Information bias, asymmetric innovation shocks, and return- and volatility-connectedness in CFDs on equities and cryptocurrencies: Evidence from high-frequency inter- and intra-class asset data

Abstract

Using 5-minute high-frequency data around the clock, inclusive of trading and non-trading periods, this study is the first to comprehensively examine information bias, leverage effects of asymmetric innovation shocks, and return- and volatility-connectedness between six major developed equity markets – US, UK, France, Germany, Australia, and Japan – and seven leading cryptocurrencies – Bitcoin (BTC), Litecoin (LTC), Ethereum (ETH), Dashcoin (DSH), EOS, Basic Attention Token (BAT), and Tron (TRX) – between August 5, 2019, and January 31, 2023. We employ different GARCH- and VAR-based asymmetric and symmetric econometric tools and study all major recent market-stress periods to rigorously guide investors. Using sign bias tests, we find that the leverage effect – a stronger impact of negative innovations on the conditional volatility of returns than the positive innovations of the same size – in equities (cryptocurrencies) is manifested in the pre-Covid (post-Covid) period. Spillovers of asymmetric innovation shocks using SAARCH, TGARCH, and APARCH models and volatility- and return-connectedness using the TVP-VAR model are higher in the post-Covid period than in the pre-Covid period. Overall, several short-lived, permanent, and transformed long-lived net transmitters and receivers of return and volatility shocks are evident during the sample period, indicating their time-varying behavior. Notably, Germany and ETH (Germany, UK, and TRX) were the main receivers, whereas BAT, EOS, LTC, and BTC (Australia, BAT, and EOS) were the main transmitters of volatility shocks in the network during the full sample (post-Covid) period. Our findings hold practical importance and guide investors in making hedging decisions, exploring diversification opportunities, and optimizing crypto-equity portfolios during different economic, geopolitical, and market conditions.

Keywords: Information bias, Asymmetric innovation shocks; Spillover effect; Connectedness; High-frequency Data; Inter-class asset; Cryptocurrency; Equity.

JEL: F21; F36; G15

1. Introduction

Volatility in asset returns is not straightforward to examine, and this complex nature of volatility makes it hard to test the performance of conditional heteroscedastic models. It is often discussed in the context of market fear, indicating its crucial nature; however, despite its noteworthy importance for investors, it cannot be detected directly from financial markets. Several empirical studies have revealed that volatility reacts differently to different events, market conditions, and the level and direction of price changes (e.g., Ali, Sensoy, and Goodell, 2023; Starkey and Tsafack, 2023). Therefore, estimating such measures becomes more complex in inter-market and inter-class asset settings. Inter-market linkage is an important factor of international finance and imperative for both portfolio managers and policymakers in terms of both hedging-related decisions and portfolio optimization. Back-to-back turbulences in financial markets, e.g., the global financial crisis 2007-2009 (GFC), Euro debt crisis 2010-2013 (EDC), Coronavirus disease 2019 (henceforth, Covid-19 and Covid will be alternatively used), and the Russia-Ukraine war 2022, have specifically motivated investors and researchers to search for assets that provide notable diversification benefits (Ali et al., 2024; Ali, Sensoy, and Goodell, 2023; Izzeldin et al., 2023; Zhang, He, and Hamori, 2023; Ali et al., 2022; Ali, Jiang, and Sensoy, 2021; Tiwari et al., 2021; Huynh et al., 2020). However, relevant recent literature shows elevated connectedness among financial markets due to several reasons, including the globalization of financial markets, economic integration, market openness, and technological advancements (Akhtaruzzaman, Boubaker, and Sensoy, 2021; Corbet, Larkin, and Lucey, 2020; Conlon and McGee, 2020). Thus, it is understandable that rational investors would prefer to carefully estimate both volatility and its spillovers to adequately diversify and protect their investment. In doing so, models that are based on GARCH (e.g., Engle, 1982, 1990; Engle and Ng 1993) and VAR (e.g., Diebold and Yilmaz, 2008, 2012, 2014; Gabauer and Gupta, 2018) are considered the two most effective empirical frameworks in estimating innovation shocks, spillover effects, and connectedness among assets. Given that knowledge about the leverage effect, spillovers, and connectedness among assets is crucial for policymakers and investors, their correct estimations using multiple methods may guide investors and policymakers in minimizing the hostile effects of volatility shocks across different financial markets.

However, a careful examination of the extant literature reveals that nearly all existing studies have at least two of the four major limitations: (i) employing low-frequency (daily or weekly) data, which fails to uncover information hidden in the high-frequency intra-day data, (ii) examining only one asset-class (equities, commodities, or cryptocurrencies only), which fails to pinpoint inter-market hedging and diversification opportunities, (iii) overlooking leverage effects of asymmetric innovation shocks, which fails to provide the understanding of whether positive and negative news equally affect financial assets, or (iv) considering only trading hours or day-end closing price, which suffers from instantaneously considering the flow of information and its spillovers. Therefore, this study aims to study information bias, asymmetric innovation shocks (so-called leverage effect) and their spillovers, and return- and volatility-connectedness within and across equity and cryptocurrency markets using high-frequency intra-day data available around the clock, inclusive of trading and non-trading periods.

For example, while Panda et al. (2021) examined the effect of asymmetric innovation shocks and their spillover effects among equity markets, the study was limited to a specific region (Asia-Pacific), one asset class (equities-only), and low-frequency (daily) data. Karim et al. (2022) examined the asymmetric reaction of conventional and Islamic equities to implied volatility; however, the study was similarly limited to one asset class (equities-only) and low-frequency data. Wajdi et al. (2020) and Kumar et al. (2022), on the other hand, emphasized spillover dynamics, co-movements, and connectedness among leading cryptocurrencies; nevertheless, it was also an intra-class asset examination (cryptocurrencies-only) using low-frequency data. While several recent studies explored market co-movements in inter-class asset settings (Ali et al., 2021, 2022; Basher and Sadorsky, 2016; Batten et al., 2021; Ghorbel and Jeribi, 2021; Ha and Nham, 2022; Ji, Zhang, and Zhao, 2020; Yildirim, Esen, and Ertuğrul, 2022), none of them employed high-frequency data or information bias.

In the context of employing high-frequency data in an inter-class asset setting, the literature is confined to unidirectional analysis, i.e., considering one asset as a key variable of interest and examining its comovements with other assets by matching the corresponding trading periods. For instance, Corbet, Larkin, and Lucey (2020) employed hourly data to examine the contagion effect at the onset of the Covid-19 pandemic between the Chinese stock market and other asset classes (Gold, WTI, Bitcoin, and Dow Jones Industrial Average), where the key variable of interest was the Chinese stock market. Thus, the results were useful for investors aiming to diversify their investments in the Chinese market. It is conceivable that the use of high-frequency data is not straightforward when different assets and asset classes traded at different exchanges are concurrently under study. There are at least two possible reasons for the lack of empirical evidence in this research direction. First, equity markets in different countries and different asset classes are traded on different exchanges using different trading and non-trading hours. Second, the selection of interval (data frequency) to calculate intra-day returns is crucial due to market microstructure frictions (i.e., infrequent trading and synchronous high-frequency). In summary, the complication that arises while employing intra-day high-frequency data across different international equity markets and other asset classes is most likely to be the main reason for the lack of proliferation of research into capturing the information bias, asymmetric innovation shocks and their spillover, and connectedness between different asset classes and equity markets using high-frequency data. Thus, a comprehensive examination that addresses these concerns and provides rigorous empirical findings is the key motivation of this study. More precisely, we are interested in studying the impact of asymmetric innovation shocks, information bias, and their spillover effects and return- and volatility-connectedness (i) among major equity markets (intra-class asset analysis), (ii) among major cryptocurrencies (intra-class class analysis), and (iii) between equities and cryptocurrencies (inter-class asset analysis) using high-frequency around the clock intra-day data.

The cryptocurrency market and its popularity have grown remarkably in recent years, which has made cryptocurrencies a new asset class to invest in and induced researchers to study them. The recognition and advancement of Spot Bitcoin ETF by the US Security and Exchange Commission (SEC) in January 2024 is similarly expected to further elevate investment in this asset class.[1] Equities and cryptocurrencies are also considered among the most heavily tradable financial assets globally. Recent studies have explored the cryptocurrency market in numerous ways; for example, the efficiency of cryptocurrencies (Mnif et al., 2020), the connectedness among cryptocurrencies (Charfeddine et al., 2022; Cui and Maghyereh, 2022; Shahzad, Bouri, Kang, and Saeed, 2021), and the hedge and safe-haven role of cryptocurrencies for different asset classes (Ali, et al., 2022, 2024; Conlon et al., 2020; Corbet et al., 2020) using daily data. Given the recognition of cryptocurrencies as a new asset class (Mamun et al. 2021), a desirable asset class that has the potential to generate high returns (Ji et al., 2019), and a less-correlated market with other traditional assets (Ali et al., 2022; Kumar et al., 2022), studying them using high-frequency data will offer new insightful guidance to market participants. In doing that, we consider both major equity markets and cryptocurrencies, which account for a

[1] See https://www.sec.gov/news/statement/gensler-statement-spot-bitcoin-011023

substantially large proportion of the total market capitalization of the global equity markets and crypto assets, respectively.

This study offers contributions in a comprehensive consideration of the growing literature on asymmetric innovation shocks and their spillover effects, and connectedness across different financial markets and asset classes using high-frequency intra-day data. In doing so, we significantly extend the literature on the (i) information bias and leverage effect; sign bias tests to differentiate the effects of asymmetric innovation shocks (Karim et al., 2022; Naeem et al., 2022; Wu et al., 2022; Panda et al., 2021), (ii) spillover of shocks; transmissions of return and volatility shocks from one asset to other assets (Wang and Xiao, 2023; Zhang and Xu, 2023; Wu et al., 2022), and (iii) return- and volatility-connectedness of cryptocurrencies and equity markets in both inter- and intra-class asset settings (Ali et al., 2024, 2023; Zhang and Xu, 2023; Charfeddine et al., 2022; Katsiampa, Yarovaya, and Zięba, 2022). In addition, we contribute to the literature that examines the time-varying behavior of innovation shocks, the direction of spillovers, and net transmitters and receivers of shocks in the network and potential reasons for such changes over time (Ren et al., 2024; Ali et al., 2023, 2022, Ustaoglu, 2022; Vidal-Tomás, 2021; Conlon and McGee, 2020). Most importantly, we are among the first few to comprehensively examine asymmetric spillovers and connectedness among major equity markets from different regions where trading and non-trading periods substantially differ, and between cryptocurrencies and equity markets using round-the-clock intra-day high-frequency data; inclusive of trading and non-trading periods. Thus, we substantially extend studies that have employed high-frequency data but focused only on intra-lass assets (Conlon, Corbet, and McGee, 2024; Chan et al., 2022; Gradojevic and Tsiakas, 2021), equities from one region or one key asset in an inter-class setting (Wu et al., 2022; Corbet, Larkin, and Lucey, 2020), and trading or matching periods (Ji, Zhang, and Zhao, 2022; Zhou and Liu, 2023; Khademalomoom and Narayan, 2020; Corbet et al., 2020).

In order to mitigate the problem of non-synchronous high-frequency trade information across different financial markets that may introduce bias into the realized covariance measure of cryptocurrencies and equity indices, as discussed earlier, this study employs contracts for the difference (CFD) on equity indices and cryptocurrencies. The selected CFDs are premeditated to reflect the best approximation of the current cash price by considering the corresponding futures contract with a fair value adjustment. The benefits of using CFDs include (i) prolonged trading hours, providing synchronous trade information for each asset to accurately examine co-movements and spillovers; (ii) higher liquidity and lower barriers to entry than future contracts, given that CFDs are traded directly with brokers; (iii) infinite expiration, different from futures, CFDs do not have an expiration date; (iv) quotation transparency and uniform platforms provided by Dukascopy for both cryptocurrency and equity indices. Thus, this study does not suffer from the asynchronicity problem triggered by employing data from multiple dissimilar sources. Furthermore, a synthesis of relevant literature reveals that using 5-60-minute intervals provides the best trade-off between accuracy and market microstructure frictions (Andersen et al., 200; Kuang, 2022; Naeem et al., 2019). Therefore, we select the highest intra-day frequency suggested to calculate intra-day returns (He et al., 2023; Wu et al., 2022; Eross et al., 2019), i.e., the 5-minute interval.

The assets we consider are six major developed equity markets from three different regions (North America, Europe, and Asia-Pacific) and seven leading cryptocurrencies. The equity markets under study are US (S&P500), UK (FTSE100), Germany (DAX), France (CAC40), Australia (S&PASX200), and Japan (Nikkei225), whereas the cryptocurrencies under study are Bitcoin (BTC), Litecoin (LTC), Ether (ETH), Dashcoin (DSH), EOS, Basic Attention Token (BAT), and Tron (TRX). Given the availability of 5-minute interval data for the selected assets, our sample period spans between August 5, 2019, and January 31, 2023, covering different market states—bull, bear, turmoil, rebound, stable, and super-bull for both equities and cryptocurrencies, indicating the wide-ranging significance of this work.

We employ different econometric tools and study all major recent market-stress periods for both asset classes studied, i.e., Bitcoin and other cryptocurrencies flash crashes, Covid-19, and Russia-Ukraine war periods, to guide investors and policymakers. Using sign bias tests, we find that the leverage effect in equities is manifested only in the pre-Covid period, whereas in cryptocurrencies it is only manifested only in the post-Covid period. It indicates that equities (cryptocurrencies) in the pre-Covid (post-Covid) period confronted a stronger impact of negative innovations on the conditional volatility of returns than the positive innovations of the same size. Further testing indicates that both (i) spillovers of random innovation shocks using SAARCH, TGARCH, and APARCH models and (ii) volatility and return connectedness using the TVP-VAR approach are higher in the post-Covid period than the pre-Covid period. Our results indicate several short-lived, permanent, and transformed long-lived net transmitters and receivers of return and volatility. Notably, Germany and ETH (Germany, UK, and TRX) were the main receivers, whereas BAT, EOS, LTC, and BTC (Australia, BAT, and EOS) were the main transmitters of volatility shocks in the network during the full sample (post-Covid) period. The findings of this study hold practical importance regarding hedging-related decisions, diversification opportunities, and portfolio optimization strategies during different market, economic, and geopolitical conditions. Thus, it may help international investors, fund managers, and researchers to understand asymmetries in innovation shocks, their spillovers, and return- and volatility-connectedness across different markets and asset classes.

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

2. Data and Sources

Our data consist of six major equity indices, including S&P500 (US), FTSE100 (UK), CAC40 (France), DAX (Germany), S&PASX200 (Australia), and Nikkei225 (Japan) and seven cryptocurrencies, including BTC, LTC, ETH, DSH, EOS, BAT, and TRX. The selected equity indices represent major developed markets from three different regions — North America, Europe, and Asia-Pacific — and account for a substantially large proportion of the total global market capitalization of the equity market. The selected cryptocurrencies similarly account for a substantially large proportion of the cryptocurrency market (capitalization) and are among the highly traded cryptocurrencies.

Given that cryptocurrencies and international equities are traded on a variety of exchanges during different trading hours, the problem of nontrading time and non-synchronous high-frequency are the major concerns. For example, regarding standard times and trading hours, on average there is a 5-to-7-hour difference between the US and selected European countries, a 6-to-8-hour difference between the selected European and Asia-Pacific countries, and more than 10-hour difference between the US and Asia-Pacific countries. Most likely, it is one of the major reasons that studies employing high-frequency data often consider only one asset class or more than one asset class where matching trading hours is possible. While the former group of studies does not explore inter-class asset dynamics, the latter group of studies does not concurrently examine inter-market dynamics and flow of information. In summary, synchronous trade information is critical when using high-frequency data to analyze intraday spillover effects and connectedness. In doing that, we use the contracts for the difference (CFD) on equities and cryptocurrencies published by the Dukascopy Swiss Banking Group. These index-tracking CFDs are designed to reflect the best estimate of the market's current cash price by using the corresponding futures contract with a fair value adjustment. Cui and Maghyereh (2022), Kuang (2022), and Le et al. (2021), among others, have recently used Dukascopy (www.dukascopy.com) to obtain high-frequency data.

The benefits of using CFDs include (i) prolonged trading hours, providing synchronous trade information for each asset to accurately examine co-movements and spillovers; (ii) higher liquidity and lower barriers to entry than future contracts, given that CFDs are traded directly with brokers; (iii) infinite expiration, different from futures, CFDs do not have an expiration date; (iv) quotation transparency and uniform platforms provided by Dukascopy for both cryptocurrency and equity indices. Thus, this study avoids the asynchronicity problem triggered by employing data from multiple dissimilar sources. While high-frequency data provides a more valuable and accurate estimation, determining the suitable interval is also essential. A synthesis of relevant literature reveals that using 5-60-minute intervals provides the best trade-off between accuracy and market microstructure frictions (Anersen et al., 2001, 2003; Kuang, 2022; Naeem et al., 2019). Therefore, we choose the 5-minute interval data for all selected assets, which is the highest frequency among the suggested intervals and used by other recent studies (e.g., Cui and Maghyereh, 2022; Hasan et al., 2021; Wu et al., 2022; Yarovaya and Zięba, 2022). The data is available around the clock from 00:00 a.m. (the first available quote for an asset during the trading sessions each day) to 11:55 p.m. (the last available quote for an asset during the trading sessions each day) Greenwich Mean Time (GMT). Our data span between August 5, 2019, and January 31, 2023, representing 363,024 observations for each asset studied. The starting date of the sample is based on the availability of the 5-minute high-frequency data on Dukascopy.com. The study period is then divided into two main subperiods: (i) the pre-Covid period, which starts from the first day of the sample period (August 5, 2019) and ends before the first infected case reported to World Health Organization (WHO) (December 31, 2019), and (ii) the post-Covid period, which starts from the day when first infected case was reported to WHO (January 1, 2020) and ends on the last day of the sample period (January 31, 2023).

To deeply understand the tenacity of our results during the Covid period, which also includes the Russia-Ukraine war period and Bitcoin flash crash in 2021, we divide the post-Covid period into two phases (sub-periods): (i) the first phase of Covid-19, when equities around the world experienced catastrophic drops in prices, whereas cryptocurrencies experienced tremendous advances in prices (January 1, 2020-December 31, 2020) (Ülkü et al., 2023); (ii) the second phase of the post-Covid period, when both cryptocurrencies and equities witnessed new peaks followed by some drops in prices, including the Russia-Ukraine war period (January 01, 2021-January 31, 2023). Thus, this study employs comprehensive high-frequency data with 4,777,344 observations [13 (assets) × 1245 (days)×288 (prices/day)]. All selected cryptocurrencies and equity indices are priced in the US dollar, and the first logarithmic price difference in two consecutive 5-minute intervals is used to calculate the returns:

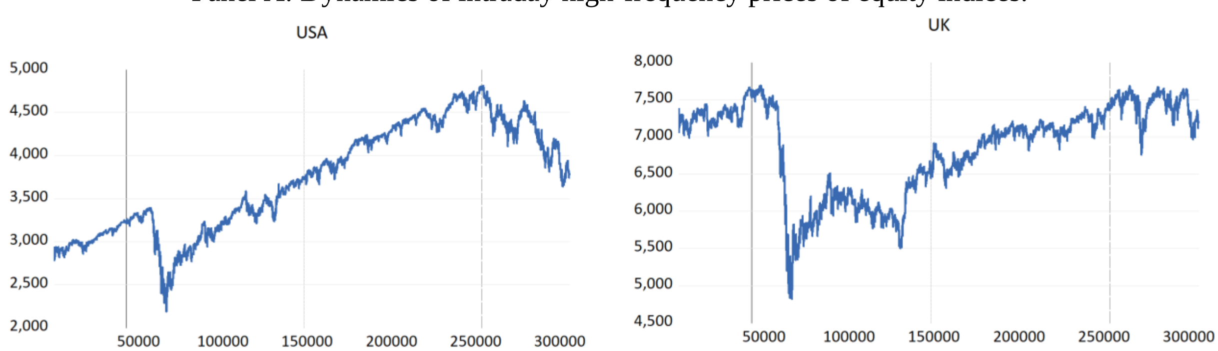
$$r_{t,i} = \left(\ln\left(p_{t,i}\right) - \ln\left(p_{t,i-1}\right)\right) \times 100 \tag{1}$$

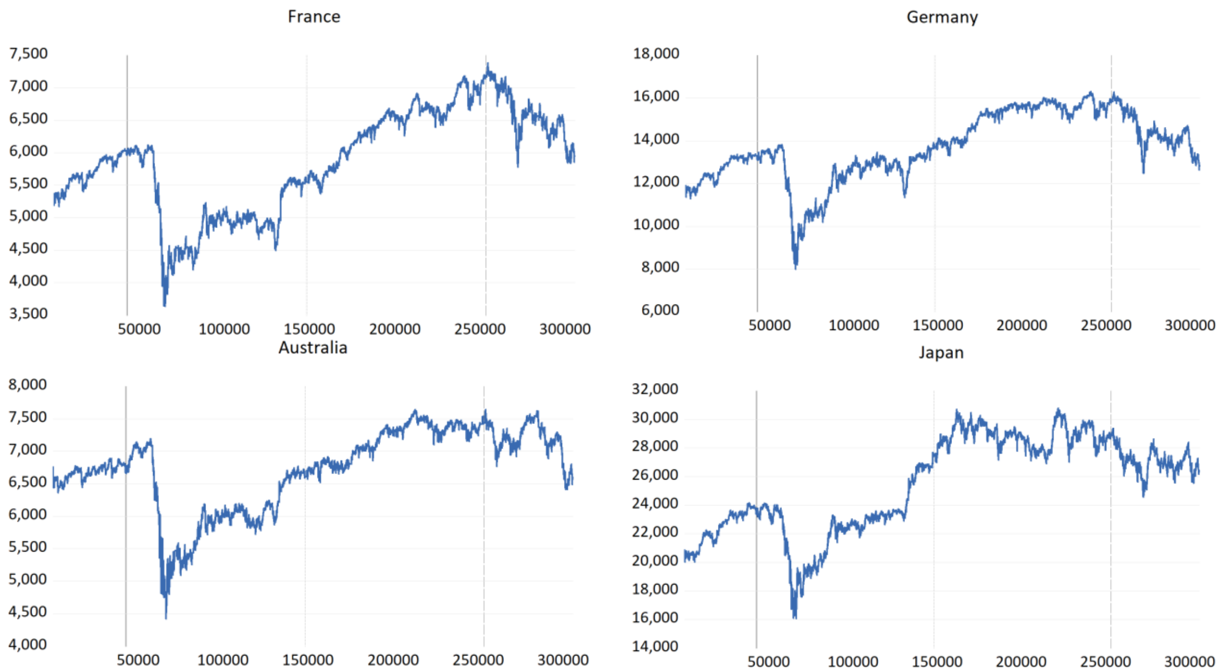
where $r_{t,i}$ denotes the intraday returns on day t for the i^{th} intraday price of the selected asset as the natural logarithmic difference between two continuous price observations ($p_{t,i}$ and $p_{t,i}$) within a trading day.

Fig.1 illustrates the dynamics of 5-minute high-frequency prices. The area (i) before the first vertical line (from the left side) represents the pre-Covid period, (ii) between the first (solid) and second (dotted) vertical lines represents the first year of the Covid period (2020), (iii) between the second (dotted) and third (long-dashed) vertical lines represents the second year of the Covid period (2021), and (iv) after the third (long-dashed) vertical line represents the latest period (2022) that includes the Russia-Ukraine war period. Panel A of Fig. 1 shows that the price pattern of the US and Australian equity indices is relatively akin: a big drop in the prices at the onset of Covid-19 in March 2020, a steady recovery followed by solid growth from late 2020 to 2021, and a consistent drop in the prices with few small retrievals in 2022. The equity indices of the UK, France, and Germany likewise exhibit analogous price evolutions: all of them had a significant drop at the onset of the Covid-19 pandemic, followed by two other price dips in the last quarter of 2020 and the first quarter of 2022. The price evolution of the Japanese equity index was distinctive from the other equity indices, in line with the findings of previous studies examining co-movements among international equity markets (Ali, Sensoy, and Goodell, 2023).

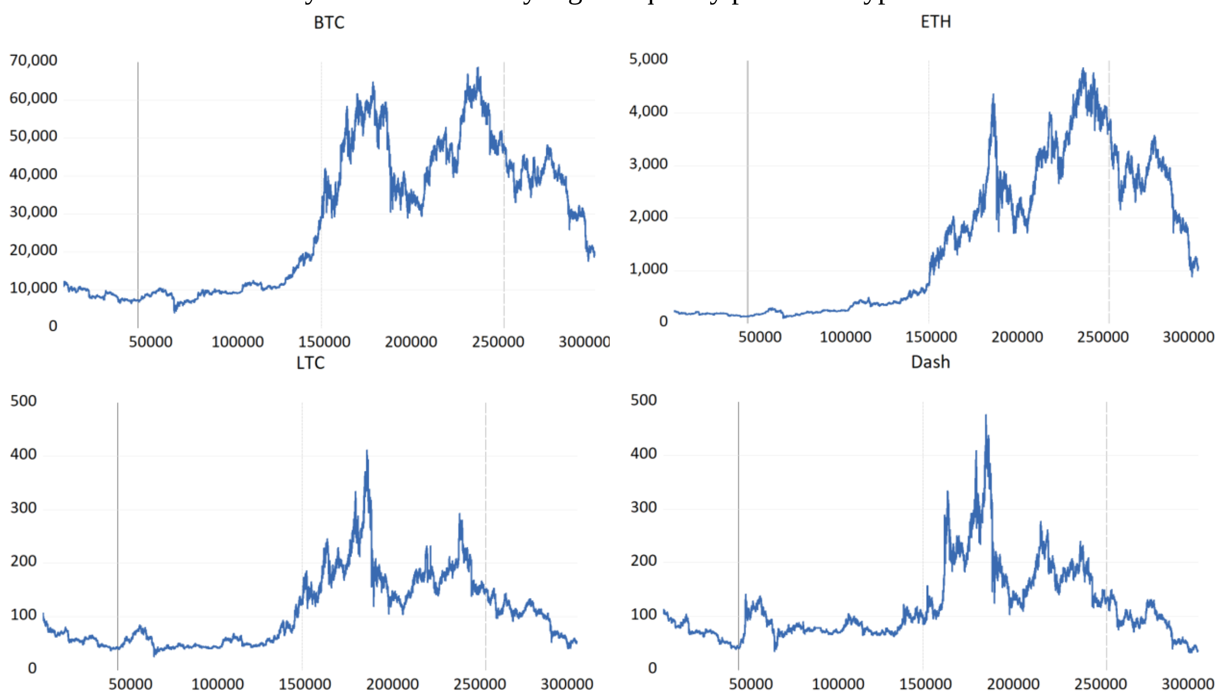
Panel B of Fig. 1 shows that BAT, BTC, and ETH reached their all-time peak two times during the sample period, first in April 2021 and second in November 2021, whereas LTC, EOS, and DSH reached their all-time peak in November 2021 during the sample period. TRX, on the other hand, reached its all-time peaks two times in April 2021, and no significant drop or rise after that. Our results contrast with studies claiming cryptocurrencies are a homogenous asset class (e.g., Corbet et al., 2018). Interestingly, we find that equity indices, specifically European equities, are more integrated than cryptocurrencies in line with the findings of Ali et al. (2022) and Ali, Sensoy, and Goodell (2023). Thus, the assets under study present an interesting sample of equities and cryptocurrencies with diverse price progressions.

Panel A: Dynamics of intraday high-frequency prices of equity indices.





Panel B: Dynamics of intraday high-frequency prices of cryptocurrencies.



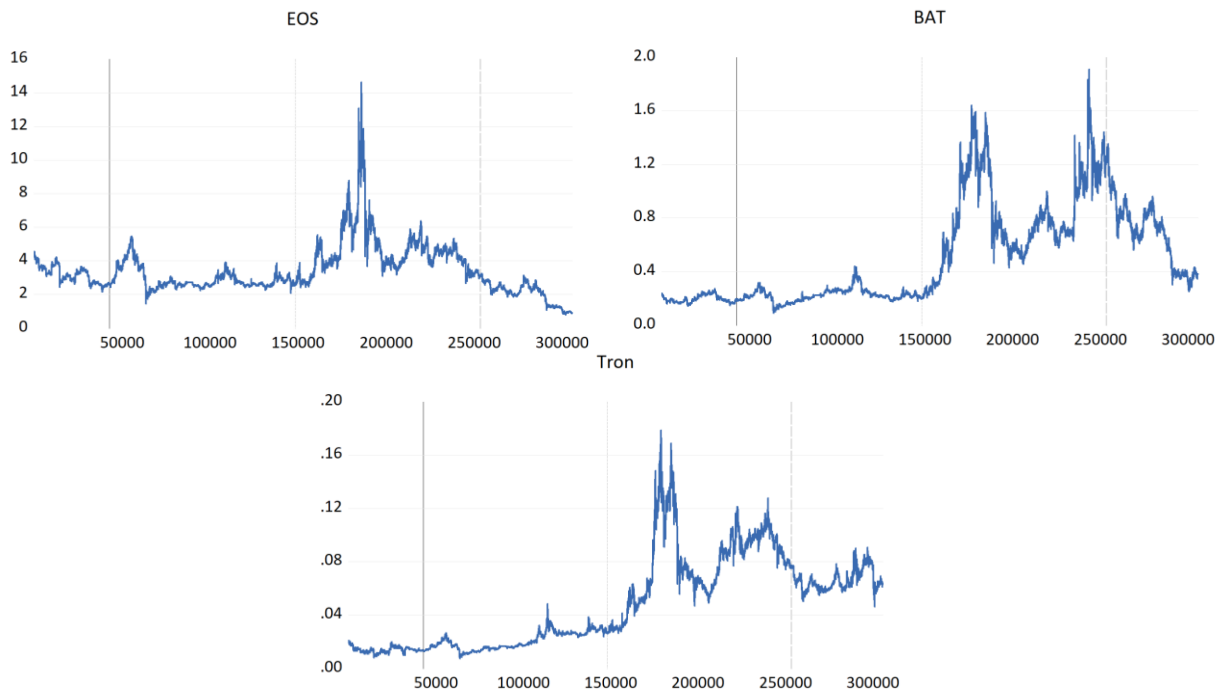


Fig. 1. Dynamics of 5-minute high-frequency intraday prices.

Notes: The range (i) before the first (from left) vertical line is the pre-Covid period, (ii) between the first (solid) and the second (dotted) vertical lines is the first year of Covid period (2020), (iii) between the second (dotted) and the third (long-dashed) vertical lines is the second year of the Covid period (2021), and (iv) after the third (long-dashed) vertical line is the latest period (2022) that includes the Russia-Ukraine war period. The sample period spans between August 5, 2019, and January 31, 2023, representing 358,560 observations for each asset. The data is at a 5-minute frequency and around the clock from 00:00:00 (a.m.) to 11:55:00 (p.m.) Greenwich Mean Time. The price data is obtained from Dukascopy (www.dukascopy.com), all selected cryptocurrencies and equity indices are priced in US$. The x-axis indicates the number of observations, whereas the y-axis indicates the price.

3. Empirical Framework

3.1. Asymmetric innovation, conditional volatility, and the sign bias test

Our empirical framework begins with estimating the asymmetric innovation and conditional volatility, followed by leverage effects and the sign bias test. Following relevant literature (Mandelbort, 1963), volatility clustering is defined as large (small) changes followed by large (small) changes, irrespective of the sign (positive or negative). Engle (1982) developed autoregressive conditional heteroskedasticity (ARCH) models that capture the pattern of volatility, where the AR framework to estimate returns can be defined as follows:

$$Y_t = \alpha + \beta Y_{t-1} + \varepsilon_t, \text{ for } t = 1, 2, 3, \dots\dots\ n \qquad (2)$$

where Y_t is the return distribution, β is the slope between the current (Y_t) and lagged (Y_{t-1}) returns. ε_t is, therefore, the innovation process: $\varepsilon_t \approx (0, \sigma^2)$.

Further, random innovation or news shock in this study is considered as $\varepsilon_t = \eta_t \sqrt{h_t}$ (Engle, 1982). While h_t is the conditional volatility, $\eta_t \mid I_{t-1}$ is a standard normal distribution conditional on the past information set (I_{t-1}). The conditional volatility is consequently derived as follows:

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 \qquad (3)$$

where $\varepsilon_t \mid I_{t-1} \approx N(0, h_t)$, $E(\eta, \varepsilon_t) = 0$, and $\varepsilon_t \mid I_{t-1} \approx N(0, h_t)$, indicating that the distribution of ε_t does not follow a constant variance (σ^2) due to heteroskedasticity and a time-dependent variance (h_t) with conditional distribution ($\varepsilon_t \mid I_{t-1}$). Following that, the ARCH model captures conditional volatility as mentioned in Eq. (3), where ω is the mean effect (or intercept) and h_t is the heterogeneity of the return distribution estimated by its conditional variance at time *t* depending on the random innovation at time $t-1$. Thus, the ARCH (1) model can be extended to a higher order as follows:

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 \tag{4}$$

While ARCH models have numerous advantages and useful applications, assuming a homogenous impact of positive and negative news on return volatility is a major limitation of these models: given that ARCH models assume squared-lagged errors. Black (1976) sheds light on this limitation and shows that the volatility of current and future returns is negatively correlated. Therefore, it is evident that negative news has a stronger/larger impact on conditional volatility than positive news, dubbed as the leverage effect. The leverage effect triumphs when arrivals of negative news cause comparatively higher volatility than arrivals of positive news in the market. Lately, Engle and Ng (1993) proposed the sign bias test to comprehend the presence of the leverage effect:

$$\widehat{\varepsilon_t^2} = a_0 + \beta_1 \widehat{\gamma_{t-1}} + \mu_t \tag{5}$$

where β_1 indicates the presence of asymmetric effects in conditional variance. The Engle and Ng (1993) model suggests incorporating all sign bias tests in a single regression model, where γ_{t-1} contains all three types of sign bias tests in a single regression model. In this model, $\gamma_{t-1} = S_{t-1}^-$, $\gamma_{t-1} = S_{t-1}^- \varepsilon_{t-1}$, and $\gamma_{t-1} = S_{t-1}^+ \varepsilon_{t-1}$ indicate the sign bias test (SBT), the negative size bias test (NSBT), and the positive size bias test (PSBT), respectively. The statistical significance of the three estimated coefficients in this process is jointly determined by employing a Lagrange Multiplier (LM) test, which follows an asymptotic χ^2 distribution (see Engle and Ng, 1993).

3.2. Asymmetric GARCH models

The treatment of various significantly diverse episodes (i.e., market crashes and advances) in existing data provides the opportunity and indicates the need to unfold any asymmetric behavior that is important to study. It is well documented that the superiority of one particular asymmetric GARCH model over other models is not straightforward and therefore cannot be directly determined. We therefore begin our asymmetric GARCH analysis using the simple asymmetric ARCH model (SAARCH), introduced by Engle (1990). It can be written as follows:

$$h_t = \omega + a\varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1} + \beta h_{t-1} \tag{6}$$

where γ estimates the leverage effect and α and β are the coefficients for the ARCH and GARCH effects, respectively.

Zakoian (1994) further extended this model and developed the threshold GARCH (TGARCH) model. Unlike Engle's (1990) squared innovations, the TGARCH model captures absolute innovations. The TGARCH model can be written as follows:

$$h_t = \omega + a|\varepsilon_{t-1}| + \gamma|\varepsilon_{t-1}|\, I(\varepsilon_{t-1} > 0) + \beta h_{t-1} \tag{7}$$

where α estimates the symmetric impact of innovation caused by news irrespective of its sign, γ indicates the leverage effect and considers only positive news.

Ding et al. (1993) similarly extended the asymmetric GARCH models by introducing the asymmetric power ARCH (APARCH) model. In the APARCH model, used in this study, the power of the model in fact describes whether we are analyzing the conditional variance or the standard deviation. The APARCH model can be written as follows:

$$h_t^{\delta} = \omega + \sum_{j=1}^{q} a_j \left(|\varepsilon_{t-1}| + \gamma_j \varepsilon_{t-1}\right)^{\delta} + \sum_{i=1}^{p} \beta_i \left(h_{t-i}\right)^{\delta} \tag{8}$$

The model assumes that $\omega > 0$, $\alpha_j \geq 0$, and $\beta_i \geq 0$, where $j = 1,2, \ldots . . q$ and $i = 1, 2, \ldots . p$. Particularly, when αj= 0 and βi= 0, then h_t^{δ} is equal to ω. However, since we assume the variance is positive, ω should be greater than zero (ω >0). Similarly, the model presented in Eq. 9 assumes that $0 \leq \sum_{j=1}^{q} a_j + \sum_{i=1}^{p} \beta i \geq 1$. Finally, the power coefficient "δ" is also assumed to be greater than zero (δ > 0).

Thus far, the models we present capture asymmetric innovation, conditional volatility, leverage effects, sign bias tests, and different asymmetric GARCH modeling. While these models are useful and used by recent studies (e.g., Panda et al., 2021; Karim et al., 2022), they do not explain the volatility spillover among assets under study. Therefore, we also consider modeling the volatility spillover effect in the following section of the paper.

3.3. Volatility spillovers using the BEKK-MGARCH model

To capture volatility spillovers, this study considers multivariate GARCH (MGARCH) models, which are superior to univariate GARCH models (Yang, 2006). Our methodology follows the guidelines of Bae et al. (2003), Katsiampa, Corbet, and Lucey (2019), Panda et al. (2021), and Arfaoui, Yousaf, and Jareño (2023), who have similarly employed MGARCH models to estimate the volatility and its transmission in a multivariate framework to examine contagion effects spillover effects. The vector autoregression (VAR) model, which is based on an implicit assumption that the variables under study are endogenous by nature, can be presented as follows:

$$Y_t = V + B_1 Y_{t-1} + B_2 Y_{t-2} + \cdots + B_p Y_{t-p} + \varepsilon_t \tag{9}$$

where random innovation is estimated as $\varepsilon_t = H_t^{1/2}(\theta) Z_t$, subject to $E(\varepsilon_t) = 0$ and $E(\varepsilon_t \varepsilon_t{}') = H_t$. The random error distribution follows a multivariate normal distribution with a mean equal to a null vector and a variance-covariance equal to H_t. Note that the key role of employing MGARCH models is to model H_t.

While the VAR process is used to capture the return, the Baba-Engle-Kraft-Kroner (BEKK) MGARCH model is used to capture the volatility spillovers (Baba et al., 1991; Engle and Kroner, 1995). The two most well-known and well-applied types of MGARCH models are the BEKK model and the Dynamic Conditional Correlation (DCC) model of Engle (2002). Given that our aim is to forecast conditional covariances, not conditional correlations, we employ the BEEK-MGARCH model (Katsiampa, Yarovaya, and Zięba, 2022; Arfaoui et al., 2023). In view of the multivariate BEKK (p,q) modeling of conditional variance proposed by Baba et al. (1991), the conditional variance of the multivariate GARCH model can be written as follows:

$$H_t = C'C + \sum\nolimits_{i=1}^{p} A_i' \varepsilon_{t-i} \varepsilon_{t-i}' \, A_i + \sum\nolimits_{j=1}^{q} B_j' H_{t-i} \, B_j \tag{10}$$

where C is an upper triangular matrix with a positive principal diagonal (Bekiros, 2014), and A_i and B_j are the coefficient matrices. The diagonal (off-diagonal) elements of matrices A and B capture the impact of the asset's own (cross-market) past shocks and past volatility (Li and Majerowska, 2008), respectively. The outlined GARCH-BEKK model satisfies a positive semi-definiteness of H_t without forcing any conditions; thus, it can be interpreted as a restricted version of the diagonal VECH model introduced by Bollerslev et al. (1988).

3.4. Modelling the connectedness framework

Accurately measuring and examining the relative intensity of shocks and their spillovers are crucial for investors and policymakers, given that they not only help in identifying changes that are arising from shocks in different financial and economic variables but also guide in effectively fine-tuning strategies to cope with such changes and their corresponding adverse impacts on investments/portfolios. The connectedness framework of Diebold and Yilmaz (2008, 2012, 2014) is widely used and considered one of the most suitable frameworks to capture the magnitude of spillover from variable '*i*' to variable '*j*'. Lately, Antonakakis, Chatziantoniou, and Gabauer (2020) introduced the TVP-VAR method that extended Diebold-Yilmaz's framework. The benefits of employing the TVP-VAR model include (i) quick adjustment of parameters to shocks and events and (ii) insensitivity to the selection of a rolling window. The former adjusts the time-varying nature of the relationships among variables, whereas the latter helps avoid the concerns of arbitrariness in window selection and loss of observations. These features are particularly important while studying volatile assets like cryptocurrencies and turmoil (bubble) periods like the Covid-19 pandemic, the Russia-Ukraine conflict, and other geopolitical and financial market stress periods (cryptocurrency bubble/boom episodes). Thus, we employ the TVP-VAR model to capture total directional connectedness, pairwise directional connectedness, net connectedness, and a total connectedness index. The TVP-VAR model can be specified as follows:

$$y_t = C_t z_{t-1} + \mu_t \mu_t | \rho_{t-1} \sim N(0, S_t) \tag{11}$$

$$vec(C_t) = vec(C_{t-1}) + v_t v_t | \rho_{t-1} \sim N(0, R_t) \tag{12}$$

where C_t denotes the coefficient matrix, ρ_{t-1} indicates the information set at time $t-1$, and z_{t-1} is a $np \times 1$ vector that includes p lags of y_t, where the lag length of p is determined by the Bayesian information criterion. v_t and $\mu_t$represent the error term with n×1 and $np \times 1$ dimensional vectors. Finally, S_t and R_t are the time-varying variance-covariance matrices representing the $n \times n$ and $n^2 p \times n^2 p$ dimensional matrix.

The variance-covariance matrices in this condition vary via the Kalman filter estimation procedure with forgetting factors (Koop and Korobilis, 2014). Bayesian criterion is used to initiate the Kalman filter, whereas H-step ahead generalized forecast error variance decomposition (GFEVD) is used independent of the variable ordering (Koop, Pesaran, and Potter, 1996). In doing so, we first transform TVP-VAR to a vector moving average (VMA) based on the Wald theorem as follows:

$$y_t = \Sigma_{i=1}^{p} C_{it} z_{t-i} + \mu_t = \Sigma_{j=0}^{\infty} A_{jt} \mu_{t-j} \tag{13}$$

where A_{jt} is a $n \times n$ dimensional matrix.

The GFEVD ($\emptyset_{ij,t}(H)$) is presented in the following formula:

$$\emptyset_{ij,t}(H) = \frac{S_{ii,t}^{-1} \sum_{t=1}^{H-1} \left(l_i' A_t S_t l_j\right)^2}{\sum_{j=1}^{k} \sum_{t=1}^{H-1} \left(l_i A_t S_t A_t' l_i\right)} \tag{14}$$

where l_j corresponds to a vector with i^{th} element equaling 1 and other elements equaling zero. Given that $\emptyset_{ij,t}(H)$ may not tally up to unity for a particular variable *i*, we normalize it using the following formula (Antonakakis et al., 2020; Diebold and Yilmaz, 2012, 2014):

$$\widetilde{\emptyset}_{ij,t}(H) = \frac{\emptyset_{ij,t}(H)}{\Sigma_{j=1}^{n} \emptyset_{ij,t}(H)} \tag{15}$$

where $\widetilde{\emptyset}_{ij,t}(H)$ indicates the percentage of the forecast error variance in variable *i* that is explained by variable *j*. We use GFEVD to calculate several connectedness measures including total directional connectedness, pairwise directional connectedness, net total directional connectedness, directional connectedness of variable *i* to all other variables, and directional connectedness of all variables to variable *i*.

Total directional connectedness with others (TO): This index indicates the shocks that asset *i* transmits to all other assets under study *j*, defined as follows:

$$\mathrm{TO}_{i\to \mathrm{j,t}}(\mathrm{H}) = \frac{\Sigma_{j=1, i\neq j}^{N} \widetilde{\emptyset}_{ji,t}(H)}{\sum_{i,j=1}^{N} \widetilde{\emptyset}_{ji,t}(H)} \times 100 \tag{16}$$

Total directional connectedness from others (FROM): This index indicates the shocks that asset *i* receives from all other markets *j*, defined as follows:

$$\mathrm{FROM}_{j\to \mathrm{i,t}}(\mathrm{H}) = \frac{\Sigma_{j=1, i\neq j}^{N} \widetilde{\emptyset}_{ij,t}(H)}{\Sigma_{i,j=1}^{N} \widetilde{\emptyset}_{ij,t}(H)} \times 100 \tag{17}$$

Note that while examining pairwise directional volatility spillovers, we accordingly correct Eqs. (16) and (17); that is, instead of using the off-diagonal sum of rows (or columns), we use the pairwise directional spillover from an asset *j* (*i*) to another *i* (*j*).

Net total directional connectedness: This index indicates the difference, “NET”, between the two spillover indices described in Eqs. (16-17), i.e., TO and FROM. Mathematically, it can be defined as follows:

$$\mathrm{NET}_{\mathrm{ij,t}}(\mathrm{H}) = \mathrm{TO}_{i\rightarrow\mathrm{j,t}}(\mathrm{H}) - \mathrm{FROM}_{j\rightarrow\mathrm{i,t}}(\mathrm{H}) \tag{18}$$

This index indicates the net influence of each asset (*i*) on the remaining assets under consideration in the model. If the net connectedness index is positive, asset *i* is considered a net transmitter of shocks (volatility or return). Likewise, if the net volatility spillover is negative, asset *i* is considered a net receiver of shocks (volatility or return). Similar to "TO' and "FROM", we can calculate pairwise 'NET' connectedness between any two variables studied.

Total connectedness index (TCI): This index indicates how a shock in one asset spills over to other assets, market interconnectedness, defined as follows:

$$\mathrm{TCI}_{t}\,(H) = \frac{\sum_{i,j=1,i\neq j}^{N}\ \widetilde{\emptyset}_{ij,t}(H)}{\sum_{i,j=1}^{N}\ \widetilde{\emptyset}_{ij,t}(H)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{N}\ \widetilde{\emptyset}_{ij,t}(H)}{N} \times 100 \tag{19}$$

Our connectedness measures are in line with several seminal studies published in leading finance and economics journals; for example, Liang, Goodell, and Li (2024), Lu, Huang, and Ma (2024), Naeem et al. (2024), Kanas, Molyneux, and Zervopoulos (2023), Sun et al. (2023).

4. Results and Discussion

4.1. Preliminary findings

Table 1 presents descriptive statistics in Panel A and realized volatility (RV) in Panel B: $RV_t = \sum_{i=1}^{T} r_{t,i}^2$ where $r_{t,i}$ denotes intraday returns and T denotes the number of intraday logarithmic returns (i =1,2,3, …, T). The mean return of all the equity indices except Australia and the UK is positive during the sample period. The US market offers the highest return followed by Japan. Among cryptocurrencies, LTC, DSH, and EOS provide negative mean returns, whereas BTC, ETH, TRX, and BAT provide positive mean returns during the sample period. While ETH and TRX provide the highest mean return, EOS and DSH provide the lowest mean return. A comparison between the pre- and post-Covid periods shows that mean returns of all the equity indices are comparatively higher in the pre-Covid period than the post-Covid period, except in Australia. The standard deviation values are similarly low during the pre-Covid period, indicating lower volatility during this period compared to the post-Covid period. On the contrary, both mean return and standard deviation values of cryptocurrencies are higher during the post-Covid period than the pre-Covid period, except TRX. Although the mean return of TRX is substantially higher during the post-Covid period, similar to other cryptocurrencies, the standard deviation of TRX is surprisingly low. It indicates that TRX not only yielded higher but also consistent returns, which could specifically be beneficial for investors searching for assets with higher Sharpe ratios.

Regarding realized volatility among equities, France and Germany have the highest mean values, whereas France and Australia have the highest standard deviation values of RV during the full sample period. This finding indicates that the volatility in German equities was persistently high, Australian equities was unsteady, and French equities was both unsteady and high on average. Among cryptocurrencies, TRX has the highest mean RV followed by LTC and DSH, whereas TRX has the highest standard deviation of RV followed by DSH. While comparing the realized volatility between pre- and post-Covid periods, we find that it is comparatively higher during the post-Covid period for most of the cryptocurrencies and equities. The realized volatility of LTC is comparable in both sub-periods, whereas it is lower for ETH and TRX in the post-Covid period. It indicates that the realized volatility of LTC remained very stable throughout the sample period, whereas ETH and TRX were more stable during the post-Covid period than the pre-Covid period.

Table 2 presents the results of stationarity tests; all return series across all the subperiods under study are stationary. The null hypothesis of the unit root is rejected at the 1% level of significance by both Augmented Dickey-Fuller (ADF) and Phillips–Perron (PP) tests, indicating that the log returns estimated using 5-minute price data are mean reverting and satisfy the conditions of models applied in this study.

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

	Full sample				**Pre-Covid-19**				**Post-covid-19**			
	Mean	St. Dev.	Kurt.	Skew.	Mean	St. Dev.	Kurt.	Skew.	Mean	St. Dev.	Kurt.	Skew.
Panel A: Daily returns using 5-minute high-frequency returns												
US	0.024	1.23	15.07	-0.33	0.067	0.82	11.98	-1.65	0.017	1.28	14.31	-0.25
UK	-0.002	1.14	17.13	-1.25	0.014	0.75	8.53	-1.69	-0.005	1.20	16.32	-1.20
FR	0.010	1.38	24.64	-2.04	0.071	0.72	5.36	-1.36	0.000	1.46	22.55	-1.96
GER	0.007	1.32	16.91	-0.84	0.065	0.82	8.20	-1.54	-0.002	1.39	15.91	-0.78
AUS	-0.002	1.16	23.77	-0.03	-0.009	0.67	14.18	-2.60	-0.001	1.22	22.11	0.04
JP	0.022	1.17	13.75	-0.57	0.079	0.78	5.69	-0.74	0.013	1.22	13.15	-0.54
BTC	0.057	4.03	22.63	-1.75	-0.290	3.18	5.12	0.69	0.113	4.15	23.20	-1.93
LTC	-0.053	5.56	10.37	-1.23	-0.550	4.14	4.14	-0.53	0.028	5.76	10.30	-1.27
ETH	0.149	5.22	17.97	-1.63	-0.369	3.79	4.71	-0.60	0.233	5.42	17.89	-1.69
DSH	-0.103	6.44	10.97	-0.16	-0.635	3.68	4.89	-0.73	-0.016	6.79	10.12	-0.17
EOS	-0.144	6.25	14.06	-0.88	-0.329	4.59	11.59	-1.00	-0.114	6.48	13.60	-0.87
TRX	0.109	6.03	11.94	-0.74	-0.273	7.04	6.13	0.43	0.172	5.85	13.68	-1.05
BAT	0.048	6.56	10.53	-0.38	-0.170	4.72	1.35	-0.29	0.083	6.81	10.37	-0.39
Panel B: Realized volatility using 5-minute high-frequency returns.												
US	0.016	0.05	86.59	8.49	0.005	0.01	6.76	2.49	0.018	0.06	74.62	7.90
UK	0.014	0.05	228.17	13.10	0.005	0.00	4.12	1.71	0.016	0.06	197.16	12.19
FR	0.018	0.07	229.75	13.15	0.005	0.01	7.34	2.36	0.020	0.08	198.55	12.23
GER	0.018	0.05	84.13	8.31	0.006	0.01	7.61	2.41	0.020	0.06	72.58	7.73
AUS	0.015	0.06	151.46	10.96	0.004	0.00	4.91	1.89	0.17	0.07	130.35	10.18
JP	0.016	0.04	83.95	8.28	0.006	0.01	6.55	2.17	0.17	0.05	72.49	7.72
BTC	0.176	0.43	246.15	13.56	0.096	0.13	10.14	2.90	0.190	0.46	217.75	12.84
LTC	0.854	0.95	87.17	7.36	0.858	0.49	1.03	1.10	0.854	1.01	80.65	7.21
ETH	0.358	0.66	169.82	11.00	0.541	0.38	1.29	0.60	0.328	0.69	166.84	11.25
DSH	0.741	7.64	770.27	26.90	0.154	0.16	7.80	2.45	0.837	8.24	662.38	24.95
EOS	0.418	0.97	246.12	12.95	0.217	0.43	51.81	6.50	0.451	1.03	224.94	12.50
TRX	6.642	23.10	17.48	4.04	45.098	45.66	-0.27	0.64	0.360	0.81	145.36	10.36
BAT	0.624	1.11	313.67	14.37	0.531	0.40	1.23	1.01	0.639	1.18	279.82	13.69

Notes: This table reports descriptive statistics of 5-minute high-frequency returns, calculated as the first logarithmic price difference in two consecutive 5-minute intervals (see Eq. (1)). Panel A reports the returns, estimated by the accumulative average of the 5-minute interval returns from 00:000 (a.m.) to 23:55 (p.m.) Greenwich Mean Time (GMT) each day. Panel B reports the realized volatility (RV); $RV_t = \sum_{i=1}^{T} r_{t,i}^2$. Here, $r_{t,i}$ denotes intraday returns and T denotes the number of intraday logarithmic returns (i =1,2,3, …, T). In our case, T is 288 (each day). The full sample period spans between August 5, 2019 (00:00 a.m.), and January 31, 2023 (11:55 p.m.), representing 363,024 observations for each asset. The pre-Covid period spans between August 5, 2019 (00:00 a.m.), and December 31, 2019 (11:55 p.m.), whereas the post-Covid period spans between January 1, 2020 (00:00 a.m.), and January 31, 2023 (11:55 p.m.). US, UK, FR, GER, AUS, and JP stand for the equity indices in the United States (S&P500), United Kingdom (FTSE100), France (CAC40), Germany (DAX), Australia (S&PASX200), and Japan (Nikkei225). BTC, LTC, ETH, DSH, EOS, TRX, and BAT represent Bitcoin, Litecoin, Ether, Dashcoin, EOS, Tron, and Basic Attention Token, respectively. The price data is obtained from Dukascopy (www.dukascopy.com), and all selected cryptocurrencies and equity indices are priced in US$.

Table 2. Stationarity tests of the high-frequency data of selected equity indices and cryptocurrencies.

	Full sample		**Pre-covid19**		**Post-Covid19**	
	ADF	PP	ADF	PP	ADF	PP
US	-132.41[a]	-565.45[a]	-206.81[a]	-206.82[a]	-232.43[a]	-524.92[a]
UK	-396.78[a]	-562.73[a]	-145.83[a]	-211.99[a]	-368.23[a]	-521.81[a]
France	-155.66[a]	-557.50[a]	-211.54[a]	-211.54[a]	-137.98[a]	-516.63[a]
Germany	-139.32[a]	-562.99[a]	-210.46[a]	-210.50[a]	-129.12[a]	-522.02[a]
Australia	-63.74[a]	-565.07[a]	-210.52[a]	-210.55[a]	-80.91[a]	-523.97[a]
Japan	-121.44[a]	-560.07[a]	-209.36[a]	-209.35[a]	-112.91[a]	-519.39[a]
BTC	-215.40[a]	-560.94[a]	-207.21[a]	-207.31[a]	-200.37[a]	-521.16[a]
LTC	-158.40[a]	-774.71[a]	-87.70[a]	-377.51[a]	-172.19[a]	-697.10[a]
ETH	-240.92[a]	-628.27[a]	-100.76[a]	-354.30[a]	-201.25[a]	-539.71[a]
DSH	-59.97[a]	-685.40[a]	-220.91[a]	-220.57[a]	-56.62[a]	-639.88[a]
EOS	-166.22[a]	-570.16[a]	-70.93[a]	-216.87[a]	-154.58[a]	-528.03[a]
TRX	-65.27[a]	-1890.98[a]	-63.35[a]	-1561.85[a]	-216.21[a]	-513.78[a]
BAT	-238.66[a]	-613.96[a]	-174.84[a]	-284.67[a]	-138.84[a]	-554.67[a]

Notes: This table reports the results of stationarity tests of the selected equity indices and cryptocurrencies. ADF stands for Augmented Dickey-Fuller test and PP stands for Phillips–Perron tests of unit root. “[a]” indicates the level of significance at 1% level. All variables and sample periods are defined in Table 1.

Table 3 presents the Pearson correlation and shows that the correlation among intra-class assets is higher than the correlation among inter-class assets. For example, correlation coefficients among equity indices (cryptocurrencies) vary between 0.69 and 0.85 (0.62 and 0.84), whereas correlation coefficients between equity indices and cryptocurrencies (the left bottom corner of each panel) vary between 0.21 and 0.41. The main reason for presenting correlations is to understand the return and price dynamics of the assets studied. To deeply understand random innovations and volatility dynamics, we empirically examine information bias and leverage effects, sign bias tests, and spillovers and connectedness in the following sections of the study.

4.2. Leverage effects on equity and cryptocurrency returns

It is often conversed in the financial markets literature that negative news has a stronger impact on the conditional volatility of market returns than that of its actual size counterpart, dubbed as “leverage effect” by Black (1976) and Christie (1982). If so, a high level of leverage effect is most likely to increase not only the possibility of a high risk but also the volatility of returns.

Table 3. Pearson correlation among the returns of selected cryptocurrencies and equity indices.

	US	**UK**	**FR**	**GER**	**AUS**	**JP**	**BTC**	**LTC**	**ETH**	**DSH**	**EOS**	**TRX**
Panel A: Full sample												
UK	0.784											
FR	0.694	0.797										
GER	0.845	0.853	0.814									
AUS	0.821	0.776	0.686	0.792								
JP	0.814	0.746	0.718	0.800	0.740							
BTC	0.400	0.337	0.322	0.390	0.339	0.407						
LTC	0.347	0.305	0.281	0.327	0.290	0.348	0.811					
ETH	0.405	0.346	0.321	0.388	0.354	0.400	0.835	0.833				
DSH	0.291	0.243	0.208	0.267	0.232	0.284	0.661	0.748	0.691			
EOS	0.310	0.251	0.239	0.289	0.254	0.312	0.721	0.812	0.757	0.755		
TRX	0.291	0.239	0.235	0.289	0.258	0.297	0.638	0.684	0.677	0.628	0.722	
BAT	0.336	0.293	0.278	0.320	0.268	0.319	0.652	0.680	0.691	0.634	0.703	0.618
Panel B: Pre-Covid-19												
UK	0.808											
FR	0.839	0.780										
GER	0.890	0.817	0.891									
AUS	0.752	0.733	0.737	0.734								
JP	0.870	0.714	0.767	0.849	0.700							
BTC	-0.041	-0.047	0.005	-0.025	-0.043	-0.072						
LTC	0.039	0.049	0.070	0.056	0.019	-0.016	0.762					
ETH	0.013	0.021	0.046	0.040	0.006	-0.019	0.798	0.846				
DSH	-0.025	-0.059	0.002	0.015	-0.014	-0.037	0.732	0.788	0.820			
EOS	0.003	0.012	0.050	0.044	0.009	-0.040	0.745	0.828	0.870	0.802		
TRX	0.235	0.208	0.234	0.238	0.222	0.195	0.486	0.645	0.573	0.507	0.575	
BAT	0.018	0.083	0.093	0.085	0.015	-0.013	0.436	0.577	0.615	0.611	0.600	0.417
Panel C: Post-Covid-19												
UK	0.782											
FR	0.688	0.799										
GER	0.842	0.855	0.811									
AUS	0.826	0.778	0.684	0.796								
JP	0.811	0.748	0.717	0.797	0.743							
BTC	0.437	0.368	0.345	0.422	0.367	0.447						
LTC	0.371	0.325	0.296	0.347	0.309	0.377	0.815					
ETH	0.435	0.370	0.339	0.413	0.377	0.432	0.838	0.831				
DSH	0.310	0.260	0.217	0.281	0.244	0.303	0.658	0.747	0.684			
EOS	0.333	0.269	0.251	0.306	0.270	0.338	0.719	0.810	0.748	0.754		
TRX	0.305	0.248	0.244	0.303	0.269	0.317	0.669	0.700	0.703	0.660	0.755	
BAT	0.359	0.309	0.289	0.336	0.284	0.344	0.670	0.688	0.697	0.637	0.711	0.657

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

To capture the impact of random innovations on the volatility of the equity indices and cryptocurrencies studied, we employ the sign bias test of Engle and Ng (1993). Table 4 reports the results of leverage effects, captured by the negative sign bias test (NSBT). The results show that on average cryptocurrencies have higher leverage effects than equity indices in the full sample, the coefficients of NSBT are negative and larger than the coefficients of the positive sign bias test (PSBT). The results of the full sample period and the post-Covid period are comparable, indicating that full sample results are not overwhelmed by the pre-Covid market conditions, they rather exhibit recent (post-Covid) market conditions. A straightforward comparison between Panels B and C suggests that a larger impact of negative news than positive news on equity indices is exacerbated before the onset of the Covid pandemic, whereas, on cryptocurrencies, it is exacerbated after the onset of the Covid pandemic. In other words, most of the equity indices are relatively equally affected by both positive and negative news after the onset of Covid-19, whereas most of the cryptocurrencies are relatively equally affected by both positive and negative news before the onset of Covid-19. The leverage effect in alternative periods is strongly manifested — before (after) Covid-19 for equities (cryptocurrencies).

The comparable intensity of responses to negative and positive shocks in equity returns at the onset of Covid-19 returns is conceivable given that while negative news caused serious turmoil in equity markets, economic relief packages and effective actions to safeguard investors by different governments caused both recovering from the downturn and achieving new peaks. Since Covid-19 was an unusual event, specifically the first year of the pandemic, the unusual stimulus packages similarly help investors gain substantial confidence. If this conjecture is true that positive news during Covid-19 had specific importance, the results should be limited to the first phase of Covid-19.

Table 4. Leverage effects.

	Panel A: Full sample			**Panel B: Pre-Covid-19**			**Panel C: Post-Covid-19**		
	SBT	**NSBT**	**PSBT**	**SBT**	**NSBT**	**PSBT**	**SBT**	**NSBT**	**PSBT**
US	0.004[a]	-0.206[a]	0.236[a]	-0.000[b]	-0.064[a]	0.053[a]	0.004[a]	-0.212[a]	0.242[a]
UK	0.004[a]	-0.132[a]	0.199[a]	-0.001[a]	-0.052[a]	0.041[a]	0.000[c]	-0.142[a]	0.186[a]
France	0.002[c]	-0.126[a]	0.150[a]	-0.001[a]	-0.056[a]	0.037[a]	0.000[c]	-0.128[a]	0.144[a]
Germany	0.003[a]	-0.151[a]	0.205[a]	-0.000[c]	-0.058[a]	0.053[a]	0.000[c]	-0.158[a]	0.196[a]
Australia	0.005[a]	-0.199[a]	0.238[a]	-0.001[a]	-0.037[a]	0.022[a]	-0.004[c]	-0.221[a]	0.217[a]
Japan	0.004[a]	-0.128[a]	0.195[a]	-0.000[c]	-0.051[a]	0.048[a]	0.004[a]	-0.132[a]	0.202[a]
BTC	0.019[a]	-0.777[a]	0.772[a]	0.007[c]	-0.327[a]	0.342[a]	0.016[a]	-0.826[a]	0.811[a]
LTC	0.284[a]	-0.764[a]	0.855[a]	0.244[a]	-0.343[a]	0.424[a]	-0.439[a]	-1.158[a]	0.622[a]
ETH	0.027[a]	-0.826[a]	0.667[a]	-0.071[a]	-0.417[a]	0.189[a]	0.011[b]	-0.979[a]	0.731[a]
DSH	1.544[a]	-1.445[a]	8.113[a]	-0.008[c]	-0.288[a]	0.310[a]	1.738[a]	-1.481[a]	8.524[a]
EOS	-0.241[a]	-2.143[a]	0.746[a]	-0.056[a]	-1.039[a]	0.187[a]	-0.291[a]	-2.282[a]	0.795[a]
TRX	1.029[a]	-3.678[a]	3.779[a]	3.712[a]	-2.108[a]	2.653[a]	-0.131[a]	-1.801[a]	0.977[a]
BAT	0.127[a]	-0.738[a]	0.923[a]	-0.058[a]	-0.455[a]	0.345[a]	0.125[a]	-0.795[a]	0.971[a]

Notes. This table reports the results of the leverage effects in the high-frequency data of the selected assets defined in Table 1. SBT, NSBT, and PSBT indicate sign bias test, negative sign bias test, and positive sign bias test, respectively. [a], [b], and [c] indicate the level of significance at the 1%, 5%, and 10% level. Table 1 defines the subsample.

For clarity, we extend our analysis by dividing the Covid-19 pandemic period into two episodes and present results in Table 5. Our high-frequency results for equity indices agree with the findings of Panda et al. (2021), who employ low-frequency data on different Asia-Pacific markets and find that Australian equities are more sensitive to negative news than positive news in the post-global financial crisis period than the pre-global financial crisis period. The NSBT values of the Australian equity market reported in Table 4 are the lowest in the pre-Covid period and highest in the post-Covid period, indicating a substantially increased leverage effect during Covid-19. Likewise, the intensity of the response to negative news (shocks) is higher for DSH, EOS, and TRX among the cryptocurrencies.

The results in Table 5 are in line with our conjecture that the absence of the leverage effect in the post-Covid period is specific to the first year of the pandemic (2020). The leverage effect in the second year of the Covid pandemic is present for all the selected assets except DSH and BAT. In sum, we show that the first year of Covid was relatively unique where the impact of positive and negative news on the assets under study was comparable, specifically for DSH and BAT. The leverage effect on the returns of EOS is the most persistent, it prevails in all subperiods. To examine the robustness of the leverage effects and volatility dynamics, we extend our analysis and employ more advanced econometric models. Specifically, to estimate and capture asymmetric innovation (volatility) shocks in the return distribution of the assets studied, we consider SAARCH, APARCH, and TGARCH models. Results are presented in Table 6.

Table 5. Further examinations of leverage effects.

	The first year of Covid-19 (2020)			**The second year of Covid-19 (2021)**		
	SBT	NSBT	PSBT	SBT	NSBT	PSBT
US	0.0063[a]	-0.2504[a]	0.2921[a]	-0.0003[a]	-0.0766[a]	0.0582[a]
UK	0.0072[a]	-0.1483[a]	0.2462[a]	-0.0005[a]	-0.0596[a]	0.0484[a]
France	0.0001	-0.1478[a]	0.1592[a]	-0.0007[b]	-0.0527[a]	0.0432[a]
Germany	0.0060[a]	-0.1738[a]	0.2516[a]	-0.0005[a]	-0.0642[a]	0.0527[a]
Australia	-0.0046[c]	-0.2501[a]	0.2575[a]	-0.0007[a]	-0.0433[a]	0.0299[a]
Japan	0.0019	-0.1543[a]	0.2436[a]	-0.001[a]	-0.0888[a]	0.0607[a]
BTC	0.1082[a]	-0.9553[a]	1.5035[a]	-0.0715[a]	-0.9316[a]	0.4819[a]
LTC	0.3433[a]	-0.7025[a]	0.8672[a]	0.2260[a]	-1.2575[a]	1.1751[a]
ETH	0.2314[a]	-0.7097[a]	1.1719[a]	-0.1767[a]	-1.6638[a]	0.6732[a]
DSH	0.0797[a]	-0.9205[a]	1.4789[a]	2.5434[a]	-1.6913[a]	10.5857[a]
EOS	-0.0835[a]	-1.7727[a]	1.0907[a]	-0.6011[a]	-3.0283[a]	0.7416[a]
TRX	0.0598[a]	-1.2472[a]	1.3513[a]	-0.4567[a]	-2.6808[a]	0.6587[a]
BAT	0.2510[a]	-0.7450[a]	1.1267[a]	0.0638[a]	-0.8577[a]	0.9650[a]

Notes. This table extends Table 4 by dividing the post-Covid period into two parts, the first year of the Covid-19 pandemic (01.01.2020-31.12.2020) and the second year of the Covid-19 pandemic (01.01.2021-31.12.2021). All selected assets are defined in Table 1. [a], [b], and [c] indicate the level of significance at the 1%, 5%, and 10% levels.

Table 6. Asymmetric GARCH models for selected equities and cryptocurrencies.

	SAARCH			**TGARCH**			**APARCH**			
	α	**γ**	**β**	**α**	**γ**	**β**	**α**	**γ**	**β**	**δ**

Panel A: Full sample										
US	0.081[a]	-0.005[a]	0.896[a]	0.098[a]	-0.057[a]	0.914[a]	0.073[a]	-0.090[a]	0.871[a]	2.849[a]
UK	0.058[a]	-0.002[a]	0.918[a]	0.055[a]	-0.018[a]	0.938[a]	0.053[a]	-0.039[a]	0.892[a]	2.964[a]
France	0.122[a]	-0.006[a]	0.794[a]	0.168[a]	-0.050[a]	0.750[a]	0.106[a]	-0.097[a]	0.777[a]	2.675[a]
Germany	0.073[a]	-0.003[a]	0.909[a]	0.075[a]	-0.028[a]	0.928[a]	0.066[a]	-0.053[a]	0.887[a]	2.884[a]
Australia	0.036[a]	-0.002[a]	0.941[a]	0.128[a]	-0.023[a]	0.807[a]	0.002[a]	-0.060[a]	0.990[a]	3.380[a]
Japan	0.080[a]	-0.003[a]	0.894[a]	0.207[a]	-0.050[a]	0.744[a]	0.067[a]	-0.070[a]	0.879[a]	2.834[a]
BTC	0.172[a]	-0.009[a]	0.786[a]	0.195[a]	-0.054[a]	0.778[a]	0.174[a]	-0.076[a]	0.781[a]	2.071[a]
LTC	0.093[a]	-0.018[a]	0.868[a]	0.150[a]	-0.025[a]	0.837[a]	0.067[a]	-0.054[a]	0.837[a]	2.909[a]
ETH	0.097[a]	-0.011[a]	0.863[a]	0.102[a]	-0.028[a]	0.882[a]	0.094[a]	-0.099[a]	0.851[a]	2.407[a]
DSH	0.128[a]	-0.006[a]	0.858[a]	0.131[a]	-0.015[a]	0.870[a]	0.132[a]	-0.056[a]	0.859[a]	1.821[a]
EOS	0.173[a]	-0.018[a]	0.804[a]	0.213[a]	-0.085[a]	0.802[a]	0.173[a]	-0.114[a]	0.800[a]	2.073[a]
TRX	0.139[a]	-0.016[a]	0.826[a]	0.126[a]	-0.012[a]	0.888[a]	0.127[a]	-0.039[a]	0.775[a]	3.106[a]
BAT	0.087[a]	-0.010[a]	0.895[a]	0.099[a]	-0.024[a]	0.901[a]	0.088[a]	-0.077[a]	0.897[a]	1.885[a]
Panel B: Pre-Covid-19										
US	0.094[a]	-0.001[a]	0.908[a]	0.082[a]	-0.027[a]	0.933[a]	0.092[a]	-0.084[a]	0.912[a]	1.817[a]
UK	0.081[a]	-0.001[a]	0.931[a]	0.074[a]	-0.023[a]	0.947[a]	0.078[a]	-0.090[a]	0.939[a]	1.540[a]
France	0.233[a]	0.000[a]	0.779[a]	0.194[a]	0.092[a]	0.739[a]	0.310[a]	-0.029[a]	0.615[a]	0.779[a]
Germany	0.093[a]	-0.001[a]	0.918[a]	0.079[a]	-0.014[a]	0.937[a]	0.092[a]	-0.045[a]	0.921[a]	1.824[a]
Australia	0.038[a]	0.000v	0.965[a]	0.163[a]	-0.027[a]	0.818[a]	0.036[a]	-0.048[a]	0.962[a]	2.221[a]
Japan	0.059[a]	-0.001[a]	0.945[a]	0.207[a]	-0.023[a]	0.767[a]	0.202[a]	-0.053[a]	0.784[a]	1.346[a]
BTC	0.401[a]	-0.021[a]	0.509[a]	0.348[a]	-0.077[a]	0.511[a]	0.466[a]	-0.075[a]	0.432[a]	2.828[a]
LTC	0.181[a]	-0.015[a]	0.747[a]	0.256[a]	-0.023[a]	0.766[a]	0.023[a]	-0.013[a]	0.578[a]	5.765[a]
ETH	0.109[a]	0.010[a]	0.885[a]	0.099[a]	-0.046[a]	0.924[a]	0.069[a]	-0.171[a]	0.933[a]	1.216[a]
DSH	0.198[a]	0.009[a]	0.670[a]	0.174[a]	0.016[a]	0.671[a]	0.197[a]	0.053[a]	0.682[a]	1.754[a]
EOS	0.272[a]	-0.034[a]	0.582[a]	0.273[a]	-0.106[a]	0.551[a]	0.315[a]	-0.137[a]	0.508[a]	3.137[a]
TRX	0.165[a]	-0.057[a]	0.840[a]	0.125[a]	0.025[a]	0.903[a]	0.255[a]	0.015[c]	0.715[a]	3.031[a]
BAT	0.105[a]	0.006[a]	0.867[a]	0.094[a]	-0.005[b]	0.884[a]	0.071[a]	0.056[a]	0.914[a]	1.175[a]
Panel C: Post-Covid-19										
US	0.081[a]	-0.005[a]	0.894[a]	0.100[a]	-0.059[a]	0.911[a]	0.071[a]	-0.091[a]	0.870[a]	2.911[a]
UK	0.056[a]	-0.002[a]	0.919[a]	0.054[a]	-0.018[a]	0.938[a]	0.048[a]	-0.035[a]	0.890[a]	3.144[a]
France	0.118[a]	-0.007[a]	0.797[a]	0.151[a]	-0.036[a]	0.764[a]	0.100[a]	-0.103[a]	0.778[a]	2.751[a]
Germany	0.071[a]	-0.003[a]	0.911[a]	0.075[a]	-0.029[a]	0.928[a]	0.062[a]	-0.054[a]	0.886[a]	2.992[a]
Australia	0.035[a]	-0.002[a]	0.941[a]	0.041[a]	-0.014[a]	0.951[a]	0.019[a]	-0.059[a]	0.915[a]	3.724[a]
Japan	0.081[a]	-0.003[a]	0.891[a]	0.199[a]	-0.037[a]	0.745[a]	0.066[a]	-0.072[a]	0.874[a]	2.951[a]
BTC	0.139[a]	-0.008[a]	0.824[a]	0.172[a]	-0.051[a]	0.811[a]	0.139[a]	-0.082[a]	0.821[a]	2.045[a]
LTC	0.082[a]	-0.017[a]	0.885[a]	0.132[a]	-0.025[a]	0.858[a]	0.062[a]	-0.061[a]	0.857[a]	2.846[a]
ETH	0.097[a]	-0.012[a]	0.851[a]	0.125[a]	-0.052[a]	0.851[a]	0.089[a]	-0.105[a]	0.838[a]	2.535[a]
DSH	0.120[a]	-0.007[a]	0.874[a]	0.131[a]	-0.017[a]	0.879[a]	0.126[a]	-0.068[a]	0.873[a]	1.745[a]
EOS	0.148[a]	-0.013[a]	0.852[a]	0.182[a]	-0.066[a]	0.854[a]	0.152[a]	-0.127[a]	0.855[a]	1.667[a]
TRX	0.132[a]	-0.006[a]	0.868[a]	0.157[a]	-0.029[a]	0.865[a]	0.139[a]	-0.075[a]	0.869[a]	1.651[a]
BAT	0.082[a]	-0.008[a]	0.909[a]	0.098[a]	-0.032[a]	0.914[a]	0.083[a]	-0.084[a]	0.912[a]	1.821[a]

Notes. This table reports the results of asymmetric GARCH modeling of selected equity indices and cryptocurrencies using three different sample periods, defined in Table 1. SAARCH, APARCH, and TGARCH represent the simple asymmetric ARCH model, asymmetric power ARCH model, and threshold GARCH model, respectively. In SAARCH modeling, α is the ARCH coefficient, γ is the leverage coefficient, and β is the GARCH coefficient. In TGARCH modeling, α is the ARCH coefficient (ABARCH), γ is the leverage coefficient, and β is the GARCH coefficient

(SDGARCH) for heterogeneity effects. In APARCH modeling, α is the ARCH coefficient (APARCH), γ is the leverage coefficient, β is the GARCH coefficient (PGARCH), and δ is the asymmetric power assigned to ARCH models, which indicates the expected nature of the dependent variable. [a], [b], and [c] indicate the level of significance at the 1%, 5%, and 10% level.

All three terms, α (ARCH coefficient), γ (leverage coefficient), and β (GARCH coefficient), are statistically significant at the 1% significance level for all equity indices and cryptocurrencies, except for BAT. The leverage effect on BAT's returns is rejected by both TGARCH and APARCH models at the 1% significance level, confirming the robustness of our earlier results reported in Table 4. As our prime interest in this analysis is to measure the leverage coefficient (γ), the results using any of the three asymmetric GARCH models indicate that the returns of all selected assets experienced leverage effects in the post-Covid and full sample periods. While results in this section indicate leverage effects in most cases, they are not straightforward in the pre-Covid period. For example, the leverage effect is rejected by the (i) SAARCH model for France, Australia, ETH, DSH, and BAT; (ii) TGARCH model for France, DSH, and TRX; and (iii) APARCH model for DSH, TRX, and BAT. However, the strong statistical significance of the three coefficients in this study indicates a substantial impact of random innovations on the returns of the selected cryptocurrencies and equity indices.

4.3. Spillover effects using BEKK-MGARCH

This section focuses on the intra- and inter-market spillovers using the BEKK-MGARCH model. Panel A of Table 7 presents volatility spillovers among the cryptocurrencies, whereas Panel B presents return volatility spillovers among the equity indices. The return volatility spillovers between equities and cryptocurrencies are presented in Table 8. The main diagonal values of the upper triangular matrix (c_{11}, c_{22}, c_{33}, … c_{nn}) show the influence of the selected market's return on its past mean values, where n indicates the total number of assets under consideration. For instance, n is 7 (6) in Panel A (B) of Table 7 as there are seven (six) cryptocurrencies (equity indices). In Table 8, n is 13 as there are thirteen assets under study. The significant off-diagonal values of the C matrix, c_{ij}, imply the cross-mean spillover of the past shocks of one asset to another.

While examining cross-mean spillovers of cryptocurrencies (Panel A) and equity indices (Panel B), we find that the spillover of random innovation shocks with lagged standardized errors for cryptocurrencies is slightly greater in the pre-Covid period than in the post-Covid period. However, this transformation is not present among equities; the spillover of random innovation shocks with lagged standardized errors is comparable in both subperiods. The comparatively weaker spillover effect during the post-Covid period for cryptocurrencies compared with equities is understandable as the downturn in the equity markets caused by the Covid-19 pandemic was a boom period for cryptocurrencies, at least during the first year of the Covid-19 pandemic. Therefore, connectedness among cryptocurrencies during this period is expected to be lower as the extant literature shows higher connectedness and co-movements among assets during times of market turmoil (Akhtarruzzaman et al., 2021; Ali et al., 2021; Bouri, Lucey, and Roubaud, 2020). In line with this inference, we find stronger conditional covariances for equity indices in the post-Covid period than both the pre-Covid period. The degree of innovation spreading from one asset to another asset in the intra-market setting is relatively stronger in the post-Covid period: ETH-BTC, DSH-BTC, BAT-LTC, and DSH-ETH among cryptocurrencies and UK-US, Japan-US, Japan-UK, and Australia-France among equity markets.

Subsequently, we extend our post-Covid analysis and examine whether the degree of innovation due to the impact of lagged standardized errors is stronger than that due to the lagged conditional covariances. We find that the degree of innovation due to the impact of lagged standardized errors is stronger for LTC-BTC, ETH-BTC, ETH-LTC, and EOS-LTC among cryptocurrencies and UK-US, Germany-US, Japan-US, Australia-Germany, Japan-Germany, and Japan-Australia among equities, indicating more volatile returns with a low level of persistence. On the contrary, volatility transmissions between DSH and ETC and France and the UK are insignificant during the post-Covid period.

Table 7. Multivariate GARCH-BEKK modeling: Volatility spillovers among cryptocurrencies and equity indices (intra-market spillovers).

	Pre-Covid-19			**Post-Covid-19**			**Full sample**		
	S	**A**	**B**	**S**	**A**	**B**	**S**	**A**	**B**
Panel A: Spillovers among the cryptocurrencies									
BTC-BTC	0.14^{a}	1.50^{a}	0.14^{b}	0.18^{a}	-0.01	0.81^{a}	0.22^{a}	-0.35^{a}	0.69^{a}
LTC-BTC	0.26^{a}	0.16^{b}	0.03^{c}	0.26^{a}	0.17^{a}	-0.04^{a}	0.66^{a}	0.42^{a}	-0.10^{a}
ETH-BTC	0.08^{a}	-1.69^{a}	-0.12^{c}	0.28^{a}	0.47^{a}	0.10^{a}	0.57^{a}	0.84^{a}	-0.07^{a}
DSH-BTC	0.20^{a}	-0.27^{b}	-0.16^{a}	0.00	0.00	-0.01^{b}	0.28^{a}	0.00	0.02^{a}
EOS-BTC	0.63^{a}	0.42^{a}	0.01	0.50^{a}	-0.04^{b}	0.00	0.88^{a}	-0.43^{a}	0.07^{a}
TRX-BTC	-4.02^{b}	0.00	0.00	0.24^{a}	-0.19^{a}	-0.02^{a}	0.51^{a}	0.01^{a}	0.00^{a}
BAT-BTC	-0.03	0.19^{b}	0.26^{a}	0.15^{a}	-0.12^{a}	-0.08^{a}	0.46^{a}	0.03^{a}	0.04^{a}
LTC-LTC	0.25^{a}	-0.37^{b}	0.13^{a}	-0.07^{a}	-0.13^{a}	0.93^{a}	0.01	0.81^{a}	0.83^{a}
ETH-LTC	-0.05^{c}	0.29	-0.78^{a}	-0.01	0.52^{a}	-0.09^{a}	0.11^{a}	1.60^{a}	-0.77^{a}
DSH-LTC	-0.11^{a}	0.01	0.02	-0.11^{a}	0.03^{a}	0.02^{a}	-0.38^{a}	0.01^{a}	-0.01
EOS-LTC	-0.25^{a}	1.14^{a}	0.04	-0.22^{a}	-0.01	-0.16^{a}	-0.72^{a}	-0.85^{a}	0.09^{a}
TRX-LTC	0.24	-0.01	-0.01^{a}	-0.16^{a}	-0.19^{a}	0.09^{a}	-0.25^{a}	0.02^{a}	0.00^{a}
BAT-LTC	0.26^{a}	-1.92^{a}	0.22^{a}	-0.16^{a}	-0.19^{a}	-0.19^{a}	-0.57^{a}	0.09^{a}	-0.01
ETH-ETH	0.10^{a}	-0.84^{a}	0.03	0.01^{b}	0.64^{a}	1.05^{a}	0.09^{a}	1.49^{a}	0.47^{a}
DSH-ETH	0.08^{b}	-0.21	-0.39^{a}	-0.06^{b}	0.01^{c}	0.00	0.39^{a}	0.00^{b}	0.03^{a}
EOS-ETH	0.13	0.23^{b}	0.15^{a}	0.02	-0.07^{a}	-0.05^{a}	0.03^{a}	-0.94^{a}	0.04^{a}
TRX-ETH	9.22^{a}	0.00^{b}	-0.01^{a}	0.02	-0.26^{a}	-0.02^{b}	0.18^{a}	0.00	0.00
BAT-ETH	0.08	0.05	0.18^{a}	0.41^{a}	-0.11^{b}	-0.14^{a}	0.21^{a}	0.03^{b}	0.02^{a}
DSH-DSH	0.00	-1.76^{a}	0.09^{c}	0.00	1.36^{a}	0.01	0.05	2.20^{a}	-0.14^{a}
EOS-DSH	0.00	0.88^{a}	-0.01	0.00	-1.09^{a}	0.21^{a}	0.06	0.53^{a}	0.39^{a}
TRX-DSH	0.00	0.00	0.00^{a}	0.00	-2.24^{a}	0.06^{c}	0.04	-0.01	-0.01^{a}
BAT-DSH	0.00	0.54^{a}	0.12^{a}	0.00	-0.39^{a}	-0.29^{a}	0.01	0.13^{b}	-0.46^{a}
EOS-EOS	0.00	1.74^{a}	0.58^{a}	0.00	-0.29^{a}	0.75^{a}	0.09^{a}	-1.48^{a}	0.58^{a}
TRX-EOS	0.00	0.02^{a}	0.01^{a}	0.00	-0.27^{a}	0.24^{a}	0.05^{b}	-0.03^{a}	0.00^{b}
BAT-EOS	0.00	0.33	0.07	0.00	-0.49^{a}	-0.18^{a}	0.08^{a}	0.77^{a}	0.21^{a}
TRX-TRX	0.00	-0.41^{a}	0.09	0.00	-0.52^{a}	0.94^{a}	0.00	3.34^{a}	0.42^{a}
BAT-TRX	0.00	26.72^{a}	2.57	0.00	-0.36^{a}	-0.25^{a}	0.02	0.08^{b}	0.05^{a}
BAT-BAT	0.00	0.52^{a}	0.19^{a}	-0.01	1.61^{a}	-0.20^{a}	-0.12^{a}	-0.76^{a}	0.37^{a}
Panel B: Spillovers among the equity indices									

US-US	0.00^{a}	1.20^{a}	0.68^{a}	0.00^{a}	-0.33^{a}	1.19^{a}	0.01^{a}	0.06^{a}	0.46^{a}
UK-US	0.00^{a}	-0.71^{a}	-0.22^{b}	0.00	0.37^{a}	-0.16^{a}	0.01^{a}	-0.39^{a}	0.37^{a}
FR-US	0.00^{a}	0.67^{a}	-0.06	0.00^{a}	-0.11^{a}	0.02^{c}	0.03^{a}	0.08^{a}	-0.22^{a}
GER-US	0.00^{a}	0.37^{a}	0.36^{a}	0.00^{b}	0.07	-0.17^{a}	0.01^{a}	-0.10^{a}	0.02^{a}
AUS-US	0.00^{a}	0.29^{b}	-0.20^{b}	0.00	0.15^{a}	0.19^{a}	0.01^{a}	-0.58^{a}	0.27^{a}
JP-US	0.00^{a}	-0.67^{a}	-0.22^{a}	0.01^{a}	-0.03	-0.26^{a}	0.01^{a}	-0.06^{a}	-0.15^{a}
UK-UK	0.00	-0.31^{a}	0.08	0.00^{a}	0.13^{b}	0.75^{a}	0.00^{a}	0.30^{a}	0.76^{a}
FR-UK	0.00^{b}	0.02	0.21	0.00^{b}	0.02^{c}	-0.01^{c}	0.00	0.12^{a}	-0.10^{a}
GER-UK	0.00	0.91^{a}	-0.36	0.00^{b}	-0.30^{a}	-0.17^{a}	0.00^{a}	-0.24^{a}	0.17^{a}
AUS-UK	0.00^{c}	0.46^{a}	-0.46^{b}	0.00^{a}	-0.20^{a}	-0.13^{a}	0.00^{a}	-0.68^{a}	-0.05^{a}
JP-UK	0.00	-0.47^{a}	0.05	0.00	-0.16^{a}	-0.08^{a}	0.00^{a}	-0.07^{a}	0.17^{a}
FR-FR	0.00	0.79^{a}	0.34^{b}	0.00	0.36^{a}	0.46^{a}	-0.01^{a}	0.44^{a}	0.51^{a}
GER-FR	0.00	0.24^{c}	0.42	0.00	-3.86^{a}	0.60^{a}	0.00^{a}	-2.14^{a}	-0.75^{a}
AUS-FR	0.00	-0.29	-0.66^{a}	0.00	0.47^{a}	0.66^{a}	0.00	0.22^{a}	0.83^{a}
JP-FR	0.00	-0.59^{a}	-0.22^{b}	0.00	-1.37^{a}	-0.35^{a}	0.01^{a}	-0.75^{a}	-0.05^{c}
GER-GER	0.00	0.64^{a}	0.48^{b}	0.00	-0.34^{a}	0.76^{a}	0.00^{c}	-0.09^{a}	0.78^{a}
AUS-GER	0.00	0.13	-0.77^{a}	0.00	0.20^{a}	-0.06^{b}	0.00	-0.09^{a}	0.06^{a}
JP-GER	0.00	-0.30^{b}	-0.10	0.00	-0.03	-0.21^{a}	0.00^{b}	-0.23^{a}	0.11^{a}
AUS-AUS	0.00	0.02	0.14	0.00	0.24^{a}	0.80^{a}	0.00	0.74^{a}	0.89^{a}
JP-AUS	0.00	-0.19^{b}	-0.25^{a}	0.00	0.04	-0.09^{a}	0.00^{b}	-0.04^{a}	-0.08^{a}
JP-JP	0.00	-0.27^{b}	0.39^{a}	0.00	-0.06	0.63^{a}	0.00	0.17^{a}	0.77^{a}

Notes: This table reports the results of the multivariate GARCH-BEKK model, which examines spillovers among cryptocurrencies (Panel A) and among equity indices (Panel B). *S* denotes sigma, i.e., the upper triangular matrix, whereas *A* and *B* denote Matrix A and Matrix B respectively. Matrix A shows the impact of lagged standardized errors measuring the degree of innovation spreading from one asset to another asset, whereas Matrix B represents lagged conditional co-variances measuring persistence in conditional volatility spreading from one stock market to another stock market. ^{a}, ^{b}, and ^{c} indicate the level of significance at the 1%, 5%, and 10% level. Subperiods and variables are defined in Table 1.

The results of cross-mean spillover effects between cryptocurrencies and equity indices in Table 8 indicate significant cross-mean spillover in most cases during the post-Covid and full sample periods. In the pre-Covid period, however, nearly half of the cross-mean spillovers are insignificant: significant for equities-BTC, equities-LTC, and equities-ETH and insignificant for equities-EOS, equities-TRX, and equities-BAT. The cross-mean spillover effect between DSH and equity indices during the pre-Covid period is significant in 6 out of 4 cases. Germany-DSH and Australia-DSH are exceptions. A comparison between pre- and post-Covid periods shows that the mean spillover effects have substantially increased during the Covid period where insignificant spillover effects only exist in 8 of 42 combinations: US-ETH, UK-DSH, France-DSH, Australia-DSH, Japan-DSH, UK-BAT, Australia-BAT, and Japan-BAT. Moreover, the degree of innovation spreading from one market to another market is likewise relatively stronger in the post-Covid period between France-BTC, Germany-BTC, Australia-BTC, Japan-BTC, US-LTC, UK-LTC, France-LTC, Germany-ETH, Australia-ETH, UK-DSH, France-DSH, Japan-DSH, France-EOS, Germany-EOS, Australia-EOS, US-TRX, UK-TRX, France-TRX, UK-BAT, France-BAT, and Germany-BAT. Note that the variance-covariance matrix A shows coefficients of ARCH effects that infer lagged standardized errors and estimate the degree of innovation from the i^{th} to the j^{th} assets of different classes.

Table 8. Multivariate GARCH-BEKK modeling: Volatility spillovers between cryptocurrency and equity markets (cross-market spillovers).

Assets	Pre-Covid-19			Post-Covid-19			Full sample		
	S	**A**	**B**	**S**	**A**	**B**	**S**	**A**	**B**
US- BTC	0.00[a]	156.74[a]	-2.55[c]	0.01[a]	2.24[a]	-0.30[a]	0.01[a]	2.51[a]	0.02
UK- BTC	0.00[a]	25.22[a]	-10.32[a]	0.01[a]	-1.72[a]	-0.32[a]	0.01[a]	-0.20[a]	0.99[a]
FR- BTC	0.00[a]	-16.25[a]	-11.57[a]	0.03[a]	-0.47[a]	-0.14[a]	0.00	0.25[a]	-0.07[a]
GER- BTC	0.00[a]	-68.37[a]	12.75[a]	0.01[a]	-0.87[a]	0.93[a]	0.01[a]	1.71[a]	0.61[a]
AUS- BTC	0.00[a]	-74.99[a]	23.93[a]	0.00	-5.42[a]	-0.14[a]	0.02[a]	-3.37[a]	-0.99[a]
JP- BTC	0.00[a]	-70.77[a]	-14.39[a]	0.01[a]	1.05[a]	0.12[a]	0.01[a]	1.02[a]	0.40[a]
US- LTC	0.00[a]	-16.90	12.42[a]	0.00[a]	20.60[a]	2.44[a]	0.00[a]	16.47[a]	-4.56[a]
UK- LTC	0.00[a]	-54.86[a]	-44.52[a]	0.00[a]	-14.72[a]	2.56[a]	0.00	-8.89[a]	1.75[a]
FR- LTC	0.00[a]	-128.07[a]	1.70	-0.03[a]	-7.03[a]	-0.76[a]	0.00	0.91[a]	0.09
GER- LTC	0.00[a]	44.47[a]	-23.64[a]	0.00[a]	6.84[a]	1.36[a]	0.00[a]	-19.49[a]	-0.44[a]
AUS- LTC	0.00[a]	52.52[a]	9.14[b]	0.00[a]	-5.31[a]	1.95[a]	0.00[a]	-9.19[a]	1.33[a]
JP- LTC	0.00[a]	91.90[a]	9.79[a]	0.00[a]	-6.33[a]	-1.07[a]	0.00	14.87[a]	2.24[a]
US- ETH	0.00[a]	8.63[b]	3.67[b]	0.00	-1.20[a]	-1.71[a]	0.00[a]	-6.05[a]	-0.63[a]
UK- ETH	0.00[a]	27.37[a]	-9.62[a]	0.00[a]	0.62[a]	1.57[a]	0.00[a]	0.89[a]	-2.56[a]
FR- ETH	0.00[a]	-4.70	7.02[a]	-0.03[a]	1.23[a]	-0.91[a]	-0.01[a]	-1.27[a]	1.25[a]
GER- ETH	0.00[a]	-28.82[a]	6.39[a]	0.00[a]	-0.41[a]	0.56[a]	0.00	-0.97[a]	4.13[a]
AUS- ETH	0.00[a]	-39.41[a]	-2.48	0.00[c]	0.05	0.22[a]	0.00[a]	-10.54[a]	-0.42[a]
JP- ETH	0.00[a]	8.15[c]	-12.46[a]	0.00[a]	-4.27[a]	1.63[a]	0.00[a]	-1.73[a]	-1.57[a]
US- DSH	0.00[a]	6.13	-0.09	0.00[a]	-20.15[a]	2.13[a]	0.01[a]	-72.14[a]	4.12[a]
UK- DSH	0.00[a]	2.00	-2.68	0.00	59.40[a]	-4.44[a]	0.00[a]	-24.99[a]	2.11[a]
FR- DSH	0.00[a]	-49.27[a]	0.82	0.00	-6.53[a]	-0.53[a]	0.00	-1.30[b]	2.50[a]
GER- DSH	0.00	20.23[a]	-10.72[a]	0.00[a]	-155.06[a]	6.99[a]	0.01[a]	1.28	-9.59[a]
AUS- DSH	0.00	43.20[a]	29.57[a]	0.00	42.41[a]	-0.64[a]	0.00[a]	25.17[a]	-1.47[a]
JP- DSH	0.00[a]	-22.23[a]	-11.28[a]	0.00	38.61[a]	-1.91[a]	0.00[a]	132.49[a]	4.19[a]
US- EOS	0.00	33.84[a]	-1.44	-0.01[a]	-38.47[a]	-3.68[a]	-0.01[a]	-15.33[a]	-3.68[a]
UK- EOS	0.00	106.11[a]	-12.08	-0.01[a]	18.91[a]	1.28[a]	-0.01[a]	7.21[a]	4.62[a]
FR- EOS	0.00	-28.39[a]	-16.16	-0.02[a]	3.71[a]	-3.15[a]	-0.02[a]	-6.74[a]	0.69[a]
GER- EOS	0.00	-162.86[a]	-0.37	-0.01[a]	17.59[a]	2.02[a]	-0.01[a]	-21.64[a]	-5.42[a]
AUS- EOS	0.00	-35.68[c]	39.46[a]	0.00[a]	8.94[a]	3.30[a]	-0.01[a]	1.12[a]	-2.03[a]
JP- EOS	0.00	30.43[b]	-7.79[b]	0.00[a]	-18.69[a]	3.91[a]	-0.01[a]	42.99[a]	8.05[a]
US-TRX	0.00	-248.85[a]	43.42	0.00[a]	23.99[a]	4.84[a]	-0.01[a]	-42.52[a]	4.71[a]
UK-TRX	0.00	-139.65[a]	-8.61	0.00[a]	23.45[a]	-1.34[a]	0.00	-54.73[a]	-0.81[b]
FR-TRX	0.00	-203.07[a]	-70.06	0.01[b]	-0.98[a]	-1.70[a]	0.01[b]	-14.87[a]	0.41[a]
GER-TRX	0.00	214.24[a]	-416.72[a]	0.01[a]	-52.82[a]	-0.87[a]	0.00[b]	104.18[a]	-5.01[a]
AUS-TRX	0.00	277.02[a]	636.27[a]	0.00[b]	-0.11	0.60[a]	0.00[c]	-7.66[a]	-0.84[a]
JP-TRX	0.00	383.65[a]	-107.02	0.00[a]	28.56[a]	1.99[a]	0.00[a]	15.05[a]	3.80[a]
US-BAT	0.00	45.64[a]	12.67[a]	0.00[a]	-2.72[a]	-3.54[a]	0.00[a]	7.35[a]	5.20[a]
UK-BAT	0.00	-5.42	-28.89[a]	0.00	4.67[a]	3.16[a]	0.00[b]	5.55[a]	-6.64[a]
FR-BAT	0.00	-28.52[a]	6.96[a]	-0.01[c]	-6.78[a]	0.68[a]	0.00	3.67[a]	1.62[a]
GER-BAT	0.00	-93.22[a]	-7.54[a]	0.00[a]	2.48[a]	-2.40[a]	0.00[a]	-5.28[a]	3.19[a]
AUS-BAT	0.00	83.53[a]	5.54	0.00	9.56[a]	-1.41[a]	0.01[a]	16.88[a]	-4.46[a]

JP-BAT	0.00	75.26 [a]	-13.62 [a]	0.00	-5.98 [a]	5.60 [a]	0.00 [a]	6.05 [a]	1.88 [a]
Notes: This table reports the results of the multivariate GARCH-BEKK model, which examines spillovers between cryptocurrencies and equity indices. All the variables and subperiods are defined in Table 1 and Table 6.									

The cross-market spillover and its persistence among the assets is significant in all cases in the post-Covid period. In this analysis, matrix B examines the lagged conditional covariance and estimates the inter-market spillover and its persistence among the assets under consideration: a significant GARCH coefficient shows that a portion of the realized conditional covariances of one asset spillovers to the current period conditional covariance of the other asset.

Another important aspect is to understand whether the degree of innovation due to the impact of lagged standardized errors is stronger than that due to the lagged conditional covariances. Table 8 shows that the degree of innovation due to the impact of lagged standardized errors is stronger than that of lagged conditional covariances in the following combinations of assets during the post-Covid period: US-BTC, US-LTC, Germany-LTC, UK-EOS, France-EOS, Germany-EOS, Australia-EOS, France-ETH, UK-DSH, Japan-DSH, Australia-DSH, US-TRX, UK-TRX, Japan-TRX, Germany-BAT, and Australia-BAT. A synthesis of pre- and post-Covid results reveals that a stronger impact of lagged standardized errors than lagged conditional covariances on the degree of innovation is stronger in the post-Covid period.

Finally, Table 8 shows significant spillovers of conditional volatility between all the inter-class assets under study during the sample period, except US-BTC and France-LTC. However, in the post-Covid period, spillover of conditional volatility among the assets studied is significant in all cases without any exception. If we compare these results with the pre-Covid period, there are numerous insignificant spillovers of conditional volatility, including France-LTC, Australia-ETH, US-DSH, UK-DSH, France-DSH, US-EOS, Germany-EOS, US-TRX, UK-TRX, France-TRX, Japan-TRX, and Australia-BAT. Our results thus far indicate stronger spillovers of cross-mean effects, cross-market innovations, and conditional volatility across all assets during the Covid period than the pre-Covid period, indicating a stronger integration and transmission of information between the assets after the onset of Covid-19.

4.4. Volatility connectedness using the TVP-VAR approach

This section discusses the results of static and dynamic volatility connectedness indices. We begin our analysis by looking at the static connectedness, results are presented in Table 9. A negative (positive) net value of connectedness indicates that the asset of our interest is a net receiver (transmitter) of volatility within the network.

The total connectedness index (TCI) in the post-Covid period, 80.84%, is relatively higher than the TCI in the pre-Covid period, 79.75%, indicating an elevated connectedness among the assets during Covid. TCI in the full sample period is similarly high, 80.72%, implying a high volatility dependence in the network. The elements in the main diagonal, corresponding to own-innovations, show that the highest (lowest) value in the pre-Covid period is 29.98 (15.22) for EOS (UK), indicating that 29.98% (15.22%) of the forecast error variance of EOS (UK) can be ascribed to own-innovations whereas the remaining error can be ascribed to other assets' influence. Likewise, while examining own-innovations during the post-Covid period, the highest (lowest) value is 26.05 (16.42) for BAT (Germany).

Table 9. Static connectedness between equity indices and cryptocurrencies

	US	UK	FR	GER	AUS	JP	BTC	LTC	ETH	DSH	EOS	TRX	BAT	FROM
Panel A: Full sample														
US	16.48	13.23	10.4	13.86	11.97	11.55	3.91	3.09	4.66	2.8	2.54	2.95	2.61	83.52
UK	12.08	16.71	12.4	14.99	11.58	11.1	3.77	3.03	4.43	2.51	2.33	2.52	2.57	83.29
FR	11.13	14.75	16.3	14.89	10.98	10.35	3.82	3.16	4.29	2.51	2.47	2.55	2.78	83.68
GER	12.49	14.63	12.6	16.49	11.4	10.94	3.92	3.12	4.52	2.5	2.35	2.51	2.53	83.51
AUS	12.39	12.53	10.9	12.84	17.68	11.3	3.92	3.18	4.88	2.59	2.49	2.81	2.48	82.32
JP	12.23	12.63	10.4	13.12	11.76	18.53	3.86	3.07	4.35	2.5	2.44	2.45	2.71	81.47
BTC	3.5	4.07	3.44	4.01	3.19	3.81	17.6	9.41	13.42	9.94	10.1	9.49	7.98	82.38
LTC	3.55	4.32	3.63	4.32	3.55	4.22	11	21.28	10.72	8.37	9.4	8.88	6.78	78.72
ETH	3.84	4.37	3.33	4.21	3.84	4.19	12.4	8.91	17.84	8.78	10.3	10.95	7.04	82.16
DSH	3.39	3.66	2.91	3.25	2.85	3.45	8	7.55	8.66	24.8	12.9	9.86	8.76	75.23
EOS	2.85	3.66	2.98	3.44	2.4	3.24	9.86	8.59	10.62	12	20	11.29	9.09	80.02
TRX	3.61	4.2	3.5	4.03	3.37	3.83	8.87	7.58	9.92	9.3	10.7	22	9.14	78
BAT	3.22	4	4.02	3.81	2.57	3.32	8.31	7.47	8.92	9.03	10.1	10.28	24.97	75.03
TO	84.26	96.05	80.4	96.76	79.46	81.3	81.6	68.16	89.39	72.8	78.1	76.54	64.49	1049.33
Inc. Own	100.8	112.8	96.7	113.3	97.14	99.83	99.2	89.44	107.2	97.6	98.1	98.54	89.46	cTCI//TCI
NET	0.75	12.75	-3.28	13.25	-2.86	-0.17	-0.78	-10.6	7.23	-2.4	-1.93	-1.46	-10.5	87.44//80.72
NPT	8	10	6	11	6	5	6	1	10	4	5	6	0	
Panel B: Pre-Covid-19														
US	18.12	10.03	11.8	14.76	12.15	11.47	1.76	3.12	4.86	1.56	2	5.55	2.78	81.88
UK	12.59	15.22	12.1	14.8	12.14	12.59	1.73	2.55	4.93	2.08	1.41	4.49	3.4	84.78
FR	13.05	12.99	15.7	15.36	12.19	10.96	1.27	2.49	4.56	1.71	1.04	5.1	3.57	84.27
GER	13.97	11.59	12.9	16.87	12.36	12.41	1.58	2.7	4.69	2.04	1.1	4.44	3.38	83.13
AUS	12.7	10.02	11.5	13.11	19.02	13.02	1.85	3.79	5.54	1.73	1.12	4.05	2.5	80.98
JP	12.88	10.53	9.71	13.54	13.53	17.66	2.13	2.94	5.73	1.93	2.08	4.41	2.92	82.34
BTC	2.5	1.29	1.47	1.52	2.1	2.44	25.8	13.69	13.41	11.2	9.27	5.05	10.34	74.24
LTC	2.42	1.68	1.9	2.07	3.29	2.74	15.2	25.99	11.09	8.96	8.79	6.47	9.42	74.01
ETH	4.92	4.98	3.72	4.92	7.07	7.34	8.73	9.56	17.4	7.62	6.55	9.24	7.97	82.6
DSH	2.22	1.35	1.34	1.54	1.54	2.77	12.2	8.99	11.52	25.2	16.3	5.66	9.42	74.83
EOS	2.62	1.03	1.16	1.09	1.06	2.81	11.3	9.03	10.54	18.6	30	3.48	7.28	70.02
TRX	6.11	6.12	5.96	6.74	7.38	6.75	4.25	6.58	10.74	5.89	6.72	17.2	9.56	82.8
BAT	4.33	4.65	4.54	5.46	4.71	5.53	7.16	7.89	10.17	8.69	7.54	10.23	19.09	80.91
TO	90.31	76.24	78.1	94.94	89.51	90.82	69.2	73.34	97.8	72	63.9	68.17	72.53	1036.8

Inc. Own	108.4	91.46	93.8	111.8	108.5	108.5	95	99.33	115.2	97.1	93.9	85.37	91.62	cTCl//TCl
NET	8.43	-8.54	-6.19	11.8	8.53	8.49	-5.04	-0.67	15.19	-2.86	-6.13	-14.63	-8.38	86.40//79.75
NPT	10	4	4	8	7	8	5	9	7	6	5	2	3	
Panel C: Post-Covid-19														
US	16.48	13.47	10.4	13.61	12.14	11.17	4.04	3.12	4.59	2.89	2.57	2.89	2.65	83.52
UK	12	16.65	12.6	15.04	11.9	10.77	3.84	3.1	4.18	2.51	2.36	2.46	2.56	83.35
FR	10.87	14.72	16.6	14.94	11.09	10.03	3.98	3.21	4.18	2.6	2.55	2.46	2.81	83.42
GER	12.3	14.98	12.9	16.42	11.36	10.48	4.04	3.22	4.34	2.54	2.42	2.45	2.52	83.58
AUS	12.58	12.97	11.2	12.81	17.63	11.03	3.91	3.14	4.4	2.62	2.52	2.79	2.47	82.37
JP	11.99	12.79	10.6	12.87	11.71	18.78	3.94	3.12	4.12	2.5	2.44	2.4	2.78	81.22
BTC	3.43	3.89	3.6	3.84	2.98	3.67	16.6	9.28	13.61	10.5	10.4	10.41	7.76	83.36
LTC	3.44	4.07	3.64	4.18	3.37	4.1	10.7	21.01	11.02	8.7	9.71	9.63	6.4	78.99
ETH	3.63	3.81	3.23	3.75	3.13	3.69	12.9	9.37	17.51	9.34	11	11.69	6.97	82.49
DSH	3.38	3.55	2.98	3.13	2.86	3.35	8.08	7.77	8.86	24.7	11.5	10.93	8.94	75.3
EOS	2.74	3.45	3.07	3.31	2.4	3.07	9.88	8.82	10.94	11.9	18.6	12.74	9.05	81.36
TRX	3.33	3.72	3.3	3.55	3.02	3.41	9.29	7.94	9.93	10	11.5	21.96	8.99	78.04
BAT	3.03	3.63	4.08	3.45	2.29	2.97	8.12	7.4	8.76	9.59	10.1	10.54	26.05	73.95
TO	82.71	95.06	81.6	94.47	78.25	77.76	82.7	69.49	88.92	75.7	79.1	81.38	63.89	1050.96
Inc. Own	99.19	111.7	98.2	110.9	95.88	96.54	99.3	90.5	106.4	100	97.7	103.3	89.94	cTCl//TCl
NET	-0.81	11.71	-1.85	10.88	-4.12	-3.46	-0.68	-9.5	6.43	0.4	-2.28	3.34	-10.1	87.58//80.84
NPT	8	10	7	10	4	5	7	1	9	5	5	6	1	

Notes: This table presents the static analysis of the dynamic volatility spillovers between the selected equity indices and cryptocurrencies. “From”’ in the last column indicates the spillover from the network of all other assets to an asset of our interest, whereas “TO” in the third last row indicates the spillover to the network of all other assets from the asset of our interest. “NET” in the second last row indicates the net directional spillover of each asset, whereas “TCI” in the bottom right corner indicates the total connectedness index of the network of all assets. All selected assets and subperiods are defined in Table and Table 6.

The highest pairwise directional connectedness in the pre-Covid period took place from DSH to EOS (18.61%), followed by EOS to DSH (16.26%) and Germany to France (15.36%). On the contrary, the highest pairwise directional connectedness in the post-Covid period took place from Germany to the UK (15.04%) and ETH to BTC (13.61%), indicating a significant level of directional spillovers from Germany to UK and ETH to BTC. In sum, referring to inter-class asset connectedness and subperiod analyses, we find that connectedness in the intra-class asset examination (post-Covid period) is stronger than the inter-class asset setting (pre-Covid period).

For example, the lowest pairwise directional connectedness from cryptocurrencies to equity indices in the pre-Covid period manifested from EOS to France (1.04%) followed by EOS to Germany (1.10%), whereas, in the post-Covid period, it manifested from EOS to UK (2.36%) followed by TRX to Japan (2.40%). Similarly, the lowest pairwise directional volatility spillover from equity indices to cryptocurrencies in the pre-Covid period occurred from UK to EOS (1.03%), followed by Australia to EOS (1.06%), whereas in the post-Covid period, it occurred from Australia to BAT (2.29%), followed by Australia to EOS (2.40%). To sum up, the results in Table 9 reveal three major findings: pairwise directional connectedness (i) among equity indices is on average stronger in the post-Covid period than in the pre-Covid period, (ii) among cryptocurrencies is on average stronger in the pre-Covid period than the post-Covid period, and (iii) from equity indices to cryptocurrencies and cryptocurrencies to equity indices are not only weaker than the intra-class asset connectedness but also time-varying, indicating several inter-market and inter-class asset diversification and hedging opportunities for investors.

Both a synthesis of existing studies and our results reported thus far reveal that the connectedness among assets is time-variant in most cases (Ali et al., 2021, 2022, 2023, 2024). Therefore, we are particularly interested in observing net transmitters and net receivers of shocks, i.e., the direction of the volatility spillovers. Interestingly, in line with our conjecture, we find markedly diverse spillovers across the two subperiods. For example, while the UK and TRX (Australia and Japan) are the two main net receivers (transmitters) of volatility in the pre-Covid period, they are among the main net transmitters (receivers) of volatility in the post-Covid period. The direction of the spillovers is also persistent in some cases; for example, Germany (BAT) is a net transmitter (receiver) in both periods. As the average connectedness analysis is static in nature and ignores the evolution of these measures over time, it is important to examine the time-varying dynamics of these connectedness measures. In doing so, we begin with the total dynamic connectedness to get a bird's-eye view of the evolution of volatility connectedness within the network, presented in Fig. 2. It is evident that TCI in the network is time-varying and reaches high levels of market interconnectedness multiple times, where the most prominent peak is manifested during March 2020.

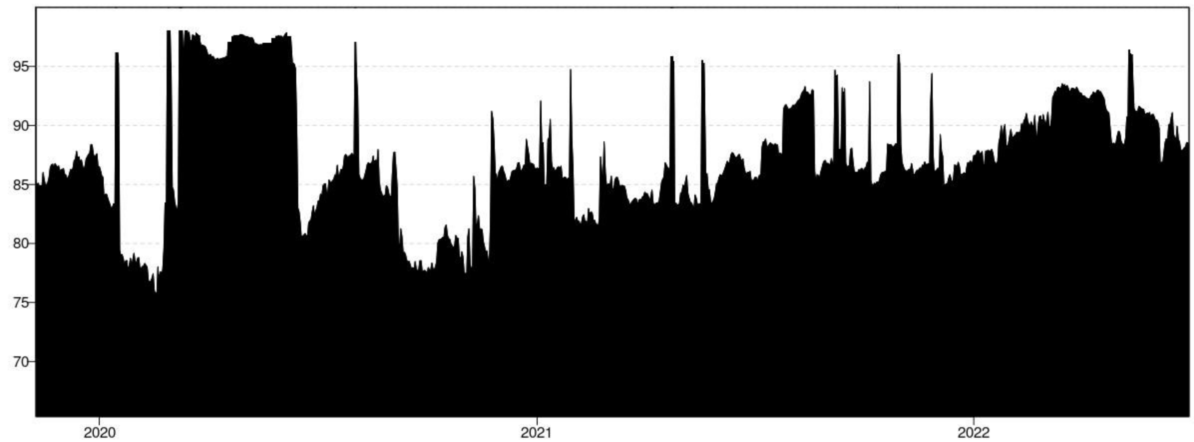


Fig. 2. Dynamic total volatility connectedness

Thereafter, a gradual decline in the volatility connectedness is noticeable until a trough is hit in November 2020. Substantially high volatility connectedness values at the onset of Covid indicate markedly high uncertainty among investors, possibly due to the lack of information regarding the disease, its contagiousness, and its ultimate impact on economies (information bias and uncertainty). Thus, the awareness of the virus, measures to control its transmission, news regarding the availability of the vaccine, and stimulus packages announced by governments around the globe to protect investors first caused recoveries, then advances and new peaks in many equity indices (see Fig. 1), resulting in a decline in the volatility connectedness later in 2020 (Apergis, Chatziantoniou, and Gabauer, 2023). In 2021, uncertainty began to rise again, which could be linked to the emergence of new variants of Covid, the prolongation of lockdowns, and the corresponding rage and concerns among people globally. While the interconnectedness among the assets studied in 2021 and 2022 remained lower than that of mid-March 2020, an increased TCI is evident during the Russia-Ukraine war in 2022. In order to understand the net transmission of shocks for each asset under study, which can be helpful in understanding the contribution of each asset in the network towards volatility connectedness, we depict the net total directional connectedness measures in Fig. 3. Notably, we find that most of the equity indices are the main transmitter, whereas the cryptocurrencies are the main receivers of shocks during the first year of Covid-19. Specifically, the UK and Germany are the main transmitters, whereas LTC is the main receiver.

However, the evolution of net directional connectedness during 2021 and 2022 is not straightforward, nearly all the cryptocurrencies and equities have acted as both transmitters and receivers of volatility. In line with Ali et al. (2023), who revealed that most of the co-movements and diversification benefits among the Asian equities were short-lived, our results similarly indicate that the connectedness among the assets under study (possible diversification benefit) is short-lived. While Fig. 3 helps us to understand the net volatility transmitted or received by each asset, it does not provide pair-wise information. That is, a net transmitter (receiver) within the network does not necessarily mean it transmits to (receives from) all the assets in the network. Therefore, it is vital to examine dynamic pairwise connectedness and net pairwise directional connectedness.

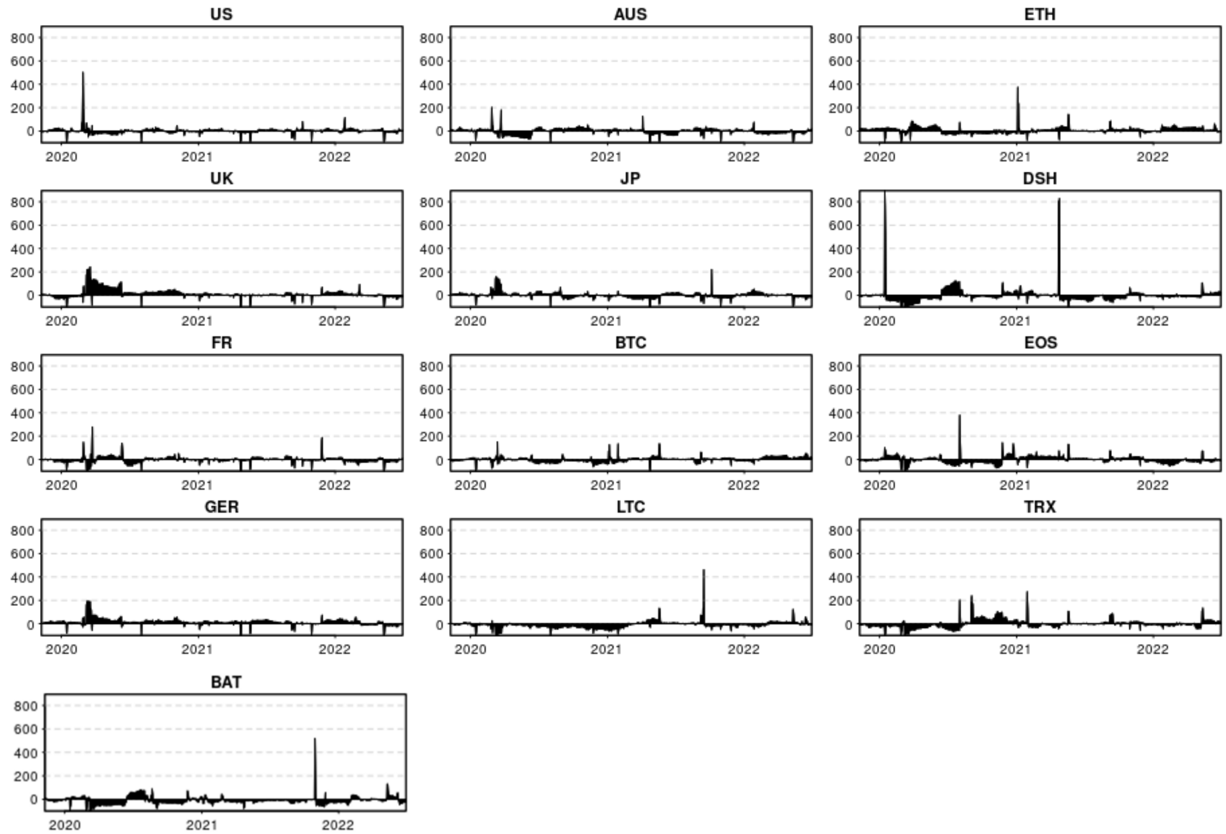


Fig. 3. Net total directional volatility connectedness

Figs 4 and 5 depict the dynamic pairwise volatility connectedness and net pairwise directional connectedness, respectively, and show that our earlier (static) results regarding the variation in connectedness between the pre- and post-Covid periods and inter- and intra-class assets reported in Table 9 are robust. More specifically, connectedness among equities is stronger during the first half of Covid-19, whereas connectedness among cryptocurrencies is stronger during the second half of Covid-19. In inter-class asset connectedness, we noticed more asymmetrical results, where high peaks were manifested during March-April 2020, followed by mid-2021 and 2022. In other periods, we did not observe any specific elevated connectedness between equities and cryptocurrencies. To sum up, we provide network graphs in Fig. 6 that show net pairwise connections between the assets during different periods. The base of the arrow from an asset specifies a net transmitter, whereas the edge of the arrow towards an asset specifies a net receiver in the system's network. The diameter of the circle indicates the magnitude of the spillover, and a larger circle indicates a stronger directional connectedness—net receivers (transmitters) are highlighted in yellow (blue). Panels a, b, and c jointly show that the most persistent transmitters (receivers) of volatility shock are Germany and ETH (Australia, BAT, and EOS) as demonstrated by the outgoing arrows and blue-colored circles (incoming edges of the arrows and yellow-colored circles) across the three periods.

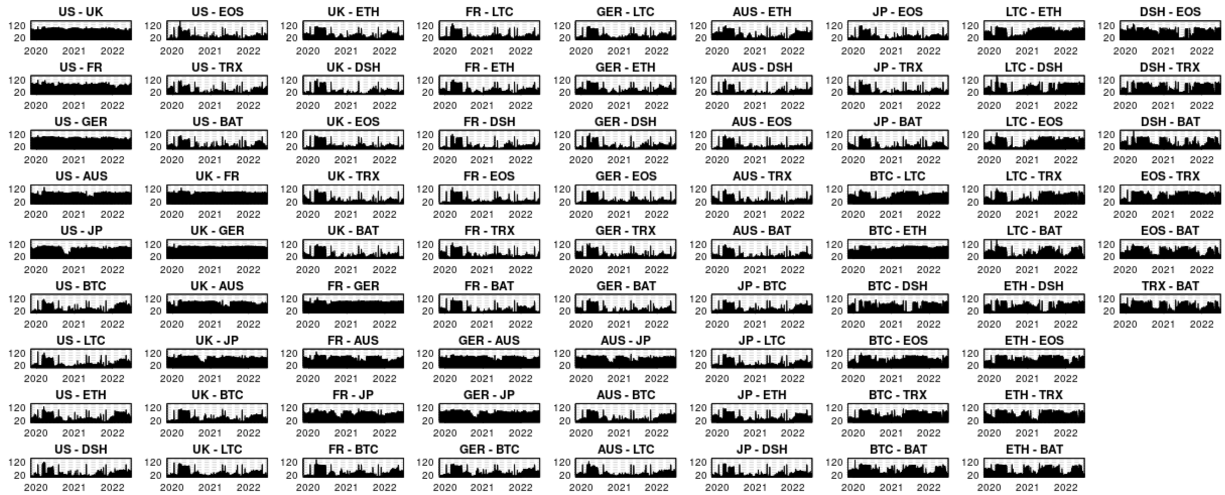


Fig. 4. Dynamic pairwise volatility connectedness

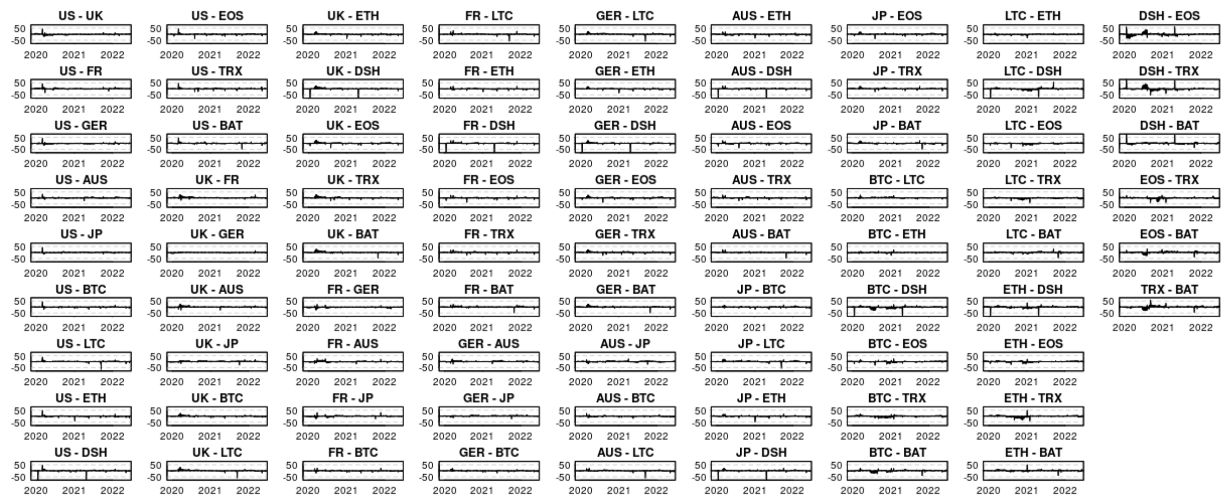


Fig. 5. Net pairwise directional volatility connectedness

Next, we divide the post-Covid period into two subperiods and report results in Panels d and e of Fig. 6: Germany, UK, and TRX are the main transmitters, whereas Australia, BAT, and EOS are the main receivers of volatility spillovers throughout the Covid period. The remaining assets under study, such as BTC, ETH, and LTC among cryptocurrencies and France, Japan, and the US among equity markets show inconsistent net-connectedness: transmitters in one period, whereas receivers in the other period and vice-versa. For example, LTC was the largest receiver during the first year of Covid; seven of the twelve assets transmitted volatility to LTC while LTC did not transmit volatility to any asset in the network. However, in the last half of Covid, LTC is found to be a net transmitter of volatility; only ETH transmits volatility to LTC while LTC transmits volatility to DSH and BAT. Variations in volatility connectedness over the period have also been observed for other assets including BTC, ETH, LTC, France, Japan, and the US.

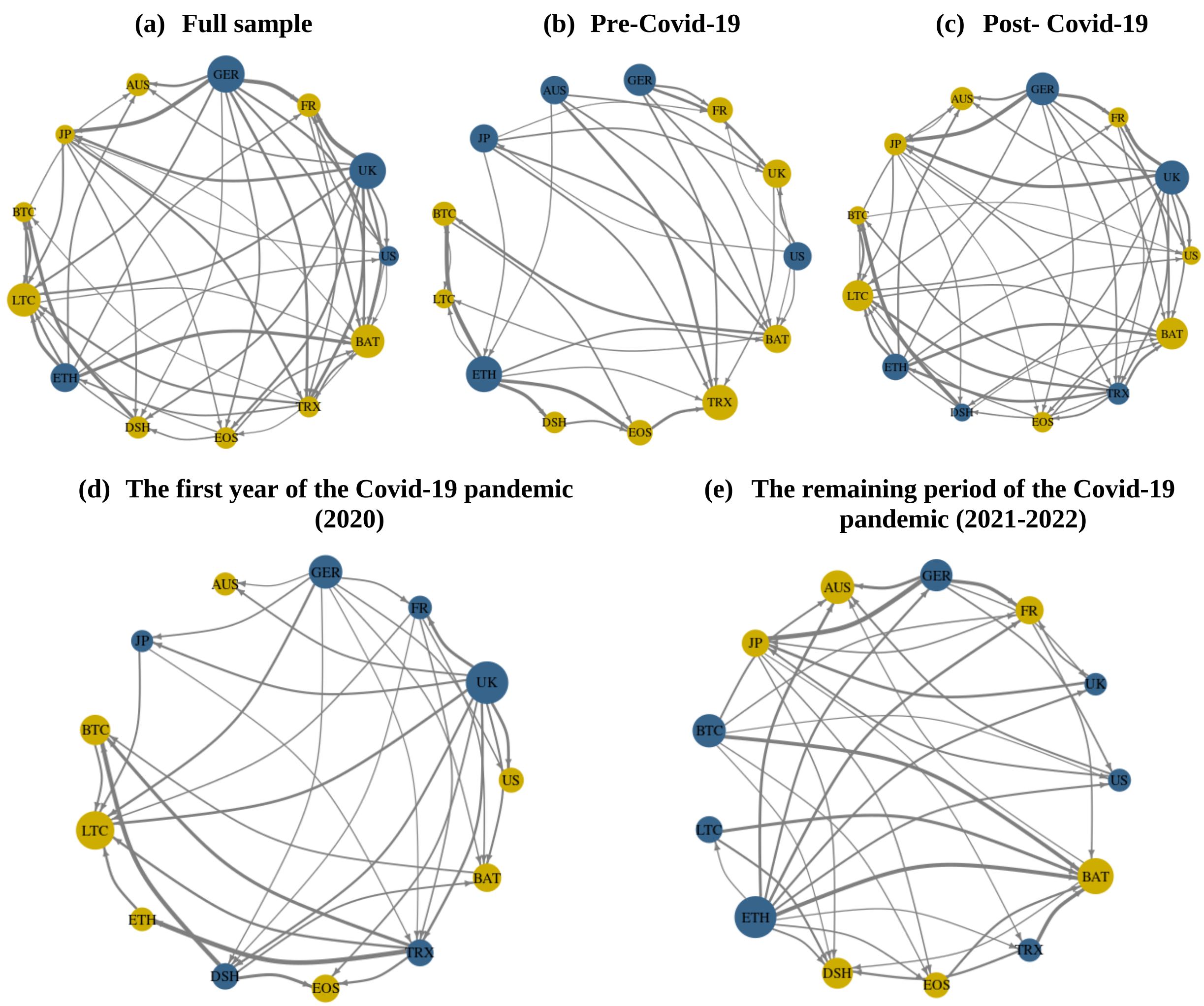


Fig. 6. Networks graph of volatility connectedness

4.5. Return connectedness using the TVP-VAR approach

The next is to examine the return connectedness between the assets studied. We follow a similar exposition to present the return spillover results, i.e., starting from average dynamic connectedness in Table 10 followed by various graphical presentations depicting total, dynamic, net, and pairwise connectedness. The results in Table 10 indicate that the total return connectedness indices in subperiods and the full sample are lower than the corresponding volatility connectedness indices reported in Table 9. For example, TCI of volatility in the full sample is 80.72%, whereas TCI of return in the full sample is 79.56%, implying a higher volatility dependence than the return dependence among the assets.

The main diagonals of Table 10 clearly show that while own-innovation in equities is manifested in return connectedness, it is manifested in volatility connectedness for cryptocurrencies (Table 9). For example, own-innovation in the volatility connectedness during the post-Covid period is 16.48% (16.65%) for the US (UK) market, whereas it is 20.21% (21.40%) in the return connectedness. On the contrary, own-innovation in the volatility connectedness during the post-Covid period is 21.01% (26.05%) for LTC (BAT), whereas it is 18.07% (23.64%) in the return connectedness.

Table 10. Static return connectedness between equity indices and cryptocurrencies.

	US	UK	FR	GER	AUS	JP	BTC	LTC	ETH	DSH	EOS	TRX	BAT	FROM
							Panel A: Full sample							
US	20.17	10.19	10.74	12.55	11.24	11.56	3.84	3.60	4.25	2.93	3.32	2.64	2.97	79.83
UK	10.43	21.35	14.08	13.66	10.87	9.82	2.87	3.13	3.23	2.91	2.60	2.52	2.53	78.65
FR	10.70	13.31	20.90	15.09	10.10	10.03	2.99	3.00	3.37	2.65	2.76	2.51	2.58	79.10
GER	12.26	12.69	14.48	20.08	10.88	10.41	3.03	2.81	3.38	2.57	2.61	2.39	2.41	79.92
AUS	12.61	11.32	11.41	12.42	21.83	10.06	3.20	2.92	3.48	2.75	2.67	2.66	2.67	78.17
JP	12.36	10.37	10.98	11.57	9.78	21.68	3.72	3.67	4.15	3.11	3.27	2.57	2.80	78.32
BTC	3.61	2.80	3.07	3.31	2.68	3.26	18.86	13.18	12.57	9.36	10.69	8.77	7.83	81.14
LTC	3.22	2.63	2.85	2.76	2.43	2.96	12.22	17.98	12.19	10.50	12.26	9.40	8.59	82.02
ETH	3.58	2.67	3.06	3.18	2.62	3.46	12.03	12.67	18.27	9.52	10.77	9.31	8.87	81.73
DSH	2.92	2.65	2.71	2.77	2.61	2.88	9.55	11.75	10.20	21.04	12.48	9.83	8.59	78.96
EOS	2.98	2.18	2.78	2.85	2.50	3.10	10.13	12.49	10.87	11.27	18.62	10.81	9.42	81.38
TRX	3.06	2.32	2.66	2.74	2.63	3.13	9.26	10.88	10.78	9.86	12.27	20.85	9.56	79.15
BAT	2.96	2.64	2.90	2.95	2.38	2.78	8.45	10.16	10.33	9.18	11.14	10.03	24.11	75.89
TO	80.70	75.76	81.71	85.84	70.72	73.46	81.28	90.27	88.78	76.61	86.86	73.45	68.83	1034.26
Inc.Own	100.87	97.11	102.61	105.92	92.55	95.14	100.13	108.25	107.05	97.65	105.48	94.30	92.93	cTCl//TCl
NET	0.87	-2.89	2.61	5.92	-7.45	-4.86	0.13	8.25	7.05	-2.35	5.48	-5.7	-7.07	86.19//79.56
NPT	4.00	3.00	9.00	10.00	0.00	2.00	7.00	12.00	11.00	6.00	8.00	3.00	3.00	
							Panel B: Pre-Covid-19							
US	21.25	11.30	15.24	14.96	12.53	10.30	1.75	2.28	2.37	1.91	2.01	3.06	1.03	78.75
UK	13.47	23.54	13.11	15.05	11.68	6.68	1.64	2.56	2.52	1.87	2.65	3.59	1.65	76.46
FR	15.97	11.33	22.61	16.82	11.42	9.33	1.22	2.06	1.94	1.38	1.80	2.54	1.58	77.39
GER	16.30	13.26	16.67	21.98	10.53	12.00	0.77	1.24	1.06	1.04	1.30	2.74	1.11	78.02
AUS	15.84	11.54	15.60	13.26	24.93	8.90	1.10	1.33	1.08	0.87	1.11	2.14	2.32	75.07
JP	13.63	8.09	12.45	14.95	10.34	26.18	2.33	2.36	2.14	2.03	2.78	1.60	1.13	73.82
BTC	2.30	1.78	1.83	1.71	2.12	1.02	20.72	14.23	14.27	12.78	13.29	8.91	5.04	79.28
LTC	2.38	1.34	1.56	1.24	1.85	0.89	12.86	18.77	15.24	13.61	14.89	8.98	6.39	81.23
ETH	2.19	1.05	1.71	1.10	1.02	0.62	12.83	15.14	18.58	14.70	14.67	9.44	6.94	81.42
DSH	2.15	1.06	1.33	1.13	1.61	0.81	11.82	14.27	15.13	19.14	14.81	9.43	7.29	80.86
EOS	2.05	1.17	1.68	1.32	1.20	0.54	11.98	15.07	14.98	14.71	19.13	9.29	6.88	80.87
TRX	3.76	3.06	2.47	2.84	2.83	1.13	8.95	11.74	10.59	10.63	11.97	24.44	5.60	75.56
BAT	2.12	1.83	1.75	1.51	1.80	0.74	6.10	10.55	11.00	12.37	11.34	6.84	32.04	67.96
TO	92.16	66.80	85.40	85.88	68.94	52.96	73.36	92.83	92.32	87.90	92.63	68.56	46.97	1006.70
Inc.Own	113.41	90.34	108.02	107.86	93.87	79.14	94.08	111.59	110.90	107.04	111.76	92.99	79.00	cTCl//TCl

NET	13.41	-9.66	8.02	7.86	-6.13	-20.86	-5.92	11.59	10.90	7.04	11.76	-7.01	-21.00	83.89//77.44
NPT	11.00	3.00	5.00	10.00	7.00	0.00	3.00	9.00	11.00	6.00	7.00	4.00	2.00	
Panel C: Post-Covid-19														
US	20.21	9.81	10.31	12.35	11.18	11.51	3.98	3.78	4.51	3.12	3.49	2.67	3.09	79.79
UK	9.93	21.40	14.20	13.74	10.82	9.87	2.90	3.18	3.22	3.07	2.55	2.50	2.62	78.60
FR	10.13	13.44	20.79	15.04	9.99	9.90	3.12	3.16	3.53	2.82	2.89	2.55	2.65	79.21
GER	11.83	12.72	14.36	20.07	11.04	9.93	3.19	2.94	3.57	2.72	2.72	2.40	2.50	79.93
AUS	12.36	11.19	11.03	12.52	21.48	10.17	3.35	3.14	3.75	2.82	2.84	2.70	2.65	78.52
JP	12.08	10.35	10.76	10.96	9.85	21.55	3.84	3.85	4.41	3.31	3.38	2.67	2.96	78.45
BTC	3.66	2.79	3.08	3.41	2.71	3.38	18.88	13.19	12.36	9.41	10.32	8.76	8.03	81.12
LTC	3.22	2.66	2.95	2.80	2.45	3.09	12.17	18.07	11.81	10.62	11.90	9.56	8.71	81.93
ETH	3.70	2.76	3.13	3.31	2.77	3.71	11.90	12.42	18.44	9.30	10.21	9.34	9.01	81.56
DSH	3.02	2.79	2.83	2.88	2.67	3.09	9.50	11.69	9.65	20.53	12.42	10.04	8.88	79.47
EOS	3.02	2.18	2.88	2.98	2.62	3.29	9.72	12.13	10.25	11.43	18.78	11.15	9.56	81.22
TRX	3.02	2.21	2.61	2.69	2.60	3.24	9.08	10.83	10.64	10.10	12.44	20.60	9.93	79.40
BAT	2.90	2.70	2.91	3.02	2.35	2.81	8.51	10.09	10.17	9.27	11.09	10.55	23.64	76.36
TO	78.88	75.61	81.06	85.71	71.05	74.00	81.25	90.39	87.87	78.00	86.26	74.89	70.59	1035.56
Inc.Own	99.09	97.01	101.84	105.78	92.53	95.55	100.14	108.46	106.31	98.52	105.04	95.49	94.23	cTCl//TCl
NET	-0.91	-2.99	1.84	5.78	-7.47	-4.45	0.14	8.46	6.31	-1.48	5.04	-4.51	-5.77	86.30//79.66
NPT	4.00	3.00	7.00	10.00	0.00	2.00	8.00	12.00	11.00	6.00	9.00	3.00	3.00	

Notes: This table presents the static analysis of the dynamic return spillovers between the selected equity indices and cryptocurrencies. “From”’ in the last column indicates the spillover from the network of all other assets to an asset of our interest, whereas “TO” in the third last row indicates the spillover to the network of all other assets from the asset of our interest. “NET” in the second last row indicates the net directional spillover of each asset, whereas “TCI” in the bottom right corner indicates the total connectedness index of the network of all assets. All selected assets, and subperiods are defined in Table and Table 6.

Based on the synthesis of Panels A, B, and C of Table 10, which indicate comparatively higher connectedness values in the post-Covid period, we give more importance to the results of the post-Covid period, which cover the most recent period that may help in optimizing ongoing portfolio allocation (Ali, Sensoy, and Goodell, 2023). The highest pairwise (off-diagonal) directional return connectedness among equities occurred from Germany to France (15.04%), whereas among cryptocurrencies it occurred from LTC to BTC (13.19%). Similar to inter-asset volatility connectedness, inter-asset return connectedness is weaker than intra-asset class return connectedness. The highest directional return connectedness from equities to cryptocurrencies is evident from Japan to ETH (3.71%), whereas the highest return connectedness from cryptocurrencies to equities is evident from ETH to the US (4.51%). Overall, the results in Table 10 and Figs. A3 and A4 suggest that spillovers from equity indices to cryptocurrencies and vice versa are weaker than the spillovers within equity indices or cryptocurrencies, indicating several cross-market/cross-asset diversification opportunities.

As the average connectedness analysis is static and ignores the evolution of the connectedness over time, we extend our analysis and present a bird's-eye-view of the evolution of return connectedness in Fig. 7. The most prominent peak in the return connectedness is manifested during March 2020, followed by a gradual decline with multiple ups and downs until a trough is hit in February 2021. Different from the volatility connectedness where uncertainty began to elevate again in 2021, the return connectedness did not elevate noticeably until the Russia-Ukraine war in February 2022. Thus, our results indicate higher return and volatility connectedness during the Russia-Ukraine war period.

Fig. 8 presents the net total directional connectedness of each asset in the network towards return spillovers and shows that most of the equity indices (cryptocurrencies) are net transmitters (receivers) of return spillovers during the first half of the Covid period. On the contrary, most of the equity indices (cryptocurrencies) are the net receivers (transmitters) of return spillovers during the 2021-2022 period. Interestingly, the results of pairwise connectedness presented in Fig. 9 and net directional connectedness presented in Fig. 10 are largely similar to the results presented in Fig. 4 and Fig. 5, respectively: intra-class asset connectedness is higher than inter-class asset connectedness on average.

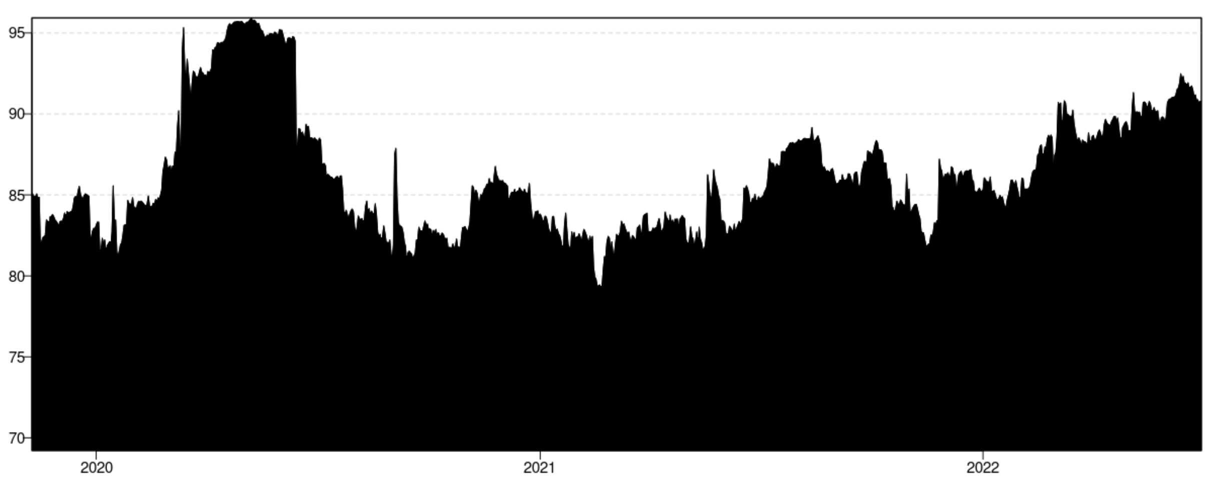


Fig. 7. Dynamic total return connectedness

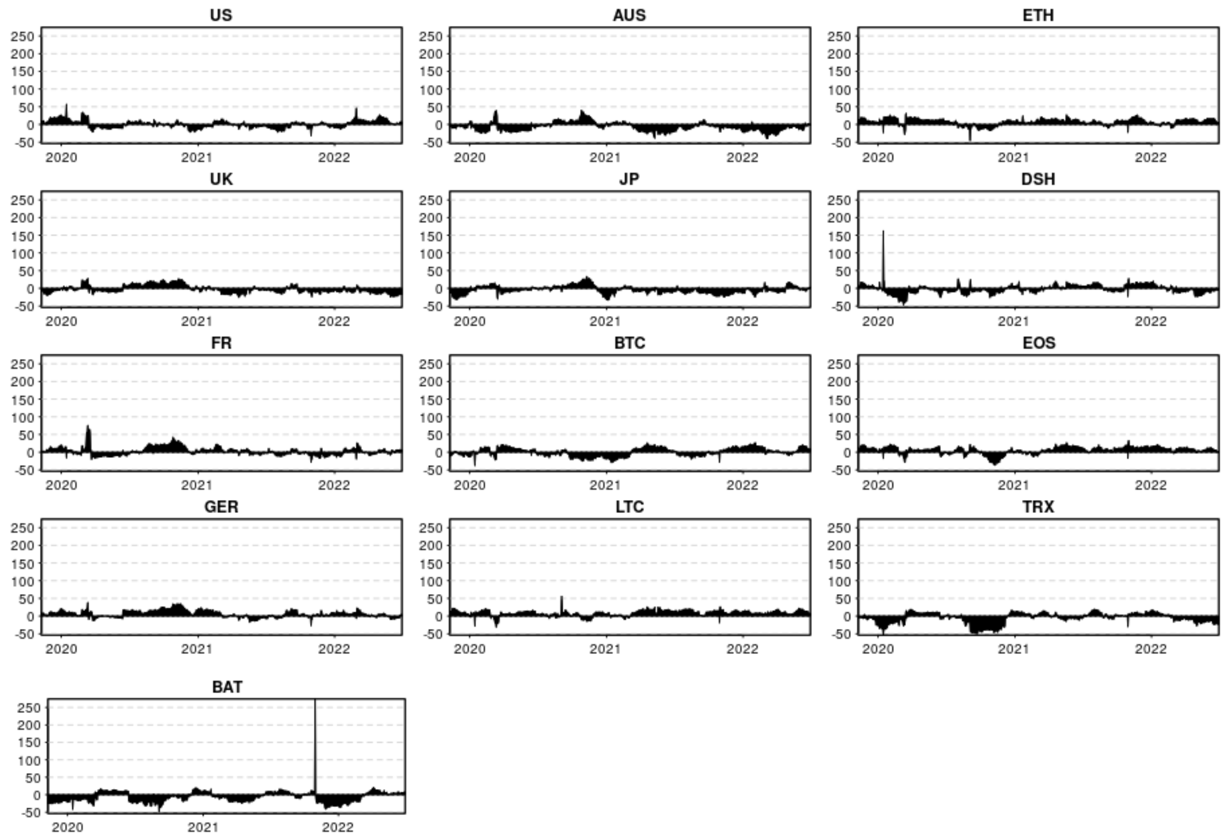


Fig. 8. Net total directional return connectedness

The other important takeaway is the evolution of connectedness, while inter-class asset connectedness is weaker than intra-class connectedness, the onset of Covid and the Russia-Ukraine war elevated the connectedness. This result validates the findings of other studies that report increased correlation among assets during periods of market turmoil (Akhtarruzzaman et al., 2021; Ali et al., 2022, 2024; Goodell and Goutte, 2021). To summarize our main results and achieve conclusive urgings, we present network graphs in Fig. 11. Panels a, b, and c of Fig. 11 show that the most persistent transmitters of return spillover are EOS, ETH, France, Germany, and LTC, whereas the most persistent receivers of slipovers are Australia, Japan, UK, BAT, and TRX in the network. The consistency of the direction of spillovers in the full sample indicates their independence from exogenous shocks caused by Covid and Russia-Ukraine conflicts. While further exploring the post-Covid period in Panels d and e of Fig. 11, we find that ETH, Germany, and LTC are the main transmitters, whereas Australia, BAT, TRX, and US are the main receivers of return spillovers during the Covid and Russia-Ukraine war periods.

The most drastic change was found in the case of UK (BTC), which was a transmitter (receiver) of return spillover for six (four) assets during the first year of the Covid period, however, during the 2021-2023 period, UK (BTC) changed its position and turned into a receiver (transmitter) of return spillover for nine (eight) assets in the network. In line with the findings of Ali et al. (2023), we identified some short-term changes that were confined to the first phase of Covid; for instance, UK among the equity indices and EOS among the cryptocurrencies.

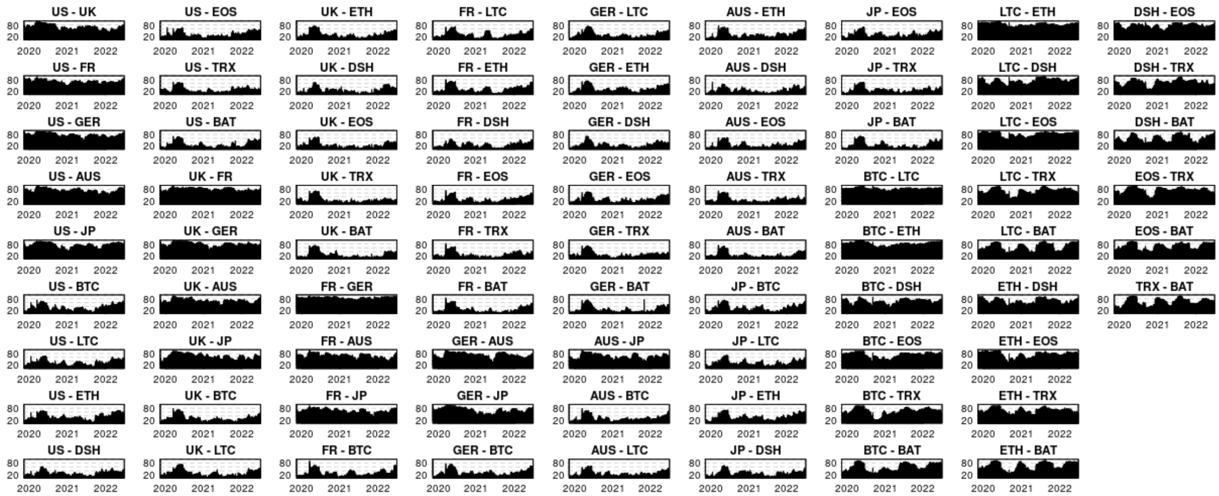


Fig. 9. Dynamic pairwise return connectedness

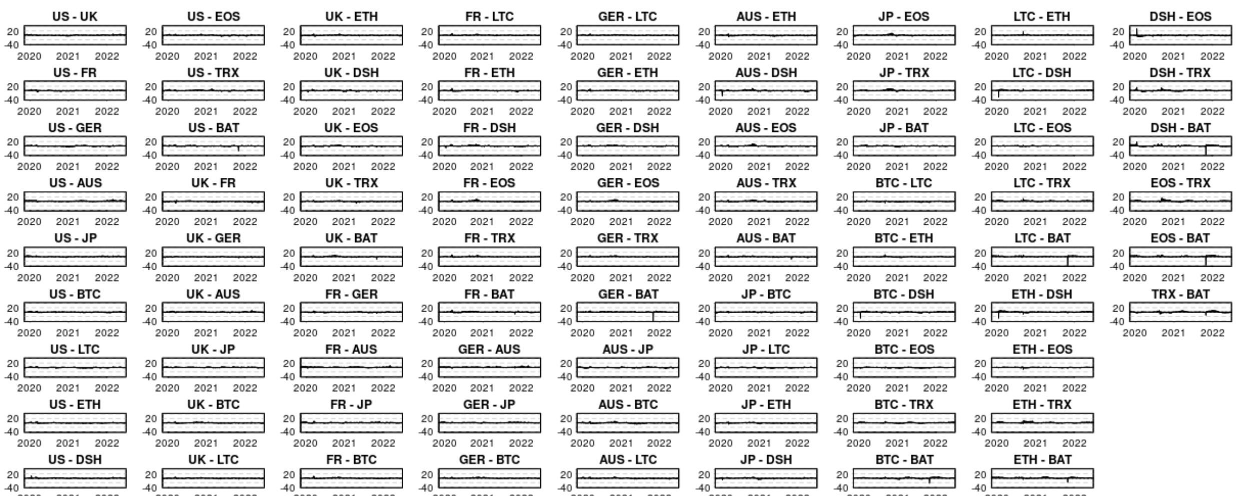
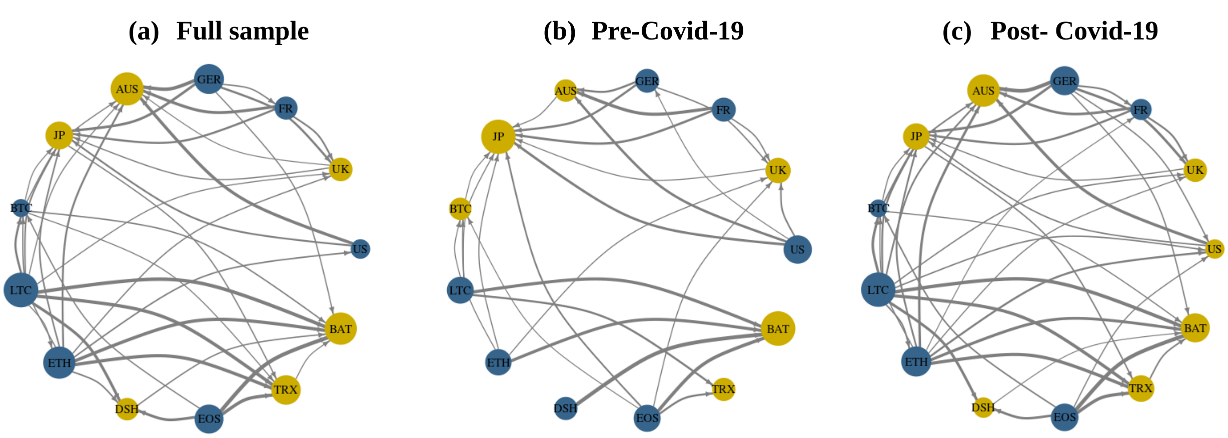


Fig. 10. Net pairwise directional return connectedness



(d) The first year of the Covid-19 pandemic (2020)

(e) The remaining period of the Covid-19 pandemic (2021-2023)

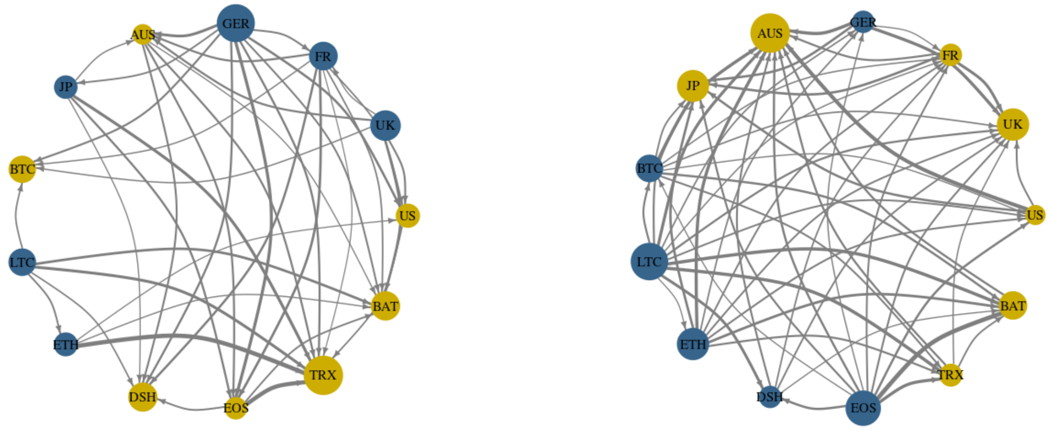


Fig. 11. Networks graph of return connectedness

Referring to all panels of Fig. 11 (full sample, pre-Covid, post-Covid, first-year of Covid, and last half of Covid), UK (EOS) is a net receiver (transmitter) of the return spillover in all periods except the first-half. Therefore, this study suggests practitioners must exercise caution while diversifying their equity and cryptocurrency investments.

5. Conclusion, Major Findings, and Implications

This study examines information bias, asymmetric innovation shocks and their spillovers, and return- and volatility connectedness between leading seven cryptocurrencies and six equity market indices in both inter- and intra-class asset settings using around-the-clock 5-minute high-frequency intra-day data inclusive of both trading and non-trading periods. The equity markets under study are the US, UK, Germany, France, Australia, and Japan, whereas the cryptocurrencies are Bitcoin, Litecoin, Ether, Dashcoin, EOS, Basic Attention Token, and Tron. The sample period spans from August 5, 2019, to January 31, 2023, which is a diverse period covering different market states for both asset classes, i.e., bull, bear, turmoil, rebound, and boom periods. Likewise, our sample period also accounts for different crisis events and geopolitical uncertainties, i.e., cryptocurrency/Bitcoin flash crashes, Covid-19, and the recent Russia-Ukraine conflict. Thus, we provide a comprehensive inter-market and both inter- and intra-class asset analyses offering multiple implications for investors, guidelines for policymakers, and future works for researchers.

First, we find that the information bias, i.e., the leverage effect, which indicates a larger impact of negative news/innovations on the conditional volatility of returns than positive news/innovations of the same size, is stronger in equities (cryptocurrencies) during the pre-Covid (post-Covid) period. Since several economic relief packages were introduced by different governments across different countries after the onset of Covid, positive news brought stability and remarkable growth in equity markets lately. Thus, both positive and negative innovations equally impacted the conditional volatility of returns during the Covid period. Specifically, Australia, EOS, and ETH appear to be more sensitive to negative news than positive news in both pre- and post-Covid periods.

Second, using GARCH-BEKK, this study finds that the degree of innovation spreading from one asset to other assets is relatively stronger in the post-Covid period and among intra-class asset combinations, specifically for ETH-BTC, DSH-BTC, BAT-LTC, and DSH-ETH among cryptocurrencies and UK-US, Japan-US, Japan-UK, and Australia-France among equity indices. In inter-class asset settings, innovation shocks spreading between cryptocurrencies and equities are stronger for BTC, LTC, ETH, and DSH with equity indices. Third, we find that the degree of innovation due to the impact of lagged standardized errors compared to lagged conditional covariances in inter-class asset spillovers is stronger for BTC-, LTC-, ETH-, and DSH-equity combinations, followed by EOS-equities.

Fourth, using the TVP-VAR methodology, we examine and find that return and volatility spillovers are time-varying. These variations are particularly pronounced at the onset of the Covid pandemic and the Russia-Ukraine conflict. The structure of spillovers is volatility-driven, the connectedness index shows higher and multiple peaks in the volatility series than in the returns series throughout the sample period. Germany among the equity indices transmits the highest directional volatility and return spillovers to the UK and France, respectively. ETH among the cryptocurrencies transmits the highest volatility spillover (to BTC), whereas LTC transmits the highest return spillover (BTC). Both volatility and return connectedness among inter-class assets are weak (less than 4.6% in any combination). The highest directional volatility (return) spillover from a cryptocurrency to an equity market is transmitted from ETH to the US, whereas the highest directional volatility spillover from an equity market to a cryptocurrency is transmitted from Germany to LTC (Japan to ETH). Interestingly, regarding the contribution of own innovations in spillovers, we find that cryptocurrencies are more connected during volatility shocks whereas equities are more connected during return shocks. These findings indicate the potential for numerous inter-market and inter-class asset diversification and hedging opportunities for investors. The most persistent net transmitters of volatility are Germany and ETH, whereas the most persistent net receivers of volatility are France, BAT, BTC, EOS, and LTC. Different from volatility spillovers, the most persistent net transmitters of return spillovers are France, Germany, EOS, ETH, and LTC, whereas the most persistent net receivers of return spillovers are Australia, Japan, UK, BAT, and TRX. The persistence of the direction of connectedness shows that exogenous shocks during the sample period caused by Covid, Bitcoin/flash-crash, cryptocurrency boom, or Russia-Ukraine war did not impact the net transmitter/receiver position of these assets, indicating their resilience.

Finally, in line with Ali et al. (2023) who find that the change in diversification benefits during the Covid periods was temporary (short-lived) in several cases, we find that the spillover of return and volatility among the assets has been transformed in most cases. In addition, we find that some assets temporarily changed their net position during the first half of Covid, indicating investors should consistently look for changing behavior of volatility and return spillovers. More precisely, Bitcoin and Litecoin (Australia and Japan) changed their net positions from receivers (transmitters) to transmitters (receivers) of volatility after Covid, which persisted till the end of the sample period, indicating long-lived recent changes in the diversification channels that are likely to persist. Similarly, France and Bitcoin (US) changed their net positions from receiver (transmitter) to transmitter (receiver) of return spillovers. Our findings, using both volatility and return connectedness, show that several (but, not all) of the changes in spillovers and diversification benefits and channels are long-lived. Thus, the findings of this study can be useful for investors to diversify their portfolios in the future; however, caution should be exercised while diversifying portfolios as a few short-lived changes are also evident in the network.

5.1. Implications and Future Agenda

Our findings offer important hands-on information for fund managers and investors searching for opportunities to diversify their portfolios internationally across different markets and asset classes. The leverage effect that indicates the response towards positive and negative news and the knowledge regarding asymmetric innovation shocks may guide market participants in timely rebalancing portfolios. Given that increased volatility and spillovers of return or volatility shocks to other assets indicate higher risks, the findings of this paper are useful for international portfolio managers and investors (both high and low-risk appetite investors) to accordingly diversify their portfolios. One important limitation of this study is the selection of assets: While the assets under study account for a substantially large market share of equity and cryptocurrency markets, there are other cryptocurrencies, equity indices, and assets that can be considered. For instance, oil is an essential input for economic growth, and a potential portfolio diversifier, and high-frequency data is available for crude oil; thus, future studies may extend this work by including the high-frequency price information of the oil market. Most importantly, our sample includes equity markets from different regions where trading and non-trading periods (both trading hours and trading days) are different and we aim to examine comprehensive real-time (using standardized time, GMT, not day-end prices) bidirectional return and volatility spillovers (both asymmetric and symmetric) across all the assets (both equity indices and cryptocurrencies), it was not possible to distinguish trading and non-trading periods as they substantially differ. For example, the trading hours and days in Japan and Australia are noticeably different than in the US and Europe, indicating that considering a uniform trading period is unrealistic. Thus, examining trading and non-trading periods, possible by segregating equities into different regions (US, Europe, and Asia-Pacific), will offer new insights and enhance our understanding of how different markets and assets interact with each other during trading and non-trading periods.

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