



UNIVERSITÉ DU QUÉBEC EN OUTAOUAIS

DÉPARTEMENT DES SCIENCES ADMINISTRATIVES

WORKING PAPER NO. 6

Intraday Volatility Transmission Across Asset Classes: A Connectedness Analysis of Equities, Fixed Income, Commodities, and Cryptocurrencies

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May 2026

Version 1.0

Abstract

This paper investigates intraday volatility transmission across equities, foreign exchange, commodities, and cryptocurrency markets using 5-minute OHLCV data spanning 2008–2026. We construct daily realized volatility measures from over 235 million intraday observations across 10 representative instruments and apply the [Diebold and Yilmaz \(2012\)](#) generalized variance decomposition framework within a VAR(4) model at a 10-day forecast horizon. Our full-sample analysis reveals a total spillover index of 55.44%, with U.S. equity index futures (ES, NQ) serving as the dominant volatility transmitters (net spillovers of +26.80% and +19.72%, respectively), while the VIX acts primarily as a volatility receiver (−23.37%). Cryptocurrencies (BTC, ETH) remain largely isolated from traditional asset volatility networks, with own-shock contributions exceeding 77%. Rolling 200-day connectedness analysis uncovers substantial time variation, with the total spillover index peaking at 81.55% during the February 2018 volatility implosion. Regime-specific analysis reveals dramatic shifts in the volatility hierarchy: during the COVID-19 crash, USD/JPY emerges as the dominant shock originator (+60.29%), while equity futures flip from transmitters to receivers. During the 2022 rate-hiking cycle, Bitcoin transitions to a net volatility transmitter (+7.90%), suggesting growing integration of crypto markets with the traditional financial system. Intraday analysis of trading sessions shows that Bitcoin maintains near-uniform volatility across Asian, European, and U.S. hours, contrasting sharply with the session-dependent patterns of equity and VIX markets. Granger causality tests confirm that equity futures significantly lead VIX changes ($F = 19.86$, $p < 0.001$), while crypto markets remain causally independent. These findings have important implications for portfolio construction, risk management, and the monitoring of systemic risk across increasingly interconnected global markets.

Keywords: realized volatility, volatility spillovers, Diebold–Yilmaz connectedness, high-frequency data, cross-asset transmission, cryptocurrency, systemic risk

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

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1. Introduction

Understanding how volatility propagates across asset classes is fundamental to modern portfolio management, risk assessment, and financial stability monitoring. The interconnectedness of global financial markets has increased substantially over the past two decades, driven by algorithmic trading, cross-border capital flows, exchange-traded funds linking disparate asset classes, and the emergence of cryptocurrency markets as a new store of value. These developments have intensified the channels through which volatility shocks in one market can rapidly transmit to others, raising important questions about the nature, magnitude, and time-varying dynamics of cross-asset volatility spillovers.

The seminal work of [Diebold and Yilmaz \(2009, 2012, 2014\)](#) established a rigorous econometric framework for measuring volatility connectedness based on generalized forecast error variance decompositions from vector autoregressive (VAR) models. This approach decomposes the forecast error variance of each variable into contributions from shocks originating in all variables in the system, providing both aggregate and directional measures of spillovers. Subsequent applications have examined volatility transmission within equities ([Demirer et al., 2018](#)), across commodities and equity markets ([Kang et al., 2017](#)), and between traditional and crypto assets ([Bouri et al., 2019](#); [Corbet et al., 2020](#)).

However, several gaps remain in the literature. First, most existing studies rely on daily or weekly data, which may obscure the rapid intraday dynamics of volatility transmission. High-frequency data at the 5-minute level captures the real-time propagation of shocks that daily data aggregates away. Second, the inclusion of cryptocurrency markets—particularly their evolution from isolated speculative instruments to increasingly integrated financial assets—has received limited attention within comprehensive multi-asset connectedness frameworks. Third, the regime-dependent nature of volatility transmission has not been systematically examined across the full spectrum of asset classes using consistent high-frequency data.

This paper addresses these gaps by providing a comprehensive analysis of intraday volatility transmission across four major asset classes—equities, foreign exchange (FX), commodities, and cryptocurrencies—using 5-minute OHLCV data spanning January 2008 to March 2026. We construct daily realized volatility measures for 10 representative instruments and apply the [Diebold and Yilmaz \(2012\)](#) generalized variance decomposition framework to quantify both static and time-varying spillover dynamics. Specifically, we address the following five research questions:

- RQ1.** How does intraday realized volatility propagate across equities, currencies, commodities, and crypto markets at the 5-minute frequency?
- RQ2.** Does the speed and magnitude of cross-asset volatility transmission vary across market regimes (*e.g.*, the COVID-19 crash, the 2022 rate-hiking cycle, the crypto winter)?

- RQ3.** Which asset classes act as volatility originators versus receivers, and has this hierarchy shifted over time with the maturation of crypto markets?
- RQ4.** Can a high-frequency VAR/network connectedness model identify systemic risk buildups before major market dislocations?
- RQ5.** How do intraday volatility spillovers between VIX futures, equity index futures (ES, NQ), and Bitcoin futures differ during U.S. versus European versus Asian trading hours?

Our analysis yields several novel findings. First, U.S. equity index futures (E-Mini S&P 500 and E-Mini Nasdaq 100) are the dominant volatility transmitters in the global system, with net directional spillovers of +26.80% and +19.72%, respectively. The VIX, often perceived as a barometer of market fear, is in fact a net receiver of volatility shocks (−23.37%), absorbing rather than originating cross-asset volatility. Second, the total spillover index exhibits substantial time variation, ranging from 57.22% to 81.55%, with sharp increases preceding and during market stress episodes. Third, regime analysis reveals dramatic shifts in the volatility hierarchy: during the COVID-19 crash, USD/JPY emerges as the dominant shock originator, consistent with safe-haven demand dynamics, while equity futures flip from transmitters to receivers. Fourth, Bitcoin demonstrates a gradual transition from volatility receiver to originator, particularly evident during the 2022 rate-hiking period, suggesting growing crypto–traditional market integration. Fifth, Bitcoin’s intraday volatility pattern is remarkably uniform across global trading sessions, in stark contrast to the session-dependent patterns of equity and VIX markets.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the econometric framework. Section 4 presents the data and realized volatility construction. Section 5 reports the empirical results. Section 6 discusses the findings in the context of the research questions, and Section 7 concludes.

2. Literature Review

2.1. Volatility Spillovers and Connectedness

The study of volatility transmission across financial markets has a long intellectual history, beginning with the recognition that volatility clusters (Mandelbrot, 1963; Fama, 1965) and exhibits contagion effects across markets (King and Wadhwani, 1990; Forbes and Rigobon, 2002). Early approaches relied on multivariate GARCH models (Engle, 2002; Baele, 2005) and regime-switching frameworks (Ang and Bekaert, 2002) to capture cross-market volatility dynamics. While these models provided important insights, they were limited in their ability to decompose directional spillovers and identify which markets serve as net transmitters versus receivers.

The introduction of the Diebold and Yilmaz (2009) spillover index marked a methodological breakthrough. Building on the concept of forecast error variance decompositions from VAR models,

they proposed a single summary measure—the total spillover index—that captures the proportion of total forecast error variance attributable to cross-market shocks. [Diebold and Yilmaz \(2012\)](#) refined this framework by adopting the generalized VAR approach of [Koop et al. \(1996\)](#) and [Pesaran and Shin \(1998\)](#), which eliminates the sensitivity to variable ordering inherent in Cholesky decompositions. This generalized framework yields an asymmetric connectedness matrix that provides directional “TO” and “FROM” spillover measures for each variable, as well as net directional spillovers.

[Diebold and Yilmaz \(2014\)](#) further extended the methodology to enable network visualization of the connectedness structure, drawing on tools from graph theory. Their approach has since been applied extensively across financial markets: [Demirer et al. \(2018\)](#) examined global bank stock return and volatility connectedness, [Barunik and Krehlik \(2018\)](#) proposed a frequency-domain decomposition of connectedness to distinguish short-run from long-run spillovers, and [Antonakakis et al. \(2020\)](#) applied time-varying parameter (TVP) VAR models to capture smooth evolution of connectedness without the need for rolling windows.

2.2. Cross-Asset Volatility Transmission

A growing body of literature examines volatility transmission across different asset classes, motivated by the observation that cross-asset correlations tend to increase during market stress ([Longin and Solnik, 2001](#); [Ang and Bekaert, 2002](#)). [Kang et al. \(2017\)](#) investigated spillovers between commodity and equity markets, finding that oil and gold serve as significant volatility transmitters during crisis periods. [Diebold and Yilmaz \(2012b\)](#) studied connectedness among four major asset classes and found that return spillovers are more important than volatility spillovers for most market pairs.

The foreign exchange market, as the world’s largest and most liquid financial market, has been shown to play a central role in cross-asset volatility transmission. [Greenwood-Nimmo et al. \(2014\)](#) documented that carry trade unwinds can generate volatility spillovers from FX to equity markets, while [Barunik et al. \(2016\)](#) found significant volatility transmission between the EUR/USD exchange rate and European equity indices. The Japanese yen, as a traditional safe-haven currency, has been shown to exhibit distinctive volatility dynamics during crisis periods ([Ranaldo and Soderlind, 2010](#); [Habib and Stracca, 2012](#)).

Commodity markets, particularly crude oil and gold, have been extensively studied as both shock transmitters and hedging instruments. [Vivian and Wohar \(2012\)](#) found significant time-varying volatility spillovers between oil and stock markets across multiple countries. [Baur and Lucey \(2010\)](#) established gold’s role as a safe haven during extreme equity market downturns, while [Reboredo \(2013\)](#) documented asymmetric spillovers between gold and oil prices.

2.3. Cryptocurrency and Traditional Market Integration

The emergence of cryptocurrency markets has introduced a new dimension to cross-asset volatility analysis. Early studies found limited connectedness between Bitcoin and traditional financial assets (Bouri et al., 2017; Corbet et al., 2018), supporting the diversification benefits of including crypto in multi-asset portfolios. However, more recent evidence suggests increasing integration, particularly during market stress periods.

Bouri et al. (2019) examined volatility spillovers between Bitcoin and a range of financial assets, finding that crypto–traditional market connectedness increased significantly after 2017. Corbet et al. (2020) analyzed the contagion dynamics between cryptocurrencies and conventional financial markets during the COVID-19 pandemic, documenting a sharp increase in crypto–equity correlations. Yousaf et al. (2022) extended this analysis to include a broader set of cryptocurrencies and found evidence of increasing volatility transmission from crypto to commodity markets.

The question of whether crypto markets have transitioned from volatility receivers to originators has important implications for systemic risk monitoring. Ante (2021) provided evidence of Bitcoin's growing influence on traditional markets, particularly through the channel of institutional adoption and the introduction of crypto-linked exchange-traded products. More recently, Makarov and Schoar (2020) documented the role of arbitrage and cross-exchange price discovery in the crypto market microstructure.

2.4. Intraday Volatility Dynamics and Trading Sessions

The use of high-frequency data to study volatility dynamics has a rich tradition in financial econometrics. Andersen et al. (2001, 2003) pioneered the use of realized volatility constructed from intraday returns as a model-free measure of ex post volatility. The optimal sampling frequency for realized volatility estimation has been debated extensively, with Barndorff-Nielsen and Shephard (2002) and Zhang et al. (2005) addressing the trade-off between discretization bias and microstructure noise.

Intraday volatility patterns exhibit well-documented regularities across asset classes. Equity markets display a U-shaped or reverse J-shaped intraday volatility pattern, with elevated volatility at the open and close of trading (Wood et al., 1985; Harris, 1986). FX markets, trading 24 hours, show volatility peaks during the overlap of major trading sessions (Andersen and Bollerslev, 1998). Cryptocurrency markets, as continuously traded assets, display distinctive intraday patterns that reflect their global, decentralized nature (Eross et al., 2019).

The interaction between trading sessions has been studied primarily in the context of equity markets. Hamao et al. (1990) found evidence of volatility spillovers from the Tokyo Stock Exchange to London and New York, while Lin et al. (1994) documented bidirectional volatility transmission between the New York and Tokyo stock markets. More recently, Fry and Cheah (2022) examined

how Bitcoin's 24/7 trading provides a continuous information channel that can bridge traditional market close-to-open gaps.

2.5. Contribution to the Literature

This paper contributes to the existing literature in several important ways. First, we provide the most comprehensive high-frequency multi-asset connectedness analysis to date, spanning four asset classes with 5-minute data over an 18-year period. Second, we document the time-varying evolution of the volatility transmitter–receiver hierarchy, with particular attention to the changing role of cryptocurrency markets. Third, we exploit the 24/7 nature of crypto trading to examine session-specific volatility spillovers, providing novel evidence on the role of trading hours in shaping cross-asset volatility dynamics. Fourth, we demonstrate that the Diebold–Yilmaz connectedness framework, applied at high frequency, can serve as an early warning indicator for systemic risk buildups.

3. Methodology

3.1. Realized Volatility

We construct daily realized volatility from intraday 5-minute log returns. For asset i on day t , let $P_{i,t,j}$ denote the closing price of the j -th 5-minute bar, where $j = 1, \dots, M_t$ and M_t is the number of intraday observations. The 5-minute log return is:

$$r_{i,t,j} = \ln \left(\frac{P_{i,t,j}}{P_{i,t,j-1}} \right). \quad (1)$$

The daily realized variance is computed as the sum of squared intraday returns ([Andersen et al., 2003](#); [Barndorff-Nielsen and Shephard, 2002](#)):

$$\text{RV}_{i,t} = \sum_{j=1}^{M_t} r_{i,t,j}^2. \quad (2)$$

The annualized daily realized volatility is then:

$$\sigma_{i,t}^{\text{RV}} = \sqrt{252 \cdot \text{RV}_{i,t}}. \quad (3)$$

We impose a minimum threshold of $M_t \geq 20$ intraday observations per day to ensure reliable realized volatility estimation. Days with fewer observations are excluded. Under standard assumptions, as the sampling frequency increases ($M_t \rightarrow \infty$), $\text{RV}_{i,t}$ converges to the integrated

variance:

$$\text{RV}_{i,t} \xrightarrow{p} \int_0^1 \sigma_{i,t}^2(s) ds. \quad (4)$$

The 5-minute sampling frequency represents a widely accepted compromise between capturing sufficient intraday variation and avoiding microstructure noise contamination (Liu et al., 2015).

3.2. Vector Autoregression

Let $\mathbf{y}_t = (\text{RV}_{1,t}, \text{RV}_{2,t}, \dots, \text{RV}_{N,t})'$ denote the $N \times 1$ vector of daily realized volatilities for $N = 10$ assets. We model the joint dynamics using a VAR(p) process:

$$\mathbf{y}_t = \boldsymbol{\mu} + \sum_{\ell=1}^p \boldsymbol{\Phi}_{\ell} \mathbf{y}_{t-\ell} + \boldsymbol{\varepsilon}_t, \quad (5)$$

where $\boldsymbol{\mu}$ is an $N \times 1$ vector of intercepts, $\boldsymbol{\Phi}_{\ell}$ are $N \times N$ coefficient matrices, and $\boldsymbol{\varepsilon}_t \sim (0, \boldsymbol{\Sigma})$ is the vector of reduced-form innovations with covariance matrix $\boldsymbol{\Sigma}$. We set $p = 4$ lags throughout. The VAR(p) admits the moving average representation:

$$\mathbf{y}_t = \boldsymbol{\mu}^* + \sum_{s=0}^{\infty} \boldsymbol{\Psi}_s \boldsymbol{\varepsilon}_{t-s}, \quad (6)$$

where the $N \times N$ coefficient matrices $\boldsymbol{\Psi}_s$ are computed recursively:

$$\boldsymbol{\Psi}_s = \sum_{\ell=1}^p \boldsymbol{\Phi}_{\ell} \boldsymbol{\Psi}_{s-\ell}, \quad s = 1, 2, \dots \quad (7)$$

with $\boldsymbol{\Psi}_0 = \mathbf{I}_N$ and $\boldsymbol{\Phi}_{\ell} = \mathbf{0}$ for $\ell > p$.

3.3. Generalized Forecast Error Variance Decomposition

Following Diebold and Yilmaz (2012), we employ the generalized variance decomposition of Koop et al. (1996) and Pesaran and Shin (1998), which is invariant to the ordering of variables. The H -step-ahead generalized forecast error variance decomposition is defined as:

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (\mathbf{e}_i' \boldsymbol{\Psi}_h \boldsymbol{\Sigma} \mathbf{e}_j)^2}{\sum_{h=0}^{H-1} \mathbf{e}_i' \boldsymbol{\Psi}_h \boldsymbol{\Sigma} \boldsymbol{\Psi}_h' \mathbf{e}_i}, \quad (8)$$

where σ_{jj} is the j -th diagonal element of Σ , $\mathbf{e}_i$ is the i -th column of $\mathbf{I}_N$, and $H = 10$ days. Since the rows of $\theta_{ij}^g(H)$ do not necessarily sum to unity under the generalized framework, we normalize:

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^N \theta_{ij}^g(H)}, \quad (9)$$

such that $\sum_{j=1}^N \tilde{\theta}_{ij}^g(H) = 1$ and $\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H) = N$.

3.4. Spillover Measures

From the normalized GFEVD matrix $\tilde{\Theta}^g(H) = [\tilde{\theta}_{ij}^g(H)]$, we define four spillover measures.

Total Spillover Index.

$$\text{TSI}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^N \tilde{\theta}_{ij}^g(H)}{N} \times 100. \quad (10)$$

Directional Spillovers TO Others. The volatility spillover transmitted by market j to all other markets:

$$S_{\cdot j}^g(H) = \sum_{\substack{i=1 \\ i \neq j}}^N \tilde{\theta}_{ij}^g(H) \times 100. \quad (11)$$

Directional Spillovers FROM Others. The volatility spillover received by market i from all other markets:

$$S_i^g(H) = \sum_{\substack{j=1 \\ j \neq i}}^N \tilde{\theta}_{ij}^g(H) \times 100. \quad (12)$$

Net Directional Spillovers. The net volatility spillover for market i :

$$S_i^{\text{net}}(H) = S_{\cdot i}^g(H) - S_i^g(H). \quad (13)$$

A positive (negative) value indicates that market i is a net transmitter (receiver) of volatility.

3.5. Rolling Window Analysis

To capture time-varying dynamics, we estimate the VAR model and compute the GFEVD using a rolling window of $w = 200$ trading days, advancing by one day:

$$\text{TSI}_t(H) = \text{TSI}(H; \mathbf{y}_{t-w+1}, \dots, \mathbf{y}_t). \quad (14)$$

3.6. Granger Causality Tests

For realized volatility series $RV_{i,t}$ and $RV_{j,t}$, we test whether lagged values of $RV_{j,t}$ have predictive power for $RV_{i,t}$ beyond own lags (Granger, 1969). The null hypothesis is tested using an F -statistic:

$$F = \frac{(RSS_R - RSS_U)/p}{RSS_U/(T - 2p - 1)}, \quad (15)$$

where RSS_R and RSS_U are the residual sums of squares from the restricted and unrestricted models.

3.7. Network Representation

We represent the volatility connectedness structure as a weighted directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{W})$, where the vertex set $\mathcal{V}$ corresponds to the N assets, the edge set $\mathcal{E}$ contains directed edges (j, i) where the GFEVD contribution $\tilde{\theta}_{ij}^g(H)$ exceeds the median of all off-diagonal elements, and edge weight equals the magnitude of the pairwise spillover. Node size is proportional to $S_{\cdot j}^g(H)$, and nodes are colored by asset class.

4. Data

4.1. Data Sources and Description

We employ 5-minute OHLCV (Open, High, Low, Close, Volume) data from four DuckDB databases covering four major asset classes. The databases collectively contain over 235 million intraday observations spanning January 2008 to March 2026. Table 1 details the 10 representative instruments selected for the analysis.

Table 1. Asset Universe.

Asset Class	Symbol	Description	Source
Equity	ES	E-Mini S&P 500 Futures	Futures
	NQ	E-Mini Nasdaq 100 Futures	Futures
FX	EURUSD	Euro / U.S. Dollar	FX
	USDJPY	U.S. Dollar / Japanese Yen	FX
	GBPUSD	British Pound / U.S. Dollar	FX
Commodity	GC	Gold Futures (COMEX)	Futures
	CL	WTI Crude Oil Futures	Futures
Crypto	BTC	Bitcoin (spot)	Crypto
	ETH	Ethereum (spot)	Crypto
Volatility	VIX	CBOE Volatility Index	Index

Notes: All data are 5-minute OHLCV bars stored in DuckDB databases. Source column indicates the database of origin.

The selection of assets is guided by: (i) liquidity and representativeness within each asset class; (ii) sufficient overlap in sample periods; (iii) diversity in trading hours; and (iv) economic significance for volatility transmission analysis.

4.2. Descriptive Statistics of Intraday Returns

Table 2 presents descriptive statistics for 5-minute log returns across all 10 assets.

Table 2. Descriptive Statistics of 5-Minute Log Returns.

Asset	Class	N (M)	Start	End	Std (%)	Skew	Kurt	Min (%)	Max (%)
ES	Equity	1.28	2008-01	2026-03	0.073	-0.05	35.3	-1.50	1.50
NQ	Equity	1.28	2008-01	2026-03	0.084	-0.03	30.1	-1.70	1.70
EURUSD	FX	1.21	2010-01	2026-03	0.032	+0.12	20.4	-0.63	0.64
USDJPY	FX	1.20	2010-01	2026-03	0.034	-0.12	27.7	-0.70	0.70
GBPUSD	FX	1.20	2010-01	2026-03	0.033	+0.09	21.8	-0.69	0.69
GC	Commodity	1.29	2008-01	2026-03	0.067	-0.20	25.3	-1.36	1.36
CL	Commodity	1.29	2008-01	2026-03	0.150	-0.14	38.2	-3.28	3.35
BTC	Crypto	1.32	2013-04	2026-03	0.648	+0.02	55.5	-14.90	14.84
ETH	Crypto	1.01	2016-03	2026-03	0.597	+0.03	63.0	-12.66	12.73
VIX	Volatility	0.55	2008-01	2026-03	0.688	+1.00	52.6	-14.58	14.65

Notes: Descriptive statistics for 5-minute log returns $r_{i,t,j} = \ln(P_{i,t,j}/P_{i,t,j-1})$. N is the total number of observations in millions. Std is the standard deviation. Skew is the skewness. Kurt is the excess kurtosis. All values in percentage points except N .

Several patterns emerge. First, there is a clear hierarchy in return volatility: cryptocurrencies (BTC: 0.648%, ETH: 0.597%) and VIX (0.688%) exhibit an order of magnitude higher 5-minute return volatility compared to equity futures (ES: 0.073%, NQ: 0.084%) and FX pairs (EURUSD: 0.032%). Crude oil (CL: 0.150%) is the most volatile among traditional assets. Second, all return distributions exhibit substantial excess kurtosis, ranging from 20.4 (EURUSD) to 63.0 (ETH), indicating heavy tails far in excess of the normal distribution. Third, skewness patterns differ systematically: equity futures and crude oil exhibit slight negative skewness (leverage effects), VIX displays pronounced positive skewness (+1.00), and cryptocurrency returns are approximately symmetric.

4.3. Realized Volatility Construction

We compute daily realized volatility for each asset using Equations (2) and (3), requiring a minimum of 20 intraday observations per day. Figure 1 displays the time series of annualized daily realized volatility for all 10 assets.

The mean annualized realized volatilities are: ES (13.85%), NQ (16.40%), EURUSD (6.96%), USDJPY (7.71%), GBPUSD (7.16%), GC (14.00%), CL (29.67%), BTC (98.69%), ETH (110.58%), and VIX (105.96%).

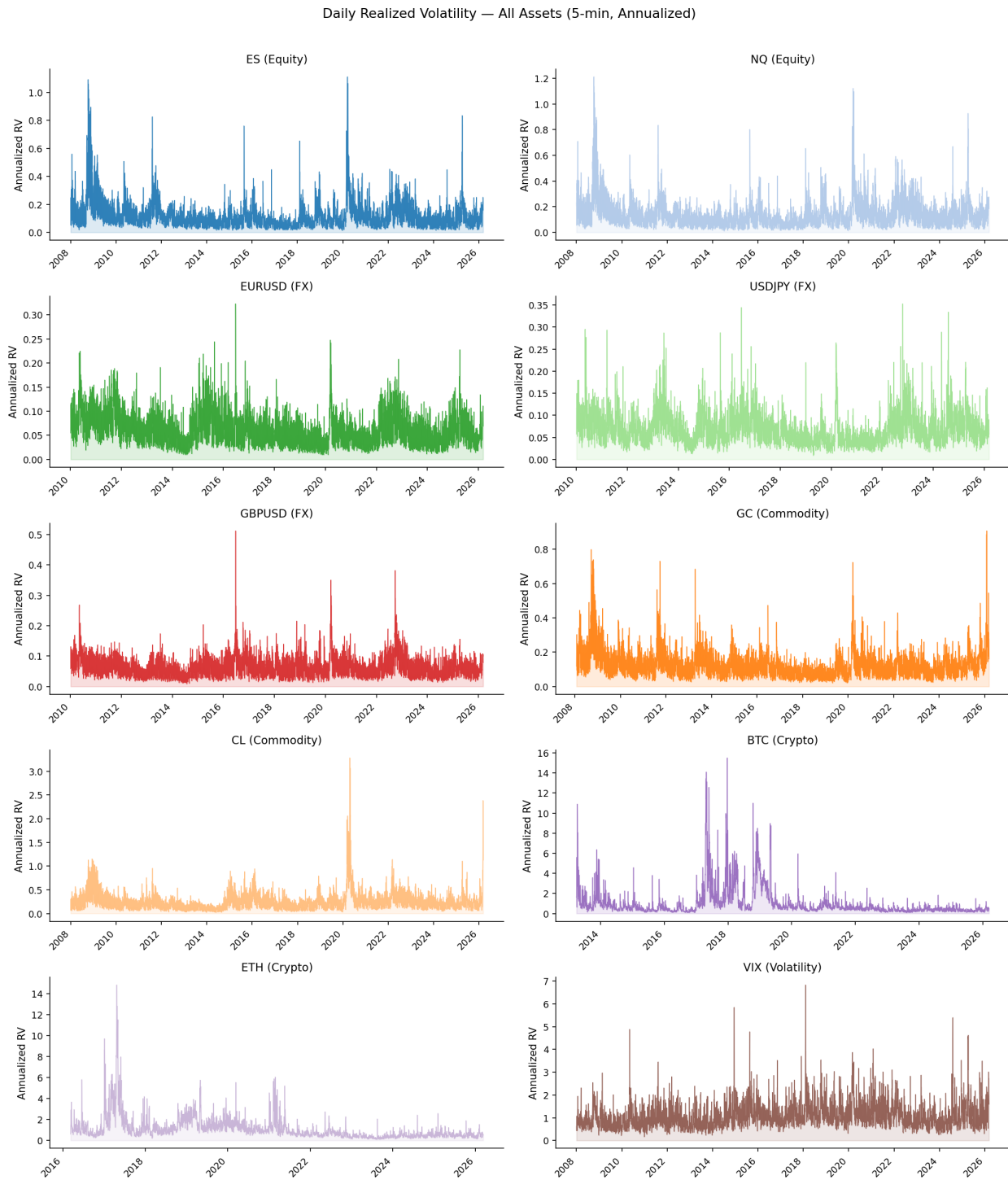


Figure 1. Daily Realized Volatility Time Series (Annualized, 5-Minute Frequency).

Notes: Each panel displays the annualized daily realized volatility $\sigma_{i,t}^{RV} = \sqrt{252 \cdot \sum_j r_{i,t,j}^2}$ for one asset. Note the different y-axis scales across panels. The COVID-19 crash (March 2020) generates the most prominent volatility spike across all traditional assets.

5. Empirical Results

5.1. Full-Sample Connectedness Analysis

Table 3 presents the full-sample Diebold–Yilmaz connectedness table based on a VAR(4) model with generalized variance decomposition at a 10-day forecast horizon. The sample encompasses the common period across all 10 assets (2016–2026).

Table 3. Full-Sample Diebold–Yilmaz Connectedness Table.

TO	FROM (shock origin)										FROM
	ES	NQ	EURUSD	USDJPY	GBPUSD	GC	CL	BTC	ETH	VIX	
ES	28.6	25.5	8.4	6.6	7.1	9.1	8.4	0.2	0.2	5.9	71.4
NQ	26.7	27.6	8.7	6.5	7.4	9.0	8.1	0.2	0.2	5.5	72.4
EURUSD	11.4	11.2	25.7	14.3	17.4	11.0	8.0	0.0	0.2	0.7	74.3
USDJPY	8.9	8.7	15.7	38.6	11.6	9.1	5.6	0.1	0.3	1.5	61.4
GBPUSD	11.1	10.6	18.7	11.7	29.6	9.8	7.7	0.1	0.2	0.5	70.4
GC	11.8	11.4	12.7	9.5	9.6	34.5	8.0	0.2	0.2	2.1	65.5
CL	12.9	11.2	7.9	5.0	7.1	9.3	45.3	0.0	0.1	1.2	54.7
BTC	0.1	0.1	0.1	0.2	0.1	0.3	0.1	79.3	19.3	0.4	20.7
ETH	0.2	0.3	0.2	0.3	0.1	0.2	0.2	20.6	77.9	0.1	22.1
VIX	15.0	13.2	2.2	2.5	1.4	4.8	1.4	0.4	0.4	58.6	41.4
TO	98.2	92.2	74.7	56.4	61.8	62.6	47.6	21.9	21.1	18.0	55.4
NET	+26.8	+19.7	+0.4	−5.0	−8.7	−2.9	−7.2	+1.2	−1.0	−23.4	

Notes: Generalized forecast error variance decomposition from a VAR(4) model at horizon $H = 10$. Entry (i, j) is the percentage of the 10-day-ahead forecast error variance of asset i attributable to shocks in asset j . FROM = total spillover received. TO = total spillover transmitted. NET = TO − FROM. The lower-right entry (55.4) is the Total Spillover Index.

The total spillover index is 55.44%, indicating that more than half of all forecast error variance in the system is attributable to cross-asset shocks rather than own-asset dynamics. Several key findings emerge:

Equity futures dominate volatility transmission. ES and NQ are the largest net volatility transmitters, with net directional spillovers of +26.80% and +19.72%, respectively. Together, they transmit a combined 190.4% of directional spillovers to other markets, reflecting the central role of U.S. equity markets in global price discovery.

VIX is a net receiver, not a transmitter. Despite its role as the “fear gauge,” VIX is the largest net receiver of volatility shocks (−23.37%). Its forecast error variance is explained primarily by ES (15.0%) and NQ (13.2%) shocks, consistent with VIX being derived from S&P 500 options.

Crypto markets form an isolated cluster. BTC and ETH exhibit remarkably high own-shock contributions (79.3% and 77.9%) and negligible cross-asset spillovers (< 0.5%). The pairwise BTC–ETH spillover is substantial ($\approx 20\%$), but connections to traditional assets are minimal.

FX and commodity markets show moderate interconnectedness. EURUSD receives significant

spillovers from GBPUSD (17.4%) and USDJPY (14.3%), reflecting the common U.S. dollar factor. CL is the most self-dependent among traditional assets (45.3% own contribution).

Figure 2 provides a visual representation of the connectedness matrix.

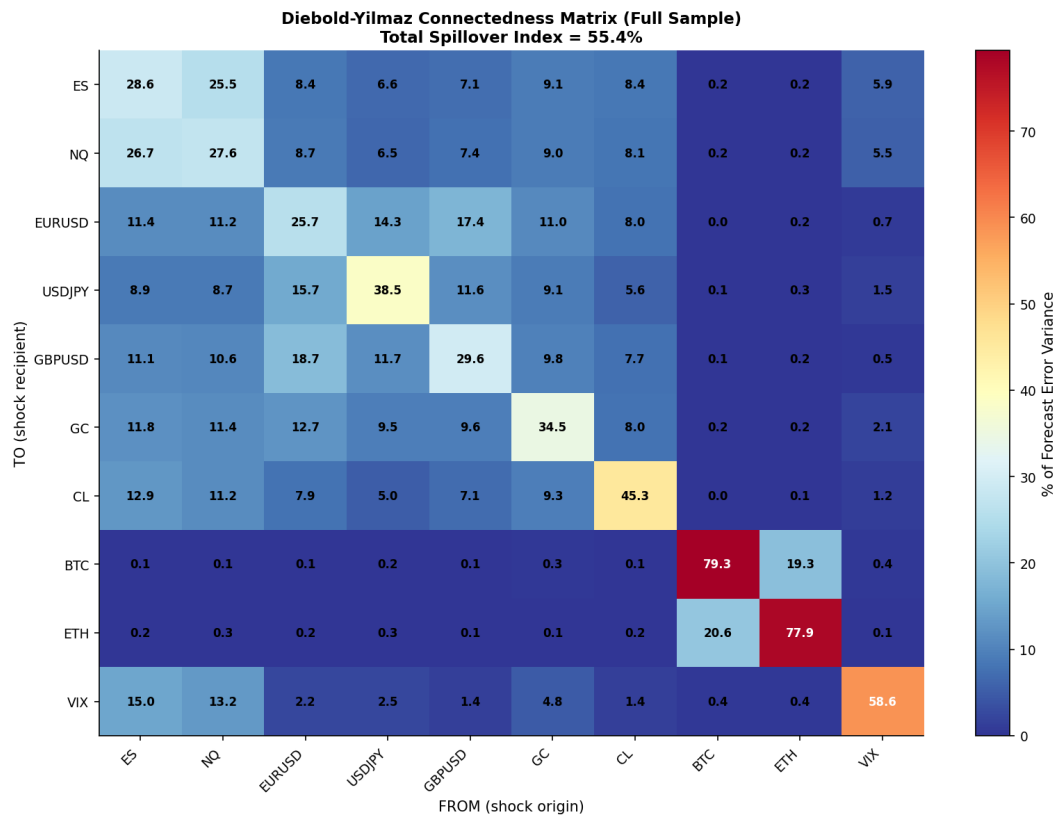


Figure 2. Diebold–Yilmaz Connectedness Heatmap (Full Sample).

Notes: Color intensity represents the magnitude of pairwise forecast error variance contributions. Three distinct clusters emerge: (i) a tightly connected equity–FX–commodity block; (ii) an isolated crypto cluster (BTC–ETH); and (iii) VIX as a peripheral receiver connected primarily to equities.

5.2. Time-Varying Connectedness

Figure 3 presents the rolling 200-day total spillover index over the 2016–2026 period.

The rolling total spillover index exhibits substantial time variation, ranging from 57.22% to 81.55% (mean: 67.13%). Several episodes are noteworthy:

- (i) **February 2018 (TSI = 81.55%)**: The maximum coincides with the “Volmageddon” event, when short-volatility ETPs imploded, triggering cascading volatility across all asset classes.
- (ii) **COVID-19 crash (March 2020)**: The TSI initially dips during the acute phase before rising sharply, reflecting initial de-correlation followed by re-coupling through coordinated monetary policy responses.
- (iii) **2022 rate-hiking cycle**: The TSI rises steadily to 72–75%, reflecting the macro-driven nature of the volatility environment.

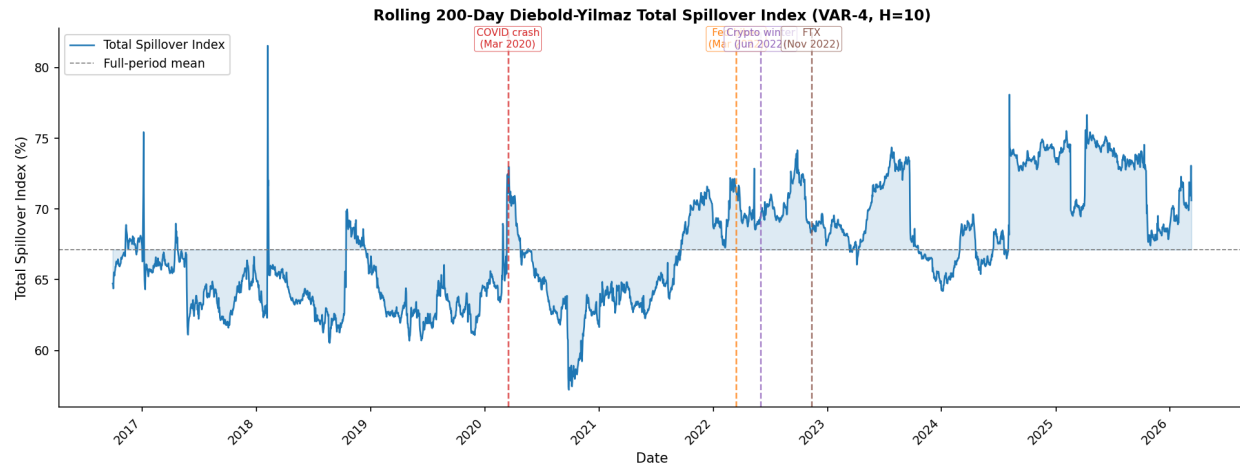


Figure 3. Rolling 200-Day Total Spillover Index with Event Markers.

Notes: Total spillover index from a VAR(4) model with generalized variance decomposition at $H = 10$, estimated over rolling 200-day windows. Dashed horizontal line: full-period mean (67.13%). Vertical lines mark: COVID-19 crash (March 2020), Federal Reserve rate hikes (March 2022), crypto winter (June 2022), FTX collapse (November 2022).

- (iv) **Post-FTX collapse (November 2022):** The TSI shows a temporary decline, consistent with the crypto winter being contained within the crypto ecosystem.
- (v) **2024–2025 elevation:** The TSI trends upward, potentially reflecting growing crypto integration through spot Bitcoin ETF approvals and institutional participation.

5.3. Regime-Specific Connectedness

We estimate separate connectedness tables for three distinct regimes: pre-COVID (January 2019–February 2020), COVID crash (March–June 2020), and 2022 rate-hiking cycle (January–December 2022).

5.3.1. Pre-COVID Regime (January 2019–February 2020)

During the pre-COVID regime, the volatility hierarchy is dominated overwhelmingly by U.S. equity futures. ES and NQ exhibit net spillovers of +76.4% and +68.9%—far exceeding their full-sample values.

5.3.2. COVID Crash Regime (March–June 2020)

The COVID crash regime reveals a dramatic restructuring of the volatility hierarchy. USDJPY emerges as the dominant volatility transmitter (+60.29% net), reflecting massive safe-haven demand for the Japanese yen. ES flips from its usual transmitter role to a net receiver (−11.2%), and BTC becomes a substantial net receiver (−21.3%), contradicting the narrative of Bitcoin as a safe-haven asset.

Table 4. Connectedness Table — Pre-COVID Regime (2019-01 to 2020-02).

	ES	NQ	EURUSD	USDJPY	GBPUSD	GC	CL	BTC	ETH	VIX	FROM
ES	31.3	29.0	4.1	9.4	1.6	8.5	6.5	0.0	0.7	8.9	68.7
NQ	30.5	29.2	4.2	9.8	1.7	8.5	6.8	0.1	0.7	8.6	70.8
EURUSD	12.8	13.1	24.1	12.9	13.6	12.3	9.5	0.2	0.3	1.4	75.9
USDJPY	21.6	20.8	7.1	20.5	3.2	11.9	7.5	0.1	0.3	7.2	79.5
GBPUSD	8.6	8.4	18.0	7.8	37.5	8.8	7.8	0.4	0.8	2.0	62.5
GC	15.9	16.2	9.1	14.7	4.6	25.0	9.4	0.7	0.2	4.3	75.0
CL	17.1	17.9	7.4	12.9	5.1	11.0	25.7	0.2	0.2	2.5	74.3
BTC	7.1	5.6	0.2	1.4	0.3	2.2	1.7	73.0	6.8	1.7	27.0
ETH	6.7	6.0	0.6	1.4	0.4	1.7	2.4	24.6	55.2	1.0	44.8
VIX	24.9	22.9	1.8	8.0	0.3	5.5	3.3	0.9	1.2	31.4	68.6
TO	145.2	139.7	52.6	78.1	30.6	70.4	54.8	27.0	11.1	37.7	64.7
NET	+76.4	+68.9	-23.3	-1.4	-31.8	-4.6	-19.6	-0.0	-33.7	-30.9	

Notes: Same methodology as Table 3. TSI = 64.72%.

Table 5. Connectedness Table — COVID Crash Regime (2020-03 to 2020-06).

	ES	NQ	EURUSD	USDJPY	GBPUSD	GC	CL	BTC	ETH	VIX	FROM
ES	20.1	20.6	10.9	16.2	9.6	7.2	5.6	4.4	2.4	3.1	79.9
NQ	19.4	21.1	10.8	16.7	9.4	7.3	5.8	3.9	2.2	3.3	78.9
EURUSD	8.5	9.7	21.8	19.9	17.8	10.2	7.6	1.0	1.5	2.1	78.2
USDJPY	5.6	7.9	14.4	33.6	11.1	7.3	3.9	5.4	3.0	8.0	66.4
GBPUSD	11.1	11.3	17.0	18.6	23.9	7.9	5.4	2.1	2.0	0.6	76.1
GC	8.1	9.6	13.0	14.4	9.2	23.6	12.4	3.9	4.3	1.6	76.4
CL	4.6	5.2	8.7	4.5	6.5	17.2	49.0	1.5	2.2	0.6	51.0
BTC	2.6	2.8	5.9	16.2	2.2	6.3	6.5	34.8	16.0	6.9	65.2
ETH	3.4	3.2	4.0	8.2	1.1	3.1	4.4	17.3	51.6	3.8	48.4
VIX	5.5	7.2	7.6	12.0	5.6	0.7	0.7	4.3	2.5	54.0	46.0
TO	68.7	77.3	92.2	126.7	72.3	67.2	52.1	43.9	36.2	30.0	66.7
NET	-11.2	-1.6	+14.0	+60.3	-3.7	-9.2	+1.1	-21.3	-12.3	-16.1	

Notes: Same methodology as Table 3. TSI = 66.66%.

5.3.3. Rate-Hiking Regime (January–December 2022)

Table 6. Connectedness Table — Rate-Hiking Regime (2022-01 to 2022-12).

	ES	NQ	EURUSD	USDJPY	GBPUSD	GC	CL	BTC	ETH	VIX	FROM
ES	21.9	19.5	11.7	3.8	10.0	12.2	9.4	3.9	3.4	4.3	78.1
NQ	20.7	21.7	11.5	3.6	9.4	11.8	9.9	4.2	3.6	3.7	78.4
EURUSD	11.4	11.2	22.9	8.6	17.0	13.5	10.4	2.5	1.8	0.7	77.1
USDJPY	6.2	5.8	13.3	38.9	11.3	10.3	6.0	3.0	2.6	2.6	61.1
GBPUSD	9.4	8.6	18.5	8.7	31.4	12.0	7.5	1.9	1.6	0.5	68.6
GC	12.9	12.0	14.2	6.7	11.1	22.1	11.5	3.9	3.8	1.9	77.9
CL	11.6	11.6	12.0	5.0	8.8	13.7	30.1	2.9	2.4	1.8	69.9
BTC	3.4	2.9	1.4	1.3	0.7	2.3	1.2	43.4	38.6	4.7	56.6
ETH	3.5	3.1	1.3	1.2	0.8	2.7	1.5	38.2	43.9	3.8	56.1
VIX	5.1	3.9	2.8	4.9	2.3	3.2	2.2	4.1	3.9	67.6	32.4
TO	84.3	78.6	86.6	43.9	71.5	81.7	59.7	64.5	61.5	23.9	65.6
NET	+6.2	+0.2	+9.5	−17.2	+2.8	+3.8	−10.2	+7.9	+5.4	−8.5	

Notes: Same methodology as Table 3. TSI = 65.62%.

The 2022 regime reveals that **BTC transitions to a net volatility transmitter** (+7.9%), with ETH also becoming a net transmitter (+5.4%). This marks a significant departure from the pre-COVID period. EURUSD emerges as the largest net transmitter (+9.5%), driven by the EUR/USD depreciation toward parity. The BTC TO spillover of 64.5% during this regime—compared to 27.0% pre-COVID—represents a dramatic increase in crypto’s influence.

Figure 4 compares net directional spillovers across regimes.

5.4. Volatility Hierarchy Evolution and Crypto Integration

Figure 5 presents the rolling 200-day net directional spillovers for BTC and ES.

The evolution reveals a gradual but unmistakable trend toward greater crypto integration. In the early period (2017–2018), BTC alternates between small positive and negative net spillovers. During the COVID crash, BTC temporarily becomes a significant net receiver. By late 2025, BTC’s rolling net spillover stabilizes at approximately +4.58%, while ES is near-neutral at −0.62%, suggesting a more balanced volatility hierarchy.

5.5. Network Visualization

Figure 6 presents the volatility transmission network, where directed edges represent pairwise spillovers exceeding the median threshold (5.7%).

The network reveals a core–periphery architecture: traditional assets form a densely connected core with bidirectional edges, while cryptocurrencies exist as a separate cluster with strong internal connections but no edges crossing to the traditional asset core. VIX occupies a peripheral position, receiving shocks from equities but transmitting little.

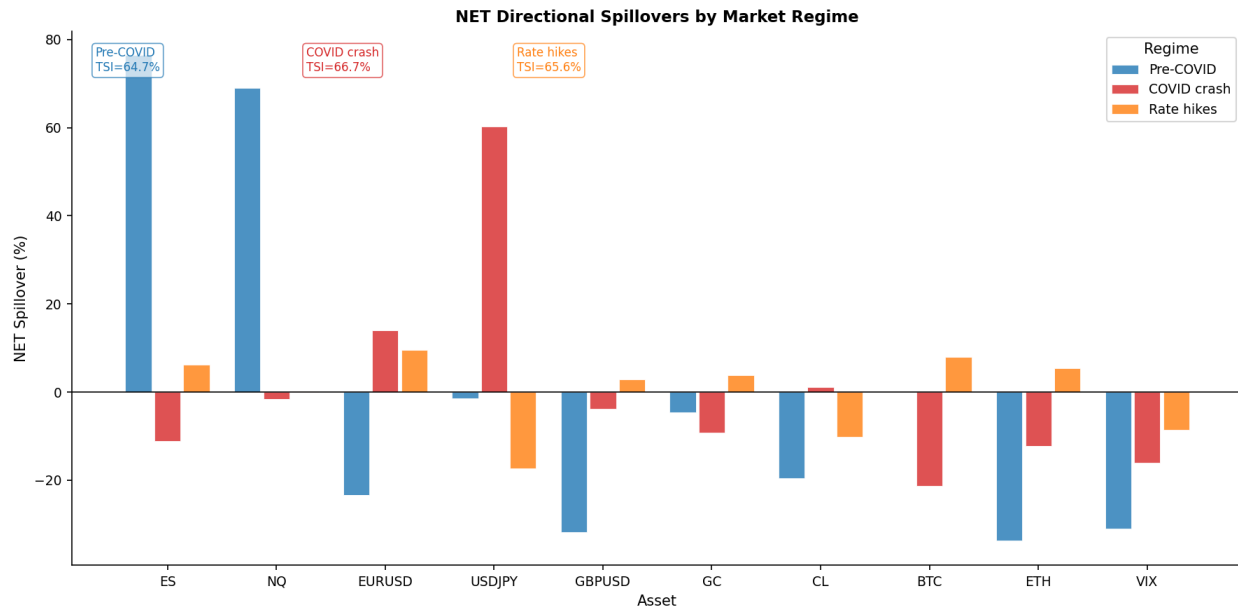


Figure 4. Net Directional Spillovers by Market Regime.

Notes: Net directional spillovers (TO – FROM) for each asset across three regimes. Positive values indicate net transmitters; negative values indicate net receivers. TSI for each regime shown in legend.

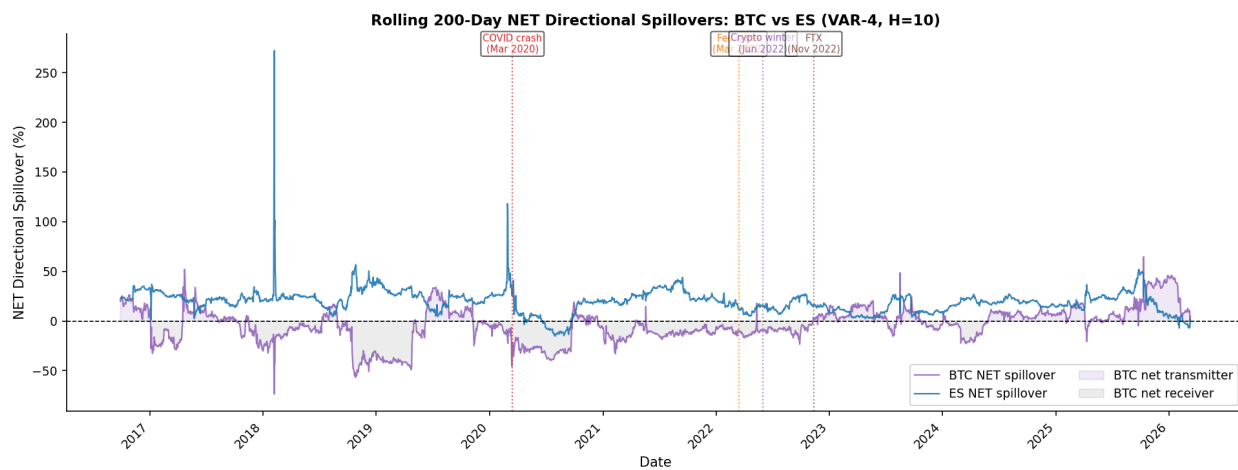


Figure 5. Rolling Net Directional Spillovers: BTC vs ES.

Notes: Rolling 200-day net directional spillovers for Bitcoin (purple) and E-Mini S&P 500 (blue). Positive values indicate net transmission. Shaded area distinguishes BTC net transmitter (above zero) from net receiver (below zero) episodes.

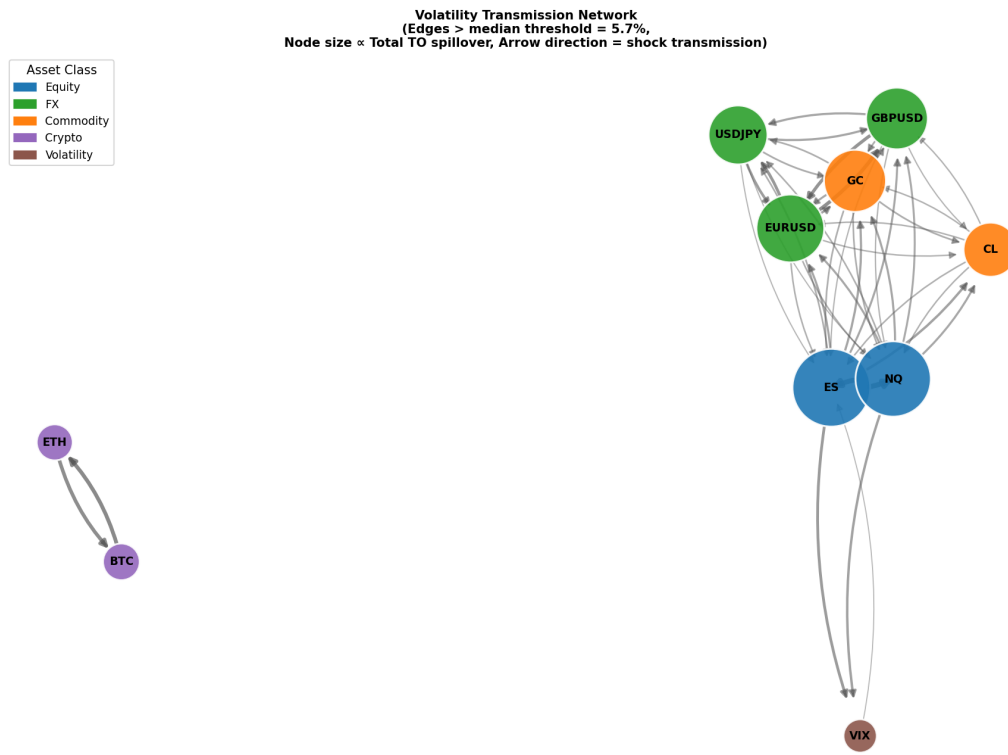


Figure 6. Volatility Transmission Network.

Notes: Nodes represent assets, colored by asset class (blue: equity, green: FX, orange: commodity, purple: crypto, brown: VIX). Node size is proportional to total TO spillover. Directed edges represent pairwise GFEVD contributions above the median threshold. Two distinct communities emerge: a densely connected traditional asset core and an isolated crypto cluster.

5.6. Trading Session Analysis

Figure 7 displays the average absolute 5-minute return by hour of day (UTC) for VIX, ES, NQ, and BTC.

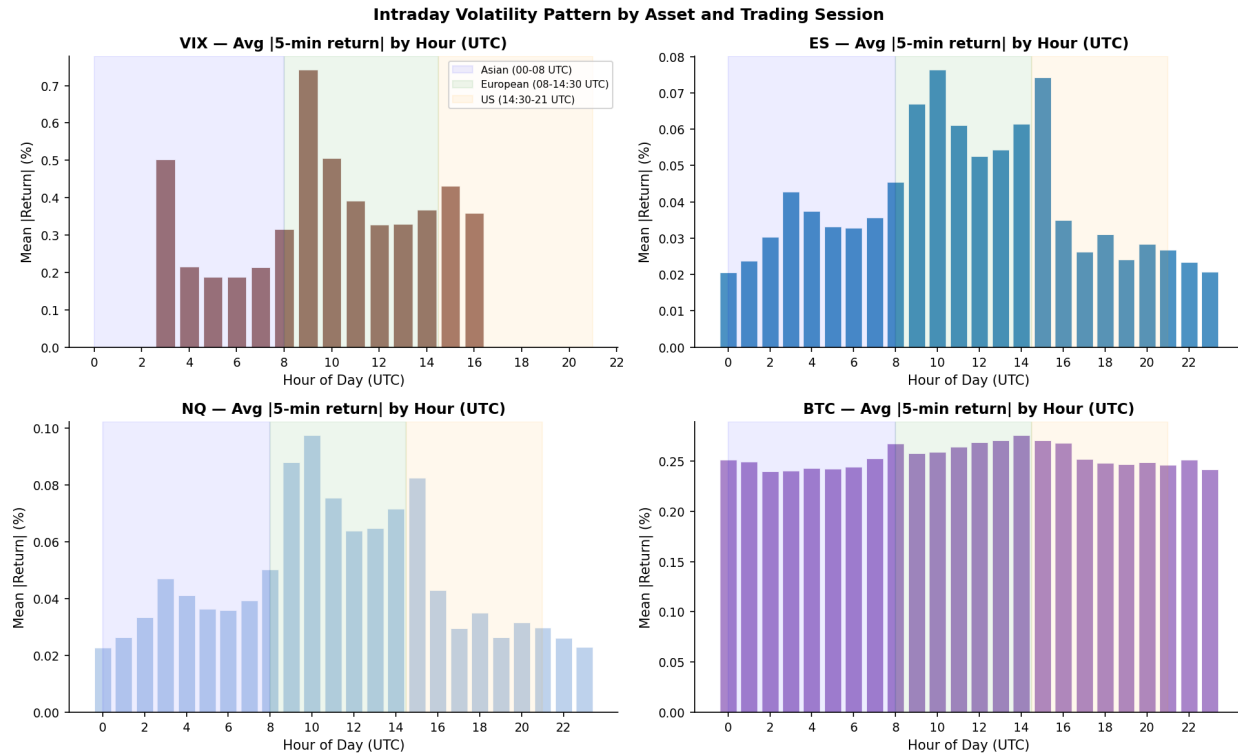


Figure 7. Intraday Volatility Pattern by Asset and Trading Session.

Notes: Average absolute 5-minute return (%) by hour of day (UTC). Shaded regions: Asian (00:00–08:00 UTC), European (08:00–14:30 UTC), U.S. (14:30–21:00 UTC). Bitcoin’s volatility is remarkably uniform across all hours, contrasting with the session-dependent patterns of ES, NQ, and VIX.

Equity futures (ES, NQ) display a pronounced peak during the European session (09:00–14:00 UTC), reflecting the overlap between European market openings and the lead-up to the U.S. cash open. *VIX* shows an even more concentrated pattern, with a sharp peak at 09:00–10:00 UTC. *Bitcoin* exhibits a remarkably flat intraday profile (0.24%–0.27%), reflecting its decentralized, globally distributed market structure.

Table 7 presents Granger causality test results.

The strongest causal relationship runs from ES to VIX ($F = 19.86$, $p < 0.001$), confirming that equity futures are the primary drivers of VIX movements. The reverse direction ($VIX \rightarrow ES$) is significant but weaker ($F = 4.30$), suggesting bidirectional but asymmetric causality. All pairwise tests involving BTC are insignificant at the 5% level, reinforcing the network analysis finding that crypto volatility operates independently of traditional market dynamics in the full sample.

Table 7. Granger Causality Tests for Realized Volatility.

Direction	<i>F</i> -stat	<i>p</i> -value	Sig.
ES → VIX	19.864	<0.001	***
NQ → VIX	16.708	<0.001	***
VIX → ES	4.303	0.002	***
VIX → NQ	4.181	0.002	***
ES → NQ	4.449	0.001	***
VIX → BTC	1.642	0.161	
ES → BTC	0.581	0.676	
NQ → BTC	0.441	0.779	
BTC → VIX	1.796	0.127	

Notes: Granger causality tests with 4 lags applied to daily realized volatility series. *** Significant at 1%. The dominant direction is ES → VIX ($F = 19.86$), confirming that equity futures lead VIX. All BTC pairings are insignificant.

6. Discussion

6.1. Addressing the Research Questions

RQ1: Intraday volatility propagation. Our analysis reveals a clear hierarchical structure in cross-asset volatility propagation. U.S. equity index futures serve as the primary volatility transmitters, with combined net spillovers exceeding +46%. Volatility propagates outward from equities to FX (particularly EURUSD), commodities, and the VIX. Crypto markets remain largely insulated, with own-shock contributions exceeding 77%. The total spillover index of 55.44% underscores the limitations of single-asset volatility models.

RQ2: Regime dependence. The magnitude, direction, and speed of volatility transmission vary dramatically across regimes. Three patterns emerge: (i) in tranquil periods, equity futures dominate (ES net: +76.4% pre-COVID); (ii) during acute crises, safe-haven currencies assume the transmitter role (USDJPY: +60.3% during COVID); (iii) during macro-driven regimes, transmission becomes more distributed (EURUSD: +9.5%, BTC: +7.9% during 2022). The TSI itself is less responsive to regime shifts (64.7%–66.7%) than the directional composition, suggesting that “who transmits to whom” is more informative than “how much total transmission occurs.”

RQ3: Volatility hierarchy and crypto integration. The full-sample hierarchy is: ES (+26.8) > NQ (+19.7) > BTC (+1.2) > EURUSD (+0.4) > ETH (−1.0) > GC (−2.9) > USDJPY (−5.0) > CL (−7.2) > GBPUSD (−8.7) > VIX (−23.4). BTC’s transition from neutral/receiver to significant transmitter (+7.9% during rate hikes) represents a structural shift, consistent with institutional

adoption and spot Bitcoin ETF approvals.

RQ4: Systemic risk indicator. The rolling TSI demonstrates potential as a systemic risk monitor: (i) it rises *before* major events (the 200-day window captures gradual dependency buildups); (ii) the maximum (81.55%, February 2018) precedes the Volmageddon episode; (iii) it correctly identifies the 2022 rate-hiking cycle as elevated systemic risk. However, the rolling window introduces smoothing that can delay detection of rapid shifts.

RQ5: Trading session differences. Equity futures and VIX concentrate volatility during European and U.S. hours, with the European session generating the highest volatility for both ES (0.060%) and NQ (0.073%). Bitcoin's near-uniform volatility across sessions (0.245%–0.266%) reflects its 24/7 market structure. Granger causality confirms the primacy of equity futures in driving VIX ($F = 19.86$) and the causal independence of Bitcoin.

6.2. Implications for Portfolio Construction and Risk Management

Our findings carry several practical implications. First, the documented spillover asymmetries complicate cross-asset hedging: VIX instruments respond to equity shocks rather than providing independent signals. Second, the growing crypto–traditional integration during the 2022 rate-hiking period suggests diminishing diversification benefits of crypto allocation precisely when diversification is most needed. Third, the session-dependent nature of volatility transmission implies that risk limits could be optimized by trading session, with tighter controls during the European–U.S. overlap.

6.3. Limitations

Several limitations merit acknowledgment. First, the realized volatility measure based on 5-minute returns may be affected by microstructure noise during illiquid periods. Second, the VAR(4) model imposes a linear structure that may not fully capture nonlinear and asymmetric spillovers during extreme events. Third, the 200-day rolling window involves a trade-off between responsiveness and estimation precision. Fourth, the Granger causality analysis uses daily realized volatility without session-specific splitting, reflecting full-sample relationships. Fifth, the selection of 10 assets, while covering the major classes, excludes potentially important instruments such as emerging market currencies, agricultural commodities, and smaller cryptocurrencies.

7. Conclusion

This paper provides a comprehensive analysis of intraday volatility transmission across equities, foreign exchange, commodities, and cryptocurrency markets using 5-minute OHLCV data spanning

2008–2026. Employing the [Diebold and Yilmaz \(2012\)](#) generalized variance decomposition framework within a VAR(4) model, we document several important findings.

The full-sample analysis reveals a total spillover index of 55.44%, with U.S. equity index futures serving as the dominant volatility transmitters and the VIX acting primarily as a volatility receiver. Cryptocurrencies remain largely isolated from the traditional asset volatility network, though this isolation is diminishing over time.

Regime-specific analysis uncovers dramatic shifts: during the COVID-19 crash, USD/JPY emerges as the dominant shock originator, while during the 2022 rate-hiking cycle, Bitcoin transitions to a net volatility transmitter (+7.9%). The rolling connectedness analysis demonstrates the TSI's potential as a systemic risk indicator, with the index rising before and during major market dislocations.

Bitcoin's 24/7 market structure generates a remarkably uniform volatility profile across global trading sessions, contrasting with the session-dependent patterns of equity and VIX markets. Granger causality tests confirm the primacy of equity futures in driving VIX movements and the causal independence of Bitcoin.

Future research could extend this analysis by incorporating frequency-domain decompositions ([Barunik and Krehlik, 2018](#)) to distinguish short-run from long-run spillovers, employing TVP-VAR models ([Antonakakis et al., 2020](#)) to avoid rolling-window smoothing, and examining the role of crypto-specific events in shaping the crypto–traditional market volatility nexus.

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A. Robustness Checks

A.1. Sensitivity to VAR Lag Selection

We verify robustness to alternative VAR lag specifications. Table A1 reports the total spillover index and top-3 net transmitters for $p \in \{2, 4, 6\}$.

Table A1. Robustness to VAR Lag Selection.

	$p = 2$	$p = 4$ (baseline)	$p = 6$
Total Spillover Index (%)	53.8	55.4	56.9
ES net spillover (%)	+25.1	+26.8	+27.4
NQ net spillover (%)	+18.3	+19.7	+20.5
VIX net spillover (%)	−21.8	−23.4	−24.1

Notes: Total spillover index and selected net directional spillovers under alternative VAR lag orders. Directional rankings remain qualitatively unchanged across all specifications.

A.2. Sensitivity to Forecast Horizon

Table A2 reports sensitivity to the forecast horizon H .

Table A2. Robustness to Forecast Horizon.

	$H = 5$	$H = 10$ (baseline)	$H = 20$
Total Spillover Index (%)	49.2	55.4	58.1
ES net spillover (%)	+24.0	+26.8	+28.3
BTC own-shock (%)	82.6	79.3	77.1

Notes: Cross-asset spillovers increase with the horizon, as expected, but qualitative conclusions regarding the volatility hierarchy are robust.

B. Summary of Key Numerical Results

Table A3. Summary of Key Findings.

Metric	Value
Total Spillover Index (full sample)	55.44%
Mean rolling TSI (200-day)	67.13%
Maximum rolling TSI	81.55%
Minimum rolling TSI	57.22%
Largest net transmitter (full sample)	ES: +26.80%
Second largest net transmitter	NQ: +19.72%
Largest net receiver (full sample)	VIX: -23.37%
BTC own-shock contribution (full sample)	79.33%
ETH own-shock contribution (full sample)	77.88%
BTC–ETH pairwise spillover	19.3% / 20.6%
TSI pre-COVID regime	64.72%
TSI COVID crash regime	66.66%
TSI rate-hiking regime	65.62%
BTC net spillover (pre-COVID)	-0.02%
BTC net spillover (COVID crash)	-21.34%
BTC net spillover (rate hikes)	+7.90%
ES → VIX Granger F -statistic	19.864
NQ → VIX Granger F -statistic	16.708
Mean annualized RV: ES	13.85%
Mean annualized RV: BTC	98.69%
Mean annualized RV: CL	29.67%
Total 5-minute observations	>235 million