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Spotting the stock and crypto markets' rings of fire: measuring change proximities among spillover dependencies within inter and intra-market asset classes

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Abstract

Crypto assets have lately become the chief interest of investors around the world. The excitement around, along with the promise of the nascent technology led to enormous speculation by impulsive investors. Despite a shaky understanding of the backbone technology, the price mechanism, and the business model, investors' risk appetites pushed crypto market values to record highs. In addition, pricings are largely based on the perception of the market, making crypto assets naturally embedded with extreme volatility. Perhaps unsurprisingly, the new asset class has become an integral part of the investor's portfolio, which traditionally consists of stock, commodities, forex, or any type of derivative. Therefore, it is critical to unearth possible connections between crypto currencies and traditional asset classes, scrutinizing correlational upheavals. Numerous research studies have focused on connectedness issues among the stock market, commodities, or other traditional asset classes. Scant attention has been paid, however, to similar issues when cryptos join the mix. We fill this void by studying the connectedness of the two biggest crypto assets to the stock market, both in terms of returns and volatility, through the Diebold Francis spillover model. In addition, through a novel bidirectional algorithm that is gaining currency in statistical inference, we locate times around which the nature of such connectedness alters. Subsequently, using Hausdorff-type metrics on such estimated changes, we cluster spillover patterns to describe changes in the dependencies between which two assets are evidenced to correlate with those between which other two. Creating an induced network from the cluster, we highlight which specific dependencies function as crucial hubs, how the impacts of drastic changes such as COVID-19 ripple through the networks—the Rings of Fire—of spillover dependencies.

Keywords: Change-points, Multiple testing, Clustering, Spillover, Networks, International financial market, Portfolio choice, Crypto asset

JEL Classification: C12, C13, C22, C38, C55, G11, G15

Introduction

The crypto market is fascinating: one tweet from Elon Musk can drive prices to their peaks. On the other hand, a piece of news about China's reluctance to adopt the asset—a negative sentiment—can push down the prices. To some extent, it is true that every investment depends on the market sentiment. Crypto assets, however, take this trepidation to a new level, promoting extreme volatility—something many investors are prone to overlook. The market size of crypto assets stands at a whopping $913.73B, nearing silver's $1.4 trillion, Amazon's and Google's $1.7 trillion, and gold's $12.3 trillion. Though its market size, currently, remains comparatively smaller, the crypto class skyrocketed to such size faster than any asset ever introduced.

Parallelly, the crypto market is suffering from the *concentration risk*. As of February 2022, Statista recorded that there are nearly over 10,000 digital coins—a massive increase from just a handful of coins in 2013 (Statista 2022a, b). However, Bitcoin has 43% share and Ethereum has 15%, so that 58% share are held by the two most popular coins (Coinmarketcap 2022). Due to this concentration, we are using Bitcoin and Ethereum to represent crypto assets in the research. In keeping with the overall market behavior, those two most popular crypto assets exhibit extreme volatilities. The price swing can reach 50% in one instance of price decrease or increase (Coinmarketcap 2022). Such roller-coaster movements can be detrimental to the overall portfolio of retail and institutional investors, and furthermore, when the connection between the crypto and the stock market is strong, a crash in the former can trigger a crash in the traditional financial system. The situation would not be unlike, what happened, quite analogously, during the 2008 financial crisis, when the banking system collapse spelled doom for the stock market. Either for assessing the relation to financial stability or as a references for international investor, who focus on diversified portfolio (Chemkha 2021), we think that it is vital to quantify the connectedness between crypto assets and the stock market.

In this work, we will characterize the connectedness between the crypto asset class and the stock market, over time. To represent the stock market, we will use the world's major stock indices. This is because financial crisis contagion could arise from any country, such as Thailand in the Asian crisis, Greece in the European crisis, or the US in the 2008 global financial crisis. We will conduct large-scale explorations with indices of 29 major countries, representing 29 major economies.

Furthermore, the time varying effect of significant shock to the crypto asset also has been studied by many researchers. One study points out that crypto is highly affected by global health crisis, which is Covid 19 pandemic, and provides evidence that market efficiency is time varying Naeem and Karim 2021). More along these lines can be found in BBC (2022), Bloomberg (2022), Coin Telegraph (2022), Trending Topics (2022).

In contrast, there is another study that point a stability of crypto. The study illustrates that the informational efficiency of cryptocurrencies (Bitcoin, BNB, Cardano, Ethereum and XRP) has successfully withstood the shocks of the COVID-19 outbreak (Fernandes 2022). This is a controversial study because the argument is clearly on the other side of the table compared to most of crypto studies.

This large-scale study will create a large collection of spillover patterns (the notion will be recalled in section 3). In this study, we have 409 spillover sequences, each describing the interaction between a pair of assets. Through these 409 combinations, we will track the evolving nature of the dependencies, and detect the change-points (defined in section 3) for each combination.

Our key contributions will be revealed alongside our analysis in three stages. In the first, we will evaluate, through spillovers for both return and volatilities, the relationship between pairs of assets at a fixed snapshot in time. In the second, we will investigate the *evolution* of the connectedness over time, through spillovers of the rolling window type (recalled in section 3). A study of such scale, involving such diverse assets, is non-existent in the literature. In the last, we implement certain accurate statistical tests to pinpoint positions on these daily time series at which the flow underwent structural shifts. Frequently, as we will find, they correspond to times of economic or social turmoil, such as the ones around COVID-19-related stress. We measure the closeness of such breakpoints across pairs of such spillover sequences and cluster these dependence patterns to highlight changes in the dependencies between which two assets are evidenced to correlate with those between which other two. This enables investors, regulators, and market participants to identify certain collections of spillover patterns which undergo changes at similar times instigating questions on whether *changes* in the relationship between one pair of assets immediately bring about changes in the relationship between some other two, similar to volcanoes in the Pacific Ring of Fire erupting in unison.

Literature review

Since crypto's inclusion as a lucrative tool for portfolio diversification, there emerged a huge interest to study this asset's relationship with others, and its behavior. Corbet et al. (2018) found that the crypto asset is highly connected in its own asset class. Furthermore, they showed that crypto's volatility is isolated in its own asset class, and to hedge value for crypto will be hard. They use different asset classes such as stock indices, bonds, and commodities, with specific focus on the stock indices such as the SP500 and the VIX. In this work, the diversity of the asset class is limited to only 3 (three) cryptos, 2 (two) stocks, 1 (one) exchange rate, and 2 (two) commodities. In our research, as a pivotal first step, we enlarge this set substantially, generalizing it to cover 29 major countries, to impart a deeper impact.

In the realm of more stock-focused research, Gil-Alana et al. (2020) confirms the lack of connectedness between crypto-assets and traditional asset classes. Using cointegration, they found no evidence of intra-cointegration between crypto asset class and inter-cointegration to other asset classes. However, because of the lack of connectedness, they argue that investors could utilize crypto as a hedging tool for other asset classes. Despite adding more individual cryptos such as Bitcoin, Ethereum, Litecoin, Ripple, Stellar, and Tether, the study, dealing only in Bond, Dollar, Gold, GSCI, S&P, and VIX, still lacks a broader representation of stock indices. We could argue that the US stock market could be a tentative representation of the world stock market. Nevertheless, in order to quantify *the general* connectedness between the crypto and the stock market, such assumptions merit closer scrutiny. Our analyses, inviting several developed and developing countries, are not tethered to such beliefs.

In another study, researchers reveal structural change in the connectedness evolving in 2020 as the market restructures in reaction to the unprecedented monetary injections as a counter to the COVID-19-induced economic standstill. The structural change is shown not only for cryptocurrencies considered separately but also when we jointly examine them with traditional assets (Kumar 2022).

Iyer (2022), in its IMF research, takes one step further by separating the emerging markets from advanced economies and analyzing both over time. This study found an increasing trajectory of interconnectedness between crypto-assets and equity assets. The study, crucially, lets time flow, in stark contrast with the previous study that only investigates a fixed snapshot in time. In our study, we aim to tread a similar temporal path, with upped complexity, laying emphasis on crucial highlights along the way. Furthermore, this IMF study also used a limited range of stock indices such as S&P500 and Russell 2000. As elaborated before, we believe every country should lend a voice in the analysis of the connection. This, among other reasons, is because global financial shocks could originate from any country and usually, smaller countries like Bolivia and Venezuela are more intertwined with the crypto world.

Through research specific to Africa, Kumah and Odei-Mensah (2021) show how an investor can integrate cryptos into his portfolio as a diversifying asset. They also found that there exists a weak integration between the African stock market and crypto-assets. While most studies found varying degrees of weak connection, in Australia, Frankovic et al. (2021) found stronger integration for CLS (cryptocurrency-linked stocks). They argue that a company's stock, which has a public business relation with crypto, will have a significant unidirectional return spillover. They found substantial spillover effects among companies that have a large business exposure to the blockchain technology. However, it is common knowledge that crypto and stock markets are highly dependent on an investor's confidence. If a global negative sentiment rises, a connection may become vivid. This phenomenon is studied by Caferra (2022). They found, by using Rényi Transfer Entropy, that sentiments heavily influence the movements in the market for stock and crypto-asset classes. This could explain why both asset classes converge in period of crisis.

In their extensive statistical analysis of the cryptocurrency market, Wątorek (2021) unveils a transformative evolution from an initial phase of weak connections (safe haven/portfolio diversification) towards a more mature market state (traditional financial asset). Employing a spectrum of correlation techniques, the study unveils the reasons that underpinning the different outcomes in prior research, which point a different conclusion differing between a strong and weak connection. In general, the cause is a different "phase of transition" of the crypto market. When the crypto are embraced as a hedge or a means of diversification, the statistic will signal a weak connection, which interpreted as the earlier stage of the market. Conversely, A strong correlation will show up when the crypto is viewed as a more normal asset, which interpreted as the mature stage. Indirectly, the conclusion further reinforces our hypothesis that crypto is mainly driven by investor sentiment.

The notion of the crypto market evolution also showed by a study that point out the co-movement between Bitcoin and S&P500, which argue as moment-dependent and varies across time and frequency. The study points out that there is very weak or even nonexistent connection between the two markets before 2018. Starting 2018, but mostly 2019 onwards, the interconnections emerge. The co-movements between the volatility of Bitcoin and S&P500 intensified around the COVID-19 outbreak, especially at mid-term scales (Bouri 2022). Furthermore, by employing multivariate transfer entropy, García-Medina (2020) arrives at a similar insight, suggesting that during periods of economic turbulence, the cryptocurrency market experiencing more interconnectedness.

In the crypto connectedness research above, Corbet et al. (2018), Frankovic et al. (2021), Iyer (2022), are using spillovers examined by Diebold and Yilmaz (2012). The model exploits generalized vector autoregression to reveal the forecast-error variance decomposition which is used subsequently to calculate gross and net directional spillovers. The advantage of the model is that it does not depend on the variable ordering—an improvement over Diebold and Yilmaz (2009). In addition, the model, through its rolling-window version, tracks dynamic spillovers over time, which will become the main objects of our change-point and cluster analysis.

We will begin this research with grand "to" and "from" spillovers over the entire period under study. This is in line with the common thread of spillover research outlined above; our key contribution at this initial stage will be Tables 4 and 5, where countries never examined before will be brought in. In addition, we will next investigate spillover movements over time, using Diebold and Yilmaz (2012)'s rolling-window offering. This analysis will enrich the study through the reported trajectory and the swings of the spillover movements. Symitsi and Chalvatzis (2018) found the difference between the short-term and long-term spillovers between bitcoin and an energy/technology company. They showed that, in the short term, the giver of spillover is the energy and technology company while, in the long term, bitcoin's volatility acts as spillover giver to the energy and technology company.

To estimate volatilities over different regimes, a researcher can use sequential Monte Carlo to implement GARCH and EGARCH-based volatility models with an unknown number of change-points. Yümlü et al. (2015) argue that multiple regime-switching state space models can be useful in comparison to fitting a global and single GARCH or EGARCH model. Other studies utilize structural breaks in the crypto and equity market to investigate optimal trading strategies for cryptocurrencies and equities. James (2022) uses cluster analysis and argues that the techniques can identify sub-groups in each market. Furthermore, the structural breaks in the equity sector are demonstrated to be more uniform than those in the crypto market.

These structural breaks—defined fully in the next section—will play an important role in this research. Telli and Chen (2020) point out that their existence in the crypto market. They show how break characteristics differ between return and volatility sequences. Price quotes matter too: series, they found, quoted in BTC remained break-free. In addition, the study also found that the period of volatility is longer for series quoted in USD than those in BTC.

In this study, after we find the change points for the return and volatility spillover using a more accurate tool, we will produce a network diagram to highlight the grouping tendency of each spillover movement, *with respect to those changes*. In other research, without regards to such change-points, Lorenzo and Arroyo (2022) used three different partitional clustering algorithm to show that the crypto market typically segmented with a few clusters. With our larger dataset, myriad spillover combinations (crypto to crypto, stock to stock, and crypto to stock), and a more pointed intention (proximity of change-points as our guiding goal), we offer a much more revealing and a much more refined network study).

Beirne et al. (2009) study the spillover patterns between mature and younger stock markets in various countries and found older stock markets gave some degree of spillovers to the emerging ones. A network analysis, was however, avoided.

We reaffirm the three key ways in which our current research contributes to the existing literature. First, we examine a large data set involving 29 major stock markets sampled throughout the world, each representing the corresponding region, and the two biggest crypto assets: Bitcoin and Ethereum. An inclusion as thorough as this has never been done before and is, understandably, both timely and urgent. We summarize their possible dependencies through grand spillovers calculated over the entire study period. Next, we monitor the temporal flow of the connectedness with spillovers of the rolling window type and detect points at which the ongoing spillover nature fluctuates drastically. Researchers can probe deeper into the causes of which these change-points are effects; we highlight a few glaring ones. Lastly, we measure the closeness of such breakpoints across pairs of such spillover sequences and cluster these dependence patterns to describe changes in the dependencies between which two assets are evidenced to correlate with those between which other two. We offer networks induced from that cluster and calculate graph statistics (such as the various kinds of centrality) to discover which changes in relationships control general shock transference, be it inter- or intra-market.

Data and methodology

Data

In this study, due to reasons mentioned before, we used Bitcoin and Ethereum to represent crypto assets, along with 27 major stock indices in countries such as (Table 1).

The crypto sample for this study are Bitcoin (hereafter BTC) and Ethereum (hereafter ETH). The period studied is recent: from 15 November 2017 to 17 May 2022, and it includes multiple world global financial events such as the economic boom, pandemic, economic crisis, subsequent recovery and the Russia-Ukraine Conflict.

Methodology

In this section, we recall the concept of spillover—the tool through which we will examine the interplay between two assets, and certain change-detection algorithms—the exact ways in which we will pinpoint locations of radical shifts in such relationships.

Table 1 List of countries sampled

Country names (Alpha-3)			
INA: Indonesia	IND: India	VNI: Vietnam	STI: Singapore
JPN: Japan	UK: United Kingdom	ARG: Argentina	AUS: Australia
BRA: Brazil	AUT: Austria	BEL: Belgium	BGR: Bulgaria
SHI: Shanghai	CHN: China	COL: Colombia	CRO: Croatia
CYP: Cyprus	DNK: Denmark	MYS: Malaysia	THA: Thailand
PHL: Philippines	TUR: Turkey	MEX: Mexico	AFS: South Africa
KOR: Korea	US: United States	FRA: France	

Directional and net spillovers

We exploit the robust framework examined by Diebold and Yilmaz (2012) to calculate spillover from the return and historical volatility sequences. The return Rt is found as:

$$R_t = \frac{(P_t - P_{t-1})}{P_{t-1}} \tag{1}$$

where

$$R_t : \textit{return atperiod } 0,\ Pt : \textit{ closing price at period } 0,\ \textit{and } P_{t-1}\ \text{closing}\,\textit{price at period } t{-}1$$

and the for the historical volatility, we modified the framework from Torun and Aksanu (2011), as follows:

$$R_i = \ln\left(\frac{C_i}{C_{i-1}}\right) \tag{2}$$

where

$$R_i : \textit{return period } i,\ ln : \textit{ natural log},\ Ci : \textit{ closing price on day } i,\ \textit{and}$$
$$C_{i-1} : \text{previous day's closing price}$$

Next, we calculate the weekly standard deviation from the daily data:

$$\sigma_i = \sqrt{\frac{\Sigma_{i=1}^{n}\left(R_i - \overline{R}\right)^2}{n-1}} \tag{3}$$

where

$$\sigma : \textit{ weekly standard deviation},\ R_i : \textit{ return}\ \text{on}\,\textit{period } i,\ \textit{and}$$
$$\overline{R} : \textit{ average weekly return},\ n : \textit{ number of observations}.$$

And finally:

$$H_i = \sqrt{T}\,\sigma_i \tag{4}$$

where H_i is the historical volatility and$\sqrt{T} = \textit{number of trading days in one year}$ (252).

We feed the resulting data into the following steps to calculate the DY spillover index. The index focuses on directional spillovers in a generalized Vector Autoregressive (VAR) with a covariance stationary N-variable VAR(p) as follows:

We consider a covariance stationary N-variable VAR(p),

$$x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t\ ,\ \textit{where } \varepsilon \sim \left(0, \sum\right) \tag{5}$$

In a stationary N variable, a value of x at point t can be determine by the sum of the influence, which are the last lagged variable (Xt-1) multiple by each of the coeefecient (Φ_i). In here (Φ_i) determines how much the lag value dictate the future value of variable (X), where the number of the lag value up to (p).

Where the vectors, independent and sharing the same disturbances, will admit of the following moving average representation:

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}, \tag{6}$$

The spillover calculation depends on these moving average coefficients and the variance decomposition(s) which allow one to parse the forecast error variance of each variable. For the total spill, the formula is (details in Diebold and Yilmaz 2012):

$$S^g(H) = \frac{\sum_{\substack{i.j=1 \\ i \neq j}}^{N} \widetilde{\theta}_{ij}^{g}(H)}{\sum_{i.j=1}^{N} \widetilde{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{\substack{i.j=1 \\ i \neq j}}^{N} \widetilde{\theta}_{ij}^{g}(H)}{N} \times 100, \tag{7}$$

The formula above explains the total of the spillover, S^g is the value and direction of pairwise spillover in a given time horison for each of asset class and (g) as the group of the financial asset. $\widetilde{\theta}_{ij}^{g}(H)$ represent a spillover of asset i and j belonging to the group (g). The sum of the spillover (exluding the self spillover) then divide by the total spillover (including total spillover), therefore it can be simplified as the total spillover (excluding self spillover) divide by the number of asset (N). Because we are using VAR as the basic of the model to calculateθ, we will first estimate the VAR model and focus on the result of impulse response analysis of asset j to a shock in asset i. The value of the response curve will be quantify to estimate the change in asset i shock influencing volatility in asset j.

and directional spillover is as follows:

$$S_{i.}^g(H) = \frac{\sum_{\substack{i.j=1 \\ j \neq i}}^{N} \widetilde{\theta}_{ij}^{g}(H)}{\sum_{i.j=1}^{N} \widetilde{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{\substack{i.j=1 \\ i \neq j}}^{N} \widetilde{\theta}_{ij}^{g}(H)}{N} \times 100. \tag{8}$$

In a similar fashion, we measure the directional volatility spillover transmitted from market i to all markets j as:

$$S_{.i}^g(H) = \frac{\sum_{\substack{i.j=1 \\ j \neq i}}^{N} \widetilde{\theta}_{ij}^{g}(H)}{\sum_{i.j=1}^{N} \widetilde{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{\substack{i.j=1 \\ i \neq j}}^{N} \widetilde{\theta}_{ij}^{g}(H)}{N} \times 100, \tag{9}$$

with net spillover defined by:

$$S_i^g(H) = S_{.i}^g - S_{i.}^g(H). \tag{10}$$

The net pairwise spillover is given, therefore, by:

$$\begin{aligned} S_{ij}^g &= \left(\frac{\widetilde{\theta}_{ji}^{g}(H)}{\sum_{i.k=1}^{N} \widetilde{\theta}_{ik}^{g}(H)} - \frac{\widetilde{\theta}_{ij}^{g}(H)}{\sum_{j.k=1}^{N} \widetilde{\theta}_{jk}^{g}(H)} \right) \times 100 \\ &= \left(\frac{\widetilde{\theta}_{ji}^{g}(H) - \widetilde{\theta}_{ij}^{g}(H)}{N} \right) \times 100. \end{aligned} \tag{11}$$

We have collected, in this subsection, the key spillover definitions needed for our work. Details of, and complications that are inherent in such setups can be had from Diebold and Yilmaz (2012). The model

Change-detection algorithms

Spillovers, both return and volatility, are frequently suspected to change over time (Yarovaya et al. 2016). Through identifying such changes, we intend to bring out a new way of questioning and subsequently, demonstrating, the underlying connectedness of the market: by measuring how close the changes from one spillover sequence (between a pair of assets) are to the changes from another spillover sequence (between a different pair of assets). The more the closeness, the more connected they are in terms of spillover changes. To generate such sequences, that is, to create a time series of spillover values on which the changes are to be found, we generalize a fixed spillover table (such as Table 4) to a rolling pairwise time-dependent chain (still using the Diebold and Yilmaz (2012) convention). Such conversions are commonplace in the literature: Corbet et al. (2018) for instance, study them to see how certain linkages vary over time. Once such time series are found, we deploy a certain change-detection algorithm to locate times at which the spillover pattern (between a pair of assets) has shifted drastically. Imagine, for the spillover between assets A and B, two such times are June 7, 2018, and December 13th, 2020. Dates such as these will be known as change-points. Further, imagine for the spillover case between assets C and D, the change point set is {June 10, 2018, December 12, 2020}, while for the case between E and F, it is {January 5, 2018, March 17, 2019, February 13, 2021}. Then, viewed through any reasonable distance metric (we used the Hausdorff, described in the following section), the spillover movements between A and B seem similar to those between C and D in terms of the times when they undergo sudden shocks. Restricting one's attention on such change points (instead of the entire sequence) is common in many areas: Bhaduri (2022) used them to measure the enormity of Covid waves, Zhan et al. (2019) to detect general non-stationarities, Bhaduri and Zhan (2018b) for quantifying time series data similarity, Bhaduri et al. (2017a, b) to detect drifts in big data, etc. In finance, such change points appear, among others, in ("Modeling Interaction between Bank Failure and Size", 2016) who explored the connection between a bank's size and its failure probability and in Huang (2012) who showed how, omitting such breaks may lead to overestimation of volatility transmission.

Formally, given a time series $\{X_1, X_2, \ldots, X_T\}$, with $X_i \sim F_i$, some probability distribution function, a change-detection exercise consists of:

1. choosing one of two competing hypotheses:

$$\begin{aligned} &H_0 : X_i \sim F_0(x;\theta_0), i = 1,2,..,T \\ &H_a : X_i \sim F_0(x;\theta_0) I_{i=1,2,..,k} + F_1(x;\theta_1) I_{i=k+1,k+2,..,T} \end{aligned} \tag{12}$$

2. sounding an alarm as soon as possible after the true change in case H_0 is rejected.

One construction that proves to be extremely useful was introduced by Hawkins et al. (2003) where with a given sample size, they have translated the entire problem into finding several of these two-sample statistics:

Table 2 Choice of $D_{k,n}$s

Competitor	Construction	Choice
CPM-Exp (Ross 2014)	$M_{k,n} = -2\log(\frac{L_0}{L_1})$	$D_{k,n} = M_{k,n}$
CPM-Adjusted Exp (Ross 2014)	$M^{c}_{k,n} = \frac{M_{k,n}}{E(M_{k,n})}$	$D_{k,n} = M^{c}_{k,n}$
CPM-Mann–Whitney (Hawkins and Deng 2010)	$U_{k,n} = \sum_{i=1}^{k} \sum_{j=k+1}^{n} sgn(X_i - X_j)$	$D_{k,n} = U_{k,n}$(scaled)
CPM-Mood (Ross et al. 2011)	$M = \sum_{X_i}((\sum_{i\neq j}^{n} I(X_i \geq X_j)) - \frac{n+1}{2})^2$	$D_n = M$(standardized)
CPM-Lepage (Ross et al. 2011)	$L = U^2 + M^2$	$D_n = L$
CPM-Kolmogorov–Smirnov (Ross and Adams 2012)	$M_{k,n} = \sup_x \lvert \hat{F}_{S_1}(x) - \hat{F}_{S_2}(x) \rvert$	$D_{k,n} = M_{k,n}$
CPM-Cramer-von-Mises (Ross and Adams 2012)	$M_{k,n} = \int_{-\infty}^{\infty} \lvert \hat{F}_{S_1} - \hat{F}_{S_2} \rvert dF_t(x)$	$D_{k,n} = M_{k,n}$

Table 3 Less demanding choice of $D_{k,n}$s

Competitor	Working
E-divergence (Matteson and James 2013)	$D(X, Y; \alpha) = \int_{R^d} \lvert\phi_X(t) - \phi_Y(t)\rvert^2 (\frac{2\pi^{d/2}\Gamma(1-\alpha/2)}{\alpha 2^{\alpha}\Gamma((d+\alpha)/2)} \lvert t\rvert^{d+\alpha})^{-1} dt > C$
Parametric (Chen and Gupta 2011)	$L_k = -2log\frac{L_0(\hat{\lambda})}{L_1(\hat{\lambda}, \hat{\lambda}')} < C$
Pettitt (Pettitt 1979)	$K_T = max_{1\leq t\leq T} \lvert \sum_{i=1}^{t} \sum_{j=t+1}^{T} sgn(X_i - X_j)\rvert > C$
Buishand (Buishand 1982)	$U = \frac{1}{n(n+1)} \sum_{k=1}^{n-1} (\frac{S_k}{D_x})^2$, where $S_k = \sum_{i=1}^{k}(X_i - \overline{X}), D_x = sd(X)$

$$D_{k,n} \Rightarrow D_n = \max_{k=2,3,..,n-1} D_{k,n} \tag{13}$$

measuring the differences between the pre- and the post-change pieces for a fixed initial guess at k. The best guess of the true change will be that k which minimizes some overall loss function:

$$\hat{\tau} = \arg \max_{k=2,3,..,n-1} D_{k,n} \tag{14}$$

Over the years, several choices of these $D_{k,n}$s have been proposed, some (shown in Table 2) assuming specific parametric families (such as the exponential) for the X_is, others (shown in Table 3), assuming less demanding assumptions (such as tractable difference in characteristic functions).

These assumptions, however, restrict the applicability of these proposals only to cases where changes are sought in specific properties (such as the mean or the variance) or when, conditional on the change-point, the observations, both pre- and post-change are otherwise independent. Such assumptions are frequently questionable in financial settings where autocorrelations persist even within the pre- and post-change regions (leading to Hawkes process structure, evidenced, among others, by Rambaldi et al. (2018). We, therefore, implement the bidirectional proposal offered by Bhaduri (2018) and Ho et al. (2023) which is documented (Bhaduri 2022) to be more accurate in detecting changes under such less-structured systems. Using $T_i = \sum_{k=1}^{i} X_k$, we define two fresh statistics:

$$Z = -2\sum_{i=1}^{n} log(t_i/t_n) \tag{15}$$

$$Z_B = -2\sum_{i=1}^{n} log\left(1 - \frac{t_i}{t_n}\right),$$

which rely on the same kernel (the log-combinations of the t-ratios) but act oppositely: Z_B inflates while Z deflates in case X_i s decrease progressively. Under a no-change scenario, these values are roughly equal.

$$R := max(Z, Z_B) \tag{16}$$

and

$$L := min(Z, Z_B)$$

offer further refinements, bettering classification power, regardless of when the change happens: early, midway, or late into the evolution. The null densities of these statistics are found to be approximately chi-squared (Bhaduri 2018). These null densities are needed to test whether the process does or does not contain a change (significantly extreme values point to the existence of one or more change-points). With such tools, the bidirectional proposal runs as follows (details in Bhaduri 2018):

- Construct a series of hypotheses: $\{H_1, H_2, ...H_m\}$, p-values: $p_1, p_2, ...p_m$.
- H_i tests stationarity on the first $i + 1$ events.
- Pick a statistic: Z, Z_B, R or L to carry these tests out with.
- Order the p-values: $p_{(1)} < p_{(2)} < \cdots < p_{(m)}$.
- Set $S_i := \{k : p_{(k)} < \frac{k}{m}\alpha\}$

$$\hat{\tau}_i := \begin{cases} \min\{k : p_{(k)} < \frac{k}{m}\alpha\}, & S_i \neq \varnothing \\ \infty, & S_i = \varnothing \end{cases}$$

- Earliest significant event: t-th $\Rightarrow$ regime change between the $t-1$-th and the t-th event.
- Start over.

The above proposal is, therefore, to do a sequence of tests, with one of the four fresh statistics, and we are claiming that if there is a test that sits on the first set of 16 observations and finds that the system is stationary, and if there is a neighboring test on the first set of 17 observations, that finds that the system is non-stationary, then a change must have happened somewhere in between the 16th and the 17th observations. Since we are doing a sequence of tests, the false discovery rate will have to be controlled. We achieve this using the proposal offered by Benjamini and Hochberg (1995). Interests in these change-point estimates are not purely theoretical: Bhaduri (2020), Bhaduri and Ho (2018a), Bhaduri et al. (2017a, b), Ho and Bhaduri (2017), Ho and Bhaduri (2015) show how such reliable estimates may improve forecasts on a compact interval sampled from the future. We apply this detection algorithm on our spillover sequences to detect general structural shifts as an additional check after implementing Hawkins et al. (2003)'s proposals listed in Tables 2 and 3. At times when the estimates disagree, we opt for those from the bidirectional approach due to its demonstrated reliability under messy systems, as mentioned above. We offer concrete examples of such change finding in the following

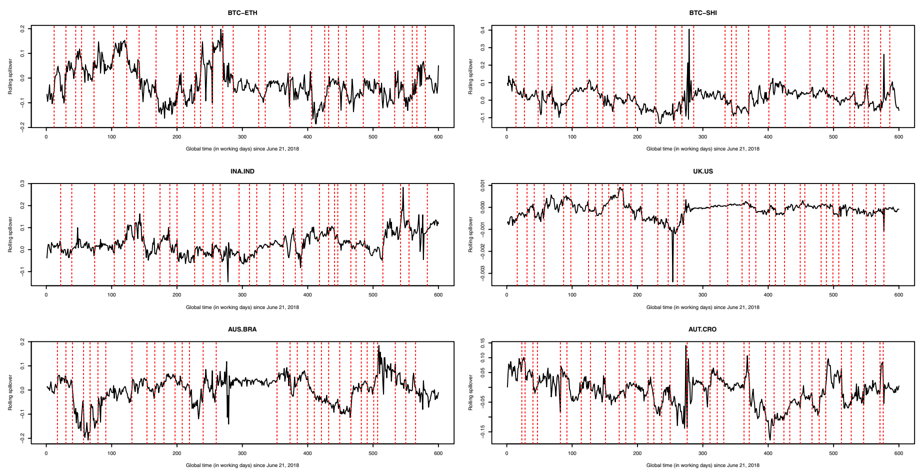

Fig. 1 Change-points on return spillovers (for an illustrative, small-scale study) using the bidirectional algorithm (Bhaduri 2018) described in section "Change-detection algorithms". Times of strong structural shifts are marked in red. The period bordered by two neighboring strips become a stationary epoch, with unaltering statistical features

section (Fig. 1) and execute certain interesting comparison tasks with such estimated change-points. This, however, remains our theoretical basis.

Empirical result

Return spillover

Our spillover findings on the returns case, for the full study period are presented in Table 4. We found interesting return spillover features that confirm earlier research results which were conducted less extensively, on distant time periods. First the spillover from the crypto to the stock market, recorded at 28.21, is not immensely noteworthy against the backdrop of the world stock market: compared to return spillovers given by the US—recorded at 139.58, and the UK—at 139.40, the magnitude of return spillover from Bitcoin and Ethereum to the stock market are more similar to return spillovers coming from Vietnam (24.01) and Shanghai (32.02) to the stock market. Furthermore, most of Bitcoin and Ethereum's return spillover power is directed to their own asset class. This piece of result is consistent with research from Corbet et al. (2018) and Gil-Alana et al. (2020), who point out that Bitcoin and Ethereum have an isolated intra-connectedness and are not hugely influential in the world financial system.

Furthermore, we found that, within their own asset class, return spillovers from BTC to ETH (28.20) and from ETH to BTC (27.59) are much higher than the individual return spillovers received from the stock market. The return spillover from crypto to the stock market (28.21) is lower than the return spillover given by stock market to the crypto (53.33). This is in keeping with Frankovic et al. (2021), Nguyen (2022), who found evidence of the stock market influencing Bitcoin prices in periods of uncertainty. However, Caferra (2022) found that the prevailing market sentiment is a key source of connection between the stock and the crypto market. So, it is not clear whether the market sentiment or the stock market or which combination of the two remain responsible for crypto price fluctuations.

Table 4 Return spillovers over the full study period (15 November 2017 to 17 May 2022)

	BTC	ETH	INA	IND	VNI	STI	JPN	UK	ARG	AUS	BRA	AUT	BEL	BGR	SHI
BTC	46.83	28.20	0.73	0.44	0.12	0.41	0.11	1.13	0.91	0.97	1.83	1.20	1.69	1.25	0.12
ETH	27.59	44.05	0.88	0.58	0.39	0.44	0.46	1.72	0.67	1.09	1.58	1.71	2.30	1.22	0.21
Sub-total	74.42	72.25	1.61	1.02	0.52	0.85	0.57	2.85	1.57	2.06	3.41	2.90	3.99	2.47	0.33
INA	0.20	0.15	25.63	3.69	1.00	3.70	1.41	3.57	0.88	2.44	3.93	3.31	3.50	2.61	0.93
IND	0.25	0.32	3.05	19.83	1.18	4.20	2.32	5.08	1.14	3.95	2.99	3.89	4.42	1.12	0.87
VNI	0.32	0.35	2.38	2.90	40.30	2.03	1.51	3.08	1.06	2.28	2.59	3.02	2.85	1.61	1.97
STI	0.34	0.24	2.97	3.93	0.83	17.86	4.05	5.40	1.23	3.51	2.80	4.90	5.02	1.41	1.61
JPN	0.78	0.61	1.03	2.49	1.01	4.95	21.12	4.89	1.22	4.05	2.29	5.92	6.15	1.26	1.82
UK	0.32	0.35	1.71	3.47	0.75	3.08	2.11	14.29	1.37	2.65	3.11	5.79	7.45	1.69	0.73
ARG	0.55	0.39	1.60	1.59	0.99	1.66	1.06	3.56	40.24	1.57	6.26	3.39	3.68	3.35	0.60
AUS	0.62	0.62	2.41	3.08	1.12	2.93	3.43	4.69	1.83	21.83	3.70	4.48	5.03	1.89	0.73
BRA	0.90	0.66	3.01	2.78	0.89	1.92	0.71	4.44	3.48	3.38	21.46	4.03	5.02	3.20	0.56
AUT	0.50	0.59	1.22	2.35	0.94	2.39	2.68	7.30	1.52	2.47	3.03	17.97	11.61	1.54	0.69
BEL	0.52	0.61	1.23	2.96	0.81	2.77	2.34	8.31	1.27	2.65	3.34	10.20	15.65	1.68	0.83
BGR	1.15	0.97	2.59	1.56	0.49	1.58	1.10	3.41	2.71	1.74	5.24	3.38	4.24	29.69	0.67
SHI	0.59	0.54	1.14	1.83	1.92	3.29	3.13	2.49	0.73	1.40	1.39	2.54	2.76	0.95	38.31
CHN	0.59	0.40	1.72	2.48	1.51	3.92	3.73	3.12	1.33	1.56	1.83	4.10	3.40	2.22	10.33
COL	0.63	0.51	3.10	2.35	1.06	1.46	0.67	4.95	2.38	2.01	6.60	5.64	6.38	3.49	0.66
CRO	0.53	0.42	2.07	2.96	0.97	2.16	1.74	5.41	0.76	5.21	2.84	7.53	6.75	1.73	0.23
CYP	0.89	0.79	1.35	2.94	1.08	1.69	1.28	3.60	0.13	3.47	1.76	6.08	5.04	0.80	0.60
DNK	0.81	0.80	1.07	3.21	0.96	1.35	1.32	6.36	1.23	3.14	2.75	5.26	7.63	1.12	1.04
MYS	0.45	0.38	3.52	3.32	0.83	4.45	2.66	4.62	1.10	2.32	2.90	3.51	3.62	1.63	0.70
THA	0.55	0.49	2.73	5.84	1.26	4.74	1.91	5.41	1.43	2.79	3.96	4.24	4.81	1.58	1.00
PHL	0.47	0.48	6.04	3.22	0.89	3.19	1.98	3.26	1.12	2.11	3.62	3.45	3.17	2.01	0.70
TUR	0.23	0.10	2.18	3.39	0.17	2.09	1.44	5.92	0.91	1.01	2.47	4.27	4.33	1.58	0.44
MEX	0.47	0.44	2.58	2.49	1.00	2.35	1.91	5.75	1.89	1.49	4.53	4.61	4.53	2.80	0.90

Table 4 (continued)

	BTC	ETH	INA	IND	VNI	STI	JPN	UK	ARG	AUS	BRA	AUT	BEL	BGR	SHI
AFS	0.51	0.58	2.43	3.66	0.80	3.46	1.87	7.48	1.11	2.75	2.73	4.75	5.46	2.03	1.59
KOR	0.31	0.25	2.78	3.95	1.01	6.03	6.49	4.48	1.19	3.34	2.32	4.00	3.72	1.67	1.86
US	0.32	0.36	1.70	3.46	0.74	3.09	2.12	14.26	1.38	2.65	3.12	5.79	7.46	1.69	0.72
FRA	1.02	0.99	2.22	2.86	0.90	1.97	1.55	6.39	1.85	3.09	6.01	4.66	6.06	2.45	0.60
To others	42.42	41.58	61.42	79.80	25.62	77.32	57.07	140.08	37.78	71.06	91.51	125.64	138.06	51.59	33.69
To others incl own	89.25	85.63	87.05	99.63	65.92	95.18	78.19	154.36	78.02	92.89	112.97	143.61	153.71	81.28	72.01
	CHN	**COL**	**CRO**	**CYP**	**DNK**	**MYS**	**THA**	**PHL**	**TUR**	**MEX**	**AFS**	**KOR**	**US**	**FRA**	**From others**
BTC	0.74	0.60	1.21	0.93	1.51	0.34	1.42	0.58	0.62	1.18	1.41	0.28	1.14	2.13	53.17
ETH	0.42	0.79	1.50	1.16	1.89	0.26	1.48	0.50	0.76	1.01	1.32	0.06	1.74	2.23	55.95
Sub-total	1.15	1.39	2.71	2.09	3.40	0.60	2.89	1.08	1.37	2.19	2.73	0.34	2.88	4.36	127.54
INA	1.51	5.41	2.80	1.20	1.52	2.93	3.32	4.48	1.70	3.05	3.77	3.49	3.56	4.28	74.37
IND	1.64	2.83	3.83	1.79	2.46	2.19	7.11	2.50	1.83	2.14	4.29	3.77	5.07	3.93	80.17
VNI	2.38	2.85	2.61	0.88	2.41	1.22	3.51	1.53	0.62	2.16	2.42	2.14	3.04	3.99	59.70
STI	2.35	2.89	2.95	1.12	1.55	2.98	4.89	2.04	1.31	2.44	4.36	5.57	5.42	4.05	82.14
JPN	2.77	2.14	2.37	0.54	2.34	2.14	2.65	1.37	1.11	1.99	2.85	7.40	4.89	5.85	78.88
UK	1.17	3.60	3.65	1.09	3.15	0.98	3.73	1.14	2.11	3.17	6.10	2.15	14.27	4.84	85.71
ARG	1.68	4.23	1.95	0.25	1.51	1.03	3.03	1.62	0.95	2.88	2.54	1.00	3.58	3.28	59.76
AUS	1.10	3.58	5.76	1.49	3.05	1.22	3.35	2.56	0.95	2.04	3.11	3.16	4.69	5.57	78.17
BRA	1.06	7.07	3.80	1.21	1.72	1.02	4.65	2.72	1.04	3.67	3.24	1.48	4.45	6.44	78.54
AUT	1.20	3.79	6.13	2.99	3.16	0.73	3.21	0.99	1.72	2.83	4.11	1.14	7.31	3.90	82.03
BEL	1.07	4.19	4.78	1.89	4.23	0.75	3.46	0.90	1.66	2.63	4.62	1.36	8.33	4.99	84.35
BGR	2.11	5.44	3.29	1.18	1.42	1.53	3.72	2.40	1.45	3.59	3.85	1.75	3.41	4.35	70.31
SHI	14.03	1.79	0.59	0.43	1.77	0.91	2.21	0.62	0.68	1.22	3.83	3.77	2.46	2.67	61.69
CHN	29.09	2.29	0.99	0.32	1.76	1.78	2.18	1.47	1.15	1.38	4.83	4.81	3.10	2.63	70.91
COL	1.46	21.22	4.29	1.42	1.79	1.08	2.99	2.49	1.38	4.00	3.98	1.25	4.96	5.77	78.78

Table 4 (continued)

	CHN	COL	CRO	CYP	DNK	MYS	THA	PHL	TUR	MEX	AFS	KOR	US	FRA	From others
CRO	0.49	3.32	24.62	3.79	2.17	0.90	4.14	2.03	1.66	2.34	3.33	1.31	5.43	3.16	75.38
CYP	0.17	2.09	6.74	40.89	1.74	0.85	2.40	2.10	1.54	1.71	1.47	0.63	3.66	2.51	59.11
DNK	1.28	3.35	2.88	1.61	28.24	0.49	2.56	0.56	1.90	1.24	4.18	1.20	6.34	6.17	71.76
MYS	1.69	2.61	2.75	1.08	1.14	26.75	5.13	4.30	1.32	1.94	4.01	3.71	4.65	2.89	73.25
THA	1.24	2.92	4.00	1.62	1.84	2.93	19.23	2.83	1.63	2.65	4.21	2.89	5.43	3.83	80.77
PHL	1.36	3.69	3.11	0.94	0.84	4.60	4.63	29.50	1.04	2.06	3.34	3.54	3.26	2.38	70.50
TUR	0.89	2.58	3.00	1.50	3.04	0.83	3.22	1.12	36.97	1.98	4.25	1.44	5.92	2.73	63.03
MEX	0.94	4.76	2.19	1.13	0.95	1.14	2.57	1.20	1.30	26.40	4.85	2.85	5.78	6.21	73.60
AFS	2.45	3.50	3.42	1.24	2.58	1.95	4.11	2.00	1.95	3.17	16.99	3.49	7.48	4.43	83.01
KOR	3.20	2.64	1.88	0.76	1.97	2.91	3.47	2.53	1.42	2.96	4.78	19.33	4.48	4.26	80.67
US	1.16	3.59	3.66	1.10	3.13	1.00	3.74	1.14	2.11	3.18	6.09	2.15	14.28	4.82	85.72
FRA	0.83	5.78	3.80	1.48	3.12	0.69	3.97	1.51	1.14	4.50	4.38	1.57	6.38	18.24	81.76
To others	52.39	94.34	89.93	36.16	59.76	41.37	96.82	51.24	38.05	69.12	105.51	69.37	140.26	114.27	73.56
To others incl own	81.48	115.57	114.55	77.04	88.00	68.13	116.05	80.74	75.01	95.52	122.50	88.69	154.53	132.51	2900.00

The rows and columns show individual asset class in case its btc, eth, and countries stock indices. The full table show the pairwise correlation of each asset class where the column show the shock coming from other asset class and the rows show the spillover to other asset class. The most right bottom cell show S^g

The second and the third biggest countries that adopted crypto are Vietnam (21%) and Philippines (20%). However, the Bitcoin and Ethereum return spillovers given to those countries are low, recorded at 0.67 and 0.95 respectively, while the return spillovers received are 0.52 and 1.08. The highest return spillover given by Bitcoin and Ethereum are recorded at 2.12 to Bulgaria and at 2.01 to France.

Next, turning to the world financial market, we discovered that two most influential stock markets are those in the US and the UK, who give out the highest return spillovers to others' markets. This result is in accordance with investors' beliefs that the US and UK stock market acted as the return for the world financial market. In addition, our results confirm the research by Yarovaya et al. (2016), Rapach et al. (2010), and Syriopoulos (2007), who also view the US or the UK as housing the most influential stock market in the world.

Volatility spillover

The volatility spillover results, condensed in Table 5 are, in certain ways, similar to those from our return analysis. From Bitcoin and Ethereum, the top three spillovers are given to Bulgaria (2.87), Colombia (2.69), and the US (2.55). Still, this volatility spillover is incomparable with those given by the two most influential stock markets: AS (124.15) and UK (120.81) and even lower than the lowest volatility spillover given by Argentina (16.99).

Crypto assets' intra-spillovers are more impactful than inter-market spillovers from the crypto to the stock market. The spillover from Bitcoin to Ethereum is recorded at 23.00; that from Ethereum to Bitcoin at 24.96. This is analogous with the return case showed earlier, where the intra-market spillover is much higher than inter-market one. On the other hand, the top three inter-market spillovers to Bitcoin are received from Croatia (6.38), Brazil (5.88) and Colombia (5.42).

In the stock market asset class, the UK and the US are the top influencers again. There are some countries that currently give more volatility spillover than return spillover; those are Croatia and France. From its spillover, among the highest, Croatia gives to Brazil (8.97), Austria (9.39), and Turkey (7.90). In addition, Croatia becomes a net spillover giver to the US and the UK instead of becoming a net spillover receiver like most countries. France's spillovers are given to Australia (10.37), Belgium (10.70), and UK (10.33), and, like Croatia, France also becomes a net spillover giver to the US and UK. This is also echoed by Yarovaya et al. (2016), where the connection between North American and the European region in terms of volatility, is found to be higher than that between Asian and South American regions.

Observations on the change-connectedness among spillover pairs

Treating the rolling windows spillover sequence between a pair of assets as a discrete stochastic process, we next proceed to locate times around which drastic shifts corrupted the flow, and subsequently, to measure the gap or the distance between the change-point sets of any two such spillover pairs. The motivation has been offered in section "Change-detection algorithms", along with the detection technique. Initially, we elaborate a small-scale study involving six spillover pairs to further clarify the approach,

Table 5 Volatility Spillover Full Period (15 November 2017 to 17 May 2022)

	BTC	ETH	INA	IND	VNI	STI	JPN	UK	ARG	AUS	BRA	AUT	BEL	BGR	SHI
BTC	47.33	24.97	0.64	0.20	1.52	0.65	0.41	0.82	0.60	1.41	2.18	1.40	1.84	0.50	0.06
ETH	23.00	44.02	1.18	0.30	1.29	0.79	0.91	1.01	0.55	1.59	3.70	1.06	1.61	1.00	0.08
Sub-total	70.33	68.99	1.82	0.49	2.81	1.43	1.32	1.84	1.15	3.00	5.88	2.45	3.45	1.50	0.13
INA	0.38	0.92	28.07	2.47	2.61	4.15	1.48	3.40	0.51	2.86	3.86	2.46	3.23	2.25	0.61
IND	0.65	0.64	2.91	19.25	1.74	3.25	0.56	4.02	0.23	4.93	5.16	3.84	5.24	2.52	0.63
VNI	0.63	0.67	2.48	0.96	51.42	2.67	1.30	1.76	0.20	1.67	1.27	2.01	1.59	0.72	1.45
STI	0.47	0.49	1.93	2.05	2.30	22.44	1.93	4.43	0.23	4.09	3.81	3.70	3.84	2.19	1.57
JPN	0.53	0.40	1.07	2.12	2.19	4.50	24.33	4.65	0.14	3.57	2.01	4.47	4.94	0.53	1.12
UK	0.69	0.66	1.43	1.87	1.52	3.18	1.20	14.77	0.62	3.67	3.12	8.03	9.46	1.20	0.39
ARG	0.30	0.18	0.70	0.18	0.42	0.41	1.00	2.18	66.78	0.63	3.74	1.26	2.28	1.97	0.46
AUS	0.76	0.77	2.15	1.86	1.42	2.59	2.29	6.17	0.90	14.99	6.81	3.64	6.24	1.34	0.40
BRA	0.98	1.11	1.41	1.03	1.10	1.75	0.34	4.63	1.48	3.95	23.01	3.77	5.47	0.92	0.77
AUT	0.95	0.63	0.79	1.36	1.09	1.88	0.45	8.19	0.69	2.87	3.12	16.33	9.74	1.67	0.22
BEL	0.77	0.59	1.18	2.24	1.38	2.71	0.78	9.01	0.65	3.35	3.53	8.89	14.92	0.91	0.48
BGR	1.90	0.98	0.64	1.68	0.76	1.08	0.90	4.23	1.10	3.79	5.78	3.61	4.81	30.74	0.14
SHI	0.21	0.40	0.53	0.84	3.37	3.12	1.61	1.05	0.38	0.79	1.91	0.93	0.74	0.30	53.22
CHN	0.47	0.38	1.15	2.40	2.95	3.78	2.14	1.99	0.29	1.63	2.14	2.90	2.21	1.03	7.39
COL	1.37	1.32	2.02	1.47	1.69	1.95	0.62	4.63	1.72	4.13	7.60	3.63	4.87	2.23	0.63
CRO	1.25	1.18	1.75	1.34	1.62	1.81	0.44	4.66	0.36	4.58	5.42	5.87	5.39	0.92	0.50
CYP	0.77	0.53	1.84	1.89	1.40	1.71	0.54	4.54	1.03	2.36	3.17	4.44	4.13	1.18	1.06
DNK	0.59	0.52	0.98	2.21	0.76	1.82	1.04	4.24	0.57	2.79	2.11	3.07	5.81	1.48	0.58
MYS	0.78	0.97	2.37	1.44	2.01	4.38	0.65	4.69	0.46	3.85	4.39	4.51	4.67	1.67	0.68
THA	0.65	0.82	2.07	2.58	1.98	3.92	0.53	3.99	0.70	3.12	4.64	3.55	4.57	1.81	0.87
PHL	0.81	0.92	2.70	0.80	1.72	3.50	0.70	4.15	0.71	3.83	5.17	4.20	3.89	1.79	0.71
TUR	0.33	0.29	0.66	3.13	1.01	2.44	1.47	4.00	0.29	1.34	3.70	3.01	3.31	1.09	1.01
MEX	0.77	0.52	1.32	1.41	1.23	2.35	0.74	4.34	1.25	2.45	4.95	3.51	4.87	1.74	0.57

Table 5 (continued)

	BTC	ETH	INA	IND	VNI	STI	JPN	UK	ARG	AUS	BRA	AUT	BEL	BGR	SHI
AFS	0.57	0.59	1.53	2.44	2.77	3.59	1.10	6.23	0.62	3.54	5.51	4.88	5.28	1.60	1.03
KOR	0.57	0.45	1.69	2.67	2.66	5.45	3.29	4.43	0.27	4.14	3.20	3.94	4.01	1.98	1.92
US	1.17	1.39	0.86	1.22	1.55	1.91	0.87	5.32	0.92	3.79	6.18	4.81	6.92	0.64	0.53
FRA	0.50	0.41	0.98	1.96	1.31	2.30	0.75	9.87	0.68	2.87	2.95	9.79	10.67	1.48	0.26
To others	42.80	43.70	40.95	46.11	47.38	73.63	30.02	122.65	18.15	83.59	111.15	111.18	131.63	38.65	26.11
To others incl own	90.13	87.72	69.01	65.36	98.80	96.08	54.35	137.42	84.93	98.58	134.16	127.51	146.55	69.39	79.33

	CHN	COL	CRO	CYP	DNK	MYS	THA	PHL	TUR	MEX	AFS	KOR	US	FRA	From others
BTC	0.28	2.46	3.20	2.41	0.42	0.16	0.96	0.32	0.18	0.89	0.90	0.35	2.15	0.79	52.67
ETH	0.30	2.96	3.18	2.46	0.40	0.11	1.77	0.25	0.19	1.25	0.84	0.26	2.92	1.04	55.98
Sub-total	0.58	5.42	6.38	4.87	0.82	0.27	2.73	0.57	0.36	2.14	1.74	0.61	5.08	1.83	108.65
INA	1.68	4.49	2.97	1.34	1.77	2.84	5.61	2.88	0.85	2.58	4.63	2.53	3.81	2.75	71.93
IND	1.38	4.89	6.15	1.85	1.59	1.38	5.61	2.07	1.78	1.91	3.81	2.31	5.35	4.33	80.75
VNI	2.26	4.96	1.91	0.60	1.34	1.33	2.03	1.03	1.02	2.20	2.47	3.52	2.30	2.23	48.58
STI	2.56	4.06	4.75	1.57	0.90	2.82	5.48	1.65	0.82	2.52	4.72	3.90	4.62	4.17	77.56
JPN	2.86	1.57	2.60	1.05	1.76	2.27	4.07	1.40	1.47	2.24	3.58	6.77	6.13	5.64	75.67
UK	0.82	3.66	6.01	2.13	2.57	1.17	4.83	0.88	1.70	2.50	4.88	1.26	5.45	10.33	85.23
ARG	0.73	3.59	0.91	1.20	0.92	0.41	1.30	0.60	0.28	0.67	1.19	0.20	2.44	3.05	33.22
AUS	0.87	5.89	6.93	2.60	2.21	1.44	4.49	0.91	1.19	3.03	3.88	1.46	7.68	5.10	85.01
BRA	0.84	6.24	8.97	3.60	1.77	1.09	6.13	0.82	1.30	2.79	2.96	0.30	6.83	4.62	76.99
AUT	1.03	4.03	9.39	3.19	1.71	1.18	3.19	0.82	1.67	2.65	3.83	0.59	6.36	10.37	83.67
BEL	0.95	3.59	6.64	2.61	2.75	1.37	4.41	0.99	1.22	2.68	4.06	1.07	5.57	10.70	85.08
BGR	0.94	7.12	5.96	2.37	1.81	0.64	3.91	1.05	2.24	2.11	2.16	0.69	3.23	3.63	69.26
SHI	12.04	0.81	1.29	1.24	0.78	1.92	1.75	1.74	1.12	0.58	2.07	2.56	1.59	1.13	46.78
CHN	35.80	1.34	1.87	1.05	1.15	2.43	2.50	2.34	1.03	1.04	5.58	4.60	2.78	3.63	64.20
COL	1.00	21.23	5.29	2.40	2.03	0.97	4.42	1.61	1.01	4.13	3.49	0.51	7.16	4.87	78.77

Table 5 (continued)

	CHN	COL	CRO	CYP	DNK	MYS	THA	PHL	TUR	MEX	AFS	KOR	US	FRA	From others
CRO	1.11	4.89	23.50	6.21	1.65	1.06	4.67	0.61	2.43	2.17	2.87	0.69	5.71	5.32	76.50
CYP	1.00	2.70	8.69	36.07	1.72	1.45	2.92	0.60	1.86	1.85	2.04	0.51	3.49	4.52	63.93
DNK	1.80	3.84	4.76	1.88	30.41	1.47	3.69	0.96	3.11	2.97	3.26	1.63	5.96	5.68	69.59
MYS	1.45	2.69	5.48	2.71	1.48	22.37	6.03	3.06	0.87	3.15	2.26	2.30	4.46	4.19	77.63
THA	1.12	5.22	7.45	3.84	1.88	2.64	22.31	2.07	1.12	2.72	4.01	1.22	4.36	4.25	77.69
PHL	1.52	4.90	4.25	2.83	1.73	1.58	4.92	22.78	1.70	2.37	4.03	1.73	5.55	4.53	77.22
TUR	1.07	1.44	7.90	2.39	2.60	1.42	3.03	0.64	41.96	1.42	2.51	0.63	2.27	3.63	58.04
MEX	0.65	4.57	4.14	2.68	2.54	1.12	4.78	1.66	1.09	29.02	4.53	1.40	5.37	4.42	70.98
AFS	2.57	4.60	5.85	1.66	1.98	1.52	4.81	1.70	1.89	2.46	16.53	1.84	5.08	6.24	83.47
KOR	3.56	2.69	2.89	0.77	1.68	3.12	4.94	2.21	1.20	1.48	3.86	22.74	4.17	4.02	77.26
US	1.04	6.38	6.96	2.39	2.80	0.95	4.43	0.67	1.60	3.73	3.95	0.71	19.83	6.50	80.17
FRA	1.15	3.99	6.13	2.60	2.76	0.87	3.86	0.72	1.51	2.48	4.78	0.79	6.44	15.13	84.87
To others	48.60	109.54	142.53	63.66	48.70	40.74	110.55	36.28	37.43	62.57	93.15	46.34	129.23	131.69	71.33
To others incl own	84.39	130.78	166.02	99.73	79.11	63.11	132.86	59.07	79.39	91.60	109.68	69.08	149.05	146.82	2900.00

before moving on, in the following subsections to the more general analysis involving (29C2) or 406 pairs.

We sample six return (a similar analysis is valid on the volatility side too) rolling spillover sequences BTC-ETH, BTC-SHI, INA-IND, UK-US, AUS-BRA, and AUT-CRO. These sequences will prove to be interesting (in terms of "centrality", defined below) in our ultimate large-scale analysis; they are graphed in various panels on Fig. 1. If we apply our bidirectional technique described in section "Change-detection algorithms" on each sequence, restarting the algorithm afresh each time a change is detected, our change point estimates will be the red vertical strips. A pair of adjoining strips enclose a phase where features of the process remained statistically stable (i.e., stationary, in a sense). Due to the demonstrated versatility of the detection method, such features need not be confined to only usual summaries like the mean, variance, skewness, kurtosis, and the process may even contain intractable dependencies. Crossing over one such separator amounts to entering a fresh period with radically different statistical properties. Most of these red change estimates are acceptable visually (they appear frequently at times of sharp gradient shifts) and historically (around, for instance, the 500 working days mark which roughly corresponds to the onset of COVID related chaos).

To quantify the temporal similarity of two such changepoint sets

$$\tau^* := \{t_1^*, t_2^*, ..., t_a^*\}, \tag{17}$$

$$\hat{\tau} := \{\hat{t}_1, \hat{t}_2, ..., \hat{t}_b\},$$

we implement the Hausdorff metric:

$$||\hat{\tau} - \tau^*||_\infty := \max\{\max_{\hat{t}\in\hat{\tau}} \min_{t^*\in\tau^*} |\hat{t} - t^*|, \max_{t^*\in\tau^*} \min_{\hat{t}\in\hat{\tau}} |\hat{t} - t^*|\} \tag{18}$$

and measure their separation through

$$\frac{1}{T} ||\hat{\tau} - \tau^*||_{\infty}. \tag{19}$$

The two sets $\hat{\tau}, \tau^*$ need not in general be of the same size which is why standard correlation or Euclidean-type metrics are unsuitable. Another key advantage behind the Hausdorff choice is it penalizes over-segmentation. Burg and Williams (2020) and Bhaduri (2022) describe other benefits of this specific metric. The smaller its value, the more similar are the two sets. As examples, consider the change points (in working days) from:

> US-UK: {16, 31, 42, 57, 87, 98, 125,136, 146, 156, 170, 178, 190, 207, 231, 247, 261, 271, 311, 338, 360, 371, 381, 402, 411, 425, 449, 456, 481, 489, 499, 508, 529, 550, 564, 577}
> INA-IND: {22, 39, 74, 104, 120, 135, 149, 174, 189, 200, 227, 240, 255, 266, 295, 311, 322, 342, 363, 381, 391, 418, 432, 441, 446, 466, 474, 487, 515, 542, 555, 583}.
> AUT-CRO: {23, 28, 40, 47, 82, 92, 114, 128, 151, 172, 182, 196, 216, 225, 237, 250, 276, 300, 311, 322, 332, 363, 371, 396, 409, 424, 433, 449, 467, 478, 488, 512, 527, 546, 571, 576}.

	BTC.ETH	BTC.SHI	INA.IND	UK.US	AUS.BRA	AUT.CRO
BTC.ETH	0.000000	0.265625	0.234375	0.234375	0.43750	0.218750
BTC.SHI	0.265625	0.000000	0.359375	0.359375	0.40625	0.359375
INA.IND	0.234375	0.359375	0.000000	0.265625	0.65625	0.187500
UK.US	0.234375	0.359375	0.265625	0.000000	0.65625	0.171875
AUS.BRA	0.437500	0.406250	0.656250	0.656250	0.00000	0.656250
AUT.CRO	0.218750	0.359375	0.187500	0.171875	0.65625	0.000000

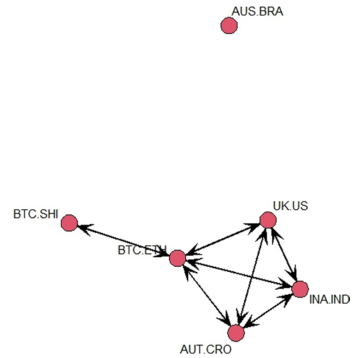

Fig. 2 Hausdorff distances for the small-scale study compiled in a matrix and the induced network that results from it

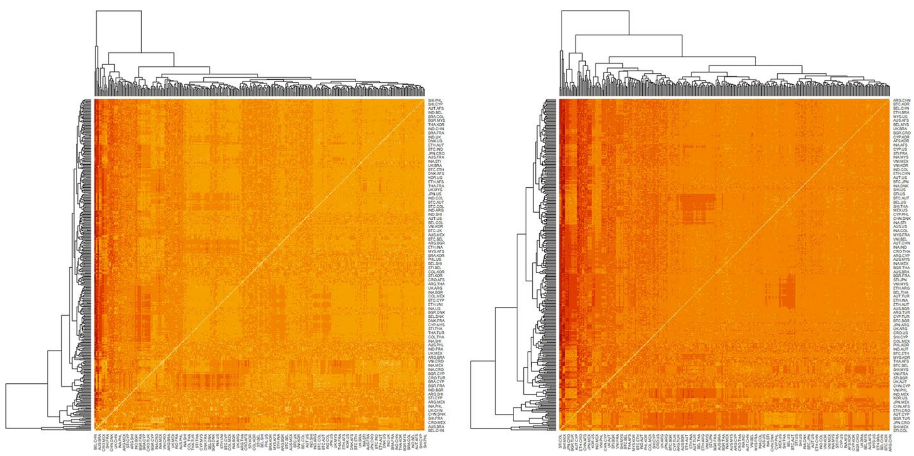

Fig. 3 Heatmaps for the return (**a**) and the volatility (**b**) cases involving all 406 spillover combinations. Lighter values indicate similarity of change-points across one spillover pair, darker values indicate dissimilarity. We find return change points across dependencies to correlate; volatility change-points slightly less so

The Hausdorff distance between the US-UK and the AUT-CRO sequences is 0.17 while the distance between the US-UK and the INA-IND sequences is 0.26. This shows that the times at which the US-UK spillover sequence undergoes drastic changes are more similar to the times at which the AUT-CRO sequence undergoes changes and less similar to the times at which the INA-IND sequence undergoes changes. For such an initial, small-scale study as this, this is also clear by inspecting the three sets above or by looking at how similarly the vertical separators are placed on the appropriate panels on Fig. 1. Such pairwise distances are stored as symmetric matrices (left panel, Fig. 2) or as larger heatmaps for the more general study involving 406 cases: Fig. 3a for the return sequences, Fig. 3b for the volatility sequences.

The distances behind these heat maps may be used to cluster spillover sequences in terms of similarities of their change patterns. The ideal number of clusters is found by marking the elbow on the within-sum-of-squares graph (Fig. 4a, b): the point beyond which additional cluster homogeneity is not worth the extra number of clusters (Rousseeuw 1987). Other methods for detecting the number of clusters exist—such as the one using "gap" statistic proposed by Tibshirani et al. (2001). We have chosen the Silhouette

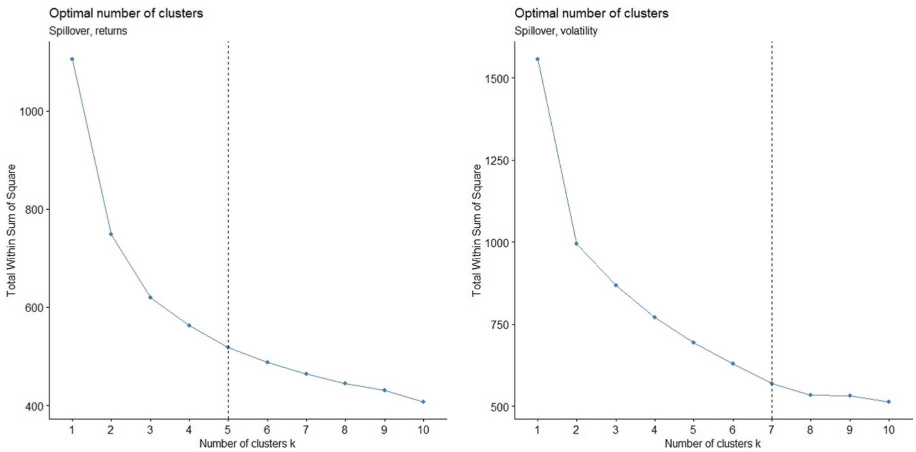

Fig. 4 Working out the right number of clusters in which to partition to spillover combinations. The returns (**a**) are more homogeneous, requiring fewer clusters than the volatilities (**b**), requiring more

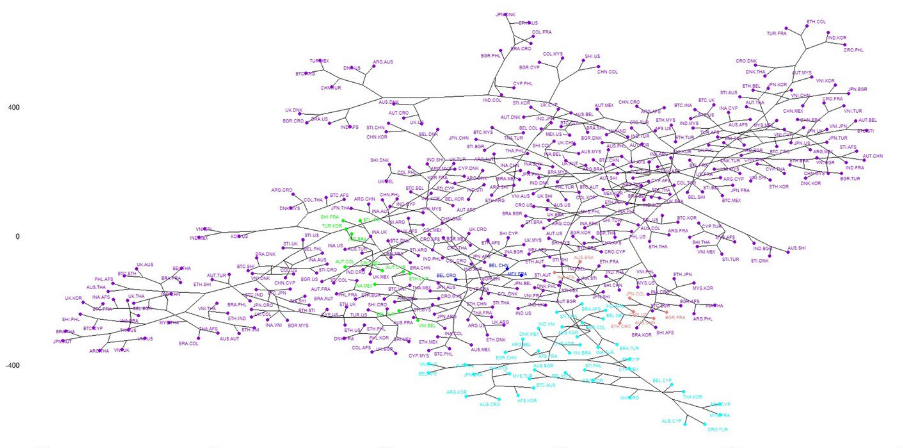

Fig. 5 Large-scale cluster, returns case. Changes in one spillover combination (formed by the relationship between two assets) from a certain group are likely to correlate with changes in a neighboring spillover combination from the same group. These five clusters form our five rings-of-fire in the returns case

method both owing to its popularity and since a sensitivity analysis with these other methods didn't generate drastically different numbers of clusters (hovers around 5 or 6, whatever the method). These optimal numbers are five for the return case and seven for the volatility case (Fig. 4, b, respectively). Accordingly, such clusters are identified on Figs. 5 and 6 with the right number of colors. Researchers can examine spillover sequences sharing the same color to conclude (and to probe deeper into why) changes in one closely mimic changes in the other. To the best of our knowledge, such a description has never been furnished even on a smaller scale with fewer assets. The study that comes closest is Wu et al. (2022) where we observe how shocks are spreading faster post-COVID, which, as our study finds, is a *specific* change-point. Our analysis, unlike the actual return and volatility sequences studied by Wu et al. (2022) looks instead at spillover dependencies and examines all general changes, not just those triggered by the pandemic.

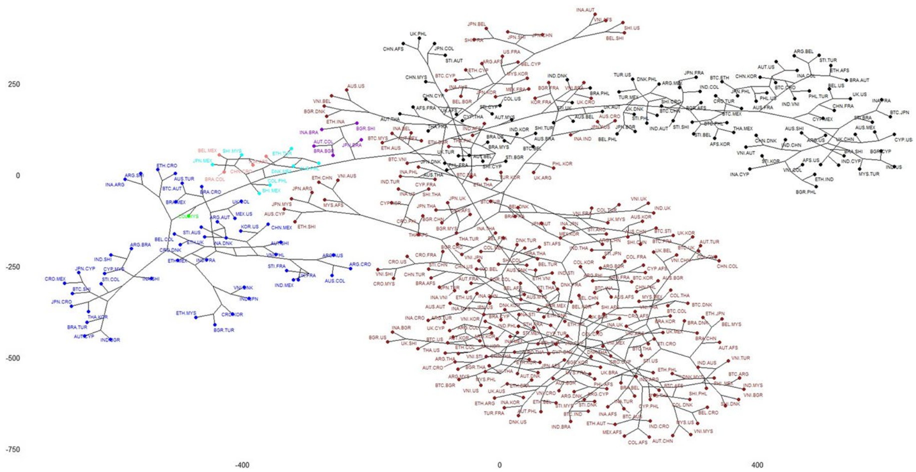

Fig. 6 Large-scale cluster, volatility case. Changes in one spillover combination (formed by the relationship between two assets) from a certain group are likely to correlate with changes in a neighboring spillover combination from the same group. These seven clusters form our seven rings-of-fire in the volatility case

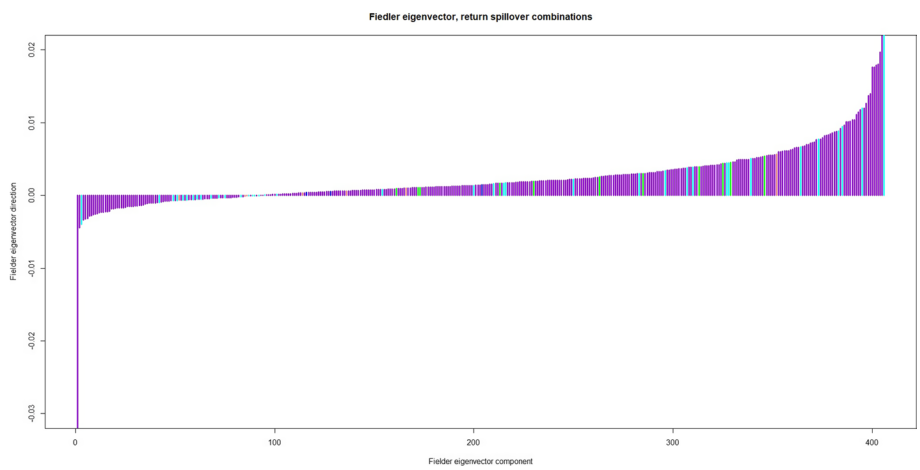

Fig. 7 Fielder eigen-components graphed for each of the 406 spillover combinations, the returns case. The same color convention has been retained from Fig. 5. With predominantly positive components, there is a general tendency among "return" nodes to stay connected

Next, we exploit results from graph theory (Newman 2010, for instance) to glean further insights into the nature of the connectedness. First, using L as the Laplacian

$$L = D - A \tag{20}$$

where A is the similarity matrix (treating similarity as one minus the distances found above) and D the diagonal matrix of A's row sums, we look at the multiplicity of zero as an eigenvalue of L. For both the return and volatility spillover cases, we found this multiplicity to be 1, ensuring the graphs in Figs. 5 and 6 are fully connected. This ensures changes in one spillover dependence structure cannot stay insulated (like AUS-BRA in our small-scale scenario, Fig. 2) from those in the rest. The Fielder eigenvectors are collected next for both the return (Fig. 7) and volatility spillover (Fig. 8) cases. The

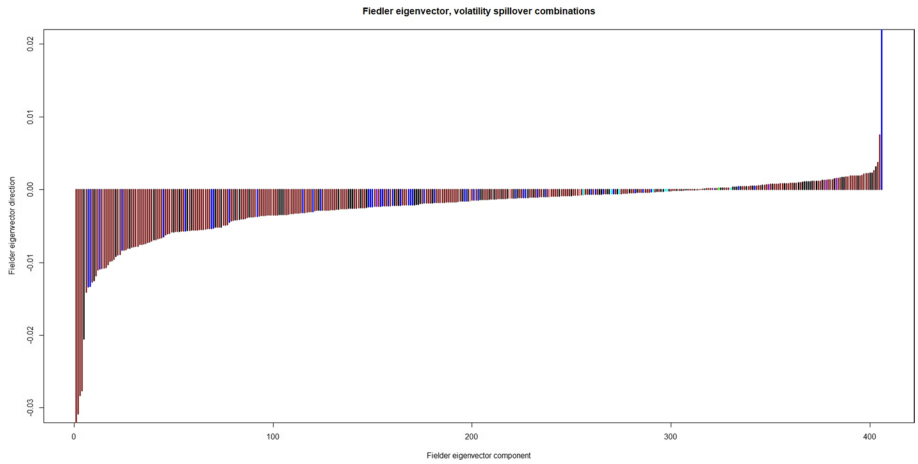

Fig. 8 Fielder eigen-components graphed for each of the 406 spillover combinations, the volatility case. The same color convention has been retained from Fig. 6. With predominantly negative components, there is a general tendency among "volatility" nodes to stay isolated

components of these vectors show how connected the vertices are: negative values correspond to nodes which are less connected, positives to those which are well-connected. These components are arranged in an ascending order in Figs. 7 and 8, following the same color convention used for the respective clustering. We notice stronger connectedness in the return case, good homogeneity (that is, a thorough mixing of colors) in either case. This shows how membership in a given cluster may not guarantee connectedness of some kind (high or low), this being more vivid in the volatility spillover scenario.

The importance of a vertex, however, may be examined not just through its connectedness. To explore some of these other options, we generate, from the pairwise distances, an induced graph where an undirected edge is formed between two nodes if the distance between the nodes falls below a certain threshold. Such induced arrangements are known as ϵ-neighborhood graphs studied by von Luxburg (2007), among others. In our cases, these thresholds were 0.35 for the return scenario and 0.45 for the volatility one. These were the median similarities in their respective cases and a sensitivity analysis with respect to these values did not produce significantly different results (to follow). For instance, the induced graph from our small-scale difference matrix is shown in the right panel of Fig. 2. We look, in the following subsection, at three key centrality measures:

1. the degree centrality: this counts the number of immediate neighbors a node has.
2. the closeness centrality: the inverse of the sum of all the distances between a given node and all other nodes.
3. the between centrality: it measures the extent a node sits between pairs of other nodes in the network such that a path between the other nodes has to go through that node.

For our small-scale study on Fig. 2, for instance, the nodes INA-IND, US-UK, AUT-CRO have degree centrality 3 each, while BTC-ETH has 4, BTC-SHI has 1 and AUS-BRA has none. BTC-ETH also has the highest between centrality of 3. The higher these values are for a given node, the more prominent a role that node plays in the network.

Frequently, but not always, these measures correlate (Luke 2015). We collect the full-scale findings in Appendix 1.

Connectedness of return spillover pairs

The analysis on return spillover connections over a fixed period, shown in section 4.1, can be extended by considering connections defined through closeness of change-point sets for a pair of asset class. The rationale and a small-scale study have been offered before; we currently conceptualize the fuller network and calculate three summaries: degree, closeness, and betweenness centralities. We will point out which pairs control the crucial hubs of change-information flow in a network induced from the cluster shown prior, with the same thresholds: 0.35 for the return and 0.45 for the volatility scenario. The spillover pair that is most connected in this "change-sense", for instance, is the one whose changes are temporally similar to the changes from the largest number of other pairs. Sudden structural shifts in the dependence dynamics of the members contributing to this spillover pair, therefore, is likely to correlate with similar jolts in the relationships between the largest number of other pairs. The pair that is the least connected, on the other hand, remains isolated in this sense. Research on non-stationary time series justify our insistence on a network manufactured through change-conscious links instead of one formed by ordinary full-scale correlations among stocks. Chapman and Killick (2020), for instance, demonstrate how forecasts improve if one restricts attention to the last stationary phase, defined by the last change-point.

We found that (Appendix 1), surprisingly, Australia and Croatia's return spillover dynamic is the one with the highest degree and closeness. The number of immediate neighbors that Australia–Croatia has, 343, trumps the one—331—of the pair formed between the most influential stock countries: UK–US, however one feels about the significance of a difference of 12 is hard to determine. In terms of closeness centrality, we report similar observations: Australia–Croatia: 0.86; the UK–US: 0.84, with a difference of 0.02. The dynamics of the Australia–Croatia return spillover is prominent in Europe, and being connected to other important countries makes it a reasonable proxy to the world stock market's global changes. We maintain, through our analysis in section 4.1, that the UK–US interaction stays key overall, and—through our results here—that in terms of shock transference among pairwise dependencies, the Austria-Croatia connection merits equal attention.

In term of betweenness centrality, the BTC—Shanghai pair is the highest (290.28) while the Australian and Croatia pair is recorded at (205.53). The 15 nodes that top the popularity table (Appendix 1) remain largely similar regardless of the centrality tool used: degree or closeness. The betweenness criteria, however, extract somewhat different actors. Through a recollection of what these three quantities are designed to measure (offered above in section 4.3), this disagreement may fuel further lines of fruitful research.

Turning next to the other extreme of isolated spillover pairs, the Belgium–Croatia and Australia–Brazil pairs have the lowest network degree with 4 connections each. Closeness centrality also points out Belgium–Croatia and Australia–Brazil as the most isolated spillover pairs with 0.35 and 0.36 closeness values respectively, Betweenness centrality detect Australia–Brazil as the most isolated pair with a value of zero.

Connectedness of volatility spillover pairs

We next move on to similar analyses on the volatility side. The most connected spillover pair based on degree is Singapore–Croatia (355), tied with Shanghai–US (355) and based on closeness, Singapore–Croatia (0.88) and Shanghai–US (0.88). On the other hand, betweenness centrality point out BTC–Thailand with 422.77 and Shanghai–US with 374.14 as the two most connected spillover pairs.

For the most isolated, a rare agreement among the three methods of centrality calculation is reached. Each metric shows that Colombia–Malaysia is the most isolated spillover pair. We note inferential research on network structures are still being developed. Point estimates such as the network's degree distribution, density or the closeness measures seen here may be extended (under certain assumptions) to include margins of error, offering confidence intervals. We point those interested in such matters to Zhang et al. (2015).

Discussion

Bitcoin and Ethereum have a predominantly isolated intra-connectedness, but they receive substantial inter-spillover from the stock market. This mean that instead of hugely influencing the stock market, Bitcoin and Ethereum are the ones influenced by the stocks. This will be a crucial insight for investors who are inclined on using Bitcoin and Ethereum as hedging tools. Due to the flow of influence from the stock market, the crypto asset class may pro-cyclically mimic the movements of stock and erode their hedging property.

Furthermore, the dynamics of spillover, we found, evolve differently in different periods. In periods of higher uncertainty, the amount of connections among the investment asset class is higher. This also applies to the crypto asset class and the stock market where they have uniform return and volatility movements in a period of crisis. Nevertheless, both markets are susceptible to news and market sentiments: information about turbulence, perceived or real, in the financial market sector, or hugely disrupting negative sentiments will push both asset classes.

Surprisingly, we found that Bulgaria is the country that receive the highest spillover from the crypto asset, not the US, the UK, or China, where interest and talks about crypto are widespread. However, this small European country actually hold most Bitcoin in the world: 1.017% more than El Salvador, which already integrated its traditional financial system to crypto. The varying degrees of connectivity observed between crypto assets and traditional financial assets can be attributed to the divergence in legal frameworks and the level of acceptance of crypto assets within each respective country, as highlighted by Raza et al. (2022).

In addition, Bulgaria is also home to the most wanted crypto queen, Ruja Ignatova. Our research uncovers how the Bulgarian stock market is receiving heat from the crypto price fluctuations. This should signal investors in the Bulgarian stock market to keep an eye on the dynamics of Bitcoin and Ethereum.

Conclusion

In this research, we explored the connectedness among major stock indices through a large-scale study exploiting Diebold and Yilmaz (2012)'s spillover setup, and described, through identifying structural breaks, how the nature of the dependence changes sequentially. We found that the connectedness between crypto assets and the traditional stock market evolves over time. This assertion finds support from the research conducted by Aslanidis (2021), which delves into the interconnected nature of the cryptocurrency market and found more interconnectedness in both volatility and returns. During stable times, the connection is weak and has a bidirectional flavor. This means that the crypto asset could become good portfolio diversifying tools. On the other hand, in a crisis, the magnitude of the connection increases considerably and exhibits a unidirectional behavior. This change of relationship is potentially dangerous. Investors who use crypto as a hedging tool to their portfolio, will be exposed to a high loss risk because of the pro-cyclical nature of crypto returns during a crisis.

Also, our findings are useful to regulators for financial stability decisions. Regulators such as the Financial Stability Board, International Monetary Fund, and European Central Bank routinely investigate (frequently underestimating) the connectedness of crypto assets to the traditional financial system. In the research, we found evidence of an increasing connectedness trajectory and based on our cluster and subsequent network, some pairs having stronger connections than most. The cluster partitions we detect—our rings of fire—along with our related network summaries, highlight the countries to which we should sound an alarm in the event of a crypto crash, apprehending shock transmissions.

Whether we detect it or not, whether we like it or not, we have been attending the funeral rites of archaic asset classes for many years and it has been a bizarre wake, especially with the emergence of potent alternatives such as cryptocurrencies. While such traditional tools as stocks, bonds, etc. may never sink into absolute oblivion, Bitcoins, Ethereum, and numerous others have lately been on an undeniable ascendancy. For a sound understanding of how well the new meshes and clashes with the old, and probably, more crucially, to instill in investors as a trust that is durable, a fuller analysis of dependence, embracing a larger sampling throughout the world, with emphasis on features like change-points that matter pragmatically (say, for, accurate forecasts), was becoming pressing by the day. Our current study, offering a thorough map of entanglement, remains devoted to these very exigencies that prompted it.

Appendix 1. Table of network summaries

	Returns				Volatilities		
	Degree	Closeness	Betweenness		Degree	Closeness	Betweenness
AUS.CRO	343	0.86	205.53	STI.CRO	355	0.89	182.31
IND.AFS	338	0.86	251.57	SHI.US	355	0.89	374.14
SHI.AFS	338	0.85	167.09	BGR.SHI	352	0.88	199.98

	Returns				Volatilities		
	Degree	**Closeness**	**Betweenness**		**Degree**	**Closeness**	**Betweenness**
CHN.COL	337	0.86	249.11	BRA.US	350	0.88	210.65
BEL.CYP	336	0.85	215.32	THA.MEX	350	0.88	150.19
INA.IND	334	0.85	146.92	VNI.CHN	347	0.87	134.08
CHN.CRO	332	0.85	267.02	STI.FRA	346	0.87	128.45
DNK.US	332	0.84	131.88	CYP.KOR	346	0.87	129.77
IND.CHN	331	0.84	232.7	BRA.CRO	345	0.87	200.88
VNI.FRA	331	0.84	120.66	INA.STI	343	0.87	197.48
UK.US	331	0.84	124.56	STI.TUR	343	0.87	163.0
THA.KOR	331	0.84	135.4	INA.MYS	342	0.87	107.92
TUR.AFS	331	0.84	154.38	BEL.CRO	342	0.86	149.26
ARG.AFS	330	0.84	147.93	PHL.MEX	342	0.86	133.81
ARG.KOR	330	0.84	179.99	TUR.US	342	0.86	101.44
BRA.SHI	330	0.84	198.86	BTC.CHN	341	0.86	155.08
COL.FRA	330	0.84	138.2	INA.AFS	341	0.86	132.86
TUR.FRA	330	0.84	106.68	IND.TUR	340	0.86	138.76
ETH.FRA	329	0.84	123.18	CYP.US	340	0.86	111.12
IND.UK	328	0.84	137.54	IND.PHL	339	0.86	137.82
INA.STI	327	0.84	131.72	VNI.JPN	339	0.86	165.69
IND.US	327	0.84	132.85	ARG.MEX	339	0.86	131.57
AUS.AFS	327	0.84	129.72	SHI.CHN	339	0.86	128.0
AUT.CRO	327	0.83	124.37	SHI.KOR	339	0.86	100.44
BEL.KOR	327	0.83	130.28	TUR.KOR	339	0.86	119.96
BGR.CHN	327	0.84	186.33	INA.CYP	338	0.86	120.78
BTC.ETH	326	0.83	153.41	IND.KOR	338	0.86	118.34
CYP.AFS	326	0.83	137.78	BGR.CYP	338	0.86	81.27
PHL.TUR	326	0.83	123.19	CYP.PHL	338	0.86	147.56
IND.ARG	325	0.83	102.92	ETH.BEL	337	0.86	114.23
ARG.MYS	325	0.83	162.16	UK.AUS	337	0.85	103.7
CRO.MYS	325	0.83	116.28	ARG.SHI	337	0.85	143.71
THA.PHL	325	0.83	140.39	BRA.CHN	337	0.86	113.35
ETH.AUS	324	0.83	91.73	CHN.DNK	337	0.86	143.81
JPN.BEL	324	0.83	170.43	JPN.MYS	336	0.85	85.42
BRA.FRA	324	0.83	113.12	SHI.PHL	336	0.85	127.37
COL.CRO	324	0.83	113.92	INA.AUT	335	0.85	221.97
INA.AFS	323	0.83	113.08	VNI.MEX	335	0.85	96.32
UK.FRA	323	0.83	137.66	STI.US	335	0.85	103.18
ARG.CRO	323	0.83	126.16	AUS.MEX	335	0.85	93.72
BEL.PHL	323	0.82	102.61	INA.VNI	334	0.85	103.44
BGR.TUR	323	0.83	140.95	AUS.FRA	334	0.85	132.03
DNK.KOR	323	0.83	106.38	BRA.BEL	334	0.85	99.48
IND.TUR	322	0.82	129.07	CHN.COL	334	0.85	111.1
CRO.CYP	322	0.83	191.81	MYS.TUR	334	0.85	145.38
IND.BEL	321	0.83	100.96	MYS.MEX	334	0.85	83.79
JPN.CRO	321	0.82	76.45	TUR.MEX	334	0.85	97.03
UK.AFS	321	0.82	116.35	MEX.AFS	334	0.85	121.51
BEL.MYS	321	0.83	130.69	INA.DNK	333	0.85	109.56
BEL.AFS	321	0.82	156.02	IND.MYS	333	0.85	112.01
ETH.AUT	320	0.83	267.57	STI.AFS	333	0.85	93.9
UK.DNK	320	0.82	164.06	ARG.CRO	333	0.85	140.89

	Returns				Volatilities		
	Degree	Closeness	Betweenness		Degree	Closeness	Betweenness
BRA.US	320	0.82	107.45	BEL.DNK	333	0.85	85.45
AUT.AFS	320	0.82	137.95	KOR.FRA	333	0.84	92.67
MYS.KOR	320	0.82	147.13	INA.UK	332	0.85	72.8
INA.KOR	319	0.82	127.37	AUS.CHN	332	0.85	125.86
AUS.BGR	319	0.82	134.11	BGR.PHL	332	0.84	135.5
SHI.CYP	319	0.82	93.65	COL.CYP	332	0.85	82.61
BTC.FRA	318	0.82	117.02	COL.AFS	332	0.84	113.54
ETH.TUR	318	0.82	160.23	CRO.THA	332	0.85	96.81
INA.BRA	318	0.82	162.28	IND.CHN	331	0.85	88.75
VNI.KOR	318	0.82	112.36	STI.CHN	331	0.85	100.65
AUT.MEX	318	0.82	102.35	CRO.CYP	331	0.84	88.24
THA.MEX	318	0.82	107.49	BTC.CRO	330	0.84	135.49
AFS.KOR	318	0.82	96.94	BTC.MYS	330	0.84	88.52
INA.DNK	317	0.82	66.26	INA.FRA	330	0.84	72.81
CHN.PHL	317	0.82	79.99	UK.CHN	330	0.84	87.92
JPN.KOR	316	0.81	90.35	BEL.AFS	330	0.84	72.09
KOR.FRA	316	0.81	79.26	BGR.COL	330	0.84	105.47
BRA.MEX	315	0.81	75.96	JPN.CHN	329	0.84	90.91
AUT.BGR	315	0.82	156.29	JPN.DNK	329	0.84	124.95
BEL.BGR	315	0.81	90.05	BGR.MEX	329	0.84	138.98
CRO.PHL	315	0.81	103.33	DNK.KOR	329	0.84	72.83
CYP.US	315	0.81	98.91	US.FRA	329	0.84	149.04
IND.STI	314	0.81	110.78	BTC.CYP	328	0.84	68.56
UK.TUR	314	0.81	110.58	INA.CHN	328	0.84	92.76
BEL.THA	314	0.81	99.41	INA.KOR	328	0.84	71.31
BGR.PHL	314	0.81	145.87	IND.AFS	328	0.84	87.0
SHI.MEX	314	0.81	90.18	AUS.BRA	328	0.84	122.63
VNI.MEX	313	0.81	89.46	AUS.US	328	0.84	81.08
JPN.DNK	313	0.81	69.25	BRA.AUT	328	0.84	221.02
AUS.BEL	313	0.81	106.14	BRA.KOR	328	0.84	112.07
BTC.UK	312	0.81	88.93	SHI.DNK	328	0.84	61.58
BTC.AFS	312	0.81	93.26	CHN.KOR	328	0.84	92.94
ETH.CYP	312	0.81	126.67	IND.BEL	327	0.84	117.73
JPN.TUR	312	0.81	147.87	IND.FRA	327	0.84	106.48
AUS.AUT	312	0.81	125.92	JPN.AFS	327	0.84	77.16
BGR.CRO	312	0.81	111.87	AUT.KOR	327	0.84	59.44
CRO.THA	312	0.81	72.08	BGR.CRO	327	0.83	73.17
BTC.US	311	0.81	91.2	CRO.TUR	327	0.84	60.98
STI.COL	311	0.81	82.07	DNK.FRA	327	0.84	61.35
UK.THA	311	0.81	78.07	THA.TUR	327	0.84	70.64
TUR.US	311	0.81	87.84	BTC.UK	326	0.84	96.75
ETH.INA	310	0.81	137.55	ETH.IND	326	0.83	111.12
INA.THA	310	0.8	134.98	ETH.AFS	326	0.84	66.7
BTC.ARG	309	0.81	72.48	INA.COL	326	0.84	61.87
UK.AUS	309	0.8	76.31	IND.AUS	326	0.84	100.36
BEL.COL	309	0.8	96.85	VNI.CYP	326	0.84	59.33
TUR.MEX	309	0.8	85.18	STI.SHI	326	0.83	93.41
ETH.IND	308	0.8	79.8	UK.BRA	326	0.83	74.66
INA.VNI	308	0.8	101.26	UK.FRA	326	0.84	182.12

	Returns				Volatilities		
	Degree	Closeness	Betweenness		Degree	Closeness	Betweenness
VNI.ARG	308	0.8	144.92	ARG.US	326	0.84	77.8
VNI.CHN	308	0.8	98.91	BRA.CYP	326	0.84	82.64
STI.AUT	308	0.8	67.52	SHI.AFS	326	0.84	75.16
JPN.FRA	308	0.8	83.47	CYP.THA	326	0.83	99.9
SHI.PHL	308	0.8	80.08	DNK.TUR	326	0.84	76.24
BTC.COL	307	0.8	93.91	ETH.CYP	325	0.84	99.38
ETH.ARG	307	0.8	54.2	IND.CYP	325	0.83	104.35
ARG.CHN	307	0.8	93.29	VNI.KOR	325	0.83	71.2
BRA.AUT	307	0.8	82.18	BRA.AFS	325	0.83	73.39
BTC.IND	306	0.8	72.11	AUT.PHL	325	0.83	88.72
ETH.JPN	306	0.8	133.55	CYP.DNK	325	0.84	78.46
INA.BEL	306	0.8	144.53	BTC.AFS	324	0.83	52.86
INA.CHN	306	0.8	73.98	BTC.KOR	324	0.83	69.86
STI.MEX	306	0.8	114.66	ETH.BRA	324	0.83	70.14
AUS.MEX	306	0.8	143.11	UK.BEL	324	0.83	73.6
BRA.COL	306	0.8	89.09	ARG.BGR	324	0.83	85.36
SHI.CRO	306	0.8	56.46	BEL.CHN	324	0.83	55.61
THA.AFS	306	0.8	89.99	CHN.FRA	324	0.83	113.32
BTC.INA	305	0.8	73.3	CYP.FRA	324	0.83	115.39
BTC.AUT	305	0.8	109.79	THA.US	324	0.83	87.01
JPN.THA	305	0.8	78.2	INA.MEX	322	0.83	59.63
AUT.CHN	305	0.8	214.99	IND.COL	322	0.83	68.21
BGR.THA	305	0.8	113.0	VNI.TUR	322	0.83	55.44
SHI.KOR	305	0.8	74.71	UK.THA	322	0.83	57.41
CHN.TUR	305	0.8	82.88	ARG.BEL	322	0.83	100.93
CYP.PHL	305	0.8	127.3	ARG.KOR	322	0.83	82.09
INA.AUS	304	0.8	97.25	AUS.CYP	322	0.83	195.91
IND.AUS	304	0.8	79.48	AUT.CHN	322	0.83	65.14
JPN.BGR	304	0.8	62.44	BEL.KOR	322	0.83	62.53
JPN.SHI	304	0.8	140.51	ETH.JPN	321	0.83	59.88
UK.BRA	304	0.79	90.37	INA.IND	321	0.83	68.8
ARG.TUR	304	0.79	118.26	VNI.AUT	321	0.82	53.93
BGR.AFS	304	0.8	131.59	AUT.CRO	321	0.82	53.86
THA.US	304	0.8	68.78	THA.PHL	321	0.82	65.95
BTC.PHL	303	0.79	99.27	AFS.KOR	321	0.82	73.78
JPN.AUT	303	0.79	89.82	BTC.STI	320	0.83	63.07
CHN.MYS	303	0.79	89.42	IND.BRA	320	0.83	89.41
COL.THA	303	0.79	79.96	VNI.BEL	320	0.82	58.99
JPN.UK	302	0.79	88.12	VNI.THA	320	0.83	53.17
KOR.US	302	0.79	67.25	STI.THA	320	0.82	100.09
ETH.AFS	301	0.79	80.83	COL.FRA	320	0.82	51.07
INA.COL	301	0.79	101.83	VNI.AUS	319	0.82	57.58
ARG.AUS	301	0.79	80.31	JPN.AUT	319	0.82	76.38
BRA.THA	301	0.79	79.82	ARG.CHN	319	0.82	59.5
BTC.VNI	300	0.79	71.28	BEL.TUR	319	0.82	53.08
IND.COL	300	0.79	84.04	BTC.TUR	318	0.82	44.1
VNI.STI	300	0.79	65.92	INA.PHL	318	0.82	113.98
JPN.US	300	0.79	82.89	BTC.AUS	317	0.82	55.15
UK.KOR	300	0.79	56.67	ETH.BGR	317	0.82	67.63

	Returns				Volatilities		
	Degree	**Closeness**	**Betweenness**		**Degree**	**Closeness**	**Betweenness**
ARG.CYP	300	0.79	102.63	INA.BEL	317	0.82	46.88
SHI.THA	300	0.79	123.95	AUS.BEL	317	0.82	119.29
CYP.MYS	300	0.79	81.32	COL.DNK	317	0.82	49.79
STI.MYS	299	0.79	55.81	BTC.ARG	316	0.82	44.93
UK.AUT	299	0.79	101.24	ARG.DNK	316	0.82	63.03
PHL.MEX	299	0.79	71.16	AUS.AFS	316	0.82	57.63
IND.THA	298	0.78	102.41	AUT.AFS	316	0.82	45.74
IND.MEX	298	0.79	79.87	BGR.FRA	316	0.82	50.41
JPN.AUS	298	0.79	77.0	MYS.FRA	316	0.82	53.08
JPN.AFS	298	0.79	93.28	ETH.PHL	315	0.82	48.19
AUS.FRA	297	0.78	53.51	VNI.UK	315	0.82	43.37
DNK.FRA	297	0.78	72.88	STI.MYS	315	0.82	46.47
MEX.KOR	297	0.78	103.86	AUS.KOR	315	0.82	48.94
BTC.CRO	296	0.78	76.04	AUT.FRA	315	0.82	79.7
BTC.KOR	296	0.78	79.7	CHN.TUR	315	0.82	59.92
INA.AUT	296	0.78	125.95	BTC.VNI	314	0.81	64.23
ARG.THA	296	0.78	59.86	IND.ARG	314	0.81	85.6
AUS.THA	296	0.78	58.23	AUS.MYS	314	0.81	46.83
AUT.FRA	296	0.78	125.6	MEX.FRA	314	0.82	92.9
CHN.KOR	296	0.78	57.74	ETH.VNI	313	0.81	57.08
DNK.AFS	296	0.78	50.51	INA.THA	313	0.81	61.75
ETH.CRO	295	0.78	146.13	UK.US	313	0.81	121.25
IND.KOR	295	0.78	241.19	AUS.COL	313	0.81	108.49
BTC.JPN	294	0.78	80.32	BRA.FRA	313	0.81	115.6
BTC.CYP	294	0.78	94.15	BEL.MYS	313	0.81	39.3
ETH.KOR	294	0.78	104.12	CRO.DNK	313	0.81	119.15
JPN.ARG	292	0.78	114.11	BTC.IND	312	0.81	41.64
UK.BGR	292	0.78	66.74	INA.TUR	312	0.81	48.81
AUT.US	292	0.78	129.01	VNI.MYS	312	0.81	80.57
ETH.US	291	0.77	81.68	AUT.BGR	312	0.81	47.08
UK.CRO	291	0.78	60.54	CHN.MEX	312	0.81	146.7
ARG.AUT	291	0.77	65.2	CYP.TUR	312	0.81	115.76
STI.BRA	290	0.77	56.57	BTC.JPN	311	0.81	62.37
ARG.DNK	290	0.78	59.44	BTC.BGR	311	0.81	65.81
COL.CYP	290	0.78	105.21	ARG.COL	311	0.81	50.87
CYP.THA	290	0.78	151.13	ARG.CYP	311	0.81	41.8
THA.TUR	290	0.77	94.1	SHI.TUR	311	0.81	85.49
ETH.UK	289	0.77	83.6	BTC.BEL	310	0.81	129.59
IND.MYS	289	0.77	87.56	ETH.CHN	310	0.81	46.9
STI.DNK	289	0.77	160.89	MYS.KOR	310	0.81	207.29
COL.DNK	289	0.77	42.53	MEX.KOR	310	0.81	71.26
BTC.MEX	288	0.77	61.12	CRO.PHL	309	0.8	58.67
INA.BGR	288	0.77	68.0	VNI.BGR	308	0.8	43.54
STI.CHN	288	0.77	121.35	VNI.AFS	308	0.81	116.79
DNK.MYS	288	0.77	111.85	ARG.PHL	308	0.81	81.25
VNI.DNK	287	0.77	138.32	AUT.US	308	0.81	40.37
UK.MYS	287	0.77	58.71	CRO.AFS	308	0.81	35.03
BGR.CYP	287	0.77	172.43	MYS.US	308	0.8	35.04
BGR.COL	286	0.77	79.13	STI.ARG	307	0.81	92.41

	Returns				Volatilities		
	Degree	Closeness	Betweenness		Degree	Closeness	Betweenness
COL.AFS	286	0.77	41.93	MYS.PHL	307	0.81	47.79
MYS.THA	286	0.77	54.74	BTC.DNK	306	0.8	40.82
PHL.FRA	286	0.77	59.39	VNI.SHI	306	0.8	68.07
ETH.PHL	285	0.76	58.44	AUT.TUR	306	0.8	60.35
ARG.BGR	285	0.77	98.94	JPN.US	305	0.8	52.23
STI.UK	284	0.77	61.4	COL.KOR	305	0.8	198.53
STI.THA	284	0.76	45.3	IND.VNI	304	0.8	101.49
STI.US	284	0.77	61.4	ARG.FRA	304	0.8	86.14
BEL.DNK	284	0.76	67.67	BRA.DNK	304	0.8	53.32
BGR.SHI	284	0.76	47.06	BGR.KOR	304	0.8	144.83
PHL.AFS	284	0.77	47.99	IND.US	303	0.79	112.48
PHL.KOR	284	0.76	62.36	UK.DNK	303	0.8	96.3
STI.TUR	283	0.77	110.22	SHI.THA	303	0.8	115.58
ARG.US	283	0.76	43.32	INA.BGR	301	0.79	60.42
BGR.MYS	283	0.76	90.16	IND.CRO	300	0.79	66.52
THA.FRA	282	0.76	47.34	VNI.CRO	300	0.79	89.93
BRA.DNK	281	0.76	126.1	STI.DNK	300	0.79	31.08
AUT.THA	281	0.76	79.31	AUS.BGR	300	0.79	69.94
SHI.CHN	279	0.76	126.19	STI.PHL	299	0.79	80.19
ETH.BGR	278	0.76	50.84	MEX.US	299	0.79	136.89
ETH.MYS	278	0.76	49.81	BTC.AUT	298	0.79	136.03
INA.CRO	278	0.76	134.21	ETH.KOR	298	0.79	59.68
IND.DNK	277	0.76	125.36	ETH.COL	297	0.78	38.55
BTC.SHI	276	0.76	290.29	STI.BRA	297	0.79	98.5
UK.COL	276	0.75	34.63	ARG.MYS	297	0.78	37.84
SHI.US	276	0.76	155.24	CHN.THA	296	0.78	137.64
BRA.CRO	275	0.75	83.56	JPN.FRA	295	0.79	96.4
COL.MEX	275	0.75	52.37	BEL.BGR	295	0.78	35.69
DNK.PHL	275	0.76	222.24	CHN.PHL	295	0.78	53.17
ETH.VNI	274	0.75	57.17	BEL.THA	294	0.78	128.24
VNI.JPN	274	0.75	130.0	BEL.US	293	0.78	94.7
ETH.DNK	273	0.75	40.74	BRA.SHI	292	0.78	158.42
VNI.UK	273	0.75	45.76	BGR.AFS	292	0.78	133.32
VNI.US	273	0.75	45.76	BGR.US	291	0.78	51.23
ETH.THA	272	0.75	77.18	DNK.MYS	291	0.77	48.02
STI.AUS	272	0.75	44.94	VNI.ARG	290	0.77	35.52
BGR.DNK	272	0.75	76.14	UK.SHI	290	0.77	55.08
STI.ARG	271	0.75	113.53	VNI.BRA	289	0.77	31.62
ETH.BRA	270	0.75	143.6	STI.JPN	289	0.77	44.9
INA.SHI	270	0.75	68.92	CHN.US	289	0.77	92.77
COL.MYS	270	0.75	99.91	BTC.COL	288	0.77	23.63
UK.BEL	269	0.74	67.32	PHL.TUR	288	0.77	107.12
BEL.MEX	269	0.75	78.16	ETH.AUT	287	0.77	63.75
CHN.THA	269	0.75	124.47	STI.KOR	287	0.77	115.07
INA.ARG	267	0.74	51.21	AUS.AUT	286	0.77	46.65
UK.CYP	267	0.74	94.23	AUS.SHI	285	0.77	121.34
STI.AFS	266	0.74	60.14	BGR.MYS	285	0.77	47.78
UK.ARG	266	0.74	23.76	CYP.MEX	285	0.77	170.73
CYP.DNK	264	0.74	104.33	STI.MEX	284	0.77	36.06

	Returns				Volatilities		
	Degree	Closeness	Betweenness		Degree	Closeness	Betweenness
VNI.TUR	263	0.74	86.34	BGR.CHN	284	0.77	58.8
BRA.PHL	262	0.73	30.08	COL.THA	284	0.77	43.54
ETH.CHN	260	0.73	59.81	ETH.THA	283	0.76	39.65
ETH.STI	259	0.73	42.54	UK.COL	283	0.77	144.17
STI.KOR	259	0.73	82.13	UK.BGR	282	0.76	25.77
AUT.TUR	255	0.72	21.26	UK.KOR	282	0.76	120.49
AUS.DNK	252	0.72	83.17	ETH.INA	281	0.76	37.65
MYS.AFS	251	0.72	86.61	MYS.THA	281	0.76	50.84
VNI.AFS	249	0.72	100.51	PHL.US	281	0.76	64.43
IND.SHI	248	0.72	91.27	AUT.DNK	280	0.76	84.68
BTC.BRA	247	0.71	96.39	BGR.THA	280	0.76	25.23
ETH.SHI	247	0.71	43.12	ETH.MEX	279	0.76	151.32
JPN.CHN	247	0.72	109.28	ARG.TUR	279	0.75	25.6
BTC.BGR	245	0.71	67.28	PHL.AFS	279	0.76	42.94
VNI.THA	245	0.71	39.37	ETH.FRA	278	0.76	54.26
STI.CRO	243	0.71	33.79	IND.UK	278	0.76	74.19
AFS.FRA	243	0.71	101.18	BEL.SHI	278	0.76	128.49
BRA.MYS	242	0.71	28.79	UK.CRO	277	0.75	48.6
ETH.MEX	240	0.7	57.31	AUS.DNK	277	0.76	77.66
AUS.CYP	239	0.71	124.26	AFS.US	277	0.76	114.64
CHN.CYP	237	0.7	83.94	TUR.FRA	276	0.75	27.11
COL.US	236	0.7	69.94	ARG.AUS	275	0.76	131.76
MEX.US	236	0.7	57.66	DNK.US	275	0.75	54.49
BTC.BEL	233	0.7	80.94	ETH.STI	273	0.75	80.26
BTC.THA	233	0.7	38.75	IND.THA	272	0.75	51.19
INA.CYP	233	0.7	66.28	ETH.ARG	271	0.75	22.98
IND.CYP	233	0.7	30.71	VNI.COL	271	0.75	99.92
BTC.CHN	232	0.7	63.26	ETH.SHI	269	0.75	72.7
INA.MYS	230	0.7	111.71	BTC.INA	266	0.74	18.81
MYS.US	229	0.7	80.27	UK.MYS	266	0.74	179.22
BTC.MYS	226	0.69	104.56	IND.MEX	265	0.74	158.09
TUR.KOR	225	0.69	103.5	DNK.THA	265	0.74	28.37
STI.BEL	224	0.69	68.9	JPN.UK	263	0.74	21.33
AUT.PHL	224	0.69	70.5	BGR.DNK	262	0.74	234.09
MYS.FRA	224	0.69	62.99	SHI.COL	261	0.73	40.76
CYP.KOR	222	0.69	81.56	AUS.THA	258	0.73	51.19
ARG.FRA	221	0.69	128.06	VNI.US	256	0.73	103.56
CRO.AFS	221	0.68	95.03	STI.AUS	255	0.73	108.15
CRO.FRA	221	0.68	66.21	CYP.AFS	252	0.73	71.54
VNI.BGR	217	0.68	55.03	JPN.SHI	249	0.72	188.45
BRA.CYP	214	0.68	58.29	ETH.AUS	248	0.72	148.5
BRA.KOR	214	0.68	74.47	STI.CYP	246	0.72	99.76
STI.PHL	213	0.68	79.5	ARG.THA	246	0.71	18.79
INA.UK	211	0.67	108.56	BTC.US	239	0.7	19.36
UK.PHL	211	0.68	104.01	JPN.TUR	234	0.7	76.62
INA.US	209	0.67	100.75	UK.MEX	233	0.7	46.62
BRA.BEL	209	0.67	99.87	INA.BRA	228	0.7	48.06
BTC.AUS	208	0.67	49.75	ARG.AUT	225	0.69	146.52
BTC.TUR	208	0.67	34.47	BTC.ETH	222	0.69	49.26

	Returns				Volatilities		
	Degree	Closeness	Betweenness		Degree	Closeness	Betweenness
PHL.US	208	0.67	43.31	JPN.PHL	222	0.69	80.53
CYP.FRA	207	0.67	43.52	IND.JPN	221	0.68	74.79
ARG.BRA	206	0.67	30.0	COL.US	220	0.69	82.53
SHI.DNK	204	0.66	29.5	VNI.PHL	219	0.68	69.09
VNI.CRO	201	0.66	63.12	BEL.CYP	217	0.68	116.58
AUS.MYS	201	0.66	71.68	VNI.FRA	214	0.68	118.03
IND.PHL	199	0.66	105.08	INA.JPN	213	0.68	135.14
AUT.DNK	199	0.66	71.36	UK.ARG	212	0.67	15.26
INA.TUR	197	0.66	120.46	STI.AUT	205	0.67	46.37
AUT.CYP	194	0.66	76.45	SHI.FRA	205	0.67	120.54
JPN.BRA	192	0.65	116.27	BTC.THA	204	0.67	422.77
JPN.MEX	190	0.65	62.71	MYS.AFS	203	0.66	107.22
BEL.SHI	190	0.65	93.55	JPN.ARG	202	0.66	12.22
VNI.PHL	188	0.65	95.96	SHI.CRO	202	0.67	71.2
US.FRA	187	0.65	56.09	CRO.MYS	200	0.66	25.79
ARG.BEL	185	0.65	116.51	BTC.FRA	199	0.66	51.61
BGR.MEX	183	0.64	30.08	STI.BEL	199	0.66	75.05
JPN.MYS	181	0.64	49.58	AUS.CRO	197	0.66	50.24
COL.KOR	179	0.64	53.61	IND.AUT	195	0.66	14.99
INA.MEX	176	0.64	170.26	JPN.AUS	194	0.66	37.26
VNI.COL	176	0.64	73.26	BRA.THA	194	0.65	32.21
MYS.TUR	176	0.64	39.73	KOR.US	194	0.66	68.5
COL.PHL	174	0.63	30.47	ARG.AFS	192	0.65	28.14
CRO.TUR	173	0.63	98.44	INA.CRO	186	0.65	14.95
STI.JPN	169	0.63	163.65	JPN.KOR	186	0.65	70.66
BEL.TUR	168	0.63	36.05	ETH.US	183	0.64	27.06
IND.FRA	163	0.62	22.35	BTC.MEX	180	0.64	23.64
ARG.PHL	163	0.62	126.45	SHI.MYS	180	0.64	111.87
BEL.FRA	163	0.62	47.94	UK.TUR	171	0.63	28.73
IND.AUT	162	0.62	56.19	VNI.DNK	170	0.63	53.36
COL.TUR	161	0.62	48.07	COL.MEX	170	0.63	27.42
DNK.THA	160	0.62	33.75	DNK.AFS	170	0.63	23.74
AUT.BEL	154	0.61	31.25	JPN.COL	165	0.63	47.05
BEL.US	153	0.61	26.61	INA.AUS	162	0.62	28.6
CRO.KOR	152	0.61	72.55	JPN.BEL	162	0.63	72.7
BRA.AFS	146	0.61	101.31	THA.AFS	160	0.62	24.0
AUS.KOR	144	0.6	56.88	IND.STI	156	0.62	19.44
ETH.COL	140	0.6	21.91	JPN.BGR	153	0.61	45.41
AUS.SHI	139	0.6	94.07	THA.KOR	152	0.61	37.25
BTC.STI	135	0.59	17.45	ETH.UK	151	0.61	28.6
INA.FRA	134	0.6	24.35	CRO.US	145	0.61	17.8
VNI.AUT	132	0.59	62.14	COL.TUR	143	0.6	10.24
VNI.BRA	131	0.59	46.73	AUT.CYP	139	0.6	49.06
ETH.BEL	129	0.59	16.57	IND.BGR	138	0.6	44.74
UK.MEX	120	0.58	24.61	JPN.CYP	133	0.6	43.13
AUT.SHI	114	0.58	22.95	BGR.TUR	133	0.6	49.76
JPN.PHL	112	0.58	33.86	VNI.STI	132	0.6	12.24
CYP.TUR	112	0.58	10.63	BRA.MEX	132	0.6	31.43
ARG.COL	107	0.57	6.57	PHL.KOR	131	0.59	23.62

	Returns				Volatilities		
	Degree	**Closeness**	**Betweenness**		**Degree**	**Closeness**	**Betweenness**
DNK.TUR	106	0.57	22.42	IND.SHI	130	0.59	38.85
CRO.US	103	0.57	44.97	JPN.THA	130	0.59	7.76
IND.BRA	102	0.57	19.67	BEL.PHL	129	0.59	32.98
BGR.FRA	102	0.57	19.38	SHI.CYP	129	0.59	27.77
BRA.CHN	100	0.57	49.9	CRO.FRA	128	0.59	7.62
CRO.DNK	95	0.56	14.37	UK.PHL	125	0.59	25.06
DNK.MEX	95	0.56	45.67	INA.US	123	0.59	19.53
SHI.FRA	93	0.56	56.54	BEL.COL	122	0.59	24.44
JPN.CYP	89	0.56	13.04	UK.CYP	121	0.59	9.01
AUS.PHL	88	0.56	7.47	AUT.COL	119	0.59	26.96
ARG.SHI	87	0.56	11.72	INA.ARG	117	0.58	9.38
STI.BGR	84	0.56	20.36	COL.CRO	111	0.58	7.16
MEX.FRA	83	0.56	55.33	BTC.SHI	109	0.58	15.66
INA.PHL	82	0.55	14.19	AUT.MEX	104	0.57	21.62
AUS.CHN	78	0.55	206.58	UK.AFS	102	0.57	11.6
AUS.US	78	0.55	11.28	DNK.PHL	97	0.57	12.18
VNI.SHI	74	0.55	9.85	CRO.MEX	96	0.56	13.59
STI.FRA	74	0.55	20.07	AUT.SHI	95	0.56	17.58
SHI.MYS	74	0.55	11.84	BRA.BGR	90	0.56	13.14
CHN.FRA	72	0.55	8.64	THA.FRA	89	0.56	6.58
AUS.COL	71	0.55	7.08	INA.SHI	88	0.56	28.48
BRA.BGR	71	0.54	4.28	AUT.THA	88	0.56	6.64
SHI.COL	71	0.54	45.67	BEL.FRA	88	0.56	2.88
BGR.US	69	0.54	7.02	AFS.FRA	88	0.56	7.23
JPN.COL	68	0.54	168.91	BTC.PHL	84	0.56	7.56
ARG.MEX	68	0.54	14.12	CYP.MYS	83	0.55	14.97
MYS.PHL	67	0.54	2.65	CHN.CYP	82	0.56	5.49
UK.SHI	66	0.54	5.62	JPN.MEX	81	0.55	36.35
CHN.AFS	66	0.54	10.27	JPN.CRO	78	0.55	8.57
STI.CYP	64	0.54	5.31	ETH.MYS	75	0.54	6.55
CYP.MEX	62	0.54	5.96	COL.PHL	73	0.55	25.59
BGR.KOR	60	0.54	4.64	DNK.MEX	73	0.55	33.98
AUS.TUR	54	0.53	13.36	ETH.DNK	71	0.55	3.46
AUT.KOR	54	0.53	4.07	PHL.FRA	67	0.54	7.14
CHN.US	53	0.53	124.76	BRA.COL	65	0.54	17.13
CRO.MEX	52	0.53	181.45	BTC.BRA	58	0.54	8.31
MYS.MEX	52	0.53	6.28	UK.AUT	56	0.53	4.69
IND.CRO	51	0.53	6.27	CRO.KOR	56	0.53	7.84
VNI.BEL	51	0.53	172.98	CHN.MYS	53	0.53	6.09
UK.CHN	51	0.53	24.42	BRA.PHL	52	0.53	1.39
VNI.MYS	48	0.53	3.74	AUT.BEL	50	0.53	2.75
IND.BGR	45	0.53	1.78	CHN.AFS	44	0.53	1.33
SHI.TUR	42	0.52	2.26	BEL.MEX	40	0.52	10.45
CHN.MEX	42	0.52	2.27	STI.BGR	39	0.52	1.91
AUT.COL	34	0.52	88.22	AUS.TUR	38	0.52	5.09
AFS.US	32	0.52	1.1	ARG.BRA	36	0.48	1.74
BTC.DNK	28	0.51	1.16	BRA.TUR	33	0.47	1.59
BRA.TUR	25	0.47	2.56	ETH.CRO	24	0.51	2.01
IND.JPN	21	0.51	0.17	STI.COL	24	0.47	0.23

	Returns				Volatilities		
	Degree	**Closeness**	**Betweenness**		**Degree**	**Closeness**	**Betweenness**
STI.SHI	21	0.51	4.26	STI.UK	23	0.51	0.5
AUT.MYS	21	0.51	0.21	IND.DNK	18	0.51	0.03
VNI.CYP	13	0.5	0.08	CHN.CRO	17	0.5	1.18
MEX.AFS	13	0.5	1.16	JPN.BRA	12	0.49	0
IND.VNI	12	0.41	0.08	AUS.PHL	12	0.45	0.84
VNI.AUS	12	0.5	0.16	SHI.MEX	11	0.45	0
BEL.CHN	8	0.4	5.99	TUR.AFS	11	0.5	0.18
CHN.DNK	8	0.49	0.27	BRA.MYS	10	0.49	0.2
INA.JPN	7	0.46	3.68	ETH.TUR	9	0.49	0.49
AUS.BRA	4	0.36	0	AUT.MYS	3	0.48	0.01
BEL.CRO	4	0.35	0.14	COL.MYS	1	0.4	0
{Centralization}	0.25	0.14	0.0	{Centralization}	0.24	0.14	0.0

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HS: Conceptualization, Investigation, Resources, Visualization, Data Curation, Writing—Original draft, Project administration. MB: Conceptualization, Methodology, Investigation, Software, Formal analysis, Visualization, Writing—Original draft, Writing—Review and editing, Supervision, Funding acquisition.

Declarations

Competing interests
The authors declare that they have no competing interests.

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