Journal of
Risk and Financial Management

MDPI

Communication

Outliers and Time-Varying Jumps in the Cryptocurrency Markets

Anupam Dutta [1,*] and Elie Bouri [2]

[1] School of Accounting and Finance, University of Vaasa, 65101 Vaasa, Finland
[2] School of Business, Lebanese American University, Beirut P.O. Box 13-5053, Lebanon; elie.elbouri@lau.edu.lb
* Correspondence: adutta@uwasa.fi

Abstract: We examine the presence of outliers and time-varying jumps in the returns of four major cryptocurrencies (Bitcoin, Ethereum, Ripple, Dogecoin, Litecoin), and a broad cryptocurrency index (CCI30). The results indicate that only Bitcoin returns are contaminated with outliers. Time-varying jumps are present in Bitcoin, Litecoin, Ripple, and the cryptocurrency index. Notably, the presence of jumps in Bitcoin is significant after correcting for outliers. The main findings point to a price instability in some major cryptocurrencies and thereby the importance of accounting for large shocks and time-varying jumps in modelling volatility in the debatable cryptocurrency markets.

Keywords: Bitcoin; cryptocurrencies; outliers; GARCH-jump; time-varying jumps

check for updates

Citation: Dutta, Anupam, and Elie Bouri. 2022. Outliers and Time-Varying Jumps in the Cryptocurrency Markets. *Journal of Risk and Financial Management* 15: 128. https://doi.org/10.3390/jrfm15030128

Academic Editor: James W. Kolari

Received: 5 December 2021
Accepted: 28 February 2022
Published: 8 March 2022

1. Introduction

Cryptocurrencies are decentralised payment systems involving technological innovation called blockchain. They have attracted much attention on the financial scene as a digital asset class, capable of offering very high returns and decent diversification benefits when combined with conventional assets (Bouri et al. 2020). Several studies have focused on Bitcoin and other major cryptocurrencies in terms of price discovery (Corbet et al. 2019; Chen et al. 2020), herding (Yousaf et al. 2021), bubble formation (Bouri et al. 2019; Chaim and Laurini 2019), interconnectedness (Ji et al. 2019), market efficiency (López-Martín et al. 2021; Noda 2021), and safe-haven ability (Bouri et al. 2020; Das et al. 2020; Dutta et al. 2020; Hatemi-J. et al. 2020). Notably, cryptocurrencies are characterised by extreme return volatility that has been the subject of volatility modelling (Chu et al. 2017; Katsiampa 2017; Tiwari et al. 2019; Walther et al. 2019; Mostafa et al. 2021), especially using GARCH processes that are capable of parameterising higher order dependence and time-evolution of conditional volatility. The largest cryptocurrency, Bitcoin, is known for extreme return volatility[1] and large abrupt price variations in the form of jumps (Chaim and Laurini 2018). Furthermore, Bitcoin and other major cryptocurrencies tend to jump with geopolitical uncertainty (Bouri et al. 2020). However, there is no empirical evidence of the presence of outliers in leading cryptocurrencies[2] and the scarce academic literature available considers jump behaviour in the Bitcoin market only, overlooking the time-varying nature of jumps. Interestingly, large cryptocurrencies such as Ethereum, Ripple, Litecoin, and Dogecoin[3] have attracted significant attention from institutional investors and business communities. Furthermore, their return volatility tends to exceed that of the largest cryptocurrency, Bitcoin (see Table 1), which makes them relevant candidates for the analysis of outliers and time-varying jumps.

In this study, we extend the limited understanding of whether outliers are present in various cryptocurrencies and whether cryptocurrencies are characterised by time-varying jumps. To do this, we detect the presence of outliers and then apply GARCH-jump models capable of uncovering evidence of time-varying jumps in the daily return series.

Our paper is related to a growing strand of literature on the volatility of Bitcoin and other major cryptocurrencies (e.g., Salisu and Ogbonna 2021; Shahzad et al. 2021) during the COVID-19 outbreak, when uncertainty in the global economy and financial markets spiked and the prices of global equity indices tumbled. Notably, Bitcoin and other major cryptocurrencies experienced large increases in their prices from the second quarter of 2020 until most of 2021, driven by an accentuated trend towards digitalisation and acceptance of Bitcoin as a means of payment by large corporations (e.g., Tesla) as well as possibilities of central banks and emerging economies to adopt cryptocurrencies (Cunha et al. 2021).

Table 1. Descriptive statistics of daily returns.

	Mean	Min	Max	Standard Deviation	Skewness	Kurtosis	PP Test (p-Value)
Bitcoin	0.2964	−46.473	22.5119	3.9934	−0.81385	11.7148	0.00
Bitcoin (outlier-free)	0.2300	−31.190	19.7621	2.9552	−0.0006	7.5791	0.00
Ethereum	0.3726	−55.0714	41.2405	6.1632	0.000903	7.6691	0.00
Ripple	0.2131	−61.638	102.7463	7.0183	2.053332	33.74518	0.00
Dogecoin	0.3243	−51.4934	151.6211	7.7355	4.287955	76.4462	0.00
Litecoin	0.1675	−44.9012	51.0348	5.6424	0.33125	11.8109	0.00
CCI30	0.2457	−48.4483	19.5679	4.4000	−1.31042	11.4226	0.00

Notes: This table reports the main descriptive statistics for the return series of major cryptocurrencies for the period 8 August 2015–23 September 2021. Cryptocurrency index (CCI30). Phillips–Perron (PP).

Our contributions are on two fronts. Firstly, we identify potential outliers occurring in various cryptocurrencies, adding to prior studies that analyse the volatility dynamics of cryptocurrencies using GARCH-type models without correcting for possible outliers (e.g., Katsiampa 2017; Chu et al. 2017; Tiwari et al. 2019; Mostafa et al. 2021). Outliers are generally present in financial variables and can lead to serious distortion of model specifications, parameter estimation, and volatility forecasting (Grané and Veiga 2010; Carnero et al. 2012), which makes the detection/removal of outliers an important step in modelling volatility and in making risk-management inferences. This is very relevant to cryptocurrencies that are highly subject to price slippage that might induce so-called outliers. Secondly, we test the presence of time-varying jumps in leading cryptocurrencies[4] that are generally characterised by extreme volatility that can be associated with specific events such as forks, hacks, and thefts. Our examination adds to prior studies that focus on Bitcoin only and argues that the existence of jumps can substantially impact the structure of losses and gains related to Bitcoin (e.g., Chaim and Laurini 2018). This is crucial given that jumps represent an important element of an asset's risk and are an input into option pricing models, and thereby can help enhance the accuracy of model prediction.

The rest of the paper is structured in three sections. Section 2 describes the dataset and methods used to detect outliers and model the time-varying jumps. Section 3 presents and discusses the empirical results. Section 4 concludes.

2. Data and Methods

2.1. Data

We collected the daily prices of five leading cryptocurrencies (Bitcoin, Ethereum, Ripple, Dogecoin, and Litecoin) against USD, from cryptomarketcap.com (accessed on 18 November 2021). We also collected price data on a broad cryptocurrency index (CCI30) from https://cci30.com (accessed on 18 November 2021).

Notably, those five cryptocurrencies were selected from the largest 20 cryptocurrencies not only because they represent 65% of the market capitalisation of all cryptocurrencies but also because they have the longest common data sample period that starts from 8 August 2015. Accordingly, our sample period is 8 August 2015–23 September 2021, yielding 2239 daily price observations.

Given that our methods require stationary data, we used log return series and the summary statistics of these return series (Table 1) to exhibit evidence of stationarity as indicated by the Phillips–Perron (PP) test.

2.2. Outlier Detection Method

We follow Ané et al. (2008) in detecting the presence of outliers. Let R_t be the log return on the cryptocurrency on day t, which follows an AR(2)-GARCH(1,1) model:[5]

$$R_t = b_0 + b_1 R_{t-1} + b_1 R_{t-2} + \varepsilon_t \quad (1)$$

$$\sigma_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + a_2 \sigma_{t-1}^2 \quad (2)$$

where $\varepsilon_t = \sigma_t z_t$ which follows Student's t distribution. I_{t-1} refers to the filtration of information at time $t-1$.

R_{t+1} is considered an outlier if it does not belong to the following interval:

$$R_{t+1} \in \left[R_{t,t+1} \pm F\left(1 - \frac{\alpha}{2}\right)\sigma_{t,t+1}\right]$$

where, $R_{t,t+1}$ is the one-step ahead return forecast given by:

$$R_{t,t+1} = E(R_{t+1}/I_t) = b_0 + b_1 R_t + b_2 R_{t-1}$$

and $\sigma_{t,t+1}^2$ denotes the one-step ahead variance forecast defined as:

$$\sigma_{t,t+1}^2 = \mathrm{var}(R_{t+1}/I_t) = a_0 + (a_1 + a_2)\sigma_t^2$$

Furthermore, $F\left(1 - \frac{\alpha}{2}\right) = P(z_t \leq 1 - \alpha/2)$ is a fractile of the assumed conditional distribution.

The above detection procedure is rolled over until the end of the sample period. Notably, the detection procedure is robust to any model misspecifications (Ané et al. 2008).

Note that a number of recent studies have used this method to detect outliers in different financial markets. Dutta (2018a), for instance, shows that outliers play a crucial role in modelling the volatility of the EU emissions market. Another study by Dutta (2018b) finds similar results for the precious metals market.

2.3. The GARCH-Jump Process

Following the model of Chan and Maheu (2002) and its recent use by Liu et al. (2021) and Li et al. (2021), the GARCH-jump specification is:

$$R_t = \pi + \sum_{i=1}^{n} \mu_i R_{t-i} + \epsilon_t \quad (3)$$

where R_t is the log return of the cryptocurrency at time t, and ϵ_t denotes the error term at time t. ϵ_t has two components:

$$\epsilon_t = \epsilon_{1t} + \epsilon_{2t} \quad (4)$$

where ϵ_{1t} is defined as:

$$\epsilon_{1t} = \sqrt{h_t} z_t, \ \ z_t \sim \text{Student's } t$$
$$h_t = \omega + \alpha \epsilon_{1t-1}^2 + \beta h_{t-1} \quad (5)$$

and ϵ_{2t} is a jump innovation that consists of abnormal price movements with $E(\epsilon_{2t}|L_{t-1}) = 0$, where L_{t-1} designates the information set. Now, ϵ_{2t} is defined as the discrepancy between the jump component and the expected total jump size between t–1 and t:

$$\epsilon_{2t} = \sum_{l=1}^{n_t} U_{tl} - \theta \lambda_t \quad (6)$$

where U_{tl} denotes the jump size, which is assumed to be normally distributed with mean θ and variance d^2, $\sum_{l=1}^{n_t} U_{tl}$ is the jump component, and n_t indicates the number of jumps. n_t follows a Poisson variable with an autoregressive conditional jump intensity as:

$$\lambda_t = \lambda_0 + \rho \lambda_{t-1} + \gamma \xi_{t-1} \quad (7)$$

where λ_t is the time-varying conditional jump intensity parameter, λ_0 refers to a constant jump intensity, and ξ_{t-1} indicates the intensity residual with $\lambda_t > 0$, $\lambda_0 > 0$, $\rho > 0$ and $\gamma > 0$.

The log-likelihood function is:

$$L(\Omega) = \sum_{t=1}^{T} \log f(R_t | I_{t-1}; \Omega) \quad (8)$$

where $\Omega = (\pi, \mu_i, \omega, \alpha, \beta, \theta, d, \lambda_0, \rho, \gamma)$.

3. Empirical Results

3.1. Outliers

The findings from the outlier detection process suggest that extreme observations occur only in the Bitcoin return series.[6] Overall, we have found 16 outliers during the sample period. We also document that these outliers are mainly present after the soar. It is worth noting that such outliers could arise due to different significant events or news including wars, political conflicts, cyberattacks, and economic downturns. Based on these findings, we consider both the original return series and the outlier-free return series. Table 1 shows that the standard deviation of Bitcoin returns is reduced by almost 26% after correcting for outliers, while outlier correction substantially increases the mean return of Bitcoin. This result suggests that Bitcoin returns are contaminated by more negative return outliers than positive ones. Additionally, outlier correction reduces the kurtosis and skewness for Bitcoin. Interestingly, the skewness converges to zero.

3.2. Time-Varying Jumps

The results of GARCH-Jump model are shown in Table 2. The GARCH parameters are statistically significant, and the sum of α and β indicates a high degree of volatility persistence. The jump intensity parameters (λ_0, ρ, γ) are statistically significant for Bitcoin and Litecoin, implying time-variability in the jump intensity and evidencing large abrupt price variations. Taking Bitcoin as an example, the parameter ρ (0.9741) being high and significant indicates that the time-varying jump intensity is persistent. The γ parameter, which measures the sensitivity of λ_t to past shock, ξ_{t-1}, is 0.3832, suggesting that a unit increase in ξ_{t-1} results in a dampened effect (0.3832) on the next period's jump intensity.

Overall, the jump intensity parameters satisfy the constraints that $\lambda_0 > 0$, $\rho > 0$ and $\gamma > 0$, implying that the GARCH-jump model is a proper choice for describing volatility dynamics and jump behaviour in the cryptocurrency markets. Additionally, the positive values of ρ and γ for Bitcoin, Litecoin, Dogecoin, Ethereum, and the CCI30 index indicate that the current jump intensity (λ_t) is influenced by the most recent jump intensity (λ_{t-1}) and the intensity residuals (ξ_{t-1}). The high values of ρ and γ, especially for Bitcoin and CCI30, suggest a high degree of persistence in the jump intensity. For Ripple returns, only the parameter of time-varying jump intensity is significant.

The results involving Bitcoin are generally in line with Chaim and Laurini (2018). The findings of the outlier-corrected data for Bitcoin show that jumps still exist after taking into account the presence of outliers. The likelihood ratio test suggests that the GARCH-jump model using Bitcoin outlier-free data outperforms the one using Bitcoin original data (i.e., Bitcoin data not corrected for outliers).

These findings suggest cryptocurrencies are not only characterised by time-varying volatility, but also by extreme price movements, which exceed the current respective market volatility. Such jump behavior points towards an instable condition in the market and hence the information on cryptocurrency prices could mislead the investment decisions (Dutta 2018b). Our analysis is, therefore, important for investors in making proper asset-allocation decisions.

It is also noteworthy that time dependent jumps may provide early signals of significant downturns in cryptocurrency markets. Earlier studies (Chan and Maheu 2002; Maheu and McCurdy 2004) also document that the conditional expected number of jumps in different asset classes tends to increase and that the information on such time-varying jumps could be used in predicting future market crashes. We thus conclude that the jump dynamics in cryptocurrency returns could capture the adverse impact of negative news or events (e.g., COVID-19 pandemic) on their price levels.

Table 2. Estimates of GARCH-jump model.

	Bitcoin	Bitcoin (Outlier-Free)	Litecoin	Ripple	Dogecoin	Ethereum	CCI30
π	0.0841 ***	0.0783 ***	−0.1179 **	−0.0051	0.2144 **	0.1159	0.0651 *
μ_1	0.0056	−0.0329	−0.0987 *	−0.0899	−0.1853 *	−0.0661 *	−0.5323 ***
μ_2	0.0062	0.0547	−0.1123 **	−0.1164 **	0.2188		
ω	0.0107 *	0.0606	0.0831 ***	0.1241 **	0.0844	0.0700 *	0.0441 **
α	0.1072 ***	0.1068 **	0.1553 ***	0.1455 ***	0.0981 **	0.1126 **	0.0676 ***
β	0.7739 ***	0.7455 ***	0.7249 ***	0.5666 ***	0.7252 ***	0.5165 ***	0.7865 ***
θ	−0.0831	−0.0961	0.4438 ***	0.0961	0.1176	−0.0762	−2.1729 ***
d^2	2.0400 ***	−0.9976 ***	3.8976 ***	2.8903 ***	2.1439 ***	1.6754 ***	−3.5208 ***
λ_0	0.0699 ***	0.0502 **	0.0986 ***	0.0346	0.0334	0.1345 ***	0.0014
ρ	0.9658 ***	0.9189 ***	0.7242 ***	0.9054 ***	0.7119 **	0.8764 ***	0.9958 ***
γ	0.3939 ***	0.2956 ***	0.3001 ***	0.1679	0.3973 **	0.4138 ***	0.3489 ***
Log-likelihood	−3857.14	−3201.57	−723.76	−998.61	−941.54	−788.18	−1922.98

Notes: This table shows the estimated coefficients of the GARCH-jump model, as described in Section 2.3. π and μ are parameters depicting the conditional mean (see Equation (3)). ω, α, and β are parameters depicting the conditional variance (see Equation (5)). λ_0, ρ, and γ are parameters describing the time-varying jump intensity (see Equation (7)). θ and d^2 are the mean and variance of the jump size, respectively (see Equation (6)). ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels, respectively.

4. Conclusions

In this paper, we have extended the limited understanding on the presence of outliers and time-varying jumps in the cryptocurrency markets. The main results show that outliers exist only in Bitcoin returns, suggesting the importance of accounting for them, and Bitcoin returns are characterised by time-varying jumps after correcting for outliers. Litecoin is also characterised by time-varying jumps. The findings complement previous studies (Katsiampa 2017; Chu et al. 2017; Chaim and Laurini 2018) and point to the presence of abrupt price variations in some cryptocurrencies, suggesting potential suitability of including jumps when pricing options on Bitcoin and Litecoin. Given recent evidence on the importance of jumps for portfolio management, future studies could consider dynamic portfolio allocation and risk management inferences in the cryptocurrency markets with time-varying jump risk (Zhou et al. 2019).

Author Contributions: Conceptualization and methodology, A.D. and E.B.; formal analysis, A.D.; data curation, A.D. and E.B.; writing—original draft preparation, A.D. and E.B.; writing—review and editing, A.D. and E.B.; visualization, A.D.; project administration, E.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data presented in this study are openly available in cryptomarketcap.com and https://cci30.com (accessed on 20 November 2021).

Conflicts of Interest: The authors declare no conflict of interest.

Notes

1. Bitcoin price skyrocketed for most of 2016–2017, then crashed for most of 2018, and then experienced large up and down swings.
2. Thies and Molnár (2018) focus on the Bitcoin market. Using a Bayesian change point model, they show evidence of structural breaks in the first and second moments of the return distribution.
3. We pay a special attention to Dogeeoin due the influence of Elon Musk's tweets on the price dynamic of Dogecoin from early 2021 and therefore the possible change in the characteristics of Dogecoin after the soar of its price from that date.
4. Cryptocurrencies can be very prone to jumps due to the presence of hacks and forks.

[5] For Ethereum and CCI30 index, the AR(1)-GARCH(1,1) process appears to be the best fitted model based on the AIC and BIC values.
[6] Quite similar findings are reported by Thies and Molnár (2018) who use a Bayesian change point model and report evidence of structural breaks in the Bitcoin market.

References

Ané, Thierry, Loredana Ureche-Rangau, Jean-Benoît Gambet, and Julien Bouverot. 2008. Robust outlier detection for Asia-Pacific stock index returns. *Journal of International Financial Markets, Institutions & Money* 18: 326–43.

Bouri, Elie, Syed Jawad Hussain Shahzad, and David Roubaud. 2019. Co-explosivity in the cryptocurrency market. *Finance Research Letters* 29: 178–83. [CrossRef]

Bouri, Elie, Rangan Gupta, and Xuan Vinh Vo. 2020. Jumps in geopolitical risk and the cryptocurrency market: The singularity of Bitcoin. *Defence and Peace Economics*, 1–12. [CrossRef]

Bouri, Elie, Syed Jawad Hussain Shahzad, David Roubaud, Ladislav Kristoufek, and Brian Lucey. 2020. Bitcoin, gold, and commodities as safe havens for stocks: New insight through wavelet analysis. *The Quarterly Review of Economics and Finance* 77: 156–64. [CrossRef]

Carnero, M. Angeles, Daniel Peña, and Esther Ruiz. 2012. Estimating GARCH volatility in the presence of outliers. *Economics Letters* 114: 86–90. [CrossRef]

Chaim, Pedro, and Marcio P. Laurini. 2018. Volatility and return jumps in Bitcoin. *Economics Letters* 114: 158–63. [CrossRef]

Chaim, Pedro, and Marcio P. Laurini. 2019. Is Bitcoin a bubble? *Physica A: Statistical Mechanics and Its Applications* 517: 222–32. [CrossRef]

Chan, Wing H., and John M. Maheu. 2002. Conditional jump dynamics in stock market returns. *Journal of Business & Economic Statistics* 20: 377–89.

Chen, Zheshi, Chunhong Li, and Wenjun Sun. 2020. Bitcoin price prediction using machine learning: An approach to sample dimension engineering. *Journal of Computational and Applied Mathematics* 365: 112395. [CrossRef]

Chu, Jeffrey, Stephen Chan, Saralees Nadarajah, and Joerg Osterrieder. 2017. GARCH modelling of cryptocurrencies. *Journal of Risk and Financial Management* 10: 17. [CrossRef]

Corbet, Shaen, Douglas J. Cumming, Brian M. Lucey, Maurice Peat, and Samuel Vigne. 2019. Investigating the Dynamics between Price Volatility, Price Discovery, and Criminality in Cryptocurrency Markets. Price Discovery, and Criminality in Cryptocurrency Markets. Available online: http://dx.doi.org/10.2139/ssrn.3384707 (accessed on 28 November 2021).

Cunha, Paulo Rupino, Paulo Melo, and Helder Sebastião. 2021. From Bitcoin to Central Bank Digital Currencies: Making Sense of the Digital Money Revolution. *Future Internet* 13: 165. [CrossRef]

Das, Debojyoti, Corlise Le Roux, Rabin K. Jana, and Anupam Dutta. 2020. Does Bitcoin hedge crude oil implied volatility and structural shocks? A comparison with gold, commodity and the US Dollar. *Finance Research Letters* 36: 101335. [CrossRef]

Dutta, Anupam. 2018a. Modeling and Forecasting the Volatility of Carbon Emission Market: The Role of Outliers, Time-varying Jumps and Oil Price Risk. *Journal of Cleaner Production* 172: 2773–81. [CrossRef]

Dutta, Anupam. 2018b. Impacts of Oil Volatility Shocks on Metal Markets: A Research Note. *Resources Policy* 55: 9–19. [CrossRef]

Dutta, Anupam, Debojyoti Das, R.K. Jana, and Xuan Vinh Vo. 2020. COVID-19 and oil market crash: Revisiting the safe haven property of gold and Bitcoin. *Resources Policy* 69: 101816. [CrossRef]

Grané, Aurea, and Helena Veiga. 2010. Wavelet-based detection of outliers in financial time series. *Computational Statistics & Data Analysis* 54: 2580–93.

Hatemi-J., Abdulnasser, Mohamed A. Hajji, Elie Bouri, and Rangan Gupta. 2020. The Benefits of Diversification between Bitcoin, Bonds, Equities and the US Dollar: A Matter of Portfolio Construction. *Asia-Pacific Journal of Operational Research 2040024*. [CrossRef]

Ji, Qiang, Elie Bouri, Chi Keung Marco Lau, and David Roubaud. 2019. Dynamic connectedness and integration in cryptocurrency markets. *International Review of Financial Analysis* 63: 257–72. [CrossRef]

Katsiampa, Paraskevi. 2017. Volatility estimation for Bitcoin: A comparison of GARCH models. *Economics Letters* 158: 3–6. [CrossRef]

Li, Shaoyu, Kaixuan Ning, and Teng Zhang. 2021. Sentiment-aware jump forecasting. *Knowledge-Based Systems* 228: 107292. [CrossRef]

Liu, Feng, Chuanguo Zhang, and Mengying Tang. 2021. The impacts of oil price shocks and jumps on China's nonferrous metal markets. *Resources Policy* 73: 102228. [CrossRef]

López-Martín, Carmen, Sonia Benito Muela, and Raquel Arguedas. 2021. Efficiency in cryptocurrency markets: New evidence. *Eurasian Economic Review* 11: 403–31. [CrossRef]

Maheu, John M., and Thomas H. McCurdy. 2004. News Arrival, Jump Dynamics and Volatility Components for Individual Stock Returns. *Journal of Finance* 59: 755–93. [CrossRef]

Mostafa, Fahad, Pritam Saha, Mohammad Rafiqul Islam, and Nguyet Nguyen. 2021. GJR-GARCH Volatility Modeling under NIG and ANN for Predicting Top Cryptocurrencies. *Journal of Risk and Financial Management* 14: 421. [CrossRef]

Noda, Akihiko. 2021. On the evolution of cryptocurrency market efficiency. *Applied Economics Letters* 28: 433–39. [CrossRef]

Salisu, Afees A., and Ahamuefula E. Ogbonna. 2021. The return volatility of cryptocurrencies during the COVID-19 pandemic: Assessing the news effect. *Global Finance Journal*, 100641. [CrossRef]

Shahzad, Syed Jawad Hussain, Elie Bouri, Sang Hoon Kang, and Tareq Saeed. 2021. Regime specific spillover across cryptocurrencies and the role of COVID-19. *Financial Innovation* 7: 1–24. [CrossRef]

Thies, Sven, and Peter Molnár. 2018. Bayesian change point analysis of Bitcoin returns. *Finance Research Letters* 27: 223–27. [CrossRef]

Tiwari, Aviral Kumar, Satish Kumar, and Rajesh Pathak. 2019. Modelling the dynamics of Bitcoin and Litecoin: GARCH versus stochastic volatility models. *Applied Economics* 51: 4073–82. [CrossRef]

Walther, Thomas, Tony Klein, and Elie Bouri. 2019. Exogenous Drivers of Bitcoin and Cryptocurrency Volatility: A Mixed Data Sampling Approach to Forecasting. *Journal of International Financial Markets, Institutions & Money* 63: 101133.

Yousaf, Imran, Shoaib Ali, Elie Bouri, and Anupam Dutta. 2021. Herding on fundamental/non-fundamental information during the COVID-19 outbreak and cyber-attacks: Evidence from the cryptocurrency market. *SAGE Open* 11: 21582440211029911. [CrossRef]

Zhou, Chunyang, Chongfeng Wu, and Yudong Wang. 2019. Dynamic portfolio allocation with time-varying jump risk. *Journal of Empirical Finance* 50: 113–24. [CrossRef]