analysis across pre-crisis, crisis, and post-crisis regimes examines whether average connectedness figures mask regime-specific heterogeneity. Finally, a reduced four-asset system (Bitcoin, the S&P 500, gold, and the DXY) is estimated as a further check on the core transmission hierarchy.

The core findings (moderate average connectedness, equity market dominance, Bitcoin as a persistent net receiver, and the contrasting frequency profiles of return and volatility spillovers) are stable across all specifications.

As a further robustness exercise, we employ a time-varying parameter VAR (TVP-VAR) in which coefficients evolve continuously. The model is:

$$X_t = A_t X_{t-1} + \varepsilon_t \tag{14}$$

The coefficient matrix follows a random walk:

$$A_t = A_{t-1} + \eta_t \tag{15}$$

where η_t governs parameter dynamics.

Relative to the rolling-window approach, the TVP-VAR provides a more flexible, data-driven characterisation of structural change in connectedness, without imposing a fixed window length.

4. Empirical Results

Descriptive Statistics

Daily log returns exhibit negative skewness across nearly all assets (Table 1), indicating a greater frequency of large negative returns relative to positive ones. Excess kurtosis is pronounced in all series, with the US 10-year Treasury yield recording the most extreme value (37.85), followed by MSCI World (20.43) and the S&P 500 (19.49). Bitcoin displays the highest mean daily return (0.20%) alongside the largest standard deviation (4.22%), reflecting its speculative character and elevated risk profile relative to traditional assets. The DXY exhibits the lowest volatility (0.42%), consistent with its role as a relatively stable reserve currency index. Jarque–Bera statistics reject normality at the 1% level for all series, and ADF tests confirm stationarity of all return series at conventional significance levels.

Table 1: Descriptive Statistics – Daily Log Returns

Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis	JB	ADF
Brent	0.0004	0.0251	-0.2798	0.1908	-1.0590	19.1608	28447.60***	-14.07**
Gold	0.0006	0.0104	-0.1207	0.0591	-0.8178	13.8327	12852.50***	-13.20**
Bitcoin	0.0020	0.0422	-0.4647	0.2251	-0.5637	12.7598	10336.11***	-12.42**
S&P 500	0.0004	0.0114	-0.1277	0.0909	-0.6775	19.4928	29324.61***	-13.59**
MSCI World	0.0004	0.0110	-0.1208	0.0871	-0.9512	20.4326	32929.77***	-13.72**
MSCI EM	0.0002	0.0130	-0.1333	0.0775	-0.7625	12.3723	9655.18***	-14.03**
DXY	0.0000	0.0042	-0.0214	0.0203	-0.1523	4.6591	304.67***	-13.79**
TNX	0.0003	0.0298	-0.3470	0.4048	0.2719	37.8477	130069.50***	-14.22**

Note: JB and ADF denote the Jarque–Bera test for normality and the Augmented Dickey–Fuller test for stationarity, respectively. *** and ** denote rejection of the null hypothesis at the 1% and 5% significance levels.

Source: Authors' calculations based on daily data from Yahoo Finance (January 2016 - March 2026).

Volatility proxies constructed from squared returns (Table 2) display substantially more extreme distributional properties than their return counterparts. Skewness and kurtosis values are dramatically higher across all assets, with gold recording a kurtosis of 794.17 and Bitcoin 620.10, reflecting the highly leptokurtic nature of squared return distributions.

Mean volatility is highest for Bitcoin (0.18%) and the US 10-year Treasury yield (0.09%), consistent with the elevated risk associated with cryptocurrency and fixed-income markets during periods of rate volatility. The DXY exhibits the lowest mean volatility, reinforcing its comparatively stable behaviour. ADF statistics reject the unit root null for all volatility series, confirming stationarity and suitability for VAR-based analysis.

Table 2: Descriptive Statistics – Realised Volatility (Squared Returns)

Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis	JB	ADF
Brent	0.0006	0.0027	0.0000	0.0783	20.1929	535.7248	30,564,444.80***	-7.73**
Gold	0.0001	0.0004	0.0000	0.0146	22.8532	794.1673	67,252,059.94***	-10.02**
Bitcoin	0.0018	0.0061	0.0000	0.2160	19.4587	620.0997	40,940,812.63***	-11.56**
S&P 500	0.0001	0.0006	0.0000	0.0163	16.5663	374.0160	14,857,883.23***	-9.21**
MSCI World	0.0001	0.0005	0.0000	0.0146	16.8097	366.8200	14,295,114.76***	-9.48**
MSCI EM	0.0002	0.0006	0.0000	0.0178	17.3554	437.6424	20,358,562.31***	-9.77**
DXY	0.0000	0.0000	0.0000	0.0005	5.2824	44.2669	194,310.33***	-9.45**
TNX	0.0009	0.0054	0.0000	0.1639	20.0858	492.6028	25,841,852.79***	-10.97**

Note: JB and ADF denote the Jarque–Bera test for normality and the Augmented Dickey–Fuller test for stationarity, respectively. *** and ** denote rejection of the null hypothesis at the 1% and 5% significance levels.

Source: Authors' calculations based on daily data from Yahoo Finance (January 2016 - March 2026).

Static Connectedness

Table 3 presents the full-sample static connectedness matrix. The baseline VAR is estimated with one lag (p = 1), selected on the basis of standard information criteria and consistency with the daily-frequency connectedness literature. The generalised forecast error variance decomposition is computed at a forecast horizon of H = 100, reflecting the high persistence typically observed in daily financial series.

Table 3. Static Return Connectedness Matrix (Full Sample)

Variable	Brent	Gold	BTC	S&P 500	MSCI World	MSCI EM	DXY	TNX	FROM
Brent	—	0.61	0.42	5.19	5.87	5.52	0.07	4.21	21.89
Gold	0.61	—	0.70	0.17	0.57	2.22	11.93	4.78	20.98
BTC	0.36	0.70	—	5.56	6.10	4.06	0.68	0.06	17.53
S&P 500	2.46	0.09	2.42	—	34.69	20.09	0.73	3.04	63.53
MSCI World	2.64	0.24	2.54	33.10	—	22.21	1.78	2.78	65.31
MSCI EM	2.89	1.02	1.95	22.50	25.88	—	3.81	2.20	60.26
DXY	0.17	10.58	0.61	2.95	5.22	7.77	—	2.82	30.12
TNX	4.13	4.03	0.19	5.85	5.65	3.43	2.84	—	26.12
TO	13.26	17.28	8.84	75.32	83.98	65.31	21.86	19.88	305.74
NET	-8.63	-3.69	-8.69	11.80	18.67	5.05	-8.27	-6.24	—

Note: Each off-diagonal cell reports the % of the H-step forecast error variance of the row variable explained by shocks to the column variable. FROM is the row sum (total connectedness received from all other variables); TO is the column sum (total connectedness transmitted to all other variables); NET equals TO minus FROM. Total Connectedness Index (TCI) = 38.22%.

Source: Authors' calculations based on daily data from Yahoo Finance (January 2016 - March 2026).

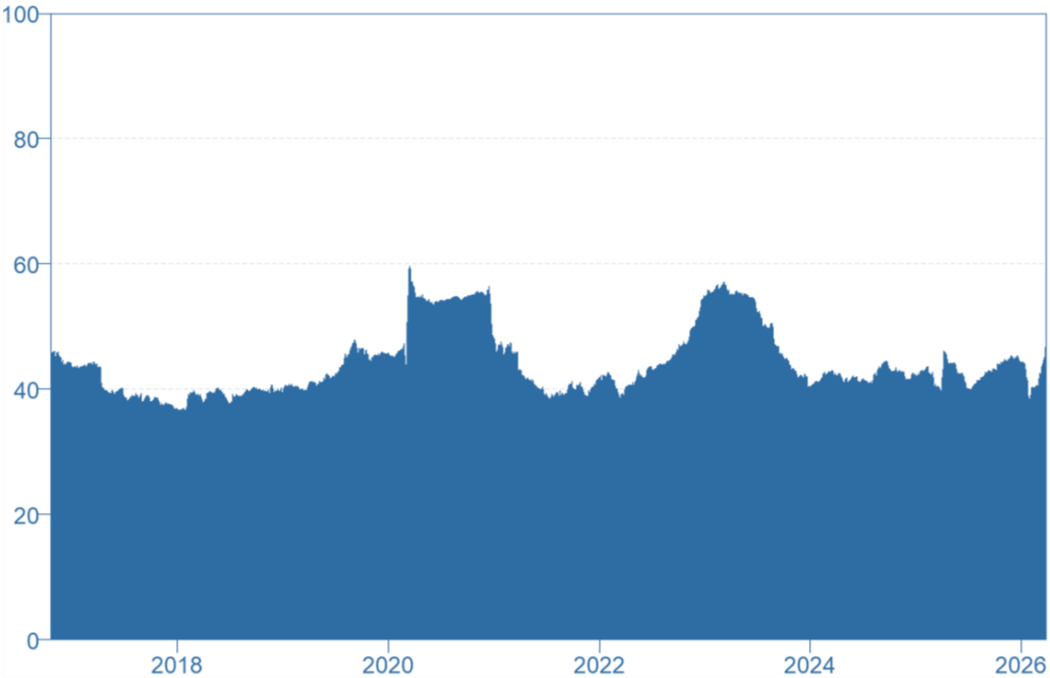
The static Total Connectedness Index (TCI) is estimated at 38.22%, indicating a moderate degree of average spillovers across the full sample. Approximately one-third of forecast error variance across the system is attributable to cross-market shocks, pointing to meaningful but incomplete global financial integration.

The net directional connectedness measures reveal a clear transmission hierarchy. MSCI World and the S&P 500 emerge as the dominant net transmitters, with net spillovers of 18.67% and 11.80% respectively. MSCI Emerging Markets also contributes positively, though to a lesser degree (5.05%). In contrast, Bitcoin (−8.69%), Brent crude oil (−8.63%), the DXY (−8.27%), US Treasury yields (−6.24%) and gold (−3.69%) are all identified as net receivers, indicating their susceptibility to external shocks rather than their role as drivers of global spillovers. These results underscore the central position of global equity markets in the cross-market transmission network.

Time-Varying Connectedness

Figure 1 presents the evolution of total return connectedness over the sample period. The rolling-window analysis reveals an average dynamic TCI of approximately 44%, with values ranging from around 36% during tranquil periods to nearly 60% during episodes of acute financial stress. The most pronounced spike occurs around 2020, coinciding with the COVID-19 pandemic, during which cross-market spillovers intensified sharply as investors rapidly repriced risk across asset classes. A secondary elevation is visible during 2022–2023, followed by a gradual stabilisation toward the end of the sample.

Figure 1: Time-Varying Return Connectedness



Source: Authors' calculations based on daily data from Yahoo Finance (January 2016 - March 2026).

These dynamics confirm the procyclical nature of financial connectedness (market integration strengthens during downturns and recedes during stable periods) consistent with prior evidence in Antonakakis et al. (2018) and Demirer et al. (2018). The divergence between the static TCI (38.22%) and the rolling average (44%) reflects the influence of stress episodes on dynamic estimates, highlighting the importance of time-varying analysis for capturing the full range of connectedness behaviour.

Frequency-Domain Connectedness

The frequency decomposition separates spillovers into short-term (1–2 trading days) and long-term (beyond 2 trading days) components. Short-term connectedness (21.3%) exceeds long-term connectedness (17.0%), indicating that cross-market transmission is driven primarily by high-frequency dynamics (investor sentiment, news shocks, and rapid portfolio rebalancing) rather than persistent macroeconomic fundamentals.

This finding has meaningful implications for diversification. Since the bulk of return spillovers materialise within a very short window, the price-based benefits of cross-asset diversification erode rapidly during periods of market turbulence, precisely when investors most need them; the volatility channel, discussed in Section 4.5, follows the opposite horizon pattern. At the asset level, equity markets maintain their dominant transmission role across both frequency bands. Bitcoin's connectedness is more heavily concentrated in the short-term component, reinforcing its characterisation as a sentiment-driven speculative asset. Bond markets, by contrast, exhibit relatively greater importance in the long-term component, consistent with their closer linkage to macroeconomic fundamentals.

Volatility Connectedness

Table 4 presents the volatility connectedness matrix, constructed by applying the GFEVD framework to squared return series. The volatility TCI stands at 44.33%, exceeding its return counterpart by more than six percentage points. This indicates that risk transmission across global markets is considerably stronger than return transmission alone would suggest, consistent with the broader literature on financial contagion and volatility spillovers.

Table 4: Static Volatility Connectedness Matrix (Full Sample)

Variable	Brent	Gold	BTC	S&P 500	MSCI World	MSCI EM	DXY	TNX	FROM
Brent	—	0.16	0.39	5.23	6.11	4.98	0.57	11.45	28.91
Gold	0.29	—	0.53	2.35	2.34	1.71	2.26	0.34	9.82
BTC	0.26	0.07	—	8.14	12.38	8.98	0.20	0.12	30.15
S&P 500	2.22	0.67	4.96	—	32.20	21.34	0.72	3.94	66.05
MSCI World	2.54	0.65	5.87	31.37	—	22.30	0.90	4.19	67.81
MSCI EM	2.45	0.66	4.70	26.33	27.38	—	1.01	4.68	67.21
DXY	1.48	1.82	0.85	7.82	8.75	6.26	—	2.44	29.42
TNX	13.73	0.11	0.91	15.09	14.83	10.31	0.25	—	55.24
TO	22.96	4.14	18.22	96.34	103.99	75.89	5.91	27.16	354.60
NET	-5.94	-5.69	-11.93	30.30	36.18	8.68	-23.51	-28.08	—

Note: Constructed by applying the generalised forecast error variance decomposition to squared return series. FROM, TO, and NET are defined as in Table 2. TCI = 44.33%.

Source: Authors' calculations based on daily data from Yahoo Finance (January 2016 - March 2026).

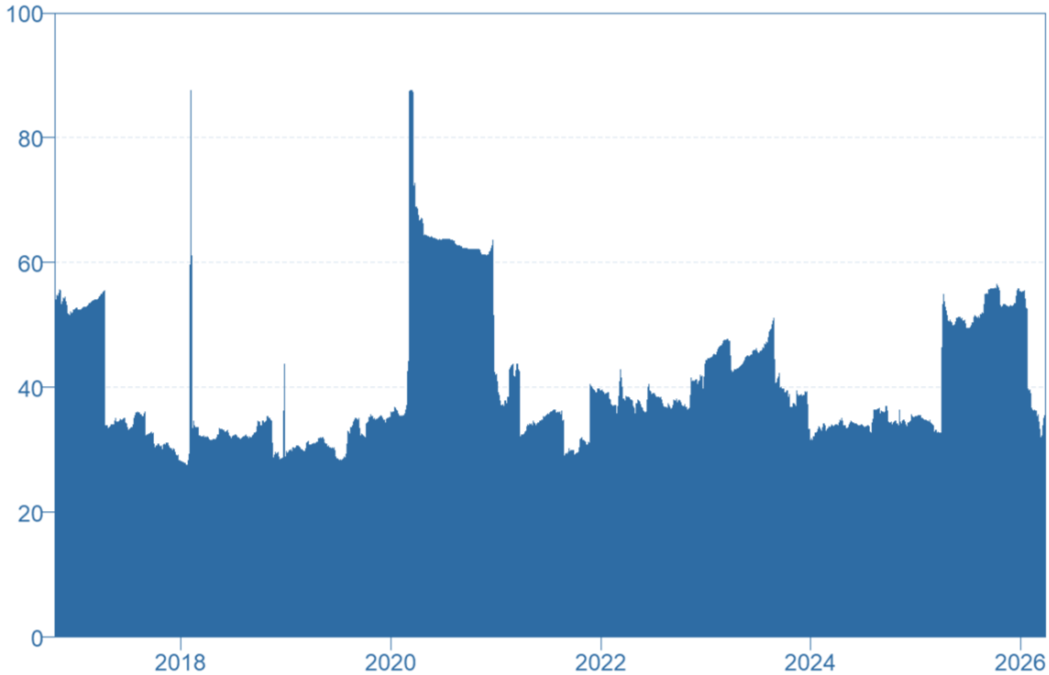
Equity markets again dominate as net transmitters. MSCI World and the S&P 500 record net volatility spillovers of 36.18% and 30.30% respectively, substantially larger than their return-based equivalents, while MSCI Emerging Markets contributes a net 8.68%. US Treasury yields (−28.08%) and the DXY (−23.51%) emerge as the strongest net receivers of volatility shocks, suggesting that fixed income and currency markets absorb rather than propagate risk disturbances.

Bitcoin records a net volatility spillover of −11.93%, reinforcing its characterisation as a risk-sensitive asset that reacts to external disturbances rather than initiating them. This finding provides little empirical support for Bitcoin's role as a safe haven. This receiver position is not fixed, however: on a rolling-window basis Bitcoin's net volatility spillover briefly turns positive during the COVID-19 period, a reversal that coincides with a broader breakdown in the transmitter-receiver hierarchy across the full asset system during that episode rather than a pattern specific to Bitcoin.

Frequency decomposition of volatility connectedness reveals a pattern opposite to that of returns: long-term spillovers (35.77%) substantially exceed short-term spillovers (8.67%). Where return transmission is dominated by rapid, sentiment-driven repricing, volatility transmission reflects slower-moving, structurally embedded risk propagation, consistent with the persistence documented in the volatility clustering literature (Engle, 1982; Bollerslev, 1986).

Figure 2 presents the evolution of volatility connectedness over the sample period. Relative to return connectedness, volatility spillovers exhibit a higher static baseline and more extreme peaks during periods of financial turbulence, even though their rolling-window average runs somewhat below that of returns. The COVID-19 episode produces the most sustained elevation in volatility connectedness, spanning several trading days in March 2020, though the single sharpest daily reading is matched by an isolated spike during the February 2018 volatility shock ("Volmageddon"). Extreme volatility transmission is therefore not unique to the pandemic period; what distinguishes COVID-19 is the duration of elevated connectedness rather than its peak intensity alone, reflecting the amplification of systemic risk during acute market stress. Unlike return connectedness, which stabilises quickly following disruptions, volatility connectedness remains elevated for extended periods, underscoring the persistence of risk transmission across global markets. This pattern is consistent with volatility clustering documented in the broader financial econometrics literature and highlights the asymmetric nature of cross-market risk propagation during downturns.

Figure 2: Time-Varying Volatility Connectedness (TCI)

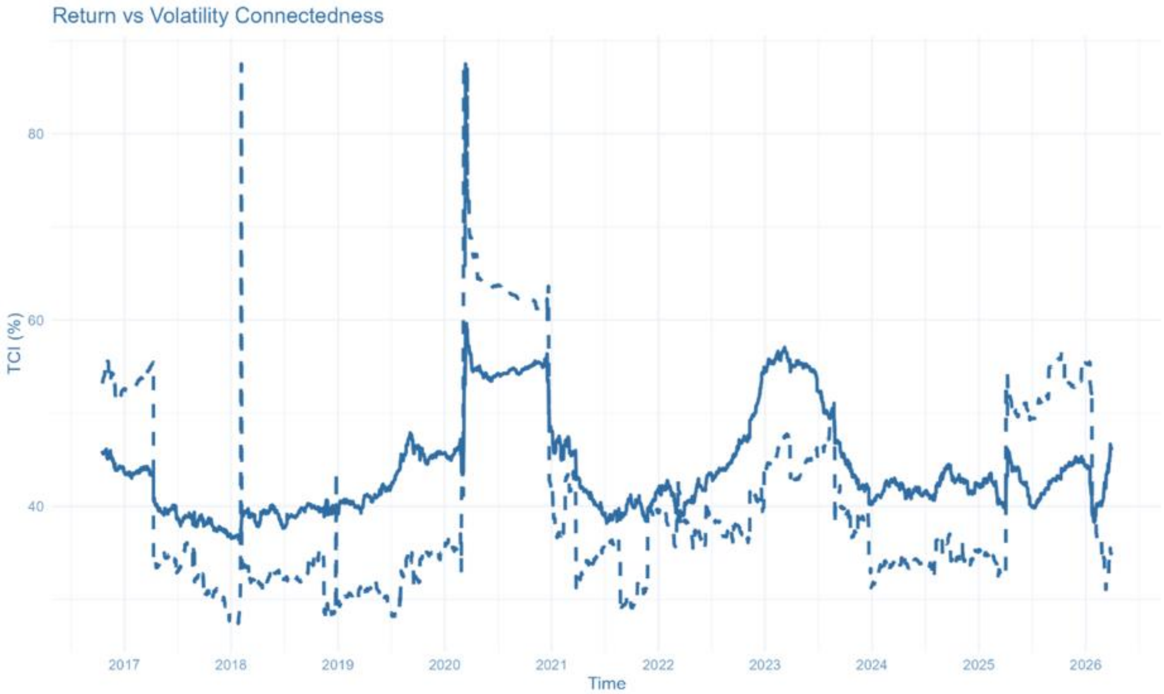


Source: Authors' calculations based on daily data from Yahoo Finance (January 2016 - March 2026).

Comparison of Return and Volatility Connectedness

Figure 3 plots return and volatility connectedness side by side over the full sample. The two series do not move in lockstep: return connectedness follows a comparatively smoother path, while volatility connectedness exhibits sharper, more abrupt swings, most visibly around the 2020 market disruption.

Figure 3: Comparison of Return and Volatility Connectedness



Source: Authors' calculations based on daily data from Yahoo Finance (January 2016 - March 2026).

During stress episodes the gap between the two series widens considerably, with volatility connectedness spiking well above its return counterpart before retreating. The two series correlate strongly overall (0.70), but volatility connectedness runs consistently below return connectedness outside of stress periods (on 81.7% of calm-period days), only closing the gap or spiking above its return counterpart during the sharpest episodes of turbulence. The key takeaway is not that one series uniformly dominates the other, but that volatility connectedness reacts more forcefully and rapidly to sudden shocks, making it a more responsive, if noisier, signal of emerging systemic stress than return-based measures alone.

Equity Subsystem Analysis

To examine intra-group dynamics within the dominant transmitter bloc, connectedness is estimated for the equity subsystem comprising the S&P 500, MSCI World, and MSCI Emerging Markets. The subsystem TCI stands at 58.86%, substantially exceeding the full-system estimate of 38.22%. This elevated internal connectedness confirms that shocks originating within the equity segment propagate rapidly and forcefully across global equity markets, leaving limited scope for intra-equity diversification during stress periods. The result is consistent with prior evidence on the high degree of synchronisation among global equity indices (Diebold & Yilmaz, 2012; Antonakakis et al., 2018).

Robustness

The robustness of the findings is assessed through several checks. Re-estimating the VAR under alternative lag orders (p = 1, 2, 3) produces no material change in connectedness estimates. Varying the rolling window length confirms that time variation in connectedness reflects genuine structural dynamics rather than sensitivity to window choice. Subsample analysis across pre-crisis, crisis, and post-crisis regimes shows that average connectedness figures are not masking substantial regime-specific heterogeneity in transmission direction. Estimation on the reduced four-asset system leaves the core findings (equity market dominance, Bitcoin as a persistent net receiver, and the contrasting frequency profiles of return and volatility spillovers) qualitatively unchanged. TVP-VAR estimation corroborates the rolling-window results, providing additional confidence that the identified dynamics are robust to the choice of time-variation approach.

Summary of Key Findings

The empirical results yield five principal findings. First, global equity markets, particularly MSCI World and the S&P 500, are the dominant net transmitters of both return and volatility shocks across the full system, confirming their central role in global financial connectedness. Second, connectedness is strongly time-varying, rising sharply during the COVID-19 pandemic and receding during calmer periods, consistent with the procyclical nature of financial linkages. Third, return and volatility spillovers diverge sharply in their frequency composition: return transmission is predominantly short-term, driven by sentiment shifts and rapid repricing, while volatility transmission is predominantly long-term, reflecting more persistent and structurally embedded risk propagation. Fourth, volatility connectedness exceeds return connectedness in its static level (44.33% versus 38.22%) and in its long-horizon persistence (35.77% versus 17.0% at frequencies beyond two days), even though its rolling-window average runs somewhat below that of returns (40.28% versus 43.99%), indicating that risk transmission is a structurally deeper channel of cross-market integration than price co-movement alone, rather than a uniformly larger one at every point in time. Fifth, Bitcoin acts predominantly as a net receiver of both return and volatility shocks, though this position weakens and briefly reverses during the most acute stress episodes, providing little empirical support for its characterisation as a safe-haven or hedging asset within the global financial system.

The connectedness measures estimated in this study translate directly into a practical monitoring framework for central banks and financial regulators. Because the rolling-window Total Connectedness Index (TCI) rises from a static baseline of 38.22% to levels approaching 60% during stress episodes, regulators can treat sustained deviations of the rolling TCI above its historical average, for example movements exceeding one or two standard deviations, as an operational early-warning signal of building systemic risk, in the same spirit as the Diebold-Yilmaz connectedness monitors already discussed in the financial-stability literature.

The volatility connectedness index is particularly well suited to this role. Its higher static level (44.33% versus 38.22% for returns) and the dominance of long-horizon transmission within it (35.77% of volatility spillovers operate beyond a two-day horizon, against 17.0% for returns) indicate that risk transmission across markets is both stronger and structurally more persistent than return transmission alone, even though its rolling-window average (40.28%) runs somewhat below that of returns (43.99%). A supervisory dashboard that tracks the volatility TCI alongside the return TCI would allow regulators to distinguish ordinary co-movement in prices from genuine increases in cross-market risk transmission, since the two indices are shown here to diverge most sharply in precisely the stress periods that matter for financial stability monitoring.

The directional connectedness results further indicate where surveillance effort should be concentrated. Because equity markets, particularly MSCI World and the S&P 500, consistently emerge as the dominant net transmitters of both return and volatility shocks, these markets function as the central nodes of the global spillover network identified in this study. Regulators seeking an early-warning system with limited monitoring resources would obtain the greatest diagnostic value by prioritising real-time surveillance of these transmitting markets, rather than spreading monitoring effort evenly across all eight markets in the system.

Finally, the frequency-domain results imply that early-warning systems need to track risk transmission at two different horizons rather than one. Return-based spillovers are predominantly short-term, meaning a monitoring framework built on quarterly or annual reporting cycles would miss the horizon at which most price-based transmission occurs, and daily or intraday rolling-window estimation is needed to capture it. Volatility-based spillovers, by contrast, are predominantly long-term, indicating that this channel of risk transmission builds up over weeks rather than days; a framework focused only on high-frequency price data would underweight the slower-building risk that volatility connectedness captures. An effective early-warning system should therefore combine both: high-frequency monitoring of return connectedness to catch fast repricing events, and lower-frequency tracking of volatility connectedness to catch persistent risk build-up. Consistent with the results on Bitcoin's role as a net receiver rather than a safe haven, this monitoring framework should not treat Bitcoin as a stabilising asset class for regulatory stress-testing purposes.

Conclusion

This article examines dynamic return and volatility connectedness across eight major global financial markets (Brent crude oil, gold, Bitcoin, the S&P 500, MSCI World, MSCI Emerging Markets, the US dollar index, and the US 10-year Treasury yield) over the period January 2016 to March 2026. Employing a VAR-based connectedness framework augmented with rolling-window estimation and frequency-domain decomposition, the analysis provides a comprehensive assessment of cross-market spillovers, their evolution through tranquil and turbulent periods, and their distribution across investment horizons.

Five principal findings emerge. Global equity markets, particularly MSCI World and the S&P 500, consistently act as the dominant net transmitters of both return and volatility shocks, confirming their central role in driving global financial connectedness. Connectedness is strongly time-varying, rising sharply during the COVID-19 pandemic and receding during calmer periods, consistent with the procyclical nature of financial linkages documented in prior literature.

Frequency decomposition reveals a clear divergence between the two channels: return spillovers are predominantly short-term, driven by sentiment and rapid information transmission, while volatility spillovers are predominantly long-term, pointing to more persistent and structurally embedded risk transmission. Volatility connectedness exceeds return connectedness in its static level and its long-horizon persistence, though not in its rolling-window average, indicating that risk propagates more durably across markets than price co-movement alone, even if not uniformly more intensely at every point in time. Finally, Bitcoin behaves predominantly as a net receiver of shocks, though this position weakens during the most acute stress episodes, offering little empirical support for its characterisation as a safe-haven or hedging asset.

These findings carry practical implications for portfolio management and risk monitoring. The time-varying nature of spillovers, and their differing horizons across return and volatility channels, implies that diversification strategies must be dynamic rather than static. Return-based co-movement is a short-horizon signal requiring frequent rebalancing, while volatility-based co-movement is a slower-building indicator of deteriorating diversification benefits over longer holding periods; both warrant particular attention during periods of elevated uncertainty when cross-market linkages intensify most sharply. The structurally deeper and more persistent nature of volatility connectedness further suggests that risk-based measures provide a more informative signal of systemic stress than price-based ones, with direct relevance for macroprudential surveillance. For investors considering Bitcoin as a portfolio diversifier, the evidence indicates that its behaviour during stress periods is inconsistent with safe-haven properties, warranting caution in diversification strategies that assign it that role.

Rather than constituting limitations in a narrow sense, several methodological choices in this analysis point to promising avenues for future research. The reliance on squared returns as volatility proxies, while standard in the connectedness literature, represents one such avenue: future work could extend the framework using realised variance or GARCH-based measures to capture volatility dynamics with greater precision.

Similarly, the assumption of linear dynamics offers a further avenue for future research, since nonlinear or threshold-based transmission mechanisms may become particularly relevant during extreme market conditions. The asset set, while broad, also remains selective, suggesting a third avenue: extending the analysis to further commodity markets, sector-level indices, or additional cryptocurrencies could enrich the characterisation of global spillover networks.

Future research pursuing these avenues might incorporate higher-frequency data, nonlinear or threshold-based connectedness models, or machine learning approaches capable of capturing complex cross-market dependencies. Extending the framework to include additional alternative assets and examining the role of macroeconomic announcements as structural drivers of time-varying connectedness represent further promising directions.

CreDit Authorship Contribution Statement

Challa Gopiraju: Conceptualisation, Methodology, Software, Formal analysis, Investigation, Data curation, Resources, Validation, Writing (original draft), Writing (review and editing), Visualisation, Project administration. Achakkagari Shashidhar: Writing (review and editing), Visualisation, Project administration. V. Mary Jessica: Supervision, Conceptualisation, Validation, Writing (review and editing).

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Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Data Availability Statement

The data used in this study are publicly available from Yahoo Finance (https://finance.yahoo.com), covering the period January 2016 to March 2026 at daily frequency. Estimation code is available from the corresponding author upon reasonable request.

Declaration of Generative AI Use

During the preparation of this work, the author(s) used Claude (Anthropic) to assist with citation verification, identification of supporting literature, and language editing. No AI tools were used to generate research ideas, design the methodology, analyse data, or draw conclusions. All figures and tables in this manuscript are exclusively data-driven outputs produced through the authors' own statistical software and estimation code. After using this tool, the author(s) reviewed and edited the content as needed and take full responsibility for the content of the published article.

Ethical Approval Statement

This study is based exclusively on publicly available secondary market data (Yahoo Finance) and does not involve human participants, personal data, or animal subjects. Therefore, ethical approval was not required.

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