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

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Abstract

This paper measures how realized volatility is transmitted across equity index futures, major exchange rates, gold and crude oil futures, the VIX, and the two largest cryptocurrencies. Daily realized volatilities are built from 5-minute bars for ten instruments over 2008–2026, and the connectedness of their logarithms is estimated on the 2,514 trading days common to all series (March 2016–March 2026) with the generalized variance decomposition of a VAR(4) at a ten-day horizon (Diebold and Yilmaz, 2012), with residual-bootstrap confidence intervals. Cross-asset shocks account for 54.8% (90% interval 53.1–56.9) of forecast-error variance. E-mini S&P 500 and Nasdaq 100 futures are the only robust net transmitters (+36.0 and +25.6 percentage points), while the realized volatility of the VIX (−20.6), crude oil (−14.2) and sterling (−13.2) are net receivers; the net positions of bitcoin and ether are statistically indistinguishable from zero. Bitcoin and ether form a tightly linked pair (27–28% of each other's variance) whose exposure to traditional assets rises from under 10% of forecast-error variance before 2020 to 20–46% in 2020–2025, with information flowing predominantly from U.S. equities to crypto: in the 2024–2026 spot-ETF period bitcoin is a significant net receiver (−12.4, interval −20.4 to −2.1). Rolling estimates show that total connectedness rose during the COVID-19 crash and reached its highest level in 2025. Intraday, after converting exchange time stamps to UTC, equity and VIX volatility concentrate in the U.S. cash session (53–63% of daily variance), whereas bitcoin's hourly profile is nearly flat (peak-to-trough ratio 1.2); U.S.-session equity volatility predicts bitcoin's next Asian-session volatility, but neither bitcoin's overnight nor its weekend volatility predicts U.S. equity volatility. The paper documents how calendar alignment of 24/7 and exchange-traded series materially affects connectedness estimates.

Keywords: realized volatility, volatility spillovers, connectedness, generalized variance decomposition, high-frequency data, cryptocurrency, trading sessions

JEL Classification: C32, C58, G12, G15

Contents

1	Introduction	3
2	Literature Review	5
2.1	From Volatility Spillovers to Connectedness	5
2.2	Cross-Asset Transmission: Exchange Rates, Commodities and the VIX	6
2.3	Cryptocurrencies and Traditional Markets	7
2.4	Realized Volatility and Intraday Periodicity	8
2.5	Contribution	8
3	Methodology	9
3.1	Realized Volatility	9
3.2	Vector Autoregression	9
3.3	Generalized Forecast-Error Variance Decomposition	10
3.4	Connectedness Measures	10
3.5	Inference	11
3.6	Rolling Windows and Sub-Samples	11
3.7	Granger Causality	12
3.8	Intraday Periodicity and Session-Ordered Predictability	12
3.9	Network Representation	13
4	Data	13
4.1	Sources and Instruments	13
4.2	Time Stamps and Alignment	13
4.3	Descriptive Statistics of 5-Minute Returns	14
4.4	Daily Realized Volatility	15
5	Empirical Results	16
5.1	Full-Sample Connectedness	16
5.2	Robustness of the Full-Sample Results	19
5.3	Time-Varying Connectedness	21
5.4	Regime-Specific Connectedness	22
5.5	Crypto Integration by Calendar Year	25
5.6	Network Representation	26
5.7	Granger Causality	27
5.8	Intraday Periodicity and Trading Sessions	28

6	Discussion	32
6.1	Answers to the Research Questions	32
6.2	Comparison with the Literature and Implications	33
6.3	Methodological Lessons	34
6.4	Limitations	34
7	Conclusion	35
	References	37
A	Audit of the Panel Construction	43
B	Lag-Order Selection	44
C	Full Connectedness Tables by Regime	44
D	Replication	44

1. Introduction

How volatility propagates from one market to another matters for portfolio construction, for the design of risk limits, and for the monitoring of systemic risk. Over the past two decades the channels of propagation have multiplied: index futures and exchange-traded funds trade almost around the clock, cross-asset strategies rebalance mechanically in response to volatility, and cryptocurrencies have grown from a marginal curiosity into an asset class with a market capitalization in the trillions of dollars and, since January 2024, spot exchange-traded funds listed in the United States. Whether these developments have altered the hierarchy of volatility transmission—which markets originate volatility shocks and which absorb them—is an empirical question, and one whose answer appears to change with the sample period and with the econometric choices made along the way.

The connectedness framework of [Diebold and Yilmaz \(2009, 2012, 2014\)](#) offers a transparent way to pose the question. A vector autoregression (VAR) is fitted to a panel of volatilities, and the forecast-error variance of each series at a given horizon is decomposed into the shares attributable to shocks in every series in the system. Aggregating the off-diagonal shares yields a total connectedness index; summing them by row and by column yields the volatility each market receives from, and transmits to, the others. The generalized decomposition of [Koop et al. \(1996\)](#) and [Pesaran and Shin \(1998\)](#) makes these quantities invariant to the ordering of the variables, which has made the framework the standard tool for cross-market spillover studies in equities ([Demirer et al., 2018](#); [Diebold and Yilmaz, 2016](#)), foreign exchange ([Baruník et al., 2017](#); [Greenwood-Nimmo et al., 2016](#)), commodities ([Kang et al., 2017](#); [Ji et al., 2019b](#)) and cryptocurrencies ([Ji et al., 2019a](#); [Corbet et al., 2018](#)).

Three features of the existing evidence motivate this paper. First, most cross-asset studies measure volatility with daily ranges or squared daily returns. Realized volatility computed from intraday returns is a far more precise ex post measure ([Andersen et al., 2003](#); [Barndorff-Nielsen and Shephard, 2002](#)), and the precision gain is greatest exactly when connectedness is of most interest, namely on turbulent days. Second, studies that include cryptocurrencies alongside exchange-traded instruments must confront a calendar problem: bitcoin and ether trade every hour of every day, whereas index and commodity futures close for roughly one hour a day and from Friday evening to Sunday evening, and the VIX is disseminated only during Chicago trading hours. How the series are aligned—which days enter the panel, how weekend crypto volatility is treated, and in which time zone the day is defined—is rarely documented, although, as this paper shows, it can shift connectedness estimates by several percentage points and change the sign of net spillovers. Third, point estimates of connectedness are commonly reported without confidence intervals, and regime comparisons are drawn from sub-samples of a few dozen observations in which a ten-variable VAR is severely over-parameterized.

This paper studies ten instruments observed at the 5-minute frequency from January 2008 to March 2026: the E-mini S&P 500 (ES) and Nasdaq 100 (NQ) futures, the EUR/USD, USD/JPY and GBP/USD exchange rates, gold (GC) and WTI crude oil (CL) futures, spot bitcoin (BTC) and ether (ETH), and the CBOE Volatility Index (VIX). Daily realized volatility is constructed for each instrument from 5-minute log returns, and the connectedness of log realized volatility is estimated on the 2,514 trading days common to all ten series, from March 2016 to March 2026, with a VAR(4) and a ten-day forecast horizon. Residual-bootstrap intervals accompany every connectedness measure. The time dimension is explored with rolling windows of 200, 250 and 500 trading days, with four regime sub-samples, and with calendar-year estimates. A second block of analyses exploits the intraday data directly: after an explicit conversion of exchange time stamps to Coordinated Universal Time, it documents the hourly periodicity of absolute returns, the share of daily variance generated in Asian, European and U.S. trading hours, and session-ordered predictive regressions between the realized volatility of equity futures, the VIX and bitcoin.

The paper addresses five questions. (i) What is the structure of daily realized-volatility connectedness across the four asset classes, and which instruments are robust net transmitters or receivers? (ii) How does this structure change across market regimes, in particular during the COVID-19 crash and the 2022 monetary tightening? (iii) Has the integration of bitcoin and ether with traditional markets increased, and in which direction does volatility flow? (iv) How does aggregate connectedness evolve over time, and how is it related to stress episodes? (v) How is intraday volatility distributed across trading sessions, and does bitcoin's round-the-clock trading carry information for the volatility of U.S. equity markets?

The main results are as follows. Cross-asset shocks explain 54.8% of the ten-day forecast-error variance of log realized volatility (90% bootstrap interval 53.1–56.9). ES and NQ are the only robust net transmitters, with net directional spillovers of +36.0 and +25.6 percentage points; the realized volatility of the VIX (–20.6), of crude oil (–14.2) and of sterling (–13.2) are robust net receivers. The VIX result is not a statement about the VIX level—which is a forward-looking price—but about the day-to-day variability of that price, more than one-fifth of which is explained by shocks to the realized volatility of the equity futures from which it is derived. The net positions of bitcoin and ether are statistically indistinguishable from zero in the full sample and in most sub-samples, and the point estimate for bitcoin changes sign across reasonable specifications. The two cryptocurrencies form a tightly linked pair—each explains 27–28% of the other's variance—whose exposure to traditional assets has grown markedly: shocks to the eight traditional instruments explained less than 10% of bitcoin's forecast-error variance in 2017 and 2019, between 20% and 34% in 2020–2024, and 46% in 2025. The direction of this integration is from equities to crypto. In the spot-ETF period (January 2024–March 2026) bitcoin is a significant net receiver (–12.4 percentage points, interval –20.4 to –2.1), and in the intraday analysis the U.S.-session volatility of ES predicts bitcoin's next

Asian-session volatility, whereas bitcoin's overnight and weekend volatility carry no incremental information for the U.S.-session volatility of ES. Rolling total connectedness rose sharply in March 2020 and reached the highest values of the sample in 2025; a previously reported peak in February 2018 turns out to be an artefact of forward-filled weekend observations. Intraday, equity and VIX volatility concentrate in the U.S. cash session, which generates 53–63% of daily variance, while bitcoin's hourly profile is nearly flat, with a peak-to-trough ratio of 1.2 against 3.9 for ES.

Relative to the May 2026 version of this paper, the present version corrects the construction of the daily panel, replaces levels by logarithms of realized volatility, adds bootstrap inference and a robustness grid, corrects the time zone of the intraday analysis, and revises the conclusions accordingly; the changes are documented in the appendix and in the revision log that accompanies the replication code. The remainder of the paper is organized as follows. Section 2 reviews the literature. Section 3 presents the realized-volatility measure, the connectedness framework, the inference procedure and the session analysis. Section 4 describes the data, the alignment of the series and the sample. Section 5 reports the results, Section 6 discusses them in relation to the research questions and the literature, and Section 7 concludes.

2. Literature Review

2.1. From Volatility Spillovers to Connectedness

The transmission of volatility across markets has been studied since the recognition that large price changes cluster in time (Mandelbrot, 1963; Fama, 1965) and that this clustering is correlated across national markets. Hamao et al. (1990) and Lin et al. (1994) documented volatility spillovers between Tokyo, London and New York with univariate and bivariate GARCH models, King and Wadhwani (1990) interpreted cross-market transmission as the outcome of rational agents inferring information from foreign price changes, Longin and Solnik (2001) showed that the correlation of international equity returns rises in bear markets but not in bull markets, and Forbes and Rigobon (2002) showed that measured increases in cross-market correlation during crises are largely a mechanical consequence of higher variance rather than evidence of contagion. Multivariate GARCH specifications, in particular the dynamic conditional correlation model of Engle (2002) and the regime-switching frameworks of Ang and Bekaert (2002) and Baele (2005), made it possible to track time-varying comovement in moderately sized systems. These approaches, however, describe comovement rather than direction: they do not say which market originates a volatility shock and which absorbs it.

Diebold and Yilmaz (2009) proposed to answer that question with the forecast-error variance decomposition of a VAR fitted to volatilities. The share of market i 's forecast-error variance attributable to shocks in market j is a natural measure of the spillover from j to i , and the

aggregate of all cross-market shares is a single index of connectedness. Because Cholesky decompositions depend on the ordering of the variables, [Diebold and Yilmaz \(2012\)](#) adopted the generalized decomposition of [Koop et al. \(1996\)](#) and [Pesaran and Shin \(1998\)](#), which allows for contemporaneously correlated shocks and delivers an asymmetric connectedness table from which directional “to”, “from” and net spillovers follow directly. [Diebold and Yilmaz \(2014\)](#) reinterpreted the table as a weighted directed network, so that total connectedness is the mean degree of the network and net pairwise spillovers are its signed edges. In their application to four U.S. asset classes, [Diebold and Yilmaz \(2012\)](#) found that equity volatility transmits to bonds, exchange rates and commodities, and that connectedness rises in crises; this ordering of equities at the top of the hierarchy recurs in most subsequent studies.

The framework has since been extended in several directions. [Baruník and Křehlík \(2018\)](#) decompose connectedness by frequency to separate short-run from long-run transmission; [Baruník et al. \(2016, 2017\)](#) distinguish spillovers generated by negative and positive returns in equity and foreign-exchange markets; [Antonakakis et al. \(2020\)](#) replace rolling-window VARs with time-varying-parameter VARs that do not discard observations; and [Lastrapes and Wiesen \(2021\)](#) propose a joint spillover index that corrects the row normalization of the generalized decomposition. Statistical inference for connectedness measures has received comparatively little attention. Most applications report point estimates, although the measures are smooth functions of VAR parameters whose sampling uncertainty can be approximated by the bootstrap methods developed for impulse responses ([Kilian, 1998](#); [Kilian and Lütkepohl, 2017](#)).

2.2. Cross-Asset Transmission: Exchange Rates, Commodities and the VIX

Within foreign exchange, [Greenwood-Nimmo et al. \(2016\)](#) apply the connectedness framework to the G10 currencies and find that risk spillovers intensify in stress episodes, while [Baruník et al. \(2017\)](#) show that negative-return volatility dominates transmission among the major pairs. The yen’s behaviour in crises is central to the present paper’s regime results: [Ranaldo and Söderlind \(2010\)](#) and [Habib and Stracca \(2012\)](#) document that the yen and the Swiss franc appreciate when global risk aversion rises, so that USD/JPY volatility reflects the unwinding of carry positions rather than idiosyncratic Japanese news.

For commodities, [Aroui et al. \(2011\)](#) and [Mensi et al. \(2013\)](#) document volatility spillovers between crude oil and equity markets and between commodities and equities more generally, [Kang et al. \(2017\)](#) measure spillovers among crude oil, precious metals and agricultural futures and find that they intensify in crises, [Vivian and Wohar \(2012\)](#) identify structural breaks in commodity volatility, and [Baur and Lucey \(2010\)](#) and [Reboredo \(2013\)](#) characterize gold as a safe haven for equities and as a hedge for the U.S. dollar. Whether these roles translate into gold being a net receiver or a net transmitter of realized-volatility shocks is an empirical matter addressed below.

The VIX requires a distinct interpretation. It is the risk-neutral expectation of 30-day S&P 500 variance implied by option prices (Whaley, 2009), and its level is closely related to, but systematically above, realized variance, the gap being the variance risk premium (Bekaert and Hoerova, 2014). The present paper does not include the VIX level in the VAR; it includes the realized volatility of 5-minute changes in the VIX, that is, the variability of the implied-volatility price itself. The finding that this series is a net receiver of shocks from equity-futures realized volatility is therefore consistent with the VIX being a derivative of the S&P 500 and does not contradict the predictive content of the VIX level for future realized variance.

2.3. Cryptocurrencies and Traditional Markets

Early studies found cryptocurrencies to be largely detached from traditional asset classes. Bouri et al. (2017) conclude that bitcoin is a diversifier rather than a hedge or a safe haven, Corbet et al. (2018) find that connectedness between cryptocurrencies and conventional assets is weak and concentrated within the crypto group, and Baur et al. (2018) show that bitcoin returns are essentially uncorrelated with those of traditional assets. The within-crypto dependence is strong: Ji et al. (2019a) document a dense connectedness network among the largest coins, and Makarov and Schoar (2020) attribute part of the common dynamics to arbitrage across exchanges. Bitcoin's volatility is also unusual in level and dynamics: Katsiampa (2017) and Chaim and Laurini (2018) document pronounced jump components, which is relevant for the choice between levels and logarithms of realized volatility in a VAR.

The COVID-19 episode changed the assessment. Conlon and McGee (2020) find that bitcoin lost value together with equities in March 2020 and did not act as a safe haven, Bouri et al. (2020) find with wavelet methods that neither bitcoin nor gold and commodities offered reliable safe-haven protection for equities at short horizons, Corbet et al. (2020) document contagion from equities to gold and cryptocurrencies, and Elsayed et al. (2022) report increased risk transmission between bitcoin and traditional assets during the pandemic. Iyer (2022) shows that the correlation of bitcoin returns with U.S. equity returns and the share of equity-volatility variance explained by crypto shocks both rose after 2020, and relates the change to the entry of institutional investors. Studies of cryptocurrency–commodity links (Ji et al., 2019b) and of meme assets (Yousaf et al., 2023) point in the same direction of growing but still modest integration. Whether the direction of transmission has shifted—whether crypto volatility now originates shocks that reach traditional markets, or mainly absorbs them—remains open, and the sign of bitcoin's net spillover reported in the literature varies with the sample and the specification. The present paper addresses this question with confidence intervals, calendar-year estimates and session-ordered predictive regressions.

2.4. Realized Volatility and Intraday Periodicity

Realized volatility, the sum of squared intraday returns, is a consistent estimator of the integrated variance of a continuous-time price process as the sampling interval shrinks (Andersen et al., 2001, 2003; Barndorff-Nielsen and Shephard, 2002). At very fine sampling intervals, however, bid–ask bounce and discreteness introduce a bias that grows with the number of observations (Hansen and Lunde, 2006; Aït-Sahalia et al., 2005; Zhang et al., 2005). In a comparison of hundreds of realized measures across asset classes, Liu et al. (2015) find that it is difficult to improve significantly on 5-minute realized variance, which justifies the sampling frequency used here. The logarithm of realized volatility is close to normally distributed and strongly persistent (Andersen et al., 2003), a persistence that the heterogeneous autoregressive model of Corsi (2009) captures parsimoniously, and realized measures are themselves estimated with error, with consequences for the dynamics of volatility models (Bollerslev et al., 2016). Jumps add a further component to realized variance that can be separated with bipower variation (Andersen et al., 2007).

Intraday volatility follows strong deterministic patterns: equity volatility is highest at the open and the close of the cash session (Wood et al., 1985; Harris, 1986), and the periodicity in exchange-rate volatility tracks the opening hours of the Asian, European and American centres and the release times of macroeconomic announcements (Andersen and Bollerslev, 1997, 1998). For bitcoin, Eross et al. (2019) find that volatility and volume are highest during U.S. trading hours despite continuous trading, and Baur et al. (2019) document time-of-day and day-of-week effects in returns and volume, with lower activity at weekends. These patterns bear on the alignment problem studied here: a “day” of volatility means different things for a market that closes and for one that does not.

2.5. Contribution

The paper contributes to this literature in four ways. First, it measures cross-asset connectedness with realized rather than range- or return-based volatility for ten instruments spanning equities, foreign exchange, commodities, implied volatility and cryptocurrencies over a decade that includes the COVID-19 crash, the 2022 tightening cycle and the launch of spot bitcoin ETFs. Second, it treats the alignment of 24/7 and exchange-traded series explicitly and quantifies its effect on the estimates: forward-filling weekend observations, a common but seldom documented practice, alters the total connectedness index by five percentage points and the net spillover of equity futures by fifteen. Third, it attaches bootstrap confidence intervals to all connectedness measures and shows that several widely discussed regime results—including the sign of bitcoin’s net spillover—are not statistically distinguishable from zero in sub-samples of the usual size. Fourth, it uses the intraday data not only to construct daily realized volatility but to test, with correctly time-zoned session volatilities, whether bitcoin’s overnight and weekend trading carries information for the volatility of U.S. equity futures.

3. Methodology

3.1. Realized Volatility

For instrument i on calendar day t , let $P_{i,t,j}$ denote the closing price of the j -th 5-minute bar, $j = 1, \dots, M_{i,t}$, where $M_{i,t}$ is the number of bars available on that day. The 5-minute log return and the daily realized variance are

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

If the log price is a continuous semimartingale with spot variance $\sigma_{i,t}^2(s)$ and the sampling interval shrinks, $\text{RV}_{i,t}$ converges in probability to the integrated variance $\int_{t-1}^t \sigma_{i,t}^2(s) ds$ (Andersen et al., 2003; Barndorff-Nielsen and Shephard, 2002); in the presence of jumps it converges to the integrated variance plus the sum of squared jumps (Andersen et al., 2007). At the 5-minute frequency the bias induced by microstructure noise is small for liquid instruments (Hansen and Lunde, 2006; Liu et al., 2015). We report realized volatility in annualized form,

$$\sigma_{i,t} = \sqrt{252 \cdot \text{RV}_{i,t}}, \quad (2)$$

and require $M_{i,t} \geq 20$ bars for a day to be retained. Because $\sigma_{i,t}$ is strongly right-skewed and heavy-tailed whereas its logarithm is close to Gaussian (Andersen et al., 2001, 2003), the connectedness analysis is conducted on

$$y_{i,t} = \ln \sigma_{i,t}, \quad (3)$$

which is equal to $\frac{1}{2} \ln \text{RV}_{i,t}$ up to a constant. The transformation matters for the VAR because the generalized variance decomposition weights observations by their squared innovations: in levels, a handful of extreme days dominates the residual covariance matrix, and the decomposition then describes those days rather than the typical transmission mechanism. Results in levels are reported as a robustness check. Stationarity of $y_{i,t}$ is assessed with the augmented Dickey–Fuller test (Dickey and Fuller, 1979) and the KPSS test (Kwiatkowski et al., 1992).

3.2. Vector Autoregression

Let $\mathbf{y}_t = (y_{1,t}, \dots, y_{N,t})'$ collect the $N = 10$ log realized volatilities on trading day t . The dynamics are approximated by a covariance-stationary VAR(p),

$$\mathbf{y}_t = \boldsymbol{\mu} + \sum_{\ell=1}^p \boldsymbol{\Phi}_\ell \mathbf{y}_{t-\ell} + \boldsymbol{\varepsilon}_t, \quad \mathbb{E}[\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t'] = \boldsymbol{\Sigma}, \quad (4)$$

estimated equation by equation by least squares (Lütkepohl, 2005). The lag order is chosen by comparing the Akaike, Schwarz and Hannan–Quinn criteria over $p \in \{1, \dots, 10\}$ (Table A3 in the appendix). The criteria select $p = 5, 3$ and 4 respectively; we adopt the Hannan–Quinn choice, $p = 4$, which coincides with the original specification of the paper, and report $p \in \{1, 2, 3, 6\}$ as robustness checks. The moving-average representation of (4) is $\mathbf{y}_t = \boldsymbol{\mu}^* + \sum_{h=0}^{\infty} \boldsymbol{\Psi}_h \boldsymbol{\varepsilon}_{t-h}$ with

$$\boldsymbol{\Psi}_0 = \mathbf{I}_N, \quad \boldsymbol{\Psi}_h = \sum_{\ell=1}^{\min(h,p)} \boldsymbol{\Phi}_{\ell} \boldsymbol{\Psi}_{h-\ell}, \quad h \geq 1. \quad (5)$$

3.3. Generalized Forecast-Error Variance Decomposition

Following Diebold and Yilmaz (2012), the H -step-ahead generalized forecast-error variance decomposition of Koop et al. (1996) and Pesaran and Shin (1998) is

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (\mathbf{e}_i' \boldsymbol{\Psi}_h \boldsymbol{\Sigma} \mathbf{e}_j)^2}{\sum_{h=0}^{H-1} \mathbf{e}_i' \boldsymbol{\Psi}_h \boldsymbol{\Sigma} \boldsymbol{\Psi}_h' \mathbf{e}_i}, \quad (6)$$

where σ_{jj} is the j -th diagonal element of $\boldsymbol{\Sigma}$ and $\mathbf{e}_i$ is the i -th unit vector. The numerator is the contribution of a one-standard-deviation shock to variable j —allowing for its contemporaneous correlation with the other shocks—to the H -step forecast-error variance of variable i , and the denominator is that forecast-error variance. Because the generalized shocks are not orthogonal, the rows of $[\theta_{ij}(H)]$ do not sum to one, and we normalize

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{k=1}^N \theta_{ik}(H)}, \quad \sum_{j=1}^N \tilde{\theta}_{ij}(H) = 1, \quad \sum_{i,j=1}^N \tilde{\theta}_{ij}(H) = N. \quad (7)$$

We use $H = 10$ trading days, as in Diebold and Yilmaz (2012), and report $H \in \{5, 20\}$ as robustness checks. Since the decomposition converges as H grows, the choice of horizon affects the level of the measures more than the ranking of the instruments.

3.4. Connectedness Measures

All measures are expressed in percent of forecast-error variance. The total spillover index is the share of forecast-error variance in the system that is due to cross-variable shocks,

$$\text{TSI}(H) = \frac{100}{N} \sum_{\substack{i,j=1 \\ i \neq j}}^N \tilde{\theta}_{ij}(H). \quad (8)$$

The directional spillover received by i from all other variables and the spillover transmitted by j to all other variables are the off-diagonal row and column sums,

$$\text{FROM}_i(H) = 100 \sum_{\substack{j=1 \\ j \neq i}}^N \tilde{\theta}_{ij}(H), \quad \text{TO}_j(H) = 100 \sum_{\substack{i=1 \\ i \neq j}}^N \tilde{\theta}_{ij}(H), \quad (9)$$

and the net directional spillover of i is

$$\text{NET}_i(H) = \text{TO}_i(H) - \text{FROM}_i(H). \quad (10)$$

FROM_i lies between 0 and 100; TO_j is unbounded above and can exceed 100 when a variable explains a large share of many others; and NET_i is positive for a net transmitter and negative for a net receiver, with $\sum_i \text{NET}_i = 0$. We express NET_i in percentage points. Finally, the net pairwise directional spillover from i to j ,

$$\text{NET}_{i \rightarrow j}(H) = 100 [\tilde{\theta}_{ji}(H) - \tilde{\theta}_{ij}(H)], \quad (11)$$

is the signed edge of the connectedness network of [Diebold and Yilmaz \(2014\)](#).

3.5. Inference

The connectedness measures are smooth functions of $(\Phi_1, \dots, \Phi_p, \Sigma)$, and we approximate their sampling distribution with a residual bootstrap ([Kilian, 1998](#); [Kilian and Lütkepohl, 2017](#)). Let $\hat{\epsilon}_t$ denote the centred least-squares residuals of (4). For each of $B = 500$ replications, residuals are resampled with replacement, an artificial sample is generated recursively from the estimated coefficients and the first p observed values, the VAR is re-estimated and the measures are recomputed. We report 90% percentile intervals. The bootstrap treats the residuals as independent and identically distributed and therefore does not capture conditional heteroskedasticity in the innovations of log realized volatility; the intervals should be read as indicative of estimation uncertainty rather than as exact. For the calendar-year sub-samples we use $B = 300$.

3.6. Rolling Windows and Sub-Samples

Time variation is examined in three complementary ways. First, the VAR and the decomposition are re-estimated over rolling windows of w trading days advancing by one day,

$$\text{TSI}_t(H; w) = \text{TSI}(H; \mathbf{y}_{t-w+1}, \dots, \mathbf{y}_t), \quad (12)$$

and similarly for $\text{NET}_{i,t}(H; w)$. A ten-variable VAR(4) with intercepts has 41 coefficients per equation, so that a 200-day window leaves fewer than five observations per coefficient; the resulting over-fitting biases the total index upwards and makes it noisy. We therefore report $w \in \{200, 250, 500\}$ and treat the 500-day window as the more reliable description of slow-moving trends. Second, four regime sub-samples are estimated separately with bootstrap intervals: the pre-COVID period (January 2019–February 2020), the COVID crash (March–June 2020), the 2022 rate-hiking cycle (January–December 2022) and the spot-ETF era (11 January 2024–March 2026). For the 85-day COVID window the lag order is reduced to $p = 1$; the VAR(4) estimates on the same window are reported in the appendix for comparison. Third, calendar-year estimates with $p = 2$ track the integration of the cryptocurrencies through the shares of bitcoin’s forecast-error variance explained by the traditional instruments and the net pairwise spillovers between bitcoin and ES.

3.7. Granger Causality

For a pair of log realized volatilities $(y_{i,t}, y_{j,t})$ we test whether p lags of y_j help predict y_i beyond p own lags (Granger, 1969), with the regression

$$y_{i,t} = \alpha + \sum_{\ell=1}^p \beta_{\ell} y_{i,t-\ell} + \sum_{\ell=1}^p \gamma_{\ell} y_{j,t-\ell} + u_t, \quad H_0 : \gamma_1 = \dots = \gamma_p = 0. \quad (13)$$

We report the conventional F -statistic, $F = [(\text{RSS}_R - \text{RSS}_U)/p] / [\text{RSS}_U / (T - 2p - 1)]$, and a Wald statistic based on a heteroskedasticity- and autocorrelation-consistent covariance matrix with ten lags (Newey and West, 1987), which is more appropriate for volatility series. Granger causality is a statement about incremental one-day-ahead predictability, not about the economic size of the effect; we therefore also report the sum $\sum_{\ell} \hat{\gamma}_{\ell}$, which measures the long-run response of y_i to a unit change in y_j in this bivariate regression.

3.8. Intraday Periodicity and Session-Ordered Predictability

The intraday analysis uses the 5-minute returns directly. Exchange time stamps are converted to Coordinated Universal Time (UTC) with the civil daylight-saving rules of the exchange’s time zone, and three sessions are defined in UTC: Asian (00:00–08:00), European (08:00–14:30) and U.S. (14:30–21:00). For each instrument the hourly profile of volatility is the mean absolute 5-minute return by hour of the day, and the session realized variance on day t is

$$\text{RV}_{i,t}^s = \sum_{j \in s} r_{i,t,j}^2, \quad s \in \{\text{Asian, European, U.S.}\}, \quad (14)$$

retained when the session contains at least twelve bars. The share of daily variance generated in session s is the average over days of $\text{RV}_{i,t}^s / \sum_{s'} \text{RV}_{i,t}^{s'}$.

The chronological ordering of sessions within a UTC day makes it possible to test whether volatility realized in an earlier session helps predict volatility realized in a later one. We estimate

$$\ln RV_{i,t}^{\text{US}} = \alpha + \sum_{\ell=1}^4 \beta_{\ell} \ln RV_{i,t-\ell}^{\text{US}} + \sum_{\ell=0}^3 \gamma_{\ell} \ln RV_{j,t-\ell}^s + u_t, \quad (15)$$

where i is ES, NQ or the VIX, j is bitcoin and s is the Asian or the European session of the same day, and test $\gamma_0 = \dots = \gamma_3 = 0$ with a HAC Wald statistic. The reverse direction replaces the dependent variable by bitcoin's Asian-session variance on day t and the predictor by the U.S.-session variance of ES, NQ or the VIX on the previous trading day. A final regression asks whether bitcoin's weekend variance (Saturday plus Sunday) predicts the Monday U.S.-session variance of ES once Friday's ES and bitcoin variances are controlled for. These regressions complement the daily VAR by exploiting an ordering of information that daily data cannot provide.

3.9. Network Representation

The full-sample decomposition is represented as a directed graph whose nodes are the ten instruments and whose edges are the net pairwise directional spillovers of (11), drawn from the net transmitter to the net receiver when $|\text{NET}_{i \rightarrow j}|$ exceeds the 60th percentile of all pairwise values. Node size is proportional to TO_j and nodes are coloured by asset class.

4. Data

4.1. Sources and Instruments

The raw data are 5-minute open–high–low–close–volume bars supplied by FirstRate Data and stored in four DuckDB databases: continuous front-month futures (ES, NQ, GC, CL), spot exchange rates (EUR/USD, USD/JPY, GBP/USD), spot cryptocurrency prices in U.S. dollars (BTC, ETH) and the CBOE Volatility Index. Together the ten series contain about 235 million bars between January 2008 and March 2026. Table 1 lists the instruments. They were chosen to be the most liquid representative of each asset class, to overlap over a decade, and to differ in trading hours: the futures trade almost continuously from Sunday evening to Friday afternoon with a daily one-hour maintenance break, the exchange rates trade continuously from Sunday evening to Friday evening, the cryptocurrencies trade every hour of every day, and the VIX is disseminated by CBOE only between 03:15 and 16:15 Eastern time (09:30–16:15 before April 2016) on U.S. trading days.

4.2. Time Stamps and Alignment

All FirstRate time stamps are expressed in U.S. Eastern time, which we verified from the location of the daily Globex maintenance break (17:00–18:00) in the futures series and of the opening bar

Table 1. Asset universe.

Asset class	Symbol	Instrument	Venue	Trading hours
Equity	ES	E-mini S&P 500 futures	CME Globex	Sun 18:00–Fri 17:00 ET, break 17:00–18:00
	NQ	E-mini Nasdaq 100 futures	CME Globex	Sun 18:00–Fri 17:00 ET, break 17:00–18:00
FX	EURUSD	Euro / U.S. dollar	Interbank spot	Sun 17:00–Fri 17:00 ET
	USDJPY	U.S. dollar / Japanese yen	Interbank spot	Sun 17:00–Fri 17:00 ET
	GBPUSD	British pound / U.S. dollar	Interbank spot	Sun 17:00–Fri 17:00 ET
Commodity	GC	Gold futures	COMEX	Sun 18:00–Fri 17:00 ET, break 17:00–18:00
	CL	WTI crude oil futures	NYMEX	Sun 18:00–Fri 17:00 ET, break 17:00–18:00
Crypto	BTC	Bitcoin, spot, USD	Composite of exchanges	24 hours, 7 days
	ETH	Ether, spot, USD	Composite of exchanges	24 hours, 7 days
Volatility	VIX	CBOE Volatility Index	CBOE	03:15–16:15 ET on U.S. trading days

Notes: 5-minute bars from FirstRate Data; futures are continuous front-month series. ET denotes U.S. Eastern time. The VIX is an index, not a traded instrument; its “realized volatility” is the realized volatility of 5-minute changes in the index.

of the VIX series (03:15 or 09:30). A calendar day is therefore an Eastern-time day, and the daily realized volatility of a futures contract on day t aggregates the bars between 00:00 and 24:00 Eastern of that day, that is, the second part of the overnight Globex session that opened the previous evening, the cash session, and the first hours of the following Globex session. This definition is common to all exchange-traded series and to the cryptocurrencies, whose trading is uninterrupted. The earlier version of this paper treated the time stamps as UTC; the intraday results of Section 5.8 are based on an explicit conversion from Eastern time to UTC.

A second alignment issue arises in the construction of the panel used for the VAR. Bitcoin and ether have a realized volatility on every calendar day, the futures and exchange rates have one on Sunday evenings (computed from a few hours of thin trading) but not on Saturdays, and the VIX has one only on CBOE trading days. The panel used in this version comprises the trading days on which all ten instruments have an own realized volatility computed from their own bars, which in practice is the CBOE calendar: 2,514 days from 11 March 2016, the first day with ether data, to 11 March 2026. No value is forward-filled, and Saturday and Sunday crypto volatility does not enter the baseline. The May 2026 version instead built a panel on all 3,651 calendar days of the same period, filling missing values forward for up to five days; 1,044 of its rows were weekends and 1,137 contained at least one forward-filled value, so that on more than 30% of the observations eight of the ten series had, by construction, zero innovation. Section A quantifies the consequences. As a robustness check we also use a weekend-inclusive crypto measure, in which the realized variance of bitcoin and ether on a trading day is the average daily variance over the calendar days elapsed since the previous trading day, so that Monday carries Saturday and Sunday information.

4.3. Descriptive Statistics of 5-Minute Returns

Table 2 summarizes the 5-minute log returns over each instrument’s full history. Returns more than twenty sample standard deviations from the mean were removed before computing realized volatility,

as a guard against data errors; the symmetric bounds in the minimum and maximum columns are the trace of this filter, which removes a very small number of observations but may also remove genuine extreme moves on crash days, a limitation discussed in Section 6.4. Three patterns stand out. Cryptocurrencies and the VIX have 5-minute standard deviations an order of magnitude larger than equity futures and exchange rates (0.60–0.69% against 0.03–0.08%), with crude oil the most volatile traditional asset (0.15%). All distributions are heavy-tailed, with excess kurtosis between 20 and 63. Skewness is small and negative for equity futures and crude oil, small and positive for the exchange rates and the cryptocurrencies, and clearly positive for the VIX (+1.00), whose 5-minute changes are dominated by upward jumps.

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: 5-minute log returns $r_{i,t,j}$ over each instrument's full history after removal of returns exceeding twenty sample standard deviations in absolute value. N is in millions of observations; Std is the standard deviation; Kurt is excess kurtosis. Std, Min and Max are in percent. Source: `results/table1_descriptive_stats.csv`.

4.4. Daily Realized Volatility

Figure 1 plots the annualized daily realized volatility of the ten instruments over their full histories, and Table 3 summarizes the series over the common 2016–2026 trading-day panel. Mean annualized realized volatility ranges from 7% for EUR/USD to 34% for crude oil among traditional assets, and exceeds 100% for bitcoin, ether and the VIX. The medians are far below the means for the cryptocurrencies (53% against 103% for bitcoin), a sign of the extreme right tail: the largest bitcoin values, above 1,000% annualized, occur in April–May and December 2017 and reflect 5-minute prices that oscillated by 5–10% between consecutive bars on a composite feed of exchanges with large and shifting premia; we verified on an independent one-minute feed from the same vendor that these values are a property of the source data and not of our processing. Skewness in levels is between 1.9 and 5.9; after the log transformation it falls to between 0.2 and 1.4 and excess kurtosis to between 0.1 and 4.0. Log realized volatility is strongly persistent, with first-order autocorrelations between 0.55 (VIX) and 0.91 (BTC) and autocorrelations at lag 22 between 0.12

and 0.66. Augmented Dickey–Fuller tests reject a unit root at the 1% level for all series except ether (5%), while KPSS tests reject level stationarity for all series except EUR/USD; the combination is the familiar signature of long memory in realized volatility (Andersen et al., 2003; Corsi, 2009), which a finite-order VAR approximates rather than reproduces.

Table 3. Daily realized volatility over the common trading-day panel, 2016-03-11 to 2026-03-11.

Asset	Class	Mean annualized RV (%)	Median	Max	Skew level	Skew log	Kurt log	ρ_1 log	ADF log	KPSS log
ES	Equity	13.9	11.2	111	3.78	0.60	0.62	0.84	-4.8***	0.98*
NQ	Equity	17.9	15.1	112	2.85	0.38	0.26	0.83	-5.2***	1.45*
EURUSD	FX	7.0	6.5	32	2.03	0.41	0.45	0.68	-4.8***	0.23
USDJPY	FX	7.7	6.9	35	1.94	0.28	0.17	0.74	-5.2***	0.97*
GBPUSD	FX	8.4	7.7	51	3.32	0.77	1.66	0.72	-5.6***	1.08*
GC	Commodity	13.6	12.1	91	3.84	0.83	1.75	0.72	-4.4***	1.75*
CL	Commodity	33.8	28.8	328	5.85	1.36	4.00	0.83	-4.1***	0.55*
BTC	Crypto	103.4	53.3	1409	3.90	1.02	0.90	0.91	-3.4**	2.51*
ETH	Crypto	113.2	79.3	1281	4.31	0.60	0.51	0.85	-3.0**	4.46*
VIX	Volatility	115.8	101.5	683	2.01	0.18	0.14	0.55	-10.8***	0.99*

Notes: $T = 2,514$ trading days. Mean, median and maximum of annualized realized volatility in percent. Skewness in levels and skewness, excess kurtosis and first-order autocorrelation ρ_1 of log realized volatility. ADF is the augmented Dickey–Fuller statistic with a constant and AIC-selected lags (***, **: rejection of a unit root at 1% and 5%; all series reject at 1% except ETH, $p = 0.04$). KPSS is the level-stationarity statistic with automatic bandwidth; * marks rejection of stationarity at the 5% level. Source: results/rev_table_rv_descriptives.csv.

5. Empirical Results

5.1. Full-Sample Connectedness

Table 4 reports the full-sample connectedness table for log realized volatility over the 2,514 trading days from March 2016 to March 2026, with a VAR(4) and $H = 10$. Entry (i, j) is the percentage of the ten-day forecast-error variance of instrument i attributable to shocks in instrument j ; the last column and the last two rows give the FROM, TO and NET measures of (9)–(10), each followed by its 90% bootstrap interval.

The total spillover index is 54.8%, with a 90% interval of 53.1–56.9%: slightly more than half of the forecast-error variance of the system is attributable to cross-asset shocks. Four features of the table organize the discussion.

First, equity index futures are the dominant transmitters. ES and NQ transmit 104% and 92% of forecast-error variance to the other nine series and receive 68% and 66%, for net spillovers of +36.0 (interval 29.9–41.5) and +25.6 (19.0–31.3) percentage points. Shocks to ES explain 12% of the variance of crude oil, 11% of gold, 8–9% of each exchange rate and 21% of the realized volatility of

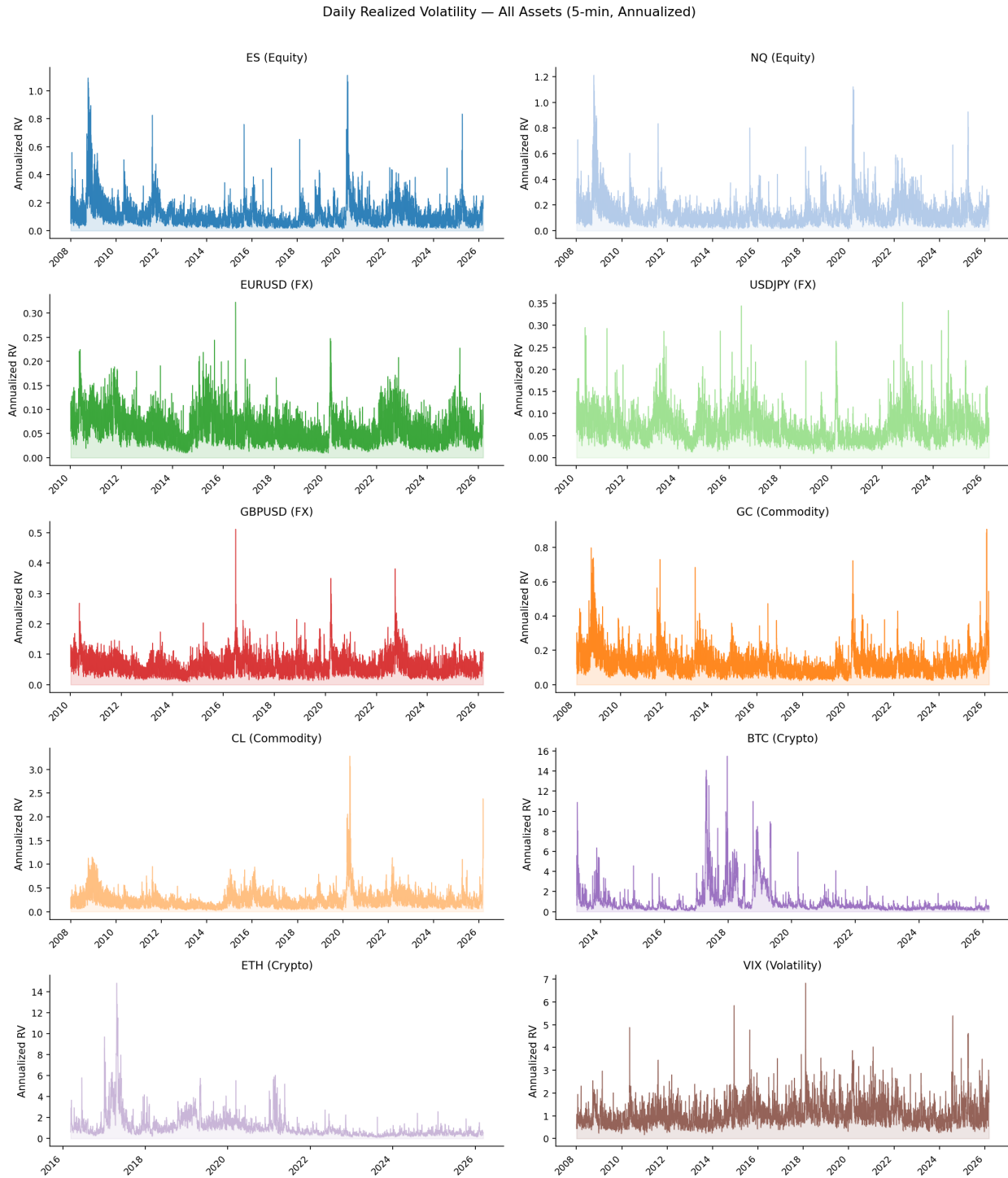


Figure 1. Daily annualized realized volatility, 2008–2026.

Notes: Annualized realized volatility $\sigma_{i,t} = \sqrt{252 \sum_j r_{i,t,j}^2}$ from 5-minute returns, Eastern-time calendar days with at least 20 bars. The y-axis scale differs across panels. The March 2020 spike is visible in every traditional asset; the 2017 spikes in bitcoin and ether reflect the quality of the composite spot feed in that year (see text).

Table 4. Full-sample connectedness table, log realized volatility, VAR(4), $H = 10$.

Recipient i	Shock origin j										FROM
	ES	NQ	EURUSD	USDJPY	GBPUSD	GC	CL	BTC	ETH	VIX	
ES	31.9	28.3	5.4	4.8	4.2	6.1	5.5	1.3	0.6	11.9	68.1
NQ	30.1	33.7	4.7	4.3	3.7	5.8	4.8	1.1	0.5	11.3	66.3
EURUSD	9.1	8.0	35.5	14.3	16.5	10.0	3.9	0.4	0.3	2.0	64.5
USDJPY	8.5	7.5	15.2	44.5	9.1	9.0	3.5	0.4	0.3	2.1	55.5
GBPUSD	8.9	7.5	19.3	10.2	40.1	7.1	3.5	0.6	0.8	1.8	59.9
GC	11.0	9.4	11.4	9.8	6.3	41.4	5.7	0.6	0.6	4.0	58.6
CL	12.2	10.4	3.9	3.8	2.8	6.8	53.9	0.8	0.9	4.5	46.1
BTC	1.8	1.5	0.4	0.2	0.5	0.4	0.4	66.7	27.0	1.1	33.3
ETH	1.4	0.9	0.6	0.3	1.1	1.4	0.8	27.9	64.9	0.8	35.1
VIX	21.2	18.5	3.3	2.5	2.4	4.9	3.8	2.1	1.5	39.9	60.1
TO	104.1	91.9	64.1	50.2	46.6	51.4	31.8	35.1	32.7	39.5	54.8
NET	+35.9	+25.6	-0.4	-5.2	-13.2	-7.2	-14.2	+1.7	-2.4	-20.6	

Notes: Generalized forecast-error variance decomposition, 2016-03-11 to 2026-03-11, $T = 2,514$ trading days. Entry (i, j) is the share (%) of the 10-day-ahead forecast-error variance of the log realized volatility of i due to shocks in j ; diagonal entries (own shares) in bold. FROM and TO are the off-diagonal row and column sums; NET = TO - FROM in percentage points; the bottom-right entry of the TO row is the total spillover index. Figures in brackets are 90% percentile intervals from a residual bootstrap with 500 replications. Source: results/rev_table_connectedness_full.csv and rev_table_connectedness_full_ci.csv.

the VIX; conversely, no other series explains more than 12% of ES. The two contracts are also each other's largest source of variance (28–30%), as expected for two indices of the same market.

Second, the realized volatility of the VIX is the largest net receiver, at –20.6 percentage points (interval –25.2 to –14.0). Shocks to ES and NQ explain 21.2% and 18.5% of its forecast-error variance, while its own shocks explain only 40%; it transmits 40% in total, of which 12% and 11% to ES and NQ. This is the pattern one expects for a price that is a deterministic function of S&P 500 option prices and whose intraday variability therefore inherits that of the underlying. It is not a statement about the information content of the VIX level for future volatility, which is a separate question (Bekaert and Hoerova, 2014). Crude oil (–14.2, interval –21.6 to –6.7) and sterling (–13.2, interval –18.0 to –7.4) are the other clear net receivers; gold (–7.2) and USD/JPY (–5.2) are mild receivers whose intervals touch or include zero, and EUR/USD is neutral.

Third, bitcoin and ether form a distinct block. Each explains 27–28% of the other's variance, and their own shares, at 67% and 65%, are the largest in the table. Their exposure to the eight traditional instruments is small but not negligible in the full sample: 6.3% of bitcoin's and 7.1% of ether's forecast-error variance, of which ES and NQ account for about half. Their net spillovers, +1.7 (interval –3.3 to 6.4) for bitcoin and –2.4 (–7.9 to 2.1) for ether, are not distinguishable from zero. The earlier version of this paper reported own shares above 77% and cross-asset shares below 0.5% for the cryptocurrencies; those figures were produced by a panel in which the traditional series were forward-filled on weekends, which mechanically breaks the contemporaneous correlation between crypto innovations and the (artificially zero) innovations of the other series.

Fourth, the exchange rates and commodities form a middle tier. EUR/USD receives 16.5% of its variance from GBP/USD and 14.4% from USD/JPY, GBP/USD receives 19.3% from EUR/USD, and gold receives about 10% each from the two European currencies, which is consistent with a common dollar factor in all these prices. Crude oil has the largest own share among traditional assets (54%), receives most of its cross-asset variance from ES and NQ (22% together) and transmits little, which is at odds with a view of oil as an originator of macroeconomic volatility over this decade.

Figure 2 displays the matrix graphically. The block structure is visible: a dense equity–FX–commodity core, a two-node crypto block linked to the core mainly through the equity futures, and the VIX attached to the core almost exclusively through ES and NQ.

5.2. Robustness of the Full-Sample Results

Table 5 re-estimates the full-sample decomposition under alternative choices. The total index lies between 53.7% and 55.5% for $p \in \{1, 2, 3, 4, 6\}$ and between 54.4% and 55.3% for $H \in \{5, 10, 20\}$; it falls to 50.0% when realized volatility enters in levels rather than logarithms, because the covariance matrix is then dominated by a few extreme days on which comovement is weaker than on ordinary days. Including weekend crypto variance in the Monday observation leaves every measure

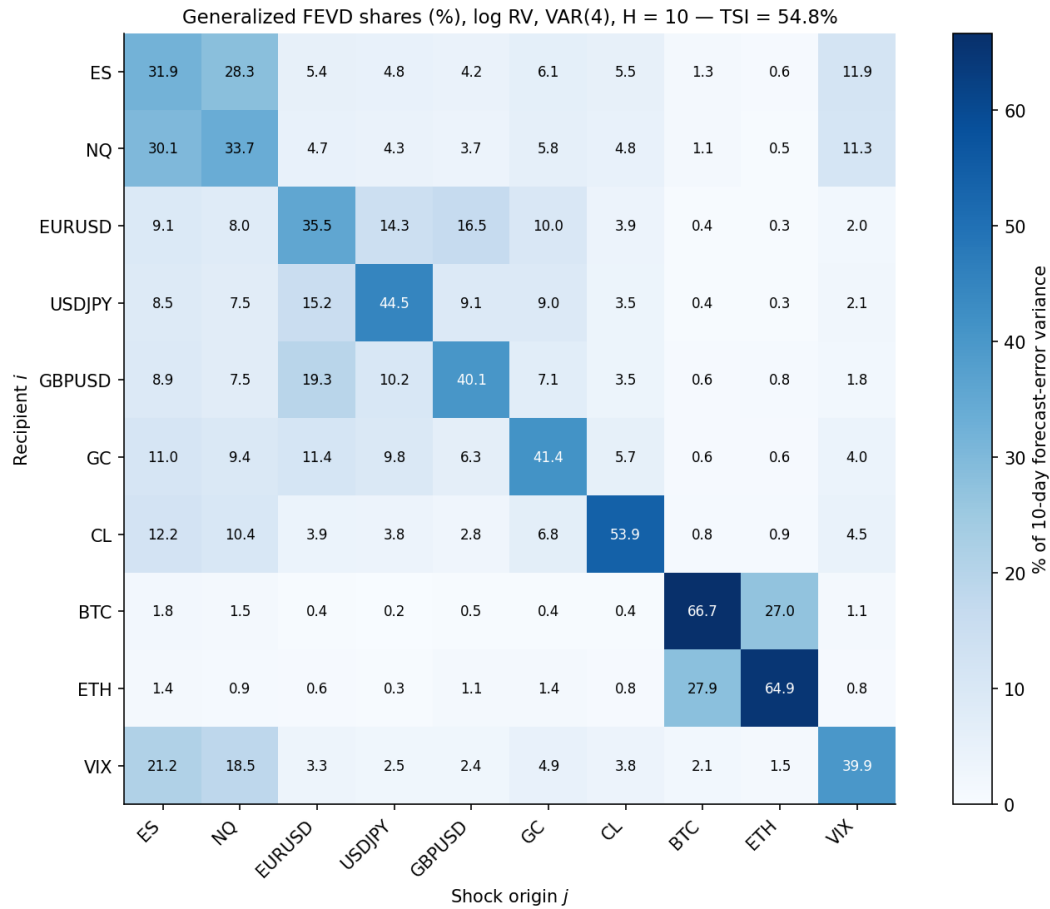


Figure 2. Full-sample variance-decomposition shares.

Notes: Shares (%) of the 10-day forecast-error variance of the row instrument attributable to shocks in the column instrument, from Table 4. Darker cells denote larger shares.

within one percentage point of the baseline. Excluding the two cryptocurrencies raises the index to 59.0%, which quantifies the dilution they induce, and excluding the VIX lowers it to 52.9%.

Table 5. Robustness of full-sample connectedness to specification and sample choices.

Specification	<i>T</i>	TSI	ES	NQ	USDJPY	CL	BTC	VIX	BTC own
Baseline: log RV, trading days, VAR(4), <i>H</i> = 10	2514	54.8	+35.9	+25.6	−5.2	−14.2	+1.7	−20.6	66.7
RV in levels (trading days)	2514	50.0	+41.6	+29.8	−8.0	−15.6	+1.6	−23.4	74.8
VAR(1)	2514	53.7	+38.6	+26.2	−5.4	−5.8	+7.4	−27.4	69.8
VAR(2)	2514	54.1	+36.6	+25.9	−4.9	−7.3	+3.5	−26.1	69.5
VAR(3)	2514	54.9	+36.0	+25.5	−5.1	−10.0	+2.7	−24.2	68.3
VAR(6)	2514	55.5	+35.0	+23.7	−5.6	−14.8	+1.3	−16.7	65.3
<i>H</i> = 5	2514	54.4	+32.5	+22.7	−5.7	−11.9	−0.3	−17.0	66.1
<i>H</i> = 20	2514	55.3	+39.8	+28.8	−5.4	−17.4	+4.4	−23.3	67.3
Weekend-inclusive crypto RV	2514	54.9	+36.3	+26.0	−5.1	−14.6	+0.3	−20.9	65.7
Sample 2018-01 to 2026-03	2063	57.4	+35.7	+27.7	−7.7	−17.3	+3.3	−19.0	61.6
Sample 2016-03 to 2019-12	954	51.5	+35.8	+23.9	+9.9	−8.9	+3.0	−14.4	77.6
Sample 2020-01 to 2026-03	1560	60.9	+36.4	+28.2	−11.3	−16.3	−8.7	−19.5	47.7
Excluding VIX	2514	52.9	+26.3	+18.1	−5.8	−13.1	+0.8		67.7
Excluding BTC and ETH	2514	59.0	+34.4	+24.1	−4.4	−13.7		−20.1	
Excluding ETH (BTC only)	2514	53.8	+35.7	+25.0	−5.3	−13.7	−1.3	−19.8	91.7

Notes: TSI in percent; ES, NQ, USDJPY, CL, BTC and VIX columns are net directional spillovers in percentage points; the last column is bitcoin's own variance share (%). Baseline: log realized volatility, trading-day panel, VAR(4), *H* = 10. "Weekend-inclusive crypto RV" averages the daily variance of BTC and ETH over the calendar days since the previous trading day. Source: `results/rev_table_robustness.csv`.

The ranking of the main transmitters and receivers is stable: ES is the largest net transmitter in every row of the table (between +26 and +42 percentage points), NQ the second, and the realized volatility of the VIX the largest net receiver (between −17 and −27), followed by crude oil (between −6 and −17). The net position of bitcoin, by contrast, is not robust in sign: it is +7.4 with one lag, +4.4 at *H* = 20, −0.3 at *H* = 5, −1.3 when ether is excluded, +3.0 in 2016–2019 and −8.7 in 2020–2026. Bitcoin's own share falls from 78% in 2016–2019 to 48% in 2020–2026, the clearest sign in the table that its integration with the system increased. The sub-sample split also reverses the sign of USD/JPY, a net transmitter before 2020 (+9.9) and a net receiver after (−11.3), and raises the total index from 51.5% to 60.9%.

5.3. Time-Varying Connectedness

Figure 3 plots the rolling total spillover index for windows of 200, 250 and 500 trading days. The three series tell the same story at different levels of smoothing. Connectedness was moderate and declining from 2016 to late 2017, reaching its minimum of 50.5% (200-day window) in October 2017, when the cryptocurrency boom decoupled bitcoin and ether from everything else. It then fluctuated between 51% and 61% until February 2020 and rose sharply during the COVID-19 crash: the 200-day index moved from 60.4% on 20 February 2020 to 69.1% on 31 March 2020 and remained above 65% until the end of June. The 2021 decline, the renewed increase through the 2022 tightening cycle (the 200-day index exceeds 70% in September–October 2022), the trough of early 2024 and the climb through 2025 are all visible in the 500-day window, which ends the sample

at its own maximum of 66.5% in March 2026. The 200-day index reaches the highest value of the entire sample, 73.4%, on 24 September 2025; the calendar-year estimates of Section 5.5 confirm that 2025 is the most connected year of the decade, at 71.5% (interval 67.9–75.2).

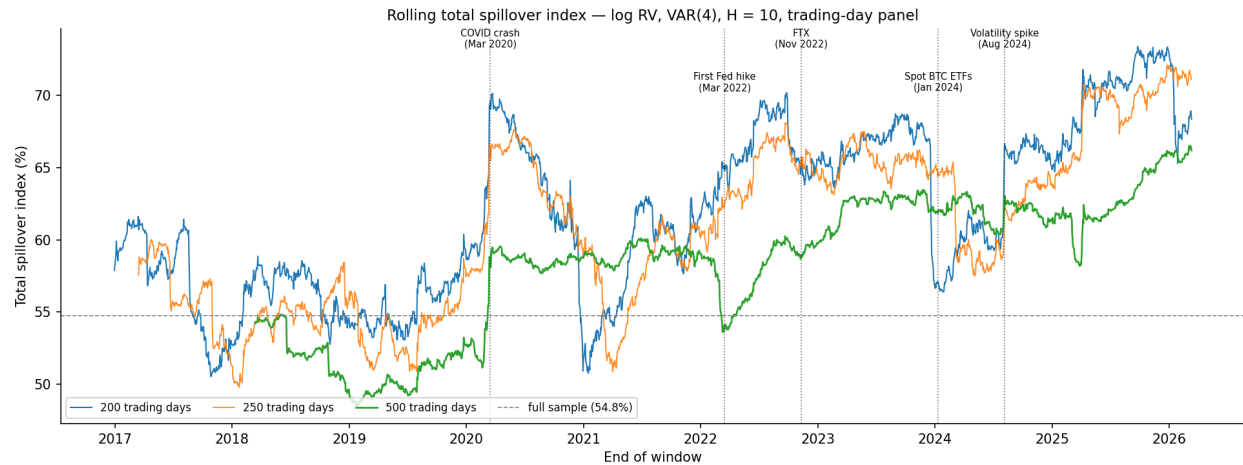


Figure 3. Rolling total spillover index.

Notes: Total spillover index (%) from a VAR(4) on log realized volatility with $H = 10$, estimated over rolling windows of 200, 250 and 500 trading days and plotted at the last day of the window. The dashed line is the full-sample estimate (54.8%). Vertical lines mark the COVID-19 crash (16 March 2020), the first Federal Reserve rate increase of the 2022 cycle (16 March 2022), the FTX collapse (11 November 2022), the launch of spot bitcoin ETFs (11 January 2024) and the volatility spike of 5 August 2024. Source: `results/rev_rolling_w200.csv`, `rev_rolling_w250.csv`, `rev_rolling_w500.csv`.

Two differences from the May 2026 version deserve mention. First, the level of the rolling index is lower (mean 61.9% for 200 trading days against 67.1% previously) and the 500-day mean of 58.3% is closer to the full-sample value of 54.8%; the gap between rolling and full-sample estimates is the small-sample upward bias of a heavily parameterized VAR, which shrinks as the window lengthens (Table A2 in the appendix). Second, the earlier version reported a maximum of 81.6% on 6 February 2018, interpreted as the signature of the “Volmageddon” episode, with the index jumping from 62% to 82% in two days. On the trading-day panel the index moves from 54.4% on 2 February to 56.4% on 6 February 2018. The earlier spike was produced by the interaction of a single extreme observation of VIX realized volatility with a panel in which most other series were forward-filled on surrounding weekend days; it is not a feature of the data.

5.4. Regime-Specific Connectedness

Table 6 summarizes the decomposition in four sub-samples, with bootstrap intervals; the full ten-by-ten tables are in Section C, and Figure 4 plots the net spillovers.

In the pre-COVID period (292 days) the equity futures dominate even more than in the full sample, with net spillovers of +41 and +47 percentage points and intervals that exclude zero by a wide margin; the European currencies and crude oil are significant net receivers; and the VIX is

Table 6. Total and net directional spillovers by regime, with 90% bootstrap intervals.

	Pre-COVID 2019-01 to 2020-02	COVID crash 2020-03 to 2020-06	Rate hikes 2022-01 to 2022-12	Spot-ETF era 2024-01 to 2026-03
<i>T</i> (trading days)	292	85	254	544
VAR lag <i>p</i>	4	1	4	4
TSI (%)	59.9 [58.9, 65.7]	71.7 [65.9, 78.1]	64.6 [63.7, 70.5]	65.5 [63.4, 69.3]
<i>Net directional spillovers (pp)</i>				
ES	+41.3 [+23.0, +55.6]	+19.4 [−23.3, +52.1]	+25.4 [+8.2, +36.7]	+29.4 [+18.4, +37.9]
NQ	+47.0 [+26.4, +60.5]	+33.3 [−12.7, +63.5]	+6.3 [−6.9, +18.8]	+28.7 [+16.3, +37.6]
EURUSD	−24.8 [−35.6, −3.3]	+0.7 [−29.1, +37.3]	+3.9 [−7.5, +18.4]	+8.9 [−2.4, +19.4]
USDJPY	+9.3 [−5.7, +30.1]	+81.8 [+7.3, +135.3]	−18.6 [−29.2, −4.1]	−11.3 [−22.5, +0.8]
GBPUSD	−29.0 [−42.5, −7.7]	−16.0 [−41.7, +27.4]	+9.0 [−3.8, +20.8]	−1.8 [−12.3, +10.0]
GC	−18.5 [−32.4, +2.2]	−1.3 [−38.0, +39.4]	+8.8 [−3.6, +22.3]	+4.1 [−9.5, +17.0]
CL	−27.3 [−40.3, −3.3]	−29.0 [−52.1, +12.0]	−21.5 [−33.5, −5.0]	−19.9 [−31.4, −4.6]
BTC	+12.7 [−14.8, +24.0]	−14.4 [−45.9, +32.9]	−3.4 [−16.7, +12.4]	−12.4 [−20.4, −2.1]
ETH	−11.4 [−27.1, +1.7]	−27.9 [−54.2, +19.1]	+0.8 [−12.0, +14.3]	−19.5 [−27.7, −9.2]
VIX	+0.6 [−19.2, +23.1]	−46.6 [−61.4, −11.2]	−10.7 [−24.1, +4.6]	−6.0 [−17.3, +8.7]

Notes: Log realized volatility, $H = 10$; $p = 4$ except for the 85-day COVID window, where $p = 1$ (the VAR(4) estimates for that window are TSI 71.4%, NET USDJPY +105.3, NET BTC −4.6). Brackets: 90% percentile intervals from 500 residual-bootstrap replications. The spot-ETF era begins on 11 January 2024, the first trading day of U.S. spot bitcoin ETFs. Source: results/rev_table_regimes.csv.

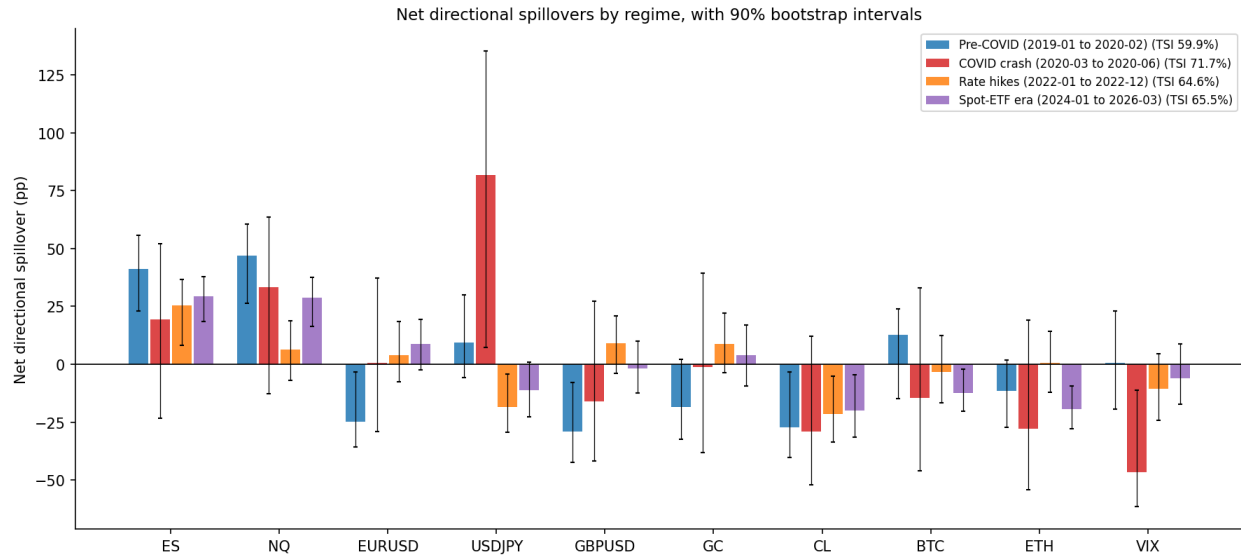


Figure 4. Net directional spillovers by regime.

Notes: Net directional spillovers (percentage points) from Table 6; whiskers are 90% bootstrap intervals. Positive values denote net transmitters.

neutral. Bitcoin's point estimate is +12.7, but its interval (−14.8 to +24.0) spans zero.

The COVID crash window (85 trading days) is the sub-sample in which inference matters most. The total index rises to 71.7% (interval 65.9–78.1), the highest of the four regimes. USD/JPY becomes the dominant transmitter, at +81.8 percentage points with an interval of +7.3 to +135.3: the sign is established, the magnitude is not. The economic reading is that the yen's safe-haven appreciation and the unwinding of carry trades in March 2020 (Ranaldo and Söderlind, 2010; Habib and Stracca, 2012), together with the dollar funding squeeze, made exchange-rate volatility the common factor of that episode. ES and NQ remain net transmitters in point estimate (+19 and +33) but with intervals that include zero, which corrects the earlier version's statement that equities "flipped" to receivers; that statement rested on a VAR(4) with 41 coefficients per equation estimated on 122 calendar days. Bitcoin is a net receiver in point estimate (−14.4), consistent with Conlon and McGee (2020), but its interval is −45.9 to +32.9. The only other significant result of the window is that the realized volatility of the VIX is a strong net receiver (−46.6, interval −61.4 to −11.2).

In the 2022 tightening cycle (254 days) the hierarchy is flatter. ES remains a significant transmitter (+25.4) but NQ is neutral; USD/JPY (−18.6) and crude oil (−21.6) are significant receivers; the European currencies and gold have positive but insignificant point estimates. Bitcoin's net spillover is −3.4 with an interval of −16.7 to +12.4. The earlier version reported +7.9 for bitcoin in this regime and described a transition to net transmitter; on the trading-day panel with log volatility the point estimate is negative and, more importantly, the interval shows that the data cannot distinguish either sign from zero in a one-year window.

The spot-ETF era (544 days) is the regime with the sharpest crypto results. The equity futures

are back at the top (+29.4 and +28.7, both significant), crude oil remains a significant receiver (−19.9), and bitcoin and ether are both significant net receivers, at −12.4 (interval −20.4 to −2.1) and −19.5 (−27.7 to −9.2). As cryptocurrencies became accessible through regulated equity-market vehicles, their realized volatility became more responsive to shocks in the traditional system without the reverse becoming true.

5.5. Crypto Integration by Calendar Year

Table 7 and Figure 5 follow the integration of the cryptocurrencies year by year. The share of bitcoin's forecast-error variance explained by the eight traditional instruments (that is, FROM excluding ether) was 13.8% in 2016, 8.7% in 2017 and 6.8% in 2019, with an intermediate 22.8% in 2018. From 2020 onwards it never falls below 20%: 34.4% in 2020, 20–26% in 2021–2024, and 46.2% in 2025. The pairwise shares with ES rise in both directions, from under 1% in 2017 and 2019 to 10.0% (BTC from ES) and 7.7% (ES from BTC) in 2025, so that integration is genuinely two-sided at the pairwise level. The net spillover of bitcoin, however, is negative in every year from 2020 to 2025 (between −1.6 and −14.6), while it was positive in 2016, 2018 and 2019; none of the yearly intervals excludes zero for bitcoin, but the interval for ether excludes zero in 2025 (−20.2, interval −31.4 to −4.5). The total index by year rises from 51–55% in 2016–2019 to 61–63% in 2020–2024 and 71.5% in 2025.

Table 7. Connectedness by calendar year, log realized volatility, VAR(2), $H = 10$.

Year	T	TSI (%)	NET BTC (pp)	NET ETH (pp)	FROM BTC excl. ETH (%)	BTC ← ES (%)	ES ← BTC (%)
2016	200	55.4 [55.1, 63.2]	+25.4 [−13.9, +51.0]	+1.4	13.8	0.4	3.3
2017	251	51.0 [51.1, 57.5]	−3.9 [−24.3, +12.0]	+5.1	8.7	0.2	0.0
2018	251	51.7 [50.7, 59.2]	+18.0 [−13.9, +44.6]	−12.6	22.8	7.5	8.8
2019	252	54.4 [52.5, 61.3]	+11.3 [−13.3, +22.3]	−10.0	6.8	0.5	0.2
2020	253	61.5 [57.7, 67.6]	−13.2 [−32.8, +11.0]	−15.2	34.4	2.3	0.9
2021	252	60.6 [57.6, 66.4]	−14.6 [−30.6, +0.1]	−6.7	23.5	4.5	1.3
2022	254	61.2 [59.9, 67.1]	−1.6 [−14.7, +12.9]	+1.0	25.7	5.9	3.8
2023	250	62.6 [59.3, 68.6]	−11.5 [−29.5, +5.7]	−7.4	20.2	3.6	0.6
2024	252	62.1 [59.5, 68.7]	−7.7 [−15.4, +4.5]	−10.3	24.2	5.2	3.2
2025	251	71.5 [67.9, 75.2]	−3.2 [−20.3, +18.5]	−20.2	46.2	10.0	7.7

Notes: 2016 covers 11 March–31 December. TSI in percent and net spillovers in percentage points, with 90% intervals from 300 bootstrap replications in brackets. “FROM BTC excl. ETH” is the share of bitcoin's forecast-error variance due to the eight non-crypto instruments. BTC ← ES is the share of bitcoin's variance due to ES shocks and ES ← BTC the share of ES variance due to bitcoin shocks. Source: `results/rev_table_yearly.csv`.

Figure 6 shows the same evolution in rolling windows. Bitcoin's 500-day net spillover drifts from slightly negative in 2018 to a maximum near +15 percentage points at the end of 2019, falls through 2020–2021, and remains between −5 and −20 from 2022 to the end of the sample, finishing

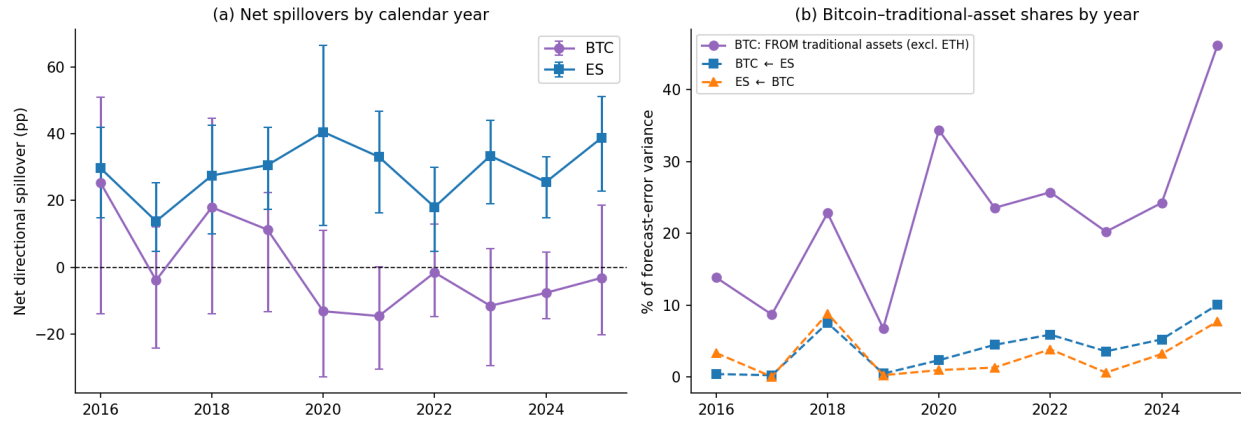


Figure 5. Bitcoin's integration with traditional assets by calendar year.

Notes: Panel (a): net directional spillovers of bitcoin and ES by year with 90% bootstrap intervals. Panel (b): share of bitcoin's 10-day forecast-error variance explained by the eight traditional instruments, and pairwise shares between bitcoin and ES. From Table 7.

at -19.1 in March 2026; it is positive in only 27% of the 500-day windows and 34% of the 200-day windows. ES is a net transmitter in every window, between $+20$ and $+57$ percentage points.

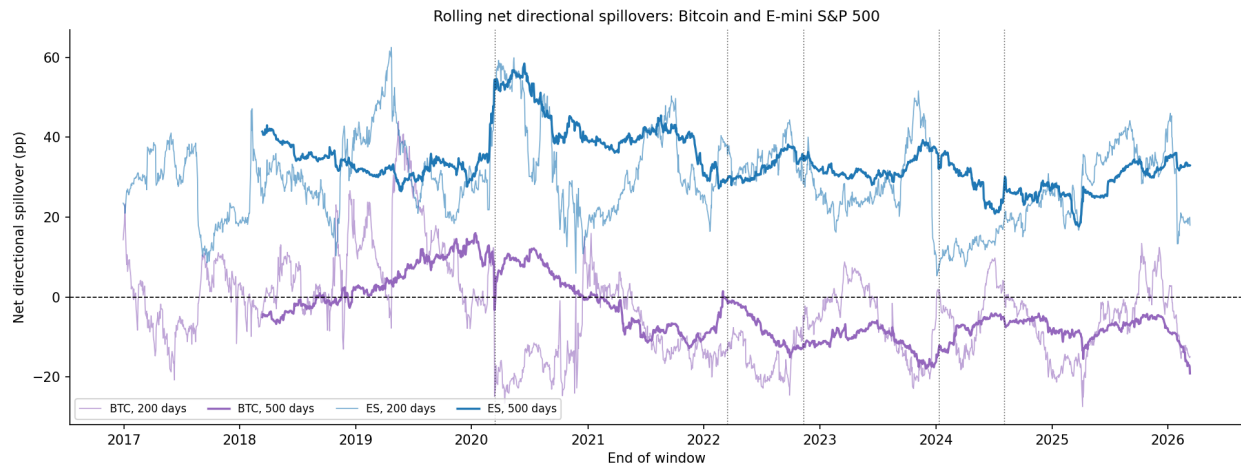


Figure 6. Rolling net directional spillovers of bitcoin and ES.

Notes: Net directional spillovers (percentage points) for bitcoin (purple) and ES (blue) from VAR(4) estimates on log realized volatility over rolling windows of 200 (thin lines) and 500 (thick lines) trading days. Vertical lines as in Figure 3. Source: `results/rev_rolling_w200.csv`, `rev_rolling_w500.csv`.

5.6. Network Representation

Figure 7 draws the net pairwise directional spillovers of (11) that exceed the 60th percentile of all pairwise values in absolute terms (1.0 percentage point). The graph has a hub-and-spoke structure: ES and NQ send net volatility to every other traditional instrument and to the VIX, the thickest edge being $ES \rightarrow VIX$; EUR/USD sends net volatility to GBP/USD, USD/JPY and gold; and gold sends a small net flow to crude oil. Bitcoin and ether are isolated at this threshold because their net

pairwise spillovers with every traditional instrument—and with each other—are smaller than one percentage point in the full sample, even though their gross exposures to equities are not zero. The network therefore summarizes the asymmetric transmission among traditional assets rather than the gross linkages of the crypto block, which Section 5.5 shows to be growing.

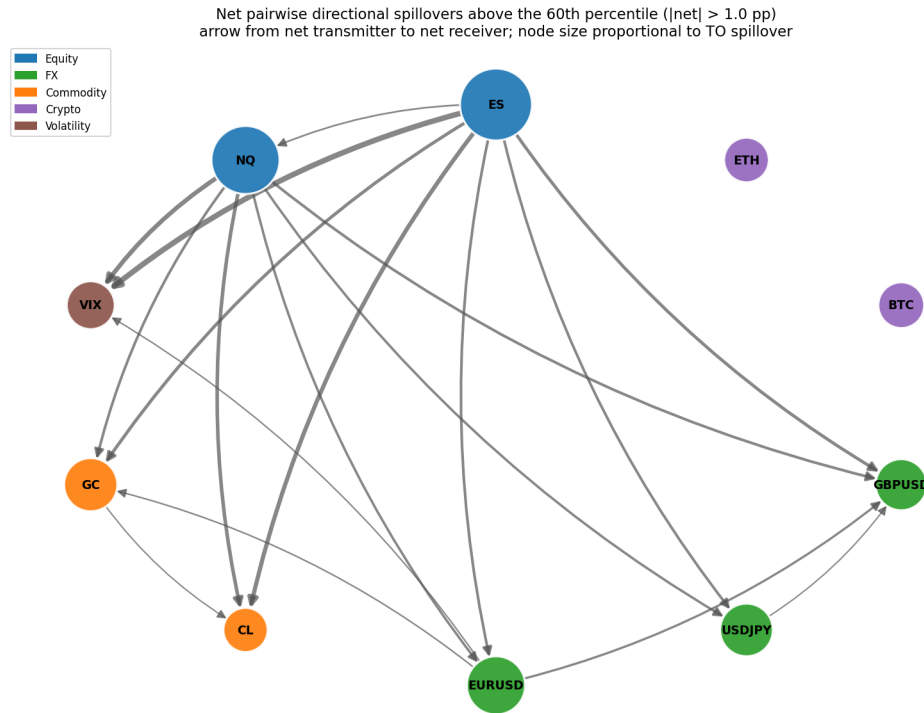


Figure 7. Network of net pairwise directional spillovers, full sample.

Notes: Nodes are the ten instruments, coloured by asset class, with size proportional to TO spillover. A directed edge from i to j is drawn when $NET_{i \rightarrow j}$ exceeds 1.0 percentage point (the 60th percentile of absolute net pairwise spillovers); edge width is proportional to its value. From the decomposition of Table 4.

5.7. Granger Causality

Table 8 reports Granger-causality tests on daily log realized volatility with four lags over the common panel. Equity futures Granger-cause the realized volatility of the VIX ($F = 19.9$ for ES and 14.4 for NQ, $p < 0.001$ under both conventional and HAC inference), and the reverse direction is also significant though weaker ($F = 5.3$ and 5.8), confirming the asymmetric two-way link of Section 5.1. ES and NQ do not Granger-cause each other beyond their own lags, which is expected for two indices whose volatilities move almost simultaneously. None of ES, NQ or the VIX Granger-causes bitcoin's realized volatility (p between 0.26 and 0.66). In the other direction, bitcoin Granger-causes the realized volatility of the VIX ($F = 5.1$, $p < 0.001$) and, marginally, of ES ($F = 2.3$, $p = 0.054$; HAC $p = 0.024$), and there is two-way predictability between bitcoin and gold. These statistics must be read with two cautions. The sums of the coefficients on the causing variable are between

−0.07 and +0.03, so that the predictive content, while statistically detectable in a sample of 2,500 days, is economically small relative to own-lag persistence. And sixteen tests are reported, so that one or two rejections at the 5% level would be expected under the global null. The session-ordered regressions of Section 5.8 provide a sharper test of the direction of information flow between bitcoin and U.S. equities.

Table 8. Granger-causality tests on daily log realized volatility, four lags.

Cause	Effect	T	F	p	Wald (HAC)	p
ES	VIX	2510	19.94***	0.000	62.78***	0.000
NQ	VIX	2510	14.40***	0.000	48.88***	0.000
VIX	ES	2510	5.33***	0.000	22.21***	0.000
VIX	NQ	2510	5.83***	0.000	22.18***	0.000
ES	NQ	2510	1.10	0.354	4.84	0.304
NQ	ES	2510	0.62	0.647	2.02	0.732
ES	BTC	2510	1.33	0.257	6.29	0.178
NQ	BTC	2510	1.17	0.324	4.77	0.312
VIX	BTC	2510	0.60	0.663	2.32	0.677
BTC	ES	2510	2.33*	0.054	11.21**	0.024
BTC	NQ	2510	1.47	0.208	6.65	0.155
BTC	VIX	2510	5.10***	0.000	24.46***	0.000
USDJPY	ES	2510	3.50***	0.007	13.69***	0.008
ES	USDJPY	2510	1.59	0.174	5.77	0.217
GC	BTC	2510	3.80***	0.004	15.32***	0.004
BTC	GC	2510	6.44***	0.000	33.08***	0.000

Notes: Common trading-day panel, 2016-03-11 to 2026-03-11. F is the conventional statistic of (13); Wald (HAC) uses a Newey–West covariance matrix with ten lags and is distributed $\chi^2(4)$ under the null. ***, **, *: significant at 1%, 5%, 10%. Source: results/rev_table_granger.csv.

5.8. Intraday Periodicity and Trading Sessions

Figure 8 plots the mean absolute 5-minute return by hour of the day in UTC for the VIX, ES, NQ and bitcoin over the common sample, after conversion of the Eastern-time stamps. The equity futures display the familiar pattern of the U.S. cash session (Wood et al., 1985; Harris, 1986): a trough around 04:00 UTC during the late Asian hours, a rise from 07:00–08:00 UTC when European markets open, a sharp peak in the hour of the U.S. cash open (13:30–14:30 UTC depending on daylight-saving time), a second peak in the hour before the cash close, and a decline after 20:00 UTC. The peak-to-trough ratio is 3.9 for ES and 4.5 for NQ. The VIX, which is disseminated from 07:15–08:15 UTC, is relatively quiet during European hours and three times as volatile in the hour of the U.S. cash open as at its 10:00 UTC minimum; because its “returns” are changes in an implied-volatility index, its hourly profile also reflects the option market’s reaction to the cash open. Bitcoin’s profile is nearly flat: the mean absolute return ranges from 0.240% at 07:00 UTC to

0.287% at 18:00 UTC, a peak-to-trough ratio of 1.2, with a mild hump during U.S. hours consistent with [Eross et al. \(2019\)](#).

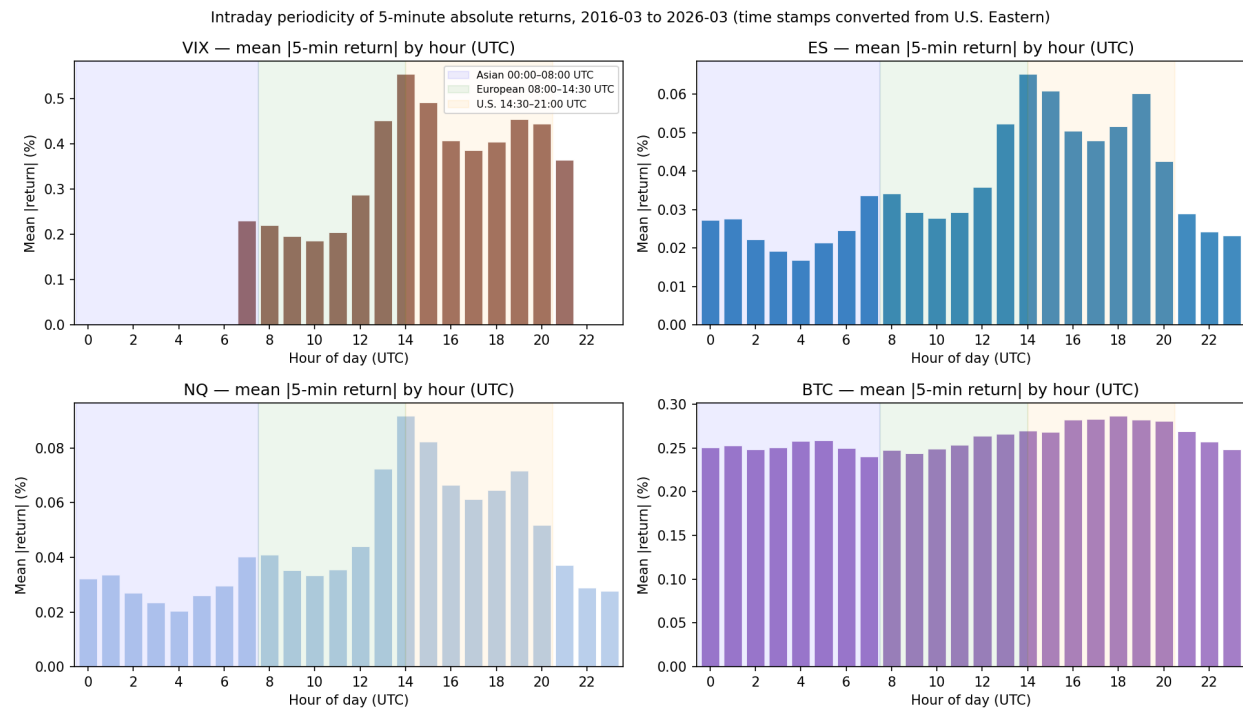


Figure 8. Intraday periodicity of absolute 5-minute returns by hour of the day (UTC).

Notes: Mean absolute 5-minute log return (%) by UTC hour, 11 March 2016 to 11 March 2026, after conversion of the vendor's U.S. Eastern time stamps with daylight-saving rules. Shaded areas mark the Asian (00:00–08:00), European (08:00–14:30) and U.S. (14:30–21:00) sessions. The VIX is disseminated only from 03:15 Eastern time. Source: `results/rev_intraday_hourly_absret_utc.csv`.

Table 9 translates the profiles into shares of daily variance. The U.S. session generates 53% of the daily variance of ES and 54% of NQ, the European session 31–32%, and the Asian session 14–16%. For the VIX the U.S. session accounts for 63% of the variance realized during its dissemination hours. For bitcoin the three sessions contribute 37%, 25% and 38%: the smaller European share reflects the shorter session (6.5 hours against 8 for the Asian session) rather than lower volatility per hour, and the U.S. session is the most volatile per unit of time. Bitcoin's weekend volatility is lower than its weekday volatility but far from negligible: Saturday and Sunday account for 22.1% of the variance of an average week (28.6% would correspond to a uniform distribution), and mean annualized realized volatility is 96–99% on weekend days against 104–106% on weekdays, in line with the day-of-week effects of [Baur et al. \(2019\)](#). The earlier version of this paper, which read the Eastern-time stamps as UTC, attributed the equity-futures peak to the European session and the VIX peak to 09:00–10:00 UTC; both statements described the U.S. cash open shifted by four to five hours.

Table 10 reports the session-ordered predictive regressions of (15). Bitcoin's Asian- and

Table 9. Volatility by trading session, 2016-03-11 to 2026-03-11.

Asset	Session (UTC)	Days	Mean $ r $ (%)	Annualized vol. (%)	Share of day (%)
ES	Asian 00:00–08:00	2583	0.024	5.1	16.2
	European 08:00–14:30	2581	0.037	7.3	30.8
	U.S. 14:30–21:00	2578	0.054	9.9	53.1
NQ	Asian 00:00–08:00	2583	0.029	6.2	14.3
	European 08:00–14:30	2581	0.046	9.5	31.8
	U.S. 14:30–21:00	2578	0.069	12.8	54.0
VIX	Asian 00:00–08:00	0	0.231	–	–
	European 08:00–14:30	2492	0.272	58.6	36.9
	U.S. 14:30–21:00	2518	0.444	80.6	63.5
BTC	Asian 00:00–08:00	2610	0.255	56.9	36.6
	European 08:00–14:30	2609	0.260	51.2	25.3
	U.S. 14:30–21:00	2608	0.287	56.8	38.2

Notes: Weekdays only. Mean $|r|$ is the average absolute 5-minute return in the session; annualized volatility is the mean over days of $\sqrt{252 \cdot RV_{i,t}^s}$, where $RV_{i,t}^s$ is the session realized variance of (14); share of day is the mean over days of the session's share of the variance realized in the three sessions. The VIX has no Asian-session bars except a few minutes before 08:00 UTC in winter. Source: results/rev_intraday_sessions.csv.

European-session variance does not help predict the U.S.-session variance of ES or NQ on the same day once four lags of the latter are included: the HAC Wald statistics have p -values between 0.16 and 0.48 and the incremental R^2 is below 0.0012. Bitcoin's earlier-session variance does predict the U.S.-session variance of the VIX ($p < 0.001$), but the incremental R^2 is 0.007 and the same-day coefficient is 0.06. In the reverse direction the evidence is stronger and uniform: the previous day's U.S.-session variance of ES, NQ and the VIX predicts bitcoin's Asian-session variance with coefficients of 0.08–0.10 and p -values below 0.002, and ES's own Asian-session (Globex overnight) variance predicts bitcoin's U.S.-session variance. For comparison, ES's overnight variance predicts its own U.S.-session variance with a coefficient of 0.38 and an incremental R^2 of 0.046, an order of magnitude larger than any cross-asset effect.

Table 11 addresses the specific hypothesis that bitcoin's weekend trading provides a continuous information channel for Monday equity volatility. Regressing the log U.S.-session variance of ES on Mondays on Friday's ES and bitcoin variances, the addition of bitcoin's Saturday–Sunday variance has a coefficient of -0.04 (standard error 0.05) and raises R^2 by less than 0.001; adding bitcoin's Monday Asian-session variance leaves both crypto coefficients insignificant at the 5% level. Over 501 Mondays, weekend bitcoin volatility carries no detectable incremental information about the volatility of the U.S. equity market when it reopens.

Table 10. Session-ordered predictive regressions for log session realized variance.

Predictive relation	T	Coef. (same day)	Wald (HAC)	p	ΔR^2
BTC Asian (t) $\rightarrow$ ES U.S. (t)	2574	+0.033 (0.019)	6.65	0.155	0.001
BTC European (t) $\rightarrow$ ES U.S. (t)	2574	+0.040 (0.021)	4.17	0.383	0.001
BTC Asian (t) $\rightarrow$ NQ U.S. (t)	2574	+0.024 (0.019)	6.29	0.179	0.001
BTC European (t) $\rightarrow$ NQ U.S. (t)	2574	+0.036 (0.022)	3.48	0.480	0.001
BTC Asian (t) $\rightarrow$ VIX U.S. (t)	2514	+0.058 (0.021)	30.92***	0.000	0.007
BTC European (t) $\rightarrow$ VIX U.S. (t)	2514	+0.056 (0.022)	28.66***	0.000	0.007
ES U.S. (t-1) $\rightarrow$ BTC Asian (t)	2482	+0.099 (0.021)	27.70***	0.000	0.003
NQ U.S. (t-1) $\rightarrow$ BTC Asian (t)	2482	+0.086 (0.022)	20.52***	0.000	0.002
VIX U.S. (t-1) $\rightarrow$ BTC Asian (t)	2242	+0.080 (0.022)	17.35***	0.002	0.002
ES Asian (t) $\rightarrow$ BTC U.S. (t)	2492	+0.093 (0.024)	19.29***	0.001	0.002
ES Asian (t) $\rightarrow$ ES U.S. (t) [own overnight]	2570	+0.382 (0.028)	222.28***	0.000	0.046

Notes: Each row is a regression of the log realized variance of the target session on four lags of itself and on the log realized variance of the predictor session on the same day and three previous days, (15). “Coef. (same day)” is $\hat{\gamma}_0$ with its HAC standard error; Wald (HAC) tests the joint nullity of the four predictor coefficients and is $\chi^2(4)$ under the null (Newey–West, ten lags); ΔR^2 is the increase in R^2 relative to the own-lags regression. In “(t-1)” rows the predictor is the U.S. session of the previous trading day. ***, **, *: significant at 1%, 5%, 10%. Source: results/rev_intraday_session_predictive.csv.

Table 11. Does weekend bitcoin volatility predict Monday U.S.-session volatility of ES?

Specification	N	$\ln RV_{\text{Fri}}^{\text{ES}}$	$\ln RV_{\text{weekend}}^{\text{BTC}}$	$\ln RV_{\text{Mon, Asian}}^{\text{BTC}}$	R^2
Friday controls only	501	+0.810	—	—	0.482
+ weekend BTC	501	+0.805	-0.043 (0.052)	—	0.483
+ weekend BTC + Monday Asian BTC	501	+0.803	-0.099 (0.061)	+0.094*	0.486

Notes: Dependent variable: log U.S.-session realized variance of ES on Mondays, 2016–2026. Regressors: log Friday U.S.-session variance of ES, log Friday daily variance of bitcoin (coefficient not shown), log Saturday-plus-Sunday variance of bitcoin and log Monday Asian-session variance of bitcoin. HAC standard errors (four lags) in parentheses. ***, **, *: significant at 1%, 5%, 10%. Source: results/rev_intraday_weekend_btc_monday_es.csv.

6. Discussion

6.1. Answers to the Research Questions

Structure of connectedness. Cross-asset shocks explain 54.8% of the ten-day forecast-error variance of log realized volatility, an estimate that is stable across lag orders, horizons and the treatment of weekend crypto variance (53.7–55.5%) and whose bootstrap interval is about four percentage points wide. The hierarchy has three robust elements: the two equity index futures are the only net transmitters whose intervals exclude zero in the full sample and in every robustness specification; the realized volatility of the VIX, crude oil and sterling are robust net receivers; and the remaining instruments—the euro, the yen, gold, bitcoin and ether—have net positions that cannot be distinguished from zero over the decade. This ordering is consistent with the primacy of U.S. equities found by [Diebold and Yilmaz \(2012\)](#) for stocks, bonds, exchange rates and commodities, and it adds two observations: the realized volatility of an implied-volatility index behaves as a derivative of its underlying, and crude oil, often cast as a source of macroeconomic volatility, has been a receiver of equity-market volatility over 2016–2026.

Regime dependence. The total index varies much less across regimes (59.9–71.7%) than the directional composition. The COVID-19 crash is the only sub-sample in which an instrument other than the equity futures takes the lead, USD/JPY, with a point estimate that is large and a sign that is established but a magnitude that the data cannot pin down (+7 to +135 percentage points). The statement in the earlier version that equity futures became net receivers during the crash is not supported once sampling uncertainty is taken into account; nor is the statement that bitcoin became a net transmitter during the 2022 tightening cycle. What the regime analysis establishes with confidence is more modest: the hierarchy is dominated by equities in calm and macro-driven periods, exchange-rate volatility became the common factor during the dollar funding squeeze of March 2020, and in the most recent period bitcoin and ether are net receivers.

Crypto integration and its direction. Integration has increased, and in a well-defined sense. The share of bitcoin's forecast-error variance explained by traditional instruments rose from below 10% in 2017 and 2019 to 20–34% in 2020–2024 and 46% in 2025, bitcoin's own share fell from 78% before 2020 to 48% after, and the pairwise shares with ES grew in both directions. The direction of net transmission, however, runs from equities to crypto: bitcoin's net spillover is negative in every calendar year since 2020 and significantly so in the spot-ETF period, its 500-day rolling net spillover has been negative since 2022, and the session-ordered regressions show that the U.S.-session volatility of ES, NQ and the VIX predicts bitcoin's next Asian-session volatility whereas bitcoin's overnight and weekend volatility does not predict U.S.-session equity volatility. The one exception,

a small but significant predictive effect of bitcoin's earlier-session volatility on the U.S.-session volatility of the VIX, is consistent with option markets pricing overnight risk-asset news before the cash open rather than with crypto volatility originating shocks. These results align with the post-2020 increase in crypto–equity comovement documented by [Iyer \(2022\)](#) and [Elsayed et al. \(2022\)](#) and with the finding of [Conlon and McGee \(2020\)](#) that bitcoin did not act as a safe haven in March 2020, and they qualify the interpretation of growing integration as growing influence: the volatility of the two largest cryptocurrencies has become more exposed to the traditional system, not the reverse.

Time variation. Total connectedness fell to its minimum during the 2017 crypto boom, rose sharply during the COVID-19 crash and again during the 2022 tightening cycle, and reached the highest values of the sample in 2025, when the calendar-year estimate was 71.5% against 51–55% in 2016–2019. Whether the 2025 level reflects a lasting change in market structure—the integration of crypto through exchange-traded funds, the growth of volatility-targeting and option-selling strategies—or the particular shocks of that year cannot be settled with one year of data. We refrain from interpreting the rolling index as an early-warning indicator: in the trading-day panel it does not rise ahead of the March 2020 crash, and the February 2018 spike that motivated this interpretation in the earlier version was an artefact of forward-filled observations.

Intraday distribution and sessions. Equity-futures volatility is concentrated in the U.S. cash session, which generates 53–54% of daily variance, with the familiar peaks at the open and before the close; the realized volatility of the VIX is even more concentrated (63%). Bitcoin's volatility is nearly uniform across the 24 hours, with a peak-to-trough ratio of 1.2 and a mild hump in U.S. hours, and weekends carry 22% of weekly variance. Round-the-clock trading does not translate into round-the-clock information for equity markets: once Friday's volatility is accounted for, the volatility of bitcoin over the weekend carries no incremental information about the volatility of ES on Monday.

6.2. Comparison with the Literature and Implications

The connectedness level of 55% is within the range reported for daily volatility systems of comparable size ([Diebold and Yilmaz, 2012, 2014](#)), and the dominance of equity futures matches most multi-asset applications. Our crypto results sit between the early finding of isolation ([Corbet et al., 2018](#); [Baur et al., 2018](#)) and the post-pandemic finding of integration ([Iyer, 2022](#)): the gross linkages have grown, the net direction is from equities to crypto, and the within-crypto block remains the dominant source of crypto variance, as in [Ji et al. \(2019a\)](#). The intraday results confirm, with ten years of 5-minute data, the U-shaped equity pattern of [Wood et al. \(1985\)](#) and [Harris \(1986\)](#) and the U.S.-hours hump

in bitcoin volatility of [Eross et al. \(2019\)](#).

For practitioners, three implications follow. The realized volatility of VIX-linked instruments responds to equity-futures volatility rather than anticipating it, so that positions in VIX products are not an independent source of volatility information at the daily frequency. The diversification benefit of cryptocurrencies has eroded in the volatility dimension since 2020 and is smallest in the most recent period, precisely when equity volatility is high. And because equity-futures variance is concentrated in the U.S. cash session while bitcoin's is spread evenly, risk limits that are calibrated on daily volatility understate the intraday concentration of equity risk and overstate that of crypto risk.

6.3. Methodological Lessons

Two methodological conclusions apply beyond this paper. First, in panels that mix 24/7 and exchange-traded instruments, the construction of the trading calendar is a modelling decision with first-order consequences: forward-filling the exchange-traded series over weekends changes the total index by five percentage points, the net spillover of ES by fifteen, and the apparent isolation of the crypto block from a cross-asset share of 6% to one below 1% (Section A). Second, connectedness estimates from short windows are imprecise: a ten-variable VAR(4) has 41 coefficients per equation, and in windows of 85–300 observations the 90% intervals of net spillovers are 30–130 percentage points wide. Regime narratives built on the sign of such estimates, including some in the earlier version of this paper, do not survive the addition of confidence intervals. Time-varying-parameter VARs ([Antonakakis et al., 2020](#)) or shrinkage estimators would be natural ways to recover time variation with fewer effective parameters.

6.4. Limitations

Several limitations remain. The 5-minute realized variance includes jump variation and, for the composite cryptocurrency feeds of 2016–2017, variation that reflects price discrepancies across exchanges rather than fundamental volatility; the results for 2018–2026 are qualitatively unchanged, but a jump-robust estimator ([Andersen et al., 2007](#)) and a single-exchange price series would be preferable. The filter that removes 5-minute returns beyond twenty standard deviations, applied before realized volatility was computed, may have removed genuine extreme moves on crash days and so understated realized volatility on the days that matter most for connectedness; its effect could not be quantified without re-processing the raw bars. The continuous futures series splice contracts at roll dates and roll returns were not removed. The VAR is linear and symmetric and does not distinguish spillovers from good and bad volatility ([Baruník et al., 2016, 2017](#)) or across frequencies ([Baruník and Křehlík, 2018](#)). The residual bootstrap ignores conditional heteroskedasticity in the innovations of log realized volatility and the intervals are therefore indicative. Finally, with ten instruments the

system omits sovereign bonds, emerging-market currencies, agricultural commodities and smaller cryptocurrencies, and the “U.S. equity” factor identified here may partly stand in for a global risk factor that a broader system would attribute differently.

7. Conclusion

This paper has measured the transmission of realized volatility across equity index futures, major exchange rates, gold and crude oil futures, the VIX and the two largest cryptocurrencies, using daily realized volatilities built from 5-minute bars and the generalized variance decomposition of a VAR estimated on the 2,514 trading days common to all ten series between March 2016 and March 2026. Cross-asset shocks account for 54.8% of forecast-error variance. The E-mini S&P 500 and Nasdaq 100 futures are the only robust net transmitters; the realized volatility of the VIX, crude oil and sterling are robust net receivers; and the net positions of the euro, the yen, gold, bitcoin and ether cannot be distinguished from zero over the decade. These conclusions hold across lag orders, forecast horizons, the treatment of weekend crypto variance, and the inclusion or exclusion of the VIX and of the cryptocurrencies.

The cryptocurrencies form a tightly linked pair whose exposure to the traditional system has grown from under 10% of forecast-error variance before 2020 to between 20% and 46% since, with the net flow running from U.S. equities to crypto: bitcoin and ether are significant net receivers in the spot-ETF period, the previous day’s U.S.-session volatility of equity futures predicts bitcoin’s Asian-session volatility, and neither bitcoin’s overnight nor its weekend volatility predicts the U.S.-session volatility of equity futures. Total connectedness rose during the COVID-19 crash, when exchange-rate volatility became the common factor, and reached its highest level of the sample in 2025. Intraday, equity and VIX volatility are concentrated in the U.S. cash session while bitcoin’s volatility is nearly uniform across the day and the week.

The revision of this paper has also been an exercise in the sensitivity of connectedness measures to data construction. Aligning 24/7 and exchange-traded series on a common trading calendar, rather than forward-filling the latter over weekends, changed the total index by five percentage points, the net spillover of equity futures by fifteen, and the apparent isolation of the crypto block from near-complete to partial; attaching bootstrap intervals to regime estimates showed that several sign changes reported in the earlier version, and in parts of the literature, are within sampling error; and converting exchange time stamps to UTC relocated the intraday volatility peaks from the European to the U.S. session. We regard these corrections as part of the paper’s contribution.

Three extensions appear most promising. A frequency decomposition of connectedness ([Baruník and Křehlík, 2018](#)) would show whether the equity-to-crypto transmission documented here operates at short or long horizons. A time-varying-parameter VAR ([Antonakakis et al., 2020](#)) or a shrinkage

estimator would recover time variation in the hierarchy with fewer effective parameters than rolling windows and would allow a formal test of the 2020 break in crypto integration. And jump-robust, single-exchange realized measures for the cryptocurrencies, together with the removal of futures roll returns, would tighten the measurement side on which the whole analysis rests.

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A. Audit of the Panel Construction

Table A1 reproduces the full-sample estimates of the May 2026 version of this paper and traces the effect of the two corrections made in the present version. The first row replicates the original computation exactly from the archived daily realized-volatility file: a panel of all 3,651 calendar days between 11 March 2016 and 11 March 2026, with missing values forward-filled for up to five days and realized volatility in levels. The second row removes the forward filling and the weekend rows, leaving the 2,514 trading days on which all ten instruments have an own realized volatility. The third row applies the log transformation to that panel and is the baseline of Section 5.

Table A1. Effect of the panel construction on full-sample connectedness, VAR(4), $H = 10$.

Construction of the panel	T	TSI	ES	NQ	VIX	BTC	USDJPY
Original: calendar days, forward-filled, RV levels	3651	55.4	+26.8	+19.7	-23.4	+1.2	-5.0
Trading days, RV levels	2514	50.0	+41.6	+29.8	-23.4	+1.6	-8.0
Trading days, log RV (revised baseline)	2514	54.8	+35.9	+25.6	-20.6	+1.7	-5.2

Notes: TSI in percent; the other columns are net directional spillovers in percentage points. The first row reproduces the published figures of the May 2026 version (TSI 55.44%, ES +26.80, NQ +19.72, VIX -23.37, BTC +1.23). Of the 3,651 rows of the original panel, 1,044 were Saturdays or Sundays and 1,137 contained at least one forward-filled value. Source: results/rev_audit_construction.csv.

The forward filling lowers the total index by about five percentage points relative to the trading-day panel in levels (55.4% against 50.0%) while compressing the net spillover of ES from +41.6 to +26.8 and of NQ from +29.8 to +19.7; the near-coincidence of the original index (55.4%) with the revised baseline (54.8%) is the result of two offsetting changes, forward filling and the log transformation, and not of robustness. The forward-filled panel also drove the own shares of bitcoin and ether above 77% and their cross-asset shares below 0.5%, because on weekend rows the innovations of the eight traditional series are identically zero while those of the cryptocurrencies are not. In the rolling analysis, the original 200-observation window covered 200 calendar days, or about 143 trading days, and the index reached 81.5% on 6 February 2018 against 56.4% on the trading-day panel (Table A2).

Table A2. Summary of rolling total spillover indices.

Window	Windows	Mean	Min	(date)	Max	(date)
original (200 calendar days, levels, forward-filled)	3451	67.1	57.2	2020-09-26	81.5	2018-02-06
200 trading days	2315	61.9	50.5	2017-10-27	73.4	2025-09-24
250 trading days	2265	60.9	49.8	2018-01-23	72.1	2025-12-26
500 trading days	2015	58.3	48.5	2019-01-24	66.5	2026-03-06

Notes: Mean, minimum and maximum of the rolling total spillover index (%) with the dates at which the extremes occur. The first row is the series published in the May 2026 version; the others are VAR(4), $H = 10$ estimates on log realized volatility over the trading-day panel. Source: results/rev_rolling_summary.csv.

B. Lag-Order Selection

Table A3 reports the information criteria for VAR(p) models of log realized volatility on the full trading-day panel. The Schwarz criterion selects $p = 3$, the Hannan–Quinn criterion $p = 4$ and the Akaike criterion $p = 5$; the baseline uses $p = 4$.

Table A3. Information criteria for the lag order of the VAR, log realized volatility, 2016–2026.

Criterion	$p = 1$	$p = 2$	$p = 3$	$p = 4$	$p = 5$	$p = 6$	$p = 7$	$p = 8$	$p = 9$	$p = 10$
AIC	-30.42	-31.16	-31.45	-31.58	-31.63	-31.62	-31.60	-31.60	-31.58	-31.57
BIC	-30.17	-30.67	-30.73	-30.62	-30.44	-30.20	-29.95	-29.71	-29.47	-29.22
HQ	-30.33	-30.98	-31.19	-31.23	-31.20	-31.11	-31.00	-30.91	-30.82	-30.72

Notes: Akaike (AIC), Schwarz (BIC) and Hannan–Quinn (HQ) criteria for VAR(p) with a constant, $p = 1, \dots, 10$, computed on a common estimation sample; the minimum of each criterion is in bold. Source: `results/rev_table_lag_selection.csv`.

C. Full Connectedness Tables by Regime

Tables A4 to A7 report the complete variance-decomposition tables for the four regimes summarized in Table 6. The COVID window uses $p = 1$; the others use $p = 4$.

Table A4. Connectedness table, pre-COVID regime (2019-01-01 to 2020-02-28), $T = 292$, VAR(4).

Recipient i	Shock origin j										FROM
	ES	NQ	EURUSD	USDJPY	GBPUSD	GC	CL	BTC	ETH	VIX	
ES	26.9	27.1	3.2	14.2	0.7	5.6	6.0	0.7	0.1	15.6	73.1
NQ	26.2	29.0	3.2	13.6	0.6	5.4	6.4	0.8	0.1	14.8	71.0
EURUSD	11.8	12.3	31.6	12.0	11.1	10.1	5.1	0.2	0.4	5.5	68.4
USDJPY	18.5	19.3	7.3	23.9	2.0	10.6	6.7	1.1	0.4	10.1	76.1
GBPUSD	8.5	7.1	13.5	5.9	49.0	4.8	2.4	0.8	2.0	5.8	51.0
GC	11.1	12.0	7.3	16.3	1.6	31.2	6.8	5.4	2.6	5.6	68.8
CL	15.9	18.7	1.7	12.5	1.2	6.0	32.5	3.2	1.5	6.8	67.5
BTC	1.3	1.0	3.8	0.6	1.3	1.9	2.0	74.5	13.0	0.6	25.5
ETH	0.8	0.7	1.3	0.6	2.5	0.6	0.8	24.6	67.5	0.6	32.5
VIX	20.4	19.9	2.3	9.7	0.9	5.3	3.9	1.4	1.0	35.2	64.8
TO	114.4	118.1	43.7	85.4	22.0	50.3	40.2	38.3	21.1	65.4	59.9
NET	+41.3	+47.0	-24.8	+9.3	-29.0	-18.5	-27.3	+12.7	-11.4	+0.6	

D. Replication

The daily realized volatilities are produced by `scripts/01_analysis.py` from the vendor's 5-minute bars (about ten minutes and 8 GB of memory); all connectedness estimates, bootstrap

Table A5. Connectedness table, COVID crash regime (2020-03-01 to 2020-06-30), $T = 85$, VAR(1).

Recipient i	Shock origin j										FROM
	ES	NQ	EURUSD	USDJPY	GBPUSD	GC	CL	BTC	ETH	VIX	
ES	20.2	20.4	9.8	18.5	8.4	8.1	2.2	5.3	2.4	4.7	79.8
NQ	18.9	21.0	9.3	18.4	7.4	8.2	2.7	6.1	3.1	4.8	79.0
EURUSD	10.4	11.8	20.3	23.0	13.5	9.0	2.4	5.3	3.2	1.0	79.7
USDJPY	10.4	11.1	12.9	36.8	10.3	7.8	0.7	5.4	3.4	1.1	63.2
GBPUSD	11.2	11.9	13.9	17.4	22.2	9.4	2.4	7.5	3.3	0.8	77.8
GC	12.1	13.3	9.3	16.0	6.3	22.5	5.0	8.8	5.4	1.3	77.5
CL	8.1	9.0	4.1	2.3	2.0	20.8	47.6	1.9	3.1	1.2	52.4
BTC	8.0	10.2	7.6	15.4	5.9	7.9	4.3	24.9	13.9	2.0	75.1
ETH	5.2	7.8	6.5	15.8	4.7	4.5	1.9	18.1	33.4	2.0	66.6
VIX	15.0	16.6	7.1	18.0	3.2	0.5	1.8	2.3	1.0	34.5	65.5
TO	99.3	112.3	80.5	145.0	61.8	76.2	23.4	60.7	38.6	18.9	71.7
NET	+19.4	+33.3	+0.7	+81.8	-16.0	-1.3	-29.0	-14.4	-27.9	-46.6	

Table A6. Connectedness table, rate-hiking regime (2022-01-01 to 2022-12-31), $T = 254$, VAR(4).

Recipient i	Shock origin j										FROM
	ES	NQ	EURUSD	USDJPY	GBPUSD	GC	CL	BTC	ETH	VIX	
ES	29.2	23.6	8.1	2.0	7.6	9.4	3.2	3.4	3.4	10.2	70.8
NQ	27.2	27.6	7.4	2.2	7.1	9.1	2.9	3.4	3.7	9.4	72.4
EURUSD	10.1	8.2	28.7	7.8	20.7	11.7	4.5	2.1	2.3	3.9	71.3
USDJPY	3.9	3.5	12.9	46.3	13.3	8.6	3.5	3.1	3.1	1.7	53.7
GBPUSD	9.1	6.5	19.0	9.4	36.5	10.7	2.3	1.6	1.6	3.3	63.5
GC	12.2	9.8	10.8	5.3	9.5	26.8	7.2	5.9	5.8	6.8	73.2
CL	6.6	4.1	6.4	2.5	3.0	14.6	45.4	4.8	4.8	7.9	54.6
BTC	7.0	6.0	2.1	1.5	2.1	5.6	2.5	35.8	33.2	4.1	64.2
ETH	6.8	6.0	1.9	1.5	2.0	5.4	3.0	31.6	38.8	2.9	61.2
VIX	13.3	11.0	6.7	2.9	7.2	6.8	4.1	4.8	4.1	39.1	60.9
TO	96.2	78.7	75.2	35.1	72.5	82.0	33.1	60.8	61.9	50.2	64.6
NET	+25.4	+6.3	+3.9	-18.6	+9.0	+8.8	-21.5	-3.4	+0.8	-10.7	

Table A7. Connectedness table, spot-ETF era (2024-01-11 to 2026-03-11), $T = 544$, VAR(4).

Recipient i	Shock origin j										FROM
	ES	NQ	EURUSD	USDJPY	GBPUSD	GC	CL	BTC	ETH	VIX	
ES	25.0	24.1	7.0	4.8	6.5	6.2	3.8	4.7	3.5	14.4	75.0
NQ	24.4	26.1	6.0	4.9	6.0	5.7	3.8	5.3	3.9	13.9	73.9
EURUSD	10.2	9.0	31.5	11.7	19.5	7.4	3.6	1.1	1.4	4.6	68.5
USDJPY	9.3	10.5	13.3	37.6	11.5	5.1	3.6	1.9	2.0	5.2	62.4
GBPUSD	10.3	9.6	21.4	10.3	27.4	8.1	4.3	1.8	1.9	5.0	72.6
GC	7.7	6.9	11.0	6.1	9.5	45.0	5.1	2.4	1.9	4.3	55.0
CL	8.6	8.8	6.4	3.7	4.6	8.9	47.8	2.4	1.6	7.3	52.2
BTC	7.5	7.9	2.0	1.8	3.1	4.9	2.8	40.1	24.7	5.3	59.9
ETH	7.0	7.2	4.2	3.8	4.5	6.2	1.6	24.2	35.8	5.5	64.2
VIX	19.3	18.7	6.0	4.1	5.6	6.6	3.7	3.6	3.7	28.6	71.4
TO	104.3	102.5	77.4	51.1	70.8	59.1	32.2	47.5	44.7	65.4	65.5
NET	+29.4	+28.7	+8.9	-11.3	-1.8	+4.1	-19.9	-12.4	-19.5	-6.0	

intervals, robustness checks, rolling windows, regime and calendar-year tables and Figures 2 to 7 are produced by `scripts/02_connectedness_revision.py` from `results/daily_rv_all.csv` in about one minute; the intraday analysis of Section 5.8 is produced by `scripts/03_intraday_sessions.py` from one-minute bars of the same vendor in about half a minute. Every table in the paper is generated by these scripts as a LaTeX fragment in `paper/tables/`.