Shock transmission between equity CFDs and cryptocurrencies: International evidence from around-the-clock high-frequency data

Abstract

Using 5-minute high-frequency intraday data that span trading and non-trading periods, this study comprehensively examines intra-market and inter-market return and volatility connectedness between six major equity markets (US, UK, Germany, France, Australia, Japan) and seven leading cryptocurrencies (Bitcoin, Litecoin, Ether, Dashcoin, EOS, Basic Attention Token, Tron). Unlike previous studies confined to trading hours or intra-class assets, we employ around-the-clock contracts for difference (CFDs) on equities and cryptocurrencies to achieve synchronous trade information, totalling more than 8.53 million observations, and apply a model-free R^2-based connectedness framework across cryptocurrencies and equity indices worldwide. Our results show that total return connectedness (71.31%) exceeds volatility connectedness (68.05%) – a reversal of the typical pattern, indicating the importance of employing high-frequency data, which daily trading-hours data may not reveal. Inter-class asset spillovers remain an order of magnitude weaker than intra-class asset spillovers, confirming noteworthy diversification prospects. Net transmitter/ receiver roles are time-varying: Germany, ETH, and the UK are the most persistent net transmitters of volatility shocks, while Australia, TRX, and BAT are the most persistent net receivers. For return spillovers, ETH, Germany, and LTC are the strongest net transmitters, whereas Australia, Japan, and TRX are the largest net receivers. These findings provide practical guidance for dynamic portfolio management, hedging, and policy monitoring across different market conditions.

Keywords: High-frequency data; Spillover effect; Intermarket connectedness; Cryptocurrency; CFD on Equity; Diversification.

JEL: F21; F36; G15

1. Introduction

Investors and policymakers frequently associate volatility in asset returns with market fear, underscoring its critical importance. Yet, volatility is not directly observable, and its transmission to other assets remains challenging to estimate accurately. Empirical evidence confirms that volatility responds disproportionately to different events, market phases, and the magnitude and sign of price changes (Ali and Khurram, 2025; Ali, Sensoy, and Goodell, 2023; Starkey and Tsafack, 2023). The difficulty intensifies in settings concerning multiple asset classes and markets. Cross-market linkages are fundamental to international finance, as they directly inform portfolio hedging strategies and policy design. A series of successive financial disruptions, the 2007–2009 global financial crisis, the 2010–2013 Euro debt crisis, the COVID-19 pandemic (hereafter referred to as COVID or COVID-19), the 2022 Russia–Ukraine war, and the US presidential elections, which have significant international impact beyond the US has driven both investors and academics to seek assets offering meaningful diversification benefits (Ali et al., 2024; Ali, Frömmel, and Kamal, 2025; Izzeldin et al., 2023; Zhang, He, and Hamori, 2023; Ali et al., 2022). Nevertheless, recent literature documents heightened connectedness across financial systems, attributed to globalization, economic integration, market liberalization, and technological progress (Ali et al., 2023; Akhtaruzzaman, Boubaker, and Sensoy, 2021). Consequently, prudent investors are motivated to measure volatility and its spillovers accurately to protect and diversify their portfolios. For this purpose, VAR-based frameworks (Diebold and Yilmaz, 2012, 2014; Gabauer and Gupta, 2018) are not only popular but also considered the most suitable methods to examine intermarket connectedness and transmission of volatility and return spillovers. Thus, reliable estimation of connectedness is essential for both market participants and regulators, enabling them to mitigate adverse volatility transmission across financial markets.

However, a closer review of the existing literature, uncovers that most studies suffer from at least two of three major shortcomings: (i) reliance on low-frequency (daily or weekly) data, which obscures information embedded in high-frequency intraday movements; (ii) focus on a single asset class (e.g., equities, commodities, or cryptocurrencies alone), thereby missing cross-market hedging and diversification possibilities; or (iii) restriction to end-of-day closing prices (or trading hours), which fails to capture the continuous flow of information (and information during non-trading hours) and its spillovers in real time. To address these gaps, this paper investigates return- and volatility-connectedness both within and between equity and cryptocurrency markets, utilizing high-frequency intraday data that span the full 24-hour cycle, covering both trading and non-trading periods.

Intra-class connectedness studies, such as those focusing exclusively on cryptocurrencies or oil (Katsiampa, Yarovaya, and Zięba, 2022; Kumar et al., 2022), even though they employ high-frequency data, do not address inter-class dynamics. Conversely, while several studies have emphasized inter-class co-movement (Ali, Kamal, and Lu, 2026; Ali et al., 2024; Ghorbel and Jeribi, 2021; Ha and Nham, 2022), they have not employed high-frequency data. More importantly, where high-frequency data have been used in inter-class settings, the analysis remains strictly unidirectional, focusing on a single reference asset and matching trading periods. For example, Corbet, Larkin, and Lucey (2020) used hourly data to study contagion from the Chinese stock market to other asset classes at the onset of the COVID-19 pandemic, with the Chinese market as the sole variable of interest. Likewise, Wu et al. (2022) examine whether volatility spillover effects matter for oil price volatility predictability, where the main variable of interest is oil predictability, limiting their international focus.

These findings, while useful for Chinese and oil markets, highlight a broader challenge: using high-frequency data across different asset classes and international equity markets is not straightforward. Two main obstacles explain the scarcity of such research (Ali and Khurram, 2025). First, equity markets in different countries operate under distinct trading and non-trading hours. Second, selecting an appropriate intraday interval is critical to mitigate market microstructure frictions such as infrequent or asynchronous trading. These complications have hindered empirical work on high-frequency connectedness between diverse asset classes. The only exception is Ali and Khurram (2025), who employed high-frequency inter-class data; however, they explored information bias and asymmetric innovation shocks using a variety of symmetric and asymmetric volatility models. To address this gap, we comprehensively examine return- and volatility-connectedness in three settings: (i) intra-class among major equity markets, (ii) intra-class among leading cryptocurrencies, and (iii) inter-class between equities and cryptocurrencies, using around-the-clock 5-minute high-frequency data. Cryptocurrencies are now considered an important and lucrative new asset class, further legitimized by the SEC's approval of a Spot Bitcoin ETF in January 2024. Thus, the data beyond Ali and Khuraam (2025), which ended in 2023, bears a vital importance as this period involves the crypto cold wave 2023-2024. Equities and cryptocurrencies rank among the heavily traded financial assets. Given that cryptocurrencies are recognized as a less-correlated asset class (Mamun et al., 2021; Ji et al., 2019; Ali et al., 2022; Kumar et al., 2022), studying them with high-frequency data offers novel insights. Accordingly, our analysis includes both major equity markets and leading cryptocurrencies, which together represent a substantial share of global equity and crypto market capitalization.

This study advances the growing literature on return- and volatility-connectedness between cryptocurrencies and equity markets in both inter- and intra-class settings (Ali and Khurram, 2025; Ali, Khurram, and Sensoy, 2025; Zhang and Xu, 2023; Charfeddine, Benlagha, and Khediri, 2022; Katsiampa et al., 2022). It also contributes to research on time-varying spillover directions and the changing roles of net transmitters and receivers (Ali, Du, and Majeed, 2025; Ren et al., 2024; Ustaoglu, 2022). Critically, we are among the first to examine connectedness across major equity markets from different regions, where trading and non-trading hours differ substantially, and between those equity markets and cryptocurrencies, using round-the-clock high-frequency intraday data that includes both trading and non-trading periods. In doing so, we extend prior high-frequency studies that were limited to intra-class assets, limited focus, or failed to examine market intermarket connectedness (e.g., Ali and Khurram, 2025; Conlon, Corbet, and McGee, 2024; Chan et al., 2022; Gradojevic and Tsiakas, 2021), a single region or key asset in inter-class asse settings (Ali et al., 2025; Leong, Alexeev, and Kwok, 2025; Wu et al., 2024; Wu et al., 2022), or only trading periods while leaving non-trading periods (Ji, Zhang, and Zhao, 2022; Zhou and Liu, 2023; Khademalomoom and Narayan, 2020). To overcome the asynchronicity problem that biases realized covariance measures across different financial markets, and makes intermarket connectedness unable to be examined due to the unavailability of the overnight data, we employ contracts for the difference (CFDs) on equity indices, which approximate current cash prices using futures contracts with fair-value adjustments. Their advantages include: (a) prolonged trading hours that provide synchronous trade information; (b) higher liquidity and lower entry barriers than futures; (c) no expiration date; and (d) transparent quotes and a uniform platform (Dukascopy) for both asset classes (Ali, Khurram, and Sensoy, 2025; Kuang, 2022). Consequently, our study avoids the asynchronicity issues of using multiple dissimilar sources.

Our analysis covers six major developed equity markets from North America, Europe, and Asia-Pacific (US S&P500, UK FTSE100, Germany DAX, France CAC40, Australia S&PASX200, and Japan Nikkei225) and seven leading cryptocurrencies (Bitcoin, Litecoin, Ether, Dashcoin, EOS, Basic Attention Token, and Tron). Using 5-minute interval data from August 5, 2019, to October 31, 2025, the sample spans diverse market states – bull, bear, turmoil, rebound, stable, and super-bull for both asset classes, underscoring the broad relevance of this work. Thus, examining the most comprehensive high-frequency intraday dataset that includes all major recent stress periods – cryptocurrency flash crashes, COVID-19, the Russia-Ukraine war, and recent geopolitical issues, during which connectedness may peak/differ – and employing the model-free R^2-based connectedness framework is another major highlight of this study. The results reveal several short-lived, permanent, and transformed long-lived net transmitters and receivers of return and volatility shocks. Notably, over the full sample, the most persistent net transmitters of volatility shocks are Germany and Ether, while Australia, Tron, and Basic Attention Token are the most persistent net receivers. For return spillovers, Ether, Germany, and Litecoin are the strongest net transmitters, whereas Australia, Japan, and Tron are the largest net receivers. These findings offer practical guidance for hedging, diversification, and portfolio optimisation across different economic, geopolitical, and market conditions, helping international investors and fund managers better understand the transmission of shocks across different asset classes.

The remainder of this paper is organized as follows. Section 2 introduces the data employed and explains the rationale behind choosing the data and its sources. Section 3 details the econometric methods. Section 4 presents the study's preliminary and main results and extends critical discussion. Finally, Section 5 provides conclusions, possible implications, and future extensions of this study.

2. Data and Sources

Our data consist of six major equity indices, including S&P500 (US), FTSE100 (UK), CAC40 (France), DAX (Germany), S&PASX200 (Australia), and Nikkei225 (Japan), and seven cryptocurrencies, including Bitcoin (BTC), Litecoin (LTC), Ether (ETH), Dashcoin (DSH), EOS, Basic Attention Token (BAT), and Tron (TRX). The selected equity indices represent major developed markets from three different regions – North America, Europe, and Asia-Pacific – and account for a substantial proportion of the total global market capitalization of the equity market. The selected cryptocurrencies similarly account for a substantially large proportion of the cryptocurrency market (capitalization) and are among the highly traded cryptocurrencies. The starting date of the sample is based on the availability of data from the Dukascopy Swiss Banking Group.

A major challenge when using high-frequency data across cryptocurrencies and international equities is the lack of synchronous trading hours. For instance, under standard time, trading hours differ by 5–7 hours between the US and major European markets, by 6–8 hours between Europe and Asia-Pacific, and by more than 10 hours between the US and Asia-Pacific. This asynchronicity largely explains why most high-frequency studies either focus on a single asset class or restrict themselves to assets with overlapping trading hours. The former approach fails to capture inter-class dynamics, while the latter cannot fully account for inter-market information flows and spillovers. Therefore, synchronous trade information is essential for any credible analysis of intraday connectedness and spillover effects. In doing that, we use the contracts for the difference (CFD) on equities and cryptocurrencies published by the Dukascopy Swiss Banking Group. These index-tracking CFDs are designed to reflect the best estimate of the market's current cash price by using the corresponding futures contract with a fair value adjustment. Ali and Khurram (2025), Ali, Khurram, and Sensoy (2025), Cui and Maghyereh (2022), and Kuang (2022), among others, have recently used Dukascopy (www.dukascopy.com) to obtain high-frequency data.

CFDs offer several advantages that make them ideal for this study. First, they provide extended trading hours, ensuring synchronous price information across all assets and enabling accurate measurement of co-movements and spillovers. Second, they offer higher liquidity and lower entry barriers than futures, as CFDs are traded directly with brokers. Third, unlike futures contracts, CFDs have no expiration date. Fourth, Dukascopy provides transparent quotes and a uniform platform for both cryptocurrency and equity CFDs. Consequently, using CFDs eliminates the asynchronicity problem that arises when combining data from multiple disparate sources. Following the relevant literature, we chose the 5-minute interval data for all selected assets, which is an often-recommended and employed frequency among other high frequencies (e.g., Ali and Khurram, 2025; Wu et al., 2024; Zhou and Liu, 2023; Cui and Maghyereh, 2022; Wu et al., 2022). The data is available around the clock from 00:00 a.m. (the first available quote for an asset during the trading sessions each day) to 11:55 p.m. (the last available quote for an asset during the trading sessions each day) Greenwich Mean Time (GMT). Our data span between August 5, 2019, and October 31, 2025, representing 656,640 observations for each asset studied. Thus, this study employs comprehensive high-frequency data with 8,536,320 observations [13 (assets)×2280 (days)×288 (prices/day)]. All selected cryptocurrencies and equity indices are priced in the US dollar, and the first logarithmic price difference in two consecutive 5-minute intervals is used to calculate the returns:

$$r_{t,i} = \left(\ln\left(p_{t,i}\right) - \ln\left(p_{t,i-1}\right)\right) \times 100 \tag{1}$$

where $r_{t,i}$ denotes the intraday returns on day t for the i^{th} intraday price of the selected asset as the natural logarithmic difference between two continuous price observations ($p_{t,i}$ and $p_{t,i}$) within a trading day.

As mentioned by Andersen et al. (2001), the realized measure of volatility constructed from the high-frequency intraday data provides more useful information; we follow Garman and Klass (1980) to estimate high-frequency realized variance. In this method, we suppose h_t, l_t, c_t, and o_t are high, low, close, and open prices at time t, respectively. We divide each of the first three (h, l, and c) by the opening price (o), as follows:

$$H_t = \ln\left({}^{h_t}/_{o_t}\right) \tag{2}$$

$$C_t = \ln\left({}^{c_t}/_{o_t}\right) \tag{3}$$

$$L_t = \ln\left({}^{l_t}/_{o_t}\right) \tag{4}$$

The realized volatility (RV) finally takes the following form:

$$RV = 0.511(\mathrm{H} - \mathrm{L})^2 - 0.019(C(H + lL) - 2HL) - 0.383C^2 \tag{5}$$

3. Empirical Framework

In this study, we employ the model-free R^2 connectedness, which examines the extent of dispersion and dynamic interconnectedness among the assets in the network: a detailed decomposition of each right-hand side (RHS) variable to identify its individual contribution to the overall R^2 (Naeem et al., 2024; Bali et al., 2023). The proposed model subsequently shows how these decomposed R^2 measures are incorporated into the dynamic connectedness framework, known as the dynamic conditional R^2 goodness of fit. Such time-varying conditional R^2 metrics are essential for assessing a model's predictive accuracy or explanatory power over time. When a particular series is used for hedging, a high dynamic conditional R^2 indicates that a large fraction of the variability in that series is explained by a single variable, suggesting the hedging strategy may be effective. Moreover, these high values are valuable for stock selection and risk management, as they provide forward-looking information about expected dependencies (Cocca et al., 2024). This method integrates the partial correlation network concept of Kenett et al. (2015) with the connectedness approach of Diebold and Yılmaz (2012, 2014). Following the model-free connectedness idea of Gabauer et al. (2023), we derive the generalized forecast error variance decomposition (GFEVD) from a VAR (p) model:

$$y_t = \Sigma_{i=1}^{p} B_i y_{t-i} + \mu_t = \Sigma_{i=1}^{\infty} A_i \mu_{t-1} \qquad A_0 = I_k \qquad \mu \sim N(0, \Sigma) \tag{6}$$

where y_t, y_{t-i}, and μ_t are $k \times 1$ vectors of demeaned endogenous variables and errors, and $\sum$ is the variance-covariance matrix. The moving average representation is $y_t = \Sigma_{i=1}^{\infty} A_i \mu_{t-1}$ with $A_i = B_1 A_{i-1} + B_2 A_{i-2} + \cdots + B_p A_{i-p}$. The GFEVD for a forecast horizon H is as follows:

$$\phi_{i \leftarrow j}^{gen}(H) = \frac{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\left(e_i' \Sigma e_j\right) \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_j\right)} = \left(\frac{\Sigma_{ij}}{\Sigma_{jj} \ \Sigma_{ii}}\right)^2 = R_{ij}^2 \tag{7}$$

Gabauer et al. (2023) show that when all variables follow a random walk, the GFEVD reduces to the bivariate R^2 goodness-of-fit measure, R_{ij}^2, which is horizon-invariant and satisfies $R_{ii}^2 = 1$ and $R_{ij}^2 = 1$. However, row sums of this matrix may exceed unity. Diebold and Yılmaz (2012) propose normalizing each row, but this can bias the contributions (Lastrapes and Wiesen, 2021; Caloia et al., 2019). Unlike in the case of orthogonal FEVD, the suggested dividing the GFEVD by each row sum:

$$\tilde{\phi}_{i \leftarrow j}^{gen}(H) = \frac{R_{ij}^2}{\Sigma_{l=1}^{k} R_{il}^2}, \qquad \Sigma_{j=1}^{k} \tilde{\phi}_{i \leftarrow j}^{gen}(H) = 1, \qquad \Sigma_{i,j=1}^{k} \tilde{\phi}_{i \leftarrow j}^{gen}(H) = k \tag{8}$$

Next, k multivariate regression models are estimated: given that each variable needs to be on the left-hand side (LHS), whereas to be considered as a right-hand side (RHS) variable in the remaining $k-1$ regression models. We estimate multivariate linear regression models as follows:

$$y_t = \beta \boldsymbol{X}_i + \mu_i \qquad \mu_i \sim N(0, \Sigma) \tag{9}$$

where $\boldsymbol{X}_i$ contains all other variables as regressors. The coefficient matrix $\boldsymbol{\beta}$ has zeros on the diagonal. The multivariate R_i^2 (the coefficient of determination) is automatically bounded between 0 and 1. However, the contributions of individual regressors to R_i^2 are not directly additive because the regressors are correlated.

To decompose R_i^2 into the shares attributable to each regressor, we apply the method of Genizi (1993) using principal component analysis (PCA). Specifically, we transform the set of regressors into $k-1$ orthogonal factors using eigenvectors $\boldsymbol{V}$ and eigenvalues $\boldsymbol{\Lambda} = diag(\lambda_1, \cdots, \lambda_{k-1})$ of the Pearson correlation matrix, R_{xx}. Thus, the R^2 decomposition for each multivariate linear regression model is computed as follows:

$$R_{xx} = \boldsymbol{V}\boldsymbol{\Lambda}\,\boldsymbol{V}' = R_{zz}\, R_{xz}' \tag{10}$$

$$R_{xz} = \boldsymbol{V}\boldsymbol{\Lambda}^{-\mathbf{1/2}}\boldsymbol{V}^{\mathbf{1}\prime} \tag{11}$$

$$R^{2G} = R_{xz}^2 \left(R_{zz}^{-1} R_{yx}\right)^2 \tag{12}$$

where R_{xz} and R_{xz} indicate the Pearson correlation coefficients between the LHS and the RHS variables of the multivariate linear regression model, as well as Pearson correlation coefficients between the RHS variables and the k uncorrelated factor variables. Finally, the scaled GFEVD that replaces the bivariate R_{ij}^2 goodness-of-fit with the R^2, R_{ij}^{2G}, is presented as follows:

$$\widetilde{\emptyset}_{i\leftarrow j}^{gen} = \frac{R_{ij}^{2G}}{\sum_{l=1}^{k} R_{il}^{2G}} \tag{13}$$

The relative R_{ij}^{2G}, $\frac{R_{ij}^{2G}}{\sum_{l=1}^{k} R_{il}^{2G}}$, and the absolute R_{ij}^{2G} now be incorporated to replace the GFEVD to estimate the connectedness between the assets under examination, following Diebold and Yilmaz (2012, 2014). Therefore, by replacing $\widetilde{\emptyset}_{i\leftarrow j}^{gen}$ with R_{ij}^{2G} to obtain connectedness measures, we compute the Diebold–Yılmaz connectedness indicators. The total directional connectedness TO others from variable *i*, and FROM others to variable *i*, are:

$$\mathrm{TO}_i = \sum_{j\neq i} R_{ji}^{2G} \tag{14}$$

$$\mathrm{FROM}_i = \sum_{j\neq i} R_{ij}^{2G} \tag{15}$$

The net total directional connectedness is $NET_i = TO_i - FROM_i$. If $NET_i > 0$ (< 0), variable *i* is a net transmitter (receiver) of shocks. Similarly, the net pairwise directional connectedness between *i* and *j* is as follows:

$$\mathrm{NPDC}_{ij} = R_{ji}^{2G} - R_{ij}^{2G} \tag{16}$$

A positive (negative) value indicates that variable *j* explains more (less) of the variation in variable *i* than the reverse.

Finally, the total connectedness index (TCI), a proxy for market risk, can be presented as follows:

$$TCI = \frac{\sum_{i=1}^{k} \mathrm{R}_i^2}{k} \tag{17}$$

Because each R_{ij}^{2G} lies between 0 and 1, the TCI is naturally bounded within the same range, unlike the original Diebold–Yılmaz TCI. This approach combines the interpretability of R^2 fractions with the network perspective of connectedness, and it avoids the normalisation biases inherent in traditional GFEVD-based methods. Our methodology is consistent with the recent seminal studies, including Tiwari et al. (2025), Naeem et al. (2024), and Balli et al. (2023).

4. Results and Discussion

4.1. Preliminary findings

Table 1 presents descriptive statistics of daily returns and realized volatility (RV) in Panels A and B, respectively. Returns and realized volatility are estimated using the cumulative 5-minute interval returns from 00:000 (a.m.) to 23:55 (p.m.) Greenwich Mean Time (GMT) each day. The mean return of all the equity indices is positive during the sample period. The Japanese market offers the highest return, followed by the US. Among cryptocurrencies, DSH, BAT, and EOS provide negative mean returns, whereas BTC, LTC, ETH, and TRX provide positive mean returns during the sample period. While ETH and TRX provide the highest mean return, BTC offers the lowest standard deviation.

Regarding realized volatility among equities, the results in Panel B of Table 1 show that France and Germany have the highest mean values, whereas France and Australia have the highest standard deviation values of RV during the full sample period. This finding indicates that the volatility in German equities was persistently high, Australian equities were unsteady, and French equities were both unsteady and high on average. Among cryptocurrencies, TRX has the highest mean RV, followed by LTC and DSH, whereas TRX has the highest standard deviation of RV, followed by DSH.

Table 1. Descriptive statistics of high-frequency returns and realized volatility.

Notes. This table reports descriptive statistics of 5-minute high-frequency returns, calculated as the first logarithmic price difference in two consecutive 5-minute intervals (see Eq. (1)). Returns are estimated using the accumulative 5-minute interval returns from 00:000 (a.m.) to 23:55 (p.m.) Greenwich Mean Time (GMT) each day. The sample period spans between August 5, 2019 (00:00 a.m.), and October 31, 2025 (11:55 p.m.), representing 683,136 observations for each asset. US, UK, FR, GER, AUS, and JP stand for the equity indices in the United States (S&P500), United Kingdom (FTSE100), France (CAC40), Germany (DAX), Australia (S&PASX200), and Japan (Nikkei225). BTC, LTC, ETH, DSH, EOS, TRX, and BAT represent Bitcoin, Litecoin, Ether, Dashcoin, EOS, Tron, and Basic Attention Token, respectively. The price data is obtained from Dukascopy (www.dukascopy.com), and all selected cryptocurrencies and equity indices are priced in US$.

	US	UK	FR	GER	AUS	JP	BTC	LTC	ETH	DSH	EOS	TRX	BAT
							Panel A: Returns						
Mean	0.044	0.014	0.022	0.036	0.014	0.048	0.104	0.002	0.133	-0.062	-0.076	0.125	-0.052
St. Err.	0.026	0.022	0.027	0.027	0.023	0.028	0.080	0.113	0.105	0.127	0.132	0.114	0.131
St. Dev.	1.14	0.97	1.20	1.17	1.00	1.25	3.52	4.97	4.63	5.58	5.81	5.02	5.76
Kurt.	14.09	19.46	24.72	15.86	24.64	16.58	22.12	10.34	16.99	12.08	12.58	31.56	10.59
Skew.	-0.123	-1.309	-1.810	-0.755	-0.106	-0.680	-1.445	-1.006	-1.234	-0.108	-0.750	0.428	-0.373
							Panel B: Realized Volatility						
Mean	0.006	0.005	0.006	0.006	0.004	0.006	0.070	0.269	0.129	0.248	0.194	1.298	3.315
St. Err.	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.023	0.005	0.045	0.009	0.138	3.081
St. Dev.	0.02	0.01	0.02	0.02	0.02	0.01	0.14	1.00	0.22	2.00	0.38	6.05	135.41
Kurt.	134.71	310.45	330.84	443.99	239.90	126.76	206.71	1549.09	136.51	1315.52	108.00	35.29	1931.96
Skew.	10.27	14.91	15.57	17.55	13.65	9.80	11.45	37.46	9.54	34.67	8.21	5.65	43.95

Table 2 presents the Pearson correlation: Panel A represents the coefficients of the return series, whereas Panel B presents the results of the RV series. The results in Panel A indicate that the correlation among intra-class assets is higher than the correlation among inter-class assets. For example, correlation coefficients among equity indices (cryptocurrencies) vary between 0.49 and 0.83 (0.56 and 0.83), whereas correlation coefficients between equity indices and cryptocurrencies (the bottom left corner of each panel) vary between 0.16 and 0.40. Interestingly, the results in Panel B exhibit a similar pattern (higher for intraclass assets than interclass assets), with one exception of negative correlations among a few cryptocurrencies. It suggests that, in terms of realized volatility, the cryptocurrency market is more heterogeneous than the equity markets.

Table 2. Pearson correlation among the returns of selected cryptocurrencies and equity indices.

Notes. This table reports the Pearson correlation coefficients. All the variables and subperiods are defined in Table 1. Correlation coefficients among the equity indices are in bold, cryptocurrencies are in italics, and equity and cryptocurrency series are in the bottom left corners of each panel.

	US	UK	FR	GER	AUS	JP	BTC	LTC	ETH	DSH	EOS	TRX
						Panel A: Returns						
UK	0.630											
FR	0.591	0.784										
GER	0.700	0.815	0.832									
AUS	0.586	0.673	0.592	0.659								
JP	0.488	0.552	0.529	0.585	0.645							
BTC	0.389	0.271	0.271	0.313	0.240	0.231						
LTC	0.344	0.256	0.243	0.274	0.211	0.214	0.761					
ETH	0.402	0.278	0.272	0.314	0.253	0.234	0.830	0.790				
DSH	0.285	0.205	0.181	0.223	0.175	0.162	0.656	0.736	0.687			
EOS	0.298	0.195	0.196	0.226	0.173	0.168	0.657	0.733	0.689	0.680		
TRX	0.250	0.204	0.189	0.228	0.202	0.198	0.567	0.587	0.591	0.575	0.612	
BAT	0.334	0.238	0.235	0.263	0.188	0.183	0.658	0.667	0.691	0.642	0.650	0.561
						Panel B: Realized volatility						

UK	0.837											
FR	0.807	0.899										
GER	0.859	0.774	0.795									
AUS	0.725	0.696	0.629	0.727								
JP	0.707	0.690	0.624	0.665	0.735							
BTC	0.366	0.375	0.329	0.336	0.391	0.430						
LTC	0.132	0.115	0.117	0.101	0.111	0.111	0.385					
ETH	0.338	0.309	0.262	0.294	0.304	0.369	0.846	0.438				
DSH	0.018	0.015	0.014	0.015	0.019	0.023	0.137	0.153	0.161			
EOS	0.165	0.138	0.121	0.137	0.141	0.168	0.646	0.414	0.707	0.202		
TRX	-0.034	-0.023	-0.029	-0.028	-0.021	-0.031	-0.014	0.025	0.140	-0.011	-0.022	
BAT	-0.007	-0.005	-0.005	-0.005	-0.004	-0.007	-0.008	-0.002	-0.008	-0.001	0.012	-0.005

4.2. Volatility connectedness

We examine volatility connectedness using the model-free R^2-based connectedness framework. Table 3 presents the static volatility connectedness measures. The total connectedness index (TCI) is 68.05%, which is lower than the volatility TCI reported in earlier short-sample studies (e.g., 80.72% for 2019–2023), indicating that the extended sample period (including the calmer post-2023 years) reduces average connectedness. The diagonal elements (own-innovation shares) are generally higher for equities (e.g., US 34.03%, AUS 38.38%, JP 39.98%) than for cryptocurrencies (e.g., BTC 23.92%, ETH 23.15%), implying that a larger portion of equity volatility is asset-specific, while cryptocurrencies are more interconnected – a finding consistent with Kumar et al. (2022) and Charfeddine, Benlagha, and Khediri (2022).

The highest pairwise directional volatility connectedness occurs between Germany and France (21.96% from France to Germany and 20.00% from Germany to France), reflecting deep integration of European equity markets (Ali, Sensoy, and Goodell, 2023). Among cryptocurrencies, the highest pairwise values are between ETH and BTC (17.56% and 17.22%) and between LTC and ETH (13.69% and 12.71%), consistent with Shahzad et al. (2021), who show that major cryptocurrencies are highly interconnected.

Inter-class volatility connectedness (equities–cryptocurrencies) remains very weak. The largest directional spillover from a cryptocurrency to an equity market is ETH to US (2.68%), and from an equity to a cryptocurrency is US to BTC (2.65%) and Japan to BTC (2.80%). These values are an order of magnitude lower than intra-class spillovers, confirming that equities and cryptocurrencies are largely decoupled in terms of volatility transmission. This supports the diversification potential of mixed equity-crypto portfolios (Ali et al., 2022, 2024; Conlon and McGee, 2020).

The net directional values in Table 3 reveal the following persistent roles: Germany (7.43), ETH (10.07), BTC (8.14), UK (3.21), LTC (2.78), and DSH (3.16) are net transmitters (positive NET), while the US (-3.28), France (-1.98), Australia (-5.74), Japan (-4.18), EOS (-0.28), TRX (-10.43), and BAT (-8.89) are net receivers. Germany and ETH are the strongest net transmitters, consistent with Germany's status as Europe's largest economy and ETH's leading position in the cryptocurrency market (Ji et al., 2019). In contrast, TRX and BAT as persistent receivers suggest they are more vulnerable to volatility shocks originating elsewhere – possibly due to their smaller market capitalisation and lower liquidity (Katsiampa, Yarovaya, and Zięba, 2022). The US being a net receiver

(-3.28) is surprising given its global financial dominance, but may reflect that during the sample period, volatility shocks from Europe and crypto markets dominated.

Dynamic volatility connectedness. Fig. 1 presents the dynamic total connectedness index (TCI) over the full sample, from August 2019 to October 2025. The TCI is highly time-varying, consistent with Diebold and Yilmaz (2012, 2014), who show that connectedness fluctuates with market conditions. It rises from 88% in 2019 to a peak of 93% in 2021, then declines sharply to 52% in 2024 before rebounding to 76% in 2025.

The elevated levels during 2020–2021 align with studies documenting increased financial contagion during the COVID-19 pandemic (Akhtaruzzaman, Boubaker, and Sensoy, 2021; Corbet, Larkin, and Lucey, 2020) and the subsequent cryptocurrency boom (Conlon, Corbet, and McGee, 2024; Katsiampa, Yarovaya, and Zięba, 2022). The sharp drop to 52% in 2024 is a novel finding: unlike earlier crises where connectedness remained high for extended periods (Izzeldin et al., 2023), the post-2023 period shows a substantial decoupling of volatility transmission, suggesting that markets have learned to operate more independently after the multiple shocks. The rebound to 76% in 2025 indicates that connectedness can rise again, underscoring its non-permanent nature.

Fig. 2 displays net total directional connectedness for each asset over time. The net positions change substantially across years, confirming that transmitter/receiver roles are time-varying (Ren et al., 2024). For example, the UK and Germany are net transmitters (positive values) in 2021–2022 but become net receivers after 2024. Conversely, ETH and EOS shift from net receivers to net transmitters after 2023. These reversals are consistent with Ali et al. (2023), who found that diversification benefits among Asian equities were short-lived. The finding that no asset has a permanent role implies that static portfolio allocation based on historical roles is insufficient; dynamic monitoring is required (Ali and Khurram, 2025).

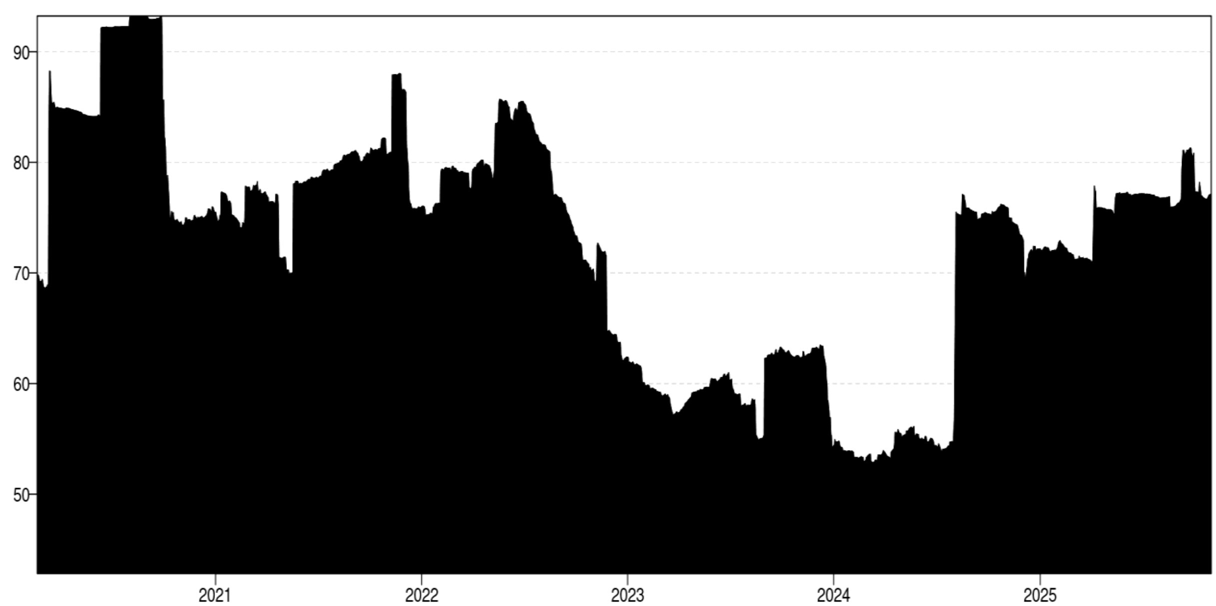

Fig. 1. Dynamic total volatility connectedness

Fig. 3 presents dynamic pairwise volatility connectedness for selected asset pairs. Most pairwise values remain near 60% throughout the sample, indicating moderate bidirectional spillovers. Inter-class pairs (e.g., US-ETH, UK-EOS) are consistently lower than intra-class pairs (e.g., FR-LTC, GER-LTC). This is in line with Ali et al. (2022, 2024) and Kumar et al. (2022), who report that cryptocurrencies are less correlated with traditional assets than with each other, offering diversification opportunities. The weak inter-class connectedness also echoes Charfeddine, Benlagha, and Khediri (2022), who documented intra-crypto dominance over inter-asset spillovers.

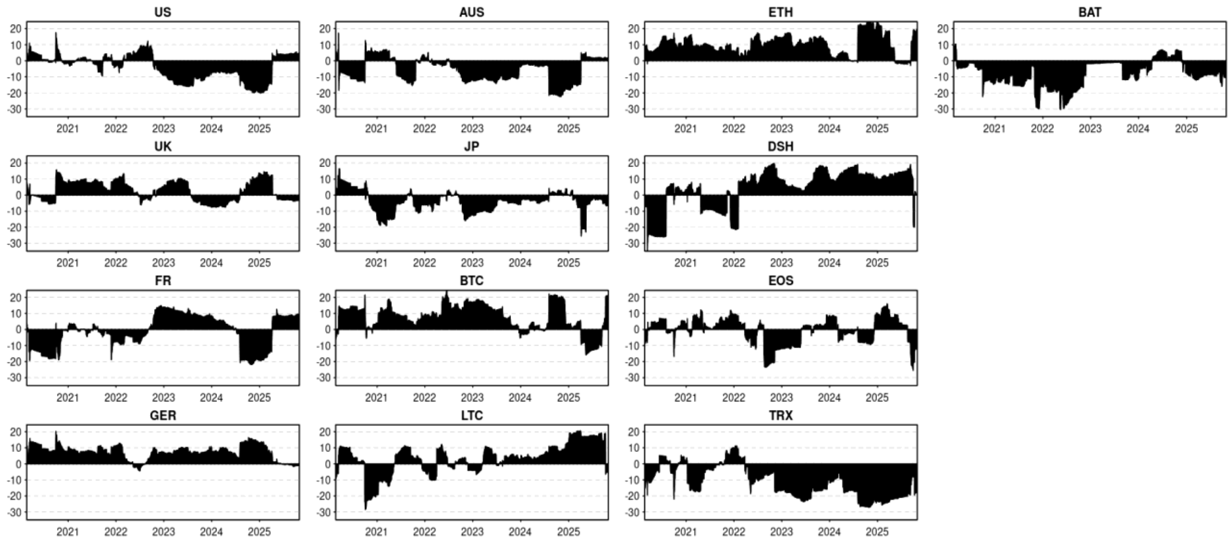

Fig. 2. Net total directional volatility connectedness

Fig. 3. Dynamic pairwise volatility connectedness

Fig. 4 shows net pairwise directional connectedness. The values are close to zero for the vast majority of pairs, implying few persistent one-way spillovers. This result supports the findings of Liang, Goodell, and Li (2024) and Lu, Huang, and Mo (2024), who argue that net directional effects are often temporary and asset-specific. The only exceptions are pairs involving LTC-ETH and DSH-EOS, which show small positive net values (0.5–0.8), indicating slight directional influence – likely due to similar technological or market microstructures within the cryptocurrency ecosystem (Shahzad et al., 2021).

The network graph in Fig. 5 summarises net pairwise connections over the full sample. Yellow nodes represent net receivers, blue nodes net transmitters. The most persistent net transmitters (blue) are Germany and ETH, while the most persistent net receivers (yellow) are Australia, TRX, and BAT. Germany's role as a volatility transmitter is consistent with its status as Europe's largest economy and a central hub for equity trading (Ali, Sensoy, and Goodell, 2023). ETH as a persistent transmitter reflects its dominant position among cryptocurrencies, often leading market movements (Ji et al., 2019). In contrast, Australia, TRX, and BAT as persistent receivers suggest they are more susceptible to external shocks – Australia due to its commodity-driven economy, and TRX/BAT as smaller tokens with lower market influence. These results align with the safe-haven and diversifier literature (Conlon and McGee, 2020; Goodell and Goutte, 2021), indicating that persistent receivers may serve as hedging assets during turmoil.

In summary, volatility connectedness among equities and cryptocurrencies is strongly time-varying and has declined notably after 2022. Inter-class connectedness remains weak relative to intra-class connectedness, offering diversification opportunities, but these benefits are not constant – they erode during stress periods and recover during calmer times. The persistent net transmitter/receiver identities provide a rule-of-thumb for systemic risk monitoring, while the frequent role reversals highlight the need for adaptive portfolio strategies.

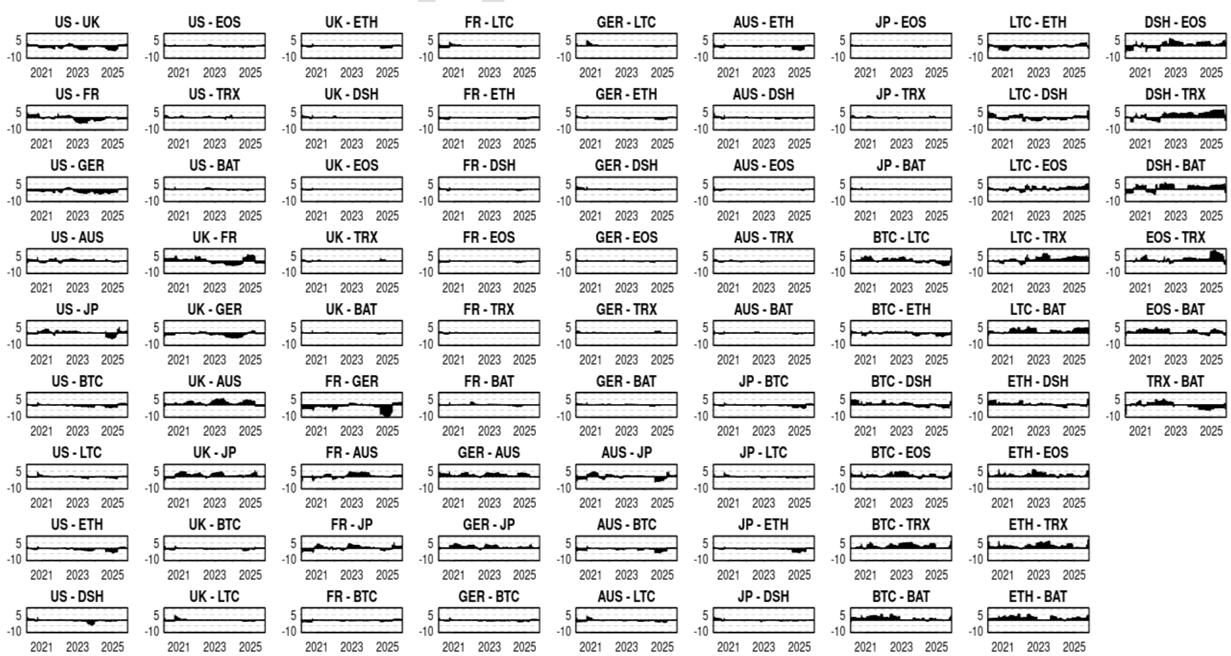

Fig. 4. Net pairwise directional volatility connectedness

Table 3. Static connectedness between equity indices and cryptocurrencies

Notes. This table presents the static analysis of the dynamic volatility spillovers between the selected equity indices and cryptocurrencies. "From"' in the last column indicates the spillover from the network of all other assets to an asset of our interest, whereas "TO" in the third last row indicates the spillover to the network of all other assets from the asset of our interest. "NET" in the second last row indicates the net directional spillover of each asset, whereas "TCI" in the bottom right corner indicates the total connectedness index of the network of all assets. All selected assets and subperiods are defined in Table 1.

	US	**UK**	**FR**	**GER**	**AUS**	**JP**	**BTC**	**LTC**	**ETH**	**DSH**	**EOS**	**TRX**	**BAT**	**FROM**
US	34.03	12.02	10.64	12.5	9.63	9.68	2.65	1.65	2.68	1.34	1.06	1.35	0.76	65.97
UK	11.06	28.24	15.44	17.32	10.02	9.49	2.21	1.41	2.12	0.72	0.74	0.53	0.70	71.76
FR	10.28	16.05	28.89	21.96	8.49	8.02	1.53	1.22	1.3	0.53	0.7	0.38	0.65	71.11
GER	11.00	16.38	20.00	25.89	9.30	8.94	2.14	1.39	1.92	0.75	0.94	0.52	0.82	74.11
AUS	10.15	11.55	9.07	10.83	38.38	10.49	2.35	1.57	2.26	0.97	0.84	0.73	0.81	61.62
JP	9.99	10.84	8.44	10.3	10.46	39.98	2.80	1.54	2.47	0.79	0.88	0.72	0.79	60.02
BTC	2.15	1.99	1.26	1.99	1.76	2.39	23.92	12.42	17.56	10.73	10.81	6.37	6.67	76.08
LTC	1.54	1.46	1.10	1.54	1.39	1.43	13.21	26.3	13.69	12.15	11.59	6.85	7.74	73.70
ETH	2.13	1.85	1.05	1.74	1.7	2.04	17.22	12.71	23.15	10.53	11.72	6.96	7.2	76.85
DSH	1.09	0.74	0.48	0.83	0.89	0.82	11.24	12.13	11.24	32.92	12.9	6.23	8.48	67.08
EOS	0.92	0.7	0.56	0.94	0.71	0.81	12.01	12.32	13.23	13.56	27.17	8.2	8.85	72.83
TRX	1.54	0.68	0.41	0.7	0.76	0.85	8.42	8.48	9.14	8.18	10.06	44.8	5.97	55.2
BAT	0.81	0.73	0.66	0.87	0.78	0.87	8.46	9.65	9.31	9.98	10.3	5.92	41.67	58.33
TO	62.69	74.97	69.12	81.53	55.89	55.84	84.23	76.48	86.92	70.23	72.55	44.77	49.44	884.66
Inc.Own	96.72	103.21	98.02	107.43	94.26	95.82	108.14	102.78	110.07	103.16	99.72	89.57	91.11	cTCI/TCI
NET	-3.28	3.21	-1.98	7.43	-5.74	-4.18	8.14	2.78	10.07	3.16	-0.28	-10.43	-8.89	73.72/68.05
NPT	4	8	5	10	1	4	11	7	12	7	7	0	2	

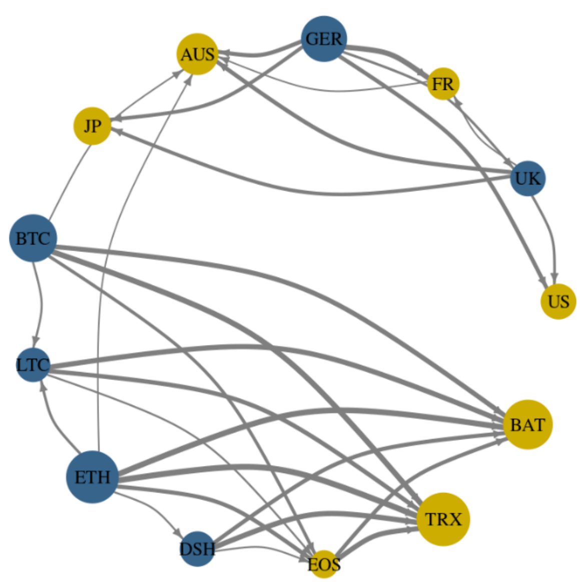

Fig. 5. Network graph of volatility connectedness

4.3. Return connectedness

Table 4 presents the static return connectedness measures for the full sample, while Figs. 6–10 depict the dynamic evolution. Our results are based on the model-free R^2-based connectedness framework.

Table 4 shows that the TCI for the full sample is 71.31%, which is higher than the volatility TCI (68.05%). This finding reverses the typical pattern documented by Diebold and Yilmaz (2012, 2014) and Antonakakis, Chatziantoniou, and Gabauer (2020), who generally find that volatility spillovers dominate return spillovers. A potential explanation is the extended post-2023 period, during which markets became more efficient at absorbing local volatility shocks (e.g., via better hedging instruments and algorithmic trading), while return co-movements persisted due to synchronised global risk appetite, central bank policies, and the increasing correlation of earnings cycles across large economies. This reversal has practical implications: return-based diversification strategies may be less effective than volatility-based strategies in the current environment. The average own-innovation share (diagonal elements) is higher for cryptocurrencies (e.g., LTC 22.58%, ETH 21.64%) than for equities (e.g., US 30.73%, UK 29.21%), indicating that a larger portion of cryptocurrency return variance is asset-specific, not transmitted from other assets. This suggests that diversification benefits across cryptocurrencies may be more limited than across equities, as noted by Kumar et al. (2022) and Charfeddine, Benlagha, and Khediri (2022).

The highest pairwise directional return connectedness occurs between Germany and France (20.28% from France to Germany and 19.37% from Germany to France), reflecting the strong integration of European equity markets (Ali, Sensoy, and Goodell, 2023). Among cryptocurrencies, the highest pairwise connectedness is between LTC and ETH (12.71% and 12.34%) and between LTC and BTC (12.07% and 12.21%), which is in line with Shahzad et al. (2021), who show that major cryptocurrencies exhibit significant return co-movements.

Notably, inter-class return connectedness (equities–cryptocurrencies) is very weak. The largest directional spillover from a cryptocurrency to an equity market is ETH to US (4.73%), and from an equity to a cryptocurrency is Japan to ETH (3.11%). These values are an order of magnitude lower than intra-class spillovers, confirming that equities and cryptocurrencies are largely decoupled in terms of return transmission. This result aligns with Ali et al. (2022, 2024) and Conlon and McGee (2020), who argue that cryptocurrencies can serve as diversifiers for equity-dominated portfolios, especially during calm periods.

The net values in Table 4 reveal the following persistent roles: Net transmitters are ETH (9.96), LTC (5.56), Germany (6.26), EOS (5.14), BTC (5.11), and DSH (0.71). Net receivers are Australia (-7.16), Japan (-5.80), TRX (-11.84), the UK (-2.07), the US (-4.88), France (-0.47), and BAT (-0.51). Among these, ETH, LTC, and Germany are the strongest transmitters, while Australia, Japan, and TRX are the largest receivers.

Germany's role as a net transmitter is consistent with its status as Europe's largest economy and a central equity hub (Ali, Sensoy, and Goodell, 2023). ETH and LTC as strong transmitters reflect their leading positions in the cryptocurrency market (Ji et al., 2019). In contrast, Australia and Japan, as net receivers, likely reflect their peripheral positions in global return transmission channels (Izzeldin et al., 2023). The UK's negative net value (-2.07) is notable: despite being a major financial centre, it is a net receiver of return shocks in the full sample, possibly due to Brexit-related structural changes (Ren et al., 2024).

Table 4. Static return connectedness between equity indices and cryptocurrencies.

Notes: This table presents the static analysis of the dynamic return spillovers between the selected equity indices and cryptocurrencies. "From"' in the last column indicates the spillover from the network of all other assets to an asset of our interest, whereas "TO" in the third last row indicates the spillover to the network of all other assets from the asset of our interest. "NET" in the second last row indicates the net directional spillover of each asset, whereas "TCI" in the bottom right corner indicates the total connectedness index of the network of all assets. All selected assets and subperiods are defined in Table 1.

	US	**UK**	**FR**	**GER**	**AUS**	**JP**	**BTC**	**LTC**	**ETH**	**DSH**	**EOS**	**TRX**	**BAT**	**FROM**
US	32.60	7.85	8.62	11.44	7.27	7.52	4.44	3.82	4.73	2.88	3.45	1.95	3.43	67.40
UK	7.97	30.36	17.60	17.18	9.05	7.40	1.67	1.75	1.85	1.29	1.32	1.12	1.45	69.64
FR	8.50	16.82	28.84	21.21	7.36	7.23	1.73	1.61	1.82	1.07	1.29	1.10	1.41	71.16
GER	10.38	15.51	20.15	27.26	7.80	7.51	2.06	1.81	2.08	1.22	1.46	1.18	1.57	72.74
AUS	8.25	10.41	8.45	9.64	38.92	14.55	1.74	1.47	1.94	1.10	1.29	1.14	1.11	61.08
JP	8.36	8.16	7.78	8.98	14.72	39.88	2.39	1.88	2.16	1.19	1.62	1.37	1.50	60.12
BTC	3.38	1.36	1.34	1.84	1.32	1.91	23.08	12.16	15.46	10.14	10.47	7.13	10.40	76.92
LTC	2.84	1.39	1.24	1.59	1.09	1.47	12.04	23.03	12.93	12.93	12.58	6.95	9.91	76.97
ETH	3.37	1.44	1.36	1.79	1.41	1.68	14.74	12.46	21.99	10.59	11.05	7.53	10.59	78.01
DSH	2.26	1.16	0.92	1.24	0.93	1.14	10.61	13.43	11.54	24.17	13.25	7.89	11.46	75.83
EOS	2.58	1.07	1.00	1.30	0.97	1.31	10.57	12.72	11.65	12.74	23.79	8.82	11.49	76.21
TRX	1.90	1.10	1.06	1.26	1.04	1.29	8.98	8.80	9.92	9.68	11.34	33.79	9.84	66.21
BAT	2.74	1.29	1.18	1.52	0.94	1.32	11.05	10.62	11.87	11.72	12.24	8.19	25.32	74.68
TO	62.51	67.57	70.69	79.00	53.92	54.32	82.03	82.53	87.97	76.54	81.36	54.37	74.17	926.97
Inc.Own	95.12	97.93	99.53	106.26	92.84	94.20	105.11	105.56	109.96	100.71	105.14	88.16	99.49	cTCI/TCI
NET	-4.88	-2.07	-0.47	6.26	-7.16	-5.80	5.11	5.56	9.96	0.71	5.14	-11.84	-0.51	77.25/71.31
NPT	3.00	2.00	4.00	7.00	1.00	0.00	10.00	11.00	12.00	7.00	9.00	5.00	7.00	

Dynamic return connectedness. Fig. 6 presents the dynamic total return TCI over time. The TCI peaks in 2021 (91%), then declines to 82% in 2022, 85% in 2023, and further to 70% in 2024 and 68% in 2025. This pattern mirrors the volatility of TCI but with lower peaks, and confirms that the COVID-19 pandemic and the Russia-Ukraine war temporarily elevated return co-movements (Akhtaruzzaman, Boubaker, and Sensoy, 2021; Goodell and Goutte, 2021). The sustained decline after 2022 indicates a structural decoupling, potentially driven by divergent monetary policies and the maturing of cryptocurrency markets.

Fig. 7 shows net total directional return connectedness over time. Consistent with the static net values, Germany and ETH remain net transmitters for most of the sample, while Australia and Japan are persistent net receivers. However, the UK and TRX switch roles: the UK was a net transmitter in 2021–2022 but became a net receiver after 2023; TRX moved in the opposite direction. These reversals echo the findings of Ren et al. (2024), who document time-varying spillover roles in cryptocurrency and equity networks.

Figs. 8 and 9 display dynamic pairwise and net pairwise return connectedness. Inter-class pairs (e.g., US-ETH, UK-EOS) exhibit consistently lower values than intra-class pairs, and net pairwise values are close to zero for most pairs, implying few persistent one-way return spillovers. This result is in line with Liang, Goodell, and Li (2024), who argue that net directional effects are typically transient.

The network graph in Fig. 10 summarises the full-sample net pairwise return connections. Based on node size and arrow direction (blue = transmitter, yellow = receiver), the most persistent net transmitters are ETH, Germany, LTC, and EOS, while the most persistent net receivers are Australia, Japan, the UK, BAT, and TRX. This visualisation confirms the static net values and provides an intuitive guide for portfolio managers: assets in blue (transmitters) are sources of systemic return risk, while assets in yellow (receivers) may serve as diversifiers or hedges.

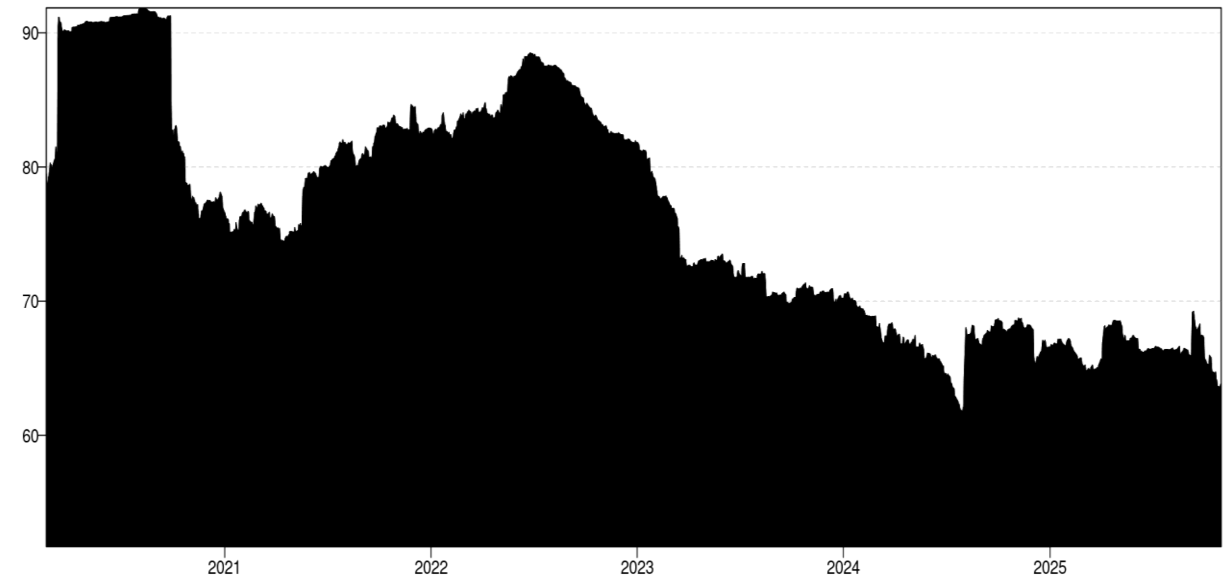

Fig. 6. Dynamic total return connectedness

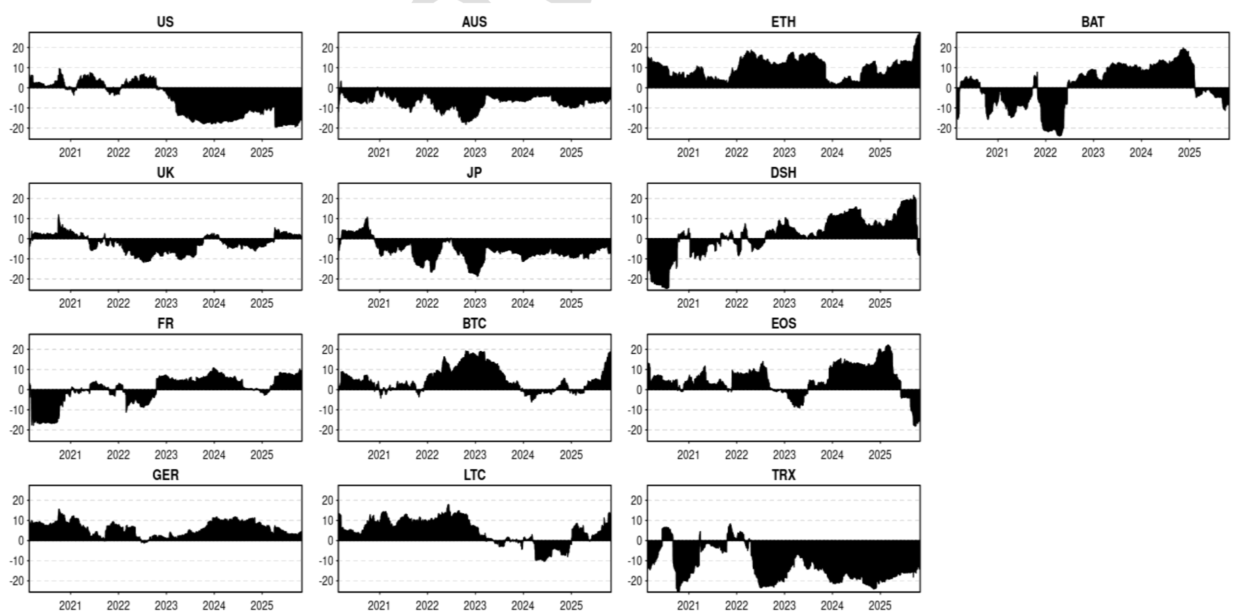

Fig. 7. Net total directional return connectedness

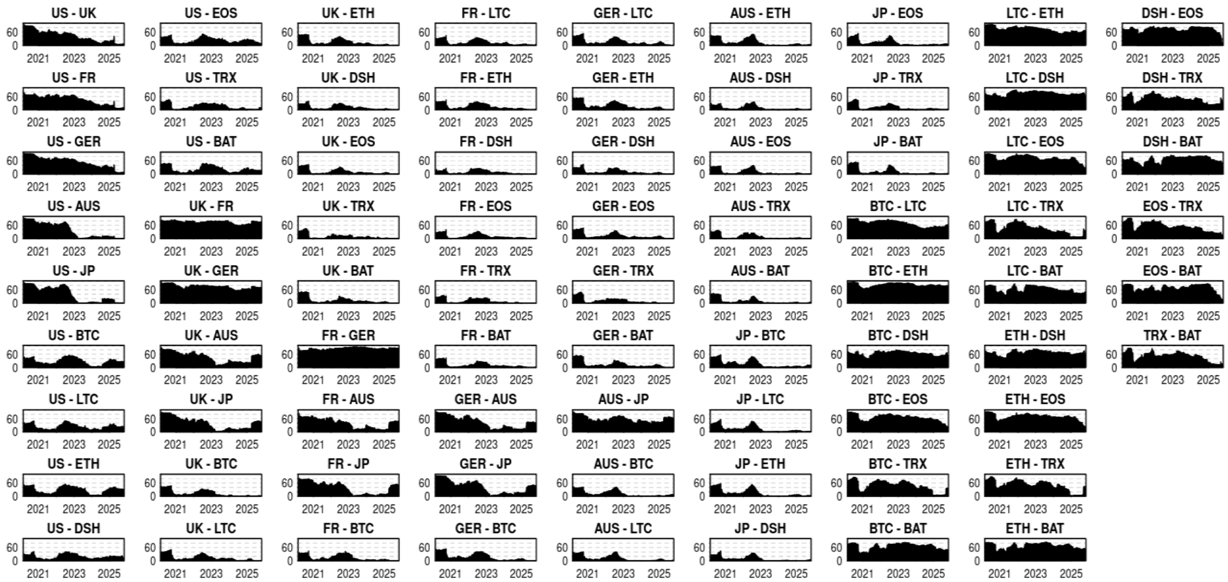

Fig. 8. Dynamic pairwise return connectedness

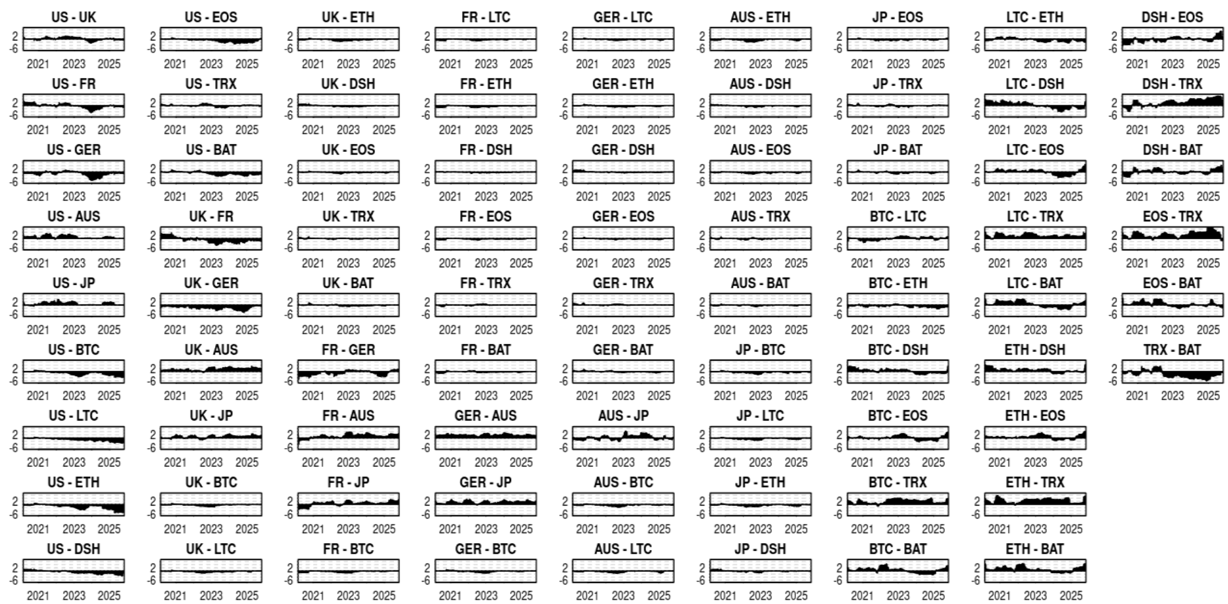

Fig. 9. Net pairwise directional return connectedness

In summary, return connectedness among equities and cryptocurrencies is higher than volatility connectedness, time-varying, and characterised by very weak inter-class spillovers. The persistent net transmitter roles of Germany, ETH, and LTC identify them as key sources of return shocks, while the persistent net receiver roles of Australia, Japan, and TRX suggest they are more vulnerable to external return transmission. The dynamic reversals (e.g., the UK switching from transmitter to receiver) underscore the need for active portfolio monitoring. Overall, the weak inter-class return connectedness supports the use of mixed equity-crypto portfolios for diversification, especially during non-crisis periods.

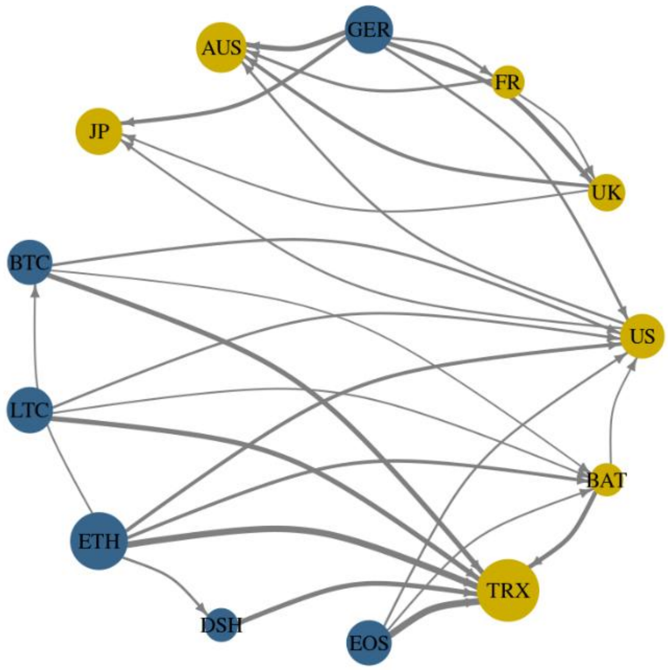

Fig. 10. Network graph of return connectedness

4.4. Trading and risk management, robustness, and discussion

For volatility traders: The volatility TCI spikes sharply during crises (e.g., 93% in 2021) but declines to 52% in calm periods. This suggests that cross-asset volatility hedging (e.g., using VIX futures to hedge crypto volatility) is inefficient during normal times but becomes highly effective during stress episodes. Dynamic volatility strategies that increase hedge ratios when TCI exceeds 80% would have improved risk-adjusted returns.

For return-based strategies: The higher return connectedness (71.31% vs 68.05%) implies that momentum and trend-following strategies across equities and cryptocurrencies may be more profitable than volatility-arbitrage strategies. However, the weak inter-class return spillovers (largest below 5%) indicate that equity-crypto pairs trading is not reliable.

For systemic risk monitoring: The persistent net transmitters (Germany, ETH, UK for volatility; ETH, Germany, LTC for return) should be monitored by regulators as early warning indicators. A sharp increase in their net transmission often precedes broader market stress.

Since this study is the first to identify a weaker volatility TCI than the return TCI, we confirm whether it is based on the methodology we opt for or robust across different methods. Thus, we employed the TVP-VAR and DCC-GARCH methods to cross-check our findings and found our results unchanged (available with the authors, on request): Average return connectedness (TCI) dominated average volatility connectedness. We then carefully observe and compare the dynamic TCIs to observe the time-varying patterns and identify that the volatility connectedness has weakened after 2023, and remains weakly connected up to the first quarter of 2025, which is known as the longest crypto winter period. Thus, we conclude that when markets are stable and price movements are minor, transmission of volatility shocks is weaker than return shocks, and vice versa.

5. Conclusion and Implications

This study provides a comprehensive analysis of return and volatility connectedness between six major equity markets and seven leading cryptocurrencies using around-the-clock 5-minute high-frequency data between August 2019 and October 2025 and employing the model-free R^2-based connectedness framework.

First, both return and volatility spillovers are highly time-varying. The total volatility connectedness index (TCI) averages 68.05% over the full sample, while the return TCI averages 71.31% – a reversal of the typical pattern where volatility spillovers dominate. This suggests that in the extended post-crisis period, return transmission has become relatively more important. Second, inter-class connectedness (equities–cryptocurrencies) remains very weak, with the largest directional spillover from a cryptocurrency to an equity market below 3%. This persistent weakness implies substantial diversification and hedging opportunities for global investors. Third, net transmitter/receiver roles are dynamic, but some assets exhibit persistent patterns.

Our results reveal clear net transmission patterns. For volatility, the most persistent net transmitters are Germany (7.43), ETH (10.07), BTC (8.14), the UK (3.21), LTC (2.78), and DSH (3.16), while the most persistent net receivers are the US (-3.28), France (-1.98), Australia (-5.74), Japan (-4.18), EOS (-0.28), TRX (-10.43), and BAT (-8.89). For return, net transmitters include ETH (9.96), LTC (5.56), Germany (6.26), EOS (5.14), BTC (5.11), and DSH (0.71), while net receivers are Australia (-7.16), Japan (-5.80), TRX (-11.84), the UK (-2.07), the US (-4.88), France (-0.47), and BAT (-0.51). Notably, the US switches from a volatility receiver to a return receiver (but weaker), while the UK is a volatility transmitter but a return receiver – a divergence with important implications for cross-asset hedging.

Importantly, some assets changed their net positions over time (e.g., the UK switched from volatility transmitter to receiver after 2023; ETH and EOS moved from receivers to transmitters). These reversals underscore that diversification benefits are not static; they evolve with market regimes and exogenous shocks. Therefore, dynamic portfolio monitoring and adaptive strategies are essential.

5.1. Practical implications

For portfolio managers and investors, the weak and time-varying connectedness between equities and cryptocurrencies offers genuine diversification potential, especially during calm periods. However, during stress episodes (e.g., March 2020, early 2022), connectedness spikes, reducing the effectiveness of cross-asset hedges. Active monitoring of dynamic connectedness indices is essential. The persistent net transmitter/receiver identities provide a rule-of-thumb: assets consistently transmitting shocks (e.g., Germany, ETH, BTC) are sources of systemic risk, while consistent receivers (e.g., Australia, TRX, BAT) may serve as diversifiers or hedges. Policymakers and regulators can use the network graphs to identify contagion channels and design targeted interventions.

5.2. Limitations and future research

Our asset selection, though large in market capitalisation, is not exhaustive. Future work should include other asset classes (e.g., commodities, bonds, green assets) and extend the high-frequency analysis to distinguish trading from non-trading periods by region. Additionally, examining the role of news sentiment or macroeconomic announcements in driving time-varying connectedness would deepen the understanding of information transmission. Finally, while CFDs solve the asynchronicity problem, they may not perfectly replicate spot prices. Future research could use alternative synchronisation methods, such as time-stamping with a common high-frequency clock or using futures data.

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Appendix

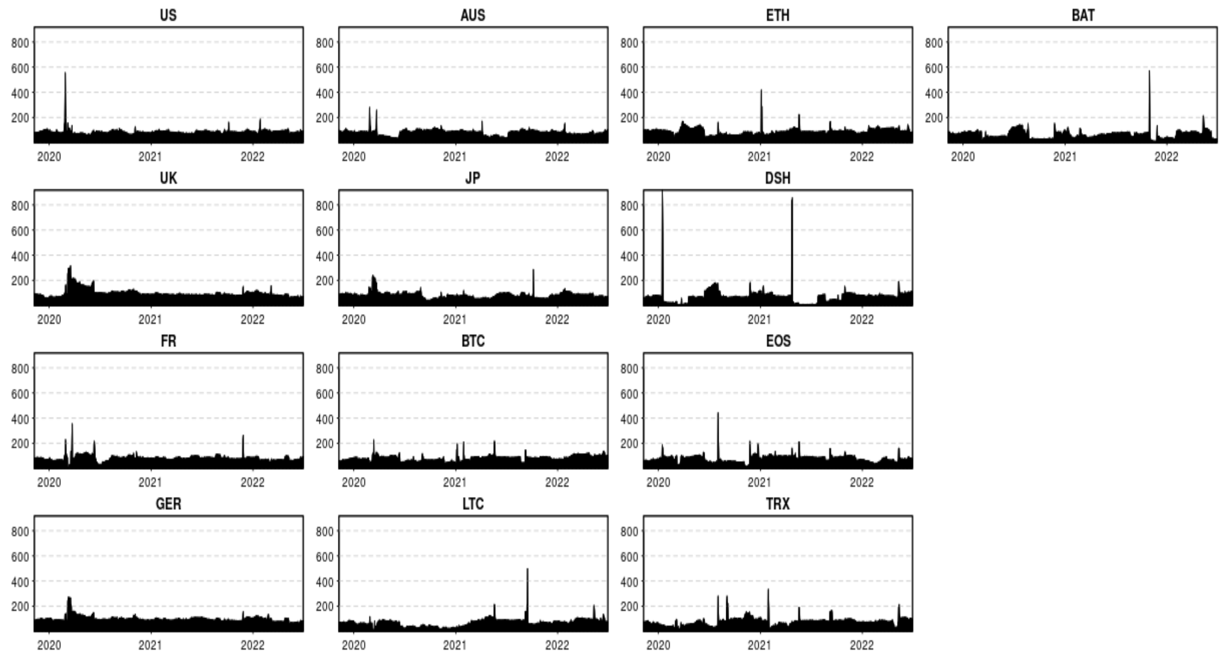

Fig. A1: Volatility Connectedness: TO Others

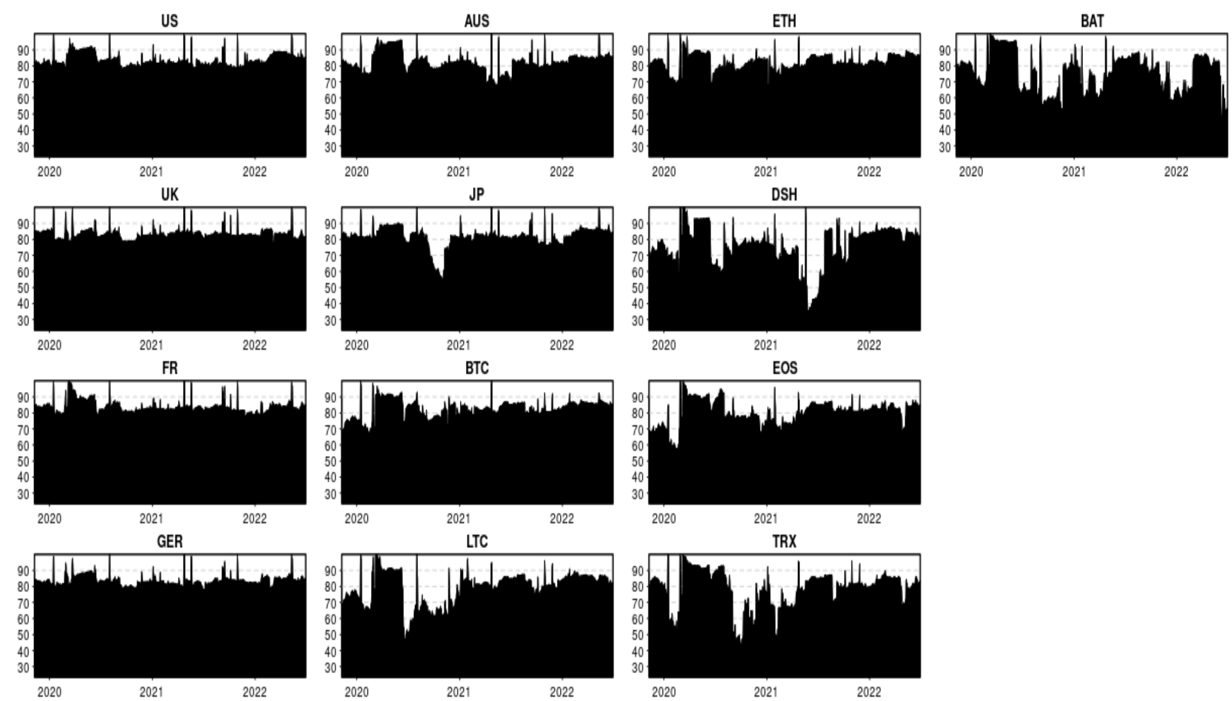

Fig. A2: Volatility Connectedness: FROM Others

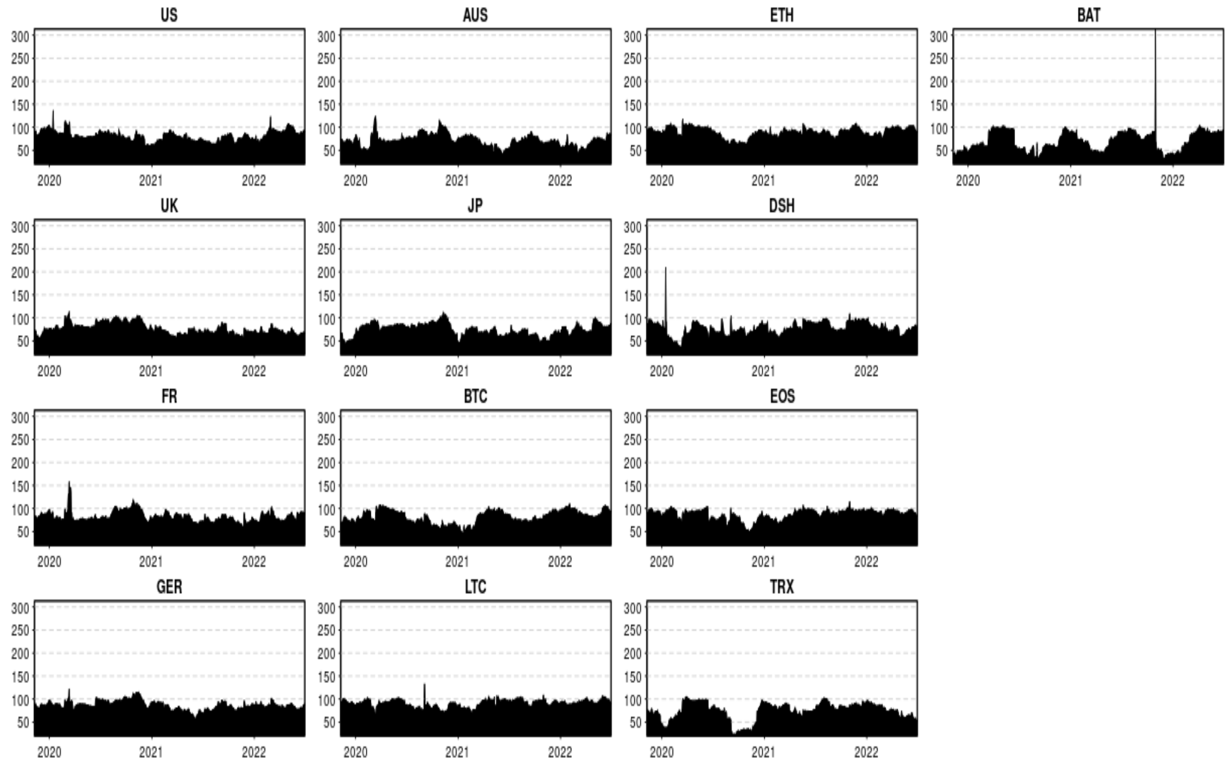

Table A3. Return Connectedness: TO Others

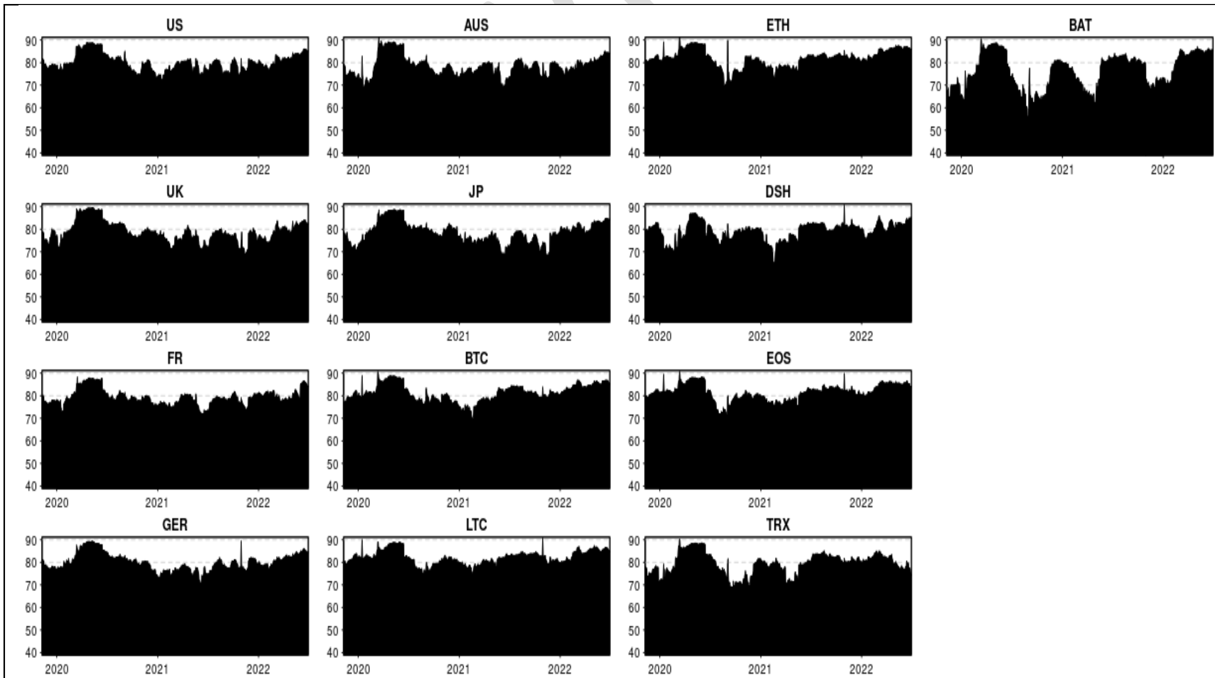

Fig. A4: Return Connectedness FROM Others