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How does COVID-19 influence dynamic spillover connectedness between cryptocurrencies? Evidence from non-parametric causality-in-quantiles techniques

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ABSTRACT

This research examines the impact of the COVID-19 on cryptocurrencies’ connectedness by employing two techniques: TVP-VAR-based connectedness and causality in the quantiles. First, the TVP-VAR-based connectedness unveils that cryptocurrencies act as a net receiver and transmitter of shocks, with Bitcoin, Ethereum are the highest transmitters among others. Moreover, the causality-in-quantile test shows that COVID-19 significantly causes spillover connectedness among cryptocurrencies, mainly at the quantiles ranging from 0.1 to 0.8, while an insignificant causal relationship is found in few cases. The study has implications for investors and policymakers.

1. Introduction

The outbreak of Coronavirus, which started in Wuhan, a city in China, rapidly spread around the world, causing thousands of deaths and infected millions of people. The World Health Organization (WHO) declared this pandemic a global pandemic on March 11, 2020. To curb the spread of COVID-19, worldwide governments impose strict restrictions, including school closures, travel bans, and curfews, which affect billions of people around the globe (Demir et al., 2020). These restrictions adversely affected the entire world, plunging the global health emergency into a global economic crisis (Singh and Neog, 2020). According to Goodell (2020), the pandemic caused unprecedented global destructive economic damage and created a strong contagion effect across financial sectors, such as banking, insurance, and stock markets. Consequently, this captures the interest of the scholars, and extensive work have been done to analyze the impact of the pandemic on financial markets (e.g., Onali 2020, Zhang et al. 2020, Akhtaruzzaman et al. 2021).

In addition to studying the impact of the COVID-19 pandemic on financial markets, research scholars have examined the impact of the COVID-19 pandemic on the cryptocurrencies market due to their unique features from conventional assets and blockchain technology (Kakinaka and Umeno, 2021). Ji et al. (2020) and Conlon et al. (2020) explored the safe haven properties of cryptocurrencies during the COVID-19 pandemic. More importantly, most of the studies have explored the cryptocurrencies efficiency and hedging property during the pandemic. Lahmiri and Bekiros (2020) used the data of 16 stock markets and 45 cryptocurrency markets to analyze the evolution of the informational efficiency during and before the COVID-19 period. The study concluded that the cryptocurrencies market is more affected compared to stock markets. Yarovaya et al. (2020) chose the four highest-traded cryptocurrencies and

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concluded that COVID-19 does not intensify herding in cryptocurrencies. Mnif et al. (2020) stated that after the outbreak, the cryptocurrency market become more efficient and thus outbreak doesn’t intensify herding. Susana et al. (2020) concluded that no herding was found in the cryptocurrency market during the pandemic period except for Dash, Litecoin, and Cardano. Naeem et al. (2021a) also stated that the efficiency of the four largest cryptocurrencies is negatively affected by the COVID-19 pandemic. Wang and Wang (2021) used the entropy-based analysis and reported that Bitcoin was less inefficient than stock markets during the COVID-19 pandemic. Kakinaka and Umeno (2021) employed the multifractal approach to examine the efficiency of cryptocurrency markets market and reported that the pandemic affected the price efficiency of cryptocurrencies differently in the short and long term.

Concerning the hedging properties of cryptocurrencies, mixed results are found. For instance, Corbet et al. (2020) claimed that Bitcoin intensifies financial contagion and does not act as a hedging property. Conlon et al. (2020) also reported that Ethereum and Bitcoin are not considered safe havens. Goodell and Goutte (2020) used the coherence wavelet approach and reported that the movement among the COVID-19 deaths and Bitcoin prices is strongly negative. Conversely, Iqbal et al. (2021) stated that Ethereum, CRO, and Bitcoin act as a hedge against extreme market conditions, and the top 10 cryptocurrencies could absorb the COVID-19 shocks. Caferra and Vidal-Tomás (2021) reported that prices of stock and cryptocurrencies fell in March 2020, but the cryptocurrency market recover promptly compared to stock markets. Corbet et al. (2020b) stated that 22 cryptocurrency returns are affected by the COVID-19 due to negative emotions. However still, they can be used as a safe haven.

From the above discussion, it can be observed that a great deal of prior literature related to cryptocurrencies has explored the properties of the cryptocurrency with other markets, and focused mainly on one type of currency, i.e., Bitcoin or a small group of transmitters. Moreover, the COVID-19 causes spillover connectedness among cryptocurrencies, mainly at the quantiles ranging from 0.1 to 0.8. In contrast, an insignificant causal relationship is found in few currencies. Besides methodological contributions, this paper has implications for investors. For instance, they can manage risk and develop strategies related to portfolio allocations and hedging.

2. Methodology

2.1. TVP-VAR based connectedness approach

As discussed previously, the volatility and return spillover between eight cryptocurrencies are measured by using the TVP-VAR based connectedness technique, which is an extension of the work of Diebold and Yilmaz, 2014. The TVP-VAR methodology has the following merits. (i) In this technique, the time-variation of the parameters can be predicted precisely, (ii) it is suitable for the short sample as it avoids the problem of loss of valuable observations, (iii) it is less sensitive to outliers, and (iv) it does not need the arbitrarily chosen rolling window size. (b) We gage the causal effect of the COVID-19 on cryptocurrencies’ connectedness by using the causality-in-quantiles technique given by Balcilar et al. (2016). It is preferred over other techniques because of novel properties, such as it explores the underlying dependency between the considered variables and robust to misspecification errors. Moreover, it also allows us to test both i.e., the causality that lies in the tails of the joint distribution of the variables and the causality-in-mean. The findings show that cryptocurrencies act as a transmitter and receiver of shocks, and among all, Bitcoin and Etherum are the highest transmitters. Moreover, the COVID-19 causes spillover connectedness among cryptocurrencies, mainly at the quantiles ranging from 0.1 to 0.8. In contrast, an insignificant causal relationship is found in few currencies. Besides methodological contributions, this paper is relevant to the existing research on cryptocurrencies during the COVID-19 outbreak (Yousaf and Ali 2020, etc.). Lastly, the outcome of this study has implications for investors. For instance, they can manage risk and develop strategies related to portfolio allocations and hedging.

\[ z_t = B_t z_{t-1} + u_t, \quad u_t \sim N(0, \Sigma_t) \]  
\[ \text{vec}(B_t) = \text{vec}(B_{t-1}) + \eta_t, \quad \eta_t \sim N(0, \Lambda_t) \]  
\[ z_t = \sum_{i=1}^{p} B_{t,i} z_{t-i} + u_t = \sum_{j=0}^{\infty} A_{t,j} u_{t-j} \]
In the above equation, $A_t$ shows the $k \times k$ dimensional time-varying VMA coefficient matrix.

After this, the H-step ahead (scaled) GFEVD (generalized forecast error variance decomposition) given by Koop et al. (1996) is computed based on the following:

$$\phi_{ij}(H) = \frac{\sum_{p=1}^{N} (\tilde{l}_t A_s l_s) ^2}{\sum_{p=1}^{N} (\hat{\tilde{l}}_t A_s l_s) ^2} \quad \phi_{ij}(H) = \frac{\sum_{p=1}^{N} \phi_{ij}(H)}{\sum_{p=1}^{N} \phi_{ij}(H)}$$

Where $\sum_{p=1}^{N} \phi_{ij}(H) = 1$ and $l_t$ shows the selection of zero vector and unity on the $j$th position.

Based on the Gabauer (2018) criteria, the (corrected) TCI is computed as:

$$C_i^j(H) = \frac{1}{k - 1} \sum_{j=1}^{i} 1 - \phi_{ij}(H)$$

The TCI values range between zero to unity and explain the market risk and the degree of interconnectedness. A high TCI value depicts that a shock in one variable has a high impact on all the other variables and has high interconnectedness. However, a low TCI value depicts that a shock in one variable has a low impact on all the other variables and has low interconnectedness.

### 2.2. Causality-in-quantiles technique

After getting the net and total spillovers, we move to the next part of the analysis. We explore the causal effect of the COVID-19 on the cryptocurrencies’ connectedness. To explore this, we used an innovative hybrid technique named causality-in-quantiles originated on the methodologies given by Jeong et al. (2012); Nishiyama et al. (2011). The COVID-19 cases are explained by $y_t$ and cryptocurrencies prices are explained by $(X_t)$. As argued by Jeong et al. (2012), $y_t$ does not lead by $X_t$ in the $\theta$-quantile, concerning the lag-vector of $(y_{t-1},...,y_{t-p},X_{t-1},...,X_{t-1})$ if:

$$Q^k = y_t | y_{t-1},...,y_{t-p},X_{t-1},...,X_{t-1}$$

in the $\theta$-quantile $X_t$ possibly cause $y_t$ regarding $(y_{t-1},...,y_{t-p},X_{t-1},...,X_{t-1})$ if:

$$Q^k = y_t | y_{t-1},...,y_{t-p},X_{t-1},...,X_{t-1}$$

in Eq (7) $Q^k = (y_t)$ symbolizes the $0 - \theta$ quantile the causality from $y_t$ to in mean means that the past of $X_t;e,X_{t-1},...,X_{t-1},X_{t-p}$ can used to predict the value of $y_t$ in the $0 - \theta$ quantile but not on others. To check this, we applied the 2nd moment causality test developed by Balcilar et al. (2017). The problem in calculating causality in higher order moments rises, since the presence of causality in the $k$th moment implies the presence of causality in the $mth$ moment for $k < m$. Therefore, the Nishiyama et al. (2011) causality in quantiles methodology is used which requires three critical choices (i) lag order $(p)$ which is determined by the SIC (ii) bandwidth $(h)$ which is selected via the least square cross-validation technique (iii) kernel type for $L(\cdot)$ and $K(\cdot)$ which are computed using the Gaussian kernels.

### 3. Data and empirical analysis

#### 3.1. Data and descriptive statistics

We start by explaining the sources and the nature of the data used. We take the everyday price data of top-eight cryptocurrencies namely Ethereum (ETH), Stellar (XLM), Bitcoin (BTC), Ripple (XRP), Binance Coin (BNB), Litecoin (LTC), Cardano (ADA), Chain Link

| Variable | Mean  | Maximum | Minimum | Std. Dev. | Skewness | Kurtosis | J-B | ADF test |
|----------|-------|---------|---------|-----------|----------|----------|-----|----------|
| BTC      | 20.550,920 | 63,503,460 | 4970,788 | 17,164,870 | 1,256 | 3.041 | 121.065*** | –20.839*** |
| ETH      | 663.511  | 2519,116 | 110,606 | 642,837   | 1,319 | 3.315 | 135.303*** | –2733*** |
| LTC      | 90.543   | 310,613 | 30,931  | 64,056    | 1,338 | 3.604 | 144.325*** | –16.188*** |
| XRP      | 0.345    | 1.839  | 0.140   | 0.257     | 3.148 | 14.534 | 3399.366*** | –19.521*** |
| XLM      | 0.164    | 0.655  | 0.033   | 0.150     | 1.410 | 3.694 | 161.550*** | –20.614*** |
| BNB      | 72,931   | 598,723 | 9,386   | 121,665   | 2.552 | 8.821 | 1148.964*** | –11.596*** |
| ADA      | 0.290    | 1.482  | 0.024   | 0.401     | 1.706 | 4.243 | 252.737*** | –20.979*** |
| LINK     | 12,650   | 42,753 | 1,780   | 9,969     | 0.994 | 2.953 | 75,764***  | –22.977*** |
| COVID    | 317,048  | 912,826 | 81      | 240,338   | 0.381 | 2.043 | 28,701***  | –6.918*** |

Note: All currencies are measured in US$ and COVID shows the total No. of new COVID-19 cases per day.

ADF = augmented Dickey and Fuller (1979) test of stationary, J-B = Jarque-Bera test of Normality.

***, **, * denotes the null hypothesis rejection at the 1%, 5% and 10%. Source: Authors’ Estimations.
The selected cryptocurrencies show 71.76% of the overall cryptocurrency market capitalization and hold a market value above 5 billion$. According to the coinmarketcap.com, the current market capitalization of Ethereum (ETH), Stellar (XLM), Bitcoin (BTC), Ripple (XRP), Binance Coin (BNB), Litecoin (LTC), Cardano (ADA), Chain Link (Link) are $371,890,674,517 (18.69%), $69,281,423,334 (0.35%), $847,721,495,277 (42.61%), $45,178,090,448 (2.27%), $64,777,710,087 (3.26%), $11,059,906,204 (0.56%), $68,707,107,356 (3.45%), $11,549,610,068 (0.58%). The COVID-19 data are taken from the world health organization (WHO). The dataset covers the period from 19 January 2020 to 26 April 2021. The detailed information related to the data is presented in Table 1. The outcome shows that, in the context of cryptocurrency prices, the mean value is found lowest in Stellar, which is 0.164$, and the mean value is found highest in Bitcoin, which is 20,550.920$. Moreover, in the context of COVID-19 cases, the mean value is found 317,048 per day. The graphical presentation of the data is also rendered in Fig. 1 to explain the possible co-movements between the top eight cryptocurrencies and COVID-19 cases.

Also, the summary statistics reveal that the value of skewness is positive for both variables. The data is skewed right and not perfectly symmetrical. The JB statistics rejects the null hypothesis of normality which is also confirmed from kurtosis and skewness values. The value of Kurtosis is above three, indicating a fat-tailed distribution and sharp peaks in the series. The fat-tail property in the variable series confirms the data’s non-normal distribution, thus affirming the application of the nonparametric causality approach rather than the linear causality technique.

3.2. Spillover results

In this study, we are more interested in knowing whether the COVID-19 cases cause the volatility spillovers across the cryptocurrencies. To check this, first, we evaluate the volatility spillovers among cryptocurrencies by applying the spillover analysis. Table 2
depicts the results; three things are important to understand while interpreting the results: net directional spillovers, total spillover from and to an individual currency, and unidirectional spillovers. The net directional spillover is the difference obtained by deducting the total contribution received from the total contribution of the currency to other currencies. If the difference value is positive, the currency is a net transmitter, whereas the negative value shows that the currency is a net receiver of shocks.

From the result, it is summarized that all cryptocurrencies act as net receivers and transmitters. Among all, Bitcoin and Ethereum are the highest givers with values 102.98 and 101.79, whereas Ripple currency is the least giver with 44.38. The result coincides with the studies of Antonakakis et al. (2019), Bouri et al. (2020). Antonakakis et al. (2019) reported that Bitcoin and Ethereum are the shock transmitters in cryptocurrency markets. Whereas, Bouri et al. (2020) stated that apart from Bitcoin, the ripple and Ethereum act as important players in cryptocurrency markets.

Moreover, the rest of the currencies are also among many givers whose values are more than 50%. Concerning shock receivers from others, the Stellar and Cardano are the highest receivers as it shows the value of 85.29 and 85.53, and the Ripple is the least receiver as it shows the value 80.55. The value of net spillover shows that Ripple, Stellar, Binance Coin, Cardano are the net receivers of shock, meaning that they get more than they transfer shocks to others The results depicted in Fig. 2 also corroborates with the results shown in Table 2. From graph 1, it is quite evident that the COVID-19 pandemic brings dynamic changes among the cryptocurrencies’ connectedness. The results are in line with previous studies that concluded that the behavior of cryptocurrencies is divergent in extreme market conditions (Iqbal et al., 2021; Jareño et al., 2021; Baumohl, 2019).

3.3. Causality test

From the net spillover test, it is quite clear that strong volatility is found among the cryptocurrencies, with Bitcoin acting as the

### Table 2

|          | BTC  | ETH  | LTC  | XRP  | XLM  | BNB  | ADA  | LINK | Contribution from others |
|----------|------|------|------|------|------|------|------|------|--------------------------|
| BTC      | 17.27| 15.69| 14.78| 5.49 | 9.81 | 11.3 | 12.77| 12.89| 82.73                    |
| ETH      | 15.88| 16.7 | 14.6 | 6    | 9.75 | 11.12| 12.17| 13.79| 83.3                     |
| LTC      | 16.12| 15.03| 16.67| 6.53 | 9.85 | 11.17| 11.97| 12.65| 83.33                    |
| XRP      | 11.73| 11.02| 12.31| 19.45| 11.06| 13.03| 11.35| 10.06| 80.55                    |
| XLM      | 15.12| 16.06| 14.53| 6.59 | 14.71| 9.04 | 11.38| 12.56| 85.29                    |
| BNB      | 13.67| 13.43| 12.88| 7.9  | 9    | 18.68| 12.88| 11.56| 81.32                    |
| ADA      | 15.17| 14.67| 13.24| 5.81 | 11.11| 12.89| 14.47| 12.62| 85.53                    |
| LINK     | 15.29| 15.88| 13.76| 6.05 | 10.24| 9.81 | 11.39| 17.58| 82.42                    |
| Contribution to others | 102.98 | 101.79 | 96.1 | 44.38 | 70.83 | 78.35 | 83.9 | 86.14 | 664.47 |
| Net directional connectedness | 20.25 | 18.49 | 12.77 | –36.17 | –14.46 | –2.97 | –1.63 | 3.72 | 83.06 |

Source: Authors’ Estimations.
highest transmitter and Ripple as the highest receiver of shock. Having established this, we now want to check the role of COVID-19 cases on cryptocurrency connectedness.

At first, the linearity test is applied, which is reported in Table 3. The result shows that the null hypothesis is accepted in most cases and rejected for spillover of Binance Coin only. The result coincides with Caporale et al. (2020) study, which reported that the phase transition and nonlinear behavior are found in cryptocurrencies. Based on the evidence of the existence of nonlinearity, we examine the possible nonlinear causal association between the variables by employing the nonlinear Granger causality test. The test findings are depicted in Table 4 and show the null hypothesis rejection on all embedding dimensions. Based on the findings, we used the causality-in-quantiles technique.

The outcomes and the graphical representation of the causality-in-quantiles from COVID-19 to cryptocurrency prices are presented in Table 5 and Fig. 3. In all the six graphs, the test statistics of nonparametric causality are shown on the vertical and on the horizontal axis the quantiles are represented. Thick black dotted lines show the test statistics, the thin two-dashed lines and the thin horizontal lines show the 10% and 5% critical values (1.65), (1.96), respectively. As seen from Fig. 2(a,b), the causal impact of COVID-19 is profound in most cases such as overall spillover Bitcoin, Ethereum, Litecoin, Ripple at 10% significance at the quantiles ranging from 0.1 to 0.8 except for Cardano, Binance Coin, Stellar. In the case of Cardano and Binance Coin, the COVID-19 causal effect is found at the middle quantiles, and no causal effect is found in Stellar. Overall, the outcome shows that COVID-19 significantly affects the spillover connectedness across the cryptocurrencies. The result coincides with Shahzad et al.’s (2021) study, which reported that COVID-19 significantly affects the network of spillovers among leading cryptocurrencies.

Table 4
BDS test.

| Variables                  | m = 2 | m = 3 | m = 4 | m = 5 | m = 6 |
|----------------------------|-------|-------|-------|-------|-------|
|                            | z-stats | p-value | z-stats | p-value | z-stats | p-value | z-stats | p-value | z-stats | p-value |
| Overall spillover          | 37.522 | 0.000  | 39.957 | 0.000  | 42.972 | 0.000  | 47.498 | 0.000  | 53.702 | 0.000  |
| Net spillover for BTC      | 44.407 | 0.000  | 47.377 | 0.000  | 51.009 | 0.000  | 56.318 | 0.000  | 63.633 | 0.000  |
| Net spillover for ETH      | 36.494 | 0.000  | 38.815 | 0.000  | 41.754 | 0.000  | 46.089 | 0.000  | 52.057 | 0.000  |
| Net spillover for LTC      | 64.909 | 0.000  | 69.376 | 0.000  | 74.591 | 0.000  | 82.371 | 0.000  | 92.898 | 0.000  |
| Net spillover for XRP      | 45.193 | 0.000  | 48.378 | 0.000  | 51.959 | 0.000  | 56.911 | 0.000  | 63.689 | 0.000  |
| Net spillover for XLM      | 46.635 | 0.000  | 50.350 | 0.000  | 54.667 | 0.000  | 60.568 | 0.000  | 68.838 | 0.000  |
| Net spillover for BNB      | 45.488 | 0.000  | 48.367 | 0.000  | 51.895 | 0.000  | 56.922 | 0.000  | 63.771 | 0.000  |
| Net spillover for ADA      | 26.174 | 0.000  | 27.408 | 0.000  | 29.138 | 0.000  | 31.725 | 0.000  | 35.364 | 0.000  |
| Net spillover for LINK     | 79.408 | 0.000  | 85.321 | 0.000  | 92.232 | 0.000  | 101.744| 0.000  | 114.704| 0.000  |

Note: m shows the embedding dimension. The entries shows the z-statistics BDS test established on the residuals of considered variables. Source: Authors’ Estimations.

Table 5
Results of Causality in Mean.

| Quantile | Overall spillover | Net spillover for BTC | Net spillover for ETH | Net spillover for LTC | Net spillover for XRP | Net spillover for XLM | Net spillover for BNB | Net spillover for ADA | Net spillover for LINK |
|----------|------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| 0.10     | 1.693*            | 1.979**               | 1.745*                | 1.705*                | 2.342*                | 1.025                 | 1.182                 | 1.042                 | 0.926                 |
| 0.15     | 1.742**           | 2.080**               | 1.935*                | 1.701*                | 2.01**                | 1.205                 | 1.626                 | 1.548                 | 1.038                 |
| 0.20     | 1.883**           | 2.040**               | 1.745*                | 1.703*                | 1.994*                | 1.077                 | 1.343                 | 1.721**               | 0.896                 |
| 0.25     | 1.948*            | 2.014**               | 1.524                 | 1.688*                | 1.731*                | 1.025                 | 1.182                 | 1.685*                | 0.836                 |
| 0.30     | 1.990**           | 2.081**               | 1.373                 | 1.723*                | 2.089**               | 1.356                 | 1.557                 | 1.403                 | 0.942                 |
| 0.35     | 1.967*            | 2.141**               | 1.104                 | 1.392                 | 2.090**               | 1.104                 | 1.392                 | 1.313                 | 0.802                 |
| 0.40     | 1.933**           | 2.156                 | 0.983                 | 1.028                 | 0.983                 | 1.028                 | 0.853                 | 0.627                 | 0.648                 |
| 0.45     | 1.848*            | 1.726                 | 1.118                 | 0.926                 | 0.747                 | 0.747                 | 0.627                 | 0.648                 | 0.627                 |
| 0.50     | 1.693*            | 1.373                 | 1.118                 | 0.926                 | 0.747                 | 0.747                 | 0.627                 | 0.648                 | 0.627                 |
| 0.55     | 1.000*            | 1.042                 | 1.118                 | 0.926                 | 0.747                 | 0.747                 | 0.627                 | 0.648                 | 0.627                 |

Note: Entries correspond to the quantile causality test statistic for the null hypothesis that considered COVID-19 does not Granger cause spillover connectedness among cryptocurrencies. **, * indicates the null hypothesis rejection at 5, and 10 percent levels respectively. Source: Authors’ Estimations.
4. Conclusion

This study uses the TVP-VAR-based connectedness and causality-in-the-quantiles technique to analyze how COVID-19 influences dynamic spillover connectedness among cryptocurrencies. The findings show that cryptocurrencies act as a transmitter and receiver of shocks, and among all, Bitcoin and Ethereum are the highest transmitters. Moreover, the COVID-19 causes spillover connectedness among cryptocurrencies, mainly at the quantiles ranging from 0.1 to 0.8. In contrast, an insignificant causal relationship is found in few
currencies. The study is helpful for the policymakers and investors for formulating policies. Investors should closely monitor the fluctuations in the global business cycle, especially in this pandemic, and adjust their portfolios accordingly to minimize their losses. Moreover, they should add those assets and cryptocurrencies to their relatively stable portfolios.

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