This is a repository copy of *Volatility spillover effects in leading cryptocurrencies: A BEKK-MGARCH analysis*.

Article:

Katsiampa, P. orcid.org/0000-0003-0477-6503, Corbet, S. and Lucey, B. (2019) Volatility spillover effects in leading cryptocurrencies: A BEKK-MGARCH analysis. Finance Research Letters, 29. pp. 68-74. ISSN 1544-6123

https://doi.org/10.1016/j.frl.2019.03.009

Volatility spillover effects in leading cryptocurrencies: A BEKK-MGARCH analysis

Abstract

Through the application of three pair-wise bivariate BEKK models, this paper examines the conditional volatility dynamics along with interlinkages and conditional correlations between three pairs of cryptocurrencies, namely Bitcoin-Ether, Bitcoin-Litecoin, and Ether-Litecoin. While cryptocurrency price volatility is found to be dependent on its own past shocks and past volatility, we find evidence of bi-directional shock transmission effects between Bitcoin and both Ether and Litecoin, and uni-directional shock spillovers from Ether to Litecoin. Finally, we identify bi-directional volatility spillover effects between all the three pairs and provide evidence that time-varying conditional correlations exist and are mostly positive.

Keywords: Bitcoin; Ether; Litecoin; Volatility Spillovers; BEKK-MGARCH
JEL classification: C5, C32, G1

1. Introduction

The exceptional speed of Blockchain development over the past decade has generated a number of avenues from which technological progress can advance. The most publicised Blockchain advancement has taken place in the development of the market for cryptocurrencies appearing to have manifested itself in substantial market valuations and product liquidity, with cryptocurrencies being mainly viewed as assets rather than currencies (Baek and Elbeck [2015]; Dyhrberg [2016]; Blau [2017]).

The literature on cryptocurrencies has rapidly emerged. For instance, the price discovery process of Bitcoin has been investigated by, e.g., Brandvold et al. [2015], Corbet, Lucey, Urquhart, and Yarovaya [2018] and Kapar and Olmo [2018], the existence of bubbles in cryptocurrencies has been examined by, e.g., Cheah and Fry [2015], Cheung et al. [2015], Fry and Cheah [2016] and Corbet, Lucey, and Yarovaya [2018], and the existence of frequent structural breaks in Bitcoin returns has been investigated by Thies and Molnár [2018], while the volatility of cryptocurrency price returns has been studied by Katsiampa [2017], Ardia et al. [2018], Phillip et al. [2018], Baur and Dimpfl [2018], Chaim and Laurini [2018] and Troster et al. [2018], among others. Nevertheless, whereas the potential for market manipulation appears to have been broadly identified in cryptocurrency cross-correlations and market interdependencies (see, e.g., Griffins and Shams [2018] and Gandal et al. [2018]), interdependencies within cryptocurrency markets continue to remain relatively under-explored. Among the few studies of interdependencies in cryptocurrency markets are those of Fry and Cheah [2016], Ciaian et al. [2018], Corbet, Lucey, Peat, and Vigne [2018], Corbet, Meegan, Larkin, Lucey, and Yarovaya [2018] and Katsiampa [2018a,b]. However, none of these studies has examined transmission or conditional volatility spillover effects within the cryptocurrency market, which are frequently observed in the behaviour of assets.

Consequently, by considering three major cryptocurrencies, namely Bitcoin, Ether and Litecoin, and by employing three pair-wise bivariate BEKK models for the pairs of Bitcoin-Ether, Bitcoin-Litecoin, and Litecoin-Ether, the aim of this paper is to study conditional volatility spillover effects and conditional correlations between pairs of cryptocurrencies. We find evidence of bi-directional shock transmission effects between Bitcoin and Ether as well as between Bitcoin and Litecoin, and uni-directional shock spillover from Ether to Litecoin. In addition, we find bi-directional volatility linkages between all the three pairs of cryptocurrencies. Finally, it is shown that time-varying conditional correlations exist and are mostly positive.

The structure of the remainder of the paper is as follows: Section 2 describes the data and methodology employed. Section 3 discusses the BEKK-MGARCH methodology.

2. Data

Our dataset consists of daily returns for Bitcoin, Ether and Litecoin, using each market's closing prices[1] from 7 August 2015 to 10 July 2018. The sample therefore consists of 1,068 observations for each time series. The prices are listed in US dollars and the data can be sourced online at coinmarketcap.com. The daily closing price returns of cryptocurrency i, $y_{i,t}$, are defined as:

$$y_{i,t} = ln(p_{i,t}) - ln(p_{i,t-1}), \tag{1}$$

where $p_{i,t}$ is the price of cryptocurrency i, $i = 1, 2, 3$, on day t. Our empirical analysis begins with calculating summary statistics for the cryptocurrency price returns. The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are also performed to examine for the existence of unit roots in the price returns. Furthermore, Engle's ARCH-LM test for ARCH effects is performed to investigate as to whether volatility modelling is required for the price returns of the three cryptocurrencies. The test results suggest that the closing price returns of all the three cryptocurrencies are stationary but display ARCH effects, and a multivariate GARCH methodology can be therefore employed not only to model the cryptocurrencies' conditional variances but also to study the volatility transmission effects between each individually.

[1]The 7th August 2015 is the earliest date available for Ether

3. Methodology

In this paper, we examine volatility transmission effects between cryptocurrencies which are captured through the conditional covariance matrix. Consequently, we utilise a simple methodological specification for the conditional mean equation, excluding potential exogenous variables that could have an effect in the volatility of the cryptocurrency price returns considered, which is given as:

$$y_t = c + \epsilon_t, \tag{2}$$

where y_t is the vector of the price returns, c is the vector of parameters that estimates the mean of the returns, and ϵ_t is the vector of residuals with a conditional covariance matrix H_t given the available information set I_{t-1}.

For the conditional variance-covariance equations, we employ the unrestricted BEKK-MGARCH methodology of Engle and Kroner [1995]. The BEKK model permits the interaction of the conditional variances and covariances of several time series. It therefore allows us to identify volatility transmission effects. The conditional covariance matrix of the BEKK model, H_t, is expressed as:

$$H_t = W'W + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \tag{3}$$

where W, A and B are matrices of parameters with appropriate dimensions, with W being an upper triangular matrix, and the diagonal elements of the three parameter matrices being restricted to be positive (Bekiros [2014]). Moreover, the diagonal elements of H_t, $h_{ii,t}$, denote the conditional variance terms, while the off-diagonal elements of H_t, $h_{ij,t}$, where $i \neq j$ are representations of conditional covariances. Consequently, the diagonal elements of matrices A and B capture the impact of the asset's own past shocks and past volatility, respectively, while the off-diagonal elements of matrices A and B, α_{ij} and β_{ij}, where $i \neq j$, capture the cross-market effects of shocks and volatility, respectively (Li and Majerowska [2008]). These cross-market effects are also known as shock transmission effects and volatility spillover effects.

The unrestricted BEKK model in bivariate form can be expressed as:

$$\begin{aligned}\begin{pmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{pmatrix} = W'W + \begin{pmatrix} a_{11} & a_{21} \\ a_{12} & a_{22} \end{pmatrix} \begin{pmatrix} \varepsilon^2_{1,t-1} & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon^2_{2,t-1} \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \\ + \begin{pmatrix} b_{11} & b_{21} \\ b_{12} & b_{22} \end{pmatrix} \begin{pmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}\end{aligned} \tag{4}$$

while the equation by equation model is given as follows:

$$
\begin{aligned}
h_{11,t} = w_{11}^2 + a_{11}^2\varepsilon_{1,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2\varepsilon_{2,t-1}^2 \\
+b_{11}^2h_{1,t-1} + 2b_{11}b_{21}h_{1,2,t-1} + b_{21}^2h_{2,t-1}
\end{aligned}
\tag{5}
$$

$$
\begin{aligned}
h_{22,t} = w_{12}^2 + w_{22}^2 + a_{12}^2\varepsilon_{1,t-1}^2 + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{22}^2\varepsilon_{2,t-1}^2 \\
+b_{12}^2h_{11,t-1} + 2b_{12}b_{22}h_{1,2,t-1} + b_{22}^2h_{22,t-1}
\end{aligned}
\tag{6}
$$

$$
\begin{aligned}
h_{12,t} = h_{21,t} = w_{12}w_{11} + a_{11}a_{12}\varepsilon_{1,t-1}^2 + (a_{12}a_{21} + a_{11}a_{22})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}a_{22}\varepsilon_{2,t-1}^2 \\
+b_{11}b_{12}h_{11,t-1} + (b_{12}b_{21} + b_{11}b_{22})h_{12,t-1} + b_{21}b_{22}h_{22,t-1}
\end{aligned}
\tag{7}
$$

After estimating the model parameters, the conditional correlation between two cryptocurrencies can be also estimated by the following equation:

$$
r_{12,t} = \frac{h_{12,t}}{\sqrt{h_{11,t}}\sqrt{h_{22,t}}} \tag{8}
$$

where $h_{11,t}$ and $h_{22,t}$ represent the two cryptocurrencies' conditional variances, while $h_{12,t}$ denotes the corresponding conditional covariance.

4. Empirical findings

Table 1 reports descriptive statistics for the price returns series of the three cryptocurrencies considered in this study. The average price returns are positive for all the three cryptocurrencies ranging from 0.27% (Litecoin) to 0.47% (Ether). Furthermore, Ether is the most volatile cryptocurrency, as measured by a standard deviation of 8.13%, while Bitcoin is the least volatile (4.09%). It can also be noticed that all price returns are leptokurtic, with Ether exhibiting the highest excess kurtosis. Moreover, the price returns of both Bitcoin and Ether are negatively skewed, indicating that the two cryptocurrencies have a longer left tail. In contrast, the opposite result is true for the price returns of Litecoin, which are positively skewed, indicating that large positive price returns are more common than large negative returns. The departure from normality for all the three price return series is also confirmed by the Jarque-Bera (JB) test results, which reject the null hypothesis of normally distributed returns for all the three returns series. In addition, the ARCH(1) and ARCH(5) test results show evidence of ARCH effects in the price returns of all the three cryptocurrencies. We can therefore proceed by modelling the cryptocurrencies' price volatility. Further, the results from unit root tests are presented in Table 2. Both the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests present large negative values rejecting the null hypothesis of a unit root at the 1% level of significance, and hence the daily closing price returns of all the three cryptocurrencies are stationary.

Insert Tables 1 and 2 about here

Figure 1 illustrates the time plots of the closing prices of the three cryptocurrencies considered in this study, which significantly fluctuate over time from mid-2017 onwards. More specifically, all the three cryptocurrencies saw remarkable price increases from the second quarter of 2017 until the end of 2017, while in 2018 all prices started decreasing. The prices of the three cryptocurrencies therefore seem to fluctuate in a similar way and could be correlated.

Insert Figure 1 about here

The Pearson correlation coefficients for the different pairs of cryptocurrencies (Table 3) further confirm the positive and significant correlation between cryptocurrencies. More specifically, the correlation between Litecoin and Bitcoin is 0.58, while the correlation between Ether and Bitcoin is 0.33. On the other hand, the correlation between Ether and Litecoin equals 0.31.

Insert Table 3 about here

Next we estimated three pair-wise models employing the bivariate BEKK framework. The modelled pairs are: Bitcoin-Ether, Bitcoin-Litecoin, and Litecoin-Ether. Table 4 reports the estimation results for each pair of cryptocurrencies. As mentioned in section three, the diagonal parameters in matrix A, α_{ii}, capture a cryptocurrency's own ARCH effects, while the diagonal parameters in matrix B, β_{ii}, capture a cryptocurrency's own GARCH effects. According to the estimation results, irrespective of the cryptocurrency pair considered, a cryptocurrency's current volatility is significantly affected by its own past squared shocks as well as by its own past volatility as a result of statistically significant α_{ii} and β_{ii} coefficient estimates at the 1% level. Moreover, for all the cryptocurrency pairs considered, we notice that $|\alpha_{ii}| < |\beta_{ii}|$, a finding that indicates the fact that current conditional variances are affected more by the magnitude of previous conditional variances rather than by the size of previous innovations.

Investigating the off-diagonal elements of matrices A and B, α_{ij} and β_{ij}, $i \neq j$, which capture cross-market effects, namely shock and volatility spillovers, respectively, between cryptocurrencies, we find evidence of significant cross-market effects between the variability of the returns of Bitcoin and Ether and Bitcoin and Litecoin in view of significant bi-directional transmission and volatility linkages between Bitcoin and Ether as well as between Bitcoin and Litecoin, as in both pair-wise models the estimates of α_{12}, α_{21} and β_{21} are statistically significant at the 1% level, while the estimate of β_{12} is statistically significant at the 10% level. More specifically, we find evidence of bi-directional shock transmission effects between Bitcoin and Ether and between Bitcoin and Litecoin, since the off-diagonal parameters, α_{12} and α_{21}, are both statistically significant. It should be noticed, though, that for the pair Bitcoin-Ether, α_{12} is positive, while α_{21} is negative. Consequently, past news about shocks in Bitcoin positively affects the current conditional volatility of Ether, while previous shocks of Ether have a negative impact on the current volatility of Bitcoin. On the other hand, in the case of the pair Bitcoin-Litecoin both α_{12} and α_{21} are negative, suggesting that lagged shocks in one cryptocurrency negatively affect the current conditional volatility of the other. In both pairs, though, the bi-directional shock spillover suggests interdependencies between Bitcoin and Ether as well as between Bitcoin and Litecoin. Moreover, we find evidence of two-way volatility spillover effect between Bitcoin and Ether as well as between Bitcoin and Litecoin, since both β_{12} and β_{21} are statistically significant, with β_{21} being significant at the 1% level, while the estimate of β_{12} is significant at the 10% level. Consequently, the current conditional volatility of one cryptocurrency depends not only on its own past volatility but also on past volatility of the other cryptocurrency, suggesting interlinkages between them. However, since β_{12} is negative, while β_{21} is positive for both pairs of cryptocurrencies, past conditional volatility of Bitcoin negatively affects the current level of volatility of both Ether and Litecoin, while past volatility of Ether or Litecoin positively affects the current volatility of Bitcoin.

With regards to the relationship between Litecoin and Ether, the significant α_{21} coefficient estimate and insignificant α_{12} parameter estimate suggest the existence of a uni-directional shock spillover from Ether to Litecoin. On the other hand, the significant and positive β_{12} and β_{21} parameter estimates indicate bi-directional positive volatility linkages between Litecoin and Ether, which further confirm interdependencies within the cryptocurrency market. Our findings thus support the studies of Fry and Cheah [2016], Ciaian et al. [2018], Corbet, Meegan, Larkin, Lucey, and Yarovaya [2018] and Katsiampa [2018a,b] on interdependencies within the cryptocurrency market. Further, according to the LR test results as reported in Table 4, the bivariate models are appropriate, suggesting that we were correct when selecting to model the pairs of cryptocurrencies simultaneously.

Insert Table 4 about here

Finally, the plots of the conditional correlations between the three different pairs of cryptocurrencies are depicted in Figures 2 through 4. The plots confirm dynamic conditional correlations between the three pairs of cryptocurrencies, with the correlations taking both positive and negative values, although positive correlations are mostly observed. These results thus indicate the inadequacy of considering unconditional correlations only. In addition, the high peaks in the conditional correlations occurring in mid or end of September 2017 appear to be associated with the same period of time when China banned Bitcoin trading and completing initial coin offerings. This result is consistent with the findings in the studies of Katsiampa (2018a, b).

Insert Figures 2 through 4 about here

5. Conclusion

Through the application of three pair-wise bivariate BEKK models for the pairs of Bitcoin-Ether, Bitcoin-Litecoin, and Litecoin-Ether, this paper investigated not only conditional volatility dynamics of cryptocurrencies but also linkages and conditional correlations between pairs of cryptocurrencies. It was found that a cryptocurrency's own past shocks and volatility significantly affect its own current conditional variance. But most importantly, we found evidence of bi-directional shock transmission effects between Bitcoin and Ether as well as between Bitcoin and Litecoin, and uni-directional shock spillover from Ether to Litecoin. Further, we identified bi-directional volatility spillover effects between all the three pairs of cryptocurrencies. Finally, it was shown that time-varying conditional correlations exist with positive correlations mostly prevailing. These results provide strong evidence supporting the progress of cryptocurrency market integration and further support earlier studies' findings on interdependencies within the cryptocurrency market.

Bibliography

Ardia, D., K. Bluteau, and M. Rüede (2018). Regime changes in (bitcoin) GARCH volatility dynamics. *Finance Research Letters Available at: https://doi.org/10.1016/j.frl.2018.08.009*.

Baek, C. and M. Elbeck (2015). Bitcoins as an investment or speculative vehicle? a first look. *Applied Economics Letters 22*(1), 30–34.

Baur, D. G. and T. Dimpfl (2018). Asymmetric volatility in cryptocurrencies. *Economics Letters 173*, 148–151.

Bekiros, S. D. (2014). Contagion, decoupling and the spillover effects of the US financial crisis: Evidence from the BRIC markets. *International Review of Financial Analysis 33*, 58–69.

Blau, B. M. (2017). Price dynamics and speculative trading in bitcoin. *Research in International Business and Finance 41*, 493–499.

Brandvold, M., P. Molnár, K. Vagstad, and O. C. A. Valstad (2015). Price discovery on bitcoin exchanges. *Journal of International Financial Markets, Institutions and Money 36*, 18–35.

Chaim, P. and M. P. Laurini (2018). Volatility and return jumps in bitcoin. *Economics Letters 173*, 158–163.

Cheah, E.-T. and J. Fry (2015). Speculative bubbles in bitcoin markets? an empirical investigation into the fundamental value of bitcoin. *Economics Letters 130*, 32–36.

Cheung, A., E. Roca, and J.-J. Su (2015). Crypto-currency bubbles: an application of the phillips–shi–yu (2013) methodology on mt. gox bitcoin prices. *Applied Economics 47*(23), 2348–2358.

Ciaian, P., M. Rajcaniova, et al. (2018). Virtual relationships: Short-and long-run evidence from bitcoin and altcoin markets. *Journal of International Financial Markets, Institutions and Money 52*, 173–195.

Corbet, S., B. Lucey, M. Peat, and S. Vigne (2018). Bitcoin futures - what use are they? *Economics Letters 172*, 23–27.

Corbet, S., B. Lucey, and L. Yarovaya (2018). Datestamping the bitcoin and ethereum bubbles. *Finance Research Letters 26*, 81–88.

Corbet, S., B. M. Lucey, A. Urquhart, and L. Yarovaya (2018). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis Available at: https://www.sciencedirect.com/science/article/pii/S1057521918305271.*

Corbet, S., A. Meegan, C. Larkin, B. Lucey, and L. Yarovaya (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters 165*, 28–34.

Dyhrberg, A. H. (2016). Bitcoin, gold and the dollar–a garch volatility analysis. *Finance Research Letters 16*, 85–92.

Engle, R. F. and K. F. Kroner (1995). Multivariate simultaneous generalized arch. *Econometric Theory 11*(1), 122–150.

Fry, J. and E.-T. Cheah (2016). Negative bubbles and shocks in cryptocurrency markets. *International Review of Financial Analysis 47*, 343–352.

Gandal, N., J. Hamrick, T. Moore, and T. Oberman (2018). Price manipulation in the bitcoin ecosystem. *Journal of Monetary Economics 95*, 86–96.

Griffins, J. and A. Shams (2018). Is bitcoin really un-tethered. *Available at SSRN 13 June 2018.*

Kapar, B. and J. Olmo (2018). An analysis of price discovery between bitcoin futures and spot markets. *Economics Letters 174*, 62–64.

Katsiampa, P. (2017). Volatility estimation for bitcoin: A comparison of garch models. *Economics Letters 158*, 3–6.

Katsiampa, P. (2018a). An empirical investigation of volatility dynamics in the cryptocurrency market. *Available at: http://dx.doi.org/10.2139/ssrn.3202317*.

Katsiampa, P. (2018b). Volatility co-movement between bitcoin and ether. *Finance Research Letters Available at: https://doi.org/10.1016/j.frl.2018.10.005*.

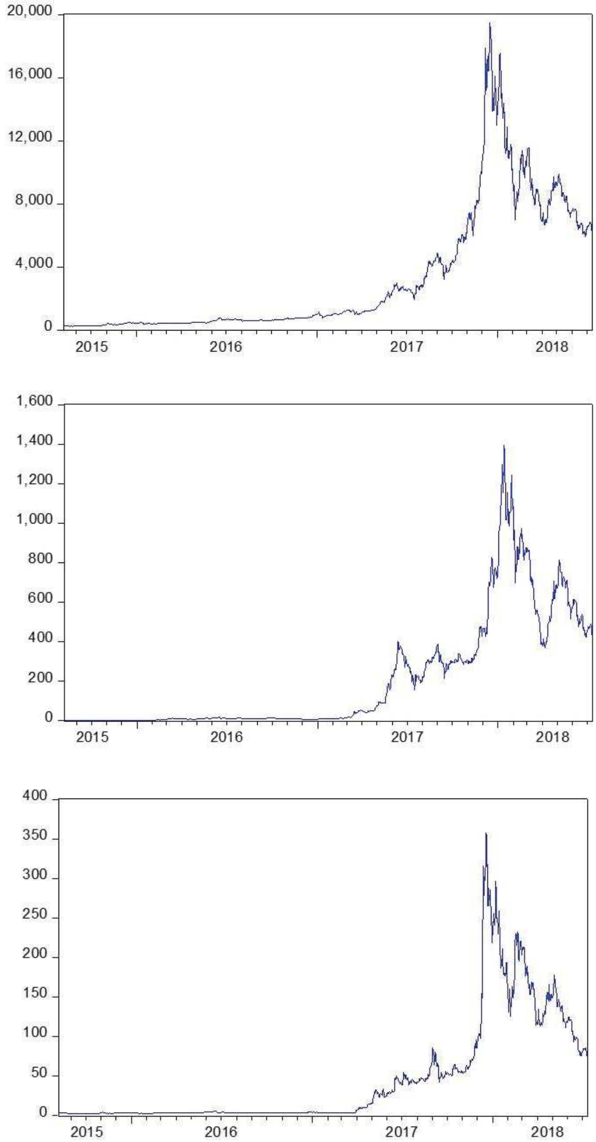
Li, H. and E. Majerowska (2008). Testing stock market linkages for Poland and Hungary: A multivariate GARCH approach. *Research in International Business and Finance 22*(3), 247–266.

Phillip, A., J. Chan, and S. Peiris (2018). A new look at cryptocurrencies. *Economics Letters 163*, 6–9.

Thies, S. and P. Molnár (2018). Bayesian change point analysis of bitcoin returns. *Finance Research Letters Available at: https://doi.org/10.1016/j.frl.2018.03.018*.

Troster, V., A. K. Tiwari, M. Shahbaz, and D. N. Macedo (2018). Bitcoin returns and risk: A general garch and gas analysis. *Finance Research Letters Available at: https://doi.org/10.1016/j.frl.2018.09.014*.

Figure 1: Daily closing prices of cryptocurrencies (in US Dollars)



Note: The above figures represent the daily closing prices of Bitcoin (top-panel), Ether (middle-panel) and Ripple (bottom-panel) respectively.

Figure 2: Conditional correlation between Bitcoin and Ether

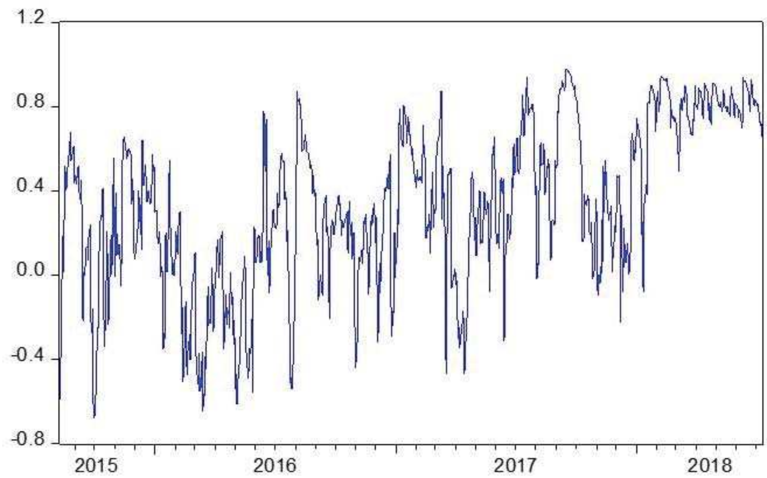


Figure 3: Conditional correlation between Bitcoin and Litecoin

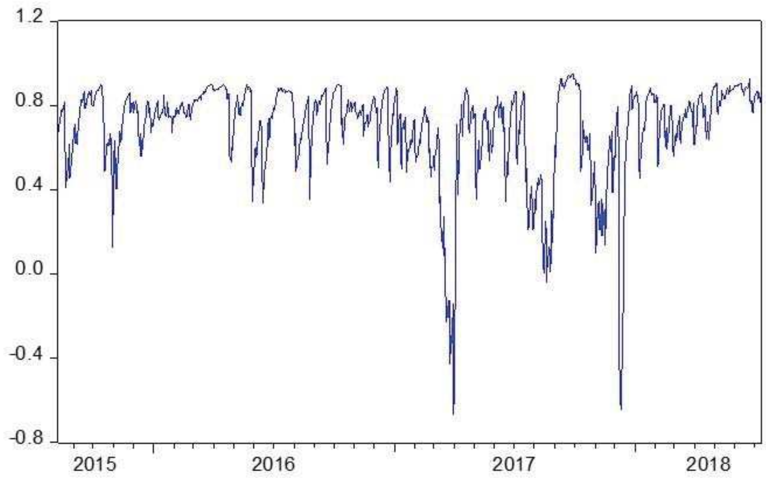


Figure 4: Conditional correlation between Litecoin and Ether

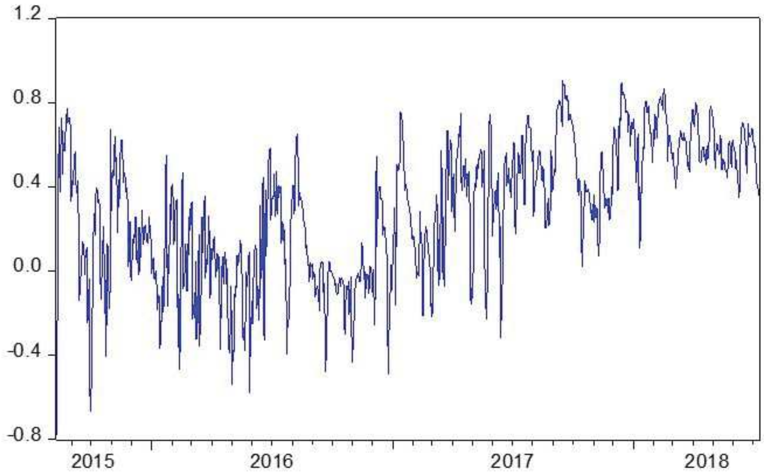


Table 1: Descriptive statistics

	Bitcoin	Ether	Litecoin
Mean	0.0029	0.0047	0.0027
Median	0.0030	-0.0005	0.0000
Maximum	0.2251	0.4123	0.5103
Minimum	-0.2075	-1.3021	-0.3952
Std. Dev.	0.0409	0.0813	0.0589
Skewness	-0.2643	-3.5191	1.3559
Kurtosis	7.7854	67.0259	16.0604
JB	1031.508***	184624.2***	7917.806***
	(0.0000)	(0.0000)	(0.0000)
ARCH(1)	51.44296***	2.288034***	23.89629***
	(0.0000)	(0.0000)	(0.0000)
ARCH(5)	72.53416***	247.5277***	38.30412***
	(0.0000)	(0.0000)	(0.0000)

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 2: Unit roots tests

	Bitcoin	Ether	Litecoin
Panel A: Constant			
ADF	-32.43040***	-35.17191***	-31.97053***
	(0.0000)	(0.0000)	(0.0000)
PP	-32.43410***	-35.16751***	-32.07389***
	(0.0000)	(0.0000)	(0.0000)
Panel B: Constant and Linear Trend			
ADF	-32.41716***	-35.16751***	-31.95995***
	(0.0000)	(0.0000)	(0.0000)
PP	-32.42087***	-35.16888***	-32.05150***
	(0.0000)	(0.0000)	(0.0000)

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 3: Correlation matrix

	Bitcoin	Ether
Bitcoin		
Ether	0.332943***	
Litecoin	0.581923***	0.312921***

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 4: BEKK model parameter estimates

	Bitcoin-Ether	Bitcoin-Litecoin	Litecoin-Ether
c_1	0.002132***	0.002305**	0.001192
	(-0.0050)	(-0.0183)	(-0.4086)
c_2	0.003192**	0.002281*	0.001161
	(-0.0301)	(-0.0724)	(-0.4721)
w_{11}	0.004939***	0.005413***	0.008997***
	(0.0000)	(0.0000)	(0.0000)
w_{12}	0.003579***	0.007734***	-0.011676***
	(-0.0037)	(0.0000)	(0.0000)
w_{22}	0.011286***	0.004459***	0.015299***
	(0.0000)	(0.0000)	(0.0000)
α_{11}	0.487193***	0.276401***	0.346068***
	(0.0000)	(0.0000)	(0.0000)
α_{12}	0.100463***	-0.264146***	0.033695
	(-0.0052)	(0.0000)	(-0.1715)
α_{21}	-0.049709***	-0.047796***	-0.082071***
	(0.0000)	(-0.0007)	(0.0000)
α_{22}	0.434519***	0.435563***	0.528378***
	(0.0000)	(0.0000)	(0.0000)
β_{11}	0.893997***	0.913228***	0.901905***
	(0.0000)	(0.0000)	(0.0000)
β_{12}	-0.019874*	-0.012721*	0.035814***
	(-0.0862)	(-0.0846)	(-0.0052)
β_{21}	0.018183***	0.050087***	0.076608***
	(0.0000)	(0.0000)	(0.0000)
β_{22}	0.892600***	0.945230***	0.805624***
	(0.0000)	(0.0000)	(0.0000)
LL	3685.358	4155.683	3264.763
AIC	-6.883521	-7.765104	-6.095151
SIC	-6.822936	-7.704519	-6.034566
HQ	-6.860567	-7.74215	-6.072197
LR	340.5155***	873.1841***	334.1871***
	(0.0000)	(0.0000)	(0.0000)

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.