INTERNATIONAL MONETARY FUND

New Evidence on Spillovers Between Crypto Assets and Financial Markets

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WP/23/213

2023
SEP

WORKING PAPER

 WP/23/213

IMF Working Paper
Strategy, Policy, and Review Department

New Evidence on Spillovers Between Crypto Assets and Financial Markets
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Authorized for distribution by Martin Čihák
September 2023

ABSTRACT: We analyze returns and volatility spillovers among a representative set of crypto and financial assets. The magnitude of spillovers increases during periods of heightened turbulence due to negative economic-financial news, crypto market events, or exogenous shocks. There is evidence of increasing spillovers over time, with a peak during the COVID-19 pandemic, implying growing interdependence. Crypto assets predominantly transmit spillovers to financial markets, though reversals occur during periods of financial stress. The increased correlation during risk-off episodes suggests that crypto assets could serve as important conduits for financial market shocks, generating financial stability risks.

JEL Classification Numbers:	C58, G12, G15, G18, G23
Keywords:	Cryptocurrencies; Crypto assets; Bitcoin; Spillovers; Return and Volatility Connectedness
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*The views in this paper are our own and should therefore not be reported as representing the views of the International Monetary Fund, its Executive Board, or IMF management. The authors would like to thank Martin Čihák, Hector Perez-Saiz, Fabian Valencia, Marco Reuter, Agnija Jekabsone, Tao Sun, Steven Lam and IMF seminar participants for their suggestions.

Introduction

Crypto assets have experienced tremendous growth over the past two decades, with the number of coins[1] increasing from just Bitcoin in 2009 to over 5,000 currently, and reaching a total market capitalization in excess of USD 3 trillion towards the end of 2021 [2]. However, this growth has been accompanied by significant volatility, with most crypto coins going through several cycles of rapid growth followed by dramatic collapses. This is reminiscent of other periods in financial history in which private forms of money have proliferated in the absence of adequate government regulation, leading to frequent financial crises (such as in the US during the "Free Banking Era" of 1837–1863).

The rapid ascent of crypto assets, coupled with their increasing mainstream adoption, has generated concerns among policymakers and regulators, who are mindful about the potential contagion risks to other financial markets as well as the broader macro-financial implications (see e.g. IMF (2021), IMF (2023b), Hacibedel and Perez-Saiz (2023)). Crypto asset markets can both act as a source of shocks or as amplifiers of overall market volatility, thereby have the potential to have significant implications for financial stability. Consequently, policymakers face an imperative to enhance their comprehension of the interconnections between crypto assets and financial markets, enabling them to devise regulatory frameworks that effectively counteract the potential adverse consequences of crypto assets on financial stability[3].

The complex and rapidly evolving nature of the crypto market pose challenges for regulators in effectively assessing and addressing associated risks (IMF (2021), IMF (2023b)). Crypto assets encompass a wide range of technological attributes and features, serving means of payment, to store of value, speculative asset, support for smart contracts, fundraising, asset transfer, decentralized finance, privacy, digital identity, governance, among others (IMF/FSB (2023)). However, their relationship with traditional financial assets, particularly in terms of diversification potential, remains a subject of debate. While substantial research has investigated the nature, direction and intensity of linkages between crypto assets and crypto assets and other financial assets, the findings are still relatively inconclusive and paint a complex pictures of interdependencies.

The multifaceted interaction channels between crypto assets and financial markets may make it challenging to assess the relationship, while it may also have changed over time.

[1] In terms of terminology, let us note that while we occasionally employ the colloquial term 'coins', we prefer using the term 'crypto assets' to emphasize that these assets are generally not well-suited to fulfill the primary functions of money, such as store of value, medium of exchange, and unit of account.

[2] It has since that peak substantially declined to around $1.1 trillion.

[3] For example, IMF (2023a) provides high level principles for designing effective policy frameworks for crypto assets.

On the one hand, a ”flight-to-safety channel” would suggest that investors may allocate their funds into crypto assets during periods of economic uncertainty or market stress if cryptos are perceived as safer and offering a good hedge to certain financial assets. Crypto assets can thus provide diversification benefits, if their correlation with certain classes of traditional assets is low. However, their tendency for high volatility raises important concerns. Another potential channel is the ”speculative demand channel”, which would suggest that demand for crypto assets may increase during times of high financial market risk appetite, as cryptos offer the potential for high returns due to their volatility. Further channels could be related to market liquidity and to information spillovers or investor sentiment, which can lead to additional comovement between various classes of financial assets and crypto markets.

This paper investigates the returns and volatility spillovers among crypto assets and their relationship with a set of representative indices of global financial markets from 2014 to the end of 2022, using the spillover approach developed by Diebold and Yilmaz's (2009, 2012). The analysis focuses on unbacked crypto assets, whose value is not linked to that of another asset, and whose prices fluctuate freely driven by their supply and demand[4]. This analysis contributes to the literature in several ways.

Our findings indicate that, on average, the interconnections between crypto assets and financial assets are lower compared to within their respective asset classes, in terms of both sending and receiving returns and volatility spillovers. Furthermore, we show that crypto assets primarily transmit spillovers to financial markets, although during periods of financial sector stress, the reverse may also occur. We find stronger interconnectedness between crypto assets and global equities, the VIX, and gold, whereas spillovers with bond indices, the USD, and other commodities are comparatively modest.

Our analysis reveals a notable increase in spillover magnitudes over time, particularly during the COVID-19 pandemic, suggesting a potential rise in interdependence (this conclusion needs to be taken with caution, given the relatively short history). Furthermore, we link the increase in spillovers during periods of heightened turbulence to economic-financial events, events in the crypto markets, or other completely exogenous events. This heightened correlation during risk-off episodes suggests that crypto assets may not function as effective diversifiers and could potentially serve as crucial conduits for transmitting shocks across financial markets. Overall, by providing a clearer understanding of the patterns of interdependency between crypto assets and global financial markets, this study

[4]For classification and differentiation between the main types of crypto assets and the financial stability risks they pose, in particular in terms of differences between unbacked crypto assets and stablecoins, the reader is referred to Bains et al. (2022a) and Bains et al. (2022b).

highlights potential risks for financial stability going forward.

The paper is structured as follows. We commence with a concise literature review and subsequently introduce the data and methodology utilized in this study. We then delve into the examination of returns and volatility spillovers exclusively within the crypto markets, encompassing both static and dynamic effects. Similarly, we conduct an analysis on financial market assets in isolation to enhance our comprehension of their comovement. Lastly, we analyze the combined sample of crypto and financial assets to identify both static and dynamic connectedness for both return and volatilities, while also investigating the network of directional spillovers, with specific emphasis on the COVID-19 pandemic.

1 Literature Review

The empirical literature exploring the determinants and drivers of crypto markets, including from the perspective of spillovers, has expanded significantly over the recent years. Some studies emphasize the significant role of Bitcoin, and in some cases, a few other key crypto assets, in shaping market dynamics and spillovers. For instance, Corbet et al. (2018b), Ji et al. (2018) and Yi et al. (2018) find that the large well-known crypto assets are the most likely to dominate in the transmission of return and volatility spillovers. The magnitude of connectedness may be variable and may have increased as over time. Antonakakis et al. (2019) find that the dynamic total connectedness across several crypto assets exhibits large variability associated with market uncertainty, in that periods of high (low) market uncertainty correspond to strong (weak) connectedness. Koutmos (2018), Yi et al. (2018) and Shahzad et al. (2021) also find that the spillovers are time-varying and there is growing interdependence among cryptos, implying a higher degree of contagion risk over time.

A growing part of the literature has explored the interconnections between crypto assets and traditional financial assets with somewhat mixed and at times contradictory findings. One strand of the literature suggests that cryptos exhibit weak correlations with traditional financial assets due to their distinct economic determinants. Cryptos' different risk profile can be influenced by a range of factors, including: specific factors of supply and demand (Ciaian et al. (2016)), technological aspects related to blockchain security breaches and regulatory announcements (Kristoufek (2018)), illicit activities (Yelowitz and Wilson (2015)), as well as technical features and adoption metrics, such as the number of active users and network capacity (Liu and Tsyvinski (2018)) or mining costs (Hayes (2017)).

However, other research indicates that crypto assets are influenced by more general events that tend to impact financial markets simultaneously, creating potential channels for comovement. Bouri et al. (2017c) showing significant impacts on Bitcoin returns from geopolitical shocks such as terror attacks and elections. Broader investor sentiment also plays a role, as evidenced by Bouri et al. (2021), who establish a link between investor happiness and volatility spillovers in the crypto market. Furthermore, Bouri et al. (2017b) find that Bitcoin exhibits some hedge properties against the VIX, making it a potential hedge against extreme global uncertainty. Macroeconomic and financial policy announcements and events can serve as another driver of comovement with other financial assets. For instance, Corbet et al. (2017) identify central bank communications and regulatory announcements as important factors driving returns and volatility in crypto markets. Additionally, Wu et al. (2019) find that Bitcoin reacts to shocks in economic policy uncertainty. However, it is worth noting that according to Benigno and Rosa (2023), Bitcoin is largely orthogonal to monetary and macroeconomic news.

Some of the academic literature highlights a weak or negative correlation between cryptos and traditional financial asset classes such as stocks, bonds and commodities, the US dollar (see, e.g. Brière et al. (2015), Baur et al. (2018), Bouri et al. (2017a), Corbet et al. (2018b), Ji et al. (2018), Bouri et al. (2017c), Trabelsi (2018)). This conclusion appears to hold both in the short and long run, as well as in normal and turmoil times. These findings would suggest that cryptos can serve as an effective diversification tool for investors, and during some periods also as a hedge and safe heaven. Furthermore, Bouri at al. (2017b) find that Bitcoin does exhibit some hedge properties against the VIX and thus could serve protect against extreme global uncertainty.

However, other studies point to stronger inter-linkages between crypto assets and various segments of financial markets. For instance, Bouoiyour et al. (2016) and Li and Wang (2017) demonstrate significant volatility spillovers between Bitcoin and major currencies, attributing it to sensitivity to global macroeconomic events and news. Corbet et al. (2018a) and Bouri et al. (2017c) find significant spillover effects of Bitcoin on both currencies and equities, but not with bonds or commodities. Iyer (2022) and Adrian et al. (2022) find that crypto and equity markets have become increasingly interconnected across economies over time. However, other studies present somewhat contrasting results. Li and Wang (2017) observe significant volatility transmission between Bitcoin and stock markets, with weaker impact on gold and foreign exchange markets. On the other hand, Fang et al. (2019) identify weak and insignificant correlations with stock market returns but significant spillovers with the US dollar, gold, and oil. More recently, Harb et al. (2022) conclude that the crypto market is detached from the US stock market but not from the US bond market.

In summary, the literature on the relationship between cryptos and traditional financial assets presents a mix set of findings, ranging from weak or insignificant relationships to significant spillovers and connectedness between the cryptos and different types of financial assets. The varying results can be attributed to several factors, including differences in asset samples, time spans, and methodological approaches (ranging from VAR analysis, DCC-GARCH, VAR-GARCH, wavelet coherence analysis, copula-based approaches, to name just a few). Notably, several papers employ a similar methodology to this study, specifically the connectedness approach of Diebold and Yilmaz (2012) and Diebold and Yilmaz (2014). Overall, the inconclusive nature of the literature suggests that a comprehensive understanding of the interlinkages between crypto and financial assets calls for further research in this area.

2 Data

2.1 Crypto assets and financial market data

This paper employs a data set consisting of daily price data on 23 crypto assets which not backed by other assets [5] and 15 financial variables[6], covering the period between October 14, 2015 to January 1, 2023.

While the data on Bitcoin dates back to 2009, most other crypto assets have emerged over the past decade (see Table 1). In this study, we employ two distinct subsets of the Coinmetrics database, each with a specific focus. The first subset, known as the ”long” sample, begins on October 15, 2014, and includes 8 crypto assets: Bitcoin, Dash, Dogecoin, Litecoin, MaidSafeCoin, Vertcoin, Monero, and Ripple. In contrast, the second subset, referred to as the ”short” data set, starts on August 3, 2017, and comprises all 23 crypto assets available in the Coinmetrics database at the time and publicly traded until now, including Bitcoin (BTC), Bitcoin Cash (BCH), Binance Coin (BNB), Dash (DASH), Decred (DCR), DigiByte (DGB), Dogecoin (DOGE), Ehereum (ETH), Ethereum Classic (ETC), Gnosis(GNO), Golem (GNT), Litecoin (LTC), MaidSafeCoin (MAID), Neo (NEO), OMG Network (OMG), Augur (REP), Status (SNP), Vertcoin (VTC), NEM (XEM), Stellar (XLM), Monero (XMR), Ripple (XRP) and Zcash (ZEC).

The selected crypto assets in this study are quite heterogenous, with each coin having unique features and functionalities. The main criterion for their inclusion is their

[5] The asset price data has been obtained from CoinMetrics. Note that our analysis does not cover any stablecoins, primarily due to their much lower volatility on account of their stabilization mechanisms. The discussion will also abstract from the dynamics of flows, which would require an alternative methodology.

[6] Obtained from Bloomberg.

longevity, which is closely linked to their importance in the crypto universe. These coins can be broadly classified into five categories based on their primary functionality [7]: a) means of exchange and payments (Bitcoin, Bitcoin Cash, Dogecoin, Litecoin, Dash, Ripple, Stellar, Zcash), b) smart-contracts (Ethereum, Ethereum Classic, Gnosis, Golem, Neo, OMG Network), c) privacy (Monero), d) utility (Binance Coin, MaidSafeCoin, Status, Vertcoin), and e) other (Decred, DigiByte, Augur).

The selected coins in this study are among the most widely traded crypto assets, based on their market capitalization. In the ”long” sample, which starts on October 15, 2014, the selected coins accounted for 100% of the total market capitalization at the time. However, by the end of the sample, their combined market capitalization had decreased to 43.2%. In comparison, the ”short” sample, starting on August 3, 2017, includes a larger selection of 23 coins, which represented 84.6% of the total market capitalization at the beginning of the sample and 61.7% at the end. Among the coins included in both subsets, the largest ones by market capitalization were Bitcoin, Ethereum, Ripple, Dogecoin, and Stellar. Table 6 displays a list of all the selected crypto assets, ranked by market capitalization, along with some descriptive statistics, such as the average price, maximum and minimum prices, average volume, and average market capitalization.

The financial data in this study comprise a representative selection of global financial market indices and variables (see Table 7 for a detailed description). The fixed income markets section includes the yield on the 10Y US Treasury yield, as well as sovereign bond indices for advanced and emerging economies, separated by investment grade and high-yield categories (S&P Global Developed Sovereign Bond Index, ICE BofA US Investment Grade Emerging Markets External Sovereign Index, and ICE BofA US High Yield Emerging Markets External Sovereign Index). We further include several corporate bond indices (S&P U.S. High Yield Corporate Bond Index and ICE BofA Diversified High Yield US Emerging Markets Corporate Plus Index). The global equity markets section includes the MSCI World Index, while the US equity markets section includes the S&P500 and the emerging markets equity markets section includes the MSCI EM Index. Other included assets are: the USD effective exchange rate and commodities indices such as the gold spot price, oil price, and the DJ Commodity Index. To better capture financial market risk aversion, this study also incorporates two additional variables in the volatility regressions: the BoFA MOVE index (which reflects implied Treasury market volatility), and the VIX (which reflects implied S&P500 volatility).

The statistical properties of crypto prices illustrate their extraordinary level of volatility,

[7] While most coins are multifaceted and provide multiple use cases lending themselves to alternative classifications, in Table 6 we provide additional background details about the coins employed in this study.

Table 1: Crypto Assets: Descriptive Summary

	Symbol	Name	Start Date	Avg Price	Min Price	Max Price	Stdev Price	Avg MktCap (USD)	Latest MktCap (USD)
1	BTC*	Bitcoin	7/18/2010	8674.5	0.1	67541.8	14486.4	160,313,561,428	458,297,300,768
2	ETH	Ethereum	8/8/2015	812.9	0.4	4811.2	1102.9	93,133,546,881	196,753,350,116
3	XRP*	XRP	8/15/2014	0.3	0.0	2.8	0.4	33,581,607,280	41,344,897,789
4	DOGE*	Dogecoin	1/23/2014	0.0	0.0	0.7	0.1	4,676,035,116	12,435,771,388
5	XLM	Stellar	9/30/2015	0.1	0.0	0.9	0.1	14,322,876,268	9,946,929,396
6	LTC*	Litecoin	4/1/2013	58.4	1.2	385.5	65.3	3,662,965,367	6,863,759,326
7	BNB	BNB	7/15/2017	8.9	0.1	24.9	5.4	1,712,135,467	4,498,109,684
8	XMR*	Monero	5/20/2014	94.7	0.2	482.1	95.6	1,628,017,719	3,392,809,863
9	ETC	Ethereum Classic	7/25/2016	17.1	0.6	133.7	17.1	2,085,472,854	3,163,236,061
10	BCH	Bitcoin Cash	8/1/2017	469.2	76.1	3678.3	425.4	8,364,720,510	2,637,179,964
11	GNO	Gnosis	5/2/2017	120.3	8.8	585.0	117.9	1,202,721,310	1,133,399,829
12	NEO	Neo	7/15/2017	26.8	5.0	190.4	26.5	2,682,935,652	839,408,412
13	DASH*	Dash	2/8/2014	115.7	0.1	1447.5	165.9	1,005,760,251	632,495,131
14	ZEC	Zcash	10/29/2016	129.5	24.4	2042.1	123.4	808,924,815	630,427,940
15	XEM	NEM	4/1/2015	0.1	0.0	1.8	0.2	1,060,270,701	355,231,758
16	DCR	Decred	5/17/2016	44.2	0.4	246.1	45.7	496,414,226	354,989,097
17	OMG	OMG Network	7/15/2017	4.7	0.4	25.6	4.5	662,829,330	214,536,406
18	SNT	Status	6/19/2017	0.1	0.0	0.6	0.1	379,250,314	185,627,767
19	DGB	DigiByte	2/10/2015	0.0	0.0	0.2	0.0	237,148,361	175,738,308
20	REP	Augur	10/4/2016	18.6	2.5	105.6	13.8	204,963,460	67,668,263
21	GNT	Golem	2/19/2017	0.2	0.0	1.1	0.2	171,911,734	66,662,621
22	MAID*	MaidSafeCoin	7/10/2014	0.2	0.0	1.3	0.2	100,861,087	62,512,300
23	VTC*	Vertcoin	1/29/2014	0.6	0.0	9.5	1.1	24,869,959	11,372,826

Notes: This table lists all the 23 crypto assets in our sample in descending order of market capitalization as of January 1, 2023. The crypto assets marked with "*" are available for the longest period of time and included in all estimations, while the other crypto assets are included only in the "short" sample starting in 2017. All the price statistics (average, minimum, maximum, standard deviation) and the average market capitalization are based on the entire history of each crypto asset (e.g. from each crypto's Start Date until January 1, 2023).

as evidenced by the wide range of prices observed across the sample period (see Table 8). For instance, Bitcoin's price has ranged from USD 0.05 to USD 67,541, with an average price of USD 8,674 and a standard deviation of around USD 16,000. All analyzed cryptos display positive skewness, implying that there are more extreme positive returns than negative returns, which is likely due to their historical tendency to experience rapid price increases followed by (somewhat fewer) sharp declines. In comparison, most financial assets also exhibit positive skewness, although to a lesser degree than cryptos, and some financial assets display negative skewness (e.g., certain bond indices and the trade-weighted USD).

Additionally, a significant number of crypto assets display exceptionally high kurtosis (leptokurtic, e.g. kurtisis larger than 3), indicating thicker tails and therefore higher risks relative to the normal distribution. In contrast, financial assets tend to have much lower kurtosis, with some even displaying platykurtic distributions (bond yields, commodity prices, MSCI indices), suggesting fewer extreme values than the normal distribution. These results highlight the greater likelihood of crypto assets to experience extreme fluctuations relative to other financial assets. Jarque-Bera tests further confirm the non-normality of the price data, while the ADF tests in general point to non-stationarity, for both crypto and financial assets.

The analysis in this paper is conducted for both asset returns and volatilities. The reason for considering both has to do with some differences in the way they capture the comovement of assets. For example, a positive comovement of returns suggests a positive correlation between prices. However, this is not necessarily true for volatilies, as positive comovement between volatilities can also occur in case that asset prices would be moving in opposite directions by a large magnitude. By virtue of being a second moment, volatilities also tend to exhibit larger ”spikes” which highlight moments of large price swings and aid the identification of timing of specific shocks.

Accordingly, for the calculation of the following derivations are applied. Returns are calculated as:

$$r_{i,t} = 100 \times [ln(P_{i,t}) - ln(P_{i,t-1})] \tag{1}$$

where P denotes the closing price. Volatilities, on the other hand, are calculated in two steps. First, inter-day variance is calculated for series *i* on day *t*:

$$\sigma^2_{i,t} = 0.361 \times [ln(P_{i,t}) - ln(P_{i,t-1})]^2 \tag{2}$$

Next, daily return volatility is then converted to annualized volatility. Since volatilities tend to be skewed, log-volatilities are generally preferred as they approximate a normal distribution. However, to control for observations where volatility is zero, the inverse hyperbolic sine function is used, namely:

$$\tilde{\sigma}_{i,t} = sinh^{-1}(\sqrt{252 \times \sigma^2_{1,t}}) \tag{3}$$

The same transformation are applied for financial assets as well, with the exception of the MOVE and VIX indices which are not transformed.

Tables 9 and 10 summarize the key statistical properties of daily returns and volatilities for each crypto asset. Mean daily returns for cryptos vary significantly, ranging from very high values (up to 0.43 for Binance Coin), to large negative values (e.g. -0.19 for Neo). Financial asset mean returns typically range between 0.1 to 0.3, with just one negative mean return over the sample (for the corporat bond index AEHYC). Furthermore, we note that crypto assets returns exhibit significantly higher variability than financial assets, with standard deviations several times larger. Additionally, the return distributions for cryptos are generally positively skewed, except for Bitcoin, while most financial asset returns display negative skewness. ADF tests suggest that both returns and volatilities series are stationary, and thus suitable for VAR modelling.

3 Methodology: Measuring Spillovers

We adopt the VAR-based connectedness methodology originally introduced by (Diebold and Yilmaz, 2012), which relies on forecast error variance decompositions obtained from vector autoregressions (VARs) to construct measures of spillover and assess the degree of interconnections among assets. To implement this methodology, we model both the returns and the volatilities of crypto assets and financial variables as VARs. By decomposing the forecast error variance of each variable, we can determine the proportion of variance attributable to shocks in each individual variable. This approach enables us to analyze the impact of each variable on the transmission and reception of shocks across different variables in the system, from which various metrics of spillovers (alternatively called connectedness) can be derived.

Building on the work of Diebold-Yilmaz (2012), we follow the generalized VAR framework developed by Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998), which is invariant to the ordering in the VAR and therefore is more robust[8]. Let θ_{ij}^{H} represent the normalized contribution of variable j to the estimated forecast error variance of variable i at horizon H (for complete notation and derivation, see Appendix 1). This is generally presented in a connectedness table (matrix), which also allows to summarize the cumulative impacts as follows.

The off-diagonal column and row sums of the table are contributions "To" others and contributions "From" others, respectively. More specifically, the directional spillover transmitted from all assets j TO assets i as:

$$C_{\mathrm{i} \leftarrow *} = \sum_{j=1,\ j\neq i}^{N} \widetilde{\theta}_{\mathrm{ij}}^{H}$$

while the directional spillover transmitted FROM asset i to all other assets j is:

$$C_{* \leftarrow i} = \sum_{i=1,\ i\neq j}^{N} \widetilde{\theta}_{\mathrm{ij}}^{H}$$

The column of contributions "From" others measures the share of volatility shocks received from other assets in the total variance of the forecast error for each asset. By definition, it is equal to 100% minus the own share of the total forecast error variance. Similarly, the column sum of all pairwise spillovers results in the corresponding assets' total directional contribution "To".

[8] We thank Jilber Urbina for sharing his R codes.

On the basis of the "From" and "To" connectenedness, one can estimate the "Net" spillover from crypto i to all other cryptos as the difference between the two, namely: $C_i^H = C_{* \leftarrow i} - C_{\mathrm{i} \leftarrow *}$

The sum of the contributions to others (including own) is 100%. The total connectedness or spillovers index (TCI or TSI) is the share of contributions to others relative to the entire forecast error variance of the system, namely:

$$TCI^H = \frac{\sum_{i,j=1,\ i \neq j}^{N} \widetilde{\theta}_{\mathrm{ij}}^H}{\sum_{i,j=1}^{N} \widetilde{\theta}_{\mathrm{ij}}^H}$$

The index represents the off-diagonal column sum (or row sum) divided by the column sum including diagonal elements (or row sum including diagonal elements). Intuitively, it captures the average spillovers in the entire system from all other variables to any given variable, while ignoring the effects due to its own lags. More details on the methodology are available in Appendix 1.

4 Empirical Results

To better understand the transmission of shocks between crypto and financial assets, we divide our empirical analysis into several sections. First, we focus on investigating the spillover effects within crypto assets alone. Then, we turn our attention to financial assets in isolation. Finally, we combine both crypto and financial assets to obtain the most important set of results. This incremental approach allows us to we gain insight into the unique characteristics and spillover patterns of each asset class, as well as potentially key drivers and events. Additionally, examining the interactions between the two groups allows us to better understand and identify any transmission channels and spillover effects that might exist across asset categories.

4.1 Spillovers within crypto markets

4.1.1 Static analysis of connectedness for crypto asset returns and volatilities

We start by estimating the static connectedness for both crypto returns and volatilities for the "long" sample starting in 2014, which are presented below in Tables 2 and 3. The estimates for the "short" sample starting in 2017 are relegated to the Appendix (see Tables 11 and 12). All estimates use a forecast horizon H = 10 days and lag order p = 3 (VAR length has been chosen on the basis of Akaike and Schwartz information criterion [9]).

Table 2: Full-sample connectenedness matrix for crypto asset *returns*: long sample

	BTC	DASH	DOGE	LTC	MAID	VTC	XMR	XRP	From
BTC	3.98	1.58	1.07	1.92	0.95	0.65	1.51	0.83	8.52
DASH	1.80	4.55	0.95	1.51	0.77	0.58	1.46	0.88	7.95
DOGE	1.43	1.10	5.31	1.35	0.59	0.73	0.95	1.04	7.19
LTC	2.05	1.41	1.09	4.24	0.73	0.67	1.27	1.02	8.26
MAID	1.44	1.02	0.66	1.03	6.08	0.58	1.10	0.58	6.42
VTC	1.06	0.83	0.96	1.02	0.63	6.47	0.89	0.64	6.03
XMR	1.78	1.50	0.84	1.41	0.86	0.65	4.68	0.78	7.82
XRP	1.21	1.08	1.12	1.37	0.56	0.56	0.94	5.66	6.84
To	**10.77**	**8.53**	**6.70**	**9.62**	**5.08**	**4.43**	**8.12**	**5.76**	**59.02**
Net	**2.25**	**0.58**	**-0.48**	**1.37**	**-1.34**	**-1.60**	**0.30**	**-1.07**	**100.00**

Notes: This table presents the static spillovers amongst the returns of the analyzed crypto assets over the period October 15, 2014 to January 1, 2023. Each *(i,j)*-th value represents the contribution of innovation in asset *j* return to the variance of the forecast error in asset *i*. The column labeled "From" aggregates the cumulative contributions to asset *i* from all other assets, while the row labeled "To" summarizes the impact of asset *j* on all other assets. The row labeled "Net" captures the net spillover transmitted by each asset to all other assets. Positive (negative) values indicate that the asset in question acts as a net transmitter (receiver) of spillovers to other assets. To aid interpretation, color scales are employed. The minimum value is highlighted in green, the maximum value in red, and the median value is denoted in yellow. It is important to note that separate color scales are applied to the "From" column, the "To" row, and the "Net" row, distinct from the main table

The total connectedness across the entire samples exhibits significant values for both returns and volatilities. In the long sample, the total connectedness reaches 59% for returns and 68% for volatilities. In the short sample, encompasses 23 crypto assets, the figures are even higher, with 88% for returns and 89% for volatilities. These substantial values indicate that crypto asset markets are highly interconnected, in the sense that spillovers with other cryptos account for a substantial portion of the forecast error variance. It is worth noting that these figures appear elevated compared to total connectedness measures observed in other asset classes, such as international stock markets or financial stocks (see, for instance, Diebold and Yilmaz, 2014).

Turning to directional connectedness indicators, in the 2014 sample, Bitcoin emerges as the largest sender of return spillovers (10.7%), followed by Litecoin (9.6%). Regarding volatility spillovers, the most influential sources are Dash, Litecoin, and Bitcoin, all with net spillover around 9%. In the broader 2017 sample, no single coin dominates the landscape in terms of net spillovers. Ethereum becomes the largest sender of return

[9] The results appear very robust to several variations of the estimation parameters. The forecast horizon has also been adjusted from 1 week to 2 weeks without significant changes. Also, we have experimented with different starting dates and samples, which has implied somewhat different mixes of available crypto assets, again with surprisingly robust results.

Table 3: Full-sample connectenedness matrix for crypto asset *volatilities*: long sample

	BTC	DASH	DOGE	LTC	MAID	VTC	XMR	XRP	From
BTC	3.51	1.52	1.24	1.74	1.16	0.90	1.43	1.00	**8.99**
DASH	1.44	3.69	1.22	1.52	1.18	0.88	1.56	1.01	**8.81**
DOGE	1.31	1.35	4.16	1.43	0.97	0.92	1.11	1.25	**8.34**
LTC	1.76	1.53	1.28	3.59	1.06	0.91	1.14	1.23	**8.91**
MAID	1.28	1.43	1.12	1.14	4.14	1.05	1.34	0.99	**8.36**
VTC	1.05	1.19	1.27	1.13	1.02	4.63	1.29	0.92	**7.87**
XMR	1.40	1.64	1.06	1.19	1.26	1.01	3.93	1.01	**8.57**
XRP	1.18	1.27	1.48	1.58	0.85	0.97	1.13	4.05	**8.45**
To	**9.42**	**9.92**	**8.67**	**9.72**	**7.50**	**6.64**	**9.00**	**7.42**	**68.30**
Net	**0.43**	**1.11**	**0.33**	**0.81**	**-0.86**	**-1.22**	**0.43**	**-1.03**	**100.00**

Notes: This table presents the static spillovers amongst the volatilities of the analyzed crypto assets over the period October 15, 2014 to January 1, 2023. Each *(i,j)*-th value represents the contribution of innovation in asset *j* volatility to the variance of the forecast error in asset *i*. The column labeled "From" aggregates the cumulative contributions to asset *i* from all other assets, while the row labeled "To" summarizes the impact of asset *j* on all other assets. The row labeled "Net" captures the net spillover transmitted by each asset to all other assets. Positive (negative) values indicate that the asset in question acts as a net transmitter (receiver) of spillovers to other assets. To aid interpretation, color scales are employed. The minimum value is highlighted in green, the maximum value in red, and the median value is denoted in yellow. It is important to note that separate color scales are applied to the "From" column, the "To" row, and the "Net" row, distinct from the main table

spillovers (5.3%), followed by Litecoin (4.9%). Neo, ZEC, Dash and Bitcoin also have net spillovers exceeding 4.5%. When looking at volatilities, a similar pattern emerges. In terms of directional spillovers, the top transmitters are a group of several coin including Neo, Litecoin, Dash, Zcash, Monero, Ethereum, NEM and DigiByte, for which spillovers fall within the range of 4-5%. Moreover, in both returns and volatility spillovers a number of coins stand out as net receivers, in particular Vertcoin, Augur, MaidSafeCoin, Doge, Binance Coin and Decred, some of which are coins with relatively lower market capitalization.

In contrast to earlier studies that emphasized the central role of Bitcoin and/or a few crypto assets in the spillover network (see, e.g. Koutmos (2018), Corbet et al. (2018b), etc.), our findings diverge in the more recent sample, which encompasses a larger number of coins. Few other papers (see e.g. Yi et al. (2018) have pointed out to the role of smaller coins as significant net-transmitter of volatility connectedness. Overall, identifying strongly dominant coins in the current crypto universe has become more challenging, as we observe that market capitalization is not the primary determinant of a coin's significance in transmitting spillovers.

Additional information can be inferred from the network structure of returns and volatility spillovers (see Figure 4 and Figure 5). The network plots depict the pairwise relationship between crypto assets, with the arrows indicating the direction of the bilateral net spillover flow, while the width of the arrow is proportional to the magnitude of the spillover. The size of the node captures *total* spillovers (the sum of "to" and "from" spillovers for each asset), while the red (vs. green) color indicate if the asset is a total *net* transmitter (vs. receiver). The estimation is done over the short sample which contains all crypto assets, and a threshold of 90% has been applied to filter out the most significant relationships.

The returns network plot corroborates our findings in Table 14 in terms of the most important net senders of spillovers, which also happen to be the assets experiencing the largest total spillovers (Ethereum, Litecoin, Neo, Dash and Bitcoin), while the most important net receivers are MaidSafeCoin, Doge and Vertcoin. Ethereum in particular stands our through the number of significant relationship with the largest number of other coins, highlighting its importance in the crypto space. The volatility plot also highlights that the large net volatility transmitters Neo, Litecoin, Dash are also dominating in terms of total spillovers received and transmitted, while the most clear net receivers Vertcoin, Augur and MaidSafeCoin continue to play a small role in terms of total spillovers, as evidence by their small node size. It is interesting to note the spillovers involving Bitcoin do not meet the 90% threshold and are therefore not plotted.

Thus, overall, both the returns and volatility spillovers reveal a similar picture in both samples, albeit with some differences in magnitudes. The existence of relatively strong spillovers among most crypto assets, in terms of both returns and volatilities, suggests a relatively integrated market. In our analysis, the evidence regarding the dominance of specific key crypto assets presents a mixed picture. For instance, in the 2014 sample, Bitcoin and Litecoin have a relatively dominant role as net senders of spillovers. However, in the more extensive 2017 sample, characterized by a significant expansion of the crypto asset universe, no single coin assumes a central role. Instead, we observe that several currencies play important roles in the transmission network.

4.1.2 Dynamic analysis of spillovers for crypto asset returns and volatilites

The previous section provided an analysis of connectedness using the full sample, which would not capture time variation. In this section, we focus on a dynamic analysis by employing a rolling-window approach to examine how these patterns have evolved over time. Specifically, we utilize 120-day rolling sample windows while keeping the forecast horizon (H) at 10 days[10] and the lag order (p) at 3.

Figure 1 illustrates the total connectedness indices for returns and volatility spillovers.

[10]The results appears robust to different rolling window size, ranging from 100 to 200 observations. Aside from the higher smoothing achieved by the longer windows, there are no significant changes to the dynamics.

The most important finding is that there is significant co-movement between the indices over time, although occasional differences arise, and magnitudes are generally larger for returns. This strong relationship between returns and volatility spillovers holds true for both the 2014 sample, consisting of 8 crypto assets, and the 2017 sample, encompassing 23 cryptos. The close correlation between the returns and volatilities soillovers tends to suggest that crypto assets generally positively co-move in terms of their price changes. The fact that return spillovers are higher than volatility spillovers may suggest that crypto assets have rather different levels of fluctuation, which may be due to their very different characteristics.

We find that starting from 2014, the return spillover indices have fluctuated within the range of 25% to 92%, while the volatility indices have oscillated between 18% and 90%. Notably, two distinct phases can potentially be distinguished. The first phase, prior to September 2017, generally saw low spillovers, in general below 50%. However, starting with September 2017, significant and sustained increases have occurred in all spillover indices. The only significant decline in this period occurred from the autumn of 2020 to the summer of 2021, and was reversed by the increase in spillovers at the end of 2021. Overall, these observations suggest that crypto asset markets have become increasingly more integrated over time, with significant implications for the transmission of shocks.

Upon further analysis of the time-varying spillover indices, it becomes evident that they exhibit a close association with significant trends observed in crypto markets, particularly reflecting the occurrence of three major cycles in crypto prices. Moreover, it is noteworthy that specific events and market shocks can be discerned, with a notable tendency for these occurrences to align with negative news events of broader relevance (see Figure 1).

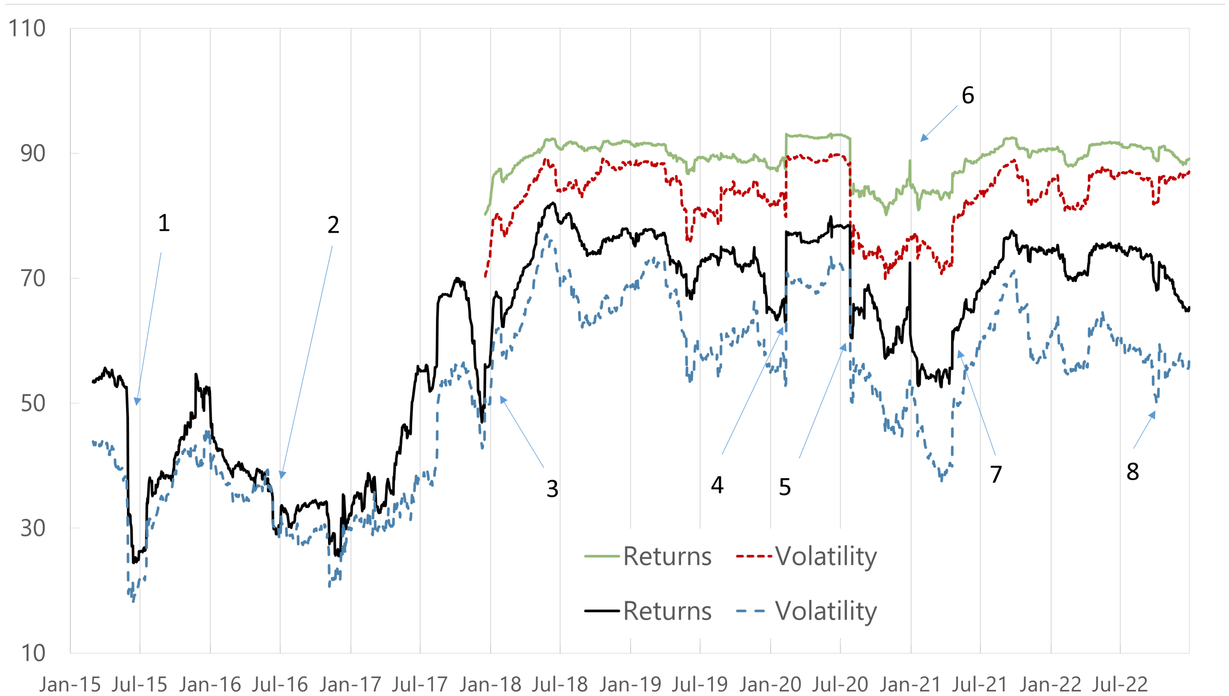
The initial segment of our sample, spanning until approximately December 2017, coincides with the first major boom in the crypto market. During this period, spillovers generally remained at relatively low levels, often staying below 50% while displaying some degree of volatility. Notably, the beginning of our long sample, specifically the first part of 2015, still witnessed the lingering impact of the Mt. Gox hack in 2014 [11].

However, the introduction of the Ethereum block chain in June 2015 brought about a positive sentiment among Bitcoin investors and the broader crypto community. The deployment of Ethereum was viewed as a significant milestone, contributing to increased confidence in the crypto ecosystem and leading to a decline in both return and volatility spillovers.

In 2016, the price of Bitcoin witnessed a significant surge, starting the year at approx-

[11] In April, the bankruptcy trustee for Mt. Gox announced the discovery of 200,000 Bitcoins (worth approximately $116 million at the time) that had been missing since the hack.

Figure 1: Spillover plot for crypto assets returns and volatilities



Notes: We plot moving return and volatility spillover indices, estimated using 120-day rolling windows, for both the ”long” sample starting in 2014 and the ”short” sample starting in 2017. The vertical black lines correspond to important events in crypto and financial markets: (1) 8/24/2015 Flash Crash (2) 6/24/2016 UK Brexit referendum (3) 2/5/2018 Stock market crash (4) 3/12/2020 Start of COVID-19 (5) 8/25/2020 Approval of COVID convalescent plasma treatment (6) 1/28/2021 Gamestop squeeze (7) 5/19/2021 Crypto market crash (8) 11/7/2022 FTX scandal.

imately $430 and reaching over $1,000 by year-end. This notable price increase can be attributed to various factors, including the growing adoption of Bitcoin and increased interest from institutional investors. The year 2017, however, witnessed an even more remarkable rally for Bitcoin, as its price skyrocketed from around $1,000 at the beginning of the year to nearly $20,000 by December.

The surge in Bitcoin’s price during 2017 was accompanied by a proliferation of Initial Coin Offerings (ICOs), which provided a new fundraising method for crypto startups. Furthermore, the majority of crypto assets experienced substantial price growth during this period, driven by factors such as heightened institutional investment, greater public awareness, and increased mainstream acceptance of crypto assets. Notably, some major companies began accepting Bitcoin as a form of payment, and the introduction of Bitcoin futures contracts on prominent exchanges like CBOE and CME provided institutional investors with a means to participate in the crypto market.

During this period, both return and volatility connectedness remained relatively low at around 40% or lower. This suggests that, despite the surge in Bitcoin’s price and the growing prominence of crypto assets in the mainstream, the degree of interconnectedness among crypto assets, as measured by spillovers, remained modest. This may indicate that the rapidly evolving market may have been less integrated market during this period, with idiosyncratic price drivers playing a somewhat more prominent role.

However, the year-end of 2017 marked a significant turning point as spillovers among crypto assets started to increase consistently. This period was marked by increased regulatory scrutiny, including warnings about the risks posed by crypto assets, as well as specific regulatory actions. For example, China banned initial coin offerings (ICOs) in September 2017, while in early 2018, both China and Korea imposed bans on crypto trading. In the US, the SEC and CFTC started taking a series of enforcement actions involving virtual currencies and ICOs, including through the issuance of statements to investors and consumers on risks stemming from crypto assets, including that many of these offerings may be illegal offerings or fraudulent.

Subsequently, the market experienced what is commonly referred to as the ”2018 Crypto Winter,” characterized by a significant sell-off across most crypto assets, particularly Bitcoin. The sell-off began in January 2018, and by February 6th, the price of Bitcoin had plummeted by approximately 65%. Subsequently, other crypto assets followed suit, resulting in an overall collapse of 80% from the peak of January 2018. During this tumultuous period, spillovers among crypto assets surged to unprecedented levels, peaking at about 80% for the volatility spillover index and 80% for the returns index (and respectively around 85% and 90%, when considering the richer 23-cryptos sample). The significant increase in spillovers during this time reflects the heightened interconnectedness and contagion effects that increased as a result of the crypto market downturn.

The crypto market witnessed a period of stabilization and gradual recovery in 2019, with increasing acceptance of crypto assets as a form of payment by businesses and individuals. Although spillovers decreased during this period, they remained relatively elevated. However, the onset of the COVID-19 pandemic in March 2020 brought about another surge in volatility within the crypto market. This resulted in a significant jump in the connectedness index, reaching its highest values in the sample. On March 12th, for instance, the price of Bitcoin experienced a rapid decline from over USD 7,000 to around USD 4,000 within a mere 24 hours, marking the largest single-day percentage drop in its history (event 4 in Figure 1). This crypto sell-off was part of a broader panic that swept through the financial markets, as investors grew concerned about the economic implications of the pandemic.

Nevertheless, despite the initial drop, the price of Bitcoin and other crypto assets rebounded relatively quickly throughout the remainder of 2020, in line with the recovery in other risk assets. This period of recovery was accompanied by a decline in the spillover indices, indicating a decrease in interconnectedness among crypto assets. In the early part of 2021, the price increases in the crypto market gained significant momentum. Bitcoin, in particular, reached another milestone, surpassing USD 60,000 in March 2021, marking the peak of the second major crypto cycle. Throughout this booming period, the connectedness indices for both returns and volatility exhibited a steady decline, reaching a trough in May 2021.

Starting in May 2021 as Bitcoin's price experienced a decline of approximately 50%, accompanied by a resurgence in spillovers (see event 7 in Figure 1). This decline may be partly driven by the broader financial market volatility throughout this period (as we will discuss more in detail in a later section). This downward trend in the crypto markets was subsequently reversed by July 2021, leading to a new phase of recovery. During this recovery, the price of Bitcoin peaked again in November 2021, reaching an all-time high of USD 64,400, representing the peak of the third cycle. Afterwards, Bitcoin started declining, entering what would later be referred to as the crypto ”winter” of 2022. By July 2022, the price of Bitcoin had fallen to around $17,000. Throughout this entire period, the spillover indices remained elevated, indicating the sustained interconnectedness among crypto assets. It is worth noting a significant spike in spillovers that occurred in November 2022, triggered by the collapse of FTX (event 8 in 1, which had a notable impact on the crypto markets, and contributed to an increase in spillovers).

Overall, we conclude that there are significant cycles in both returns and volatility spillovers, which are associated to the observed peaks in crypto asset valuations, but also driven by other events. Our findings suggest that there appears to be a significant increase in crypto spillovers starting towards the end of 2017 to very elevated levels, pointing to increasingly highly integrated crypto markets, without any strongly dominant coin. Yet, it is not entirely clear at this stage whether a regime shift has occurred since 2017, or we are observing temporary effects driven by exceptional circumstances. In particular, the steep decline in connectedness in the second part of 2020 until the start of the pandemic in early 2021 points to difficulties in identifying a clear trend, given the relatively short sample.

4.2 Analysis of connectedness for financial assets returns and volatilities

Before delving into the spillovers between crypto and financial markets, it is insightful to examine the spillovers exclusively within the financial markets. Existing literature on this subject covers various assets and time periods (see, e.g. Apostolakis et al. 2021; Mensi et al. 2021; Škrinjarić and Orlović, 2020).

To begin, we analyze the static spillover table for both financial market returns and volatilities, over the same long sample we have analysed for crypto assets (see e.g. Table 4 and Table 5). For brevity, we discuss the results for the long sample only, as they largely overlap with those from the short sample.

A couple of interesting findings emerge. First, the overall intensity of connectedness between our selected financial assets is comparatively lower than that observed within the crypto market itself. Specifically, the total connecteness index for returns slightly surpassed 63%, whereas for volatilities, the TCI is lower, reaching 54.7%.

Table 4: Full-sample connectenedness matrix for financial asset returns: long sample

	EMIGS	EMHYS	EMHYC	AEIGS	AEHYC	USTNX	MSCIEM	MSCIW	SP	USD	DJCOM	OIL	GOLD	**From**
EMIGS	2.42	1.28	0.76	0.36	0.78	0.15	0.34	0.47	0.39	0.41	0.13	0.08	0.12	**5.27**
EMHYS	1.10	2.12	0.94	0.01	0.83	0.04	0.53	0.68	0.58	0.42	0.22	0.15	0.07	**5.57**
EMHYC	0.88	1.27	1.89	0.01	0.84	0.05	0.61	0.70	0.58	0.39	0.26	0.15	0.06	**5.80**
AEIGS	0.45	0.02	0.01	4.07	0.01	2.17	0.21	0.22	0.20	0.01	0.11	0.10	0.13	**3.62**
AEHYC	0.71	0.90	0.76	0.01	2.11	0.06	0.49	0.97	0.87	0.33	0.27	0.17	0.03	**5.58**
USTNX	0.13	0.11	0.09	1.79	0.13	3.51	0.27	0.58	0.57	0.04	0.17	0.18	0.12	**4.19**
MSCIEM	0.32	0.59	0.43	0.11	0.49	0.16	2.12	1.20	0.93	0.55	0.47	0.23	0.09	**5.57**
MSCIW	0.27	0.51	0.32	0.10	0.63	0.28	0.86	1.89	1.68	0.48	0.40	0.23	0.04	**5.80**
SP	0.22	0.46	0.25	0.11	0.58	0.34	0.65	2.01	2.26	0.26	0.31	0.22	0.02	**5.43**
USD	0.43	0.52	0.33	0.00	0.38	0.03	0.67	0.81	0.47	2.75	0.65	0.26	0.39	**4.94**
DJCOM	0.12	0.23	0.17	0.07	0.27	0.13	0.52	0.58	0.39	0.61	2.67	1.48	0.44	**5.02**
OIL	0.10	0.20	0.18	0.08	0.23	0.17	0.32	0.43	0.33	0.31	1.86	3.36	0.14	**4.33**
GOLD	0.17	0.08	0.04	0.17	0.04	0.18	0.13	0.09	0.02	0.61	0.83	0.21	5.12	**2.57**
To	**4.90**	**6.16**	**4.29**	**2.81**	**5.22**	**3.74**	**5.61**	**8.73**	**7.03**	**4.41**	**5.70**	**3.46**	**1.63**	**63.71**
Net	**-0.37**	**0.59**	**-1.51**	**-0.82**	**-0.36**	**-0.44**	**0.04**	**2.93**	**1.60**	**-0.53**	**0.68**	**-0.87**	**-0.93**	**100.00**

Notes: This table presents the static spillovers amongst the returns of the analyzed financial assets over the period October 15, 2014 to January 1, 2023. Each *(i,j)*-th value represents the contribution of innovation in asset *j* return to the variance of the forecast error in asset *i*. The column labeled ”From” aggregates the cumulative contributions to asset *i* from all other assets, while the row labeled ”To” summarizes the impact of asset *j* on all other assets. The row labeled ”Net” captures the net spillover transmitted by each asset to all other assets. Positive (negative) values indicate that the asset in question acts as a net transmitter (receiver) of spillovers to other assets. To aid interpretation, color scales are employed. The minimum value is highlighted in green, the maximum value in red, and the median value is denoted in yellow. It is important to note that separate color scales are applied to the ”From” column, the ”To” row, and the ”Net” row, distinct from the main table.

In comparison to other financial assets, equity market indices stand out by exhibiting both high ”from” and ”to” connectedness. Specifically, the MSCI World equity index and the S&P500 are the largest senders of both returns and volatility spillovers to the entire system. The MSCIW index dominates as the most important net-emitter of shocks (2.9%) for returns, 1.57% for volatilities). Other risky assets, such as the MSCI Emerging Markets (EM) equity index, as well as emerging markets high-yield sovereign bond market index (EMHYS), also have relatively large net contributions to both returns and volatility shocks to the system. On the other hand, AE investment grade bonds and EM investment grade bonds have lower sending and receiving contribution and overall appear net receivers. Commodity prices and the dollar index are moderately high contributors to shocks, with the commodity index being a net sender, and the dollar index a net receiver. Notably, gold stands out in terms the least directional connectedness, acting as a net receiver of shocks. This is perhaps unsurprising given gold’s status as a safe heaven asset.

Table 5: Full-sample connectenedness matrix for financial asset volatilities: long sample

	EMIGS	EMHYS	EMHYC	AEIGS	AEHYC	USTNX	MSCIEM	MSCIW	SP	USD	DJCOM	OIL	GOLD	VIX	MOVE	**From**
EMIGS	2.38	1.10	0.59	0.34	0.53	0.27	0.22	0.26	0.19	0.28	0.09	0.06	0.10	0.16	0.10	**4.28**
EMHYS	0.89	2.26	0.73	0.22	0.62	0.24	0.30	0.32	0.22	0.26	0.14	0.10	0.09	0.19	0.08	**4.41**
EMHYC	0.61	1.07	2.54	0.06	0.76	0.10	0.29	0.27	0.20	0.16	0.09	0.05	0.05	0.30	0.13	**4.12**
AEIGS	0.37	0.34	0.06	3.18	0.18	1.17	0.07	0.22	0.16	0.19	0.16	0.15	0.12	0.10	0.21	**3.49**
AEHYC	0.50	0.76	0.68	0.16	2.52	0.19	0.19	0.41	0.31	0.13	0.08	0.11	0.03	0.44	0.16	**4.15**
USTNX	0.15	0.20	0.03	1.02	0.13	3.26	0.06	0.29	0.31	0.16	0.20	0.20	0.23	0.26	0.18	**3.41**
MSCIEM	0.22	0.40	0.25	0.10	0.24	0.11	2.94	0.74	0.29	0.32	0.31	0.12	0.21	0.30	0.12	**3.72**
MSCIW	0.15	0.29	0.13	0.14	0.28	0.23	0.50	2.12	1.47	0.27	0.27	0.12	0.15	0.47	0.09	**4.55**
SP	0.10	0.22	0.10	0.13	0.23	0.29	0.22	1.75	2.48	0.10	0.17	0.11	0.12	0.55	0.10	**4.18**
USD	0.34	0.35	0.19	0.19	0.19	0.25	0.34	0.42	0.15	3.16	0.44	0.18	0.28	0.11	0.08	**3.51**
DJCOM	0.10	0.18	0.08	0.13	0.11	0.23	0.28	0.37	0.20	0.35	2.87	1.12	0.38	0.16	0.10	**3.79**
OIL	0.12	0.19	0.07	0.19	0.17	0.35	0.11	0.22	0.19	0.17	1.24	3.21	0.19	0.17	0.06	**3.46**
GOLD	0.12	0.14	0.04	0.16	0.06	0.32	0.29	0.28	0.18	0.27	0.51	0.20	3.86	0.11	0.12	**2.81**
VIX	0.07	0.23	0.19	0.09	0.29	0.20	0.15	0.50	0.41	0.05	0.13	0.03	0.05	3.85	0.44	**2.81**
MOVE	0.10	0.12	0.10	0.34	0.12	0.34	0.05	0.06	0.08	0.03	0.02	0.01	0.07	0.60	4.60	**2.06**
To	**3.83**	**5.56**	**3.26**	**3.27**	**3.91**	**4.30**	**3.06**	**6.12**	**4.35**	**2.73**	**3.85**	**2.57**	**2.06**	**3.94**	**1.97**	**54.76**
Net	**-0.46**	**1.15**	**-0.87**	**-0.22**	**-0.23**	**0.89**	**-0.66**	**1.57**	**0.17**	**-0.78**	**0.05**	**-0.90**	**-0.76**	**1.12**	**-0.10**	**100.00**

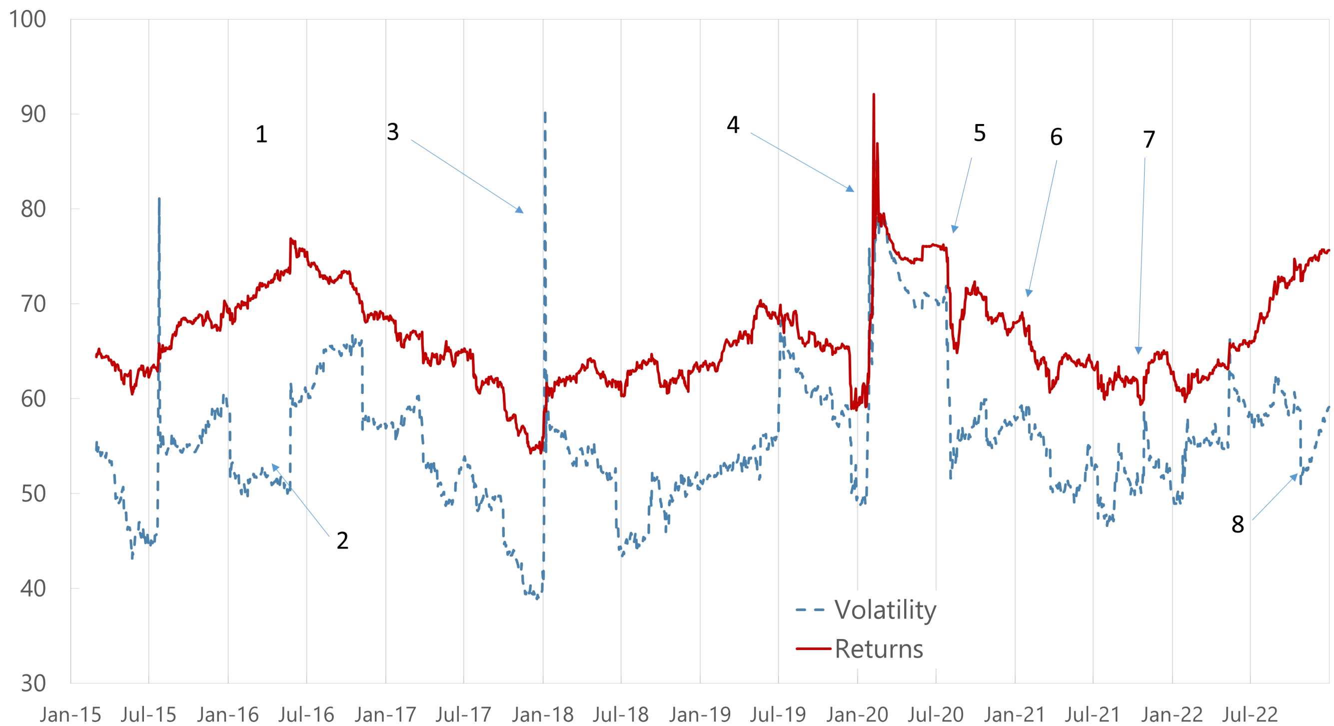
Notes: This table presents the static spillovers amongst the volatilities of the analyzed financial assets over the period October 15, 2014 to January 1, 2023. Each *(i,j)*-th value represents the contribution of innovation in asset *j* volatility to the variance of the forecast error in asset *i*. The column labeled "From" aggregates the cumulative contributions to asset *i* from all other assets, while the row labeled "To" summarizes the impact of asset *j* on all other assets. The row labeled "Net" captures the net spillover transmitted by each asset to all other assets. Positive (negative) values indicate that the asset in question acts as a net transmitter (receiver) of spillovers to other assets. To aid interpretation, color scales are employed. The minimum value is highlighted in green, the maximum value in red, and the median value is denoted in yellow. It is important to note that separate color scales are applied to the "From" column, the "To" row, and the "Net" row, distinct from the main table.

Turning now on to the rolling volatility connecteness plot (see Figure 2), we can discern several notable events and movements in financial cycles. The fact that episodes of heightened returns and volatility spillovers can be distinctly linked to significant occurrences within the global financial markets increases our confidence that the method identifies important pattern of market (co)movements.

The initial phase of our sample is characterized by multiple episodes that contributed to increased spillovers in financial markets, coinciding with the conclusion of the Federal Reserve's third round of quantitative easing (QE3) by December 2014, which served as a significant turning point for the US economy. Subsequently, spillover indices for financial markets exhibited a gradual increase until the end of 2016, driven by various factors.

Equity markets faced considerable turbulence during 2015-2016. A stock market crash in China from June to August 2015 lead to global contagion. In the United States, the Dow Jones index fell by 1,300 points from August 18 to 21. By the time of the "Flash Crash" on Monday, August 24, stock markets worldwide had erased all the gains achieved in 2015 (this is marked as event 1 in Figure 2). The interconnected market decline affected commodities, currencies, and other risk assets alike, leading to a particularly high spike in volatility spillovers. Government bonds also experienced significant volatility on several occasions, such as the "Bund Tantrum" occurring between May and July 2015, as well as the Brexit vote on June 23, 2016 (event 2 in Figure 2).

Figure 2: Spillover plot for financial assets returns and volatilities



Notes: We plot moving return and volatility spillover indices, estimated using 120-day rolling windows, for the "long" sample starting in 2014. The market events represent: (1) 8/24/2015 Flash Crash (2) 6/24/2016 UK Brexit referendum (3) 2/5/2018 Stock market crash (4) 3/12/2020 Start of COVID-19 (5) 8/25/2020 Approval of COVID convalescent plasma treatment (6) 1/28/2021 Gamestop squeeze (7) 5/19/2021 Crypto market crash (8) 11/7/2022 FTX scandal.

The first half of 2017, on the other hand, witnessed a notable stock market rally, fueled by optimism about the global economy. During this period, there was a decline in spillovers, especially in terms of volatility. However, spillovers started increasing again as turbulence affected markets again in 2018. In early 2018, global stock markets experienced a significant sell-off, driven by concerns over rising interest rates and trade tensions between the US and China. Notably, the stock market crash of February 6, 2018 (event 3 in Figure 2) stands out, when the Dow Jones Industrial Average dropped by more than 1,000 points, triggering a widespread sell-off across global stock markets.

The most significant surge in spillover indices for financial assets within our sample occurred during the initial phases of the COVID-19 pandemic in the spring of 2020. The pandemic unleashed a wave of uncertainty, leading to a stock market crash (event 4 in Figure 2). The S&P 500 index experienced a sharp decline of 34%, shedding 1,145 points from its peak on February 19 to March 23. Both volatility and returns spillovers reached their highest levels on record, peaking at 81% and 93% respectively. However, owing to the exceptional policy responses by central banks and governments worldwide, aimed at bolstering the economy and stabilizing financial markets, the crash was swiftly reversed. The second half of 2020 witnessed the onset of a major bull market, driven by the supportive measures implemented. As a result, spillover indices gradually declined for the remainder of the pandemic.

The resumption of an upward trend in spillover indices occurred in February 2022, following the Russian invasion of Ukraine. This geopolitical event, particularly its impact on commodity markets, reignited spillovers across markets, as participants reacted to and grappled with the implications of the increased uncertainty.

4.3 Connectedness between Financial and Crypto Markets

4.3.1 Static analysis of connectedness for between crypto and financial market returns and volatilities

As in our previous analysis, we start by examining the static directional spillovers between crypto and financial assets, focusing both on returns and volatilities. The analysis encompasses both the long and short sample and results are presented in Tables 13, 14, 15, 16. Unsurprisingly given our earlier findings, the total connectedness indices are relatively high. When considering the smaller set of assets starting in 2014, the indices hover around 63% for returns and 60% for volatilities. However, in the shorter but more comprehensive sample, the indices increase to 82% and 77% respectively. The increase in the second sample is influenced by both the increase in the number of crypto assets and perhaps more significantly, by an increase in the underlying level of linkages between the assets during the more recent period.

Unsurprisingly, the combined samples corroborate several findings previously documented for crypto and financial assets analyzed separately. However, the joint analysis enables a more precise examination of interlinkages between the two asset classes, offering insights into the magnitude and directionality of these spillovers. This combined approach also facilitates a direct comparison of spillover magnitudes, which was not feasible when analyzing the samples in isolation.

The analysis of the connectedness matrix yields an important finding regarding the degree of connectedness between crypto and financial assets. The color map reveals two distinct off-diagonal rectangles, which represent the interactions cross asset classes (spillovers from cryptos to financials and respectively from financials to cryptos). These cross asset spillovers are ranked as the lowest values throughout the entire matrix, depicted in varying shades of green and occasionally yellow. This indicates that crypto and financial assets, on average, are relatively less interconnected across asset class than they are within their own asset class, in terms of both sending and receiving relatively lower spillovers. In more simple terms, connectedness between crypto and financial assets is not very strong, when compared to measures of connectedness between crypto or financial markets taken individually.

Upon closer examination, the connectedness between cryptos and equities stands out as the most pronounced among the cross-asset returns spillovers. Specifically, when examining returns connectedness in both the long and short samples, the MSCIW and S&P500 exhibit the strongest spillover effects with cryptos in both directions (see Tables 13 and 14). Notably, the return spillovers ”from” crypto assets to the MSCIW and S&P500 tend to dominate in magnitude the spillovers ”to” cryptos from those financial assets. Additionally, it is worth highlighting that crypto markets appear to transmit relatively larger returns spillovers to gold compared to the spillovers they receive from the precious metal. At the same time, it is interesting to note that the spillovers between crypto assets and the various types of bonds included in the sample appears relatively insignificant in both directions.

When examining volatilities, the most prominent spillovers are observed between crypto assets and the riskier EM stock markets represented by MSCIEM. Notably, in terms of magnitudes, the spillovers from crypto assets to MSCIEM tend to be larger than the spillovers sent by equity markets (refer to Tables 15 and 16). Additionally, it is worth mentioning the significant volatility spillovers between crypto assets and the VIX and commodity prices, including gold. The spillovers from the VIX to crypto assets are larger in magnitude compared to the reverse direction. For commodity prices, volatility spillovers with crypto assets are approximately comparable in both direction. However, for gold, the larger volatility spillovers occur from the direction of crypto markets. In line with the findings for returns, we observe relatively modest spillovers between crypto assets and bond markets, including the MOVE index. However, there appear to be some weak volatility spillovers between crypto assets and oil, as well as the USD, mostly with crypto asset being net senders.

Next, we aim to compare and rank spillovers from both types of asset classes. Focusing first on returns spillovers, we observe that in the long sample, the MSCI World equities index emerges as the largest sender of overall and net spillovers (5% and 1.45% respectively), closely followed by the S&P 500 and high yield bonds from both AEs and EMs. Notably, in this sample, Bitcoin and Litecoin also play a significant role as net spillover senders, consistent with previous findings. However, in the 2017 sample, Ethereum takes the lead as the most influential transmitter of both overall and net returns spillovers (3.65% and 1.10% respectively), with Litecoin, Neo, Bitcoin, and Dash following closely, as well as global equity markets (MSCIW). However, it is interesting to note that over this sample, other financial assets appear to be mostly net receivers of spillovers.

As concerns volatilities spillovers, the findings are largely similar, with some interesting nuances. In particular, in the long sample, the MSCI World equity index is the largest sender of total spillovers, while the VIX is the largest sender of net spillovers. EM markets high yield bonds, Bitcoin and Litecoin also send significant volatility spillovers to the system. However, in the 2017 sample, more cryptos play important roles as both total and net senders of volatility spillovers (Neo, Litecoin, Ethereum, Dash, NEM). The net spillovers transmitted by cryptos tend to exceed the spillovers generated by financial variables (where again the MSCIW and the VIX stand out as important net volatility transmitters).

The connectedness matrices highlight another difference between the two types of assets. Spillovers between crypto assets tend to be relatively homogeneous in size, without large differences between pairs (in terms of the color map, the shading of the top left panel is not very differentiated). However, interlinkages between financial assets show much larger variability, as the color map highlights, with spillovers ranging from green to the deepest red. Some of the largest bilateral spillovers in the tables occur between pairs of financial assets, such as between the various equity indices, or between bond indices. Unsurprisingly, the US ten year yield has strong linkages with the AE sovereign bond yield and we also find strong connectedness between the oil price and the broader commodity index. However, spillovers between some financial assets can at times also be rather low, such as some weak relationships between oil or gold and certain bond or equity indices.

Turning now on to the network of pairwise directional connectedness, we first present a snapshot of all the spillovers between cryptos and financial assets which rank in the top 95% percentile (see Figures 6 and 8). As previously, the size of the nodes captures the total spillovers (”to” and ”from” each assets), while the color red (green) reflects whether the assets is a net transmitter (receiver) of spillovers. The width of the arrows is proportional to the strength of the relationship. Additionally, arrows are colored in black for spillovers between cryptos, blue for spillovers between financial assets, and red for spillovers between crypto and financial assets. Let us also note that the network results presented in this section are derived for the 2017 sample, as it contains the largest set of assets (however, using the longer sample does not change the key findings).

As has been discussed before, the key finding that the networks also support is that spillovers within each asset class are significantly larger than those cross asset class. For example, the chart on returns (see Figure 6) has only few red lines (between Dash and S&P500 and MSCIW). The largest bilateral spillovers occur between certain pairs of financial assets, as has been highlighted before (such as from the 10 year US Treasury yield (USTNX) to the index of sovereign bonds in advanced economies (AEGIS)). It is also notable that a large number of bilateral spillovers between crypto assets also are significant enough to exceed the threshold, and point to the strong integration within the crypto universe itself.

In the network for volatilities (Figure 8), however, more spillovers between cryptos and financial assets exceed the 95% threshold (as evidenced by the larger number of red arrows). In terms of the direction of the relationship, one can note that in all cases, crypto assets are the net sender. For example, a large number of cryptos send spillovers to gold, several cryptos send spillovers to VIX, and one to MSCIEM. It should be also noted that these spillovers are not the most significant among the selected snapshot either. As was the case for returns, transmission between certain pairs of financial assets dominate in terms of magnitudes ((blue arrows), such as: important transmission links between emerging economies and high yield bonds (EMHYC, EMIGS, AEHYC), between equity markets (S&P500, MSCIW and MSCIEM) and VIX, between advanced economy treasuries (USTNC, AEIGS) and MOVE, as well as links between equity markets volatility (VIX) and commodities (DJCOM, Oil), to name but the most important.

In order to analyze more in detail the spillovers between crypto and financial assets, we present also versions of these networks where the spillovers between assets of the same class (cryptos to cryptos and financials to financials, have been filtered out. These networks plot the top 90% most significant relationships post filtering, while arrow size has been normalized (thus is is not comparable across charts). This selection process allows us to analyze more closely cross-asset spillovers. For example, the chart on returns (see Figure 7) now plots fewer assets but identifies the largest cross asset return spillovers. However, as before, we find that all the financial assets which were selected as having the largest cross-asset spillovers with cryptos (namely DJCOM, MSCIEM, MSCIW, S&P500, Oil, Gold, USD, USTNX) are in all instances net-receivers of spillovers from crypto assets. This is the case also for financial assets which are, overall, net-emitters (such as MSCIW or S&P500). The cryptos sending the most numerous and strongest spillovers are Ethereum, Bitcoin and Litecoin (the strongest connectedness appears to be between Ethereum and S&P500). It is also interesting to note that most cryptos send relatively strong spillovers to gold.

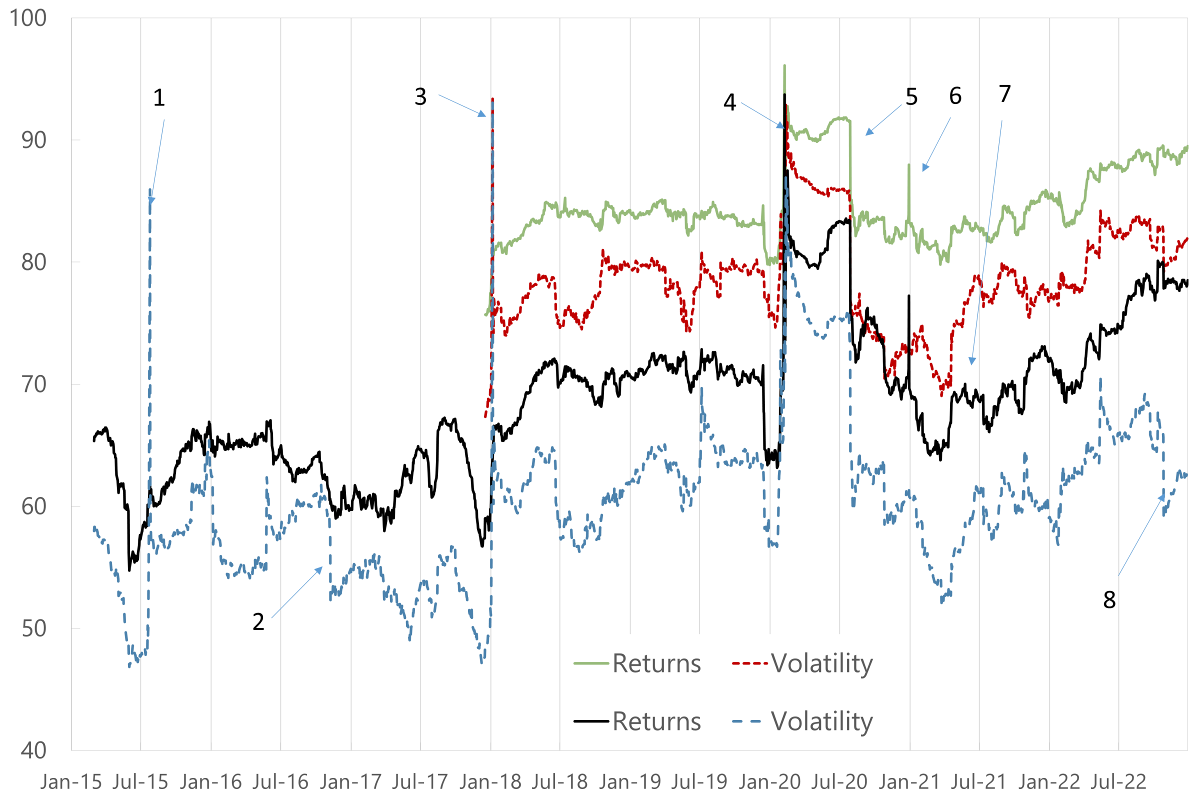
The inspection of the network for volatilities (see Figure 9) reveals some similarities and some differences with the chart for returns. First, the selected financial assets are almost the same (e.g. AEIGC, DJCOM, Gold, MSCIEM, USD and VIX) and second, crypto assets are net transmitters to financial assets in all bilateral pairs. Also, gold remains the financial asset to which almost all cryptos are sending spillovers, which suggests that the price of gold is significantly influenced by shocks in crypto markets. Many cryptos are also sending spillovers to equity markets (MSCIEM), some the the VIX and the USD. It is somewhat surprising that some of the smaller cryptos such as GNT, DGB, XMR, XLM appear to have the largest spillovers to financial assets (in all cases, to gold).

4.3.2 Dynamic Analysis of Connectedness for Crypto and Financial Market Returns and Volatilities

While the assessment so far has been an average representation of the relationship over the entire sample, this section will go into detail as to how spillovers between financial markets and crypto assets have evolved over time. As we did previously separately for crypto assets and financial markets, we proceed in this section to analyze the total spillover plots derived from rolling-window regressions.

The spillovers indices for both crypto and financial assets have varied substantially over time and appear to have gradually increased in the sample under consideration (see Figure 3). Moreover, the relationship has been punctuated by occasional spikes of very high spillovers, which correspond to significant shocks in either crypto or financial markets, as well as to other exogenous events which may be associated with a deterioration in risk sentiment. In the following discussion we will emphasize a few such key events for illustration purposes. The reader will notice that we have already highlighted these events in the separate analysis on crypto and financial markets, while this section aims to bring

Figure 3: Spillover plot for *combined* crypto and financial assets returns and volatilities



Notes: We plot moving return and volatility spillover indices, estimated using 120-day rolling windows, for both the "long" sample starting in 2014 and the "short" sample starting in 2017. The marked events represent: (1) 8/24/2015 Flash Crash (2) 6/24/2016 UK Brexit referendum (3) 2/5/2018 Stock market crash (4) 3/12/2020 Start of COVID-19 (5) 8/25/2020 Approval of COVID convalescent plasma treatment (6) 1/28/2021 Gamestop squeeze (7) 5/19/2021 Crypto market crash (8) 11/7/2022 FTX scandal.

them together and allow for better comparability.

In examining the spillover dynamics, we observe that volatility spillovers tend to be lower compared to returns spillovers in both time samples, which aligns with findings observed across different categories of assets. Additionally, the spillover indices in the shorter sample are relatively larger, primarily due to the inclusion of a broader range of crypto assets. Furthermore, we note a high level of comovement between both returns and volatility spillovers, as well as between the two time samples.

At the start of our sample, in August 2015, the devaluation of the Chinese yuan and the subsequent stock market sell-off in China led to a decline in financial markets around the world (the "Flash Crash" of August 24). In this period, a parallel decline in the price of Bitcoin and other cryptos occurred. As a result, the spillover indices for both volatility and returns experience a sharp rise, as indicated by event 1 in 3.

In June 2016 (event 2), the Brexit vote in the United Kingdom triggered a decline in the pound and a sell-off in financial markets, impacting both traditional assets and crypto assets like Bitcoin. Investors sought refuge in safe-haven assets such as U.S. Treasury bonds. However, this increase in spillovers was short-lived. A stock market rally occurred in the first half of 2017, accompanied by a corresponding rally in the prices of crypto assets. During late 2017 and early 2018this period, both financial markets and crypto assets experienced a surge in prices, driven by bullish investor sentiment and a surge in popularity for crypto assets. The spillover index displayed a downward trend during this period, declining to some of the lowest levels in our sample.

However, these favorable trends were sharply reversed towards the end of 2017 and beginning of 2018. The price of Bitcoin reached its peak on December 17, 2017, only to experience a significant 45% decline on December 22 of the same year. Similarly, while the stock market was reaching record highs in January 2018, on February 5, the Dow Jones Industrial Average dropped by 1,175 points, its biggest single-day point decline in history. The stock market crash of Feb 5, 2018 (event 3) had a significant impact on connectedness. Subsequently, all the connectedness indices for returns and volatilities remained at persistently elevated levels.

The most significant increase in connectedness within our sample occurred in March 2020, with all the connectedness indices jumping by approximately 20 percent. This notable spike coincided with the onset of the COVID-19 pandemic, which triggered a widespread market sell-off across both traditional financial markets and crypto assets. During this period, investors sought refuge in safe-haven assets like U.S. Treasury bonds. However, by the end of the summer, spillover indices decline sharply, with news of the approval of a coronavirus treatment and expectations of vaccines lifting investors' sentiment. On August 25, 2020 US stock markets reached all time highs, surpassing their pre-pandemic peaks (event 5). The positive sentiment fueled a surge in risk-taking across financial markets, leading to a rally in both stock markets and crypto assets, which continued until the spring of 2021. Throughout this period, the spillover indices displayed a downward trajectory.

The charts allows the identification of the speculative Gamestop squeeze, which occurred on January 28, 2021 (event 6). This event lead to a temporary spike in returns spillovers. Subsequently, on May 19, 2021, the crypto market experienced a notable crash (event 7), with the price of Bitcoin plummeting by approximately 30% from its recent all-time high of around $64,000 to around $30,000). Although Bitcoin prices swiftly recovered in the second half of 2021, this period marked a reversal in the previous trends and the beginning of a new phase of gradually increasing spillovers.

However, starting with January 2022, most risk assets and cryptos entered into bear market territory. In stock markets, the S&P 500 index peaked at 4,796 on January 3 close and dropped 23.55% to 3,666 by June 16, 2022. As part of the global decline in most risk assets, the price of Bitcoin collapsed 59% during the same time period, and 72% from its November 8 all time high. A temporary spike in volatility on November 11, 2022, associated with the collapse of the crypto exchange FTX, also had a detectable impact on the spillover indices.

Overall, this analysis reveals that both returns and volatility spillovers between crypto and financial assets have exhibited significant fluctuations since 2014. These fluctuations can be attributed to the broader cyclical behavior observed in the underlying crypto and financial markets, as well as the impact of various exogenous shocks. Although there is some indication that the magnitude of spillovers has gradually increased over time, it is important to note that it is still premature to draw definitive conclusions.

Consistent with findings in prior literature, our analysis also supports the notion that the amplitude of spillovers between crypto and financial markets tends to increase during periods of stress. These episodes of heightened market stress can stem from various sources, including crypto market events (e.g. crashes, FTX), financial market events (e.g. stock market crashes, speculation), or significant exogenous events (such as Brexit or the COVID-19 pandemic). The observed increased comovement during risk-off episodes implies that crypto assets may not effectively serve as diversifiers and have the potential to play a significant role in transmitting shocks across financial markets. This finding underscores the importance of monitoring and analyzing the interactions between crypto and financial markets, as well as the developing effective risk management strategies and ensure the stability and resilience of the overall financial system.

4.3.3 Results During the COVID-19 Pandemic

In this section, we narrow our focus to a specific period characterized by heightened spillovers, delving into the first phase of the COVID-19 pandemic from March 2020 to January 2021. While the previous section found that the pandemic period stands out in terms of the magnitude of the total connectedness index, our objective here is to provide a more nuanced understanding of the spillover dynamics between crypto and financial assets during this period. To accomplish this, we examine the network of pairwise directional spillovers.

The pandemic sub-sample analysis reveals notable differences compared to the results obtained over longer periods. Specifically, when examining the networks of spillovers encompassing both cross-asset spillovers and those within the same asset class, there is a significant increase in the selected cross-asset spillovers (denoted by red arrows). This indicates that a larger number of bilateral cross-asset spillovers surpass the 90% threshold, as depicted in Figures 10 and 11. The stronger cross-asset spillovers observed during the pandemic sub-sample signifies a heightened interconnectivity between crypto and financial markets.

Next, we consider the network of cross-asset spillovers only, where linkages between the same asset class have been filtered out (see Figure 13 and 12). In these charts, we differentiate between spillovers from cryptos to financials, represented by the color red, and from financials to cryptos, which appear in blue. It is worth recalling that for the entire sample networks, the spillovers from financial assets to cryptos were relatively low, resulting in their exclusion. The interesting findings is that during the pandemic we observe significant spillovers from financial assets (primarily bond yields and the MOVE index) to various crypto assets. This is interesting given that in the overall sample, the relationship between crypto assets and bond yields stood out as particularly weak.

These findings are further supported when considering the dynamic directional net connectedness for both returns and volatilities. In Figure 14 we present several key financial and crypto assets and the net directional spillovers they send to the system, computed over the short sample. Dotted vertical lines mark the beginning and end of our pandemic sub-sample (March 2020 to January 2021). One can notice a sharp spike in both returns and volatility spillovers for all the series at the beginning of March 2020, at the time of exceptionally high market turbulence. However, what stands out the most is the persistent increase in net sending spillovers exhibited by the MOVE index, as well as by high yield bonds (EMHYC and EMHYS). While several cryto assets also somewhat increase their net positive spillovers (Ethereum, Bitcoin, Bitcoin Cash, Binance Coin), gold and the US 10Y yield assume the role of net-receivers, consistent with their widely recognized safe-heaven status.

This dynamic provides further corroboration of the earlier observations made from the network plots. It can plausibly be attributed to the exceptional policy response at the beginning of the pandemic, in particular the forceful reduction of policy rates. It can be argued that the monetary easing impact on bond yields was subsequently transmitted to the broader financial system and exerted a discernible influence on crypto markets as well. However, many crypto assets during this period acted as net spillover emitters, implying that they contributed to the propagation of the shocks. The network charts and the directional plots provide support for this intuition by showcasing a stronger-than-usual transmission from bond markets to crypto assets during this period, as well as the further amplification through crypto markets.

The period marked by the pandemic serves as a noteworthy illustration of how the direction and strength of spillovers between financial markets and crypto markets can undergo substantial shifts. This finding emphasizes the importance of comprehending the dynamic nature of these spillovers, as it enhances the ability of policymakers to anticipate and effectively respond to potential feedback loops that could give rise to risks to financial stability. By recognizing and addressing these evolving interconnections, policymakers can take proactive measures to mitigate potential disruptions and safeguard the overall health of the financial system.

5 Conclusion

This paper provides an investigation into the relationship between crypto assets and traditional financial markets using Diebold and Yilmaz's spillover approach. The study expands the range of crypto and financial assets considered compared to previous studies, providing a more comprehensive view of their relationship. It also covers the COVID-19 outbreak and the crypto winter of 2022, which were important periods of change in the intensity of spillovers.

The paper analyzes the dynamics separately within the crypto and financial markets, taking a step towards understanding the joint relationship and providing a clearer understanding of the complex co-movements between these asset classes. By doing so, this study aims to enhance our understanding of the interdependencies between crypto assets and global financial markets and their potential implications for financial stability. While this paper does not include stablecoins in the analysis, it is important to note that volatility spillovers to financial markets may also occur due to events originating in the stablecoin universe. An analysis on the magnitudes and channels of such spillovers is left for further work, potentially with a different methodology better suited to the specific features of such coins (including by leveraging information from transaction volumes).

The paper finds that crypto asset markets exhibit a high level of integration, potentially surpassing other asset classes, with significant spillovers in terms of both returns and volatilities. Over time, this connectedness has shown an upward trend, especially following 2017, reaching its peak during the early phase of the COVID-19 pandemic. In the early years, Bitcoin (closely followed by Litecoin) generally played dominant roles in the network of spillovers. However, in the more recent period, which coincided with the notable expansion of the crypto universe, the overall market connectedness has increased, while also becoming more evenly distributed. Although Ethereum stands out in terms of the number of spillovers to other coins in the more recent period, various other coins also play significant roles in transmitting spillovers driven by other specific factors, including their unique roles and functions.

Our findings indicate that, on average, crypto and financial assets are less interconnected than within their respective asset classes in terms of both sending and receiving relatively lower returns and volatility spillovers. In terms of the most notable cross-asset class links, we find that crypto assets exhibit a significant level of connectedness with global equities, while the spillovers with bond indices and the USD are relatively modest. Volatility spillovers between crypto assets and the VIX and commodity prices are also pronounced, with gold in particular receiving substantial spillovers from crypto assets. In terms of the direction of spillovers, crypto assets predominantly transmit spillovers to financial markets, although this relationship may reverse during periods of financial sector stress, such as the initial phase of the policy response to the pandemic.

Consistent with prior literature, our analysis supports the idea that the magnitude of spillovers between crypto and financial markets tends to amplify during periods of stress caused by events in the crypto or financial markets, as well as significant exogenous factors like political events, pandemics, or other uncertainty creating shocks. Moreover, the spillovers indices for both crypto and financial assets displaying a gradual increase, peaking during the initial phases of the COVID-19 pandemic. The increased co-movement observed during risk-off episodes suggests that crypto assets may not effectively serve as diversifiers and have the potential to play a substantial role in transmitting shocks across financial markets.

Overall, the findings of this paper indicate that while crypto and financial assets continue to maintain distinct characteristics as separate asset classes, there is also evidence of a growing interconnection between them over time. This has significant implications for investors seeking to diversify their portfolios with crypto assets and for policy-makers and regulators aiming to comprehend the potential impact of these assets on broader financial markets. These results emphasize the importance of actively monitoring and analyzing the interactions between crypto and financial markets, as well as the need to develop effective risk management strategies, in order to ensure the stability and resilience of the overall financial system.

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6 Appendix 1: Diebold-Yilmaz Methodology

Consider a reduced-form VAR model written as:

$$y_t = \nu + A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_p y_{t-p} + \varepsilon_t$$

where y_t is a K-dimensional vector of endogenous variables; A_p is a K-by-K matrix.

The VAR(p) can be casted in the companion VAR(1) form as follows:

$$Y_t = \mathbf{v} + \mathbf{A} Y_{t-1} + E_t$$

where

$$Y_t \equiv \begin{pmatrix} y_t \\ y_{t-1} \\ \vdots \\ y_{t-p+1} \end{pmatrix}, \mathbf{A} \equiv \begin{bmatrix} A_1 & A_2 & \ldots & A_{p-1} & A_p \\ I_K & 0 & \ldots & 0 & 0 \\ 0 & I_K & 0 & 0 & 0 \\ \vdots & & \ddots & \vdots & \vdots \\ 0 & 0 & \ldots & I_K & 0 \end{bmatrix}, E_t \equiv \begin{pmatrix} \varepsilon_t \\ 0 \\ \vdots \\ 0 \end{pmatrix}$$

If we assume the VAR(p) process is stationary, then by the Wold theorem it can be written as a linear combination of a lagged values of a white noise process (this is the MA() representation), which can be obtained by successive substitution for Y_{t-i}, e.g.:

$$y_t = A(L)^{-1}\nu + A(L)^{-1}\varepsilon_t = A(L)^{-1}\nu + \sum_{i=1}^{\infty} J\mathbf{A}^{\mathbf{i}}J' JE_{t-i} = \mu + \sum_{i=1}^{\infty} \Phi_i \varepsilon_{t-i}$$

where $J \equiv [I_K, 0_{K\times K(p-1)}]$ is the selection matrix; $A(L)^{-1} = \sum_{i=0}^{\infty} \Phi L_i = J\mathbf{A}^{\mathbf{i}}J$ for $i = 0, 1, \ldots$, so that these matrices are recursively computed as:

$\Phi_0 = I_K$, and $\Phi_i = \sum_{j=1}^{i} \Phi_{i-j}A_j$ for $i = 1, 2, \ldots$, with $A_j = 0$ for $j > p$.

The matrix $\Phi_i \equiv \left[\phi_{\mathrm{kj},\ i}\right]_{K\times K}$ is also called the response of variable k to a unit shock $\varepsilon_{\mathrm{jt}}$, $j = 1, 2, \ldots K$, i periods ago.

Next, to calculate the variance contribution of (one standard deviation shock to) variable j to variable i, the generalized H-step ahead forecast error variance decomposition (FEVD) is defined as:

$$\theta_{ij}^{H} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \Phi_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \Phi_h \Sigma \Phi_h' e_j\right)^2}$$

where Σ is the variance matrix of the vector of errors ε, σ_{jj}^{-1} is the standard deviation of ε_j and e_i is a selection vector with a value of one for the i^{th} element, and zero elsewhere.

Given the use of the generalized impulse responses for the forecast error variance decomposition, the row sums of the variance decomposition matrix are not necessarily equal to one, each entry in the FEVD matrix $\theta(H)$ is normalized by the row sum as:

$$\widetilde{\theta}_{\text{ij}}^{H} = \frac{\theta_{\text{ij}}^{H}}{\sum_{j=1}^{K} \theta_{\text{ij}}^{H}}$$

such that $\sum_{j=1}^{N} \widetilde{\theta}_{\text{ij}^{H}} = 1$.

One can further define directional spillovers in the following way:

- total directional spillovers *from* others to variable i^{th} is defined as:

$$C_{\text{i} \leftarrow *} = \sum_{j=1,\ j\neq i}^{N} \widetilde{\theta}_{\text{ij}}^{H}$$

- total directional spillovers *to* others from variable i^{th} is defined as

$$C_{* \leftarrow i} = \sum_{i=1,\ i\neq j}^{N} \widetilde{\theta}_{\text{ij}}^{H}$$

- net spillovers of variable to all other variables is defined as: j^{th}

  $C_{i}^{H} = C_{* \leftarrow\, i} - \ C_{\text{i} \leftarrow\, *}$

- pairwise directional connectedness between variable i^{th} and variable j^{th} is:

  $C_{\text{ij}}^{H} = C_{j \leftarrow\, i}^{H} - C_{i \leftarrow j}^{H}$.

The total spillover index measures the contribution of spillovers from volatility shocks among variables in the system to the total forecast error variance, and is defined as:

$$TCI^{H} = \frac{\sum_{i,j=1,\ i\neq j}^{N} \widetilde{\theta}_{\text{ij}}^{H}}{\sum_{i,j=1}^{N} \widetilde{\theta}_{\text{ij}}^{H}}$$

7 Appendix 2: Tables and Charts

Table 6: Crypto Assets: Description and Functionality

	Name	Symbol	Description
1	Bitcoin	BTC	Bitcoin is the first and most well-known cryptocurrency. It is a peer-to-peer electronic cash system that allows users to send and receive payments without the need for a third party, such as a bank.
2	Bitcoin Cash	BCH	Bitcoin Cash is a fork of Bitcoin that was created in 2017. It has a larger block size than Bitcoin, which allows it to process more transactions per second.
3	BNB	BNB	Binance Coin is the native cryptocurrency of the Binance exchange. It can be used to pay for trading fees on the exchange, and it can also be used to purchase other cryptocurrencies.
4	Dash	DASH	Dash is a privacy-focused cryptocurrency that uses a technique called "mixing" to obfuscate the sender and recipient of transactions.
5	Decred	DCR	Decred is a self-governing cryptocurrency that is managed by a community of stakeholders. It is designed to be more resistant to attack than other cryptocurrencies.
6	DigiByte	DGB	DigiByte is a fast and secure cryptocurrency that is based on the Bitcoin codebase. It has a very large network of miners, which makes it very resistant to attack.
7	Dogecoin	DOGE	Dogecoin is a meme cryptocurrency that was created as a joke. It is not designed to be a serious currency, but it has gained a large following among cryptocurrency enthusiasts.
8	Ethereum	ETH	Ethereum is a decentralized platform that runs smart contracts. Smart contracts are self-executing contracts that can be used to automate a variety of tasks. Ethereum is the most popular platform for developing and deploying smart contracts.
9	Ethereum Classic	ETC	Ethereum Classic is a fork of Ethereum that was created in 2016. It is a continuation of the original Ethereum blockchain, which was hacked in 2016.
10	Gnosis	GNO	Gnosis is a decentralized prediction market platform. It allows users to bet on the outcome of future events.
11	Golem	GNT	Golem is a decentralized computing platform. It allows users to rent out their unused computing power to other users.
12	Litecoin	LTC	Litecoin is a fork of Bitcoin that was created in 2011. It is a faster and cheaper alternative to Bitcoin.
13	MaidSafeCoin	MAID	MaidSafeCoin is a cryptocurrency that is designed to create a decentralized internet.
14	Neo	NEO	Neo is a blockchain platform that is designed to support smart contracts and decentralized applications.
15	OMG Network	OMG	OMG Network is a decentralized payment network that is built on top of Ethereum. It aims to improve the speed and scalability of Ethereum-based payments.
16	Augur	REP	Augur is a decentralized prediction market platform. It allows users to bet on the outcome of future events.
17	Status	SNP	Status is a decentralized messaging platform that is built on top of Ethereum. It allows users to send and receive messages without the need for a centralized server.
18	Vertcoin	VTC	Vertcoin is a privacy-focused cryptocurrency that uses a technique called "staking" to secure its network.
19	NEM	XEM	NEM is a blockchain platform that is designed to be easy to use and scalable. It has a unique feature called "Mijin" that allows businesses to create their own private blockchains.
20	Stellar	XLM	Stellar is a blockchain platform that is designed to facilitate cross-border payments. It has a low transaction fee and it is very fast.
21	Monero	XMR	Monero is a privacy-focused cryptocurrency that uses a variety of techniques to obfuscate the sender, recipient, and amount of transactions. It is designed to be more resistant to government surveillance than other cryptocurrencies.
22	Ripple	XRP	Ripple is a blockchain platform that is designed to facilitate cross-border payments. It has a low transaction fee and it is very fast.
23	Zcash	ZEC	Zcash is a privacy-focused cryptocurrency that uses a technique called "zero-knowledge proofs" to hide the sender, recipient, and amount of transactions. It is designed to be more resistant to government surveillance than other cryptocurrencies.

Notes: This table summarizes the main functionality and features of the 23 crypto assets in our sample.

Table 7: Financial Assets: Descriptive Summary

Symbol	Name	Description
EMIGS	ICE BofA US Investment Grade Emerging Markets External Sovereign Index	Tracks US dollar (USD) and Euro denominated emerging markets investment grade sovereign debt.
EMHYS	ICE BofA US High Yield Emerging Markets External Sovereign Index	Tracks US dollar (USD) and Euro denominated emerging markets high yield sovereign debt.
EMHYC	ICE BofA Diversified High Yield US Emerging Markets Corporate Plus Index	Tracks U.S. dollar-denominated bonds issued by non-sovereign emerging markets issuers that are rated below investment grade and issued in the major domestic or eurobond markets.
AEIGS	S&P Global Developed Sovereign Bond Index Total Return	Tracks the performance of local currency-denominated securities publicly issued by developed countries for their domestic markets.
AEHYC	S&P U.S. High Yield Corporate Bond Index	Tracks U.S. dollar-denominated, high-yield corporate bonds issued by companies whose country of risk use official G-10 currencies.
USTNX	US Generic Govt 10 Yr	Yield on US Generic Govt 10 Yr Treasury
MSCIEM	MSCI Emerging Markets Index	Free-float weighted equity index that captures large and mid cap representation across (Emerging Market) EM countries. The index covers approximately 85% of the free float-adjusted market capitalization in each country.
MSCIW	MSCI World Index	Free-float weighted equity index that captures large and mid-cap representation across 23 Developed Markets (DM) countries*
SP	S&P 500 INDEX	Large-cap U.S. equities, includes 500 leading companies and captures approximately 80% coverage of available market capitalization.
USD	Broad Dollar Index	The effective exchange rate (also known as a trade-weighted exchange rate) is a weighted average of the individual exchange rates of a particular country with its main trading partners.
DJCOM	Dow Jones Commodity Index TR	Broad measure of the commodity futures market.
OIL	US Crude Oil WTI Cushing OK Spot	Benchmark WTI crude oil.
GOLD	XAUUSD Spot Exchange Rate - Price of 1 XAU in USD	Gold Spot ($/Oz)
VIX	Chicago Board Options Exchange Volatility Index	Measure of the stock market's expectation of volatility based on S&P 500 index options.
MOVE	ICE BofA MOVE Index	Measure of fixed income market volatility, based on the implied volatility on 1-month Treasury options.

Notes: This table lists all the financial assets in our sample, together with a description. The symbols represent our own abbreviations.

Table 8: Summary Statistics for Crypto and Financial Asset Prices

Asset	Period (years)	Mean	Standard deviation	Skewness	Kurtosis	Jarque-Bera	ADF	ADF (pval)
BTC	8.29	13034.39	16164.42	1.52	1.25	972.94	-2.03	0.56
ETH*	5.49	1094.67	1167	1.27	0.55	400.92	-1.78	0.67
XRP	8.29	0.34	0.36	1.74	4.64	3033.74	-4.15	0.01
DOGE	8.29	0.04	0.08	2.92	10.13	12308.63	-3.5	0.04
XLM*	5.49	0.18	0.14	1.26	1.49	512	-2.59	0.33
LTC	8.29	67.51	67.15	1.33	1.73	902.64	-3.04	0.14
BNB*	5.49	141.84	180.83	1.05	-0.25	264.17	-2.33	0.44
XMR	8.29	99.08	95.47	0.99	0.48	371.85	-3.24	0.08
ETC*	5.49	19.43	17.49	1.75	3.99	1680.54	-2.49	0.37
BCH*	5.49	468.52	424.51	2.77	10.43	8309.43	-3.37	0.06
GNO*	5.49	116.09	118.09	1.38	1.31	556.1	-2.29	0.46
NEO*	5.49	27.01	26.53	2.26	5.73	3170.08	-3.01	0.15
DASH	8.29	124.64	169.08	3.27	14.24	22110.79	-2.71	0.28
ZEC*	5.49	127.42	106.33	2.14	5.76	3072.2	-2.24	0.48
XEM*	5.49	0.16	0.19	3.69	18.44	23492.48	-3.78	0.02
DCR*	5.49	52.15	46.32	1.55	1.69	742.05	-1.77	0.67
OMG*	5.49	4.76	4.48	1.55	2.06	827.25	-2.63	0.31
SNT*	5.49	0.06	0.06	3.6	19.96	26831.82	-3.49	0.04
DGB*	5.49	0.03	0.02	2.26	6.6	3813.16	-3.28	0.07
REP*	5.49	19.74	14.04	2.45	8.29	5525.85	-2.96	0.17
GNT*	5.49	0.24	0.19	1.07	1.24	362.86	-2.96	0.17
MAID	8.29	0.23	0.21	1.57	2.96	1676.18	-3.35	0.06
VTC	8.29	0.57	1.16	4.37	21.96	50287.6	-3.35	0.06
EMIGS	8.29	360.61	42.99	0.55	-1.1	218.8	-0.85	0.96
EMHYS	8.29	447.26	42.77	-0.45	-0.96	153.68	-2.37	0.42
EMHYC	8.29	259.97	31.27	0.01	-0.79	55.59	-2.09	0.54
AEIGS	8.29	189.58	9.51	0.38	-1.14	171.25	-0.11	0.99
AEHYC	8.29	76.37	3.98	-1.36	1.18	787.92	-2.56	0.34
USTNX	8.29	2.1	0.74	0.06	-0.08	1.77	-0.99	0.94
MSCIEM	8.29	1037.95	152.36	0.36	-0.29	54.31	-2.08	0.54
MSCIW	8.29	2191.9	462.55	0.64	-0.68	190.59	-2.71	0.28
SP	8.29	2965.42	818.16	0.58	-0.89	194.19	-2.74	0.26
USD	8.29	113.86	5.1	-0.11	1.08	109.54	-3.27	0.08
DJCOM	8.29	302.06	62.62	1.29	0.99	690.29	-1.91	0.61
OIL	8.29	58.89	18.2	0.89	1.05	384.42	-3.03	0.14
GOLD	8.29	1459.83	275.26	0.46	-1.36	241.25	-2.43	0.39

Note: The table shows the summary statistics for all the crypto and financial assets for the longest sample included in the analysis (e.g. from October, 15, 2014 for most series, with the exception of the cryto assets marked with "*", for which the sample starts in August 3, 2017). The shaded section represents financial assets.

Table 9: Summary Statistics for Returns

Asset	Count	Mean	Median	Standard Deviation	Min	Max	Skewness	Kurtosis	Jarque-Bera	ADF	ADF (pval)
BTC	2163	0.14	0.19	4.15	-47.06	22.41	-0.83	10.97	11089.94	-12.34	0.01
ETH*	1432	0.01	0.01	5.49	-56.56	30.06	-0.9	9.87	6004.64	-10.11	0.01
XRP	2163	0.22	-0.12	6.92	-63.65	58.29	0.53	13.52	16569.73	-11.55	0.01
DOGE	2163	0.12	-0.16	7.31	-44.87	140.71	4.19	73.08	487698.5	-12.48	0.01
XLM*	1432	0.05	-0.15	7.06	-41.50	66.43	1.27	12.69	9998.84	-11.08	0.01
LTC	2163	0.04	-0.05	5.97	-55.59	55.68	0.23	14.4	18710.99	-12.63	0.01
BNB*	1432	0.43	0.17	6.89	-53.18	54.07	0.65	11.97	8655.88	-11.65	0.01
XMR	2163	-0.03	0.02	6.28	-49.22	47.63	0.01	8.02	5795.37	-11.73	0.01
ETC*	1432	-0.04	-0.14	6.7	-50.75	35.21	-0.08	6.75	2716.23	-10.53	0.01
BCH*	1432	-0.16	-0.28	7.2	-56.08	48.86	0.31	10.16	6177.71	-11.13	0.01
GNO*	1432	-0.09	-0.03	6.58	-44.27	49.74	-0.16	7.24	3137.4	-10.09	0.01
NEO*	1432	-0.19	-0.08	6.84	-49.05	48.72	-0.12	6.89	2836	-10.8	0.01
DASH	2163	0.02	-0.10	6.02	-47.45	42.56	-0.09	6.39	3684.55	-12.3	0.01
ZEC*	1432	-0.13	-0.13	6.3	-48.49	24.34	-0.6	5.19	1695.5	-10.6	0.01
XEM*	1432	-0.12	-0.06	6.83	-41.50	87.06	1.21	22.78	31305.84	-10.08	0.01
DCR*	1432	-0.13	-0.17	6.4	-49.27	70.12	0.64	14.29	12283.87	-10.39	0.01
OMG*	1432	-0.04	-0.17	7.54	-55.53	57.94	0.33	8.18	4022.72	-11.06	0.01
SNT*	1432	-0.16	-0.18	7.47	-44.71	69.59	0.86	12.2	9064.34	-11.56	0.01
DGB*	1432	-0.16	-0.23	7.5	-54.11	40.52	-0.14	4.53	1231.08	-10.74	0.01
REP*	1432	-0.17	-0.10	6.86	-52.57	55.86	0.38	9.88	5858.05	-10.92	0.01
GNT*	1432	0.05	0.06	7.23	-57.19	50.22	0.13	8.78	4604.19	-10.61	0.01
MAID	2163	0.03	-0.04	7.13	-55.14	49.45	0.05	6.05	3297.37	-12.88	0.01
VTC	2163	-0.1	-0.50	9.05	-47.87	77.17	1.09	9.49	8535.46	-10.81	0.01
EMIGS	4713	0.02	0.03	0.34	-4.71	3.58	-2.07	35.48	250507.4	-15.42	0.01
EMHYS	4713	0.02	0.04	0.47	-6.03	3.91	-1.96	24.71	122904.3	-14.6	0.01
EMHYC	4713	0.02	0.04	0.33	-4.81	3.65	-2.86	37.94	289106.3	-12.81	0.01
AEIGS	4713	0.01	0.01	0.16	-1.06	1.27	0	5.09	5085.82	-15.9	0.01
AEHYC	4713	-0.01	0.01	0.29	-3.78	3.25	-2.1	34.35	235145.9	-14.06	0.01
USTNX	4713	0	0.00	2.73	-34.12	40.62	0.14	34.18	229490.2	-16.83	0.01
MSCIEM	4713	0.01	0.08	1.24	-16.53	10.07	-0.98	14.22	40486.76	-15.47	0.01
MSCIW	4713	0.02	0.06	1.05	-10.44	9.10	-0.71	12.38	30503.19	-15.73	0.01
SP	4713	0.03	0.04	1.22	-12.77	10.96	-0.53	13.33	35100.31	-16.42	0.01
USD	4713	0	0.00	0.34	-2.56	1.90	-0.01	4.68	4300.49	-15.82	0.01
DJCOM	4713	0.01	0.00	1.06	-7.00	6.47	-0.4	3.62	2703.49	-15.28	0.01
OIL	4713	0.03	0.02	2.64	-28.22	24.89	0.16	15.91	49720.69	-14.35	0.01
GOLD	4713	0.03	0.05	1.09	-9.51	10.25	-0.37	6.27	7825.87	-17.01	0.01

Note: The table shows the summary statistics for the returns for all the crypto and financial assets for the longest sample included in the analysis (e.g. from October, 15, 2014 for most series, with the exception of the cryto assets marked with ”*”, for which the sample starts in August 3, 2017). The shaded section represents financial assets.

Table 10: Summary Statistics for Volatilities

Asset	Count	Mean	Median	Standard Deviation	Min	Max	Skewness	Kurtosis	Jarque-Bera	ADF	ADF (pval)
BTC	2163	0.25	0.16	0.25	0.0002	2.21	1.83	4.6	3112.81	-8.63	0.01
ETH*	1432	0.33	0.26	0.3	0.0002	2.39	1.49	3.13	1114.84	-8.63	0.01
XRP	2163	0.35	0.23	0.36	0.0000	2.50	2	4.97	3665.87	-8.82	0.01
DOGE	2163	0.35	0.24	0.35	0.0001	3.29	2.11	6.55	5469.94	-8.13	0.01
XLM*	1432	0.39	0.28	0.35	0.0001	2.55	1.73	4.09	1712.74	-7.83	0.01
LTC	2163	0.32	0.22	0.32	0.0001	2.37	1.9	5.12	3669.08	-8.66	0.01
BNB*	1432	0.37	0.28	0.35	0.0001	2.34	1.87	4.84	2235.52	-8.02	0.01
XMR	2163	0.37	0.28	0.33	0.0004	2.25	1.56	3.23	1820.81	-9.55	0.01
ETC*	1432	0.37	0.27	0.35	0.0006	2.28	1.62	3.03	1171.02	-7.39	0.01
BCH*	1432	0.38	0.28	0.36	0.0000	2.38	1.79	4.07	1746.89	-8.29	0.01
GNO*	1432	0.38	0.29	0.34	0.0002	2.26	1.54	3	1099.64	-7.28	0.01
NEO*	1432	0.4	0.31	0.34	0.0007	2.25	1.46	2.77	969.44	-7.34	0.01
DASH	2163	0.36	0.27	0.32	0.0001	2.22	1.53	2.89	1595.71	-8.92	0.01
ZEC*	1432	0.39	0.31	0.32	0.0006	2.24	1.31	2.12	677.14	-8.02	0.01
XEM*	1432	0.38	0.29	0.34	0.0016	2.81	1.73	4.43	1888.1	-8.13	0.01
DCR*	1432	0.37	0.28	0.33	0.0002	2.60	1.61	3.68	1423.1	-8.49	0.01
OMG*	1432	0.43	0.33	0.37	0.0015	2.41	1.4	2.54	855.3	-8.55	0.01
SNT*	1432	0.41	0.31	0.36	0.0007	2.59	1.63	3.58	1403.87	-7.48	0.01
DGB*	1432	0.44	0.35	0.37	0.0005	2.34	1.25	1.58	523.14	-7.15	0.01
REP*	1432	0.39	0.29	0.35	0.0000	2.37	1.64	3.6	1412.38	-8.31	0.01
GNT*	1432	0.41	0.31	0.36	0.0000	2.40	1.49	2.86	1017.28	-8.38	0.01
MAID	2163	0.42	0.35	0.35	0.0000	2.36	1.31	2.23	1062.4	-11.27	0.01
VTC	2163	0.46	0.34	0.42	0.0003	2.69	1.54	2.72	1523.8	-9.29	0.01
EMIGS	4713	0.02	0.01	0.03	0.0000	0.44	5.94	62.25	788754.2	-9.75	0.01
EMHYS	4713	0.03	0.02	0.04	0.0000	0.55	4.95	42.56	374881.4	-9.54	0.01
EMHYC	4713	0.02	0.01	0.03	0.0000	0.44	5.98	55.9	641790	-9.43	0.01
AEIGS	4713	0.01	0.01	0.01	0.0000	0.12	2.62	11.91	33210.59	-8.87	0.01
AEHYC	4713	0.01	0.01	0.02	0.0000	0.35	5.63	53.47	586412.2	-9.4	0.01
USTNX	4713	0.16	0.12	0.17	0.0000	2.06	2.97	18.32	72809.95	-8.55	0.01
MSCIEM	4713	0.08	0.06	0.08	0.0000	1.24	3.33	21.69	101119.5	-8.18	0.01
MSCIW	4713	0.06	0.04	0.07	0.0000	0.88	3.42	19.77	85919.88	-7.9	0.01
SP	4713	0.07	0.05	0.09	0.0000	1.03	3.31	18.33	74575.48	-7.89	0.01
USD	4713	0.02	0.02	0.02	0.0000	0.24	2.42	10.51	26301.68	-8.59	0.01
DJCOM	4713	0.07	0.05	0.07	0.0000	0.63	2.12	6.94	12971.06	-9.29	0.01
OIL	4713	0.16	0.11	0.17	0.0000	1.72	2.78	13.69	42861.97	-7.59	0.01
GOLD	4713	0.07	0.05	0.07	0.0000	0.87	2.48	11.68	31632.65	-9.2	0.01
VIX	4713	0.14	0.11	0.12	0.0000	1.00	2.38	8.4	18319.09	-5.14	0.01
MOVE	4713	0.2	0.16	0.14	0.0000	1.00	1.64	3.37	4354.67	-3.87	0.02

Note: The table shows the summary statistics for the volatilities for all the crypto and financial assets for the longest sample included in the analysis (e.g. from October, 15, 2014 for most series, with the exception of the crypto assets marked with ”*”, for which the sample starts in August 3, 2017). The shaded section represents financial assets.

Table 11: Full-sample Connectenedness Matrix for Crypto Asset *Returns*: Short Sample

	BCH	BNB	BTC	DASH	DCR	DGB	DOGE	ETC	ETH	GNO	GNT	LTC	MAID	NEO	OMG	REP	SNT	VTC	XEM	XLM	XMR	XRP	ZEC	**From**
BCH	0.48	0.14	0.22	0.24	0.15	0.17	0.11	0.23	0.26	0.13	0.14	0.25	0.10	0.22	0.18	0.15	0.17	0.10	0.17	0.15	0.21	0.17	0.22	**3.87**
BNB	0.16	0.56	0.25	0.20	0.13	0.17	0.09	0.18	0.24	0.17	0.15	0.23	0.09	0.24	0.22	0.14	0.16	0.10	0.16	0.15	0.20	0.15	0.20	**3.79**
BTC	0.19	0.19	0.42	0.21	0.17	0.18	0.12	0.19	0.28	0.17	0.15	0.26	0.12	0.21	0.18	0.13	0.17	0.11	0.15	0.16	0.23	0.15	0.21	**3.93**
DASH	0.21	0.15	0.21	0.41	0.16	0.18	0.11	0.21	0.25	0.15	0.15	0.24	0.09	0.22	0.20	0.16	0.17	0.11	0.17	0.15	0.22	0.16	0.26	**3.93**
DCR	0.17	0.13	0.22	0.20	0.53	0.20	0.10	0.18	0.25	0.17	0.16	0.22	0.11	0.21	0.18	0.16	0.16	0.13	0.17	0.15	0.20	0.15	0.20	**3.81**
DGB	0.17	0.15	0.21	0.21	0.18	0.48	0.13	0.18	0.23	0.16	0.17	0.22	0.09	0.20	0.18	0.14	0.19	0.12	0.18	0.18	0.20	0.17	0.21	**3.87**
DOGE	0.16	0.12	0.21	0.19	0.13	0.20	0.73	0.21	0.19	0.15	0.13	0.21	0.08	0.19	0.16	0.11	0.16	0.12	0.16	0.19	0.19	0.18	0.17	**3.62**
ETC	0.21	0.14	0.20	0.23	0.15	0.17	0.13	0.44	0.26	0.17	0.14	0.24	0.09	0.22	0.20	0.15	0.18	0.10	0.18	0.17	0.19	0.17	0.22	**3.91**
ETH	0.20	0.16	0.24	0.22	0.17	0.18	0.10	0.21	0.36	0.20	0.15	0.26	0.10	0.22	0.20	0.15	0.18	0.10	0.17	0.16	0.21	0.18	0.22	**3.98**
GNO	0.14	0.16	0.22	0.19	0.17	0.17	0.11	0.20	0.29	0.52	0.16	0.22	0.11	0.20	0.18	0.15	0.16	0.11	0.17	0.17	0.20	0.15	0.20	**3.83**
GNT	0.16	0.15	0.19	0.19	0.16	0.19	0.09	0.17	0.23	0.17	0.54	0.20	0.10	0.19	0.21	0.18	0.21	0.14	0.19	0.15	0.19	0.16	0.18	**3.81**
LTC	0.21	0.16	0.24	0.22	0.16	0.18	0.12	0.22	0.28	0.17	0.14	0.39	0.10	0.21	0.20	0.14	0.17	0.11	0.18	0.16	0.21	0.18	0.22	**3.96**
MAID	0.16	0.12	0.23	0.17	0.16	0.16	0.09	0.16	0.23	0.17	0.15	0.21	0.81	0.17	0.15	0.11	0.15	0.12	0.15	0.16	0.20	0.14	0.17	**3.54**
NEO	0.19	0.18	0.20	0.22	0.16	0.18	0.11	0.20	0.25	0.16	0.15	0.22	0.09	0.41	0.24	0.14	0.19	0.11	0.18	0.17	0.21	0.18	0.21	**3.94**
OMG	0.17	0.17	0.20	0.22	0.15	0.17	0.10	0.21	0.25	0.16	0.17	0.22	0.09	0.26	0.45	0.15	0.18	0.12	0.18	0.16	0.19	0.16	0.20	**3.90**
REP	0.18	0.14	0.17	0.22	0.17	0.17	0.09	0.19	0.24	0.17	0.20	0.20	0.08	0.20	0.20	0.58	0.17	0.11	0.18	0.15	0.19	0.15	0.21	**3.77**
SNT	0.17	0.14	0.19	0.20	0.14	0.19	0.10	0.20	0.23	0.15	0.18	0.20	0.09	0.22	0.19	0.14	0.47	0.12	0.22	0.23	0.18	0.21	0.19	**3.88**
VTC	0.14	0.13	0.19	0.18	0.17	0.17	0.12	0.16	0.20	0.15	0.18	0.19	0.11	0.20	0.19	0.13	0.17	0.72	0.18	0.17	0.19	0.13	0.17	**3.63**
XEM	0.17	0.14	0.17	0.20	0.15	0.19	0.10	0.19	0.23	0.16	0.17	0.22	0.09	0.21	0.19	0.15	0.22	0.12	0.49	0.20	0.18	0.21	0.20	**3.86**
XLM	0.16	0.13	0.19	0.18	0.13	0.18	0.13	0.20	0.22	0.16	0.14	0.20	0.10	0.21	0.18	0.13	0.24	0.12	0.21	0.5	0.20	0.24	0.20	**3.85**
XMR	0.19	0.15	0.23	0.23	0.16	0.19	0.11	0.19	0.25	0.16	0.15	0.23	0.11	0.22	0.18	0.14	0.17	0.11	0.16	0.17	0.43	0.16	0.24	**3.91**
XRP	0.18	0.13	0.18	0.19	0.14	0.18	0.12	0.19	0.24	0.14	0.15	0.24	0.09	0.21	0.18	0.13	0.22	0.09	0.22	0.24	0.18	0.5	0.20	**3.85**
ZEC	0.19	0.15	0.21	0.27	0.16	0.18	0.10	0.21	0.25	0.16	0.14	0.23	0.09	0.22	0.19	0.15	0.17	0.10	0.17	0.17	0.24	0.17	0.42	**3.93**
To	**3.88**	**3.23**	**4.56**	**4.58**	**3.44**	**3.94**	**2.39**	**4.28**	**5.34**	**3.54**	**3.44**	**4.91**	**2.12**	**4.66**	**4.20**	**3.15**	**4.00**	**2.44**	**3.89**	**3.76**	**4.40**	**3.69**	**4.52**	88.36
Net	**0.01**	**-0.55**	**0.63**	**0.65**	**-0.37**	**0.07**	**-1.23**	**0.37**	**1.35**	**-0.29**	**-0.37**	**0.95**	**-1.42**	**0.72**	**0.30**	**-0.62**	**0.12**	**-1.19**	**0.03**	**-0.09**	**0.48**	**-0.16**	**0.59**	**100.00**

Notes: This table presents the static spillovers amongst the returns of the analyzed crypto assets over the period August 3, 2017 to January 1, 2023. Each *(i,j)*-th value represents the contribution of innovation in crypto *j* returns to the variance of the return forecast error in crypto *i*. The column labeled ”From” aggregates the cumulative contributions to crypto *i* from all other crypto assets, while the row labeled ”To” summarizes the impact of crypto *j* on all other assets. The row labeled ”Net” captures the net spillover transmitted by each crypto asset to all other crypto assets. Positive (negative) values indicate that the crypto asset in question acts as a net transmitter (receiver) of spillovers to other crypto assets. To aid interpretation, color scales are employed. The minimum value is highlighted in green, the maximum value in red, and the median value is denoted in yellow. It is important to note that separate color scales are applied to the ”From” column, the ”To” row, and the ”Net” row, distinct from the main table. The diagonal elements are not included in the color scale (white).

Table 12: Full-sample Connectenedness Matrix for Crypto Asset *Volatilities*: Short Sample

	BCH	BNB	BTC	DASH	DCR	DGB	DOGE	ETC	ETH	GNO	GNT	LTC	MAID	NEO	OMG	REP	SNT	VTC	XEM	XLM	XMR	XRP	ZEC	**From**
BCH	0.42	0.15	0.2	0.22	0.15	0.18	0.15	0.2	0.22	0.14	0.14	0.24	0.13	0.22	0.18	0.14	0.17	0.12	0.19	0.19	0.21	0.18	0.22	**3.93**
BNB	0.18	0.52	0.17	0.2	0.14	0.21	0.16	0.16	0.19	0.16	0.17	0.21	0.14	0.24	0.19	0.12	0.15	0.13	0.18	0.17	0.2	0.15	0.2	**3.83**
BTC	0.2	0.16	0.4	0.21	0.17	0.2	0.14	0.17	0.23	0.16	0.15	0.23	0.15	0.21	0.17	0.14	0.16	0.13	0.18	0.18	0.23	0.15	0.21	**3.95**
DASH	0.21	0.15	0.19	0.48	0.16	0.19	0.16	0.21	0.21	0.13	0.15	0.23	0.14	0.22	0.18	0.15	0.16	0.12	0.2	0.16	0.22	0.16	0.25	**3.95**
DCR	0.18	0.15	0.19	0.21	0.48	0.19	0.14	0.17	0.2	0.17	0.16	0.2	0.16	0.21	0.17	0.15	0.15	0.14	0.18	0.18	0.21	0.15	0.2	**3.87**
DGB	0.17	0.18	0.17	0.2	0.15	0.19	0.16	0.17	0.18	0.16	0.17	0.19	0.16	0.23	0.18	0.14	0.18	0.13	0.19	0.19	0.21	0.15	0.21	**3.87**
DOGE	0.18	0.14	0.16	0.2	0.14	0.2	0.59	0.21	0.18	0.14	0.15	0.2	0.14	0.2	0.14	0.13	0.18	0.12	0.2	0.2	0.19	0.18	0.17	**3.76**
ETC	0.21	0.14	0.18	0.23	0.15	0.19	0.19	0.44	0.22	0.14	0.14	0.22	0.14	0.21	0.17	0.15	0.18	0.11	0.19	0.18	0.19	0.16	0.21	**3.91**
ETH	0.2	0.14	0.22	0.22	0.17	0.18	0.14	0.19	0.37	0.19	0.15	0.24	0.14	0.22	0.19	0.15	0.16	0.12	0.19	0.16	0.22	0.17	0.22	**3.98**
GNO	0.17	0.16	0.18	0.19	0.18	0.2	0.15	0.16	0.23	0.5	0.17	0.19	0.15	0.21	0.16	0.14	0.15	0.12	0.18	0.18	0.2	0.14	0.22	**3.85**
GNT	0.17	0.16	0.15	0.19	0.15	0.2	0.15	0.18	0.18	0.17	0.51	0.19	0.16	0.21	0.18	0.17	0.18	0.14	0.19	0.16	0.2	0.14	0.2	**3.83**
LTC	0.21	0.15	0.21	0.23	0.16	0.19	0.15	0.2	0.23	0.15	0.15	0.39	0.14	0.21	0.18	0.14	0.15	0.12	0.21	0.17	0.2	0.19	0.22	**3.96**
MAID	0.16	0.14	0.19	0.21	0.17	0.21	0.15	0.18	0.2	0.17	0.17	0.19	0.57	0.19	0.16	0.14	0.15	0.14	0.19	0.15	0.2	0.15	0.2	**3.77**
NEO	0.2	0.18	0.18	0.2	0.16	0.2	0.16	0.19	0.2	0.16	0.16	0.21	0.13	0.39	0.2	0.13	0.18	0.13	0.21	0.19	0.21	0.17	0.21	**3.96**
OMG	0.19	0.16	0.18	0.22	0.16	0.21	0.14	0.18	0.2	0.16	0.17	0.21	0.14	0.25	0.42	0.14	0.18	0.13	0.2	0.17	0.2	0.14	0.21	**3.93**
REP	0.19	0.14	0.17	0.21	0.16	0.18	0.14	0.19	0.19	0.16	0.18	0.2	0.15	0.21	0.17	0.47	0.19	0.12	0.2	0.16	0.2	0.15	0.22	**3.88**
SNT	0.18	0.15	0.17	0.18	0.14	0.2	0.16	0.19	0.18	0.14	0.18	0.19	0.14	0.23	0.18	0.16	0.43	0.13	0.24	0.23	0.18	0.19	0.19	**3.92**
VTC	0.19	0.16	0.17	0.19	0.16	0.19	0.16	0.18	0.16	0.15	0.17	0.18	0.15	0.2	0.16	0.14	0.17	0.55	0.19	0.2	0.21	0.14	0.19	**3.8**
XEM	0.17	0.15	0.17	0.2	0.15	0.2	0.15	0.18	0.19	0.15	0.16	0.21	0.15	0.22	0.17	0.14	0.2	0.13	0.45	0.21	0.2	0.2	0.2	**3.89**
XLM	0.19	0.16	0.16	0.18	0.14	0.2	0.16	0.19	0.19	0.16	0.14	0.2	0.13	0.22	0.16	0.12	0.21	0.13	0.22	0.46	0.2	0.22	0.2	**3.89**
XMR	0.21	0.15	0.21	0.23	0.17	0.19	0.15	0.18	0.21	0.15	0.16	0.21	0.15	0.22	0.16	0.15	0.15	0.13	0.19	0.17	0.43	0.15	0.23	**3.92**
XRP	0.2	0.14	0.16	0.19	0.13	0.18	0.17	0.18	0.21	0.14	0.14	0.24	0.12	0.21	0.16	0.12	0.19	0.1	0.24	0.25	0.19	0.46	0.19	**3.89**
ZEC	0.2	0.14	0.18	0.26	0.16	0.19	0.15	0.2	0.21	0.16	0.15	0.23	0.14	0.21	0.18	0.15	0.15	0.11	0.2	0.16	0.21	0.16	0.42	**3.93**
To	**4.18**	**3.33**	**3.96**	**4.57**	**3.43**	**4.3**	**3.37**	**4.08**	**4.4**	**3.42**	**3.48**	**4.62**	**3.14**	**4.76**	**3.78**	**3.1**	**3.74**	**2.75**	**4.38**	**3.99**	**4.46**	**3.61**	**4.59**	**89.45**
Net	**0.25**	**-0.5**	**0.01**	**0.63**	**-0.44**	**0.43**	**-0.39**	**0.17**	**0.43**	**-0.43**	**-0.36**	**0.66**	**-0.63**	**0.8**	**-0.15**	**-0.78**	**-0.18**	**-1.04**	**0.48**	**0.11**	**0.54**	**-0.27**	**0.66**	**100**

Notes: This table presents the static spillovers amongst the volatilies of the analyzed crypto assets over the period August 3, 2017 to January 1, 2023. Each *(i,j)*-th value represents the contribution of innovation in crypto *j* volatility to the variance of the forecast error in crypto *i*. The column labeled "From" aggregates the cumulative contributions to crypto *i* from all other crypto assets, while the row labeled "To" summarizes the impact of crypto *j* on all other assets. The row labeled "Net" captures the net spillover transmitted by each crypto asset to all other crypto assets. Positive (negative) values indicate that the crypto asset in question acts as a net transmitter (receiver) of spillovers to other crypto assets. To aid interpretation, color scales are employed. The minimum value is highlighted in green, the maximum value in red, and the median value is denoted in yellow. It is important to note that separate color scales are applied to the "From" column, the "To" row, and the "Net" row, distinct from the main table. The diagonal elements are not included in the color scale (white).

Table 13: Full-sample Connectenedness Matrix for Crypto and Financial Asset *Returns*: Long Sample

	BTC	DASH	DOGE	LTC	MAID	VTC	XMR	XRP	EMIGS	EMHYS	EMHYC	AEIGS	AEHYC	USTNX	MSCIEM	MSCIW	SP	USD	DJCOM	OIL	GOLD	**From**
BTC	1.44	0.56	0.38	0.68	0.35	0.23	0.54	0.29	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.07	0.07	0.01	0.01	0.01	0.01	**3.32**
DASH	0.65	1.65	0.34	0.55	0.28	0.21	0.53	0.32	0.01	0.01	0.01	0.01	0.02	0.01	0.03	0.06	0.05	0.01	0.01	0.00	0.01	**3.11**
DOGE	0.52	0.40	1.96	0.50	0.22	0.27	0.34	0.38	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.04	0.04	0.01	0.01	0.01	0.01	**2.80**
LTC	0.74	0.51	0.40	1.55	0.27	0.24	0.46	0.37	0.01	0.01	0.01	0.00	0.02	0.01	0.02	0.05	0.05	0.01	0.01	0.00	0.01	**3.21**
MAID	0.53	0.37	0.24	0.38	2.18	0.21	0.40	0.21	0.02	0.02	0.01	0.01	0.04	0.01	0.01	0.05	0.04	0.01	0.01	0.00	0.02	**2.58**
VTC	0.39	0.31	0.36	0.37	0.23	2.40	0.33	0.23	0.01	0.01	0.01	0.00	0.01	0.00	0.01	0.03	0.03	0.01	0.01	0.01	0.01	**2.36**
XMR	0.64	0.54	0.30	0.50	0.32	0.24	1.70	0.28	0.02	0.02	0.01	0.01	0.02	0.00	0.02	0.06	0.05	0.02	0.01	0.01	0.01	**3.06**
XRP	0.44	0.40	0.41	0.50	0.21	0.20	0.34	2.09	0.01	0.01	0.01	0.00	0.01	0.00	0.01	0.05	0.05	0.01	0.01	0.00	0.01	**2.67**
EMIGS	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.00	1.29	0.70	0.62	0.33	0.55	0.14	0.16	0.26	0.20	0.21	0.05	0.05	0.12	**3.47**
EMHYS	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.61	1.16	0.73	0.02	0.60	0.02	0.27	0.42	0.33	0.24	0.13	0.11	0.04	**3.60**
EMHYC	0.02	0.01	0.01	0.02	0.01	0.01	0.01	0.00	0.59	0.81	1.08	0.02	0.63	0.03	0.31	0.40	0.31	0.20	0.16	0.11	0.04	**3.68**
AEIGS	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.43	0.03	0.01	2.47	0.04	1.29	0.05	0.05	0.05	0.00	0.04	0.04	0.23	**2.30**
AEHYC	0.03	0.01	0.01	0.02	0.01	0.01	0.02	0.01	0.49	0.60	0.57	0.04	1.12	0.03	0.25	0.57	0.49	0.19	0.16	0.11	0.04	**3.64**
USTNX	0.03	0.01	0.00	0.02	0.02	0.01	0.01	0.01	0.10	0.08	0.10	1.02	0.11	2.02	0.13	0.34	0.34	0.02	0.09	0.10	0.20	**2.74**
MSCIEM	0.03	0.02	0.01	0.02	0.01	0.01	0.02	0.02	0.22	0.38	0.39	0.04	0.39	0.08	1.46	0.58	0.43	0.28	0.22	0.11	0.03	**3.30**
MSCIW	0.06	0.04	0.02	0.04	0.03	0.02	0.04	0.03	0.19	0.36	0.29	0.02	0.51	0.15	0.34	1.12	1.04	0.20	0.16	0.11	0.01	**3.65**
SP	0.07	0.04	0.03	0.05	0.03	0.02	0.04	0.03	0.16	0.31	0.25	0.03	0.47	0.18	0.27	1.18	1.26	0.12	0.13	0.11	0.00	**3.50**
USD	0.02	0.02	0.01	0.02	0.01	0.01	0.01	0.01	0.30	0.38	0.29	0.01	0.32	0.01	0.31	0.36	0.21	1.80	0.30	0.12	0.25	**2.96**
DJCOM	0.02	0.02	0.01	0.01	0.00	0.01	0.01	0.01	0.06	0.17	0.16	0.03	0.22	0.08	0.22	0.26	0.19	0.28	1.78	1.06	0.14	**2.98**
OIL	0.02	0.01	0.01	0.01	0.00	0.01	0.01	0.00	0.07	0.16	0.16	0.03	0.22	0.09	0.15	0.23	0.20	0.14	1.21	2.04	0.02	**2.73**
GOLD	0.03	0.03	0.01	0.02	0.03	0.01	0.02	0.02	0.15	0.05	0.04	0.28	0.04	0.31	0.03	0.02	0.01	0.36	0.23	0.03	3.04	**1.72**
To	**4.23**	**3.32**	**2.57**	**3.73**	**2.06**	**1.70**	**3.16**	**2.23**	**3.48**	**4.13**	**3.67**	**1.90**	**4.27**	**2.46**	**2.61**	**5.09**	**4.17**	**2.35**	**2.94**	**2.09**	**1.21**	**63.38**
Net	**0.91**	**0.21**	**-0.23**	**0.51**	**-0.52**	**-0.66**	**0.10**	**-0.44**	**0.01**	**0.53**	**0.00**	**-0.39**	**0.63**	**-0.28**	**-0.69**	**1.45**	**0.67**	**-0.61**	**-0.04**	**-0.64**	**-0.51**	**100.00**

Notes: This table presents the static spillovers amongst the returns of the analyzed crypto and financial assets over the period October 15, 2014 to January 1, 2023. Each *(i,j)*-th value represents the contribution of innovation in asset *j* returns to the variance of the forecast error in asset *i*. The column labeled "From" aggregates the cumulative contributions to asset *i* from all other assets, while the row labeled "To" summarizes the impact of asset *j* on all other assets. The row labeled "Net" captures the net spillover transmitted by each asset to all other assets. Positive (negative) values indicate that the asset in question acts as a net transmitter (receiver) of spillovers to other assets. To aid interpretation, color scales are employed. The minimum value is highlighted in green, the maximum value in red, and the median value is denoted in yellow. It is important to note that separate color scales are applied to the "From" column, the "To" row, and the "Net" row, distinct from the main table. The diagonal elements are not included in the color scale (white).

Table 14: Full-sample Connectenedness Matrix for Crypto and Financial Asset *Returns*: Short Sample

	BCH	BNB	BTC	DASH	DCR	DGB	DOGE	ETC	ETH	GNO	GNT	LTC	MAID	NEO	OMG	REP	SNT	VTC	XEM	XLM	XMR	XRP	ZEC	EMIGS	EMHYS	EMHYC	AEIGS	AEHYC	USTNX	MSCIEM	MSCIW	SP	USD	DJCOM	OIL	GOLD	From
BCH	0.30	0.08	0.14	0.16	0.09	0.11	0.07	0.14	0.16	0.08	0.09	0.16	0.06	0.14	0.11	0.09	0.11	0.06	0.11	0.09	0.13	0.10	0.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.00	0.00	0.00	**2.47**
BNB	0.10	0.36	0.15	0.13	0.08	0.10	0.06	0.11	0.15	0.10	0.09	0.14	0.05	0.15	0.13	0.08	0.10	0.06	0.10	0.09	0.12	0.09	0.12	0.01	0.01	0.00	0.00	0.01	0.00	0.01	0.02	0.02	0.01	0.00	0.00	0.01	**2.42**
BTC	0.12	0.11	0.27	0.13	0.11	0.11	0.08	0.11	0.17	0.10	0.09	0.16	0.08	0.13	0.11	0.08	0.11	0.07	0.09	0.10	0.14	0.09	0.13	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.02	0.02	0.01	0.00	0.00	0.00	**2.51**
DASH	0.13	0.09	0.13	0.26	0.10	0.11	0.07	0.13	0.15	0.09	0.09	0.15	0.06	0.14	0.13	0.09	0.11	0.06	0.10	0.09	0.14	0.10	0.16	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.00	0.00	0.00	**2.52**
DCR	0.10	0.07	0.14	0.13	0.34	0.12	0.06	0.11	0.15	0.11	0.10	0.13	0.07	0.13	0.11	0.09	0.10	0.08	0.11	0.09	0.12	0.09	0.13	0.00	0.01	0.00	0.00	0.01	0.00	0.01	0.02	0.02	0.01	0.01	0.00	0.00	**2.44**
DGB	0.11	0.09	0.13	0.13	0.11	0.30	0.08	0.11	0.14	0.10	0.10	0.13	0.06	0.13	0.11	0.08	0.12	0.07	0.11	0.11	0.13	0.11	0.13	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.02	0.02	0.01	0.01	0.01	0.00	**2.47**
DOGE	0.10	0.08	0.13	0.12	0.08	0.13	0.46	0.13	0.12	0.09	0.08	0.14	0.05	0.12	0.10	0.07	0.10	0.07	0.10	0.12	0.12	0.11	0.11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.00	0.00	0.00	**2.31**
ETC	0.13	0.09	0.12	0.14	0.09	0.11	0.08	0.28	0.16	0.10	0.09	0.15	0.06	0.14	0.12	0.09	0.12	0.06	0.11	0.11	0.12	0.10	0.14	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.02	0.02	0.01	0.00	0.00	0.00	**2.50**
ETH	0.12	0.10	0.15	0.14	0.10	0.11	0.06	0.13	0.23	0.13	0.09	0.16	0.07	0.13	0.12	0.09	0.11	0.06	0.11	0.10	0.13	0.11	0.14	0.00	0.01	0.00	0.00	0.01	0.00	0.01	0.02	0.02	0.01	0.01	0.00	0.00	**2.55**
GNO	0.09	0.10	0.13	0.12	0.10	0.11	0.07	0.12	0.18	0.33	0.10	0.13	0.07	0.12	0.11	0.10	0.10	0.07	0.11	0.10	0.12	0.09	0.12	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.02	0.02	0.01	0.00	0.00	0.00	**2.45**
GNT	0.10	0.09	0.11	0.12	0.10	0.12	0.06	0.10	0.14	0.10	0.34	0.12	0.07	0.12	0.13	0.11	0.13	0.08	0.12	0.09	0.12	0.10	0.11	0.01	0.01	0.00	0.00	0.01	0.00	0.01	0.02	0.02	0.01	0.01	0.00	0.00	**2.44**
LTC	0.13	0.10	0.15	0.14	0.10	0.11	0.07	0.13	0.17	0.10	0.09	0.25	0.07	0.13	0.12	0.09	0.11	0.07	0.11	0.10	0.13	0.11	0.14	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.02	0.02	0.01	0.00	0.00	0.00	**2.53**
MAID	0.10	0.07	0.14	0.11	0.10	0.10	0.06	0.10	0.14	0.10	0.09	0.13	0.50	0.11	0.10	0.07	0.10	0.07	0.09	0.10	0.12	0.09	0.11	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.02	0.01	0.01	0.00	0.00	0.01	**2.28**
NEO	0.12	0.11	0.13	0.14	0.10	0.11	0.07	0.13	0.15	0.10	0.09	0.14	0.06	0.26	0.15	0.09	0.12	0.07	0.11	0.11	0.13	0.11	0.13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.01	0.01	0.01	0.00	0.00	**2.52**
OMG	0.10	0.11	0.12	0.14	0.09	0.11	0.06	0.13	0.16	0.10	0.11	0.14	0.06	0.17	0.28	0.10	0.12	0.07	0.11	0.10	0.12	0.10	0.13	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.02	0.01	0.01	0.00	0.00	0.00	**2.49**
REP	0.11	0.09	0.11	0.13	0.10	0.10	0.05	0.12	0.15	0.11	0.12	0.13	0.05	0.12	0.12	0.37	0.11	0.07	0.11	0.09	0.12	0.09	0.13	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.02	0.02	0.01	0.00	0.00	0.00	**2.41**
SNT	0.10	0.08	0.12	0.12	0.09	0.12	0.07	0.12	0.14	0.09	0.11	0.12	0.06	0.14	0.12	0.09	0.29	0.07	0.13	0.14	0.11	0.13	0.12	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.02	0.02	0.01	0.01	0.00	0.00	**2.49**
VTC	0.09	0.08	0.12	0.11	0.10	0.11	0.08	0.10	0.13	0.09	0.11	0.12	0.07	0.12	0.12	0.08	0.11	0.46	0.11	0.11	0.12	0.08	0.10	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.02	0.02	0.01	0.00	0.00	0.00	**2.32**
XEM	0.11	0.09	0.10	0.12	0.09	0.12	0.07	0.12	0.14	0.10	0.11	0.13	0.06	0.13	0.12	0.09	0.14	0.07	0.31	0.13	0.11	0.13	0.12	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.02	0.02	0.01	0.00	0.00	0.00	**2.47**
XLM	0.10	0.08	0.12	0.11	0.08	0.12	0.08	0.12	0.14	0.10	0.09	0.13	0.06	0.13	0.11	0.08	0.15	0.07	0.13	0.32	0.12	0.15	0.13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.02	0.01	0.00	0.00	0.00	**2.46**
XMR	0.11	0.10	0.15	0.15	0.10	0.12	0.07	0.12	0.16	0.10	0.09	0.14	0.07	0.13	0.11	0.09	0.11	0.07	0.10	0.11	0.27	0.10	0.15	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.02	0.02	0.01	0.00	0.00	0.01	**2.50**
XRP	0.11	0.08	0.11	0.12	0.09	0.11	0.08	0.12	0.15	0.09	0.09	0.15	0.06	0.13	0.11	0.08	0.14	0.06	0.14	0.15	0.11	0.32	0.13	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.02	0.01	0.01	0.00	0.00	0.00	**2.46**
ZEC	0.12	0.09	0.13	0.17	0.10	0.11	0.06	0.13	0.16	0.10	0.09	0.15	0.06	0.14	0.12	0.09	0.11	0.06	0.11	0.11	0.15	0.11	0.26	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.02	0.02	0.01	0.01	0.00	0.00	**2.51**
EMIGS	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.72	0.39	0.34	0.21	0.31	0.08	0.06	0.15	0.11	0.12	0.03	0.03	0.08	**2.06**
EMHYS	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.32	0.61	0.38	0.01	0.33	0.02	0.13	0.23	0.18	0.16	0.08	0.05	0.03	**2.17**
EMHYC	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.32	0.45	0.59	0.02	0.34	0.02	0.14	0.21	0.16	0.14	0.09	0.05	0.04	**2.19**
AEIGS	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.29	0.02	0.01	1.39	0.04	0.70	0.03	0.03	0.02	0.01	0.02	0.02	0.14	**1.39**
AEHYC	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.27	0.33	0.29	0.03	0.58	0.02	0.11	0.30	0.26	0.12	0.08	0.05	0.04	**2.20**
USTNX	0.01	0.01	0.02	0.01	0.02	0.01	0.00	0.01	0.03	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.01	0.01	0.07	0.06	0.08	0.50	0.07	1.05	0.08	0.19	0.18	0.03	0.05	0.05	0.09	**1.73**
MSCIEM	0.01	0.01	0.02	0.01	0.02	0.02	0.01	0.02	0.03	0.02	0.02	0.03	0.01	0.02	0.01	0.01	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.09	0.20	0.18	0.03	0.18	0.05	0.79	0.28	0.22	0.16	0.11	0.05	0.03	**1.99**
MSCIW	0.02	0.03	0.04	0.03	0.03	0.03	0.02	0.03	0.05	0.03	0.03	0.04	0.02	0.03	0.03	0.03	0.03	0.02	0.03	0.03	0.03	0.02	0.03	0.09	0.18	0.13	0.01	0.24	0.07	0.14	0.51	0.48	0.12	0.08	0.05	0.01	**2.27**
SP	0.02	0.03	0.04	0.03	0.03	0.03	0.02	0.03	0.05	0.03	0.04	0.04	0.02	0.03	0.03	0.03	0.03	0.02	0.03	0.03	0.03	0.03	0.03	0.08	0.15	0.11	0.01	0.22	0.08	0.12	0.54	0.56	0.09	0.07	0.05	0.01	**2.22**
USD	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.03	0.03	0.02	0.02	0.03	0.02	0.02	0.02	0.01	0.02	0.01	0.01	0.01	0.02	0.02	0.02	0.14	0.22	0.17	0.01	0.20	0.01	0.14	0.21	0.15	0.79	0.13	0.05	0.13	**1.98**
DJCOM	0.01	0.01	0.02	0.02	0.02	0.02	0.01	0.02	0.03	0.01	0.02	0.02	0.01	0.02	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.03	0.09	0.09	0.01	0.12	0.04	0.11	0.14	0.12	0.14	0.91	0.52	0.09	**1.87**
OIL	0.01	0.01	0.02	0.01	0.01	0.02	0.00	0.01	0.02	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.01	0.04	0.08	0.09	0.01	0.12	0.06	0.08	0.13	0.12	0.06	0.63	1.12	0.02	**1.66**
GOLD	0.01	0.02	0.03	0.03	0.02	0.02	0.01	0.02	0.03	0.02	0.02	0.03	0.02	0.03	0.02	0.01	0.01	0.01	0.01	0.01	0.03	0.01	0.03	0.11	0.04	0.03	0.14	0.04	0.13	0.03	0.03	0.02	0.20	0.13	0.02	1.40	**1.37**
To	**2.55**	**2.14**	**3.09**	**3.08**	**2.33**	**2.64**	**1.59**	**2.88**	**3.65**	**2.38**	**2.32**	**3.30**	**1.52**	**3.10**	**2.78**	**2.07**	**2.74**	**1.62**	**2.58**	**2.50**	**2.95**	**2.45**	**3.01**	**1.93**	**2.32**	**1.95**	**1.03**	**2.37**	**1.30**	**1.30**	**2.88**	**2.40**	**1.48**	**1.58**	**1.03**	**0.81**	**81.63**
Net	**0.07**	**-0.28**	**0.58**	**0.56**	**-0.11**	**0.17**	**-0.72**	**0.38**	**1.10**	**-0.07**	**-0.12**	**0.77**	**-0.77**	**0.58**	**0.29**	**-0.33**	**0.25**	**-0.70**	**0.11**	**0.03**	**0.44**	**-0.01**	**0.49**	**-0.13**	**0.15**	**-0.24**	**-0.36**	**0.17**	**-0.43**	**-0.69**	**0.60**	**0.18**	**-0.50**	**-0.29**	**-0.63**	**-0.56**	**100.00**

Notes: This table presents the static spillovers amongst the returns of the analyzed crypto and financial assets over the period August 3, 2017 to January 1, 2023. Each *(i,j)*-th value represents the contribution of innovation in asset *j* returns to the variance of the forecast error in asset *i*. The column labeled "From" aggregates the cumulative contributions to asset *i* from all other assets, while the row labeled "To" summarizes the impact of asset *j* on all other assets. The row labeled "Net" captures the net spillover transmitted by each asset to all other assets. Positive (negative) values indicate that the asset in question acts as a net transmitter (receiver) of spillovers to other assets. To aid interpretation, color scales are employed. The minimum value is highlighted in green, the maximum value in red, and the median value is denoted in yellow. It is important to note that separate color scales are applied to the "From" column, the "To" row, and the "Net" row, distinct from the main table. The diagonal elements are not included in the color scale (white).

Table 15: Full-sample Connectenedness Matrix for Crypto and Financial Asset *Volatilities*: Long Sample

	BTC	DASH	DOGE	LTC	MAID	VTC	XMR	XRP	EMIGS	EMHYS	EMHYC	AEIGS	AEHYC	USTNX	MSCIEM	MSCIW	SP	USD	DJCOM	OIL	GOLD	VIX	MOVE	From
BTC	1.36	0.45	0.38	0.58	0.28	0.24	0.42	0.29	0.01	0.03	0.01	0.01	0.02	0.02	0.03	0.03	0.03	0.03	0.04	0.01	0.03	0.06	0.02	**2.99**
DASH	0.46	1.46	0.38	0.49	0.26	0.20	0.46	0.30	0.01	0.02	0.01	0.01	0.01	0.03	0.04	0.01	0.01	0.03	0.04	0.02	0.04	0.05	0.02	**2.89**
DOGE	0.41	0.38	1.70	0.45	0.21	0.23	0.29	0.41	0.00	0.01	0.00	0.01	0.00	0.01	0.03	0.01	0.02	0.03	0.04	0.01	0.02	0.03	0.01	**2.64**
LTC	0.60	0.46	0.40	1.43	0.30	0.24	0.31	0.40	0.00	0.01	0.00	0.01	0.01	0.02	0.03	0.02	0.01	0.02	0.04	0.01	0.02	0.04	0.01	**2.92**
MAID	0.38	0.35	0.31	0.30	1.78	0.22	0.32	0.27	0.00	0.02	0.00	0.01	0.01	0.04	0.05	0.01	0.01	0.05	0.06	0.04	0.05	0.04	0.03	**2.56**
VTC	0.31	0.28	0.38	0.32	0.18	1.92	0.31	0.25	0.00	0.01	0.00	0.00	0.00	0.03	0.04	0.01	0.01	0.06	0.08	0.08	0.04	0.01	0.01	**2.43**
XMR	0.44	0.46	0.30	0.34	0.26	0.22	1.55	0.28	0.01	0.03	0.01	0.00	0.02	0.03	0.05	0.02	0.02	0.06	0.07	0.05	0.05	0.05	0.02	**2.80**
XRP	0.35	0.34	0.48	0.50	0.17	0.24	0.29	1.67	0.00	0.02	0.00	0.00	0.01	0.02	0.04	0.02	0.02	0.03	0.05	0.02	0.03	0.03	0.01	**2.67**
EMIGS	0.01	0.01	0.00	0.01	0.01	0.00	0.01	0.01	1.46	0.60	0.48	0.19	0.43	0.18	0.12	0.19	0.15	0.16	0.02	0.02	0.03	0.16	0.09	**2.89**
EMHYS	0.02	0.01	0.01	0.01	0.01	0.00	0.02	0.01	0.47	1.35	0.65	0.07	0.48	0.13	0.15	0.21	0.16	0.14	0.07	0.04	0.03	0.20	0.11	**3.00**
EMHYC	0.01	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.38	0.68	1.33	0.04	0.56	0.13	0.15	0.25	0.21	0.09	0.07	0.06	0.02	0.19	0.12	**3.02**
AEIGS	0.03	0.02	0.03	0.03	0.02	0.01	0.02	0.01	0.26	0.16	0.10	2.02	0.13	0.65	0.04	0.09	0.06	0.09	0.05	0.02	0.10	0.13	0.28	**2.32**
AEHYC	0.02	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.34	0.49	0.53	0.07	1.29	0.11	0.14	0.40	0.29	0.10	0.06	0.06	0.02	0.28	0.12	**3.05**
USTNX	0.05	0.02	0.02	0.03	0.04	0.04	0.05	0.02	0.08	0.12	0.08	0.51	0.09	1.94	0.05	0.17	0.17	0.06	0.10	0.06	0.19	0.30	0.13	**2.40**
MSCIEM	0.06	0.05	0.06	0.06	0.03	0.04	0.06	0.04	0.12	0.22	0.20	0.04	0.20	0.08	1.92	0.29	0.17	0.12	0.13	0.07	0.08	0.23	0.08	**2.43**
MSCIW	0.04	0.02	0.02	0.03	0.01	0.02	0.02	0.01	0.09	0.18	0.13	0.04	0.28	0.12	0.17	1.35	1.12	0.08	0.08	0.04	0.04	0.41	0.06	**3.00**
SP	0.04	0.01	0.02	0.03	0.01	0.02	0.02	0.02	0.06	0.13	0.09	0.03	0.19	0.14	0.10	1.26	1.51	0.03	0.06	0.02	0.03	0.46	0.06	**2.83**
USD	0.04	0.04	0.05	0.04	0.04	0.07	0.08	0.05	0.24	0.23	0.18	0.08	0.18	0.11	0.14	0.14	0.06	2.06	0.14	0.05	0.17	0.07	0.07	**2.29**
DJCOM	0.04	0.04	0.04	0.03	0.03	0.05	0.08	0.03	0.03	0.12	0.12	0.03	0.10	0.12	0.11	0.12	0.08	0.11	1.93	0.79	0.10	0.16	0.10	**2.42**
OIL	0.03	0.03	0.02	0.02	0.02	0.04	0.07	0.01	0.02	0.09	0.13	0.02	0.12	0.16	0.07	0.11	0.09	0.04	0.88	2.07	0.05	0.20	0.07	**2.28**
GOLD	0.09	0.07	0.07	0.05	0.07	0.07	0.11	0.08	0.04	0.07	0.06	0.11	0.05	0.26	0.10	0.07	0.05	0.19	0.14	0.07	2.35	0.11	0.07	**2.00**
VIX	0.06	0.03	0.03	0.06	0.02	0.01	0.03	0.01	0.04	0.17	0.10	0.05	0.16	0.20	0.07	0.42	0.38	0.01	0.06	0.00	0.04	2.14	0.26	**2.21**
MOVE	0.01	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.08	0.06	0.10	0.30	0.10	0.24	0.01	0.02	0.02	0.02	0.04	0.01	0.02	0.43	2.80	**1.55**
To	**3.51**	**3.11**	**3.00**	**3.40**	**1.92**	**1.99**	**3.01**	**2.53**	**2.30**	**3.48**	**2.98**	**1.63**	**3.15**	**2.82**	**1.75**	**3.91**	**3.12**	**1.53**	**2.31**	**1.55**	**1.20**	**3.66**	**1.75**	**59.61**
Net	**0.52**	**0.22**	**0.35**	**0.48**	**-0.64**	**-0.44**	**0.21**	**-0.14**	**-0.58**	**0.48**	**-0.04**	**-0.69**	**0.09**	**0.42**	**-0.68**	**0.91**	**0.28**	**-0.76**	**-0.11**	**-0.72**	**-0.80**	**1.45**	**0.20**	**100.00**

Notes:This table presents the static spillovers amongst the volatilities of the analyzed crypto and financial assets over the period October 15, 2014 to January 1, 2023. Each *(i,j)*-th value represents the contribution of innovation in asset *j* volatility to the variance of the forecast error in asset *i*. The column labeled "From" aggregates the cumulative contributions to asset *i* from all other assets, while the row labeled "To" summarizes the impact of asset *j* on all other assets. The row labeled "Net" captures the net spillover transmitted by each asset to all other assets. Positive (negative) values indicate that the asset in question acts as a net transmitter (receiver) of spillovers to other assets. To aid interpretation, color scales are employed. The minimum value is highlighted in green, the maximum value in red, and the median value is denoted in yellow. It is important to note that separate color scales are applied to the "From" column, the "To" row, and the "Net" row, distinct from the main table. The diagonal elements are not included in the color scale (white).

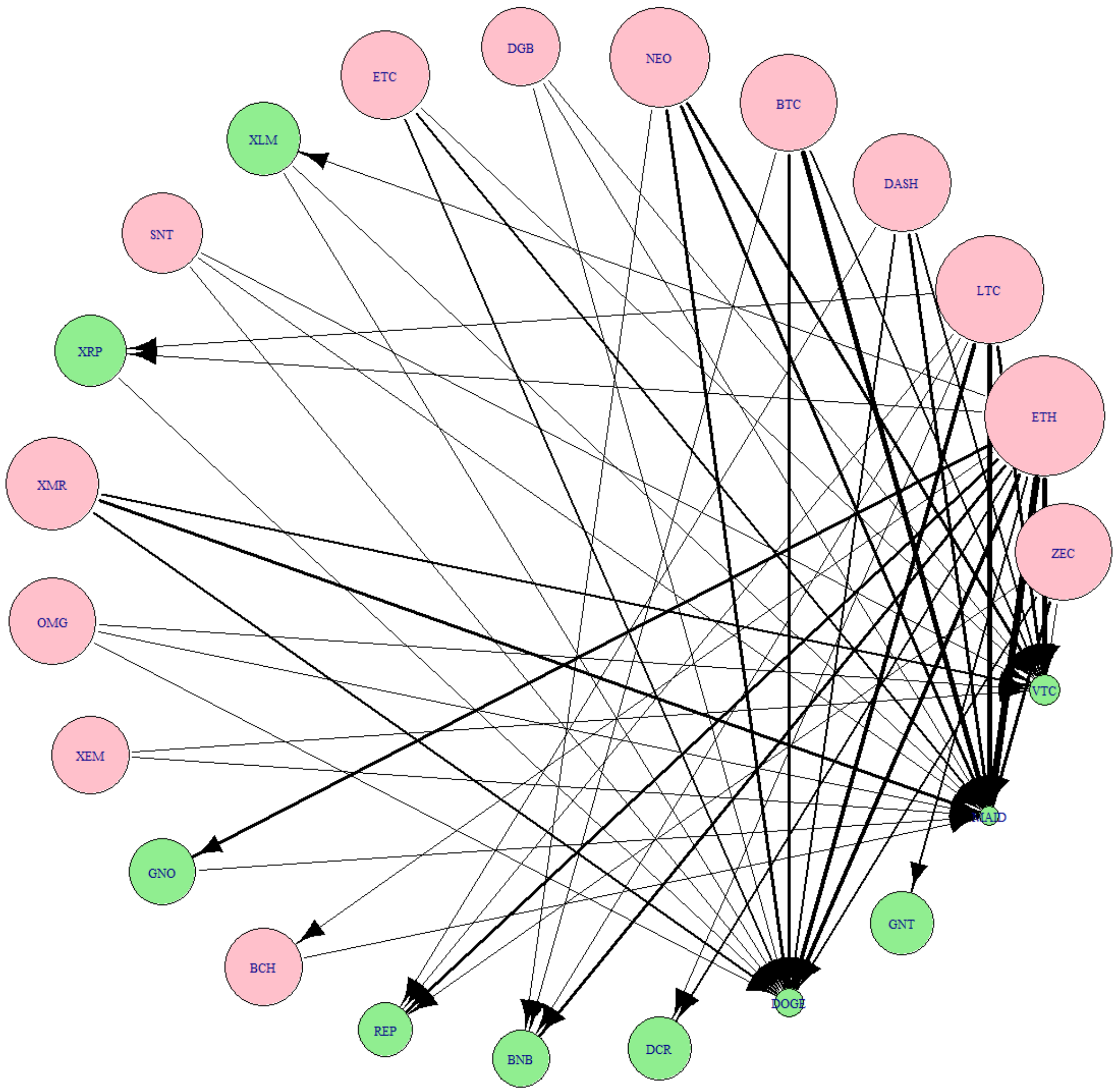
Table 16: Full-sample Connectenedness Matrix for Crypto and Financial Asset *Volatilities*: Short Sample

	BCH	BNB	BTC	DASH	DCR	DGB	DOGE	ETC	ETH	GNO	GNT	LTC	MAID	NEO	OMG	REP	SNT	VTC	XEM	XLM	XMR	XRP	ZEC
BCH	0.30	0.09	0.12	0.13	0.08	0.09	0.09	0.12	0.13	0.08	0.07	0.15	0.05	0.13	0.10	0.08	0.09	0.06	0.11	0.11	0.12	0.11	0.12
BNB	0.10	0.38	0.10	0.11	0.07	0.12	0.09	0.09	0.11	0.09	0.09	0.12	0.06	0.14	0.11	0.06	0.08	0.07	0.10	0.10	0.11	0.09	0.10
BTC	0.12	0.09	0.29	0.12	0.09	0.11	0.08	0.10	0.14	0.09	0.08	0.14	0.07	0.12	0.10	0.08	0.09	0.07	0.10	0.10	0.13	0.09	0.11
DASH	0.13	0.09	0.11	0.28	0.08	0.10	0.09	0.12	0.12	0.07	0.08	0.14	0.06	0.13	0.11	0.08	0.09	0.07	0.11	0.09	0.13	0.10	0.15
DCR	0.10	0.09	0.12	0.11	0.37	0.10	0.07	0.10	0.12	0.09	0.08	0.12	0.07	0.12	0.09	0.08	0.08	0.08	0.10	0.10	0.12	0.08	0.10
DGB	0.10	0.11	0.10	0.11	0.08	0.36	0.09	0.10	0.11	0.08	0.09	0.11	0.06	0.14	0.10	0.07	0.10	0.07	0.11	0.12	0.12	0.09	0.11
DOGE	0.11	0.08	0.09	0.11	0.07	0.11	0.45	0.13	0.10	0.07	0.07	0.12	0.06	0.12	0.07	0.07	0.10	0.06	0.11	0.12	0.11	0.11	0.09
ETC	0.13	0.08	0.11	0.13	0.08	0.10	0.11	0.32	0.13	0.08	0.07	0.13	0.06	0.13	0.10	0.09	0.11	0.06	0.11	0.11	0.11	0.10	0.12
ETH	0.13	0.09	0.13	0.12	0.09	0.09	0.08	0.12	0.26	0.11	0.08	0.15	0.06	0.13	0.11	0.08	0.09	0.06	0.11	0.10	0.13	0.10	0.13
GNO	0.10	0.10	0.11	0.10	0.10	0.10	0.08	0.09	0.15	0.38	0.10	0.11	0.06	0.12	0.09	0.07	0.08	0.07	0.10	0.11	0.11	0.07	0.12
GNT	0.10	0.09	0.09	0.10	0.08	0.11	0.08	0.10	0.10	0.10	0.39	0.11	0.07	0.12	0.10	0.10	0.11	0.08	0.11	0.09	0.11	0.08	0.10
LTC	0.14	0.09	0.13	0.13	0.08	0.10	0.08	0.12	0.15	0.08	0.08	0.28	0.06	0.12	0.11	0.08	0.09	0.07	0.12	0.10	0.11	0.12	0.12
MAID	0.10	0.08	0.11	0.10	0.08	0.10	0.08	0.09	0.11	0.09	0.09	0.11	0.50	0.10	0.08	0.07	0.08	0.07	0.10	0.09	0.11	0.08	0.09
NEO	0.13	0.11	0.11	0.12	0.08	0.11	0.09	0.11	0.12	0.09	0.08	0.13	0.06	0.27	0.13	0.07	0.11	0.07	0.12	0.11	0.12	0.10	0.11
OMG	0.12	0.10	0.10	0.13	0.08	0.11	0.07	0.11	0.12	0.08	0.10	0.12	0.06	0.16	0.31	0.08	0.10	0.07	0.12	0.10	0.11	0.08	0.11
REP	0.12	0.08	0.09	0.12	0.08	0.09	0.08	0.11	0.11	0.08	0.10	0.12	0.06	0.12	0.10	0.36	0.11	0.06	0.11	0.09	0.11	0.08	0.11
SNT	0.11	0.09	0.10	0.10	0.07	0.10	0.09	0.11	0.10	0.07	0.10	0.11	0.06	0.13	0.10	0.09	0.32	0.07	0.14	0.15	0.10	0.12	0.10
VTC	0.11	0.10	0.10	0.11	0.08	0.10	0.09	0.09	0.09	0.08	0.10	0.11	0.06	0.12	0.09	0.07	0.09	0.45	0.11	0.12	0.12	0.07	0.09
XEM	0.10	0.09	0.10	0.11	0.08	0.11	0.08	0.10	0.11	0.08	0.09	0.12	0.06	0.13	0.10	0.08	0.12	0.07	0.33	0.13	0.11	0.13	0.11
XLM	0.11	0.09	0.09	0.10	0.07	0.11	0.09	0.11	0.11	0.09	0.07	0.12	0.05	0.13	0.09	0.07	0.13	0.07	0.13	0.33	0.11	0.14	0.11
XMR	0.13	0.09	0.13	0.14	0.09	0.10	0.08	0.10	0.13	0.08	0.08	0.12	0.07	0.13	0.09	0.08	0.08	0.07	0.11	0.10	0.31	0.09	0.13
XRP	0.13	0.08	0.09	0.11	0.07	0.10	0.10	0.11	0.12	0.07	0.08	0.15	0.05	0.12	0.09	0.06	0.12	0.05	0.15	0.17	0.10	0.34	0.10
ZEC	0.12	0.09	0.11	0.16	0.08	0.10	0.08	0.12	0.13	0.09	0.08	0.14	0.05	0.13	0.10	0.08	0.08	0.05	0.11	0.10	0.13	0.10	0.30
EMIGS	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.00	0.01	0.01	0.01	0.00	0.01	0.00	0.01	0.00	0.00	0.01	0.01	0.01	0.00	0.00
EMHYS	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.00	0.00	0.01	0.01	0.01	0.00	0.01
EMHYC	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.00	0.00
AEIGS	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.02	0.01	0.02	0.01	0.01	0.02	0.01	0.02	0.01	0.01	0.02	0.01	0.01	0.01	0.02
AEHYC	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00
USTNX	0.01	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.01	0.02	0.01	0.01	0.01	0.01	0.02	0.02	0.01	0.01	0.01
MSCIEM	0.03	0.03	0.03	0.03	0.03	0.02	0.03	0.02	0.02	0.02	0.03	0.03	0.01	0.03	0.02	0.02	0.02	0.02	0.03	0.04	0.03	0.02	0.03
MSCIW	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.00	0.02	0.01	0.02	0.01	0.01	0.02	0.02	0.01	0.01	0.01
SP	0.02	0.02	0.02	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.01	0.00	0.02	0.01	0.02	0.01	0.01	0.02	0.02	0.01	0.02	0.01
USD	0.03	0.03	0.02	0.02	0.03	0.03	0.03	0.03	0.02	0.04	0.03	0.03	0.02	0.04	0.02	0.03	0.02	0.03	0.03	0.04	0.03	0.02	0.03
DJCOM	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.03	0.02	0.02	0.03	0.02	0.01	0.03	0.01	0.02	0.01	0.02	0.03	0.02	0.03	0.01	0.02
OIL	0.02	0.01	0.01	0.01	0.01	0.03	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.02	0.00	0.01	0.01	0.01	0.01	0.02	0.02	0.00	0.01
GOLD	0.03	0.04	0.04	0.03	0.02	0.04	0.03	0.02	0.03	0.03	0.05	0.04	0.03	0.04	0.03	0.02	0.03	0.03	0.04	0.05	0.04	0.03	0.03
VIX	0.04	0.01	0.02	0.03	0.03	0.02	0.01	0.02	0.02	0.03	0.02	0.03	0.01	0.03	0.02	0.02	0.01	0.00	0.03	0.02	0.02	0.01	0.03
MOVE	0.01	0.00	0.00	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.02
To	**2.82**	**2.19**	**2.61**	**2.81**	**2.01**	**2.46**	**2.05**	**2.61**	**2.83**	**2.09**	**2.18**	**2.99**	**1.45**	**3.07**	**2.30**	**1.92**	**2.28**	**1.64**	**2.79**	**2.71**	**2.78**	**2.27**	**2.68**
Net	**0.49**	**-0.06**	**0.27**	**0.46**	**-0.25**	**0.18**	**-0.13**	**0.30**	**0.46**	**-0.15**	**-0.06**	**0.63**	**-0.68**	**0.71**	**-0.03**	**-0.35**	**-0.03**	**-0.55**	**0.49**	**0.41**	**0.47**	**-0.02**	**0.35**

	EMIGS	EMHYS	EMHYC	AEIGS	AEHYC	USTNX	MSCIEM	MSCIW	SP	USD	DJCOM	OIL	GOLD	VIX	MOVE	**From**
BCH	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.00	**2.33**
BNB	0.00	0.01	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.00	**2.25**
BTC	0.00	0.01	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.00	**2.35**
DASH	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	**2.35**
DCR	0.00	0.01	0.00	0.00	0.00	0.01	0.02	0.01	0.00	0.02	0.02	0.01	0.01	0.02	0.00	**2.26**
DGB	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.02	0.02	0.01	0.01	0.01	0.00	**2.27**
DOGE	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.02	0.01	0.00	0.01	0.01	0.00	**2.18**
ETC	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.00	**2.31**
ETH	0.00	0.01	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.00	**2.37**
GNO	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.02	0.02	0.00	0.01	0.01	0.00	**2.25**
GNT	0.00	0.01	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.02	0.01	0.00	0.01	0.01	0.00	**2.25**
LTC	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	**2.35**
MAID	0.00	0.01	0.00	0.00	0.00	0.01	0.02	0.00	0.00	0.02	0.02	0.01	0.01	0.01	0.01	**2.14**
NEO	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.00	0.02	0.01	0.00	0.01	0.01	0.00	**2.36**
OMG	0.00	0.01	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.00	**2.33**
REP	0.00	0.01	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.02	0.01	0.00	0.01	0.01	0.00	**2.27**
SNT	0.00	0.01	0.00	0.00	0.00	0.01	0.01	0.01	0.00	0.02	0.02	0.01	0.01	0.01	0.00	**2.32**
VTC	0.00	0.01	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.02	0.01	0.01	0.01	0.01	0.00	**2.18**
XEM	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.00	0.02	0.01	0.00	0.01	0.01	0.00	**2.30**
XLM	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.02	0.02	0.01	0.01	0.01	0.00	**2.30**
XMR	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.02	0.02	0.00	0.01	0.01	0.00	**2.32**
XRP	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.00	**2.29**
ZEC	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.01	0.01	0.00	0.01	0.01	0.00	**2.33**
EMIGS	0.80	0.33	0.26	0.10	0.26	0.10	0.07	0.13	0.11	0.09	0.02	0.01	0.02	0.12	0.07	**1.83**
EMHYS	0.25	0.73	0.33	0.04	0.28	0.09	0.10	0.14	0.11	0.11	0.06	0.03	0.02	0.12	0.07	**1.91**
EMHYC	0.21	0.37	0.72	0.03	0.30	0.09	0.08	0.18	0.15	0.06	0.05	0.04	0.01	0.12	0.08	**1.91**
AEIGS	0.15	0.10	0.07	1.05	0.08	0.35	0.03	0.05	0.03	0.05	0.04	0.01	0.07	0.07	0.18	**1.58**
AEHYC	0.21	0.29	0.27	0.04	0.71	0.08	0.07	0.26	0.21	0.07	0.04	0.04	0.01	0.16	0.08	**1.93**
USTNX	0.04	0.08	0.04	0.28	0.04	1.08	0.03	0.11	0.10	0.01	0.06	0.02	0.11	0.20	0.09	**1.55**
MSCIEM	0.06	0.14	0.09	0.02	0.10	0.05	1.03	0.13	0.09	0.05	0.07	0.03	0.03	0.12	0.04	**1.60**
MSCIW	0.05	0.11	0.06	0.02	0.15	0.07	0.08	0.71	0.62	0.05	0.04	0.02	0.02	0.23	0.04	**1.92**
SP	0.03	0.08	0.04	0.01	0.10	0.09	0.05	0.71	0.81	0.02	0.02	0.01	0.02	0.26	0.04	**1.82**
USD	0.11	0.16	0.11	0.04	0.11	0.03	0.06	0.08	0.04	0.96	0.08	0.01	0.07	0.06	0.04	**1.67**
DJCOM	0.02	0.09	0.08	0.02	0.06	0.07	0.05	0.07	0.04	0.07	0.98	0.39	0.04	0.11	0.07	**1.65**
OIL	0.02	0.06	0.08	0.01	0.06	0.09	0.03	0.07	0.06	0.01	0.49	1.17	0.02	0.14	0.04	**1.46**
GOLD	0.03	0.05	0.03	0.07	0.01	0.14	0.04	0.04	0.03	0.08	0.08	0.03	1.14	0.07	0.03	**1.49**
VIX	0.03	0.10	0.04	0.02	0.07	0.16	0.04	0.26	0.23	0.00	0.03	0.00	0.02	1.00	0.14	**1.63**
MOVE	0.05	0.04	0.05	0.21	0.05	0.16	0.01	0.01	0.01	0.01	0.03	0.00	0.00	0.21	1.66	**0.97**
To	**1.31**	**2.12**	**1.56**	**0.96**	**1.73**	**1.73**	**0.97**	**2.39**	**1.96**	**1.06**	**1.42**	**0.75**	**0.69**	**2.26**	**1.10**	77.56
Net	**-0.51**	**0.22**	**-0.34**	**-0.62**	**-0.20**	**0.18**	**-0.63**	**0.48**	**0.14**	**-0.61**	**-0.23**	**-0.72**	**-0.80**	**0.62**	**0.13**	100.00

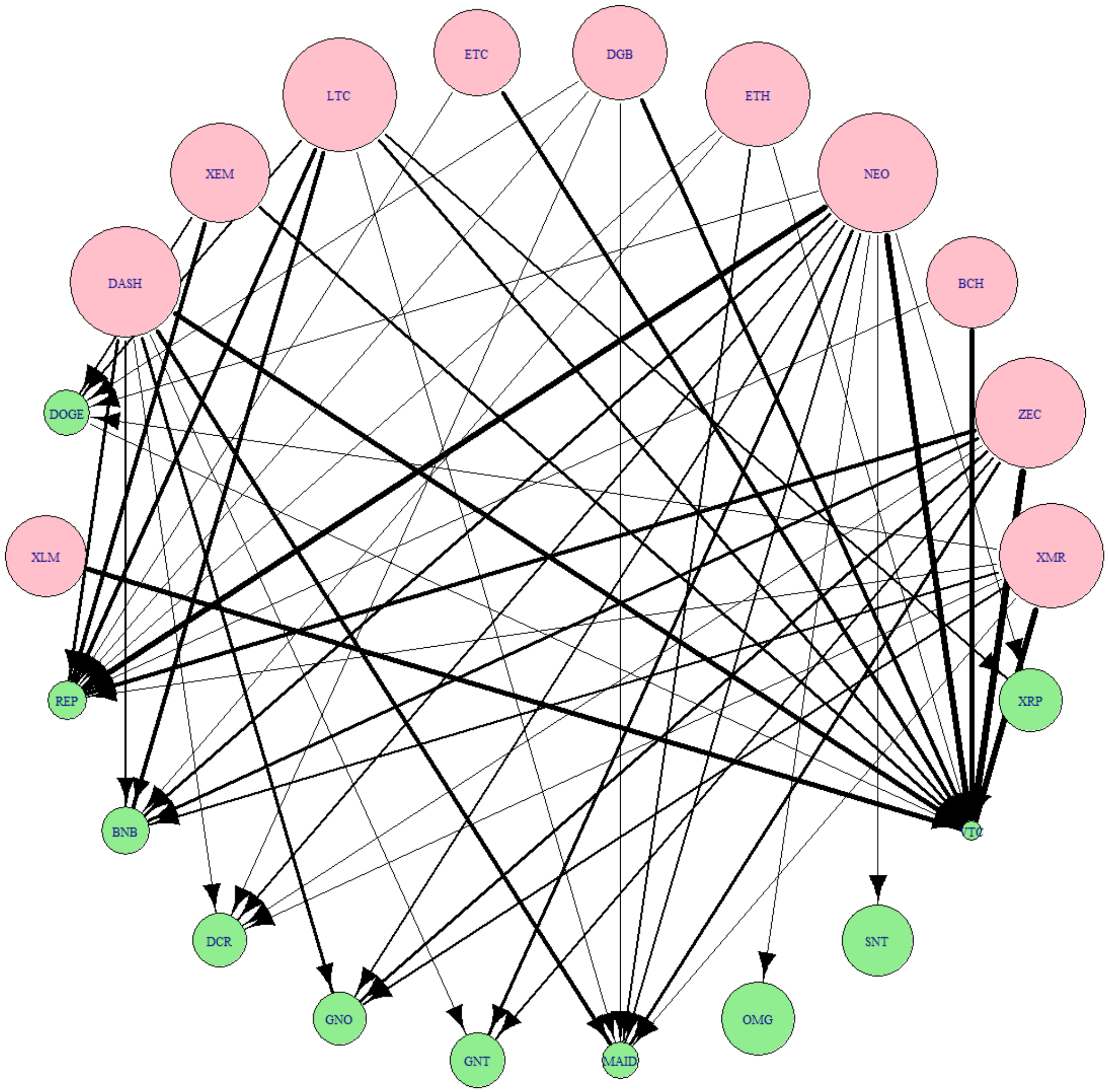
Notes: This table presents the static spillovers amongst the volatilities of the analyzed crypto and financial assets over the period August 3, 2017 to January 1, 2023. Each *(i,j)*-th value represents the contribution of innovation in asset *j* volatility to the variance of the forecast error in asset *i*. The column labeled "From" aggregates the cumulative contributions to asset *i* from all other assets, while the row labeled "To" summarizes the impact of asset *j* on all other assets. The row labeled "Net" captures the net spillover transmitted by each asset to all other assets. Positive (negative) values indicate that the asset in question acts as a net transmitter (receiver) of spillovers to other assets. To aid interpretation, color scales are employed. The minimum value is highlighted in green, the maximum value in red, and the median value is denoted in yellow. It is important to note that separate color scales are applied to the "From" column, the "To" row, and the "Net" row, distinct from the main table. The diagonal elements are not included in the color scale (white).

Figure 4: Net Pairwise Directional Connectedness for Crypto Asset *Returns*



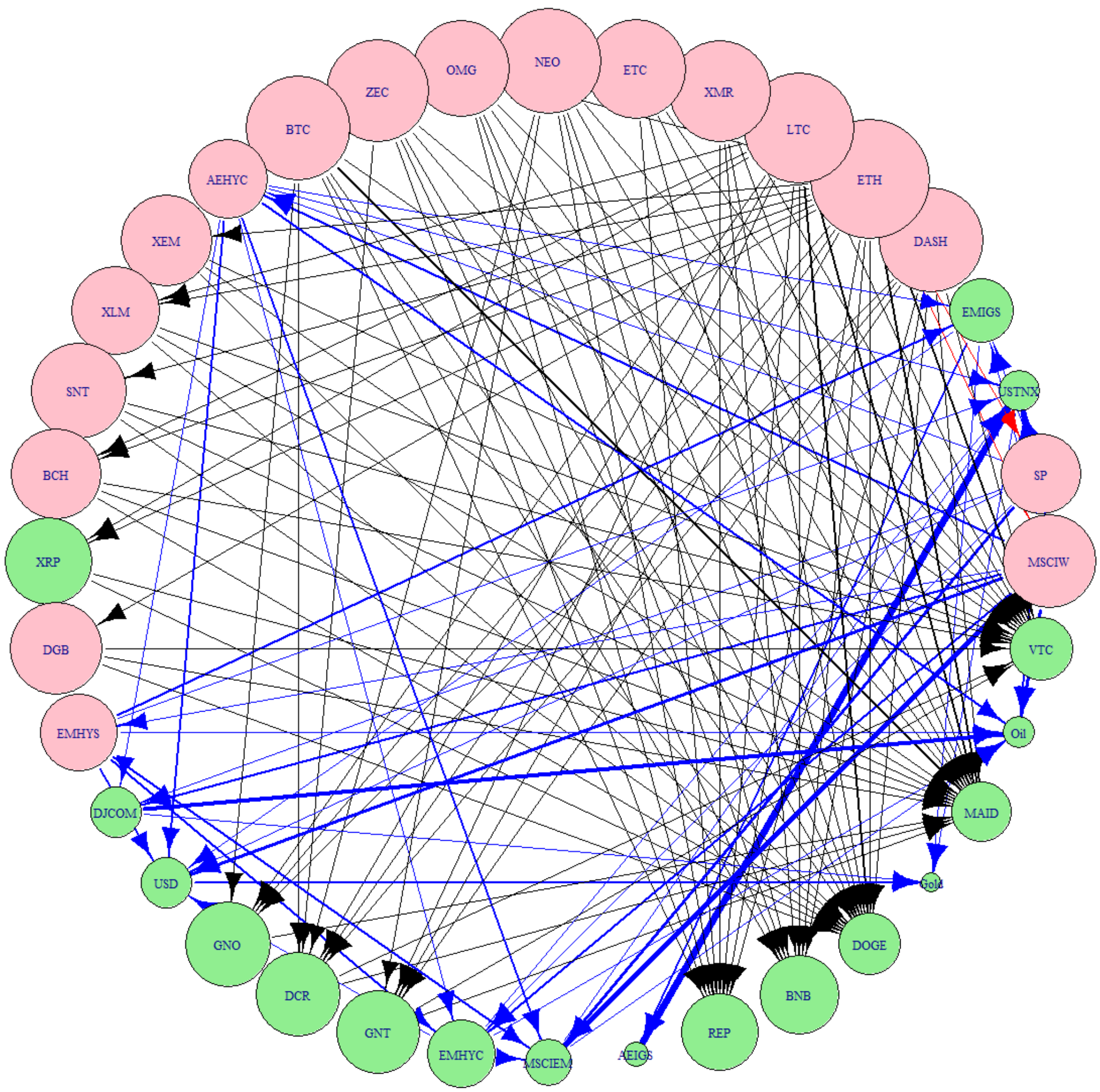
Notes: We show the most important directional connections among the pairs of crypto assets. Node size indicates the size of the total spillovers (sum of to and from) for each asset. The color of the node indicates whether the asset is a net sender (red) or a net receiver (green). The thickness of the arrows represents the strength of the spillovers (normalized to improve visibility), with only the top 95% percentile of bilateral spillovers shown. .

Figure 5: Net Pairwise Directional Connectedness for Crypto Asset *Volatilities*: Long Sample



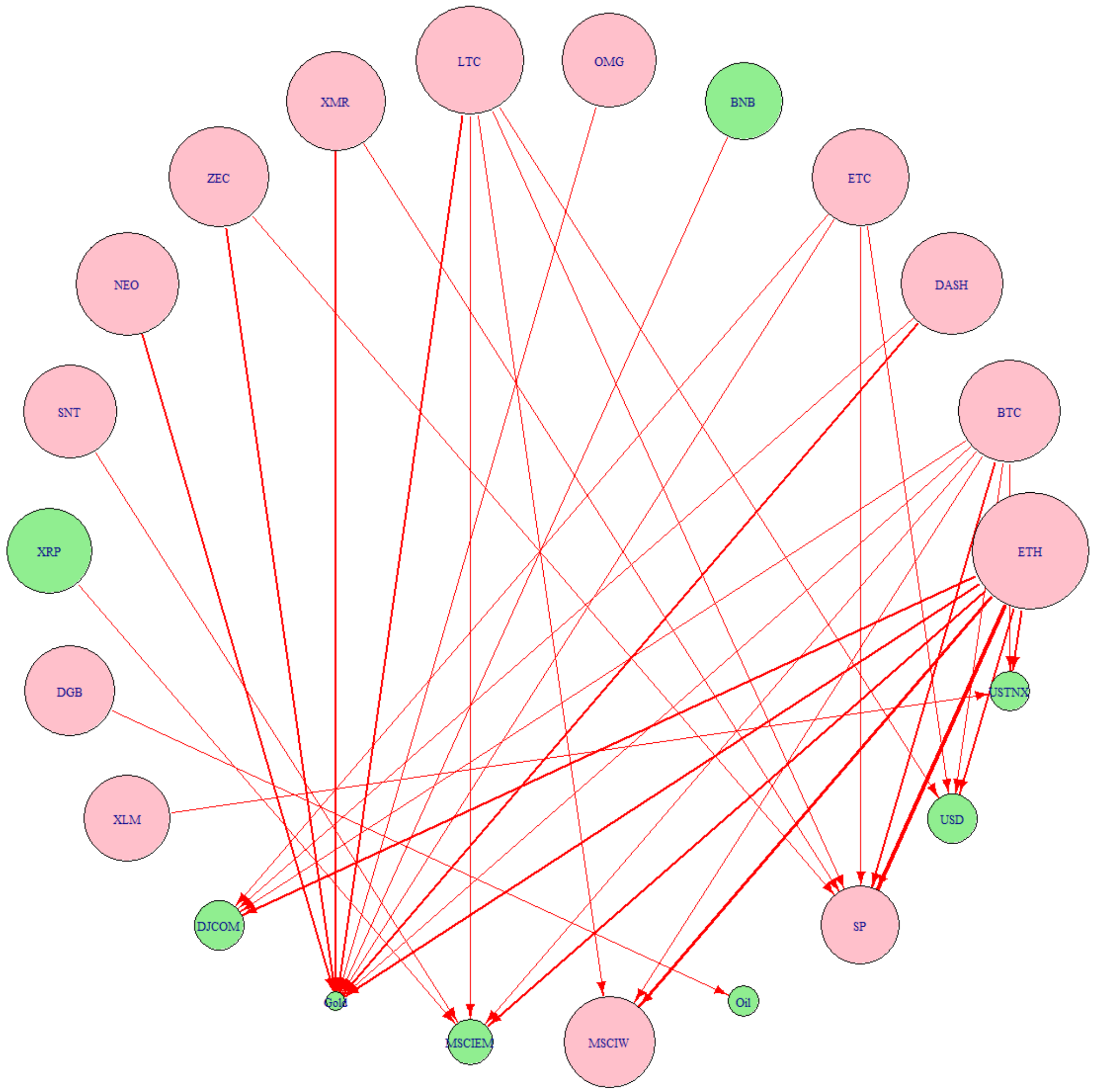
Notes: We show the most important directional connections among the pairs of crypto assets. Node size indicates the size of the total spillovers (sum of to and from) for each asset. The color of the node indicates whether the asset is a net sender (red) or a net receiver (green). The thickness of the arrows represents the strength of the spillovers (normalized to improve visibility), with only the top 95% percentile of bilateral spillovers shown.

Figure 6: Net Pairwise Directional Connectedness for Crypto and Financial Asset *Returns*: All Spillovers



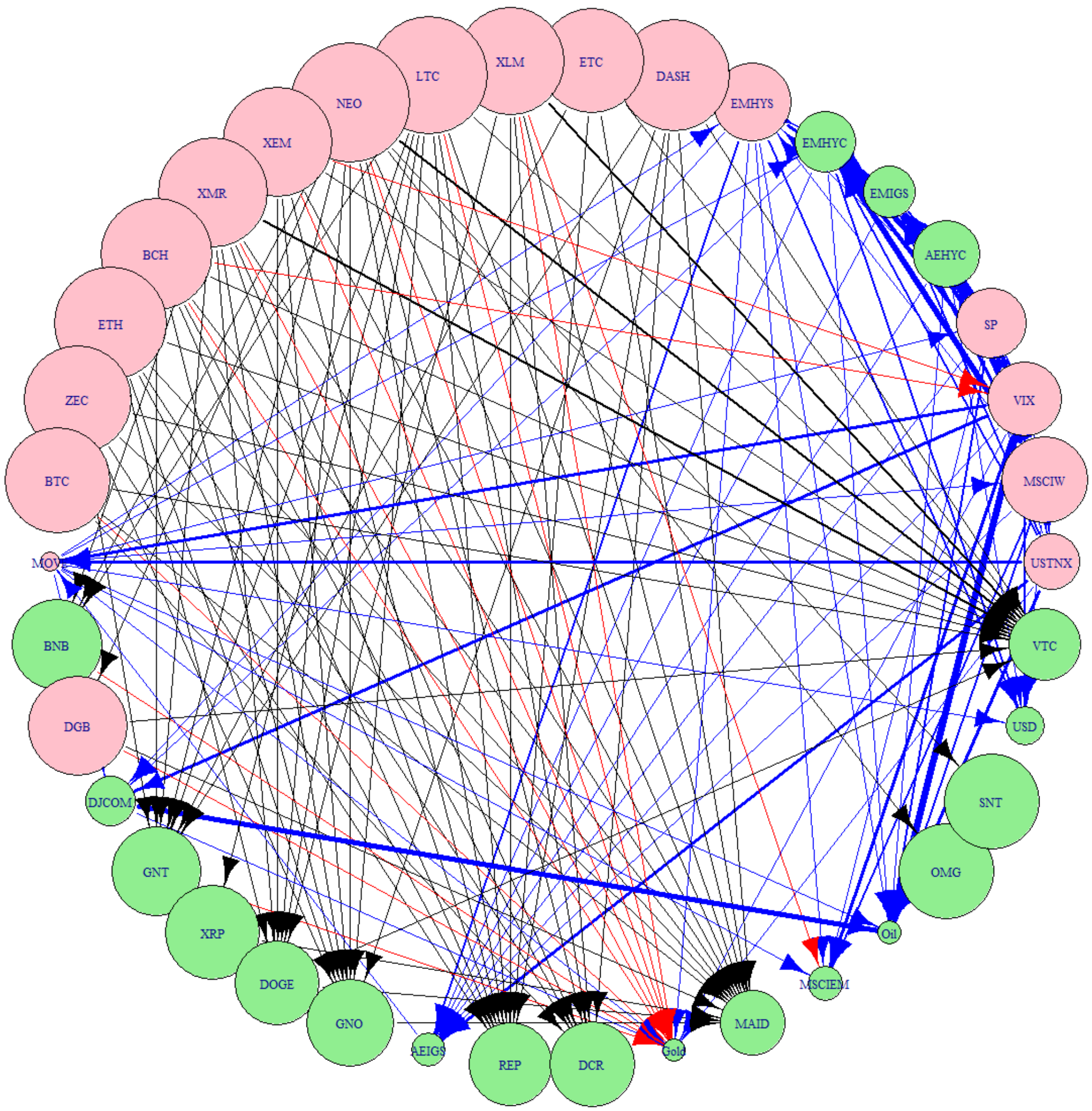
Notes: We show the most important directional connections among the pairs of crypto and financial assets. Node size indicates the size of the total spillovers (sum of to and from) for each asset. The color of the node indicates whether the asset is a net sender (red) or a net receiver (green). The thickness of the arrows represents the strength of the spillovers (normalized to improve visibility), with only the top 95% percentile of bilateral spillovers shown. Black corresponds to crypto-crypto, blue to financial-financial and red to crypto-financial spillovers.

Figure 7: Net Pairwise Directional Connectedness for Crypto and Financial Asset *Returns*: Cross Asset Spillovers



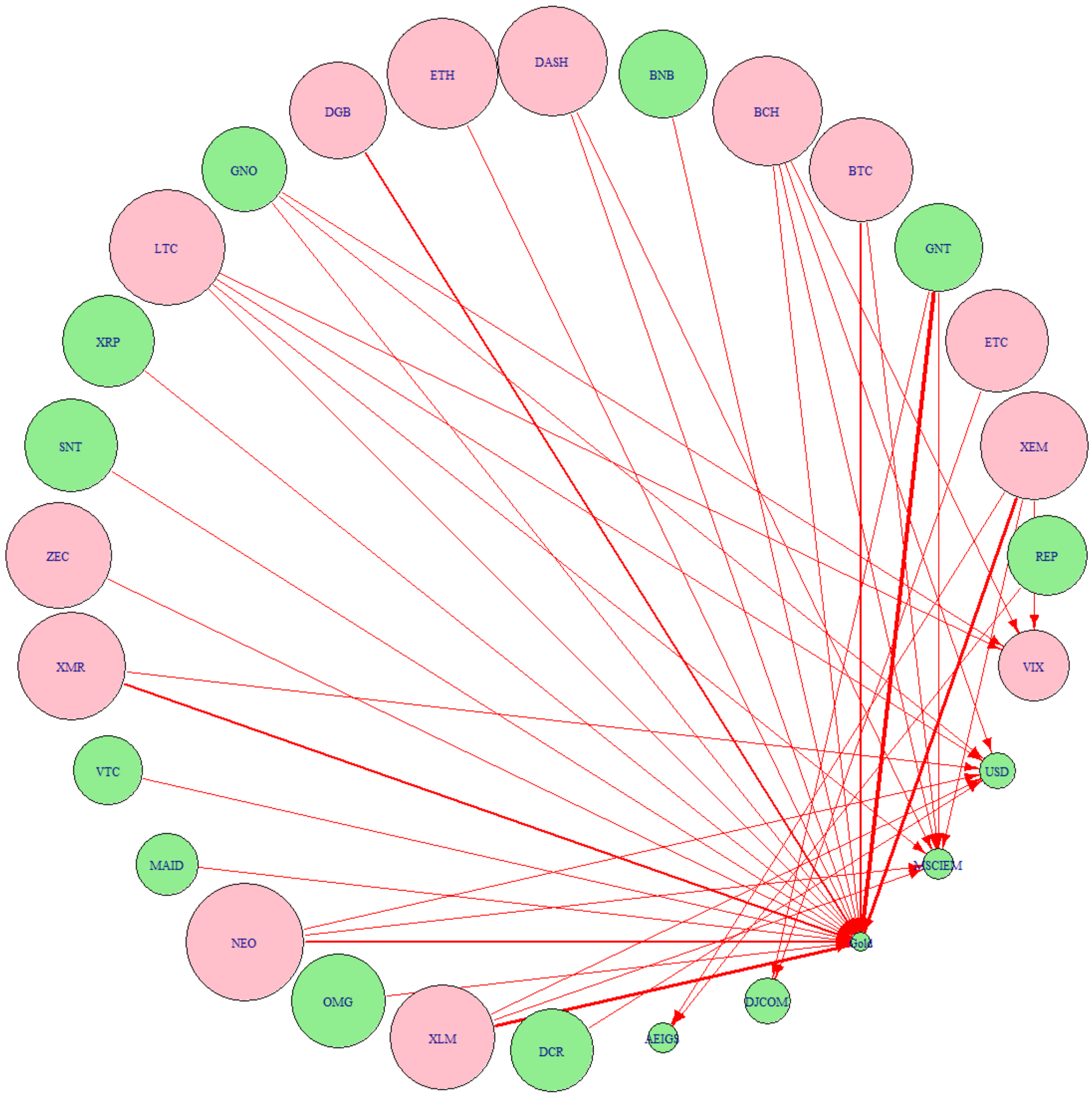
Notes: We show the top cross asset class spillovers (e.g. between crypto and financial assets, while same asset class spillovers have been filtered out). Node size indicates the size of the total spillovers (sum of to and from) for each asset. The color of the node indicates whether the asset is a net sender (red) or a net receiver (green). The thickness of the arrows represents the strength of the spillovers (normalized to improve visibility), with only the top 90% percentile of bilateral spillovers shown.

Figure 8: Net Pairwise Directional Connectedness for Crypto and Financial Asset *volatilities*: All Spillovers



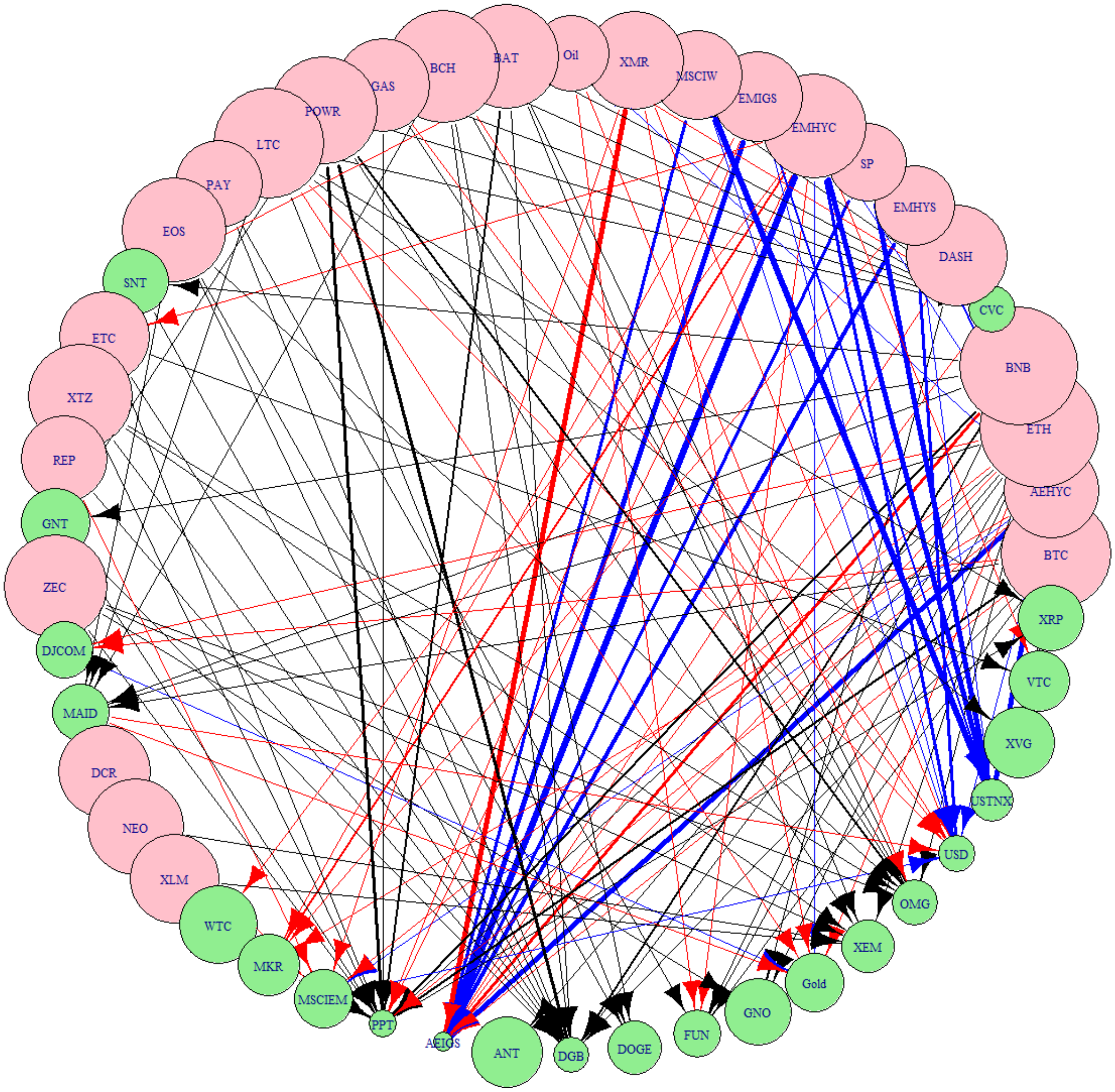
Notes: We show the most important directional connections among the pairs of crypto and financial assets. Node size indicates the size of the total spillovers (sum of to and from) for each asset. The color of the node indicates whether the asset is a net sender (red) or a net receiver (green). The thickness of the arrows represents the strength of the spillovers (normalized to improve visibility), with only the top 95% percentile of bilateral spillovers shown. Black corresponds to crypto-crypto, blue to financial-financial and red to crypto-financial spillovers.

Figure 9: Net Pairwise Directional Connectedness for Crypto and Financial Asset *Volatilities*: Cross Asset Spillovers



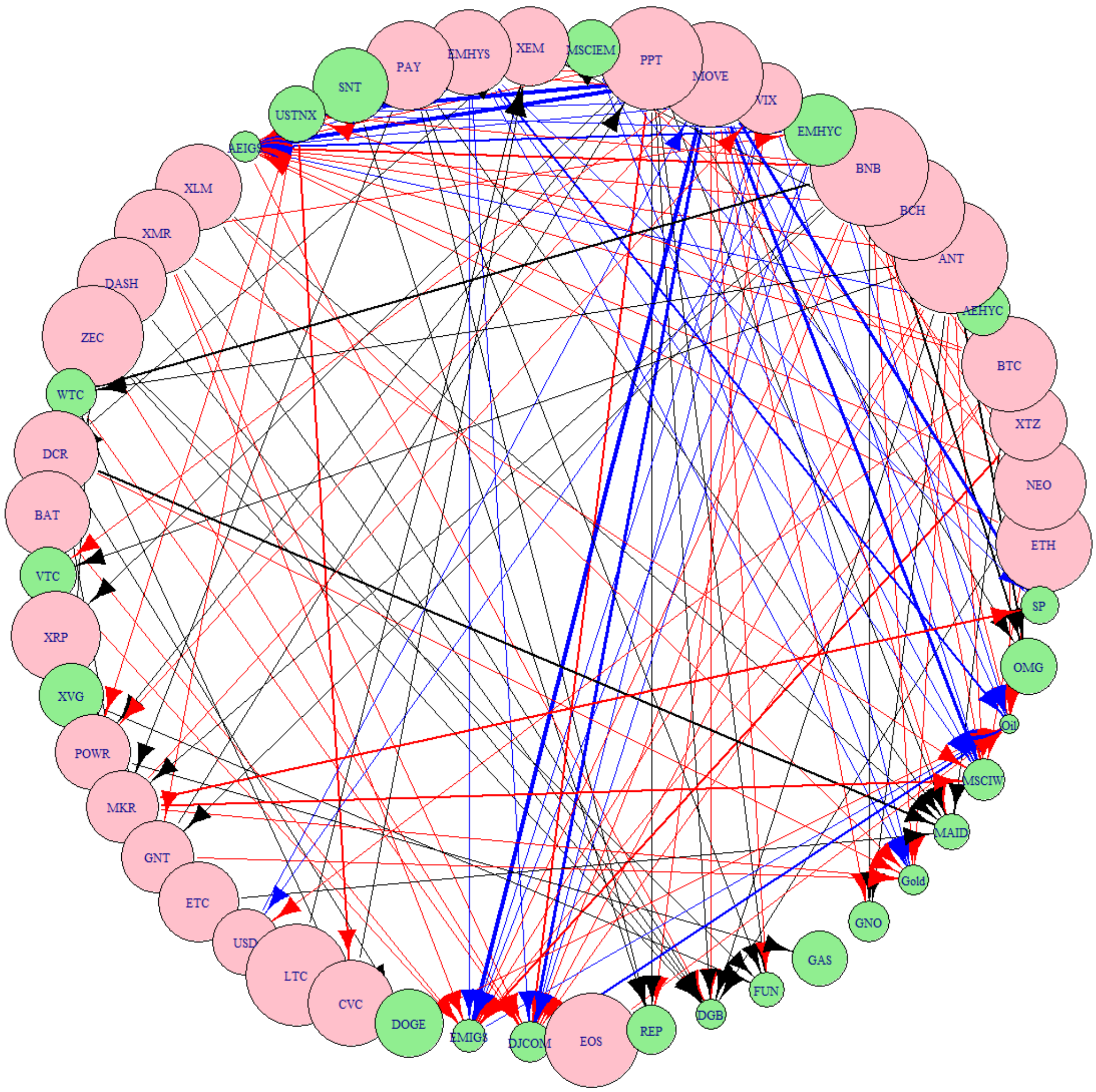
Notes: We show the top cross asset class spillovers (e.g. between crypto and financial assets, while same asset class spillovers have been filtered out). Node size indicates the size of the total spillovers (sum of to and from) for each asset. The color of the node indicates whether the asset is a net sender (red) or a net receiver (green). The thickness of the arrows represents the strength of the spillovers (normalized to improve visibility), with only the top 90% percentile of bilateral spillovers shown.

Figure 10: Net Pairwise Directional Connectedness for Crypto and Financial Asset *Returns* during the COVID-19 Pandemic: All Spillovers



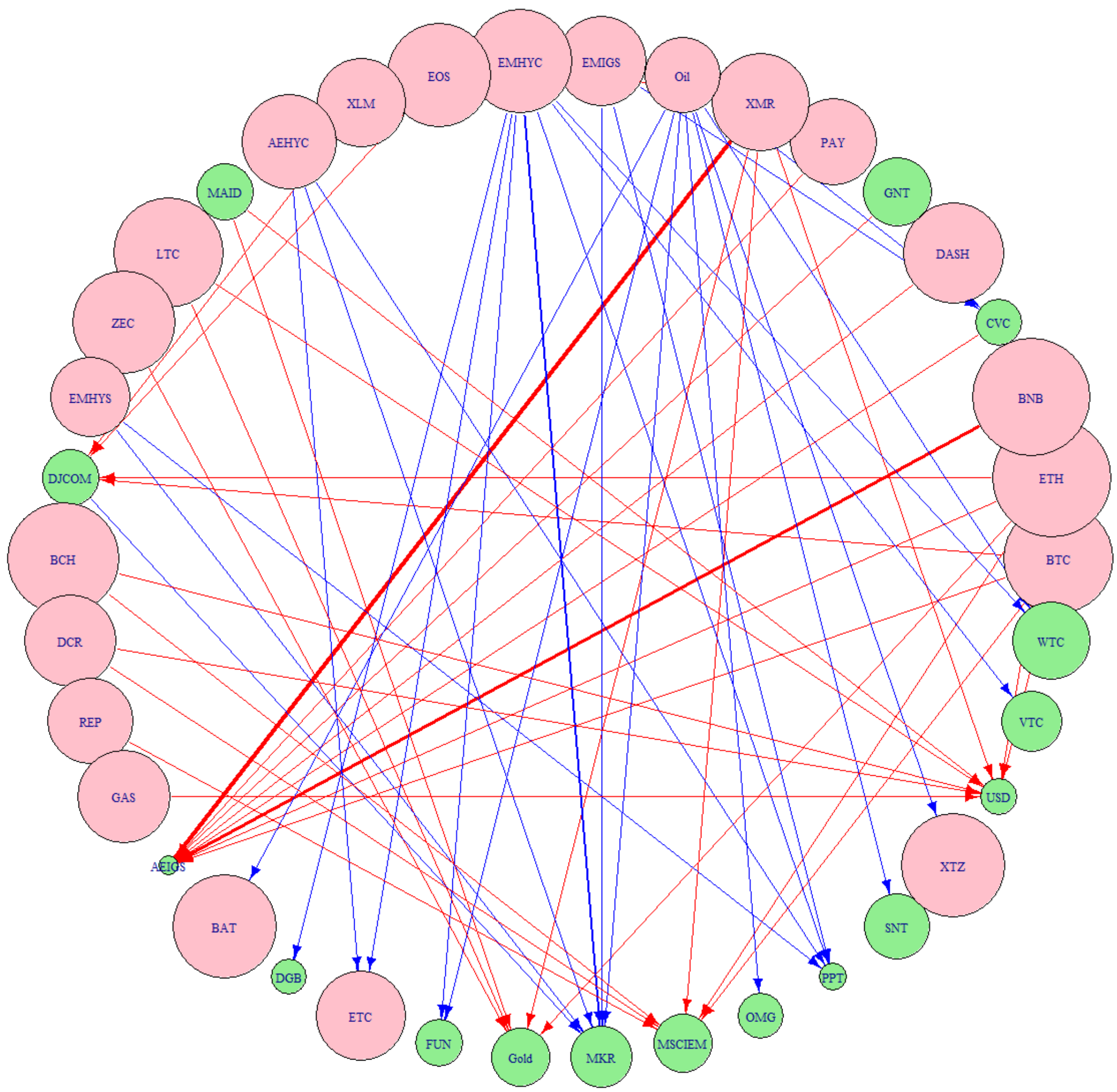
Notes: We show the most important directional connections among the pairs of crypto and financial assets during the COVID-19 pandemic. Node size indicates the size of the total spillovers (sum of to and from) for each asset. The color of the node indicates whether the asset is a net sender (red) or a net receiver (green). The thickness of the arrows represents the strength of the spillovers (normalized to improve visibility), with only the top 95% percentile of bilateral spillovers shown. Black corresponds to crypto-crypto, blue to financial-financial and red to crypto-financial spillovers.

Figure 11: Net Pairwise Directional Connectedness for Crypto and Financial Asset *Volatilities* during the COVID-19 Pandemic: All Spillovers



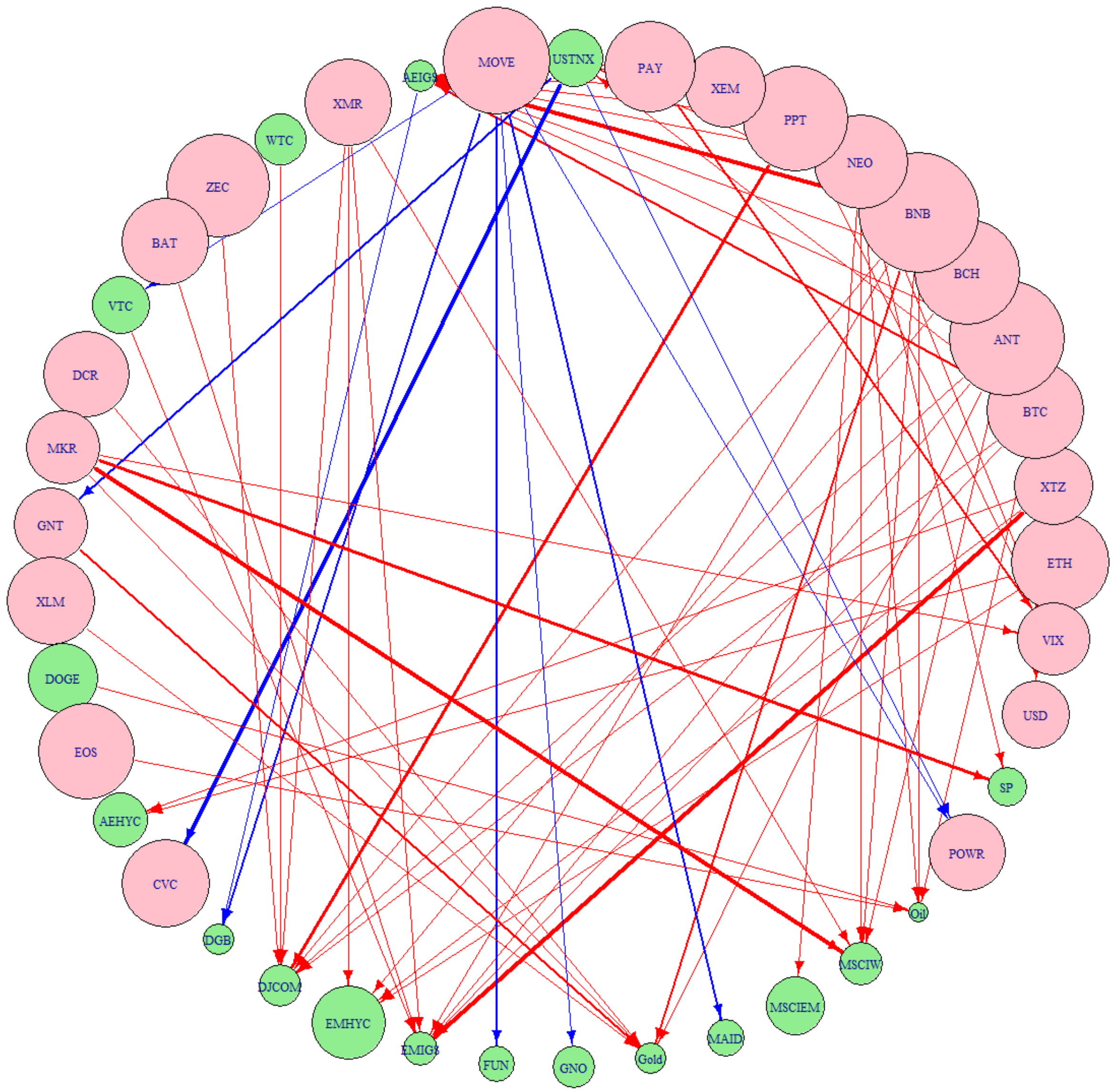
Notes: We show the most important directional connections among the pairs of crypto and financial assets during the COVID-19 pandemic. Node size indicates the size of the total spillovers (sum of to and from) for each asset. The color of the node indicates whether the asset is a net sender (red) or a net receiver (green). The thickness of the arrows represents the strength of the spillovers (normalized to improve visibility), with only the top 95% percentile of bilateral spillovers shown. Black corresponds to crypto-crypto, blue to financial-financial and red to crypto-financial spillovers.

Figure 12: Net Pairwise Directional Connectedness for Crypto and Financial Asset *Returns* during the COVID-19 Pandemic: Cross Asset Spillovers



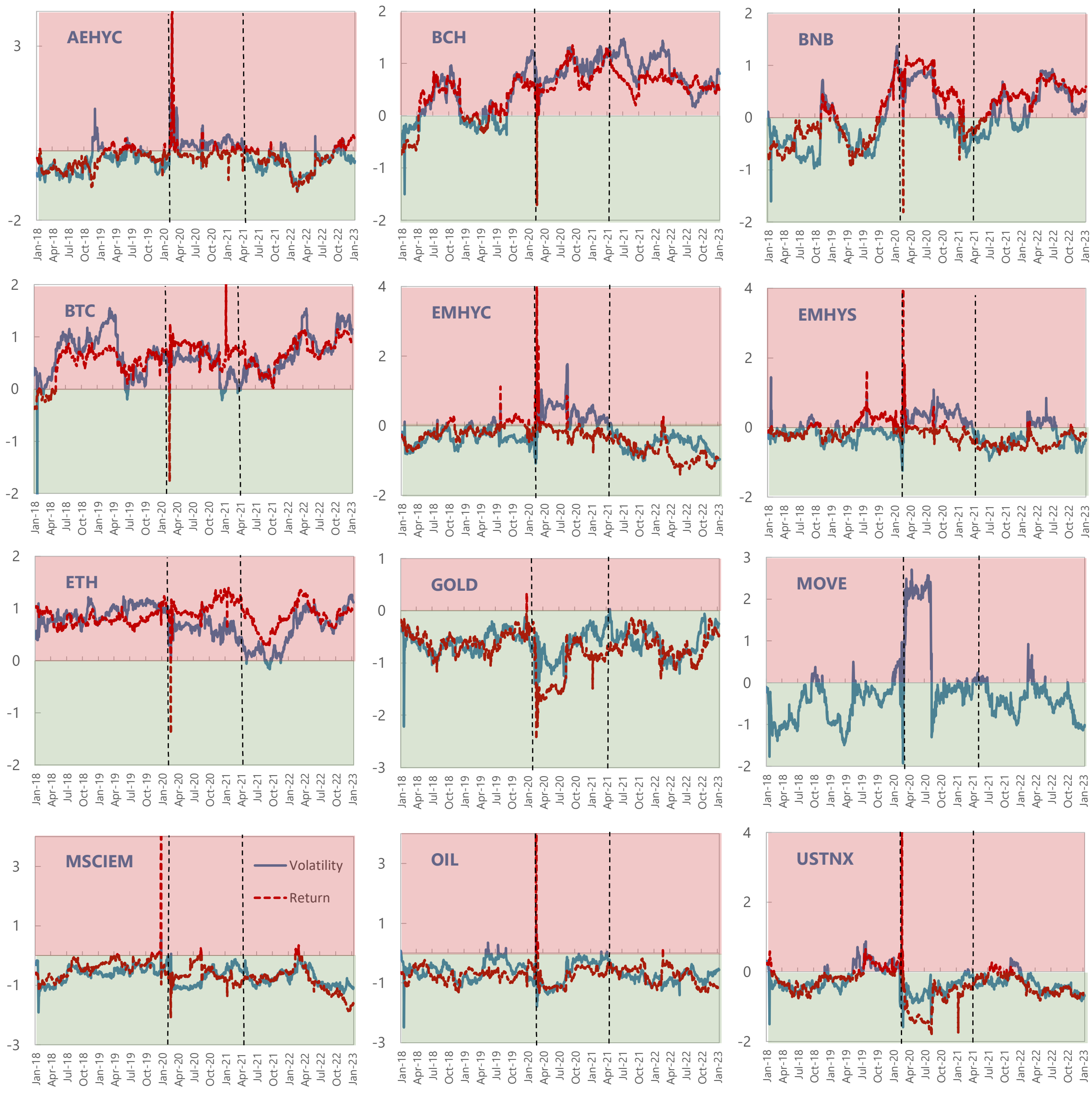
Notes: We show the top cross asset class spillovers during the COVID-19 pandemic. Node size indicates the size of the total spillovers (sum of to and from) for each asset. The color of the node indicates whether the asset is a net sender (red) or a net receiver (green). The thickness of the arrows represents the strength of the spillovers (normalized to improve visibility), with only the top 90% percentile of bilateral spillovers shown. Red correspondes to crypto-to- financials spillovers, while blue represents financials-to-crypto spillovers.

Figure 13: Net Pairwise Directional Connectedness for Crypto and Financial Asset *Volatilies* during the COVID-19 Pandemic: Cross Asset Spillovers



Notes: We show the top cross asset class spillovers during the COVID-19 pandemic. Node size indicates the size of the total spillovers (sum of to and from) for each asset. The color of the node indicates whether the asset is a net sender (red) or a net receiver (green). The thickness of the arrows represents the strength of the spillovers (normalized to improve visibility), with only the top 90% percentile of bilateral spillovers shown. Red correspondes to crypto-to- financials spillovers, while blue represents financials-to-crypto spillovers.

Figure 14: Total Directional Connectedness, Returns and Volatilities, Selected Financial and Crypto Assets



Notes: This figure shows total net directional connectedness for returns (red) and volatilies (blue) for selected financial and crypto assets. The estimation period corresponds to August 3, 2017 to January 1, 2023. The horizontal dash lines mark the beginning of the COVID-19 pandemic sample (March 1, 2020 till January 31, 2021). Assets are net transmitters if the net connectedness is positive (in the top red panel, and are net receivers otherwise (bottom green).

PUBLICATIONS

New Evidence on Spillovers Between Crypto Assets and Financial Markets

Working Paper No. WP/2023/213