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Dynamic Volatility Connectedness among Cryptocurrencies: Evidence from Time-Frequency Connectedness Networks [1] [2]

Onur POLAT [3]

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Abstract

This study examines the time-varying connectedness among the realized volatilities of seven major cryptocurrencies between January 2020 and May 2022. To this end, we implement the time and frequency connectedness time-varying parameter vector autoregression (TVP-VAR) approaches. Our findings propose that (i) the COVID-19 pandemic significantly affected the dynamic connectedness; (ii) the total connectedness index hits its apex around the official announcement of the pandemic; (iii) in line with previous studies Ethereum, Bitcoin, and Link are the largest propagators/recipients of shocks; (iv) the tightest volatility interdependencies are related to the short-run.

Keywords: *Cryptocurrency Connectedness, TVP-VAR, Connectedness Networks, Spillovers*

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[1] This study does not require ethics committee permission.

[2] This manuscript is an extended and revised version of the study presented at the EconAnadolu2022 congress entitled "*Frequency-Based Interdependency Volatility Networks for Cryptocurrencies: A TVP-VAR Connectedness Approach*".

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Kriptoparalar Arasındaki Dinamik Oynaklık Bağlantılılığı: Zaman-Frekans Bağlantılılık Ağlarından Kanıtlar

Onur POLAT [4]

Başvuru Tarihi: 30.02.2022 **Kabul Tarihi:** 26.12.2022 **Makale Türü:** Araştırma Makalesi

Öz

Bu çalışma, 2020 Ocak ile 2022 Mayıs döneminde yedi kripto para biriminin tarihsel oynaklıkları arasındaki zamanla değişen bağlantılılığı incelemektedir. Bu bağlamda, zamanla değişen parametre vektör otoregresyon (TVP-VAR) yöntemine dayanan zaman ve frekans bağlantılılık yöntemleri analizde kullanılmaktadır. Çalışmanın bulguları, (i) COVID-19 pandemisinin dinamik bağlantılılığı önemli ölçüde etkilediğini; (ii) toplam bağlantılılık endeksinin pandeminin resmi olarak ilan edilmesi ile birlikte zirveye ulaştığını; (iii) önceki çalışmalarla uyumlu olarak, Ethereum, Bitcoin ve Link'in, şokların en büyük yayıcıları/alıcıları olduğunu; (iv) en yüksek oynaklık bağlantılılıklarının kısa dönemde gerçekleştiğini göstermektedir.

Anahtar Kelimeler: *Kriptopara Bağlantılılığı, TVP-VAR, Bağlantılılık Ağları, Yayılmalar*

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Introduction

Cryptocurrencies are peer-to-peer digital cash mechanisms designed to render direct transactions among parties without an intermediary. Furthermore, the digital architecture of a cryptocurrency is structured by blockchain technology, which serves as a fungible ledger allowing decentralized transactions (Zheng et al., 2017). Despite main drawbacks stemming from the scalability, security, and excess volatility issues (Corbet et al. 2019), the cryptocurrency market has taken overwhelming interest from investors, stakeholders, and traders.

Bitcoin is the first initialized cryptocurrency (Nakamoto, 2008), and it has remained the leader in the cryptocurrency market. As of the date of the study, the close price of Bitcoin is around $29,300 with a market capitalization of $557,864,070. 10064 cryptocurrencies are traded in the market and the global cryptocurrency market has $1.25T[5]. Despite the debate on the safe haven feature of cryptocurrencies persists, the cryptocurrency market experienced a noteworthy price surge starting from the outbreak of the COVID-19 pandemic. Nonetheless, the market is fragile to shocks due to the short sales following a bubble such as the 2018 cryptocurrency and the 2022 crypto crashes. Moreover, the bubble (Geuder et al., 2019) and the herd behaviors (da Gama Silva, 2019) have been the focus of some researchers.

Financial or geopolitical bursts significantly change the linkages between financial assets and the COVID health crisis sets an example of this (Abuzayed et al., 2021; Samitas et al., 2022). Even though the detrimental impacts of the pandemic have expeditiously dispersed into global financial markets, it has also served as an unprecedented diversification opportunity for investors (Goodell and Goutte, 2021; Nasrin et al., 2021; Li and Meng, 2022).

In this work, we aim to examine the dynamic realized volatility connectedness of seven major cryptocurrencies by market capitalization, which dated to the earliest (Bitcoin, Ethereum, BNB, Ripple, Dogecoin, Link, Bitcoincash) between 1 January 2020 and 11 May 2022. In this context, we utilize two newly engineered approaches: The TVP-VAR connectedness methodology of Antonakakis et al. (2020) and the TVP-VAR frequency-based connectedness network approach of Barunik and Ellington (2020). The first methodology is an extended version of the connectedness approach of Diebold and Yilmaz (2014) in the spirit of the approach of Koop and Korobilis (2014) and has several advantages over the extant connectedness approaches. Particularly, the model doesn't entail an arbitrary rolling window size for the connectedness and outliers do not influence outcomes. This methodology has been extensively implemented to investigate connectedness among various financial assets (Bouri et al., 2021; Chatziantoniou et al., 2021; Umar et al., 2021; Foglia and Dai, 2021; Papathanasiou et al., 2022). The second methodology uses a locally-stationary TVP-VAR model structured on the Quasi-Bayesian Locally Likelihood (QBLL) methods. The Bayesian architecture of the approach allow us to integrate both the prior shrinkage and the posterior distribution of the network. Besides, the methodology estimates connectedness in the short-, medium-, and long-term, which can valuable insights into the frequency-based linkages among financial assets.

Our study contributes to the extant literature in three ways: First, we investigate the time-varying linkages among the realized volatilities (RVs) of major cryptocurrencies by employing two recent approaches based on the TVP-VAR. Second, we focus on the frequency-based connectedness networks for the RVs of cryptocurrencies in a period that covers geopolitical distress incidents such as the COVID-19 pandemic, and the 2021 cryptocurrency crash. Finally, we estimate the temporary interconnectedness of RVs at a turmoil time (the official announcement of COVID-19 on 11 March 2020).

[5] See https://coinmarketcap.com/. A.D.: 21 May 2022.

The rest of the study is structured as follows: Section 2 delineates previous studies on the dynamic connectedness of various financial markets. Section 3 presents the data and the empirical approaches of the work. Section 4 discusses empirical results and Section 5 summarizes the main findings of the study.

Literature Review

In this section, we discuss studies examining the spillovers between cryptocurrencies and various financial assets. Besides, we provide studies focusing on the impact of COVID-19 financial connectedness.

Cryptocurrency Connectedness

The cryptocurrency market has attracted stakeholders and investors since the initiation of bitcoin in 2008 by Nakamoto (2008), and the volume of the market has substantially amplified since then. The peer-to-peer design of a cryptocurrency structured by blockchain technology allows direct transactions between parties and hence supports de-centralized financialization. Furthermore, the cryptocurrency market is characterized by vast price inflation accompanied by excess volatility, thereby can provide important trade opportunities for investors. Nevertheless, the cryptocurrency market suffers from cybersecurity and bubble behavior issues.

A plethora of studies has examined spillovers between cryptocurrencies and traditional financial assets. In this vein, a body of literature has investigated returns or volatilities spillovers among cryptocurrencies and stocks, bonds, commodities, and currencies (Symitsi and Chalvatzis, 2018; Mensi et al., 2019, Vardar and Aydogan, 2019; Naeem et al., 2020; Su and Li, 2020; Rehman, 2020; Aharon et al., 2021; Jiang et al., 2022). The results of these studies suggest that the interdependence between assets strengthens around geopolitical distress times. Moreover, their results have valuable insights for investors and authorities concerning the hedging and safe haven features of bitcoin. A strand of recent studies has investigated the impact of COVID-19 on the dynamic linkages between cryptocurrencies and financial assets (Nguyen, 2021; Guo et al., 2021). These studies detected tightening linkages between assets due to the COVID-19 pandemic.

A body of studies has investigated static/dynamic connectedness among major cryptocurrencies by employing the Diebold-Yilmaz (DY) spillover analysis or wavelet methodology (Yi et al., 2018; Kumar and Anandarao, 2019; Katsiampa et al., 2019; Moratis, 2021). The findings of these studies state that cryptocurrencies are positively and strongly interdependent. Furthermore, some studies examined the relationship between economic uncertainty and cryptocurrencies and financial variables (Fasanya et al., 2021a; Wang et al., 2022b).

Static/Dynamic Financial Connectedness and COVID-19

As extensively investigated by scholars, financial connectedness is prone to significant surges around financial/geopolitical upheavals (Minoiu et al., 2015; Baruník and Křehlík, 2018; Barigozzi et al., 2021). The COVID-19 crisis sets an example of such turmoil and various studies have analyzed the impact of the pandemic on financial connectedness. In this context, some studies have examined the connectedness among stock indices of countries before and during the pandemic (Abuzayed et al., 2021; Samitas et al., 2022; Choi, 2022). The findings of their studies demonstrate that the stock market connectedness becomes stronger during the pandemic.

Along similar lines, some studies have examined the impact of the pandemic on risk transmissions between various financial assets including commodities, foreign exchanges (FXs), and cryptocurrencies. For example, Borgards et al. (2021) analyzed the overreaction behavior of 20 commodity futures before and during the pandemic. The authors detected a high number and amplitude of overreactions during the pandemic. Some studies investigated connectedness in FX market by employing the DY model (Fasanya et al., 2021b; Gunay, 2021). These studies found that the volatility spillover index notably surged during the pandemic as compared to the before pandemic era. Moreover, Kumar et al. (2022) and Naeem et al. (2022) examined spillovers among cryptocurrencies during the pandemic. Kumar et al. (2022) stated that the connectedness among cryptocurrencies is frequency-dependent and more sensitive to the short term than the long term. Naeem et al. (2022) examined the cryptocurrency returns connectedness by utilizing the standard and quantile-based VAR models. Their results indicate that the return spillovers are higher during the pandemic compared to the pre-pandemic period.

A body of studies examines spillovers between different asset classes for different countries during the pandemic. In this vein, some studies explore the relationship between financial indicators from China (Shahzad et al., 2021; Wang et al., 2022b), the US (Sakurai and Kurosaki, 2020; Adekoya and Oliyide, 2021), and the BRICS (Rai and Garg, 2021). These studies detected strengthened spillovers between country-specific financial indicators during COVID-19.

A body of studies has focused on the impact of the COVID-19 news-related indices (Coronavirus Media Coverage Index, sentiment index, media hype heat index, fake news index, panic emotion index, and contagion index) on financial connectedness (Umar et al., 2021; Zhang et al., 2022). These studies found a significant impact of the news-related indices on connectedness.

Empirical Methodology

The TVP-VAR Connectedness

Antonakakis et al. (2020) defined the $TVP - VAR(p)$ model as follows:

$$y_t = B_t x_{t-1} + \varepsilon_t \qquad \varepsilon_t | \Omega_{t-1} \sim N(0, \Pi_t) \tag{1}$$

$$vec(B_t) = vec(B_{t-1}) + \eta_t \qquad \eta_t \,|\, \Omega_{t-1} \sim N(0, \Sigma_t) \tag{2}$$

with

$$x_{t-1} = \begin{pmatrix} y_{t-1} \\ y_{t-2} \\ \vdots \\ y_{t-p} \end{pmatrix} \qquad B_t' = \begin{pmatrix} B_{1t} \\ B_{2t} \\ \vdots \\ B_{pt} \end{pmatrix}$$

where Ω_{t-1} shows all information available up to $t-1$, y_t and x_t denote $n \times 1$ and $np \times 1$ vectors, respectively. B_t and B_{it} are $n \times np$ and $np \times 1$ dimensional matrices. ε_t is an $n \times 1$ vector, and η_t is $n^2 p \times 1$ dimensional vector. Π_t, and Σ_t are $n \times n$ and $n^2 p \times n^2 p$ dimensional matrices, respectively. $vec(B_t)$ is the vectorization of B and is an $n^2 p \times 1$ dimensional vector.

The VMA representation of y_t can be introduced as $\sum_{i=0}^{\infty} A_{it} \varepsilon_{t-i}$, where A_{it} is $n \times n$ dimensional matrix.

The $GIRF\left(\Psi_{ij,t}(H)\right)$ represents the responses of all variables j, following a shock in i computed with an $H-step$ ahead forecast. $GIRF\left(\Psi_{ij,t}(H)\right)$ can be defined as follows:

$$GIRF(H,\sigma_{j,t},\Omega_{t-1}) = E(x_t + H|e_j = \sigma_{j,t},\Omega_{t-1}) - E(x_{t+j}|\Omega_{t-1}) \quad (3)$$

$$\Psi_{j,t}(H) = \frac{A_{H,t}\Pi_t e_j}{\sqrt{\Pi_{jj,t}}}\frac{\sigma_{j,t}}{\sqrt{\Pi_{jj,t}}} \qquad \sigma_{J,t} = \sqrt{\Pi_{JJ,t}} \quad (4)$$

$$\Psi_{j,t}(H) = \Pi_{jj,t}{}^{-1/2}A_{H,t}\Pi_t e_i \quad (5)$$

here, e_j is an $n \times 1$ selection vector with a value of 1 with the selection of jth element, and 0 o.w. Therefore, the $GFEVD\left(\widetilde{\Phi}_{ij,t}(H)\right)$ is calculated based on $\widetilde{\Phi}_{ij,t}(H)$, which is given as follows:

$$\widetilde{\Phi}_{ij,t}(H) = \frac{\sum_{t=1}^{H-1}\Psi_t^2}{\sum_{j=1}^{n}\sum_{t=1}^{H-1}\Psi_t^2} \quad (6)$$

with $\sum_{j=1}^{n}\widetilde{\Phi}_{ij,t}(H) = 1$, and $\sum_{i,j=1}^{n}\widetilde{\Phi}_{ij,t}(H) = n$.

In line with the above formulation the total connectedness index (TCI) is introduced as:

$$C_t(H) = \frac{\sum_{i,j=1,i\neq j}^{m}\widetilde{\Phi}_{ij,t}(H)}{\sum_{i,j=1}^{m}\widetilde{\Phi}_{ij,t}(H)} * 100 = \frac{\sum_{i,j=1,i\neq j}^{m}\widetilde{\Phi}_{ij,t}(H)}{m} * 100 \quad (7)$$

Total directional connectedness to others:

$$C_{i\to j,t}(H) = \frac{\sum_{j=1,i\neq j}^{n}\widetilde{\Phi}_{ji,t}(H)}{\sum_{j=1}^{m}\widetilde{\Phi}_{ji,t}(H)} * 100 \quad (8)$$

Total directional connectedness from others:

$$C_{i\leftarrow j,t}(H) = \frac{\sum_{j=1,i\neq j}^{n}\widetilde{\Phi}_{ij,t}(H)}{\sum_{i=1}^{n}\widetilde{\Phi}_{ij,t}(H)} * 100 \quad (9)$$

Net total directional connectedness.

$$C_{i,t}(H) = C_{i\to j,t}(H) - C_{i\leftarrow j,t}(H) \quad (10)$$

The Frequency-Dependent TVP-VAR Network Connectedness

Lets $\left(Y_{t,T}\right)_{1 \leq t \leq T, T \epsilon N}$ with $Y_{t,T} = \left(Y_{t,T}^{1}, \dots, Y_{t,T}^{N}\right)^{T}$, where t denotes the time index, and T represents "*sharpness of the local approximation of the time series* $\left(Y_{t,T}\right)_{1 \leq t \leq T, T \epsilon N}$ *by a stationary one*" (Ellington & Baruník, 2020).

$\left(Y_{t,T}\right)_{1 \leq t \leq T, T \epsilon N}$ is stuctures as follows:

$$Y_{t,T} = \phi_1(t/T)Y_{t-1,T} + \cdots + \phi_p(t/T)Y_{t-p,T} + \epsilon_{t,T} \tag{11}$$

where $\epsilon_{t,T} = \Sigma^{-\frac{1}{2}}(t/T)\zeta_{t,T}$ with $\zeta_{t,T} \sim NID(0, I_N)$, and $\phi(t/T) = \left(\phi_1(t/T), \dots, \phi_p(t/T)\right)^{T}$ are time-varying autoregressive coefficients. In a fixed time neighbourhood of $\upsilon_0 = t_0/T$, the stationary process $Y_{t,T}$ is estimated by $\tilde{Y}_t(\mu_0)$ as:

$$\tilde{Y}_t(\upsilon_0) = \phi_1(\upsilon_0)\tilde{Y}_{t-1}(\upsilon_0) + \cdots + \phi_p(\upsilon_0)\tilde{Y}_{t-p}(\upsilon_0) + \epsilon_t \tag{12}$$

Time-varying $VMA(\infty)$ representation of the process is defined as:

$$Y_{t,T} = \sum_{\mathrm{h}=-\infty}^{\infty} \psi_{t,T}(\mathrm{h})\epsilon_{t-\mathrm{h}} \tag{13}$$

where, $\psi_{t,T} \approx \psi(t/T, h)$ and $sup_l \|\psi_t - \psi_l\|^2 = O_p(h/t)$ for $1 \leq h \leq t$ as $t \to \infty$. "*The spectral density of* $X_{t,T}$ *at frequency* d *is defined as*" (Ellington and Baruník, 2020):

$$S_Y(\upsilon, \omega) = \sum_{h=-\infty}^{\infty} E\left[\tilde{Y}_{t+m}(\upsilon)\tilde{Y}_t^{\,T}(\upsilon)\right] e^{-i\omega h} \tag{14}$$

The dynamic adjacency matrix is introduced as:

$$[\theta(\upsilon, d)]_{j,k} = \frac{\sigma_{kk}^{-1} \int_a^b \left|\left[\psi(\upsilon)e^{-i\omega}\Sigma(\upsilon)\right]_{j,k}\right|^2 d\omega}{\int_{-\pi}^{\pi}[\{\psi(\upsilon)e^{-i\omega}\}\Sigma(\upsilon)\{\psi(\upsilon)e^{+i\omega}\}^T]_{j,j} d\omega} \tag{15}$$

where $d = \{(a, b): a, b \epsilon(-\pi, \pi), a < b\}$.

The 'local network connectedness':

$$C(v,d) = 100 \times \sum_{\substack{j,k=1 \\ j\neq k}}^{N} \left[\tilde{\theta}(v,d)\right]_{j,k} / \sum_{j,k=1}^{N} \left[\tilde{\theta}(v)\right]_{j,k}. \tag{16}$$

In Eq. (16),

$$\tilde{\theta}(v,d) = \theta(v,d) / \sum_{k=1}^{N} [\theta(v)]_{j,k} \tag{17}$$

FROM connectedness for $k \neq j$, is introduced as:

$$C_{j\leftarrow \cdot}(v,d) = 100 \times \sum_{\substack{k=1 \\ k\neq j}}^{N} \left[\tilde{\theta}(v,d)\right]_{j,k} / \sum_{j,k=1}^{N} \left[\tilde{\theta}(v)\right]_{j,k} \tag{18}$$

TO connectedness for $k \neq j$, is defined as:

$$C_{j\rightarrow \cdot}(v,d) = 100 \times \sum_{\substack{k=1 \\ k\neq j}}^{N} \left[\tilde{\theta}(v,d)\right]_{j,k} / \sum_{k,j=1}^{N} \left[\tilde{\theta}(v)\right]_{k,j} \tag{19}$$

Data

To examine dynamic cryptocurrency connectedness, our study utilizes seven major cryptocurrencies by virtue of market capitalization on 11 May 2022, and that is available on the earliest date: Bitcoin, Ethereum, BNB, Ripple, Dogecoin, Link, Bitcoincash. The data is gathered from Binance, spanning from 1 January 2020 to 11 May 2022[6].

Following Garman and Class (1980), and Diebold and Yilmaz (2017), we model the realized volatilities by the following formula:

$$RV = 0.511(H-L)^2 - 0.019[(C-O)(H+L-2O) - 2(H-0)(L-O)] - 0.383(C-O)^2 \tag{20}$$

In Eq. (20), H, L, C, and O represent the log of daily high, low, close, and open prices, respectively.

[6] The COVID-19 pandemic first emerged in China in late 2019 and has dispersed around the globe since then. We select start date of the study as 1 January 2020 to capture the impacts of the pandemic on cryptocurrency market.

We provide dynamics of close prices of seven cryptocurrencies, summary statistics, and trends in their realized volatilities (RVs) in Table 1 and Figure 1, respectively.

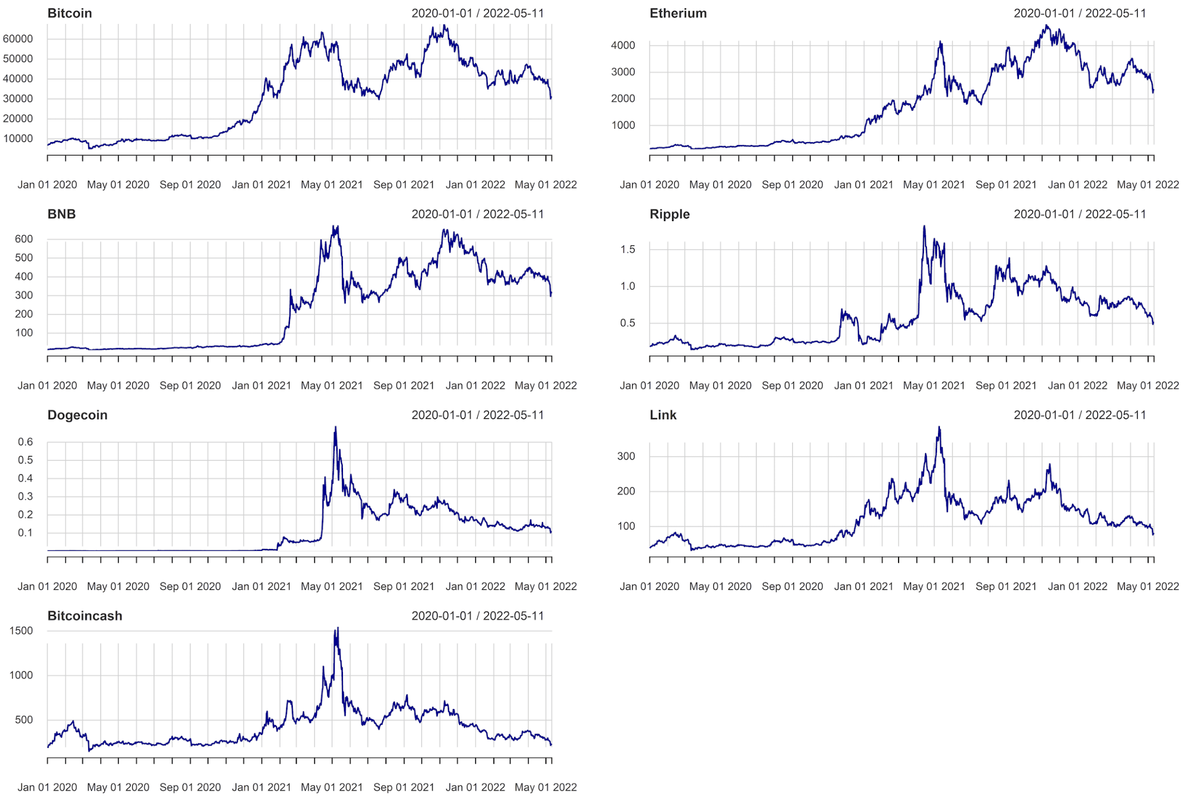

Figure 1. Close Prices of Seven Cryptocurrencies

Table 1
Descriptive Statistics of RVs

	Mean	**Maximum**	**Minimum**	**Skewness**	**Kurtosis**	**Jarque-Bera**
Bitcoin	0.00	0.20	0.000062	15.10	308.27	3462205.50***
Etherium	0.01	0.22	0.000171	10.42	145.15	775928.52***
BNB	0.01	0.34	0.000155	12.09	206.45	1559059.07***
Ripple	0.01	0.52	0.000101	11.11	183.22	1229186.56***
Dogecoin	0.01	0.78	0.000075	9.40	123.96	567278.60***
Link	0.01	0.24	0.000167	9.61	129.27	616349.94***
Bitcoincash	0.01	0.29	0.000221	9.41	137.06	690672.84***

Notes: *** indicates 1% significance level.

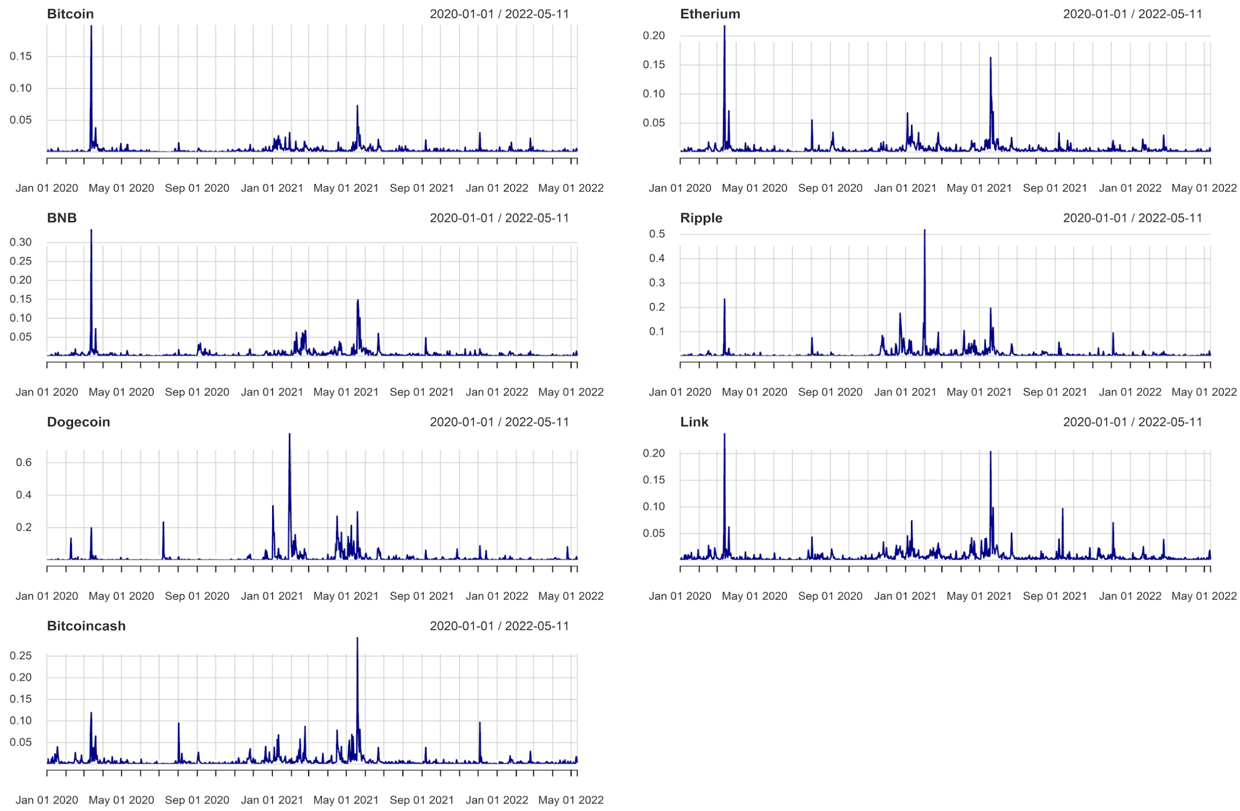

Figure 2. Trends in RVs

Figure 1 reveals that the close prices of all cryptocurrencies remarkably soar starting from early 2020. This can be related to the safe haven or herding behavior of cryptocurrencies led by the COVID-19 pandemic (Corbet et al., 2020).

By the results in Table 1, Dogecoin has the highest average volatility, whereas Bitcoin has the lowest volatility. All volatilities series are tailed to the right and characterized by excess kurtosis. Therefore, all volatility series have leptokurtic behavior. High JB values indicate that all volatilities are non-normally distributed.
Sharing a common feature, the volatility series exhibited noteworthy spikes in early 2020 and May 2021 due to the COVID-19 outbreak and the crypto crash. This is more prominent for Bitcoin, Ethereum, and Link. On the other hand, the RVs of Dogecoin, and Ripple show noteworthy spikes in January 2021 triggered by the rapid price surge in their close prices.

Empirical Findings

In this section, we provide time-varying connectedness and frequency-dependent connectedness networks for the RVs.

First, we estimate the total connectedness index (TCI) for the RVs by implementing the methodology of Antonakakis et al. (2020).

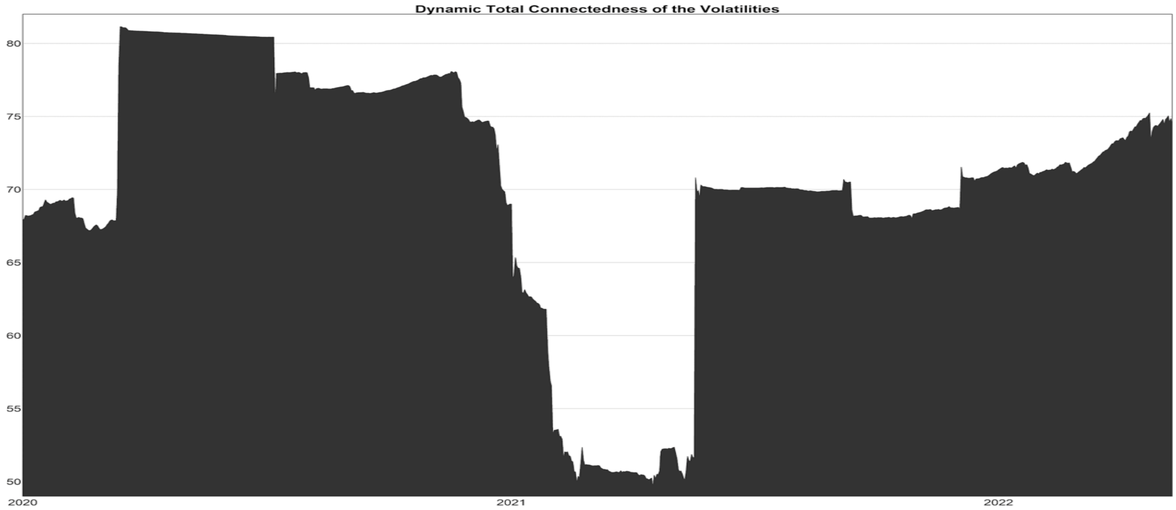

Figure 3. TCI for the RVs of Seven Cryptocurrencies

The TCI fluctuated between 49% and 82% over the sample episode. The index skyrocketed around March 2020, which coincides with the declaration of COVID-19 as a pandemic by the World Health Organization (WHO). This finding is consistent with the previous studies Polat and Günay (2020) and Aslanidis et al. (2021). The TCI gradually plummeted afterward and hit its trough on 17 April 2021 (49.58%). With the crypto crash emerging in May 2021, the TCI dramatically elevated and soared 70%. The index has had an increasing trend since January 2022 due to the 2022 cryptocurrency crash[7]. Next, we report the average connectedness results for the realized volatilities in Table 2.

Table 2
Average Connectedness Results for the RVs

	Bitcoin	**Etherium**	**BNB**	**Ripple**	**Dogecoin**	**Link**	**Bitcoincash**	**FROM others**
Bitcoin	23.47	19.05	14.76	8.57	6.35	16.4	11.4	76.53
Etherium	17.35	22.67	15.95	8.23	5.43	17.06	13.32	77.33
BNB	15.22	17.9	26.61	8.93	4.86	15.18	11.29	73.39
Ripple	10.87	10.84	10.88	37.4	6.82	12.24	10.95	62.6
Dogecoin	10.41	8.39	7.35	7.64	48.51	8.99	8.71	51.49
Link	15.71	17.47	13.98	9.48	5.56	22.75	15.06	77.25
Bitcoincash	12.49	15.78	11.26	9.87	6.61	17.44	26.55	73.45
TO others	82.04	89.42	74.17	52.73	35.64	87.31	70.73	492.04
NET	5.51	12.09	0.78	-9.87	-15.85	10.05	-2.72	**TCI** =70.29%

[7] By 21 January 2021, the crash had erased $1T of market value, and in May 2022 the stable TerraUSD fell to 10 cents which led to Luna falling to virtually zero from all time high of $119.51. Major cryptocurrencies have experienced dramatic price declines simultaneously.

Table 2 reveals that the average total connectedness index for the RVs is 70.29%, corroborating a tight volatility connectedness among cryptocurrencies over the study period. Ethereum is the largest transmitter/recipient of volatilities shock and followed by Link and Bitcoin. This finding demonstrates that major cryptocurrencies propagate/receive high volatility spillovers in line with the previous studies (Yi et al., 2018; Bouri et al., 2021). Furthermore, Dogecoin, Ripple, and Bitcoincash are the net recipients of volatility shocks, whereas the rest of the cryptocurrencies are the net transmitters of volatility shocks. We continue our analysis with the total net time-varying volatility spillovers and provide them in Figure 4.

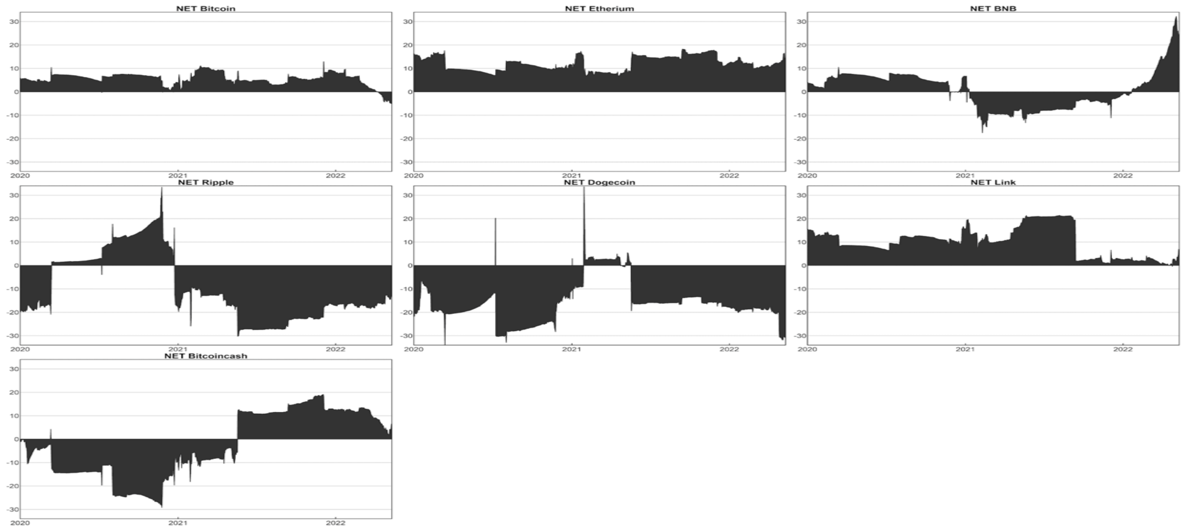

Figure 4. Total Net Time-Varying Connectedness for the RVs

Bitcoin, Ethereum, and Link are the net transmitters of volatility shocks, whereas the other cryptocurrencies are the net transmitters/receivers of shocks dependent on the period. Distinctly, Ripple and Dogecoin transmit noteworthy volatility shocks around January 2021. Furthermore, they are mostly the net receivers of shocks since 2021. Bitcoincash, and BNB flip their roles to the net transmitters of volatilities shocks from the second half of 2021, and early 2022, respectively.

In the next step, we compute the short-term (temporary), medium-term, and long-term (persistent)[8] connectedness networks for the RVs. Figure 5 displays the frequency-dependent connectedness networks for the RVs.

[8] Temporary, medium-term, and persistent connectedness roughly denote 1 to 5 days (1 week), 5 to 20 days (1 week to 1 month), and more than 20 days (more than a month), respectively.

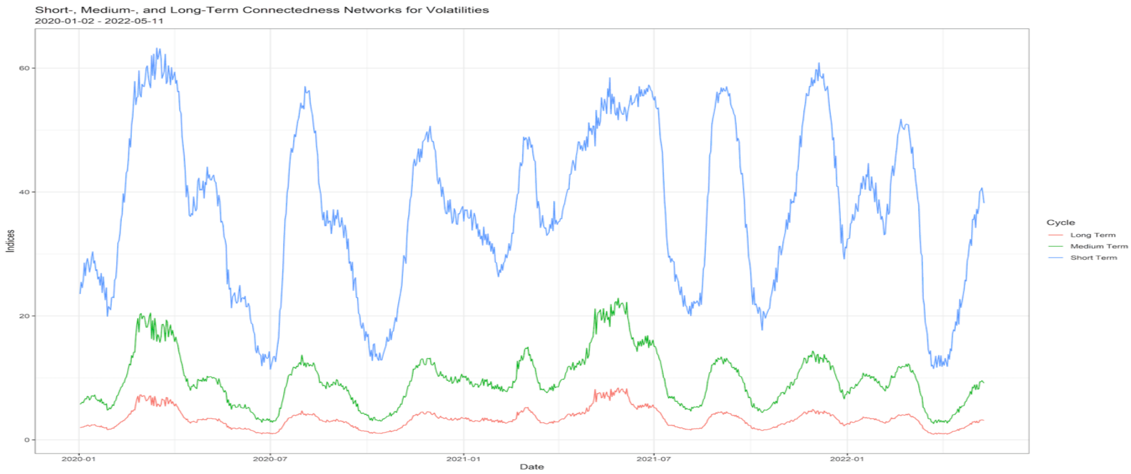

Figure 5. Frequency-dependent Network Connectedness for the RVs

As Figure 5 indicates, the temporary connections are stronger than the medium-term, and the persistent interdependencies, indicate that the volatility shocks are related to the short-term.

In the final step, since the temporary linkages are tighter we examine the temporary volatility connectedness network at a turmoil time (the COVID-19 announcement on 11 March 2020. Figure 6 exhibits the temporary connectedness network[9] for the RVs on 11 March 2020.

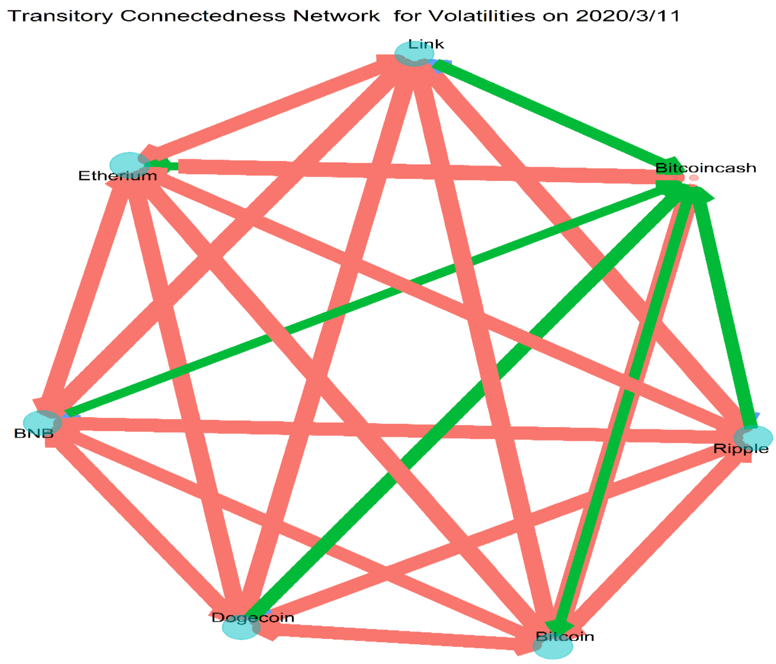

Figure 6. Transitory Connectedness Network for the RVs on 11 March 2020

[9] Arrows reflect the direction of linkages, the thickness of the arrows corresponds to the strength of the connectedness, and the sizes of the nodes are denoted by the total TO spillovers indicating that node.

We report the following results by the temporary network topology. i) Bitcoin-Etherium, BNB-Link, BNB-Bitcoincash, and Link-Bitcoincash have the strongest temporary connectedness, while Bitcoincash-BNB has the weakest transitory volatility interdependence. ii) Bitcoin and Etherium are the largest transmitter of volatilities shocks in the short run. iii) Bitcoincash propagates the lowest volatility shocks in the temporary connectedness network[10].

Conclusion

In this study, we explore the time and frequency connectedness among realized volatilities of seven major cryptocurrencies (Bitcoin, Ethereum, BNB, Ripple, Dogecoin, Link, Bitcoincash) between 1 January 2020 and. 11 May 2022. Furthermore, we estimate the frequency-dependent connectedness network for the realized volatilities.

Both time and frequency-based connectedness approaches provide several interesting results with practical implications. The COVID-19 pandemic prominently influenced the time-varying volatility connectedness, and the TCI peaked on 14 March 2020 (81.14%), 3 days after the official announcement of the pandemic by the WHO. Moreover, the TCI has had an increasing trend starting in early 2022 due to the 2022 crypto crash.

Average connectedness results indicate that Etherium is the largest transmitter/receiver of volatilities shocks and followed by Link and Bitcoin. Bitcoin, Etherium, Link, and BNB are net transmitters, while the rest cryptocurrencies are net receivers based on the results. Additionally, Bitcoin, Ethereum, and Link keep their role of being the net transmitters of volatility shocks, whereas the rest of the cryptocurrencies are the net transmitter/recipient of shocks dependent on the period. For example, Bitcoincash and BNB flip their roles to net transmitters in the recent period. Besides, Ripple and Dogecoin propagate significant volatilities shock around January 2021.

Frequency-dependent connectedness networks reveal that the temporary interdependencies are stronger than the medium-term and persistent linkages. Finally, we estimate the transitory connectedness network on the official announcement of the COVID-19 pandemic. According to the topology, the first two cryptocurrencies by market capitalization are found to be the largest transmitters of volatility shocks. Moreover, most cryptocurrencies are characterized by moderate or strong connectedness on announcement day.

Our study has the following policy implications: First, the dynamic connectedness among the cryptocurrencies provides valuable insights into their portfolio strategies. Second, the relationship between frequency-dependent connectedness can be used to predict whether the market has entered a bearish condition. Finally, the understanding of the linkages between digital assets provides a flexible regulatory framework for policymakers for a stable financial system.

[10] Sizes of the nodes in the network represent total TO spillovers from that not and available upon request.

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Genişletilmiş Özet

Amaç

Bu çalışma, 1 Ocak 2020 - 11 Mayıs 2022 döneminde yedi kripto paranın (Bitcoin, Ethereum, BNB, Ripple, Dogecoin, Link, Bitcoincash) tarihsel oynaklıkları arasındaki zamanla değişen bağlantılılığı incelemeyi amaçlamaktadır. Zamanla değişen parametre vektör otoregresyon (TVP-VAR) yöntemine dayanan zaman ve frekans bağlantılılık yöntemleri analizde kullanılmaktadır.

Tasarım ve Yöntem

Kripto paralar, taraflar arasında aracı olmadan işlem gerçekleştirmek amacıyla tasarlanmış noktadan noktaya dijital nakit mekanizmalarıdır. Ayrıca, bir kripto para biriminin dijital mimarisi, merkezi olmayan işlemlere izin veren değiştirilebilir bir defter görevi gören blok zinciri teknolojisi ile yapılandırılmıştır (Zheng vd., 2017). Ölçeklenebilirlik, güvenlik ve aşırı oynaklık sorunlarından kaynaklanan dezavantajlara rağmen (Corbet vd., 2019), kripto para piyasası yatırımcılardan büyük ilgi görmektedir.

Kripto para birimlerinin güvenli liman özelliğinin devam edip etmediği konusundaki tartışmaların devam etmesine rağmen, kripto para piyasasının işlem hacmi ve piyasa kapitilizasyonu, COVID-19 pandemisinin ortaya çıkmasından itibaren önemli ölçüde yükselmiştir.

Finansal veya jeopolitik çalkantılar, finansal varlıklar arasındaki bağlantılığı önemli ölçüde etkilemektedir (Abuzayed vd., 2021; Samitas vd., 2022). Küresel salgının olumsuz etkileri hızla küresel finans piyasalarına dağılmış olsa da, yatırımcılar için benzeri görülmemiş bir çeşitlendirme fırsatı sunmuştur (Goodell ve Goutte, 2021; Nasrin vd., 2021; Li ve Meng, 2022).

Bu çalışma, 1 Ocak 2020 - 11 Mayıs 2022 döneminde yedi kripto paranın (Bitcoin, Ethereum, BNB, Ripple, Dogecoin, Link, Bitcoincash) tarihsel oynaklık bağlantılılığını incelemeyi amaçlamaktadır. Bu doğrultuda, çalışmada iki yeni yaklaşım kullanılmaktadır: Antonakakis vd.'nin (2020) TVP-VAR bağlantılılık metodolojisi ve Barunik ve Ellington'ın (2020) TVP-VAR frekans tabanlı bağlantılılık ağı yöntemi. İlk metodoloji, Diebold ve Yılmaz'ın (2014) bağlantılılık yaklaşımının Koop ve Korobilis'in (2014) metodolojisine uygun genişletilmiş bir versiyonudur ve mevcut bağlantılılık yaklaşımlarına göre çeşitli avantajlara sahiptir. Özellikle model, bağlantılılık için değişen pencere boyutu seçmeyi gerektirmemektedir. Bu metodoloji, çeşitli finansal varlıklar arasındaki bağlantıyı araştırmak için araştırmacılar tarafından kullanılmıştır (Bouri vd., 2021; Chatziantoniou vd., 2021; Umar vd., 2021; Foglia ve Dai, 2021; Papathanasiou vd., 2022). İkinci yöntem, Quasi-Bayesian Yerel Olabilirlik (QBLL) yöntemleri üzerinde yapılandırılmış yerel olarak durağan bir TVP-VAR modeli kullanmaktadır. Yöntemin Bayes mimarisi, ağın hem önceki (prior) büzülmesini hem de sonraki (posterior) dağılımını entegre etmeyi mümkün kılmaktadır. Ayrıca, metodoloji kısa (geçici), orta ve uzun (kalıcı) vadede bağlantılılığın tahmin edilmesini sağlamaktadır. Yöntem, finansal varlıklar arasındaki frekansa dayalı bağlantılıklara ilişkin değerli bilgiler sunmaktadır.

Bulgular

Çalışmanın bulgularına göre, COVID-19 pandemisi zamanla değişen volatilite bağlantılılığı belirgin bir şekilde etkilemektedir. Toplam yayılma endeksi, DSÖ tarafından pandeminin resmi olarak ilan edilmesinden 3 gün sonra 14 Mart 2020'de (%81,14) zirve değerine ulaşmaktadır. Ayrıca, toplam yayılma endeksi, 2022 kripto çöküşü nedeniyle 2022'nin başlarında başlayan bir yükselme eğilimine sahiptir.

Ortalama bağlantılılık sonuçları, Ethereum'un volatilite şoklarının en büyük vericisi/alıcısı olduğunu ve onu Link ve Bitcoin'in izlediğini göstermektedir. Bitcoin, Ethereum, Link ve BNB net şok vericileri iken, diğer kripto para birimleri sonuçlara göre net şok alıcılarıdır. Ayrıca, Bitcoin, Ethereum ve Link, oynaklık şoklarının net vericisi olma rollerini dönem boyunca korurken, kripto para birimlerinin geri kalanı döneme bağlı olarak şokların net vericisi/alıcısı olmaktadırlar. Örneğin, Bitcoincash ve BNB'nin son dönemdeki net şok alıcısı rolleri net şok vericisi olarak değişmektedir. Ayrıca, Ripple ve Dogecoin, Ocak 2021 civarında önemli volatilite şoku yaymaktadır.

Frekans temelli bağlantılılık ağları, kısa-dönemli (geçici) bağlantılılıklarının orta vadeli ve kalıcı bağlantılardan daha güçlü olduğunu ortaya koymaktadır. Son olarak, çalışma COVID-19 pandemisinin resmi olarak ilan edildiği tarihte kısa-dönemli bağlantılılık ağını tahmin etmektedir. Ağ topolojisi, piyasa kapitalizasyon büyüklüğüne göre ilk iki sırada yer alan kripto para birimlerinin volatilite şoklarının en büyük vericileri olduğu göstermektedir. Ek olarak, çoğu kripto para birimi pandeminin resmi olarak ilan edildiği tarihte orta veya güçlü bağlantı ile karakterize edilmektedir.

Finansal bağlantılılık, finansal/jeopolitik çalkantılar etrafında önemli ölçüde dalgalanmalara eğilimlidir (Minoiu vd., 2015; Baruník ve Křehlík, 2018; Barigozzi vd., 2021). COVID-19 krizi böyle bir çalkantıya örnek teşkil etmektedir Bu kapsamda pandemi öncesi ve pandemi sırasında ülkelerin hisse senedi endeksleri arasındaki bağlantılılığı inceleyen bazı araştırmalar yapılmıştır (Abuzayed vd., 2021; Samitas vd., 2022; Choi, 2022). Çalışmalarının bulguları, pandemi döneminde hisse senedi bağlantılılığının önemli ölçüde yükseldiğini göstermektedir.

Bazı araştırmalar, salgının emtialar, dövizler (FX'ler) ve kripto para birimleri dahil olmak üzere çeşitli finansal varlıklar arasındaki risk aktarımları üzerindeki etkisini incelemiştir. Örneğin, Borgards vd. (2021), pandemi öncesinde ve sırasında 20 emtia vadeli işleminde aşırı tepki davranışını analiz etmiştir. Bazı çalışmalar Diebold-Yilmaz modelini kullanarak döviz piyasasında bağlantılılığı araştırmıştır (Fasanya vd., 2021b; Günay, 2021). Bu çalışmalar, volatilite yayılma endeksinin pandemi sırasında pandemi öncesi döneme kıyasla belirgin şekilde arttığını bulmuştur. Kumar vd. (2022) ve Naeem vd. (2022), pandemi sırasında kripto para birimleri arasındaki yayılmaları incelemiştir. Kumar vd. (2022), kripto para birimleri arasındaki bağlantının frekansa bağlı olduğunu ve kısa vadeye uzun vadeden daha duyarlı olduğunu belirtmiştir. Naeem vd. (2022), standart ve nicelik tabanlı VAR modellerini kullanarak kripto para birimi getirilerinin bağlantılılığını incelemiştir. Çalışmanın sonuçları, pandemi sırasında pandemi öncesi döneme göre getiri yayılmalarının daha yüksek olduğunu göstermektedir.

Çalışmaların bir bölümü pandemi sırasında farklı ülkeler için farklı varlık sınıfları arasındaki yayılmaları incelemiştir. Bu bağlamda, bazı araştırmalar Çin (Shahzad vd., 2021; Wang vd., 2022b), ABD (Sakurai ve Kurosaki, 2020; Adekoya ve Oliyide, 2021) ve BRICS (Rai ve Garg, 2021). Bu çalışmalar, COVID-19 sırasında ülkeye özgü finansal göstergeler arasında güçlü yayılmalar tespit etmiştir.

COVID-19 haberleriyle ilgili endekslerin (Coronavirus Medya Kapsam Endeksi, duyarlılık endeksi, medya ısı endeksi, sahte haber endeksi, panik duygu endeksi ve bulaşıcılık endeksi) finansal bağlantılılık üzerindeki etkisine odaklanan bir dizi çalışma bulunmaktadır (Umar vd., 2021; Zhang vd., 2022). Bu çalışmalar, haberle ilgili endekslerin bağlantılılık üzerinde önemli bir etkisi olduğunu tespit etmiştir.

Sınırlılıklar

Daha fazla sayıda kripto paranın çalışmaya dâhil edilmemiş olması çalışmanın temel sınırlılığını oluşturmaktadır. Fakat, daha fazla sayıda kriptoparanın analizde kullanılması bağlantılılık ağ topolojilerinin görsel olarak ifade edilmesini zorlaştırmaktadır. Bu nedenle piyasa kapitalizasyon değeri en yüksek olan ve tarihsel olarak en eskiye giden yedi kriptopara analizde kullanılabilmiştir.

Öneriler

Çalışmamız aşağıdaki politika önerilerine sahiptir: İlk olarak, kripto para birimleri arasındaki dinamik bağlantılılık, portföy stratejileri hakkında değerli bilgiler sağlamaktadır. Ayrıca, frekansa bağlı bağlantılılıklar, piyasanın yapısını analiz etmek amacıyla kullanılabilir. Bulgular, yatırımcılara ve politika yapıcılara piyasanın yapısı ile ilgili önemli bilgiler sunmaktadır. Son olarak, dijital varlıklar arasındaki bağlantıların anlaşılması, politika yapıcıların istikrarlı bir finansal sistem için esnek düzenleyici çerçeve geliştirmesini sağlayacaktır.

Özgün Değer

Çalışma, piyasa kapitalizasyonuna göre en üst sırada yer alan kriptoparalar arasındaki dinamik bağlantılılığı iki yeni yaklaşımla incelemektedir. Ayrıca, kriptoparalar arasındaki frekansa bağlı bağlantılıkların ağ topolojileri elde edilmektedir. Bu hususlar, çalışmanın temel özgün değerini yansıtmaktadır.

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