Cryptocurrency liquidity and volatility interrelationships during the COVID-19 pandemic

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ARTICLE INFO

ABSTRACT

We examine the interactions between cryptocurrency price volatility and liquidity during the outbreak of the COVID-19 pandemic. Evidence suggests that these developing digital products have played a new role as a potential safe-haven during periods of substantial financial market panic. Results suggest that cryptocurrency market liquidity increased significantly after the WHO identification of a worldwide pandemic. Significant and substantial interactions between cryptocurrency price and liquidity effects are identified. These results add further support to the argument that substantial flows of investment entered cryptocurrency markets in search of an investment safe-haven during this exceptional black-swan event.

1. Introduction

The rapidly developing COVID-19 pandemic generated much confusion with regards to the severity and economic ramifications. The slow and heterogeneous response resulted in substantial variation of virus reproductive rates, manifesting as broad differentials in the magnitude of cross-border cases and subsequent fatalities. Financial markets and investors have also been the subject of much confusion and uncertainty when attempting to quantify the scale of the impact of COVID-19. Chinese financial markets have been identified as the initial epicentre of the shock (Corbet et al., 2020b; Conlon et al., 2020) while international economic contagion effects quickly escalated (Uddin et al., 2020). Substantial abnormal market pressures, combined with geopolitical pressure and broad concerns based on the severity of the COVID-19 pandemic, contributed to the price of West Texas Intermediate oil falling[1] to below -$37 (Corbet et al., 2020a). Investors subsequently struggled to identify credible safe-havens (Akhtaruzzaman et al., 2020; Goodell, 2020; Corbet et al., 2020d; 2021a).

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[1] In late 2020, the CFTC investigation into the events found that '*On or about April 1, the CME advised CFTC staff that CME was taking operational steps towards supporting negative pricing.*' Therefore, market participants appear to have been ready for such an event, which has been identified as a 'super-contangoed WTI futures market' (Fernandez-Perez et al., 2020).

Within cryptocurrency markets, this new influx of trading liquidity has the potential to improve the flow of information within these digital products (Akyildirim et al., 2019), while promoting increased operational and trading efficiency (Chordia et al., 2008). That cryptocurrencies could potentially act as a financial safe haven is quite an incredible development, given their relatively short history, frequency of substantial black-swan events and the ever-increasing probability of economic decoupling resulting from intermittent lock-downs to mitigate reoccurring pandemics. Further, we must consider issues with regards to the storage of significant assets in products that are observed as high-risk and under constant threat of cybercriminality, notwithstanding the exceptional concerns surrounding the inherent technical and regulatory ambiguity that has been observed and identified in detail by policy-makers and regulators (Gandal et al., 2018; Corbet et al., 2019; Griffin and Shams, 2020; Akyildirim et al., 2020). This research sets out to establish whether such safe-haven behaviour can be identified in the relationship between cryptocurrency price-volatility and liquidity, as evidenced in shifting dynamics after the Chinese identification of COVID-19 in mid-November 2019 and the official WHO announcement of a pandemic in early-January 2020.

This paper is structured as follows: Section 2 describes the data and the selected methodology. Section 3 describes and analyses the results of our test for price and liquidity effects in cryptocurrency markets during the COVID-19 pandemic. Finally, Section 4 present our conclusions.

2. Data and methodology

To test the interactions between cryptocurrency pricing and liquidity during the key periods of the growth of the COVID-19 pandemic in China and throughout the world, we utilise both a VAR methodology and a DCC-GARCH-SNP methodology to investigate volatility spillovers. The VAR methodology takes the following form:

$$
\begin{cases}
\Delta P_t = \alpha_1 + \alpha_2 \Delta P_{t-1} + \delta_1 d_{1t} \Delta V_{t-1} + \delta_2 d_{2t} \Delta V_{t-1} + \delta_3 d_{3t} \Delta V_{t-1} + e_{1,t} \\
\Delta V_t = \alpha_3 + \alpha_4 \Delta V_{t-1} + \delta_4 d_{1t} \Delta P_{t-1} + \delta_5 d_{2t} \Delta P_{t-1} + \delta_6 d_{3t} \Delta P_{t-1} + e_{2,t}
\end{cases}
\tag{1}
$$

where ΔP_t and ΔV_t are the first-order differences of natural logarithms of daily prices and volume of cryptocurrencies, respectively. Note that the lag order of VAR model is chosen to be one according to Schwarz Information Criterion (SIC). d_{1t}, d_{2t} and d_{3t} are dummy variables that identify different stages of the COVID-19 outbreak. These dates were denoted as per the work of Corbet et al. (2021b), it is important to separate the development of the COVID-19 pandemic into two specific stages. The first period covers the initial outbreak of the pandemic, that developed in Wuhan, China in late-2019, where the first reported case of an individual suffering from COVID-19 can be https://www.theguardian.com/world/2020/mar/13/first-COVID-19-case-happened-in-november-china-government-records-show-report traced to 17 November 2019 according to a number https://www.scmp.com/news/china/society/article/3074991/coronavirus-chinas-first-confirmed-COVID-19-case-traced-back media reports, while the first official https://www.who.int/westernpacific/emergencies/COVID-19 announcement recognising international transmission was made by the World Heath Organisation (WHO) on 31 December 2019. Given these information, d_{1t} identifies a phase where there is no COVID-19 contagion; d_{2t} identifies a phase where the COVID-19 is contagious in domestic China only; and d_{3t} identifies a phase of international contagion of the COVID-19. Residuals from the VAR model are fitted in a bivariate DCC-GARCH-SNP model. If we let $e_t = [e_{1,t}, e_{2,t}]'$', the model is shown as

$$
e_t \sim \text{SNP}(0, H_t, s_i, k_i)(i = 1, 2),
\tag{2}
$$

$$
H_t = D_t R_t D_t
\tag{3}
$$

$$
D_t = \text{diag}\left(h_{11,t}^{1/2}, h_{22,t}^{1/2}\right),
\tag{4}
$$

$$
R_t = \text{diag}\{Q_t\}^{-1/2} Q_t \text{diag}\{Q_t\}^{-1/2},
\tag{5}
$$

where H_t is the conditional variance-covariance matrix. s_i and k_i are marginal skewness and kurtosis parameters as defined in a semi non-parametric (SNP) distribution, respectively. $h_{11,t}$ and $h_{22,t}$ are conditional variances of $e_{1,t}$ and $e_{2,t}$, respectively. $h_{11,t}$ and $h_{22,t}$ are specified as

$$
\begin{cases}
h_{11,t} = \omega_1 + \alpha_1 e_{1,t-1}^2 + \beta_1 h_{11,t-1} + \theta_1 d_{1t} e_{2,t-1}^2 + \theta_2 d_{2t} e_{2,t-1}^2 + \theta_3 d_{3t} e_{2,t-1}^2 \\
h_{22,t} = \omega_2 + \alpha_2 e_{2,t-1}^2 + \beta_2 h_{22,t-1} + \theta_4 d_{1t} e_{1,t-1}^2 + \theta_5 d_{2t} e_{1,t-1}^2 + \theta_6 d_{3t} e_{1,t-1}^2
\end{cases}
\tag{6}
$$

where d_{1t}, d_{2t} and d_{3t} are dummy variables that identify different stages of the COVID-19 outbreak. Q_t is the conditional variance-covariance matrix of standardised innovations $\epsilon_{it} = \frac{e_{it}}{\sqrt{h_{ii,t}}}$ $(i = 1, 2)$. Q_t is defined as $Q_t = (1 - a - b)\overline{Q} + a\epsilon_{t-1}\epsilon'_{t-1} + bQ_{t-1}$, where $\epsilon_t = [\epsilon_{1t}, \epsilon_{2t}]'$ and $\overline{Q} = E[\epsilon_t \epsilon_t^T]$. In Eq. (6), we examine the effects of lagged shocks of volume (price) changes on volatility of price (volume) changes in different stages of the COVID-19 outbreak. A Maximum Likelihood Estimation (MLE) procedure based on the SNP

Table 1

Descriptive Statistics of price changes.

Cryptocurrency	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Bitcoin	0.002	0.002	0.225	-0.465	0.044	-0.897	15.150	7806.5***
Ethereum	0.003	0.000	0.290	-0.551	0.059	-0.421	12.439	4646.9***
Tether	0.000	0.000	0.057	-0.049	0.007	0.192	13.701	5933.5***
Bitcoin Cash	-0.001	-0.003	0.432	-0.561	0.079	0.252	12.115	3607.8***
Bitcoin SV	0.002	-0.001	0.886	-0.624	0.097	1.563	26.377	13,100.0***
XRP	0.003	-0.002	1.027	-0.616	0.076	2.710	40.486	74,200.0***
Binance	0.005	0.001	0.675	-0.543	0.077	0.949	16.977	8596.4***
EOS	0.001	0.000	0.987	-0.503	0.080	1.859	28.083	28,400.0***
Tezos	0.000	0.000	0.569	-0.605	0.076	-0.385	13.188	4210.0***
Cardano	0.001	0.000	0.862	-0.504	0.077	2.373	29.360	29,000.0***
Litecoin	0.002	0.000	0.510	-0.449	0.063	0.751	13.551	5877.3***
Stellar	0.003	-0.002	0.723	-0.410	0.081	1.831	19.359	14,600.0***

Note: This table reports descriptive statistics of daily price changes and volume changes. Price changes and volume changes are the first-order differences of logarithmic prices and volume. Std. Dev. denotes standard deviation. Jarque-Bera denotes the Jarque-Beta test on normality. *** stands for scientific notation. a represents significance at the 1% level. For brevity, only the twelve largest cryptocurrencies by market capitalisation are presented. Further results are available from the authors upon request.

Table 2

Descriptive Statistics of volume changes.

Cryptocurrency	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Bitcoin	0.004	-0.010	0.988	-0.860	0.233	0.288	4.589	147.9***
Ethereum	0.005	-0.009	1.783	-1.255	0.297	0.509	6.670	750.5***
Tether	0.008	-0.012	1.943	-1.294	0.306	0.688	6.716	812.5***
Bitcoin Cash	0.010	-0.028	4.116	-1.239	0.386	1.964	18.410	10,900.0***
Bitcoin SV	0.011	-0.029	1.848	-1.051	0.328	1.256	8.603	887.7***
XRP	0.007	-0.023	2.322	-1.963	0.454	0.646	5.476	403.5***
Binance	0.007	-0.020	9.063	-9.092	0.500	0.066	211.421	1,880,000.0***
EOS	0.005	-0.023	3.159	-1.067	0.329	1.606	13.936	5,743.5***
Tezos	0.005	-0.005	1.660	-1.723	0.385	0.174	5.179	196.4***
Cardano	0.001	-0.028	1.801	-1.366	0.413	0.468	4.328	106.7***
Litecoin	0.004	-0.023	3.116	-1.193	0.341	1.569	12.870	5,551.1***
Stellar	0.007	-0.016	3.472	-1.290	0.415	1.063	8.909	2,042.6***

Note: This table reports descriptive statistics of daily price changes and volume changes. Price changes and volume changes are the first-order differences of logarithmic prices and volume. Std. Dev. denotes standard deviation. Jarque-Bera denotes the Jarque-Beta test on normality. *** stands for scientific notation. a represents significance at the 1% level. For brevity, only the twelve largest cryptocurrencies by market capitalisation are presented. Further results are available from the authors upon request.

distribution is employed to obtain estimates of the DCC GARCH model, aligning with Del Brio et al. (2011), Ñíguez and Perote (2016), and Del Brio et al. (2017). We collect daily prices and trading volume of a group of well-known cryptocurrencies that are actively traded in the world. Our sample starts from January 1, 2017 and ends on May 27, 2020. We calculate price changes and volume changes as the first-order differences of logarithms of daily prices and volumes, respectively.

3. Results

In Table 1, we present the descriptive statistics associated with the prices changes of the twelve largest cryptocurrencies ranked by market capitalisation[2] as of April 2020. While in Table 2 we observe the key statistics associated with respective changes in trading volumes, where both Bitcoin Cash and Bitcoin SV are identified as substantially vulnerable to liquidity shocks, that is, trading days where liquidity sharply deviates from average levels. Bitcoin, Litecoin, Ethereum and Cardano are identified as the most stable cryptocurrencies in terms of liquidity reliance. In Fig. 1, we observe further support to the sharp increase in liquidity, as observed through volumes traded, for most of the cryptocurrencies analysed throughout 2019. However, as particularly evident in the markets for Bitcoin, Ethereum, Tether, Bitcoin SV, Binance, Tezos and Litecoin, there is a sharp secondary phase of growth during late 2019, and indeed throughout Q1 and Q2 2020. We set out to quantify as to whether this liquidity growth was simultaneous to the phases of announcement based on the severity of the COVID-19 outbreak, and whether such liquidity growth conditioned the sharp periods of volatility that occurred during this same time-period.

The results of the VAR methodology are presented in Table 3. It becomes quite clear from the results that before the COVID-19

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[2] For brevity, only the twelve largest cryptocurrencies are presented. Results for a larger sample of companies are available from the authors upon request.
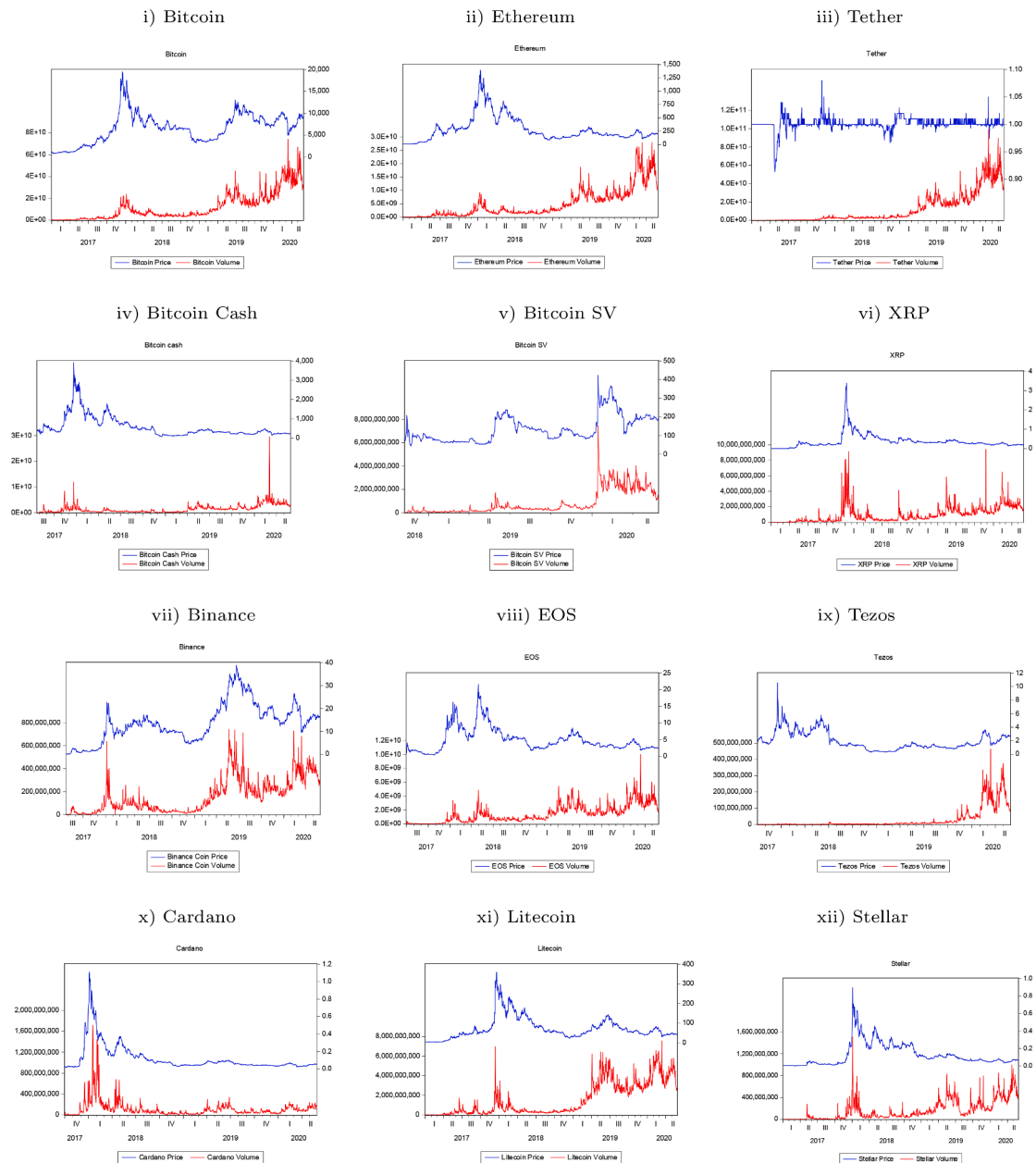
Fig. 1. Cryptocurrency daily prices and volume. Note: I, the first quarter; II, the second quarter; III, the third quarter; IV, the fourth quarter. For brevity, only the twelve largest cryptocurrencies by market capitalisation are presented. Further results are available from the authors upon request.

outbreak takes place, in the sample of largest cryptocurrencies as denoted by market capitalisation, the lagged price changes are found to possess significant influence on volume changes. No significant effects are evidenced after the advent of the COVID-19 outbreak. Further, the lagged volume changes are also found to possess the ability to significantly affect price changes, but again, this effect is only found to be significant in the period without the COVID-19. The magnitude of effects from lagged volume changes to price changes is smaller than the effects of the other way around. The result is evidenced in a smaller group of cryptocurrencies.

In the next stage of our analysis, we focus on estimating the dynamic conditional correlation behaviour of cryptocurrency interactions between pricing and liquidity. We present the results of the estimated DCC-GARCH-SNP model in Table 4. The Ljung-Box test suggests that the model is well specified given no autocorrelation and heteroscedasticity detected in standardised innovations. Results indicate that the lagged shocks of volume changes have significant effects on the volatilities of price changes before the COVID-

Table 3
VAR model results.

Coeff.	Bitcoin	Ethereum	Tether	Bitcoin cash	Bitcoin SV	XRP	Binance	EOS	Tezos	Cardano	Litecoin	Stellar
a_1	0.002	0.003	0.000	-0.001	0.001	0.003	0.004*	0.000	0.000	0.001	0.002	0.002
	(0.149)	(0.116)	(0.983)	(0.746)	(0.736)	(0.190)	(0.075)	(0.931)	(0.872)	(0.761)	(0.310)	(0.302)
a_2	-0.024	-0.020	-0.376***	0.036	-0.018	-0.044	0.099***	-0.003	-0.001	-0.012	-0.010	0.087***
	(0.396)	(0.482)	(0.000)	(0.286)	(0.697)	(0.149)	(0.004)	(0.929)	(0.983)	(0.727)	(0.738)	(0.004)
δ_1	-0.003	0.002	0.001	0.021***	0.012	0.007	0.025	0.033***	-0.013**	0.005	0.002	0.007
	(0.574)	(0.748)	(0.406)	(0.003)	(0.414)	(0.191)	(0.130)	(0.000)	(0.050)	(0.486)	(0.718)	(0.222)
δ_2	-0.007	-0.022	0.003	-0.025	-0.005	-0.006	0.031	-0.023	0.032	0.002	0.006	-0.001
	(0.812)	(0.693)	(0.611)	(0.681)	(0.958)	(0.847)	(0.235)	(0.694)	(0.427)	(0.962)	(0.943)	(0.988)
δ_3	0.001	-0.003	-0.004	-0.027	-0.055*	0.013	-0.002	-0.005	0.018	0.015	-0.005	-4.68e-04
	(0.943)	(0.924)	(0.179)	(0.223)	(0.074)	(0.671)	(0.663)	(0.697)	(0.426)	(0.505)	(0.873)	(0.990)
R^2	0.001	0.001	0.142	0.015	0.009	0.002	0.019	0.016	0.005	0.001	1.83e-04	0.011
a_3	0.004	0.006	0.009	0.010	0.011	0.005	0.004	0.002	0.007	0.001	0.004	0.007
	(0.531)	(0.503)	(0.283)	(0.420)	(0.440)	(0.690)	(0.786)	(0.835)	(0.539)	(0.939)	(0.647)	(0.557)
a_4	-0.174***	-0.198***	-0.204***	-0.049	-0.078*	-0.110***	-0.398***	-0.177***	-0.284***	-0.143***	-0.174***	-0.208***
	(0.000)	(0.000)	(0.000)	(0.147)	(0.096)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
δ_4	0.301*	0.203	1.261	0.084	-0.021	0.347*	1.183***	0.385**	0.361**	0.362*	0.191	0.783***
	(0.064)	(0.196)	(0.326)	(0.638)	(0.914)	(0.060)	(0.000)	(0.011)	(0.039)	(0.058)	(0.265)	(0.000)
δ_5	-2.024	-1.546	-1.508	-1.147	-1.471	-1.917	1.638**	0.159	-0.204	-1.078	-0.835	-0.349
	(0.126)	(0.243)	(0.798)	(0.477)	(0.229)	(0.404)	(0.014)	(0.791)	(0.857)	(0.542)	(0.548)	(0.860)
δ_6	-0.366	-0.231	7.238**	-0.412	-0.069	-0.329	0.293	0.024	-0.393	-0.247	-0.462	-0.476
	(0.300)	(0.520)	(0.014)	(0.342)	(0.777)	(0.643)	(0.269)	(0.922)	(0.307)	(0.631)	(0.310)	(0.413)
R^2	0.034	0.039	0.047	0.004	0.010	0.012	0.151	0.029	0.084	0.020	0.029	0.044

Note: Coef. denotes model coefficients. *p*-value denotes *p* value of test statistic for significance check on coefficient. R2 is goodness of fit. e stands for scientific notation. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. For brevity, only the twelve largest cryptocurrencies by market capitalisation are presented. Further results are available from the authors upon request.

Table 4
The DCC-GARCH-SNP model and volatility spillovers.

Coeff.	Bitcoin	Ethereum	Tether	Bitcoin cash	Bitcoin SV	XRP	Binance	EOS	Tezos	Cardano	Litecoin	Stellar
Panel A: Conditional variance equation												
ω_1	0.001***	0.001***	0.001***	0.001***	0.006***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α_1	0.167***	0.169***	0.211***	0.090***	0.250***	0.148***	0.172***	0.036***	0.149***	0.115***	0.048***	0.126***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_1	0.765***	0.739***	0.829***	0.860***	0.723***	0.590***	0.810***	0.891***	0.779***	0.848***	0.880***	0.831***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
θ_1	-0.001***	-0.001***	-0.001***	0.001***	-0.001***	-0.003***	0.001	0.001***	-0.001*	0.001**	0.001***	0.003***
	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)	(0.374)	(0.009)	(0.059)	(0.043)	(0.000)	(0.000)
θ_2	-0.002**	-0.009***	8.37e-06	-0.007***	-0.012***	-0.003***	0.001	0.001	-0.002*	-0.002***	-0.009***	-0.001*
	(0.015)	(0.000)	(0.910)	(0.000)	(0.000)	(0.000)	(0.633)	(0.802)	(0.070)	(0.000)	(0.000)	(0.064)
θ_3	-0.004***	-0.006***	-0.001***	0.003***	0.015***	-0.030***	-6.51e-05	-0.002***	0.006***	5.50e-05	0.003***	0.018***
	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.194)	(0.000)	(0.000)	(0.931)	(0.003)	(0.000)
ω_2	0.003***	0.001**	0.001***	0.002***	0.007***	0.001*	2.03e-04	0.002***	0.009***	1.72e-04	2.14e-04***	0.002***
	(0.000)	(0.016)	(0.001)	(0.000)	(0.000)	(0.018)	(0.670)	(0.000)	(0.000)	(0.612)	(0.006)	(0.000)
α_2	0.130***	0.018***	0.019***	0.061***	0.150***	0.044***	0.090***	0.022***	0.134***	0.021***	0.026***	0.084***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
β_2	0.814***	0.980***	0.981***	0.935***	0.759***	0.951***	0.815***	0.940***	0.780***	0.975***	0.973***	0.892***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
θ_4	-0.046	-0.061	-7.947***	-0.380***	0.571	0.001	1.906***	0.350**	0.933***	0.045	-0.084*	0.466***
	(0.794)	(0.100)	(0.000)	(0.000)	(0.100)	(0.995)	(0.000)	(0.011)	(0.000)	(0.451)	(0.053)	(0.003)
θ_5	1.606	-0.031	-4.752	-0.287	-1.370**	3.127***	1.035	-0.231**	-1.661	0.452	-0.196	-1.307*
	(0.504)	(0.845)	(0.166)	(0.632)	(0.010)	(0.004)	(0.121)	(0.015)	(0.216)	(0.559)	(0.150)	(0.057)
θ_6	0.196	0.025	-0.734	-0.353***	0.250	-0.026	5.005***	-2.05e-04	0.143	0.036	0.005	0.051
	(0.257)	(0.106)	(0.740)	(0.000)	(0.119)	(0.543)	(0.000)	(0.997)	(0.602)	(0.329)	(0.726)	(0.496)
Panel B: Conditional correlation												
a	0.271***	0.171***	0.084***	0.268***	0.206***	0.174***	0.403***	0.186***	0.065***	0.174***	0.103***	0.009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
b	0.361***	0.645***	0.750***	0.379***	0.394***	0.110	0.231***	0.703***	0.934***	-0.028	0.452***	0.996***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.120)	(0.000)	(0.000)	(0.000)	(0.213)	(0.000)	(0.000)
Panel C: Marginal skewness and kurtosis												
s_1	0.004	0.190	-0.054	-0.256	-1.307**	-0.014	0.212	-0.060	-0.160	-0.046	-0.148	-0.103
	(0.956)	(0.297)	(0.750)	(0.113)	(0.025)	(0.876)	(0.198)	(0.728)	(0.491)	(0.764)	(0.322)	(0.336)
k_1	2.927***	5.423***	4.371***	3.883***	11.269***	3.079***	5.499***	5.097***	6.883**	4.800***	4.935***	3.651***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.024)	(0.000)	(0.000)	(0.000)
s_2	0.450	0.018	0.357	0.321	-2.048	-0.025	0.027	0.145	0.107	0.426	0.371	0.390
	(0.393)	(0.942)	(0.341)	(0.309)	(0.197)	(0.955)	(0.895)	(0.595)	(0.602)	(0.214)	(0.159)	(0.147)
k_2	13.378**	7.346**	9.465*	7.888*	19.136**	13.479**	5.114***	6.441**	6.291***	8.695***	6.882***	7.542***
	(0.029)	(0.016)	(0.072)	(0.059)	(0.022)	(0.017)	(0.004)	(0.018)	(0.005)	(0.001)	(0.007)	(0.000)
Log-L	2,919.1	2,123.2	1,581.2	1,868.4	-38,400.0	2,618.7	1,837.5	1,843.2	1,654.7	1,623.5	2,128.2	2,223.8
$LB(12)$	14.701	13.578	7.368	7.409	16.390	17.251	13.927	12.145	13.965	16.053	12.919	15.949
$LB^2(12)$	3.245	8.914	0.106	6.552	16.338	17.187	11.090	6.715	3.753	6.711	4.832	7.957

Note: Coef. denotes model coefficient. p-value denotes p value of test statistic for significance check on coefficient. LB(12) and LB2(12) represent the Ljung-Box Q test statistic for standardised innovations and its squares up to the 12th order, respectively. e stands for scientific notation. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. For brevity, only the twelve largest cryptocurrencies by market capitalisation are presented. Further results are available from the authors upon request.
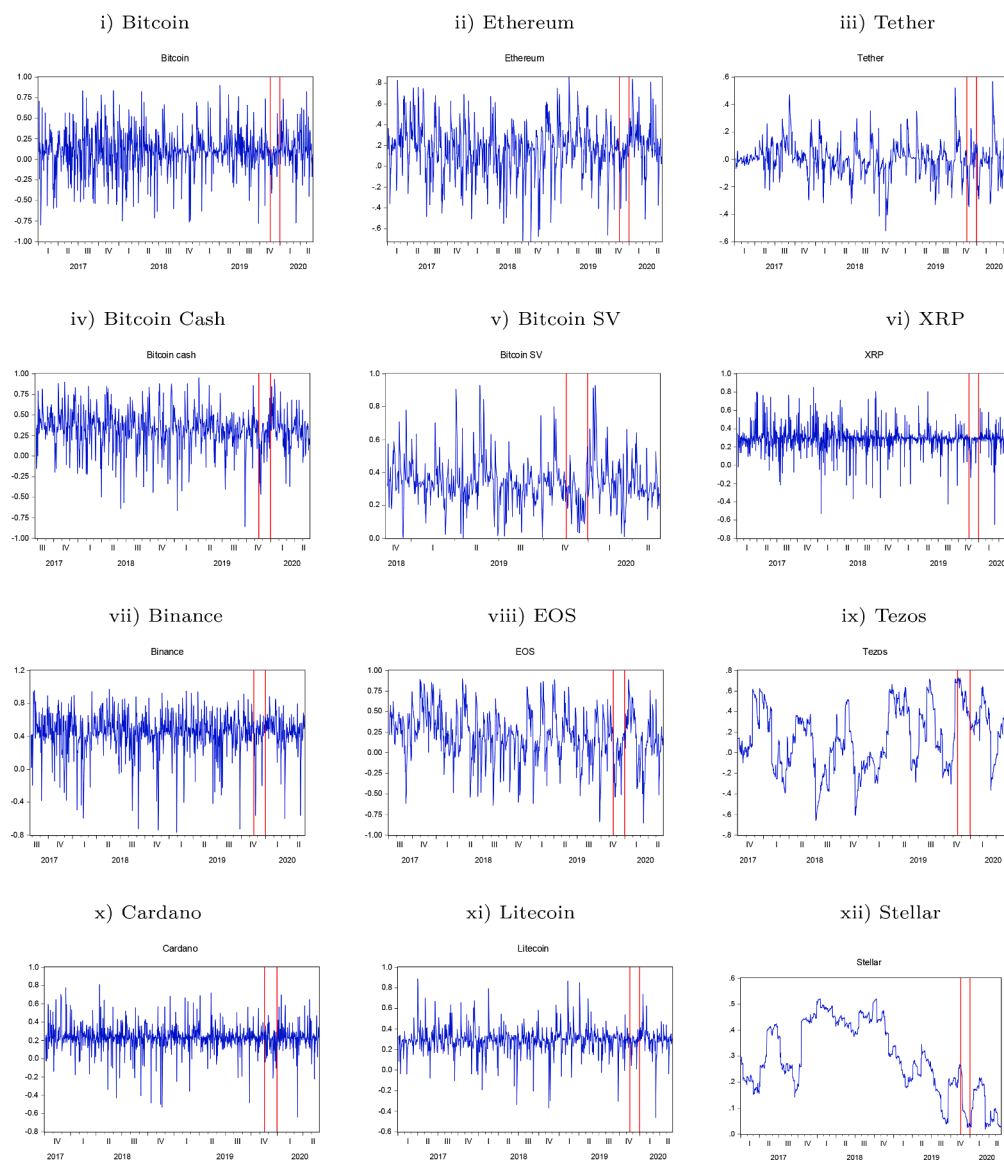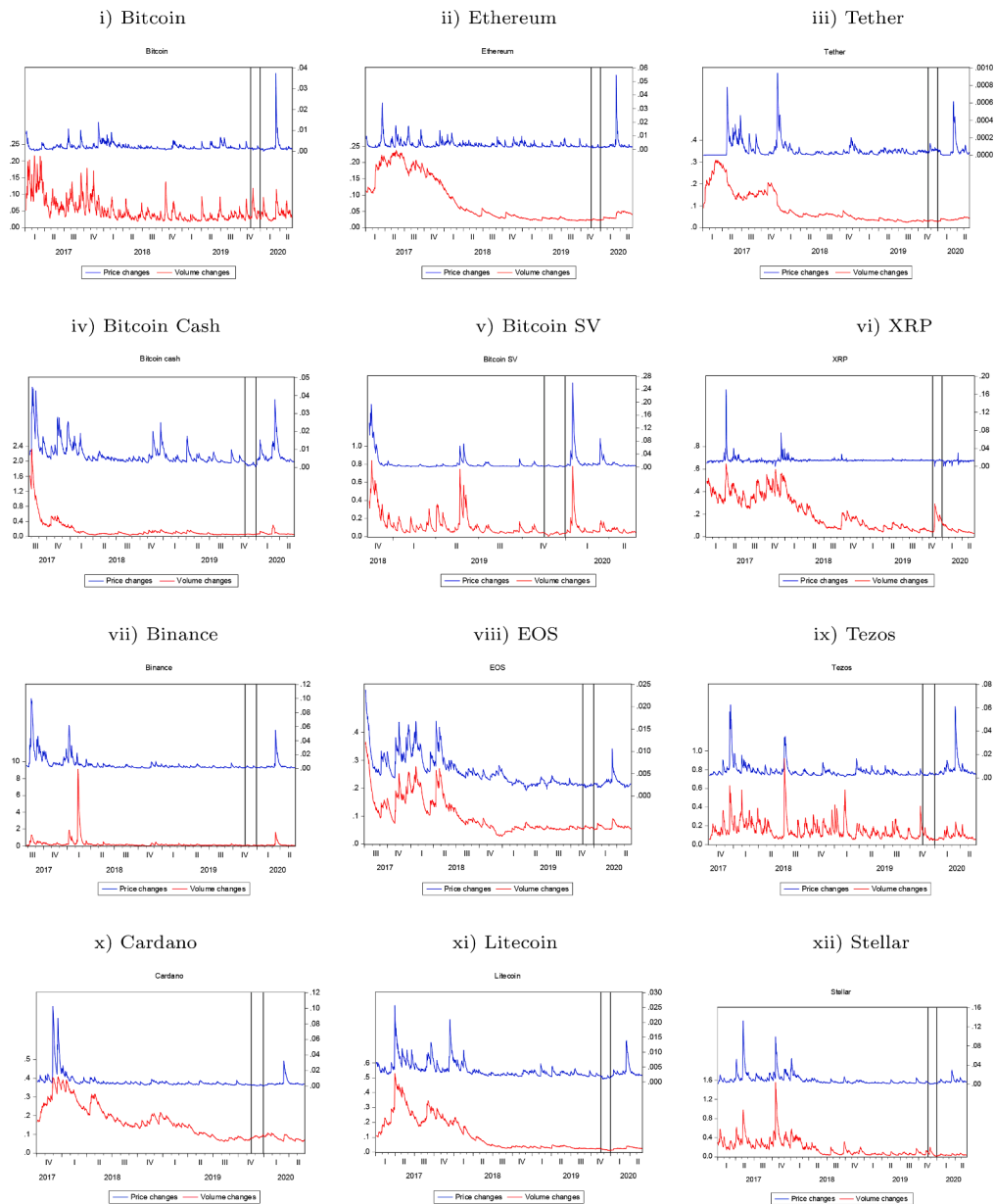
Fig. 2. Conditional correlation between price changes and volume changes. Note: The first black vertical line refers to the date November 16, 2019. The second black vertical line refers to the date December 30, 2019. I, the first quarter; II, the second quarter; III, the third quarter; IV, the fourth quarter. For brevity, only the twelve largest cryptocurrencies by market capitalisation are presented. Further results are available from the authors upon request.

19 outbreak occurs. The effects intensify during both denoted stages of the outbreak of COVID-19, whether it be domestic contagion in China or international contagion throughout the world as denoted through the identified sample periods. This is evidenced across most of the cryptocurrencies contained within our sample. The lagged shocks of price changes are found to possess significant effects on the volatilities of volume changes, representing liquidity, where the estimated size effects are found to be both strong and significant. This is evidenced in some cryptocurrencies in one or two stages of the COVID-19 outbreak. There is no typical changing behaviour across the stages of the COVID-19 outbreak. It becomes quickly evident that the correlation between liquidity changes and price changes is conditioned on the past information.

In Fig. 2 we present the estimated conditional correlation between price and liquidity changes both before and during the COVID-19 outbreak and subsequent international transmission, identifying a positive correlation between price changes and changes in liquidity. The oscillation of correlation is very intensive. When moving to the phase of domestic contagion of COVID-19 in China, the volatility of conditional correlation is squeezed, while the level of correlation is found to decrease sharply. However, after the 30 December 2019, when the WHO formally announces the transmission of the COVID-19 pandemic, the conditional correlation rises in size, which is followed by a big trough in the first quarter in 2020. The variation of the estimated correlation is found to be higher than that in the previous stage of Chinese COVID-19 contagion.

Fig. 3. Conditional volatilities of price changes and volume changes. Note: Each denoted red line in the figures represent the volume changes and are measured on the left-hand vertical axis. The blue line represents price changes and are reflected on the right-hand vertical axis. The first black vertical line refers to the date November 16, 2019. The second black vertical line refers to the date December 30, 2019. I, the first quarter; II, the second quarter; III, the third quarter; IV, the fourth quarter. For brevity, only the twelve largest cryptocurrencies by market capitalisation are presented. Further results are available from the authors upon request. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Finally, in Figure 3 we observe the conditional volatilities of price and liquidity changes during the investigated periods of analysis. Results indicate that the volatility of price changes moves in tandem with volatility of liquidity changes. Increases in the volatility of price changes are found to follow shifts in the volatility of liquidity. A cluster of volatility increases are identified in the phase where there is no COVID-19 contagion, especially during the years of 2017 and 2018, adding to the substantial evidence that exists surrounding the substantial period of growth in cryptocurrency markets. There is no evidence of sharp spikes of volatilities of both price changes and liquidity during the period of domestic contagion of the COVID-19 in China (supporting the results of Corbet et al. (2020c, 2021b)). However, there are several significantly pronounced and prolonged increases in the volatility of cryptocurrency prices during the international contagion phase of the COVID-19 pandemic, corresponding with spikes in liquidity volatility at the similar time.

4. Conclusions

Cryptocurrencies have presented many periods of pronounced price volatility during their rapid growth and development. Since the onset of the COVID-19 pandemic, there is evidence to suggest that cryptocurrencies have played a new role as a potential safe-haven during periods of substantial financial market panic. This was buoyed by substantial difficulties in estimating the severity of international issues such as simultaneous COVID-19 and geopolitical pressures. Results suggest that cryptocurrency market liquidity increased, both sharply and significantly, in line with the WHO announcements of a worldwide pandemic. In the period after the COVID-19 outbreak, significant and substantial interactions between cryptocurrency price and liquidity effects are identified. Results indicate that shocks determined through liquidity shifts have significant effects on the volatilities of price changes before the COVID-19 outbreak occurs. The effects intensify during both denoted stages of the outbreak of COVID-19, whether it be domestic contagion in China or international contagion in the identified sample periods. These results add further support to the view that cryptocurrencies have been used as a store of value to protect from financial losses during the COVID-19 pandemic financial market panic. Further robustness is provided through the verification of sharp increases in conditional correlation channels.

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