

# The COVID-19 outbreak and high frequency information transmission between major cryptocurrencies: Evidence from the VAR-DCC-GARCH approach

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## Abstract

Using intraday data, this study employs the VAR-DCC-GARCH model to examine return and volatility transmission among Bitcoin, Ethereum, and Litecoin during the pre-COVID-19 and COVID-19 periods. We find that the return spillovers differ across both periods for the Bitcoin-Ethereum, Bitcoin-Litecoin, and Ethereum-Litecoin pairs. The volatility transmission is not significant between cryptocurrencies during the pre-COVID-19 period. We also find that the volatility spillover is unidirectional from Bitcoin to Ethereum and bidirectional between Ethereum and Litecoin during the COVID-19 period. Moreover, volatility transmission is not significant between Bitcoin and Litecoin during the COVID-19 period. The dynamic conditional correlations between all pairs of cryptocurrencies are higher during the COVID-19 period than during the pre-COVID-19 period. Lastly, we compute the optimal portfolio weights, time-varying hedge ratios, and hedging effectiveness for all pairs of cryptocurrencies during the pre-COVID-19 and COVID-19 periods. Overall, our findings provide new insights into channels of information transmission, which may improve the investment decisions and trading strategies of portfolio investors during crisis and non-crisis periods.

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## 1. Introduction

Cryptocurrencies, *i.e.*, newly emerged digital assets, continually fascinate the financial press, policymakers, and the financial community (Makarov & Schoar, 2020). Many cryptocurrencies have emerged since the creation of Bitcoin, reaching a total of 6766 digital currencies on August 31, 2020.<sup>1</sup> Many factors contribute to the tremendous growth of the cryptocurrency market, such as the use of smart

technologies, the fourth industrial revolution, the acceptance of cryptocurrencies as legal currency in different countries, and their acceptance by large companies. It is therefore essential to understand the dynamics of the cryptocurrency market, especially the linkages among cryptocurrencies during a crisis. When volatility is transmitted from one cryptocurrency to another in a crisis period, portfolio managers need to adjust their asset allocation and policymakers need to adapt their policies to mitigate the risk of contagion. Hence, the transmission of information (return and volatility) among cryptocurrencies, particularly during a crisis, provides valuable insights into portfolio diversification, optimal hedging, options pricing, and risk management.

Several studies have investigated the return and/or volatility linkages across different cryptocurrencies (Baur & Dimpfl,

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<sup>1</sup> <https://coinmarketcap.com/>.

2018; Koutmos, 2018; Ji, Bouri, Lau, & Roubaud, 2019; Katsiampa, 2019; Katsiampa, Corbet, & Lucey, 2019a; Katsiampa, Corbet, & Lucey, 2019b; Liu & Serletis, 2019; Beneki, Koulis, Kyriazis, & Papadamou, 2019; Qureshi, Aftab, Bouri, & Saeed, 2020; Qiao, Zhu, & Hau, 2020; Wang & Ngene, 2020). For example, Koutmos (2018) investigates the transmission of return and volatility across eighteen major cryptocurrencies using the approach of Diebold and Yilmaz (2009) and reports that Bitcoin is the main transmitter of return and volatility effects to other cryptocurrencies. Katsiampa (2019) employs the diagonal Baba, Engle, Kraft, and Kroner (diagonal BEKK) model and finds a significant volatility co-movement between Bitcoin and Ethereum. Ji et al. (2019) examine the return and volatility transmission between the six major cryptocurrencies using the approach of Diebold and Yilmaz (2012). They report that Bitcoin and Litecoin are the net transmitters of return and volatility effects to the other cryptocurrencies, and that Ethereum is the net recipient of the spillovers. Katsiampa et al. (2019a) apply the BEKK multivariate GARCH model to investigate the transmission of shocks and volatility among Bitcoin, Ethereum, and Litecoin. They report bidirectional shock spillovers between the pairs Bitcoin-Ethereum and Bitcoin-Litecoin. They also find that the volatility spillover is bidirectional for the pairs Bitcoin-Ethereum, Bitcoin-Litecoin, and Ethereum-Litecoin. Liu and Serletis (2019) use the GARCH-in-mean model and find significant volatility spillovers among Bitcoin, Ethereum, and Litecoin. Qureshi et al. (2020) examine the interdependencies across five major cryptocurrencies (Bitcoin, Ethereum, Litecoin, Ripple, and Bitcoin Cash) using wavelet-based analyses. The results provide evidence of short-run and long-run market integration among some cryptocurrency pairs. Using wavelet coherence analysis, Qiao et al. (2020) report significant co-movement between Bitcoin and twelve other cryptocurrencies. Wang and Ngene (2020) apply the BEKK-GARCH model to examine the transmission of shocks and volatility between cryptocurrencies using intraday data. They find that shock and volatility are mostly transmitted from Bitcoin to the other six cryptocurrencies. However, none of the above-mentioned studies investigates the transmission of return and volatility among cryptocurrencies during a crisis period. Although, several studies have examined return and volatility transmission between various asset classes, *i.e.*, equity, bonds, and commodities (Aloui, Aissa, and Nguyen, 2011; Bekaert, Ehrmann, Fratzscher, & Mehl, 2014; Chen, Firth, & Rui, 2002; Diebold & Yilmaz, 2009; Forbes & Rigobon, 2002), but not between cryptocurrencies. Therefore, this study will address this literature gap.

This paper makes several important contributions to the literature. First, this study examines return and volatility transmission among the major cryptocurrencies (Bitcoin, Ethereum, and Litecoin) during the pre-COVID-19 and COVID-19 periods. We chose the COVID-19 period as an indicator of a crisis period because the majority of the financial markets have been adversely affected by the COVID-19 pandemic (Goodell, 2020; Zhang, Hu, & Ji, 2020). For instance, Bitcoin prices declined by 19% from January 1,

2020, to March 23, 2020. Moreover, Bitcoin's biggest one-day fall (36%) was observed on March 13, 2020. The S&P 500 sharply declined by 33% from February 19, 2020, to March 23, 2020, and the price of West Texas Intermediate crude was -\$37.63 per barrel on April 20, 2020.<sup>2</sup> Because cryptocurrencies have also been affected by the COVID-19 pandemic, the findings regarding return and volatility transmission can be useful to investors for portfolio diversification and risk management during the COVID-19 pandemic.

Second, we use the vector autoregressive-dynamic conditional correlation-GARCH (VAR-DCC-GARCH) approach to estimate return and volatility spillover between cryptocurrencies. The main advantages of the DCC-GARCH model are the positive definiteness of the conditional covariance matrices and the model's ability to estimate time-varying volatilities, covariances, and correlations among the assets in a parsimonious way. This model is also used to calculate time-varying hedge ratios, optimal weights, and hedging effectiveness. Many studies have applied the DCC-GARCH model in crisis and non-crisis periods to analyze spillover across different asset classes (Aslanidis, Bariviera, & Martinez-Ilbañez, 2019; Creti, Joëts, & Mignon, 2013; Karanasos, Ali, Margaronis, & Nath, 2018; Sadorsky, 2012), but none have applied the VAR-DCC-GARCH model to estimate return and volatility spillover among cryptocurrencies during the COVID-19 pandemic.

Third, we examine the linkages between cryptocurrencies using high-frequency hourly data, which provides better and deeper insights to crypto investors. Except for Katsiampa et al. (2019b), all of the studies discussed above use daily data to investigate linkages between cryptocurrencies.

Finally, we also estimate the optimal weights, time-varying hedge ratios, and hedging effectiveness for the pairs of cryptocurrencies during both sample periods to provide useful insights to portfolio managers regarding optimal asset allocation and portfolio risk management during crisis and non-crisis periods.

The results of this study reveal that the return spillovers differ across the pre-COVID-19 and COVID-19 periods for the pairs Bitcoin-Ethereum (BTC/ETH), Bitcoin-Litecoin (BTC/LTC), and Ethereum-Litecoin (ETH/LTC), whereas the volatility spillover is found to be unidirectional from Bitcoin to Ethereum, and bidirectional between Ethereum and Litecoin during the COVID-19 period. Volatility transmission is not significant between any cryptocurrencies during the pre-COVID-19 period, and is not significant between Bitcoin and Litecoin during the COVID-19 period. The dynamic conditional correlations between all pairs of cryptocurrencies are higher during the COVID-19 period than during the pre-COVID-19 period. The optimal portfolio weights suggest that investors should decrease their investments (a) in Bitcoin for the portfolio of BTC/ETH and BTC/LTC, and (b) in Ethereum for the portfolio of ETH/LTC during the COVID-19 period. The time-varying hedge ratios are observed to be higher during the COVID-19 period, implying a higher

<sup>2</sup> <https://www.forbes.com/>.

hedging cost during that period than in the pre-COVID-19 period. Lastly, hedging effectiveness is also higher during the COVID-19 period than during the pre-COVID-19 period.

The rest of the paper is organized as follows: Section 2 describes the methodology, and section 3 provides the data and preliminary analysis. Section 4 reports the empirical findings, and Section 5 concludes the whole discussion.

## 2. Methodology

This section consists of three subparts. In the first part, we explain the VAR-DCC-GARCH model then describe the method to calculate optimal weights and hedge ratios. Lastly, we provide the mechanism to calculate hedging effectiveness for the pairs of cryptocurrencies.

### 2.1. VAR-DCC-GARCH model

In this study, the econometric specification consists of two components. The returns are modeled through the VAR specifications with one lag. This allows for the cross-correlations and autocorrelations in the returns. Then we use the DCC-GARCH model, proposed by Engle (2002), as a benchmark to estimate the time-varying covariances and variances.

The VAR model is employed as a conditional mean equation of the DCC-GARCH model. The mean equation is specified as follows:

$$R_t = \mu + \emptyset R_{t-1} + e_t \text{ with } e_t = D_t^{1/2} \eta_t \quad (1)$$

$R_t$  is the  $3 \times 1$  vector of returns on the x, y, and z cryptocurrencies at time  $t$ ,  $\mu$  denotes a  $3 \times 1$  vector of constants, and

$$\emptyset = \begin{pmatrix} \emptyset_{11} & \emptyset_{12} & \emptyset_{13} \\ \emptyset_{21} & \emptyset_{22} & \emptyset_{23} \\ \emptyset_{31} & \emptyset_{32} & \emptyset_{33} \end{pmatrix}$$

refers to a  $3 \times 3$  matrix of parameters measuring the influence of own-lagged and cross-mean transmissions between three series.  $e_t$  is the residual of the mean equation for the three series of cryptocurrency returns at time  $t$ ,  $\eta_t$  indicates a  $3 \times 1$  vector of independently and identically distributed random vectors, and  $D_t^{1/2} = \text{diag}(\sqrt{h_t^x}, \sqrt{h_t^y}, \sqrt{h_t^z})$ , where  $h_t^x$ ,  $h_t^y$ , and  $h_t^z$  represent the conditional variances of the returns for cryptocurrency x, y, and z, respectively.

The Engle (2002) dynamic conditional correlation (DCC) model is estimated in two steps. In the first step, the GARCH parameters are estimated. In the second step, the correlations are estimated. The specifications of the conditional variance equation of the DCC-GARCH model are given as follows:

$$H_t = D_t R_t D_t \quad (2)$$

$H_t$  represents the  $3 \times 3$  conditional covariance matrix.  $R_t$  is the conditional correlation matrix, and  $D_t$  is a diagonal matrix with time-varying standard deviations on the diagonal.

$$D_t = \text{diag}\left(h_{11t}^{1/2}, \dots, h_{33t}^{1/2}\right) \quad (3)$$

$$R_t = \text{diag}\left\{q_{11t}^{-1/2}, \dots, q_{33t}^{-1/2}\right\} Q_t \text{ diag}\left\{q_{11t}^{-1/2}, \dots, q_{33t}^{-1/2}\right\} \quad (4)$$

$Q_t$  is a symmetric positive definite matrix.

$$Q_t = (1 - \theta_1 - \theta_2) \bar{Q} + \theta_1 e_{t-1} e_{t-1}' + \theta_2 Q_{t-1} \quad (5)$$

where  $\bar{Q}$  indicates the  $3 \times 3$  unconditional correlation matrix of standardized residuals. The parameters  $\theta_1$  and  $\theta_2$  are non-negative with a sum of less than unity. The time-varying correlation's estimator is then extracted by calculating the following:

$$\rho_{xy,t} = \frac{q_{xy,t}}{\left(\sqrt{q_{x,t}} \sqrt{q_{y,t}}\right)} \quad (6)$$

Lastly, the multivariate DCC-GARCH models are estimated by quasi-maximum likelihood estimation (QMLE) using the Broyden, Fletcher, Goldfarb and Shanno (BFGS) algorithm.

### 2.2. Optimal weights and hedge ratios

The estimates of the VAR-DCC-GARCH model can be used to calculate optimal portfolio weights. This study follows Kroner and Ng (1998) to calculate the optimal portfolio weights for the pairs of the cryptocurrencies (x, y):

$$w_{xy,t} = \frac{h_{y,t} - h_{xy,t}}{h_{x,y} - 2h_{xy,t} + h_{y,t}} \quad (7)$$

$$w_{xy,t} = \begin{cases} 0, & \text{If } W_{xy,t} < 0 \\ w_{xy,t}, & \text{If } 0 \leq w_{xy,t} \leq 1 \\ 1, & \text{If } w_{xy,t} > 1 \end{cases}$$

where  $w_{xy,t}$  is the weight of cryptocurrency (x) in a \$1 portfolio of cryptocurrency(x) and cryptocurrency (y) at time  $t$ ,  $h_{xy,t}$  is the conditional covariance between the two cryptocurrencies,  $h_{x,t}$  and  $h_{y,t}$  are the conditional variance of cryptocurrency (x) and cryptocurrency (y), respectively, and  $1-w_{xy,t}$  is the weight of cryptocurrency (y) in a \$1 portfolio of cryptocurrency (x) and cryptocurrency (y).

It is also essential to estimate the risk-minimizing optimal hedge ratios for the portfolio of different pairs of cryptocurrencies. The estimates of the VAR-DCC-GARCH model can also be used to calculate optimal hedge ratios. This study follows Kroner and Sultan (1993) to calculate the optimal hedge ratios.

$$\beta_{xy,t} = \frac{h_{xy,t}}{h_{y,t}} \quad (8)$$

where  $\beta_{xy,t}$  represents the hedge ratio. This shows that a short position in cryptocurrency (y) can hedge a long position in the cryptocurrency (x).

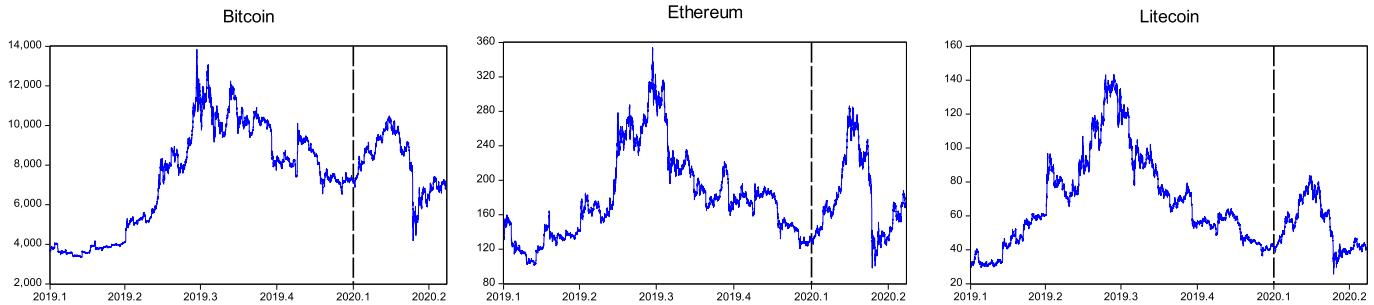


Fig. 1. Hourly prices of cryptocurrencies.

### 2.3. Hedging effectiveness

Hedging effectiveness is estimated to compare the performance of optimal portfolios. If the hedging effectiveness is 1, it represents the perfect hedge and vice versa. Thus, a higher hedging effectiveness score shows greater risk reduction. Following [Ku, Chen, and Chen \(2007\)](#) and [Pan, Wang, and Yang \(2014\)](#), this study estimates the hedging effectiveness (HE) as follows:

$$HE = \frac{\text{variance}_{\text{Unheded}} - \text{variance}_{\text{hedged}}}{\text{variance}_{\text{Unheded}}} \quad (9)$$

where  $\text{variance}_{\text{Unheded}}$  represents the variance of the unhedged portfolio (only x assets) returns, and  $\text{variance}_{\text{hedged}}$ <sup>3</sup> indicates the variation in the returns for the portfolio of x and y assets.

## 3. Data and preliminary analysis

### 3.1. Data

We use the hourly data of Bitcoin, Ethereum, and Litecoin, which represent 76% of cryptocurrency market capitalization (as of April 1, 2020). We use two sample periods: the pre-COVID-19 period (January 1 to December 31, 2019) and the COVID-19 period (January 1 to April 22, 2020). The data of cryptocurrency prices are taken from Bittrex, and the prices are listed in US dollars.

### 3.2. Preliminary analysis

[Fig. 1](#) presents the hourly prices of Bitcoin, Ethereum, and Litecoin. It can be seen that the prices of these three cryptocurrencies increased in the first and second quarters of 2019, but then decreased in the third and fourth quarters. The prices of all cryptocurrencies increased (decreased) in the first half (second half) of the first quarter of 2020, and ultimately rose in the second quarter. The considerable decline in prices indicates that COVID-19 adversely affected cryptocurrency prices during the second half of the first quarter of 2020. Almost all currencies follow a similar trend during the reported six quarters. [Fig. 2](#) reveals the hourly returns of Bitcoin, Ethereum, and Litecoin

and shows volatility clustering in the returns of all of the cryptocurrencies in different quarters. However, peaks of volatilities can be observed in Bitcoin, Ethereum, and Litecoin during the first quarter of 2020 (COVID-19 period).

[Table 1](#) presents the summary statistics of the returns of Bitcoin, Ethereum, and Litecoin during the pre-COVID-19 (Panel A) and COVID-19 (Panel B) periods. The average returns of Bitcoin are positive in the pre-COVID-19 period but highly negative during the COVID-19 period. This shows that Bitcoin is highly and adversely affected by the COVID-19 global pandemic. In contrast, the mean returns of Ethereum are negative during the pre-COVID-19 period but highly positive during the COVID-19 period. As regards Litecoin, the mean returns are positive in the pre-COVID-19 period, but negative in the COVID-19 period.

During both sample periods, unconditional volatility is lowest in Bitcoin and highest in Litecoin. In all three cryptocurrencies, the returns are skewed to the left (in most cases), kurtosis is significantly higher than 3, and the Jarque-Bera statistics reject the normality hypothesis. The results also confirm the presence of autocorrelation and ARCH effects in the returns of all three cryptocurrencies during both sample periods. Moreover, the results of the Augmented Dickey-Fuller (ADF) test indicate that all series are significant, suggesting that the returns of all three cryptocurrencies are stationary during both sample periods.

Lastly, [Table 2](#) provides the correlation matrix for the three pairs of cryptocurrencies, namely BTC-ETH, BTC-LTC, and ETH-LTC, in the pre-COVID-19 and COVID-19 periods. The correlations are positively significant and above 0.620 for all three pairs during both sample periods. These correlations are consistent with those of [Katsiampa et al. \(2019b\)](#), who find a correlation above 0.717 for the pairs BTC-ETH, BTC-LTC, and ETH-LTC using hourly returns data. In addition, the unconditional correlations are found to be higher during the COVID-19 period than in the pre-COVID-19 period, implying a higher degree of association among cryptocurrencies during the COVID-19 period.

## 4. Empirical results

### 4.1. Return and volatility spillovers

To analyze the return and volatility spillovers among Bitcoin, Ethereum, and Litecoin, we use the multivariate VAR-

<sup>3</sup>  $\text{Variance}_{\text{hedged}} = h_{x,t} + \beta_{xy,t}^2 h_{y,t} - 2\beta_{xy,t} h_{xy,t}$ .

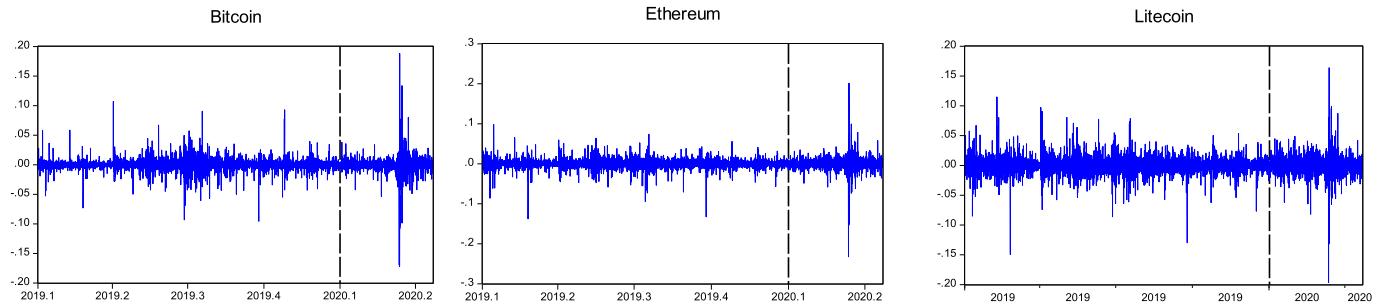


Fig. 2. Hourly returns of cryptocurrencies.

Table 1  
Descriptive statistics.

	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Q-stat	ARCH	ADF
<b>Panel A. Pre COVID-19</b>										
BTC	0.000046	0.107	-0.096	0.007	0.095	31.718	301039 <sup>a</sup>	67.378 <sup>a</sup>	85.142 <sup>a</sup>	-94.789 <sup>a</sup>
ETH	-0.000059	0.098	-0.138	0.009	-1.121	27.940	228861 <sup>a</sup>	129.66 <sup>a</sup>	26.704 <sup>a</sup>	-36.281 <sup>a</sup>
LTC	0.000007	0.115	-0.150	0.011	-0.097	18.485	87539 <sup>a</sup>	74.014 <sup>a</sup>	68.407 <sup>a</sup>	-100.17 <sup>a</sup>
<b>Panel B. COVID-19</b>										
BTC	-0.000012	0.188	-0.172	0.011	-0.897	88.175	816214 <sup>a</sup>	157.10 <sup>a</sup>	121.431 <sup>a</sup>	-40.169 <sup>a</sup>
ETH	0.000117	0.201	-0.232	0.013	-1.624	71.186	524043 <sup>a</sup>	130.12 <sup>a</sup>	49.627 <sup>a</sup>	-57.123 <sup>a</sup>
LTC	-0.000016	0.164	-0.196	0.014	-0.637	34.558	112178 <sup>a</sup>	98.634 <sup>a</sup>	198.439 <sup>a</sup>	-58.761 <sup>a</sup>

Notes: BTC, Bitcoin; ETH, Ethereum; LTC, Litecoin. Q-stat denotes the Ljung-Box Q-statistics. The ARCH test refers to the LM-ARCH test of [Engle \(1982\)](#). ADF refers to the augmented Dickey-Fuller test with constant. <sup>a</sup>, <sup>b</sup>, <sup>c</sup> indicate the statistical significance at 1%, 5%, and 10% respectively.

Table 2  
Correlation matrix.

	Pre COVID-19			COVID-19		
	BTC	ETH	LTC	BTC	ETH	LTC
BTC	1			BTC	1	
ETH	0.765 <sup>a</sup>	1		ETH	0.887 <sup>a</sup>	1
LTC	0.620 <sup>a</sup>	0.695 <sup>a</sup>	1	LTC	0.811 <sup>a</sup>	0.849 <sup>a</sup>

Notes: BTC, Bitcoin; ETH, Ethereum; LTC, Litecoin. <sup>a</sup>, <sup>b</sup>, <sup>c</sup> indicate the statistical significance at 1%, 5%, and 10% respectively.

DCC-GARCH model stated in equations (1)–(6). The results are reported in [Table 4](#). As shown in [Table 1](#), there are significant autocorrelation and ARCH effects for the returns of all three cryptocurrencies. We can therefore employ a multivariate VAR-DCC-GARCH model in our analysis.

The results of the principal component analysis for the three cryptocurrencies' return series are presented in [Table 3](#). The first and largest principal component captures 79% and 90% of the total variation during the pre-COVID-19

and the COVID-19 period, respectively. The explanatory power of the principal components declines substantially for both periods after subtracting the first component. We can therefore infer that a common factor drives a higher portion of the total variation for the cryptocurrencies' return series during the COVID-19 period than during the pre-COVID-19 period.

#### 4.1.1. Return spillovers

[Table 4](#) presents the return transmission results for Bitcoin, Ethereum, and Litecoin during the pre-COVID-19 and COVID-19 periods. In Panel A, the coefficients of own-mean spillover ( $\phi_{11}$ ,  $\phi_{22}$ , and  $\phi_{33}$ ) are significantly negative during both sample periods, indicating that the lagged returns inversely affect their current returns in Bitcoin, Ethereum, and Litecoin during both periods. These results are consistent with the findings of [Liu and Serletis \(2019\)](#), who find that own-mean spillovers are significant in Bitcoin, Ethereum, and

Table 3  
Principal component analysis of cryptocurrency returns.

	Eigenvalue	Proportion of variances	Cumulative eigenvalue	Cumulative proportion of variances
<b>Pre COVID-19 period</b>				
First principal component	2.388	0.796	2.388	0.796
Second principal component	0.390	0.130	2.778	0.926
Third principal component	0.222	0.074	3.000	1.000
<b>COVID-19 period</b>				
First principal component	2.698	0.900	2.698	0.900
Second principal component	0.194	0.065	2.893	0.964
Third principal component	0.107	0.036	3.000	1.000

Table 4

Estimates of multivariate VAR-DCC-GARCH model for Bitcoin, Ethereum, and Litecoin.

	Pre COVID-19		COVID-19	
	Coefficient	P-value	Coefficient	P-value
<b>Panel A. Mean equation</b>				
$\mu_1$	-0.000	0.191	0.000	0.975
$\varnothing_{11}$	-0.146 <sup>a</sup>	0.000	-0.116 <sup>b</sup>	0.014
$\varnothing_{12}$	-0.000	0.816	0.040	0.388
$\varnothing_{13}$	0.047 <sup>c</sup>	0.052	0.060	0.182
$\mu_2$	-0.001 <sup>c</sup>	0.074	0.001	0.336
$\varnothing_{21}$	0.049 <sup>b</sup>	0.022	0.018	0.581
$\varnothing_{22}$	-0.102 <sup>a</sup>	0.000	-0.171 <sup>a</sup>	0.000
$\varnothing_{23}$	0.123 <sup>a</sup>	0.000	0.114 <sup>b</sup>	0.025
$\mu_3$	-0.001	0.107	-0.000	0.684
$\varnothing_{31}$	0.015	0.173	0.020	0.409
$\varnothing_{32}$	0.034 <sup>b</sup>	0.015	0.047	0.186
$\varnothing_{33}$	-0.185 <sup>a</sup>	0.000	-0.221 <sup>a</sup>	0.000
<b>Panel B. Variance equation</b>				
$c_1$	0.000 <sup>a</sup>	0.001	0.000 <sup>b</sup>	0.011
$c_2$	0.000 <sup>b</sup>	0.022	0.001 <sup>a</sup>	0.000
$c_3$	0.000 <sup>a</sup>	0.003	0.000 <sup>a</sup>	0.000
$a_{11}$	0.085 <sup>a</sup>	0.000	0.020	0.654
$a_{12}$	0.000	0.447	0.035	0.111
$a_{13}$	0.000	0.146	-0.001 <sup>c</sup>	0.091
$a_{21}$	0.013	0.292	-0.026	0.277
$a_{22}$	0.052 <sup>a</sup>	0.001	0.104 <sup>a</sup>	0.000
$a_{23}$	0.000	0.277	0.000	0.403
$a_{31}$	0.019	0.280	-0.029	0.295
$a_{32}$	0.025 <sup>c</sup>	0.094	0.071 <sup>a</sup>	0.003
$a_{33}$	0.029 <sup>b</sup>	0.047	0.034 <sup>a</sup>	0.000
$b_{11}$	0.888 <sup>a</sup>	0.000	0.968 <sup>a</sup>	0.000
$b_{12}$	-0.010	0.377	-0.050 <sup>c</sup>	0.083
$b_{13}$	-0.001	0.208	0.001	0.824
$b_{21}$	-0.001	0.612	0.042	0.251
$b_{22}$	0.902 <sup>a</sup>	0.000	0.895 <sup>a</sup>	0.000
$b_{23}$	0.010	0.549	-0.029 <sup>b</sup>	0.041
$b_{31}$	-0.019	0.397	0.025	0.522
$b_{32}$	-0.040	0.144	-0.071 <sup>b</sup>	0.031
$b_{33}$	0.961 <sup>a</sup>	0.000	0.955 <sup>a</sup>	0.000
$\theta_1$	0.023 <sup>b</sup>	0.017	0.010 <sup>b</sup>	0.028
$\theta_2$	0.952 <sup>a</sup>	0.000	1.336 <sup>a</sup>	0.000
<b>Panel D: Robustness tests</b>				
Log L	96820.6		29815.3	
AIC	-21.383		-20.694	
SIC	-21.235		-20.294	
$Q_1[20]$	40.953 <sup>a</sup>	0.003	36.597 <sup>b</sup>	0.013
$Q_2[20]$	44.763 <sup>a</sup>	0.001	39.179 <sup>a</sup>	0.006
$Q_3[20]$	38.926 <sup>a</sup>	0.006	29.083 <sup>c</sup>	0.086
$Q_1^2[20]$	2.947	0.989	22.156	0.332
$Q_2^2[20]$	4.891	0.986	19.200	0.183
$Q_3^2[20]$	12.061	0.913	12.089	0.912

Notes: # of lags for VAR is decided using SIC and AIC criteria. JB, Q(20), and Q<sup>2</sup>(20) indicate the empirical statistics of Jarque -Bera test for normality, Ljung-Box Q-statistics of order 20 for autocorrelation applied to the standardized residuals and squared standardized residuals, respectively. BTC, Bitcoin; ETH, Ethereum; LTC, Litecoin. Variable order is Bitcoin (1), Ethereum (2), and Litecoin (3). In the mean equations,  $\mu$  denotes the constant terms, whereas  $\varnothing_{12}$  denotes the return spillover from Bitcoin to Ethereum. In the variance equation, “c” denotes the constant terms, “a” denotes the ARCH terms, and “b” denotes the GARCH terms. In the variance equation,  $a_{12}$  indicates the shock spillover from Bitcoin to Ethereum, whereas  $b_{12}$  denotes the long-term volatility spillover from Bitcoin to Ethereum. <sup>a,b,c</sup> indicate the statistical significance at 1%, 5%, and 10% respectively.

Litecoin. These findings highlight the potential for making short-term predictions of current returns based on past Bitcoin, Ethereum, and Litecoin returns.

Regarding the return spillovers between Bitcoin and Ethereum in the mean equation ( $\varnothing_{12}, \varnothing_{21}$ ), the results indicate unidirectional and positive return spillover from Ethereum to Bitcoin during the pre-COVID-19 period. It shows that when the returns of Ethereum increase, investors tend to increase investments in Bitcoin to optimize their portfolios, thus bidding up the price of Bitcoin and vice versa. These results are consistent with the findings of [Liu and Serletis \(2019\)](#), who find that lagged returns of Ethereum significantly influence the current returns of Bitcoin. This implies that during the pre-COVID-19 period the Ethereum returns are useful for forecasting the Bitcoin returns. In contrast, the return spillover is not significant between Bitcoin and Ethereum during the COVID-19 period, suggesting that the Bitcoin (Ethereum) returns cannot be used to forecast the Ethereum (Bitcoin) returns during that period due to the considerable uncertainty and fear in the markets.

The findings regarding return spillovers between Bitcoin and Litecoin ( $\varnothing_{13}, \varnothing_{31}$ ) reveal that return transmission is unidirectional and positive from Bitcoin to Litecoin during the pre-COVID-19 period, but that return transmission is not significant between Bitcoin and Litecoin during the COVID-19 period. This implies that the Litecoin (Bitcoin) returns cannot be used to forecast the Bitcoin (Litecoin) returns during the COVID-19 period. Moreover, the Ethereum-Litecoin return transmission results ( $\varnothing_{23}, \varnothing_{32}$ ) indicate bidirectional and positive return spillover between Ethereum and Litecoin during the pre-COVID-19 period and unidirectional return transmission from Ethereum to Litecoin during the COVID-19 period. This indicates that when the returns of Ethereum decrease during the COVID-19 period, investors tend to decrease their investments in Litecoin as well, due to fear of loss and to optimize their portfolio. They thus bid down the price of Litecoin. The implication is that Ethereum returns can be used to forecast the Litecoin returns during the COVID-19 period.

#### 4.1.2. Volatility spillovers

[Table 4](#) presents the volatility transmission (Panel B) among Bitcoin, Ethereum, and Litecoin during the pre-COVID-19 and COVID-19 periods. Regarding own-shock ( $a_{11}, a_{22}$ , and  $a_{33}$ ) and own volatility spillovers ( $b_{11}, b_{22}$ , and  $b_{33}$ ), the findings show that the lagged shocks and volatility significantly and positively influence current conditional volatility in Ethereum and Litecoin during both sample periods, and in Bitcoin during the pre-COVID-19 period. These results are in line with the findings of [Katsiampa et al. \(2019b\)](#). During the COVID-19 period, the own-shock spillover is not significant in Bitcoin, suggesting that past shocks do not affect current volatility in Bitcoin in the COVID-19 period. Overall, the coefficients of past own volatility are higher than the coefficients of past own shocks, implying that

during both sample periods, past own volatilities are a more important factor in predicting current volatilities as compared to the past own shocks.

With respect to cross-market shock spillover ( $a_{12}$ ,  $a_{13}$ ,  $a_{21}$ ,  $a_{23}$ ,  $a_{31}$  and  $a_{32}$ ), the results indicate that the shock spillover is not significant between Bitcoin and Ethereum in either sample period. It is negative and unidirectional from Bitcoin to Litecoin during the COVID-19 period, whereas shock transmission is positive and unidirectional from Litecoin to Ethereum during both sample periods.

With regard to volatility spillovers between Bitcoin and Ethereum ( $b_{12}$  and  $b_{21}$ ), the findings reveal that the volatility spillover is not significant between Bitcoin and Ethereum during the pre-COVID-19 period, which implies that a portfolio of Bitcoin and Ethereum would have provided maximum diversification benefits during that period. During the COVID-19 period, volatility transmission is negative and significant from Bitcoin to Ethereum, indicating that when Bitcoin market volatility increases, Ethereum volatility decreases. Risk-averse crypto investors should therefore invest in Ethereum if Bitcoin volatility rises during the COVID-19 period. Regarding cross-market volatility spillover between Bitcoin and Litecoin ( $b_{13}$  and  $b_{31}$ ), the results indicate that volatility transmission is not significant between Bitcoin and Litecoin in either sample period, highlighting that investors can get the maximum benefit of diversification by constructing a portfolio of Bitcoin and Litecoin during crisis and non-crisis periods. As regards Ethereum and Litecoin,

the cross-market volatility spillover ( $b_{23}$  and  $b_{32}$ ) results provide no evidence of volatility transmission between these two cryptocurrencies during the pre-COVID-19 period, but during the COVID-19 period the volatility transmission is negative and bidirectional between them. This shows that if the lagged volatility of Ethereum increases, the current volatility of Litecoin decreases and investors can ultimately expect an increase in Ethereum's volatility in the next period. In short, the volatility of Ethereum and Litecoin move in opposite directions, and risk-averse and risk-taking crypto investors should invest accordingly.

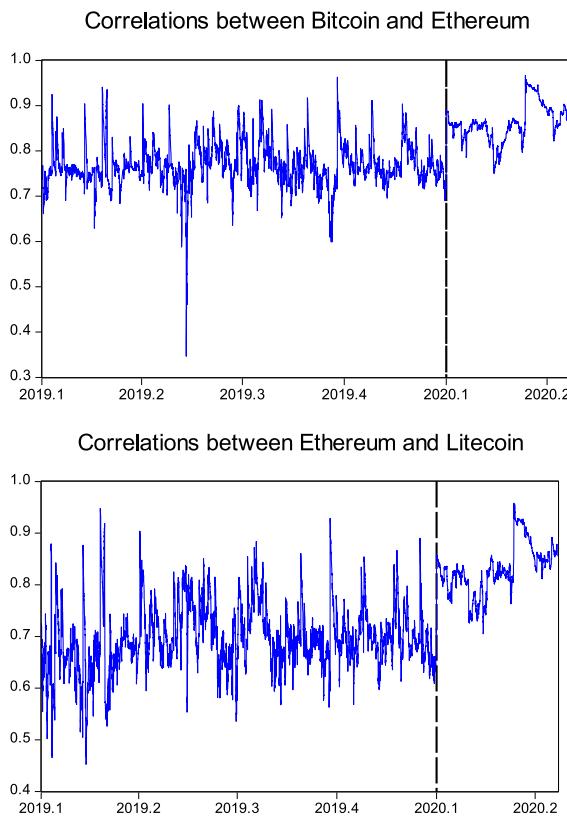
#### 4.1.3. Dynamic conditional correlations

The time-varying correlations are presented in Fig. 3 for the pairs BTC/ETH, BTC/LTC, and ETH/LTC during the pre-COVID-19 and COVID-19 periods. The time-varying conditional correlations are significantly positive for all

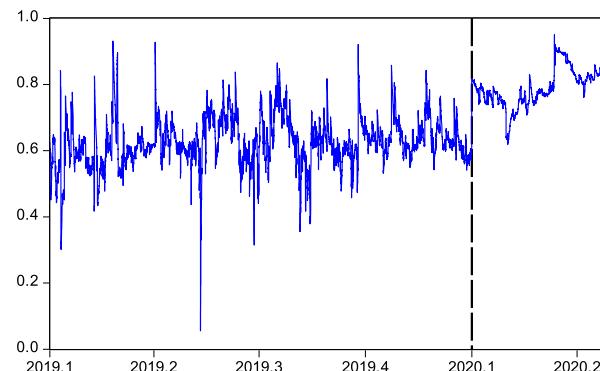
Table 5  
Optimal weights and hedge ratios for pairs of cryptocurrencies.

	BTC/ETH	BTC/LTC	ETH/LTC
<b>Pre COVID-19 period</b>			
$w_t$	0.87	0.90	0.83
$\beta_t$	0.63	0.41	0.56
<b>COVID-19 period</b>			
$w_t$	0.86	0.88	0.66
$\beta_t$	0.67	0.56	0.76

Note:  $w_t$  and  $\beta_t$  refer to the optimal weights and hedge ratios, respectively.



Correlations between Bitcoin and Ethereum



Correlations between Bitcoin and Litecoin

Fig. 3. Dynamic conditional correlations.

pairs during both sample periods, consistent with the findings of [Katsiampa et al. \(2019b\)](#) and [Canh, Wongchoti, Thanh, and Thong \(2019\)](#). In addition, the correlations are higher during the COVID-19 period than during the pre-COVID-19 period, which implies that cryptocurrencies are highly linked during the COVID-19 period. These higher correlations in the COVID-19 period can be explained by the fear factor and herding behavior in the cryptocurrency markets (and other financial markets) around the globe during this crisis period.

#### 4.2. Optimal weights and hedge ratios-portfolio implications

[Table 5](#) reports the optimal weights and hedge ratios for the pairs BTC/ETH, BTC/LTC, and ETH/LTC during the pre-COVID-19 and COVID-19 periods. The findings reveal that the optimal weight is 0.87 for BTC/ETH during the pre-COVID-19 period, indicating that for a \$1 portfolio of BTC/ETH, \$0.87 should be invested in Bitcoin and the remaining \$0.13 in Ethereum. [Katsiampa \(2019\)](#) also finds that Bitcoin should outweigh Ethereum in terms of optimal portfolio weight. The interpretations of all optimal weights are not mentioned here for the sake of brevity, but overall, the optimal weights are found to be lower for BTC/ETH and BTC/LTC during the COVID-19 period as compared to the pre-COVID-19 period. This suggests that for the portfolio containing BTC/ETH and BTC/LTC, cryptocurrency investors should decrease

Table 6  
Hedging effectiveness (%) for the pairs of cryptocurrencies.

	BTC/ETH	BTC/LTC	ETH/LTC
<b>Pre COVID-19 period</b>			
HE	57.06	38.25	50.32
<b>COVID-19 period</b>			
HE	77.74	63.45	72.93

their Bitcoin investments during the COVID-19 period. The optimal weights for ETH/LTC are also found to be lower during the COVID-19 period, such that for the portfolio of ETH/LTC, the results suggest that investors should reduce their Ethereum-allocated assets during that period.

Regarding optimal hedge ratios (see [Table 5](#)), the results indicate that the optimal hedge ratio is 0.63 for BTC/ETH during the pre-COVID-19 period, meaning that a \$1 long position in Bitcoin can be hedged for \$0.63 with a short position in Ethereum. The interpretations of all optimal hedge ratios are not given here for the sake of brevity, but overall, the optimal hedge ratios are higher for BTC/ETH during the COVID-19 period. This implies that more Ethereum is needed during the COVID-19 period than in the pre-COVID-19 period to minimize Bitcoin risk. The optimal hedge ratios are also higher for BTC/LTC and ETH/LTC during the COVID-19 period. We provide the time-varying hedge ratios in [Fig. 4](#), which shows that the hedge ratios are higher during the COVID-19 period than in the pre-COVID-19 period.

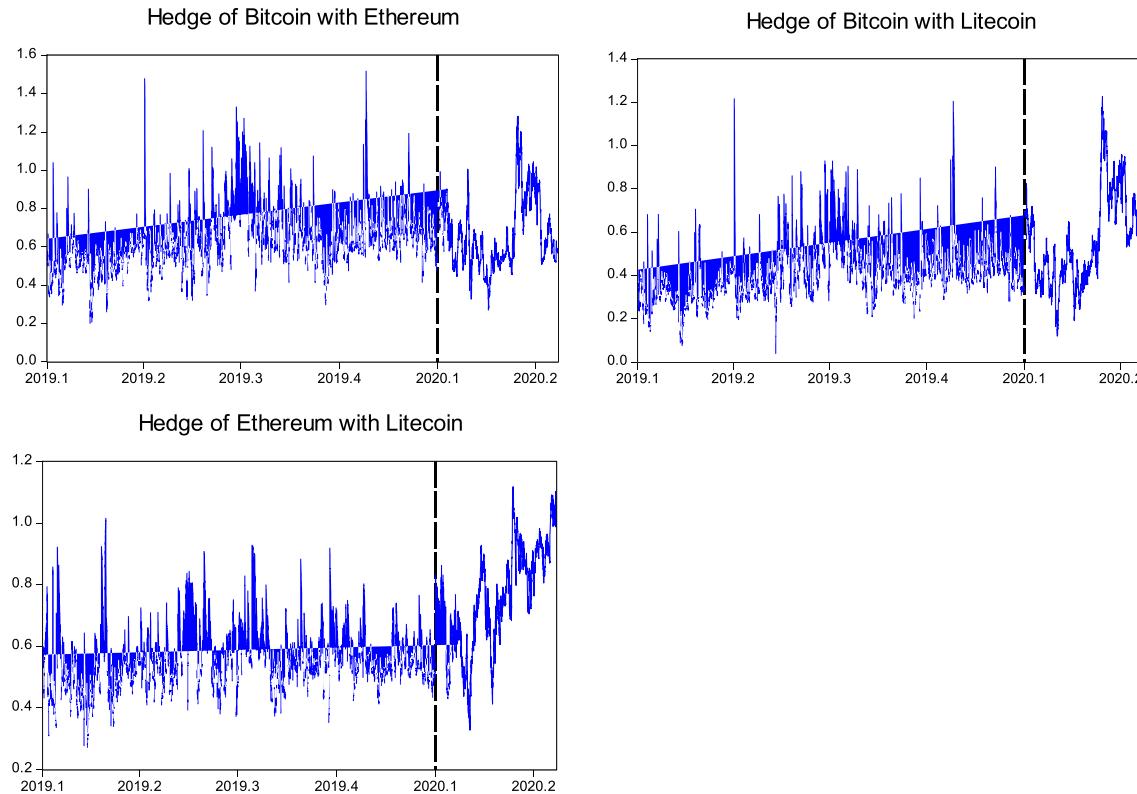


Fig. 4. Time-varying hedge ratios computed from the VAR-DCC-GARCH model.

### 4.3. Hedging effectiveness

We also estimate the hedging effectiveness for BTC/ETH, BTC/LTC, and ETH/LTC during the pre-COVID-19 and COVID-19 periods (see Table 6). We estimate hedging effectiveness using the optimal weights and hedge ratios. The results reveal that the risk-adjusted returns improve in both periods if portfolios are built with BTC/ETH, BTC/LTC, and ETH/LTC. For all three pairs, the hedging effectiveness is higher during the COVID-19 period than in the pre-COVID-19 period.

## 5. Conclusion

Using intraday data, this study employs the VAR-DCC-GARCH model to examine the transmission of return and volatility among Bitcoin, Ethereum, and Litecoin during the pre-COVID-19 and COVID-19 periods. We also estimate the optimal weights, hedge ratios, and hedging effectiveness of the pairs of cryptocurrencies during both of those periods.

The findings reveal that during the pre-COVID-19 period, the return spillovers are unidirectional from Ethereum to Bitcoin and from Bitcoin to Litecoin, whereas they are bidirectional between Ethereum and Litecoin. This suggests that in the short run, one cryptocurrency's returns can be used to forecast another cryptocurrency's returns during that period. During the COVID-19 period, the return spillovers are not significant between Bitcoin and Ethereum or between Bitcoin and Litecoin. This implies that the Bitcoin returns are not useful in forecasting the returns of Ethereum and Litecoin during the COVID-19 period. In contrast, the return transmission is found to be unidirectional from Ethereum to Litecoin during the COVID-19 period, implying that the Ethereum returns can be used to forecast the Litecoin returns during that period. Overall, the return spillovers vary across both periods for all three of our cryptocurrency pairs.

Regarding volatility spillover, the findings show that volatility transmission is not significant for any of the cryptocurrency pairs during the pre-COVID-19 period. This implies that during that period, investors could obtain maximum diversification benefits by building a portfolio of pairs of cryptocurrencies. During the COVID-19 period, the volatility spillover is unidirectional from Bitcoin to Ethereum and bidirectional between Ethereum and Litecoin. Volatility transmission between Bitcoin and Litecoin is not found to be significant during the COVID-19 period, suggesting that investors should construct a portfolio of Bitcoin and Litecoin to diversify their risk during the COVID-19 period. Overall, volatility transmission varies across both periods for BTC/ETH and ETH/LTC.

Based on optimal weights, investors are advised to decrease their investments during the COVID-19 period (a) in Bitcoin for the portfolios of BTC/ETH and BTC/LTC, and (b) in Ethereum for the portfolio of ETH/LTC. The optimal hedge ratios are found to be higher for BTC/ETH, BTC/LTC, and ETH/LTC during the COVID-19 period, which implies that hedging is more expensive during that period than in the pre-COVID-19 period. Lastly, a higher hedging effectiveness score

shows greater risk reduction, and our results reveal that hedging effectiveness is higher during the COVID-19 period than in the pre-COVID-19 period.

Our findings are of great interest to investors and portfolio managers that are actively dealing with Bitcoin, Ethereum, and Litecoin. Optimal portfolios and hedge ratios are useful for helping investors build portfolios that reduce risk exposure during crisis and non-crisis periods. However, any change in Bitcoin requires close monitoring of other cryptocurrencies and careful follow-up from policymakers if they want to avoid adverse consequences from contagious shocks. Overall, these findings provide useful insights to investors and policymakers regarding diversification, optimal asset allocation, hedging, and risk management.

## Conflict of interest

There is no conflict of interest.

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I. Yousaf, S. Ali

Borsa İstanbul Review xxx (xxxx) xxx

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