The current issue and full text archive of this journal is available on Emerald Insight at:
https://www.emerald.com/insight/2754-4214.htm

Journal of Electronic Business & Digital Economics

151

Received 19 August 2024
Revised 2 October 2024
Accepted 9 October 2024

Spillover effects among cryptocurrencies in a pandemic: a time frequency approach

Pearl Seyram Kumah
Department of Accounting Education, Akenten Appiah-Menka University of Skills Training and Entrepreneurial Development, Kumasi, Ghana, and
Joseph Antwi Baafi
Department of Economics Education, Akenten Appiah-Menka University of Skills Training and Entrepreneurial Development, Kumasi, Ghana

Abstract

Purpose – This study investigates the time-varying volatility spillover connectedness among seven major cryptocurrencies before and during the COVID-19 pandemic. It aims to understand contagion risk and its implications for diversification and financial stability, especially during periods of extreme price volatility.
Design/methodology/approach – Using the frequency-domain spillover index, the study analyzes the interconnectedness of cryptocurrency markets with daily data from 10 August 2015 to 10 December 2021. This method allows for examining volatility spillovers across different time frequencies.
Findings – The study finds that cryptocurrencies are highly interconnected at higher frequencies, indicating significant contagion risk and limited short-term diversification opportunities. The spillover effects are frequency-dependent, varying across different time horizons.
Practical implications – The findings suggest the need for targeted regulatory policies focused on short-term cryptocurrency behavior to maintain financial stability. Investors should exercise caution when using cryptocurrencies for portfolio diversification, given the high interconnectedness and contagion risk.
Originality/value – This study uniquely contributes to the literature by applying a frequency-domain approach to analyze volatility spillovers across multiple cryptocurrencies, particularly in the context of the COVID-19 pandemic. It provides novel insights into the frequency-dependent nature of spillover effects, offering a deeper understanding of the contagion risk in cryptocurrency markets.

Keywords Cryptocurrencies, Volatility, Spillover index, Time-varying
Paper type Research paper

1. Introduction

The international financial market has increasingly embraced cryptocurrencies as novel financial instruments (Corbet, Meegan, Larkin, Lucey, & Yarovaya, 2018), evidenced by their rapid growth in both number and market value (Ji, Bouri, Lau, & Roubaud, 2019). Although Bitcoin continues to dominate the cryptocurrency market, alternative coins, commonly

JEL Classification — C13, C14, C22, C51, D53

Conflict of interest: No potential conflict of interest was reported by the authors.
Funding: This research did not receive any specific grant from funding agencies in the public, commercial or not-for-profit sectors.

Journal of Electronic Business & Digital Economics
Vol. 4 No. 1, 2025
pp. 151-166
Emerald Publishing Limited
e-ISSN: 2754-4222
p-ISSN: 2754-4214
DOI 10.1108/JEBDE-08-2024-0027

referred to as altcoins – such as Ethereum, Litecoin, Ripple, Dash, Monero and Stellar – are progressively gaining market share. This trend indicates that economic actors are diversifying their investments beyond Bitcoin, seeking higher returns through altcoins. Altcoins share the foundational technological concept of cryptography with Bitcoin, and several have achieved substantial market capitalizations, reaching billions and millions of dollars (Liu, 2019; http://www.coinmarketcap.com). The rise of altcoins offers significant diversification benefits to investors, as some altcoins are relatively isolated from others (Corbet *et al.*, 2018), provide lower transaction costs (Kim, 2017), and enable swift transactions (Fantazzini, Nigmatullin, Sukhanovskaya, & Ivliev, 2016) compared to traditional forex markets, contributing to increased liquidity within the cryptocurrency market.

Despite the notable growth and active participation of investors in the cryptocurrency market, there remains limited empirical evidence on the interaction among cryptocurrencies, particularly during periods of market stress such as pandemics (Apergis, 2022). The cryptocurrency market is relatively shallow and exhibits excessive price volatility compared to traditional financial markets, raising concerns about potential market collapses should fluctuations or shocks impact the leading cryptocurrencies (Kumar & Ajaz, 2019). Furthermore, the integration of cryptocurrencies with traditional assets (Henriques & Sadorsky, 2018; Guesmi, Saadi, Abid, & Ftiti, 2019; Klein, Thu, & Walther, 2018) could heighten investor attention and contribute to excessive liquidity in the cryptocurrency market. Such a phenomenon necessitates an in-depth understanding of the interconnections among leading cryptocurrencies over time, enabling economic agents interested in cryptocurrencies to develop informed trading and investment strategies for portfolio optimization and risk management. Additionally, understanding volatility transmissions across cryptocurrencies during pandemics is crucial for comprehending the market's microstructure and overall functioning.

This study aims to investigate the time-varying volatility spillovers among seven leading cryptocurrencies, namely Bitcoin, Ethereum, Litecoin, Ripple, Dash, Monero and Stellar, using the Barunik and Křehlík (2018) frequency domain spillover index. Specifically, the study seeks to decompose the contribution of each cryptocurrency to total market volatility across different frequencies and identify the main transmitters and receivers of spillover effects over time. By focusing on the frequency-dependent behavior of these spillovers, the study aims to provide a nuanced understanding of the interconnectedness within the cryptocurrency market, particularly during periods of heightened market stress.

This study makes several important contributions to the existing body of knowledge. First, it extends the literature on cryptocurrency market dynamics by applying a frequency domain approach to analyze volatility spillovers, which allows for a more detailed examination of short-term, medium-term and long-term interconnectedness among leading cryptocurrencies. Second, the study contributes to the ongoing debate on the role of cryptocurrencies as potential diversifiers in investment portfolios by providing empirical evidence on the frequency-dependent contagion risks within the market. Third, by identifying the cryptocurrencies that serve as the primary transmitters and receivers of volatility spillovers, the study offers valuable insights for investors and policymakers interested in optimizing portfolio strategies and managing risks associated with cryptocurrency investments.

While this study offers significant insights into the dynamics of cryptocurrency markets, it is not without limitations. One limitation is the reliance on data from a specific period, which may not capture the full range of market conditions, especially given the rapidly evolving nature of the cryptocurrency market. Additionally, the study focuses on a select group of seven cryptocurrencies, which, while representative of the market's leading assets, excludes a large number of other digital currencies that may also play significant roles in market dynamics. Moreover, the frequency domain spillover index used in this study, while robust, is subject to the limitations of the models it is based on, including potential sensitivity to extreme market events and structural breaks. Future research could address these limitations by incorporating a broader range of cryptocurrencies, extending the analysis over a longer time horizon, and exploring alternative methodologies to capture the complex interactions within the cryptocurrency market.

The remainder of this study is structured as follows: Section 2 discusses the methodology. Section 3 provides a description of the data and its statistical properties. Section 4 presents the results and discusses spillover frequency connectedness. Section 5 concludes the study and outlines policy implications.

2. Literature review

2.1 The evolution of cryptocurrencies and their market dynamics

Cryptocurrencies have emerged as a significant innovation in the global financial market, representing a departure from traditional fiat currencies through their decentralized, cryptographic underpinnings. Bitcoin, introduced by Nakamoto (2008), was the first cryptocurrency, and it has since remained the dominant player in the market. However, the emergence of alternative cryptocurrencies, commonly known as altcoins, such as Ethereum, Litecoin, Ripple, Dash, Monero and Stellar, has transformed the market landscape (Corbet *et al.*, 2018). These altcoins have introduced diversity into the market, offering distinct technological features and use cases, which has attracted a broad spectrum of investors and users.

The literature on cryptocurrency market dynamics has predominantly focused on Bitcoin due to its pioneering status and substantial market capitalization. Studies like Bouri, Molnár, Azzi, Roubaud, and Hagfors (2017) have analyzed Bitcoin's role as a potential hedge or safe haven against traditional financial assets. Similarly, Dyhrberg (2016) explored Bitcoin's volatility and its comparisons to gold and the US dollar, positioning Bitcoin as a unique asset class with features of both commodities and currencies.

As the cryptocurrency market has evolved, so too has the academic focus on the interconnectedness among various cryptocurrencies. Ji *et al.* (2019) documented the increasing market value and number of cryptocurrencies, highlighting the diversification benefits they offer. However, they also pointed out the market's inherent risks, particularly the extreme volatility that characterizes cryptocurrencies, which differentiates them from traditional assets. The integration of cryptocurrencies into mainstream finance, such as through the introduction of cryptocurrency derivatives, has further fueled academic interest in understanding the market dynamics and volatility spillovers between cryptocurrencies and other financial assets (Guesmi *et al.*, 2019).

Volatility is a critical characteristic of cryptocurrency markets, distinguishing them from more established financial markets. Several studies have explored the nature of this volatility, often finding that it is not only higher but also more persistent and erratic compared to traditional assets (Katsiampa, 2018). Volatility in cryptocurrency markets is influenced by various factors, including market sentiment, regulatory news, technological developments and macroeconomic events (Liu & Tsyvinski, 2018). The extreme price fluctuations observed in cryptocurrencies are often linked to their limited market depth, speculative trading and the absence of central regulatory oversight (Kumar & Ajaz, 2019).

The interconnectedness of cryptocurrencies has been a subject of extensive research, with many studies focusing on the spillover effects between different coins. Katsiampa (2018) applied an asymmetric diagonal BEKK multivariate GARCH model to examine volatility spillovers among Bitcoin, Litecoin, Ripple, Ethereum and Stellar, finding significant positive associations among these cryptocurrencies. The study highlighted that shocks in one cryptocurrency could propagate to others, creating a network of volatility spillovers that complicates risk management strategies.

Similarly, Ji *et al.* (2019) used the Diebold and Yilmaz (2012) and Diebold and Yilmaz (2016) approach to investigate return and volatility spillover connectedness across six major cryptocurrencies. Their findings suggested that Bitcoin and Litecoin have substantial spillover effects on other cryptocurrencies, emphasizing the role of these coins as central nodes in the cryptocurrency network. This interconnectedness implies that movements in Bitcoin, for example, can have widespread implications for the entire market, thereby influencing investor behavior and market stability.

Another study by Koutmos (2018) employed a VAR model to analyze the volatility spillovers among cryptocurrencies, identifying strong interdependence among the coins. The study pointed out that the volatility spillover patterns are not static but vary over time, particularly during periods of market stress. This time-varying nature of spillovers is further supported by research using wavelet-based methods, which show that cryptocurrency interconnectedness is frequency-dependent (Omane-Adjepong & Alagidede, 2019).

The COVID-19 pandemic provided a unique opportunity to study the resilience and behavior of cryptocurrency markets during an extreme global event. Apergis (2022) investigated how cryptocurrencies interacted during the pandemic, finding that the market experienced heightened volatility and increased interconnectedness. The study highlighted that during crises, investors often treat cryptocurrencies as a homogenous asset class, leading to synchronized movements across the market. This behavior contrasts with the pre-pandemic period, where diversification benefits were more pronounced.

Huynh (2019) extended the analysis of extreme events by applying Granger causality, VAR-SVAR, and Student's-t Copulas to study spillover risks in cryptocurrency markets. The research found that Bitcoin was a primary recipient of spillover effects, while Ethereum often acted independently. This finding underscores the complexity of the cryptocurrency market, where different coins can exhibit varying degrees of sensitivity to external shocks.

Moreover, Trabelsi (2018) employed a VAR model to explore volatility spillovers during the pandemic, finding that spillover effects intensified as the crisis deepened. The study emphasized the importance of understanding these dynamics for investors seeking to manage risks in their cryptocurrency portfolios. The findings also suggest that during pandemics or similar extreme events, traditional diversification strategies may become less effective due to the increased correlation among cryptocurrencies.

Despite the growing body of research on cryptocurrency markets, several gaps remain. One significant gap is the limited understanding of the frequency-dependent nature of volatility spillovers among cryptocurrencies, particularly during periods of extreme market stress such as pandemics. While studies like Omane-Adjepong and Alagidede (2019) have explored frequency-based interconnectedness, there is still a lack of comprehensive analysis that decomposes spillover effects across different frequencies over time.

Additionally, most existing studies focus on a static analysis of spillovers without adequately considering how these dynamics evolve over different time horizons. The reliance on models that do not capture the time-varying nature of spillovers limits the ability to fully understand how cryptocurrencies interact in the short term, medium term and long term. Moreover, while Bitcoin and a few other major cryptocurrencies have been extensively studied, there is a need for more research on how lesser-known altcoins contribute to or are affected by volatility spillovers.

This study addresses these gaps by employing the Barunik and Křehlík (2018) frequency domain spillover index to analyze the time-varying volatility spillovers among seven leading cryptocurrencies. With the focus on frequency-based analysis, this research provides a more complex understanding of the interconnectedness within the cryptocurrency market, particularly during periods of high volatility, such as the COVID-19 pandemic. The study's findings will contribute to the ongoing discourse on cryptocurrency market dynamics, by giving information that could improve portfolio diversification strategies and risk management practices in this rapidly evolving market.

3. Methodology

The study investigates the volatility spillover connectedness among seven cryptocurrencies applying Barunik and Křehlík (2018) frequency domain spillover index, which is based on Dew-Becker and Giglio (2016) spectral representations of variance decomposition. This methodology has theoretical root to Diebold and Yilmaz (2012), but its time-frequency connectedness was first introduced by Barunik and Krehlik (2016) and extended by Barunik and Křehlík (2018).

As noted by Barunik and Krehlik (2016), the generalized impulse response function is decomposed considering the spectral behavior of series X_t as follows:

$$S_x(w) = \sum_{h=0}^{\infty} E(X_t X_{t-h}) e^{-ihw} = \psi\left(e^{ihw}\right), \tag{1}$$

where w is frequency, ∞ is infinite horizon connectedness, and $\psi(e^{-ihw}) = \sum_{h=0}^{\infty} \psi(e^{-ihw})$. The unconditional generalized forecast error variance decomposition (GFVED) is calculated on a particular frequency w as follows:

$$(\Theta(w))_{i,j} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{\infty} \left(\psi\left(e^{-ihw}\right) \sum\right)_{i,j}^{2}}{\sum_{h=1}^{\infty} \left(\psi(e^{-ihw}) \sum \psi(e^{ihw})\right)_{i,j}}, \tag{2}$$

which is standardized to the following equation:

$$(\Theta(w))_{i,j} = \frac{(\Theta(w))_{i,j}}{\sum_{j=1}^{k} (\Theta(w))_{i,j}}. \tag{3}$$

We follow Barunik and Krehlik (2016) and express accumulative connectedness table over an arbitrary frequency band $d = (a;, b)$ as follows:

$$(\Theta_d)_{i,j} = \int_a^b (\Theta(w))_{i,j} dw. \tag{4}$$

We then specify the overall connectedness within a frequency band d as follows:

$$C^d = \frac{\sum_{i=1, i \neq j}^{k} (\Theta_d)_{i,j}}{\sum_{i,j} (\Theta_d)_{i,j}} = 1 - \frac{\sum_{i=1}^{k} (\Theta_d)_{i,i}}{\sum_{i,j} (\Theta_d)_{i,j}}. \tag{5}$$

Within the spectral band $d = (a;, b)$, strong connectedness is indicated when C^d is close to unity. The contribution of a market $(i \neq j)$ to another i on the spectral band d is measured using the *within from* connectedness specified as follows:

$$C^d_{i\leftarrow} = \sum_{j=1, i\neq j}^{k} (\Theta_d)_{i,j}. \tag{6}$$

whereas the contribution to a market $(i \neq j)$ from another i on the spectral band d is measured using the *within to* connectedness specified as follows:

$$C^d_{i\rightarrow} = \sum_{j=1, i\neq j}^{k} (\Theta_d)_{i,j}. \tag{7}$$

Following Diebold and Yilmaz (2012), we measure total connectedness as $Sg(H) = \sum_d C^d$ and pairwise connectedness as $\theta_{ij} \neq \theta_{ji}$.

4. Data description and preliminary analysis

In this study, we focus on seven cryptocurrencies (Bitcoin, Ethereum, Litecoin, Das, Ripple, Monero and Steller) which have existed for the past seven years with market capitalization above 1 billion USD. These cryptocurrencies are among the top fifteen currencies by market capitalization and can proxy for the cryptocurrency market. We use daily data sourced from CoinMarketCap (2019) and spans 10th August 2015 to 10th December 2021. We calculate returns as change in log price, Monday-to-Friday and there were 1,097 observations.

Table 1 presents summary statistics on the seven daily cryptocurrency return series studied. Average daily return range from 0.2% for Bitcoin and Ethereum to 0.55% for Steller and daily variance range from 0.18% for Bitcoin and Ethereum to 0.88% for Steller. Litecoin, Ripple, Das, Monero, and Steller are positively skewed except Bitcoin and Ethereum. Kurtosis and skewness values show leptokurtic and non-normality in cryptocurrency returns which is confirmed by the Shapiro–Wilk test by rejecting the normality assumption at all conventional levels of significance. These go on to support the need for using asymmetric distributions in modeling the volatility spillover connectedness among cryptocurrencies.

5. Results and discussion

Following Barunik and Křehlík (2018) approach as used by Tiwari, Cunado, Gupta, and Wohar (2018), and Qarni, Gulzar, Fatima, Khan, and Shafi (2019), we first of all estimate a seven variable VAR with two lag lengths. We then construct the directional spillover

	Bitcoin	Ethereum	Litecoin	Ripple	Das	Monero	Steller
Observ	1,097	1,097	1,097	1,097	1,097	1,097	1,097
Mean	0.002	0.002	0.0007	0.0026	0.0021	0.0026	0.0055
Variance	0.0018	0.0018	0.0038	0.0044	0.0035	0.0044	0.0088
Skewness	−0.2356	−0.2356	1.2575	4.5132	0.2983	4.5132	2.1108
Kurtosis	4.7234	4.7234	12.1915	76.4051	3.383	76.4051	17.9168
Normtest.W	0.914	0.914	0.8425	0.5981	0.9463	0.5981	0.8568
Normtest.p	0	0	0	0	0	0	0

Note(s): Observ. – Observations, Shapiro–Wilk test reject the normality assumption at all conventional levels of significance
Source(s): Authors' own work

Table 1. Summary statistics of cryptocurrencies

connectedness index, the pairwise net directional spillover connectedness, and the rolling window spillover and results discussed in Sections 4.1, 4.2, and 4.3 respectively. As noted by Barunik and Krehlik (2016, 2018) the spillover table has four frequency bands, and we choose the first and second bands [1] (freq. 1 and 2) as short-term connectedness, third band [2] (freq. 3) as medium-term connectedness and fourth band [3] (freq. 4) as long-term connectedness of the cryptocurrencies.

5.1 Directional spillover connectedness

We construct the directional spillover connectedness table using a variance decomposition forecasting horizon (H) of 100 period ahead since Barunik and Křehlík (2018) approach does not support a forecasting horizon less than 100 (H < 100) and results shown in Table 2. From the decomposed spillover exhibited in Table 2, we observe that the shortest horizon (freq. 1) contributes most (30.46%) of total connectedness followed by freq. 2 which is also a short-time horizon (7.88%). The medium-term horizon (freq. 3) contributes (2.57%) to total connectedness whiles the long-term movement of the currencies (freq. 4) contributes only (0.43%) to total connectedness. We can conclude from this result that, the total spillover connectedness index among the seven cryptocurrencies is high in the short-time horizon than in the medium and long-time horizons suggesting contagion and that portfolio diversification benefits are low in the short-term. The result for total spillover connectedness supports the findings of Trabelsi (2018) which incorporate time-decomposition to VAR to investigate the volatility spillover effects among cryptocurrencies and reports connectedness within the cryptocurrency market.

The across frequencies FROM_ABS (TO_ABS) expose the cryptocurrency that highly contributes to (receives from) the total spillover effects across frequencies. From panels 1 and 2 of Table 2, it is evident that Bitcoin is the major contributor and receiver of total spillover effects in the short-term connectedness (freq. 1 and 2), followed by Litecoin, Das, Monero, Ethereum, Steller and Ripple. However, panels 3 and 4 which shows the medium-term (freq. 3) and long-term (freq.4) connectedness, respectively, depicts Litecoin, Bitcoin, and Das as the major contributors and receivers of total spillover effects whiles Ripple neither contributes to nor receives spillover effects from any of the cryptocurrencies. This suggests Ripple as the independent coin among the cryptocurrencies. This finding is in line with Ji *et al.* (2019) who document Bitcoin and Litecoin as the two largest transmitters and receivers of spillover effects from other cryptocurrencies. From this result, we suggest that Bitcoin, Litecoin and Das markets should be given regulatory initiatives since these cryptocurrencies contributes and receives most of the total volatility spillovers in the cryptocurrency market.

The difference between TO_ABS and FROM_ABS (TO_ABS – FROM_ABS) measures the net directional spillover connectedness (Net_ABS) of cryptocurrencies across time. This shows the cryptocurrencies that are net transmitters (positive values) and recipients (negative values) of spillover effects to (from) other cryptocurrencies across frequencies. We observe from Table 2 that, the shortest horizon (freq.1) show Bitcoin, Litecoin and Das as the net transmitters of spillover effects, whiles Ethereum, Ripple, Monero and Steller are the net recipients of spillover effects. Nevertheless, frequencies 2, 3 and 4 depict Bitcoin, Ethereum and Steller as the net transmitters of spillover effects whiles Litecoin, Ripple, Das and Monero are the net recipients of spillover effects. We once again confirm the findings of Ji *et al.* (2019) which shows Bitcoin and Litecoin as the largest net transmitters of spillovers and Ethereum and Das as the largest net spillover effect receivers.

5.2 Pairwise directional spillover connectedness

Furthermore, we investigate the results in more detail by constructing a net-pairwise directional spillover connectedness of the currencies and results shown in Table 3. The net-

	BTC	ETH	LTC	XRP	DASH	XMR	XLM	FROM_ ABS	FROM_ WTH
Freq. 1									
BTC	32.50	4.76	13.20	0.02	9.39	9.44	4.55	5.91	7.95
ETH	7.10	42.73	7.34	0.01	7.51	6.21	2.39	4.36	5.87
LTC	13.49	4.97	32.86	0.00	8.08	7.31	5.48	5.62	7.56
XRP	0.09	0.02	0.08	71.41	0.20	0.05	0.16	0.09	0.11
DASH	9.91	5.52	8.40	0.02	38.30	8.95	3.91	5.24	7.06
XMR	11.07	4.47	8.37	0.01	9.32	40.77	2.94	5.17	6.96
XLM	6.87	2.61	8.66	0.01	6.16	4.16	48.42	4.07	5.47
TO_ ABS	6.93	3.19	6.58	0.01	5.81	5.16	2.77	*30.46*	
TO_ WTH	9.33	4.30	8.85	0.01	7.82	6.94	3.73		40.99
Net _ABS	1.0226	−1.1708	0.9610	−0.0747	0.5647	−0.0089	−1.2938		
Freq. 2									
BTC	8.29	1.16	3.56	0.00	1.82	2.34	1.72	1.51	8.19
ETH	1.24	12.99	1.45	0.00	1.72	1.14	0.82	0.91	4.92
LTC	3.55	1.40	8.66	0.00	1.94	2.04	2.54	1.64	8.86
XRP	0.04	0.00	0.01	19.19	0.01	0.00	0.06	0.02	0.09
DASH	2.32	1.69	2.24	0.00	7.87	2.16	1.80	1.46	7.89
XMR	2.46	1.69	2.07	0.01	2.20	7.28	1.06	1.36	7.33
XLM	1.86	0.95	2.09	0.00	1.08	0.88	10.02	0.98	5.30
TO_ ABS	1.64	0.98	1.63	0.00	1.25	1.22	1.14	*7.88*	
TO_ WTH	8.86	5.33	8.83	0.02	6.77	6.61	6.18		42.59
Net _ABS	0.1246	0.0741	−0.0050	−0.0144	−0.2071	−0.1334	0.1613		
Freq. 3									
BTC	2.74	0.38	1.17	0.00	0.56	0.77	0.59	0.50	8.03
ETH	0.39	4.37	0.45	0.00	0.51	0.32	0.27	0.28	4.49
LTC	1.18	0.48	2.83	0.00	0.59	0.66	0.86	0.54	8.73
XRP	0.01	0.00	0.00	7.39	0.00	0.00	0.02	0.01	0.09
DASH	0.81	0.57	0.76	0.00	2.44	0.71	0.63	0.50	8.06
XMR	0.81	0.56	0.69	0.00	0.69	2.26	0.36	0.45	7.23
XLM	0.62	0.31	0.66	0.00	0.31	0.27	3.15	0.31	5.05
TO_ ABS	0.55	0.33	0.53	0.00	0.38	0.39	0.39	*2.57*	
TO_ WTH	8.86	5.32	8.67	0.02	6.16	6.32	6.35		41.68
Net _ABS	0.0509	0.0514	−0.0039	−0.0043	−0.1177	−0.0564	0.0799		
Freq. 4									
BTC	0.46	0.06	0.19	0.00	0.09	0.13	0.10	0.08	8.01
ETH	0.06	0.73	0.07	0.00	0.08	0.05	0.04	0.05	4.45
LTC	0.20	0.08	0.47	0.00	0.10	0.11	0.14	0.09	8.71
XRP	0.00	0.00	0.00	1.25	0.00	0.00	0.00	0.00	0.08
DASH	0.14	0.10	0.13	0.00	0.40	0.12	0.11	0.08	8.07
XMR	0.14	0.09	0.12	0.00	0.11	0.37	0.06	0.07	7.22
XLM	0.10	0.05	0.11	0.00	0.05	0.05	0.52	0.05	5.03

(*continued*)

Table 2.
Directional Spillover index results

	BTC	ETH	LTC	XRP	DASH	XMR	XLM	FROM_ ABS	FROM_ WTH
TO_ ABS	0.09	0.05	0.09	0.00	0.06	0.06	0.07	*0.43*	
TO_ WTH	8.85	5.32	8.65	0.02	6.11	6.29	6.35		41.58
Net _ABS	0.0086	0.0089	−0.0007	−0.0007	−0.0202	−0.0095	0.0136		

Note(s): Freq. 1& 2 = short-term (1 to 16 days), freq. 3 = medium-term (16 to 64 days) and freq. 4 = long-term (>64 days) connectedness of the currencies. WTH and ABS = within and absolute in the estimated system, respectively. BTC, ETH, LTC, XRP, DASH, XMR and XLM denote Bitcoin, Ethereum, Litecoin, Ripple, Das, Monero and Steller, respectively
Source(s): Authors' own work

Table 2.

Currencies	Freq. 1	Freq. 2	Freq. 3	Freq. 4
BTC-ETH	−0.3334	−0.0123	−0.0014	−0.0002
BTC-LTC	−0.0402	0.0024	−0.0012	−0.0002
BTC-XRP	−0.0105	−0.0047	−0.0014	−0.0002
BTC-DASH	−0.0736	−0.0724	−0.0355	−0.0061
BTC-XMR	−0.2334	−0.0171	−0.0058	−0.0010
BTC-XLM	−0.3316	−0.0206	−0.0055	−0.0009
ETH-LTC	0.3382	0.0075	−0.0038	−0.0007
ETH-XRP	−0.0011	0.0001	0.0000	0.0000
ETH-DASH	0.2838	0.0039	−0.0094	−0.0017
ETH-XMR	0.2488	−0.0795	−0.0346	−0.0059
ETH-XLM	−0.0323	−0.0183	−0.0050	−0.0008
LTC-XRP	−0.0116	−0.0016	−0.0006	−0.0001
LTC-DASH	−0.0456	−0.0426	−0.0244	−0.0042
LTC-XMR	−0.1510	−0.0040	−0.0047	−0.0008
LTC-XLM	−0.4547	0.0631	0.0286	0.0048
XRP-DASH	0.0257	0.0007	−0.0001	0.0000
XRP-XMR	0.0053	−0.0011	−0.0006	−0.0001
XRP-XLM	0.0205	0.0086	0.0029	0.0005
DASH-XMR	−0.0525	−0.0057	0.0023	0.0004
DASH-XLM	−0.3219	0.1024	0.0460	0.0078
XMR-XLM	−0.1738	0.0261	0.0130	0.0022

Note(s): Freq. 1& 2 = short-term (1 to 16 days), freq. 3 = medium-term (16 to 64 days), and freq. 4 = long-term (>64 days) connectedness of the currencies
Source(s): Authors' own work

Table 3.
Net-pairwise Spillover

pairwise directional spillover effect from one currency to another is measured by subtracting the second variable from the first. A negative (positive) value depicts that the first cryptocurrency is a net receiver (transmitter) of spillover effects from (to) the corresponding cryptocurrency. It is evident from Table 3 that the net-pairwise directional spillover effects switches between positive and negative connectedness indicating that at any given point of time, each cryptocurrency can act as a net transmitter or receiver of spillover effects. Specifically, all Bitcoin pairs (BTC-ETH, BTC-LTC, BTC-XRP, BTC-DASH, BTC-XMR, BTC-XLM) exhibit negative connectedness across frequencies suggesting Bitcoin as net spillover effect recipient from corresponding currencies. The Ethereum pairs ETH-LTC and ETH-DASH (except freq. 3 and 4), ETH-XRP (except freq. 1), show positive connectedness depicting Ethereum as net spillover effect transmitter to corresponding currencies across the frequencies, however, except for freq. 1 of ETH-XMR pairs, Ethereum receives spillover effects from Monero and Steller. The Litecoin pairs LTC-XRP, LTC-DASH, LTC-XMR and LTC-XLM (only freq.1) indicate Litecoin as net receiver of spillover effects from corresponding cryptocurrencies across time. The Steller pairs XRP-DASH (except freq. 3), XRP-XMR (only freq. 1) and XRP-XLM show Steller as a net transmitter of spillover effects to corresponding currencies. DASH-XMR (freq. 2 and 3), DASH-XLM (freq. 2 to 4) and XMR-XLM (freq. 2 to 4) depicts Das and Monero as the net transmitters of spillover effects to corresponding currencies. From this result we can conclude that, the net connectedness between pairs of cryptocurrencies is mostly negative and Bitcoin is the largest spillover effect receiver from other cryptocurrencies. This finding provides evidence in support of Huynh (2019) study which indicates Bitcoin as the spillover effect recipient in the cryptocurrency market.

5.3 Rolling window analysis

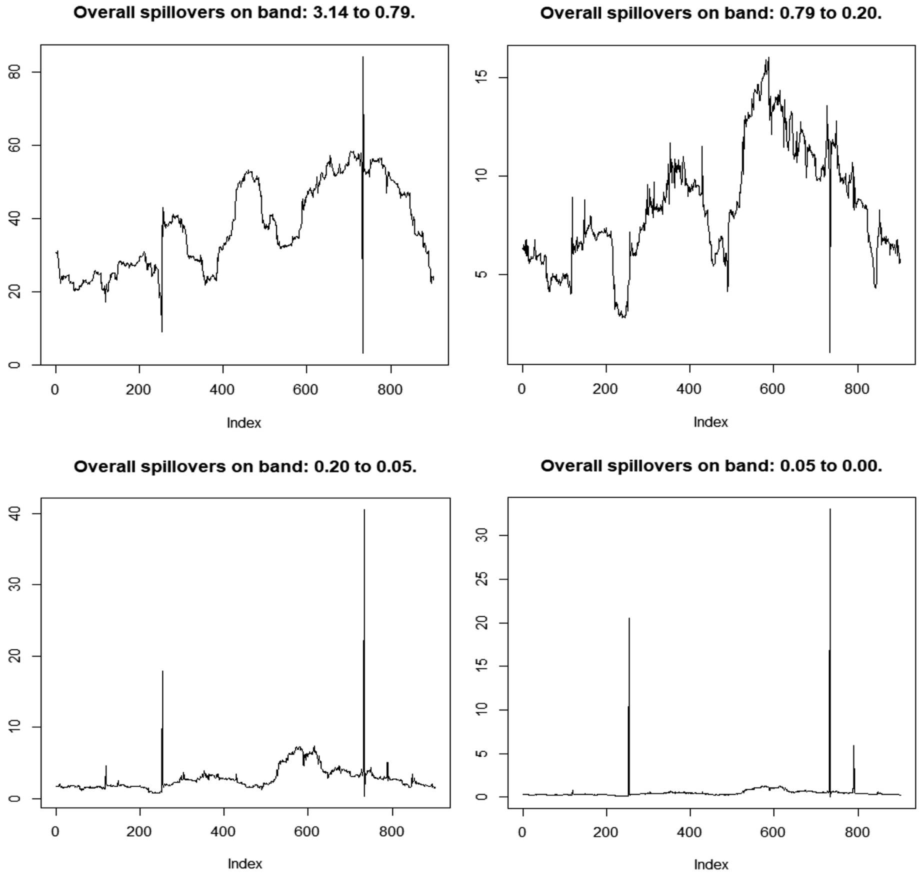
To better appreciate and visualize the direction, strength and structure of spillovers, we capture the time-varying net-pairwise directional and overall spillover connectedness among the cryptocurrencies using the rolling window approach. Figure 1 exhibit the overall spillover connectedness of cryptocurrencies at frequency bands. The horizontal axis of the graphs depict the period of analysis where 200, 400, 600 and 800 represent connectedness in 2015–2016, 2017–2018, 2019–2020 and 2021, respectively, which corresponds with our period of analysis. The vertical axis indicates the level of connectedness of the system. We observe that the overall spillover connectedness at the various frequency bands (Figure 2) confirm the results of the directional spillover connectedness (Table 2) which indicates that cryptocurrencies are highly connected in the short-term than medium- and long-terms. This result is in line with previous studies (Barunik & Křehlík, 2018; Tiwari *et al.*, 2018; Qarni *et al.*, 2019; Belke & Gokus, 2014) that document a time-varying volatility spillover effects.

The net-pairwise directional connectedness between cryptocurrencies in Figure 2 shows high volatility with mostly negative connections especially for Bitcoin pairs which is in line with the results in Table 3.

6. Conclusion and policy implication

The study explores the time-varying volatility spillovers connectedness among cryptocurrencies in the pandemic adopting Barunik and Křehlík (2018) approach. The result from time-varying directional spillover index suggests that the total spillover connectedness among the seven cryptocurrencies is high in the short-time horizon than in the medium and long-time horizons indicating low portfolio diversification benefits in the short-term. However, the net transmitters and receivers of volatility spillovers across cryptocurrencies are contingent on the frequency under consideration.

Our study provides evidence in support of the findings of Corbet *et al.* (2018), and Ji *et al.* (2019) that leading cryptocurrencies are interconnected but differs in showing that the interconnectedness is time-varying and that stronger interconnectedness occurs at higher frequencies. The evidence of all cryptocurrencies alternating between being receivers and transmitters of spillover effects across time suggest that Bitcoin is losing its dominant role in the cryptocurrency market.



Source(s): Authors' construct (2024)

Figure 1. Overall across-frequencies spillovers

We also find from the pairwise spillover that the net connectedness between pairs of cryptocurrencies is mostly negative and Bitcoin is the largest spillover effect receiver from other cryptocurrencies. Nevertheless, the rolling window analysis confirms the results depicted by the directional and pairwise spillover tables. The evidence of weak and negative connections in the medium and lower frequencies may benefit economic agents interested in investing in cryptocurrencies to enhance hedging and portfolio diversifications in the medium and long-term horizons. As policy decisions are frequency-dependent, the horizon-based result of volatility spillovers among cryptocurrencies is clearly important since it highlights the need of regulatory policies to be directed to Bitcoin, Litecoin and Das markets across all horizons but especially in the short-term to reduce global risk.

This study investigates the volatility spillover frequency connectedness across seven leading cryptocurrencies. Future studies can replicate this study by extending the enquiry into several cryptocurrencies and other financial instruments to broaden our understanding of the volatility of financial instruments.

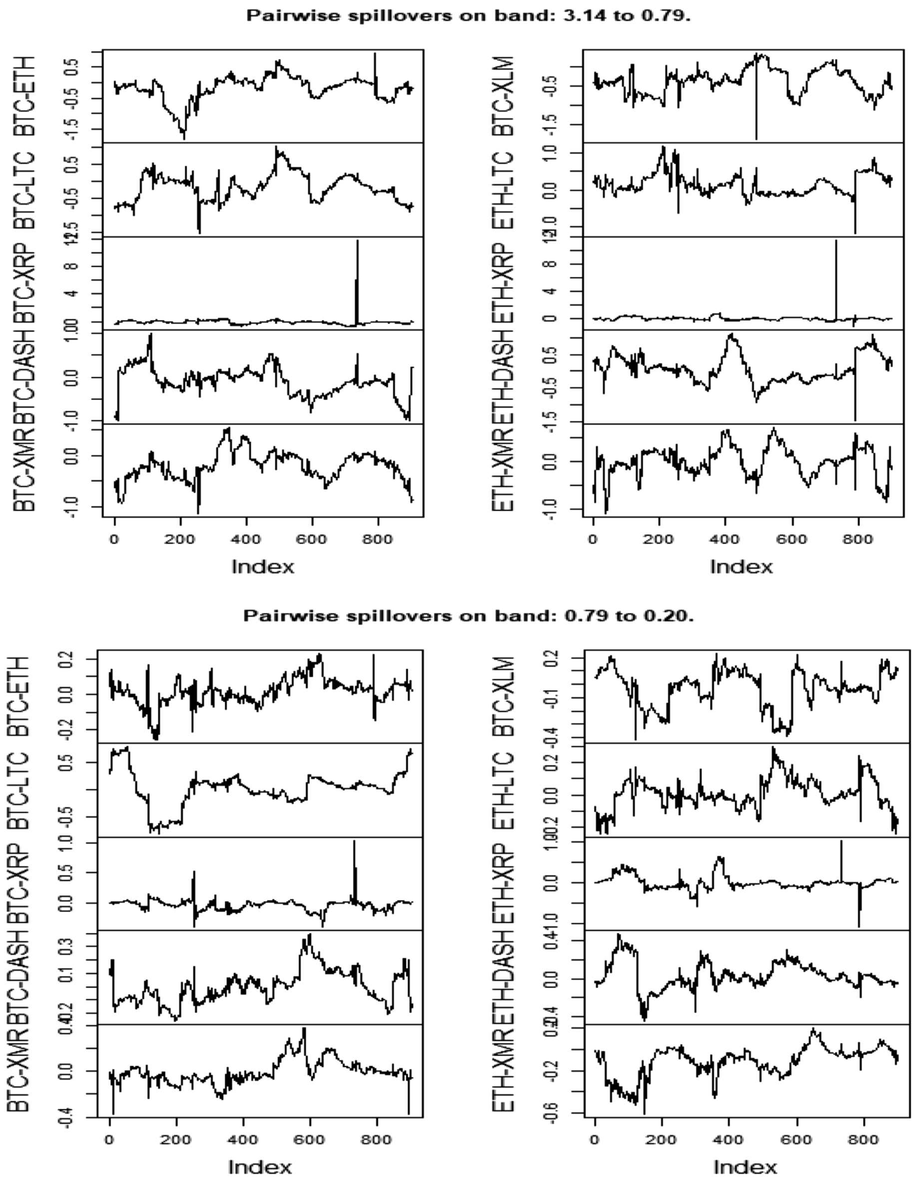
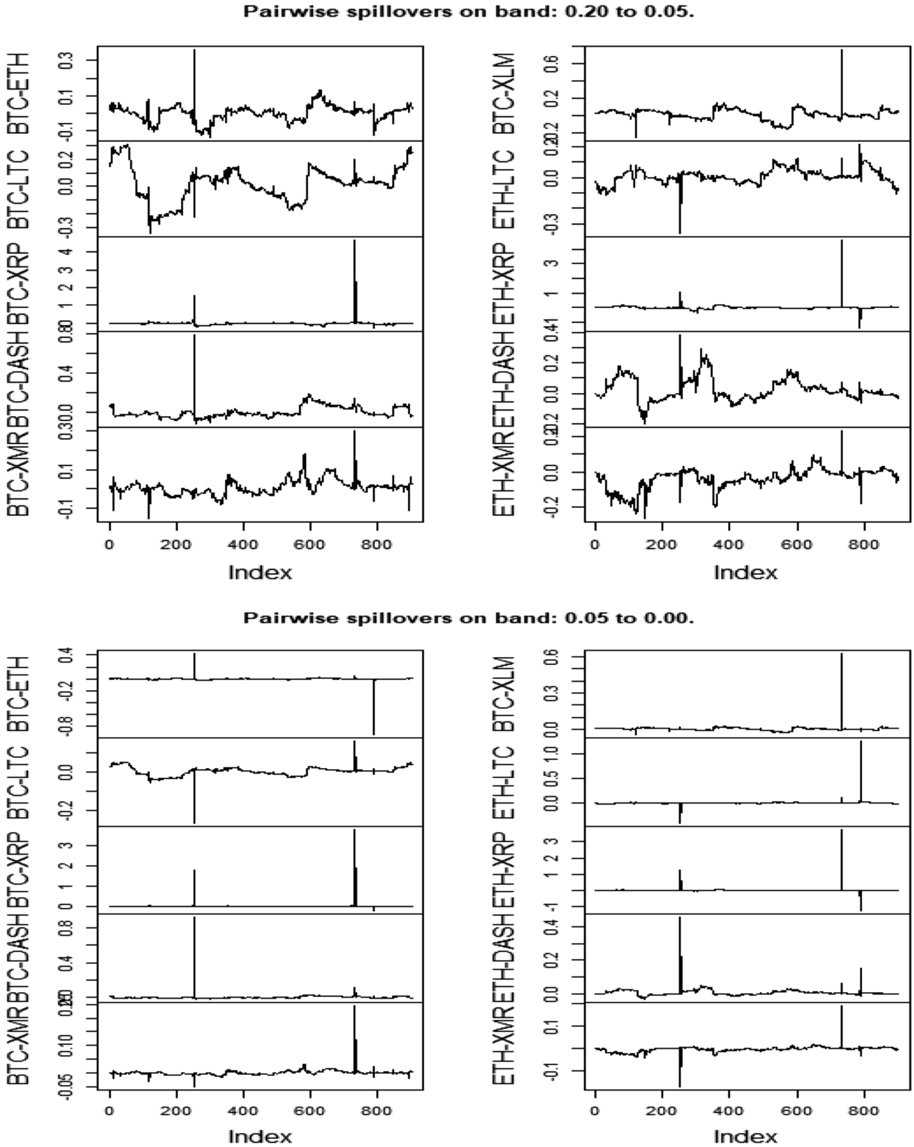


Figure 2.
Pairwise net directional connectedness across-frequencies

(*continued*)



Note(s): The vertical axis represents the cryptocurrencies examined in the study, while the horizontal axis shows the time periods covered
Source(s): Authors' construct (2024)

Figure 2.

Notes

1. The spillover table for first band (freq. 1) 3.14 to 0.79 roughly corresponds to 1 to 4 days, and second band (freq. 2) 0.79 to 0.20 roughly corresponds to 4 to 16 days.
2. The spillover table for third band (freq. 3) 0.20 to 0.05 roughly corresponds to 16 to 64 days.
3. The spillover table for fourth band (freq. 4) 0.05 to 0.00 roughly corresponds to more than 64 days.

References

Apergis, N. (2022). COVID-19 and cryptocurrency volatility: Evidence from asymmetric modelling. *Finance Research Letters*, *47*, 102659. doi: 10.1016/j.frl.2021.102659.

Barunik, J., & Krehlik, T. (2016). Measuring the frequency dynamics of financial and macroeconomic connectedness (No. 54). FinMaP-Working Paper.

Barunik, J., & Křehlík, T. (2018). Measuring the frequency dynamics of financial connectedness and systemic risk. *Journal of Financial Econometrics*, *16*(2), 271–296. doi: 10.1093/jjfinec/nby001.

Belke, A., & Gokus, C. (2014). Volatility patterns of CDS, bond and stock markets before and during the financial crisis: Evidence from major financial institutions. *International Journal of Economics and Finance*, *6*(7), 53–70. doi: 10.5539/ijef.v6n7p53.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier?. *Finance Research Letters*, *20*, 192–198. doi: 10.1016/j.frl.2016.09.025.

CoinMarketCap (2019). Cryptocurrency market capitalizations and data. Available from: https://coinmarketcap.com/ (accessed 26 August 2019).

Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters*, *165*, 28–34. doi: 10.1016/j.econlet.2018.01.004.

Dew-Becker, I., & Giglio, S. (2016). Asset pricing in the frequency domain: Theory and empirics. *Review of Financial Studies*, *29*(8), 2029–2068. doi: 10.1093/rfs/hhw027.

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, *28*(1), 57–66. doi: 10.1016/j.ijforecast.2011.02.006.

Diebold, F. X., & Yilmaz, K. (2016). Trans-Atlantic equity volatility connectedness: U.S. and European financial institutions, 2004–2014. *Journal of Financial Econometrics*, *14*, 81–127.

Dyhrberg, A. H. (2016). Hedging capabilities of Bitcoin. Is it the virtual gold?. *Finance Research Letters*, *16*, 139–144. doi: 10.1016/j.frl.2015.10.025.

Fantazzini, D., Nigmatullin, E., Sukhanovskaya, V., & Ivliev, S. (2016), "Everything You Always wanted to know about Bitcoin Modelling but were afraid to ask". Available from: https://ssrn.com/abstract=2794622

Guesmi, K., Saadi, S., Abid, I., & Ftiti, Z. (2019). Portfolio diversification with virtual currency: Evidence from bitcoin. *International Review of Financial Analysis*, *63*, 431–437. doi: 10.1016/j.irfa.2018.03.004.

Henriques, I., & Sadorsky, P. (2018). Can bitcoin replace gold in an investment portfolio?. *Journal of Risk and Financial Management*, *11*(3), 48. doi: 10.3390/jrfm11030048.

Huynh, T. L. D. (2019). Spillover risks on cryptocurrency markets: A look from VAR-SVAR granger causality and student's-t Copulas. *Journal of Risk and Financial Management*, *12*(2), 52. doi: 10.3390/jrfm12020052.

Ji, Q., Bouri, E., Lau, C. K. M., & Roubaud, D. (2019). Dynamic connectedness and integration in cryptocurrency markets. *International Review of Financial Analysis*, *63*, 257–272. doi: 10.1016/j.irfa.2018.12.002.

Katsiampa, P. (2018). An empirical investigation of volatility dynamics in the cryptocurrency market. *Research in International Business and Finance*, *50*, 322–335. doi: 10.2139/ssrn.3202317.

Kim, T. (2017). On the transaction cost of bitcoin. *Finance Research Letters*, *23*, 300–305. doi: 10.1016/j.frl.2017.07.014.

Klein, T., Thu, H. P., & Walther, T. (2018). Bitcoin is not the New Gold–A comparison of volatility, correlation, and portfolio performance. *International Review of Financial Analysis*, *59*, 105–116. doi: 10.1016/j.irfa.2018.07.010.

Koutmos, D. (2018). Return and volatility spillovers among cryptocurrencies. *Economics Letters*, *173*, 122–27. doi: 10.1016/j.econlet.2018.10.004.

Kumar, A. S., & Ajaz, T. (2019). Co-Movement in crypto-currency markets: Evidences from wavelet analysis. *Financial Innovation*, *5*(1), 33. doi: 10.1186/s40854-019-0143-3.

Liu, W. (2019). Portfolio diversification across cryptocurrencies. *Finance Research Letters*, *29*, 200–205. doi: 10.1016/j.frl.2018.07.010.

Liu, Y. & Tsyvinski, A. (2018), Risks and returns of cryptocurrency. NBER Working Paper No. w24877.

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system. Available from: https://bitcoin.org/bitcoin.pdf

Omane-Adjepong, M., & Alagidede, I. P. (2019). Multiresolution analysis and spillovers of major cryptocurrency markets. *Research in International Business and Finance*, *49*, 191–206. doi: 10.1016/j.ribaf.2019.03.003.

Qarni, M. O., Gulzar, S., Fatima, S. T., Khan, M. J., & Shafi, K. (2019). Inter-markets volatility spillover in US bitcoin and financial markets. *Journal of Business Economics and Management*, *20*(3), 526–546. doi: 10.3846/jbem.2019.8316.

Tiwari, A. K., Cunado, J., Gupta, R., & Wohar, M. E. (2018). Volatility spillovers across global asset classes: Evidence from time and frequency domains. *The Quarterly Review of Economics and Finance*, *70*, 194–202. doi: 10.1016/j.qref.2018.05.001.

Trabelsi, N. (2018). Are there any volatility spill-over effects among cryptocurrencies and widely traded asset classes?. *Journal of Risk and Financial Management*, *11*(4), 66. doi: 10.3390/jrfm11040066.

Further reading

Catania, L., Grassi, S., & Ravazzolo, F. (2018). Forecasting cryptocurrencies financial time series. *CAMP Working Paper Series*. Norwegian Business School, no. 5.

Chan, S., Chu, J., Nadarajah, S., & Osterrieder, J. (2017). A statistical analysis of cryptocurrencies. *Journal of Risk and Financial Management*, *10*(12), 1–23. doi: 10.3390/jrfm10020012.

Gkillas, K., & Katsiampa, P. (2018). An application of extreme value theory to cryptocurrencies. *Economics Letters*, *164*, 109–111. doi: 10.1016/j.econlet.2018.01.020.

Huynh, T. L. D., Nguyen, S. P., & Duong, D. (2018). Contagion risk measured by return among cryptocurrencies. *International Econometric Conference of Vietnam* (pp. 987–998). Springer.

Katsiampa, P. (2019). An empirical investigation of volatility dynamics in the cryptocurrency market. *Research in International Business and Finance*, *50*, 322–335. doi: 10.1016/j.ribaf.2019.06.004.

Katsiampa, P., Corbet, S., & Lucey, B. (2019). Volatility spillover effects in leading cryptocurrencies: A BEKK-MGARCH analysis. *Finance Research Letters*, *29*, 68–74. doi: 10.1016/j.frl.2019.03.009.

King, M. A., & Wadhwani, S. (1990). Transmission of volatility between stock markets. *Review of Financial Studies*, *3*(1), 5–33. doi: 10.1093/rfs/3.1.5.

Omane-Adjepong, M., Alagidede, P., & Akosah, N. K. (2019). Wavelet time-scale persistence analysis of cryptocurrency market returns and volatility. *Physica A: Statistical Mechanics and Its Applications*, *514*, 105–120. doi: 10.1016/j.physa.2018.09.013.

Shahzad, S. J. H., Hernandez, J. A., Rehman, M. U., Al-Yahyaee, K. H., & Zakaria, M. (2018). A global network topology of stock markets: Transmitters and receivers of spillover effects. *Physica A: Statistical Mechanics and Its Applications*, *492*, 2136–2153. doi: 10.1016/j.physa.2017.11.132.

Yi, S., Xu, Z., & Wang, G. (2018). Volatility connectedness in the cryptocurrency market: Is bitcoin a dominant cryptocurrency?. *International Review of Financial Analysis*, *60*, 98–114. doi: 10.1016/j.irfa.2018.08.012.

Appendix

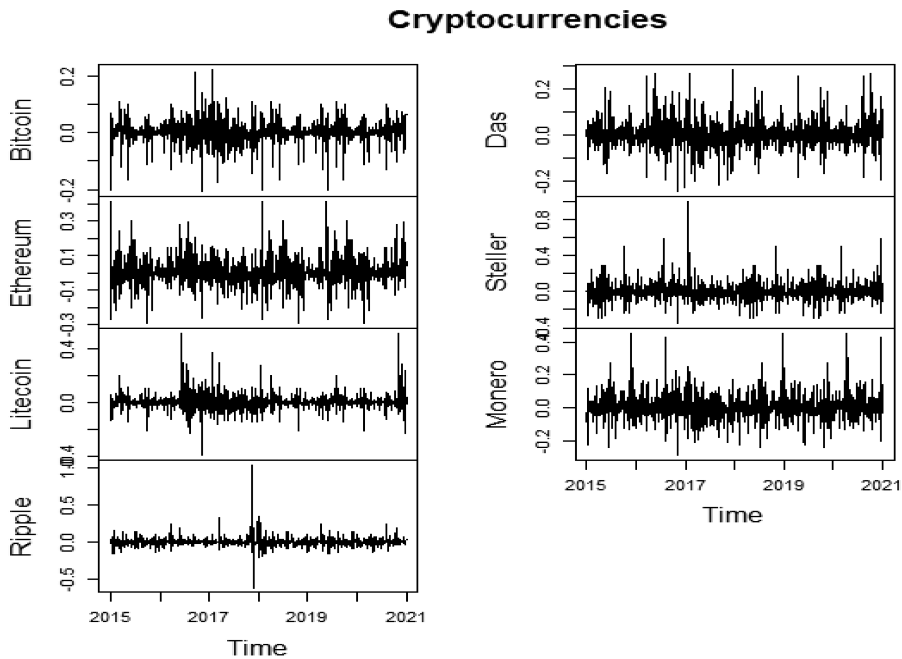


Figure A1. Time series plot of selected cryptocurrencies

Note(s): The vertical axis represents the cryptocurrencies studied, while the horizontal axis indicates the analysis period

Source(s): Authors' own work

Corresponding author
Joseph Antwi Baafi can be contacted at: jobash5@hotmail.com