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An empirical investigation of volatility dynamics in the cryptocurrency market

Abstract: By employing an asymmetric Diagonal BEKK model, this paper examines volatility dynamics of five major cryptocurrencies, namely Bitcoin, Ether, Ripple, Litecoin, and Stellar Lumen. It is shown that the conditional variances of all the five cryptocurrencies are significantly affected by both previous squared errors and past conditional volatility. Moreover, in the case of Bitcoin, Ether, Ripple, and Litecoin, asymmetric past shocks have a significant effect in the current conditional variance. Similar results are obtained for the cryptocurrencies' conditional covariances, which are significantly affected by cross products of previous error terms and past covariance terms while capturing asymmetric effects of past shocks accordingly. It is also shown that time-varying conditional correlations exist and are mostly positive. Finally, the cryptocurrencies' volatility dynamics are found to be responsive to major news, with Bitcoin and Litecoin exhibiting one structural breakpoint each in the conditional variance. The results improve our understanding of interdependencies between cryptocurrencies as well as of the events that affect their volatility dynamics and thus have important implications for both cryptocurrency users and investors.

Keywords: Bitcoin, Cryptocurrency, Asymmetric Diagonal BEKK, MGARCH, Volatility, Conditional correlations

JEL classification: C32, C5, G1

1. Introduction

Over the last few years, cryptocurrency markets have significantly evolved. Amid huge public interest, the use of cryptocurrencies has increased in response to the perceived issues of the already existing monetary and payment system which were brought to light during the financial market turmoil of 2008 (Weber, 2014) but also due to the cryptocurrencies' unprecedented price increases providing their users with the potential of reaching extremely high gains in merely few weeks or months (Kristoufek, 2013), while posing legal, regulatory and ethical challenges to central authorities (Fry and Cheah, 2016). Cryptocurrencies are peer-to-peer electronic cash systems allowing for online payments to be processed without passing through central banks or any other banking system (Corbet et al., 2019).

Cryptocurrencies as a medium of exchange could seem attractive to potential users due to user anonymity, low transaction costs resulting from no intermediary involvement as well as the fact that more and more retailers have started accepting Bitcoin payments and hence cryptocurrency users could purchase goods, including illegal ones (Baur et al., 2018). Indeed, Foley et al. (2019) argue that about a quarter of Bitcoin users and half of Bitcoin transactions are related to illegal activities, which reach up to a value of 72 billion US Dollars per year. Nevertheless, apart from the potential to fund illegal activities, cryptocurrencies are primarily used for speculation purposes instead of as a traditional medium of exchange (Glaser et al., 2014; Baek and Elbeck, 2015; Yermack, 2015; Dyhrberg, 2016; Blau, 2017), despite concerns about risks associated with their price fluctuations raised by economists and financial institutions. In addition, cryptocurrencies resemble more financial assets rather than currencies (Yermack, 2015) due to their volatility (Chu et al., 2017; Katsiampa, 2017), vulnerability to speculative bubbles (Cheah and Fry, 2015), persistence (Caporale et al., 2018), heavy tail behaviour (Osterrieder and Lorenz, 2017; Osterrieder et al., 2017; Gkillas and Katsiampa, 2018; Phillip et al., 2018) and leverage effects (Phillip et al., 2018), among other properties, while Corbet et al. (2018a, 2018b) argue that cryptocurrencies constitute a new investment asset class.

Recently cryptocurrencies have become a popular topic in academic research as well. However, although it could be expected that the prices of Bitcoin and other cryptocurrencies are interdependent, due to Bitcoin's dominance within the market and the fact that most altcoin orders are executed in Bitcoin (Ciaian et al., 2018), the literature on interlinkages and volatility dynamics within cryptocurrency markets still remains underexplored. Volatility spillovers are frequently witnessed in the behaviour of different assets, and understanding covariances and correlation coefficients are of utmost importance to investors in order to determine the risk of their portfolios (Coudert et al., 2015), as high levels of volatility co-movements among cryptocurrencies can limit the benefits of diversification. Consequently, studying volatility dynamics in cryptocurrency markets is of great importance in order for cryptocurrency users and traders to improve their understanding of interdependencies within cryptocurrency markets and make more informed decisions, especially since cryptocurrency users face undifferentiated risks (Gkillas and Katsiampa, 2018).

Motivated by the huge cryptocurrency price volatility, the risks cryptocurrency users and traders face and the apparent interdependencies within cryptocurrency markets, the primary research objective of this paper is therefore to study volatility dynamics of five major cryptocurrencies, namely Bitcoin, Ether, Ripple, Litecoin and Stellar Lumen, while allowing for asymmetric responses between negative and positive shocks in cryptocurrencies' conditional volatility and covariances. As will be shown, the price returns of all the five cryptocurrencies considered in this study are non-normal and heteroskedastic, a finding which is in accordance with the results of earlier studies. Moreover, it is found that in the case of Bitcoin, Ether, Ripple, and Litecoin conditional volatility also captures asymmetric effects between good and bad news, while for Stellar Lumen asymmetric past shocks do not have a significant effect in the current conditional variance. Most importantly, though, it is shown that significant volatility co-movements exist and that conditional correlations between different pairs of cryptocurrencies are dynamic and susceptible to various news related to cryptocurrencies, taking both positive and negative values. This study therefore contributes to the literature of interlinkages within cryptocurrency markets.

A secondary research objective of this study is to identify specific news which resulted in spikes in the cryptocurrencies’ volatility dynamics as well as to investigate whether any events caused instability in the cryptocurrencies’ conditional variances using structural breakpoint tests. Several spikes are identified in the cryptocurrencies’ conditional variance, covariance and correlation plots, and it is demonstrated that Bitcoin and Litecoin exhibit one structural breakpoint each in the conditional variance.

The layout of this article is as follows: Section 2 reviews the academic literature on cryptocurrencies. Section 3 presents the data, methodology and model employed in this study. Section 4 discusses the results. Finally, section 5 summarises the key findings of the paper and provides some concluding remarks.

2. Literature review

Due to their popularity, cryptocurrencies have recently drawn not only significant public attention, but also academic attention, as the literature on cryptocurrencies has rapidly emerged. From quite early, a topic of interest of several academics has been the price discovery process of Bitcoin and its price determinants, which has been examined by Kristoufek (2013), Brandvold et al. (2015), Georgoula et al. (2015), Ciaian et al. (2016), and Panagiotidis et al. (2018), among others. More specifically, Brandvold et al. (2015) examined the role of various exchanges in the price discovery process of Bitcoin and found that Mt. Gox, one of the largest Bitcoin exchanges at that time, dominated the price discovery process in the first period of their sample, while Ciaian et al. (2016) showed that market forces of both Bitcoin supply and demand have significant effects in the Bitcoin price. Moreover, Kristoufek (2013) and Panagiotidis et al. (2018) showed that Bitcoin's search queries and prices are connected, while Georgoula et al. (2015) demonstrated that the Twitter sentiment ratio is positively correlated with Bitcoin prices. Georgoula et al. (2015) further showed that in the short-run both the amount of Wikipedia search queries and the hash rate have a positive impact on the Bitcoin price, while in the long-run the Bitcoin price is positively associated with the Bitcoin circulating supply.

Some other studies have also examined the relationship between cryptocurrency prices and trading volumes. For instance, while Blau (2017) showed that the level of speculative trading is not directly linked to Bitcoin's level of volatility, Balcilar et al. (2017) found evidence of strong dependence between Bitcoin price fluctuations and transaction volume levels. Furthermore, Koutmos (2018) found evidence of bidirectional linkages between Bitcoin price returns and transaction activity, with the impact of return shocks on transaction activity being larger in magnitude. On the other hand, Katsiampa et al. (2018) studied the extreme dependence between returns and trading volumes for eight major cryptocurrencies using bivariate extreme value theory and found that, irrespective of the cryptocurrency under consideration, the extreme correlation between return and volume decreases when moving towards the distribution tails.

The market efficiency of cryptocurrencies has also been extensively studied in the literature. More specifically, in a relatively early study of the efficiency of Bitcoin, Urquhart (2016) concluded that the Bitcoin market is an inefficient market, although it could be in the process of becoming an efficient market. Bariviera (2017) further argued that daily Bitcoin returns become more efficient across time. Later, Nadarajah and Chu (2017) considered a simple power transformation of the Bitcoin returns and showed that the transformed Bitcoin returns are actually market efficient. Consistent results on the efficiency of Bitcoin prices were also obtained by Tiwari et al. (2018), who employed a battery of long-range dependence estimators while allowing for time variation. More recently, Brauneis and Mestel (2018) considered several cryptocurrencies and found that cryptocurrencies become more efficient as liquidity increases, with Bitcoin representing the most efficient cryptocurrency among those considered in their study.

Several studies have also examined whether cryptocurrency markets exhibit speculative bubbles. Cheah and Fry (2015) showed that the fundamental value of Bitcoin is zero and that Bitcoin prices are prone to speculative bubbles, while Cheung et al. (2015), applying the Phillips et al. (2015) methodology to Bitcoin prices, detected several short-lived bubbles as well as three large bubbles during the period 2011–2013 lasting between 66 and 106 days. Later, Fry and Cheah (2016) considered Bitcoin and Ripple prices and found evidence of negative bubbles in both the Bitcoin and Ripple markets. On the other hand, Corbet et al. (2018a) studied the existence of bubbles in Bitcoin and Ether prices and concluded that, although Bitcoin has been in a bubble phase since its price exceeded the landmark of $1000, there is a lack of clear evidence of a persistent bubble in the Bitcoin or Ether markets, without this suggesting that their prices are correct, though.

Furthermore, a lot of research has been conducted on cryptocurrencies' price volatility. Katsiampa (2017) compared several GARCH-type models and found that the Component CARCH model, which consists of both a short-run and a long-run component of conditional variance, fits Bitcoin price returns better than the other GARCH-type models considered in her study. Later, Lahmiri et al. (2018) employed the FIGARCH model and found that volatility in all the Bitcoin markets considered in their study exhibits long-range dependence, while Mensi et al. (2018) found that, after accounting for structural breaks, long memory in the mean and variance decreases. Among other authors who have studied the price volatility of cryptocurrencies are Chu et al. (2017), Liu et al. (2017), and Takaishi (2018), all of whom also used GARCH-type models, while Phillip et al. (2018) employed the stochastic volatility model. It is worth mentioning that all of the aforementioned studies employed univariate volatility models. Nevertheless, univariate models are not appropriate for studying co-movements of cryptocurrencies. In addition, the extreme value behaviour of cryptocurrencies has been studied by Osterrieder and Lorenz (2017), Osterrieder et al. (2017), and Gkillas and Katsiampa (2018), all of whom have shown that cryptocurrencies exhibit heavier tail behaviour and are thus riskier than fiat currencies.

Some studies have also investigated the interconnectedness between cryptocurrencies and different exchange rates or financial assets. Examples include the studies of Yermack (2015), Bouri et al. (2017), Baur et al. (2018), Lee et al. (2018), and Corbet et al. (2018b), the empirical findings of all of which agree that Bitcoin and other cryptocurrencies are not correlated with mainstream assets, such as gold, oil, bonds, and equity indices, among others. However, despite the extensive research conducted on cryptocurrencies, interlinkages within the cryptocurrency market are still rather underexplored. To the best of the author's knowledge, only Fry and Cheah (2016), Ciaian et al. (2018), Corbet et al. (2018b), and Katsiampa (2018) have examined interdependencies of cryptocurrencies. While Fry and Cheah (2016) tested for contagion during bubbles and negative bubbles and found evidence of a spillover from Ripple to Bitcoin, Ciaian et al. (2018) used an Autoregressive Distributed Lag (ARDL) model to study interdependencies between Bitcoin and altcoin markets in the short and long-run and found that the markets are interdependent, with the interdependencies being significantly stronger in the short-run. Nevertheless, none of these two studies considered cryptocurrencies' volatility co-movements, which are important in order for cryptocurrency users and investors to better comprehend cryptocurrency markets and make more informed decisions. On the other hand, although Corbet et al. (2018b) and Katsiampa (2018) studied conditional correlations between cryptocurrencies in order to examine interdependencies within cryptocurrency markets, the former considered only three cryptocurrencies, namely Bitcoin, Ripple, and Litecoin, while their dataset did not cover the second half of 2017 during which important events occurred and significant appreciations in the prices of cryptocurrencies were observed (see Figure 1), and the latter studied volatility co-movements only between Bitcoin and Ether. In addition, none of the previous studies on interconnectedness of cryptocurrencies considered asymmetric effects of positive and negative shocks in the volatility dynamics within the cryptocurrency market.

This paper thus extends the studies of Corbet et al. (2018b) and Katsiampa (2018) not only by considering a wider range of cryptocurrencies and an updated dataset but also by employing an asymmetric Multivariate GARCH model, namely the Asymmetric Diagonal BEKK model, which not only examines the dynamic conditional volatility and correlations between cryptocurrencies but also allows for asymmetric responses of negative and positive shocks to cryptocurrencies' conditional volatility and covariances, while still guaranteeing the positive definiteness of the conditional covariance matrix. Consequently, this study aims to contribute to the literature by investigating volatility dynamics and interdependencies within cryptocurrency markets.

3. Data and methodology

3.1 Data

This study restricts to the top ten most highly capitalised cryptocurrencies that have been in existence for more than two years, as of 12th February 2018. The dataset is further restricted to cryptocurrencies with a market capitalisation in excess of five billion dollars (as of 12th February 2018). The cryptocurrencies meeting these criteria are Bitcoin, Ether, Ripple, Litecoin, and Stellar Lumen. The dataset therefore consists of daily closing prices for Bitcoin, Ether, Ripple, Litecoin, and Stellar Lumen from 7th August 2015 (as the earliest date available for Ether) to 10th February 2018 resulting in a total of 919 observations for each cryptocurrency. The data are publicly available online at https://coinmarketcap.com/coins/ and the prices are listed in US Dollars. A short description of each of the five cryptocurrencies considered in this study can be found in Appendix A.

The daily price returns of Bitcoin ($i = 1$), Ether ($i = 2$), Ripple ($i = 3$), Litecoin ($i = 4$), and Stellar Lumen ($i = 5$) are defined as follows

$$R_{i,t} = \ln(P_{i,t}) - \ln(P_{i,t-1}), \tag{1}$$

where $\ln(P_{i,t})$ is the natural logarithm of the closing price of cryptocurrency i on day t and $\ln(P_{i,t-1})$ is the natural logarithm of the closing price of cryptocurrency i on day $t-1$.

3.2 Methodology

The empirical analysis begins with producing descriptive statistics for the closing price returns of the five aforementioned cryptocurrencies. Two unit-root tests, namely the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit-root tests of Dickey and Fuller (1979) and Phillips and Perron (1988), respectively, are then used in order to examine the stationarity of the price returns of the five cryptocurrencies considered in this study by testing the null hypothesis of a unit root against the alternative hypothesis of stationarity. In order to verify the results, the KPSS stationarity test of Kwiatkowski et al. (1992) is also employed, testing the null hypothesis of stationarity of the returns against the alternative hypothesis of no stationary returns. Once the stationarity of the price returns is ensured, sequential Bai-Perron (Bai, 1997; Bai and Perron, 1998) tests are performed, allowing for up to five unknown breakpoints and for error distributions to differ across breaks, in order to test for stability, and then Engle's ARCH-LM test for ARCH effects is used in order to examine whether volatility modelling is required for the returns series. As will be shown in Section 4, the results suggest that the price returns of all the five cryptocurrencies are stationary, without exhibiting any breakpoint in the mean equation, but exhibit volatility clustering, and hence a multivariate GARCH model can be employed in order to study both their conditional variances and covariances and therefore examine their volatility co-movements. Upon estimation of the model parameters, sequential Bai-Perron tests are performed in the conditional variance of each cryptocurrency as well, allowing for up to five unknown breakpoints and for error distributions to differ across breaks similar to the tests performed for the mean equations, in order to test for potential structural breakpoints in the variance equations too. Any breakpoint identified by the Bai-Perron tests is further tested using Chow's breakpoint test (Chow, 1960) in order to verify the results.

3.3 Model

In this sub-section, the model employed in this study is presented. Following Corbet et al. (2018b) and Katsiampa (2018), a simple specification for the conditional mean equation is employed, since this study's interest lies mainly in the cryptocurrencies' volatility co-movements and hence in their conditional covariance matrix. The conditional mean equation of the cryptocurrency price returns is thus given as

$$r_t = \mu + \varepsilon_t, \tag{2}$$

where r_t is the vector of the price returns as defined in the previous section, μ is a vector of parameters that estimates the mean of the return series, and ε_t is the vector of residuals with a conditional covariance matrix H_t given the available information set I_{t-1}. It should be noticed that all the three components of the conditional mean equation are (5×1) vectors, since five cryptocurrencies are considered in this study.

For the conditional covariance matrix, H_t, this study employs the Asymmetric Diagonal BEKK model of Kroner and Ng (1998), which is an extension of the Diagonal BEKK model by allowing for asymmetric effects of positive and negative shocks and is based on the univariate GJR-GARCH model of Glosten et al. (1993) (Terrell and Fomby, 2006. Diagonal BEKK models are special cases of the unrestrictive Baba-Engle-Kraft-Kroner (BEKK) model of Baba et al. (1990) and Engle and Kroner (1995) and have several advantages over the full

BEKK model, including the fact that the number of parameters to be estimated is significantly reduced, while still maintaining the positive definiteness of H_t (Terrell and Fomby, 2006), among others[1]. As a result, interpretation of the parameters is easier, and the parameters' net effects on the future conditional variances and covariances can be more easily observed. BEKK models can also be preferred to other Multivariate GARCH models, including Engle's (2002) Dynamic Conditional Correlation (DCC) model (Caporin and McAleer, 2012; Boldanov et al., 2016), due to the fact that consistency and asymptotic normality of the estimated parameters of any version of the DCC model have not yet been derived (Caporin and McAleer, 2012; 2013), despite the fact that BEKK and DCC models can be applied for similar investigations[2].

The conditional covariance matrix of the asymmetric Diagonal BEKK model is given as

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

where W, A, B, and D are matrices of parameters with appropriate dimensions, with W being an upper triangular matrix, while the diagonal elements of H_t, $h_{ii,t}$, $i = 1, \dots, 5$, denote the conditional variances, and the off-diagonal elements of H_t, $h_{ij,t}$, $i \neq j$, $i, j = 1, \dots, 5$, represent the corresponding conditional covariances, whereas $\eta_t = (\eta_{1,t}, \eta_{2,t}, \dots, \eta_{5,t})'$ and $\eta_{i,t} = \min\{\varepsilon_{i,t}, 0\}$, $i = 1, \dots, 5$. The elements of matrix A measure the effects of past squared errors (news) in current conditional variances, while the elements of matrix B show how past conditional variances affect the current levels of volatility (Begiazi and Katsiampa, 2019). On the other hand, the elements of matrix D capture the asymmetric effects of negative and positive shocks.

The conditional variance of cryptocurrency i, h_{it}, $i = 1, \dots, 5$, is given as follows

$$h_{it} = \widetilde{w}_{ii} + {a_{ii}}^2{\varepsilon_{it-1}}^2 + {d_{ii}}^2{\eta_{it-1}}^2 + {\beta_{ii}}^2 h_{it-1}, \tag{4}$$

while the conditional covariance between any two cryptocurrencies i and j, h_{ijt}, $i, j = 1, \dots, 5$, $i \neq j$, can be expressed as

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[1] For a more detailed overview of limitations of the BEKK model regarding its parameters, see Tse (2000), Tse and Tsui (2002), and Terrell and Fomby (2006). For issues with statistical properties of the BEKK model as well as for advantages of Diagonal BEKK models over the unrestrictive BEKK model, see, e.g., Allen and McAleer (2017), Chang et al. (2017), and Chang and McAleer (2019).

[2] For a more detailed presentation of the differences between BEKK and DCC models, see, e.g., Caporin and McAleer (2012). For limitations of DCC models, see Caporin and McAleer (2013).

$$h_{ijt} = \widetilde{w}_{ij} + a_{ii}a_{jj}\varepsilon_{it-1}\varepsilon_{jt-1} + d_{ii}d_{jj}\eta_{it-1}\eta_{jt-1} + \beta_{ii}\beta_{jj}h_{ijt-1}, \quad (5)$$

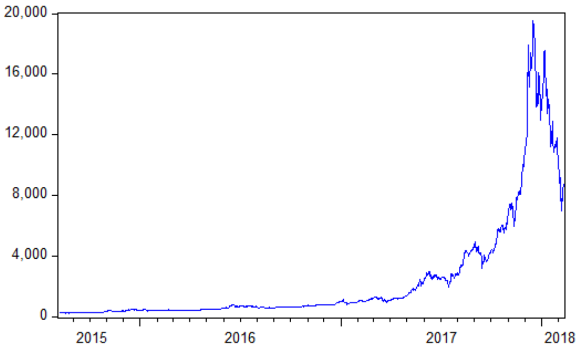
where $\widetilde{w}_{ij}$ is the ij^{th} element of $W'W$. It can be noticed from the above equations that the current volatility of cryptocurrency i is a function of its own lagged value and own lagged squared shocks and reacts to negative shocks, η_{it}, as determined by the estimated asymmetry parameter, d_{ii}, while the current conditional covariance of cryptocurrencies i and j is a function of its own lagged covariance as well as of cross-products of the corresponding shocks and captures asymmetric effects of negative and positive shocks accordingly. Consequently, the asymmetric Diagonal BEKK model can not only investigate volatility dynamics between cryptocurrencies but can also capture asymmetric responses of negative and positive shocks to their conditional volatility and covariances, which is the primary objective of this study.

The conditional mean, variance and covariance equations are estimated simultaneously. Since cryptocurrencies have Student-t error distributions (Liu et al., 2017; Katsiampa, 2018; Phillip et al., 2018), the model parameters are estimated by the maximum likelihood approach under the multivariate Student's t error distribution, while the likelihood function is estimated using the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm. Once the model parameters are estimated, the conditional correlations between two cryptocurrencies i and j, r_{ijt}, $i, j = 1, \ldots, 5$, $i \neq j$, are derived by the following formula

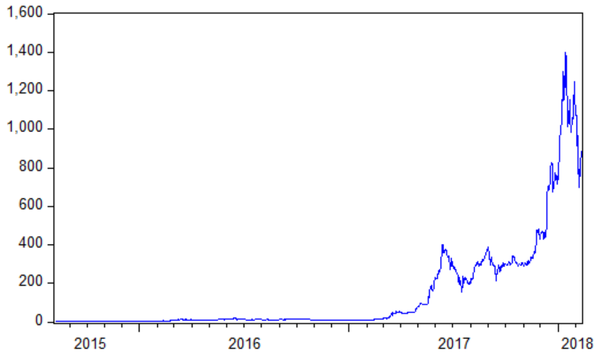
$$r_{ij,t} = \frac{h_{ij,t}}{\sqrt{h_{ii,t}}\sqrt{h_{jj,t}}}\,. \quad (6)$$

4. Empirical findings

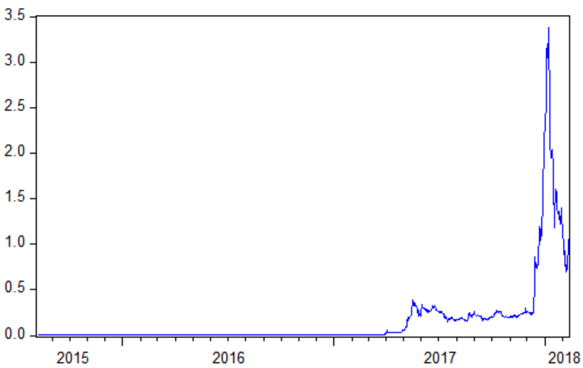
Figure 1 depicts the plots of the closing prices of the five cryptocurrencies considered in this study. It can be easily noticed that the prices of Ripple, Litecoin and Stellar Lumen would be stable while the prices of Bitcoin and Ether would steadily increase until the end of the first quarter of 2017. However, from the second quarter of 2017 until the end of 2017 there were remarkable price increases for all the five cryptocurrencies, while from the beginning of 2018 onwards all prices gradually decreased. All prices therefore seem to move in the same pattern, suggesting that they could be correlated.



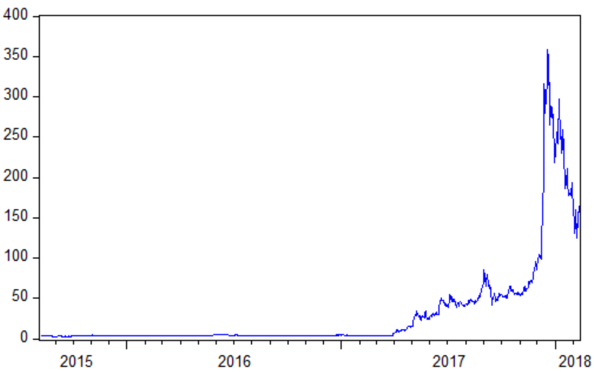
(i) Bitcoin



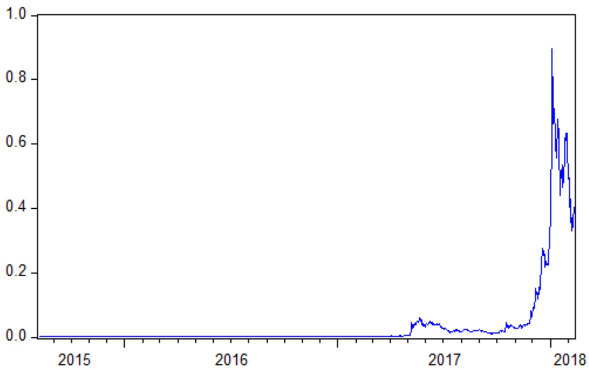
(ii) Ether



(iii) Ripple



(iv) Litecoin



(v) Stellar Lumen

Fig. 1 Daily closing prices of cryptocurrencies (in US Dollars)

Summary statistics for the price returns series are reported in Table 1 (Panel A). The average daily closing price returns are positive for all the five cryptocurrencies and range from 0.3735% (Bitcoin) to 0.6251% (Ether), while the standard deviation ranges from 4.0750% (Bitcoin) to 9.1027% (Stellar Lumen). Moreover, all price returns series are leptokurtic as a result of high kurtosis, with Ether in particular exhibiting the highest excess kurtosis. Nevertheless, while the price returns of Bitcoin and Ether are negatively skewed suggesting that they have a longer left tail, the opposite result holds for the price returns of Ripple, Litecoin, and Stellar Lumen. It can also be noticed that the Jarque-Bera (JB) test confirms the departure from normality for all the price returns series. In addition, as both the Augmented Dickey-Fuller and Phillips-Perron unit root tests reject the null hypothesis of a unit root for all the cryptocurrency returns series at the 1% level and the KPSS stationarity test accepts the null hypothesis of stationarity of all the returns series at the 5% level (Panel B of Table 1), the stationarity of all the five price returns series is confirmed, and hence the daily closing price returns of Bitcoin, Ether, Ripple, Litecoin, and Stellar Lumen are appropriate for further analysis. Furthermore, the Bai-Perron test results indicate that the null hypothesis of no breakpoint cannot be rejected against the alternative hypothesis of one breakpoint suggesting that the price returns of the five cryptocurrencies exhibit no structural breakpoint in the mean equation, while the results of the ARCH(5) test provide evidence of ARCH effects in the price returns of all the five cryptocurrencies considered in this study, a finding which is consistent with the results of Katsiampa (2017, 2018), Brauneis and Mestel (2018), and Phillip et al. (2018). Consequently, a multivariate GARCH model can be employed in order to model the conditional variances and covariances of the price returns of the five cryptocurrencies.

Table 1

Descriptive statistics and unit roots tests

	Bitcoin	**Ether**	**Ripple**	**Litecoin**	**Stellar**
Panel A: Descriptive statistics					
Mean	0.003735	0.006251	0.005313	0.003932	0.005577
Median	0.003179	-0.000438	-0.003383	0.000000	-0.003436
Maximum	0.225119	0.412337	1.027356	0.510348	0.723055
Minimum	-0.207530	-1.302106	-0.616273	-0.395151	-0.366358
Std. Dev.	0.040750	0.085219	0.081244	0.059550	0.091027
Skewness	-0.302667	-3.579475	3.126062	1.416657	2.086897
Kurtosis	8.580752	64.70359	41.51925	16.88910	17.33769
JB	1205.304***	147590.8***	58247.93***	7685.759***	8529.365***
Panel B: Test statistics					
ADF	-29.75359***	-32.77106***	-18.57982***	-29.37554***	-27.68017***
PP	-29.74982***	-32.65120***	-31.32579***	-29.43170***	-27.68589***
KPSS	0.188330	0.196512	0.318571	0.416944	0.447692

Bai-Perron	2.078482	3.474224	5.901686	4.722631	3.700106
ARCH(5)	67.42905***	213.4967***	87.46571***	35.70054***	163.1361***

*** significant at the 1% level.

Table 2 presents the Pearson correlation coefficients for the different pairs of cryptocurrencies. It can be noticed that all the correlations are positive and significant. More specifically, both Litecoin and Ether display the highest correlation with Bitcoin (0.5433 and 0.2833, respectively), while Stellar Lumen has the highest correlation with Ripple (0.5148), a fact that could have been expected since Stellar is built upon the Ripple protocol. On the other hand, Ripple, Stellar Lumen, and Litecoin display the lowest correlation with Ether (0.1282, 0.1729, and 0.2675, respectively), while both Bitcoin and Ether have the lowest correlation with Ripple (0.20927 and 0.12823, respectively).

Table 2

Correlation matrix

	Bitcoin	**Ether**	**Ripple**	**Litecoin**
Bitcoin				
Ether	0.28328***			
Ripple	0.20927***	0.12823***		
Litecoin	0.54327***	0.26745***	0.27294***	
Stellar	0.28386***	0.17288***	0.51481***	0.31685***

*** significant at the 1% level.

Table 3 reports the estimation results for the asymmetric Diagonal BEKK model, while the conditional variance and covariance equations with substituted coefficients can be found in Tables 4 and 5, respectively. Due to excess kurtosis as well as departure from normality as evidenced by the Jarque-Bera test results, it is recommended to apply a non-normal distribution for the errors. This is also consistent with the studies of Liu et al. (2017), Katsiampa (2018), and Phillip et al. (2018). The parameters of the asymmetric Diagonal BEKK model were therefore estimated by the maximum likelihood approach under the multivariate Student's t error distribution.

According to the estimation results (Table 3), the estimated parameters of the conditional mean equations for Bitcoin, Ether, and Ripple are statistically significant at the 5% or 1% level.

With regards to the conditional variance equations, it can be noticed that both the ARCH and GARCH coefficients are statistically significant at the 1% level for all the price returns series. This suggests that the current conditional volatility of the price returns of any of the five cryptocurrencies considered in this study is significantly affected by past squared errors as well as by past conditional volatility. By looking at the substituted coefficients (Table 4), the estimated values of the ARCH coefficient range from 0.1901 (Litecoin) to 0.4311 (Stellar Lumen), suggesting that traders pay the most attention to news arriving in the Stellar Lumen market and the least attention to news arriving in the Litecoin market. On the other hand, the estimated values of the GARCH coefficient range from 0.7689 (Stellar Lumen) to 0.8894 (Litecoin), indicating rather high persistence of volatility over time for all the five cryptocurrencies and that shocks in the Litecoin market persist the most, while shocks in the Stellar Lumen market persist the least. In addition, the asymmetry term is found positive for all the cryptocurrencies, indicating that negative shocks increase the volatility levels more than positive shocks of equal magnitude, and ranges from 0.0017 (Stellar Lumen) to 0.0982 (Ether). Furthermore, the asymmetry parameter estimate is significant at the 1% level for Bitcoin, Ether, and Ripple, and at the 10% level for Litecoin, suggesting that there is statistically significant asymmetric effect between good and bad news in the conditional volatility of the price returns of these four cryptocurrencies. However, the asymmetry parameter estimate is not significant for Stellar Lumen, and hence negative values of the residuals do not have a different effect in the current conditional volatility than positive ones in the Stellar Lumen market.

Similar results are obtained for the cryptocurrencies' conditional covariances, which are significantly affected by both cross products of previous error terms and previous conditional covariance terms. This result supports the findings of the studies of Fry and Cheah (2016), Ciaian et al. (2018), Corbet et al. (2018b), and Katsiampa (2018) on the interlinkages within the cryptocurrency market. The conditional covariances also capture asymmetric effects of past shocks accordingly.

Table 3

Asymmetric Diagonal BEKK model parameter estimates

Panel A					
	Bitcoin	**Ether**	**Ripple**	**Litecoin**	**Stellar**
c_{ii}	0.002510***	0.002901**	-0.002283***	-0.000126	-0.001904
$\widetilde{w}_{ij}$	0.000044***	0.000015	0.000011	0.000028***	0.000024

		0.000539***	0.000034	0.000022	0.000126*
			0.000188***	0.000012	0.000069**
				0.000031***	0.000024
					0.000607***
a_{ii}	0.472846***	0.579671***	0.460279***	0.435956***	0.656609***
d_{ii}	0.274221***	0.313344***	0.249989***	0.109645*	0.040756
β_{ii}	0.933842***	0.896910***	0.915857***	0.943062***	0.876848***
	t-Distribution (Degrees of Freedom)		2.522044		

Panel B

LL	8354.125	BIC	-17.93317
AIC	-18.12228	HQ	-18.05011

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

Variance specification: $h_{it} = \widetilde{w}_{ii} + {a_{ii}}^2 {\varepsilon_{it-1}}^2 + {d_{ii}}^2 {\eta_{it-1}}^2 + {\beta_{ii}}^2 h_{it-1}$.

Covariance specification: $h_{ijt} = \widetilde{w}_{ij} + a_{ii} a_{jj} \varepsilon_{it-1} \varepsilon_{jt-1} + d_{ii} d_{jj} \eta_{it-1} \eta_{jt-1} + \beta_{ii} \beta_{jj} h_{ijt-1}$.

Table 4

Conditional variance equations - substituted coefficients

Bitcoin	$h_{11,t} = 0.00004 + 0.2236\varepsilon_{1,t-1}^2 + 0.0752{\eta_{1t-1}}^2 + 0.8721 h_{11,t-1}$
Ether	$h_{22,t} = 0.0005 + 0.3360\varepsilon_{2,t-1}^2 + 0.0982{\eta_{2t-1}}^2 + 0.8044 h_{22,t-1}$
Ripple	$h_{33,t} = 0.0002 + 0.2119\varepsilon_{3,t-1}^2 + 0.0625{\eta_{3t-1}}^2 + 0.8388 h_{33,t-1}$
Litecoin	$h_{44,t} = 0.00003 + 0.1901\varepsilon_{4,t-1}^2 + 0.0120{\eta_{4t-1}}^2 + 0.8894 h_{44,t-1}$
Stellar	$h_{55,t} = 0.0006 + 0.4311\varepsilon_{5,t-1}^2 + 0.0017{\eta_{5t-1}}^2 + 0.7689 h_{55,t-1}$

Table 5

Conditional covariance equations - substituted coefficients

	Bitcoin
Ether	$h_{12,t} = 0.00002 + 0.2741\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 0.0859\eta_{1t-1}\eta_{2t-1} + 0.8376 h_{12,t-1}$
Ripple	$h_{13,t} = 0.00001 + 0.2176\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 0.0686\eta_{1t-1}\eta_{3t-1} + 0.8553 h_{13,t-1}$
Litecoin	$h_{14,t} = 0.00003 + 0.2061\varepsilon_{1,t-1}\varepsilon_{4,t-1} + 0.0301\eta_{1t-1}\eta_{4t-1} + 0.8807 h_{14,t-1}$

Stellar	$h_{15,t} = 0.00002 + 0.3105\varepsilon_{1,t-1}\varepsilon_{5,t-1} + 0.0112\eta_{1t-1}\eta_{5t-1} + 0.8188h_{15,t-1}$
	Ether
Ripple	$h_{23,t} = 0.00003 + 0.2668\varepsilon_{2,t-1}\varepsilon_{3,t-1} + 0.0783\eta_{2t-1}\eta_{3t-1} + 0.8214h_{23,t-1}$
Litecoin	$h_{24,t} = 0.00002 + 0.2527\varepsilon_{2,t-1}\varepsilon_{4,t-1} + 0.0344\eta_{2t-1}\eta_{4t-1} + 0.8458h_{24,t-1}$
Stellar	$h_{25,t} = 0.0001 + 0.3806\varepsilon_{2,t-1}\varepsilon_{5,t-1} + 0.0128\eta_{2t-1}\eta_{5t-1} + 0.7865h_{25,t-1}$
	Ripple
Litecoin	$h_{34,t} = 0.00001 + 0.2007\varepsilon_{3,t-1}\varepsilon_{4,t-1} + 0.0274\eta_{3t-1}\eta_{4t-1} + 0.8637h_{34,t-1}$
Stellar	$h_{35,t} = 0.00007 + 0.3022\varepsilon_{3,t-1}\varepsilon_{5,t-1} + 0.0102\eta_{3t-1}\eta_{5t-1} + 0.8031h_{35,t-1}$
	Litecoin
Stellar	$h_{45,t} = 0.00002 + 0.2863\varepsilon_{4,t-1}\varepsilon_{5,t-1} + 0.0045\eta_{4t-1}\eta_{5t-1} + 0.8269h_{45,t-1}$

The plots of the conditional variances and covariances of the price returns of the five cryptocurrencies are illustrated in Figure 2. With regards to the volatility plots, it can be noticed that for Ripple, Litecoin, and Stellar Lumen increased levels of volatility are observed from 2017 onwards, which could be the result of the increased media coverage and popularity of cryptocurrencies bringing in an influx of new users since Bitcoin's price exceeded the $1000 threshold for the first time in 3 years on 3rd January 2017. It can also be noticed that Bitcoin is the cryptocurrency with the largest amount of spikes in its conditional variance. More specifically, two remarkable spikes in the Bitcoin conditional volatility series occurred on 21st July and 15th September 2017 which seem to be associated with the effects of news related to Bitcoin's miners starting signalling for the controversial scaling proposal Segwit2x earlier, which later resulted in a Bitcoin hard fork splitting it into Bitcoin and Bitcoin Cash, and the fact that Chinese authorities shat down China-based cryptocurrency exchanges on 15th September 2017, respectively. These spikes were also found in the study of Katsiampa (2018). Another spike in the volatility of Bitcoin is observed on 17th January 2018, one day after Bitconnect - an anonymously-run cryptocurrency exchange - announced it would shut down its operation after regulators issued a cease and desist order against it as it was suspected of being fraudulent. However, the two largest spikes in the Bitcoin volatility series occurred in December 2017 and February 2018 when the conditional variance of the Bitcoin price returns rose to unprecedented levels. The former spike seems to be linked to the Chicago Board Options Exchange (CBOE), the world's largest options exchange, launching Bitcoin futures on 10th December 2017, while the latter spike seems to be associated with the fact that several major US and UK banks banned customers from purchasing cryptocurrencies using credit cards on 5th February 2018. Two spikes in September and December 2017 can also be noticed in the conditional variance of Litecoin. From the evolution of the conditional volatility of Litecoin, another spike, which is associated with a sudden price surge, can be further observed at the end of March 2017. This price surge could be linked to the fact that Litecoin started signalling Segregated Witness activation on 30th March 2017, which is a proposal for improvement of the Bitcoin network in terms of handling greater trading volumes. Two large spikes, which took place in June 2016 and March 2017, can also be observed in the conditional volatility of the Ether price returns. The former seems to be linked to the fact that the DAO, the distributed autonomous organisation that had collected over $150m worth of Ether, was hacked on 17th June 2016, while the latter seems to be associated with the effects of rumours about a potential hard fork execution of Bitcoin Unlimited, one of the two existing systems at the time, which started in mid-March 2017, resulting in sharp declines in Bitcoin's price but in increases in the price of other cryptocurrencies like Ether, in order for Bitcoin traders to offset some of their exposure in case of a hard fork, with Ether appearing to be the most promising alternative, especially since the formation of the Enterprise Ethereum Alliance, a group of global enterprises dedicated to developing ethereum into an enterprise grade blockchain. On the other hand, the conditional variances of Ripple and Stellar Lumen exhibit only one important spike each taking place in the beginning of April and beginning of May 2017, respectively. While the debate continued within the Bitcoin community during March and April 2017, several altcoins, including Ripple, experienced a significant surge in overall value. However, the spike appearing in the volatility plot of Ripple seems to be related to the effects of regular news related to several major banks joining the Ripple network. For instance, in late March 2017 Japan's MUFG's Bank of Tokyo-Mitsubishi UFJ (BTMU) publicly announced that it would join Ripple's Global Payments Steering Group, an interbank group for global payments system that is based on distributed financial technology. On the other hand, the spike appearing in the conditional variance plot of Stellar Lumen seems to be associated with the presentation of the Stellar Consensus Protocol, which forms the backbone of the Stellar payment network where it secures financial transactions, at the Interdisciplinary Centre for Security, Reliability and Trust. An overview of cryptocurrency related events which seem to have caused increased levels of cryptocurrency price volatility can be found in Table B.1 (Appendix B).

Nevertheless, it is worth noting that there are several other events that occurred during the sample period which interestingly do not seem to have caused significant spikes in the conditional volatility of the cryptocurrencies under investigation[3]. According to Feng et al. (2018), who assessed informed trades in trading data of Bitstamp ahead of cryptocurrency-related events by using transaction data and found evidence of informed trading in the Bitcoin market ahead of cryptocurrency-related negative Bitcoin market events and ahead of large positive events, a small event may not even lead to price appreciation in Bitcoin's volatile market, while large events are supposed to bring higher profits of informed trading. The authors further argued that some of the insiders who have prior information of minor events probably select not to trade on this information and that only the informed traders of large events build positions before the events, and found that insiders of large positive news prefer to build their position two days before the event, while insiders of large negative news prefer to trade at the day before the event.

It can also be noticed from Figure 2 that the conditional covariances between the different pairs of cryptocurrencies are time-varying and mostly positive. Interestingly, distinct spikes in the conditional covariances between the price returns of Bitcoin and the price returns of any of the other four cryptocurrencies considered in this study are observed in mid-September 2017 and seem to be linked to China banning Bitcoin trading. Spikes are also noticed in mid-September 2017 in the conditional covariances of all the other pairs of cryptocurrencies except for the conditional covariance of Ripple and Stellar Lumen. Moreover, increased levels of conditional covariances between Bitcoin and all the altcoins are observed in the beginning of February 2018 and could be associated with news related to major US and UK banks banning customers from purchasing cryptocurrencies using credit cards. Elevated conditional covariance levels between Bitcoin and all the altcoins as well as between Ether and all the other cryptocurrencies are also noticed in mid-January 2018 and coincide with Bitconnect's announcement of shutting down its cryptocurrency exchange and lending operation. Increased levels in the conditional covariance between Ether and Ripple as well as in the conditional covariances between Litecoin and all the altcoins can also be observed on the launch of Bitcoin futures in December 2017, with the conditional covariance of Bitcoin and Litecoin becoming negative, though. Indeed, Akyildirim et al. (2019) found that information flows and price discovery were transmitted from Bitcoin futures to spot markets. A spike can be further observed in the conditional covariances of Stellar Lumen and all the other altcoins on 8th May

[3] Such events include the U.S. Securities and Exchange Commission denying Intercontinental Exchange Inc's NYSE Arca exchange the ability to list and trade the SolidX Bitcoin Trust, an exchange-traded product that would trade like a stock and track the digital asset's price, in March 2017 (http://www.reuters.com/article/us-bitcoin-etp-idUSKBN16Z2HH/ accessed 31st May 2018).

2017, which occurred on the day the Stellar Consensus Protocol was presented at the Interdisciplinary Centre for Security, Reliability and Trust. Finally, a spike is noticed in the conditional covariances between Ripple and all the other altcoins in the beginning of April 2017, although the spike in the conditional covariance between Ripple and Ether was negative.

It is also worth noting that, although the cryptocurrencies' conditional covariances are not stable over time, increasing levels of volatility co-movements, and thus of interconnectivity, are observed during the second half of the sample period, and specifically from 2017 onwards, as illustrated in Figure 2. This finding raises questions regarding the practical viability and usage of cryptocurrencies for portfolio diversification in portfolios consisting of cryptocurrecies solely and has therefore important implications for investors. This result is consistent with the study of Gkillas and Katsiampa (2018) who argued that investors in cryptocurrencies are exposed to a highly undifferentiated risk.

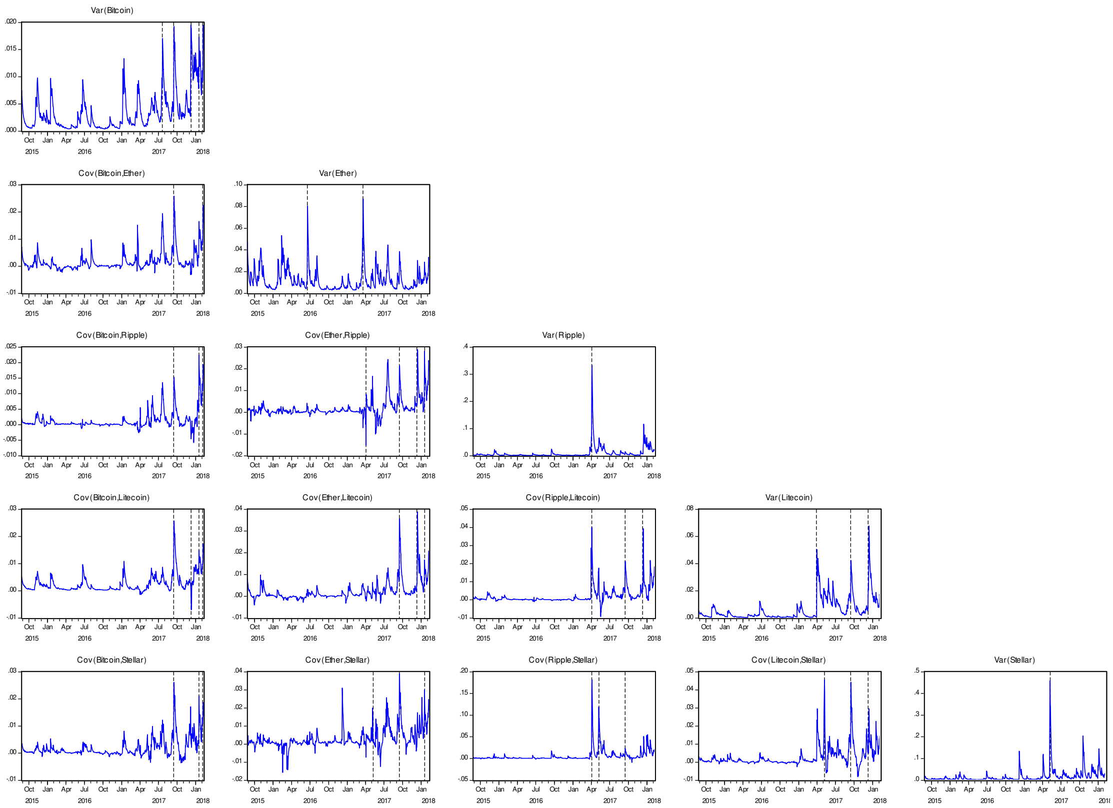


Fig. 2 Conditional variances and covariances

In order to investigate whether any events have caused instability in the conditional variances, sequential Bai-Perron tests have also been performed in the cryptocurrencies' volatility series. Table 6 presents the test results. According to the results, Ether, Ripple, and Stellar Lumen exhibit no structural breakpoint in their conditional variances. However, for

Bitcoin and Litecoin, the null hypothesis of no breakpoint is rejected in favour of the alternative hypothesis of one breakpoint, suggesting that Bitcoin and Litecoin exhibit one structural break each in the conditional variance. It can be noticed, though, that for Litecoin the null hypothesis of no breakpoint is rejected at the 1% level of significance, while for Bitcoin the null hypothesis is rejected at the 10% level. The breakpoint dates identified by the Bai-Perron tests for Bitcoin and Litecoin are 16th July 2017 and 31st March 2017, respectively, which coincide with news related to Bitcoin's controversial scaling proposal Segwit2x and Litecoin signalling Segregated Witness activation. These results are confirmed by the Chow test, which rejects the null hypothesis of no structural change on the specified dates at the 1% level.

Table 6

Breakpoint tests in conditional variances

	Bai-Perron test Scaled F-statistic	Bai-Perron test Breakpoint date	Chow test F-statistic
Bitcoin	8.331290*	16/7/2017	477.6640***
Ether	1.184011	None	
Ripple	2.526508	None	
Litecoin	14.16537***	31/3/2017	664.8907***
Stellar	3.100936	None	

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

Finally, the plots of the conditional correlations (Figure 3) confirm time-varying correlations between the different pairs of cryptocurrencies. Moreover, although the conditional correlations between the different pairs of cryptocurrencies fluctuate in both the positive and negative regions, positive correlations mostly exist as might have been expected. More specifically, the conditional correlation between Bitcoin and Ether ranges from -0.38 to 0.96, between Bitcoin and Ripple from -0.41 to 0.87, between Bitcoin and Litecoin from -0.28 to 0.90, and between Bitcoin and Stellar Lumen from -0.29 to 0.81. It can also be noticed that around mid-September 2017 high conditional correlations were observed for all the pairs of cryptocurrencies. This seems to reflect once again the fact that Chinese authorities shat down China-based cryptocurrency exchanges, which took place in September 2017.

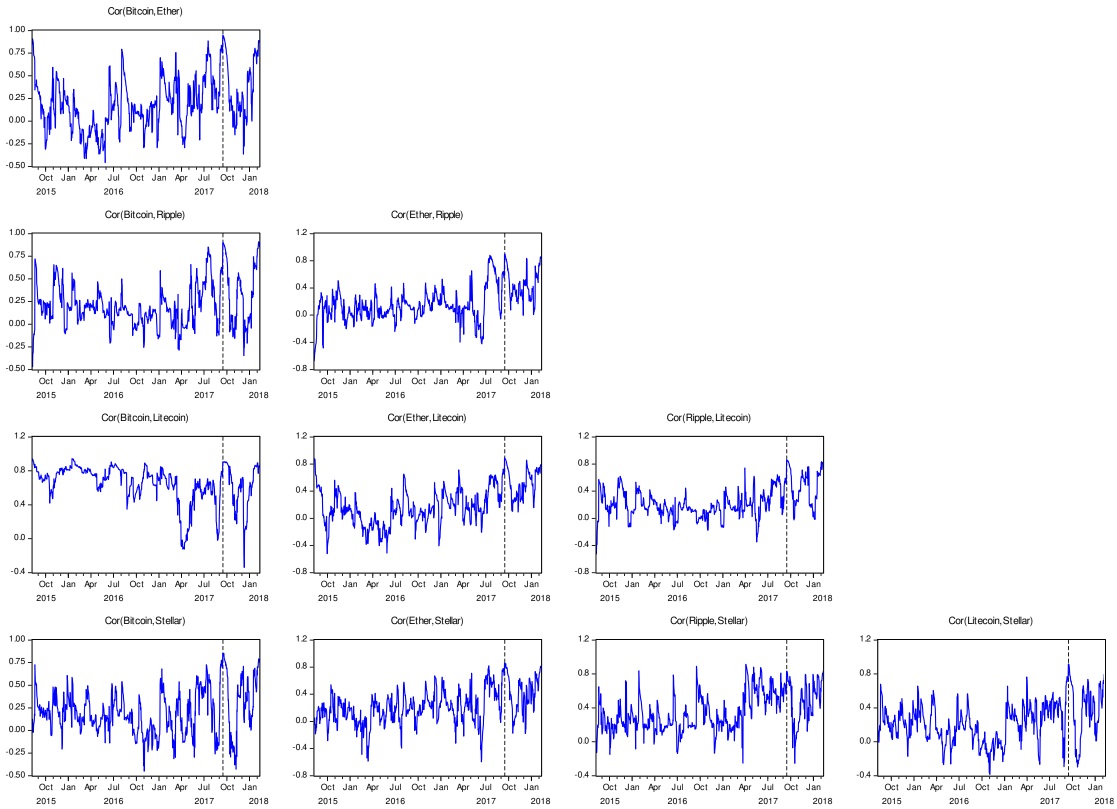


Fig. 3 Conditional correlations

5. Conclusions

Motivated by the recent cryptocurrency price fluctuations and the interdependencies of cryptocurrencies, this study sheds light on volatility dynamics within cryptocurrency markets. By employing an Asymmetric Diagonal BEKK model, this paper examined volatility co-movements between five major cryptocurrencies, namely Bitcoin, Ether, Ripple, Litecoin, and Stellar Lumen, while accounting for asymmetric effects of negative and positive shocks in the conditional variances and covariances.

The empirical findings confirmed the non-normality and heteroskedasticity of the cryptocurrencies' price returns complementing earlier studies. Moreover, it was shown that the conditional variances of all the five cryptocurrencies considered in this study are significantly affected by both past squared errors and past conditional volatility, with traders paying the most attention to news arriving in the Stellar Lumen market, while shocks persist the most in the Litecoin market. It was further found that the conditional volatility of Bitcoin, Ether, Ripple, and Litecoin also captures asymmetric effects between good and bad news, while for Stellar Lumen asymmetric past shocks do not have significant effects in the current conditional volatility.

In addition, the multivariate framework has enabled not only the study of cryptocurrencies' individual conditional variances but also the investigation of the movements of their conditional covariances and correlations. According to the empirical findings, the conditional covariances were found to be significantly affected by cross products of previous error terms and previous covariance terms, and hence significant volatility co-movements between cryptocurrencies exist, while capturing asymmetric effects of previous shocks accordingly. Furthermore, it was shown that time-varying conditional correlations exist and are mostly positive. Consequently, conditional correlations between cryptocurrencies do not remain constant but rather behave differently over different time periods. The above results support the findings of previous studies on interdependencies within cryptocurrency markets, and this paper thus contributes to the literature on the interconnectedness of cryptocurrencies.

Finally, this study attempted to identify spikes in the cryptocurrencies' volatility dynamics and to examine whether any events caused instability in the conditional variances. Several spikes were identified in the cryptocurrencies' conditional variance, covariance and correlation plots, indicating that they seem to have been susceptible to various news related to cryptocurrencies, such as Chinese authorities shutting down China-based cryptocurrency exchanges, with news related to Bitcoin's controversial scaling proposal Segwit2x in July 2017 and Litecoin signalling Segregated Witness activation in March 2017 resulting in structural breakpoints in the conditional variance of Bitcoin and Litecoin, respectively.

As cryptocurrencies are increasingly used for investment and speculation purposes, understanding their price volatility movements and co-movements is of great importance, since volatility dynamics can affect investment decisions. The results of this study provide insights into interlinkages within cryptocurrency markets and could thus have important implications for traders, investors and risk managers alike.

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Appendix A - Description of cryptocurrencies

In this section, a short description of the five cryptocurrencies considered in this study, namely Bitcoin, Ether, Ripple, Litecoin, and Stellar Lumen, is presented[4]. Although there are currently more than 1600 cryptocurrencies in existence, these five cryptocurrencies together represent 67.1% of the total cryptocurrency capitalisation at present (coinmarketcap.com accessed on 31st May 2018).

1) Bitcoin (BTC)

Originally introduced in 2008 by an unknown person or group of individuals, under the alias Satoshi Nakamoto, Bitcoin constitutes the first implementation of a cryptocurrency. It is based on Blockchain and employs peer-to-peer technology in order to allow payments to be sent online without the need for any intermediary. Despite the huge growth of cryptocurrency markets, Bitcoin still remains the most popular coin, with a market capitalisation which is currently estimated at $128.8 billion accounting for 39% of the total market capitalisation (coinmarketcap.com accessed on 31st May 2018)[5]. There are currently more than 17 million bitcoins in circulation, with the maximum limit being 21 million coins (coinmarketcap.com accessed on 31st May 2018). Recently there has been an increase in merchants accepting Bitcoin as a form of payment, as a result of the remarkable increase in public interest. More information about Bitcoin and its underlying technology can be found in, e.g., Frisby (2014), Dwyer (2015), Böhme et al. (2015), and Karame and Androulaki (2016), among others.[6]

2) Ether (ETH)

Initially released in July 2015, Ethereum is an open-source Blockchain-based platform featuring smart contracts, with Ether representing the digital token of the platform. Despite its relatively recent launch, Ether constitutes the second largest cryptocurrency with an estimated market capitalisation of $56.5 billion, which currently accounts for around 17% of the total estimated cryptocurrency market capitalisation, and a circulating supply of around 100 million coins (coinmarketcap.com accessed on 31st May 2018), a figure that is more than five times

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[4] For a more extensive description of cryptocurrencies and their technology, see, e.g., Narayanan et al. (2016).

[5] It should be noticed that Bitcoin represented about 94% of the total estimated market capitalisation in May 2013, and its market share drop resulted from the increase in popularity and, thus, in market capitalisation of more recently launched cryptocurrencies.

[6] For a description of Bitcoin's mining process, see Kroll et al. (2013) and Böhme et al. (2015).

higher than that of Bitcoin. Recently several industry giants supported Ethereum through the Enterprise Ethereum Alliance foundation.

3) Ripple (XRP)

Released in 2012, Ripple is built on the most advanced blockchain technology. It has been increasingly adopted by banks as settlement infrastructure technology, as it connects banks, payment providers, digital asset exchanges and corporates via the RippleNet, while its aim is to improve the speed of financial transactions, and mainly international banking transactions, with payments settling in only four seconds. Ripple can be used as a bridge currency for real-time settlement, allowing for efficient cross-border payments for financial institutions (Corbet et al., 2018c). As of 31st May 2018, Ripple is the third largest coin in terms of market capitalisation, which is estimated at $24 billion, with around 39 billion coins currently in circulation and a maximum limit of 100 billion coins (coinmarketcap.com accessed on 31st May 2018).

4) Litecoin (LTC)

Litecoin was initially released in 2011. It is an open source, fully decentralised global payment network which is based on Blockchain. The digital currency enables instant, near-zero cost global payments. Litecoin features faster transaction confirmation times and improved storage efficiency than Bitcoin. More specifically, the main differences between Bitcoin and Litecoin include the block generation time, which is 2.5 minutes per block for Litecoin compared to 10 minutes per block for Bitcoin, and the maximum limit of coins, which is 84 million for Litecoin, a figure that is four times higher than that of Bitcoin (Lee et al., 2018). Litecoin's market capitalisation is currently estimated at $6.8 billion and has around 57 million coins in circulation (coinmarketcap.com accessed on 31st May 2018).

5) Stellar Lumen (XLM)

Released in 2014, the Stellar network is an open source, distributed and community owned technology that processes financial transactions, with the platform aiming to connect banks, payment systems and people. However, Stellar aims to contribute to financial inclusion focusing on developing markets. Lumen constitutes the digital coin of the Stellar network and can be used for fast mobile payments and micropayments with very small fees. Stellar Lumen's market capitalisation is currently estimated to be worth $5.4 billion with 18.6 billion coins in circulation and a maximum limit of 104 billion coins (coinmarketcap.com accessed on 31st May 2018).

Appendix B – Cryptocurrency related events

Table B.1

Cryptocurrency related events causing increased volatility levels

Date	**Event**
17/6/2016	The DAO, the distributed autonomous organisation that had collected over $150m worth of Ether, is hacked, sparking a broad market sell-off (https://www.coindesk.com/dao-attacked-code-issue-leads-60-million-ether-theft/ accessed on 31st May 2018).
17/3/2017	Bitcoin exchanges are preparing for a potential hard fork execution of Bitcoin Unlimited, one of the two existing systems at the time, following an attack that occurred on 15th March 2017 and that led to a 6-hour downtime for miners and node operators, with miners losing over $200,000 in revenue and nodes crashing (https://cointelegraph.com/news/community-reacts-to-bitcoin-unlimited-bug-calls-for-segwit-activation/ accessed on 31st May 2018). A group of nearly 20 exchanges releases contingency plans in the event that the Bitcoin network splits in two, creating two competing currencies (https://www.coindesk.com/bitcoin-exchanges-unveil-emergency-hard-fork-contingency-plan/ accessed on 31st May 2018). The potential of a hard fork results in sharp declines in Bitcoin's price but in increases in the price of other cryptocurrencies like Ether in order for Bitcoin traders to offset some of their exposure in case of a hard fork (https://www.cnbc.com/2017/03/17/bitcoin-price-blockchain-fork-ethereum.html/ accessed on 31st May 2018).
30/3/2017	While the debate continues within the Bitcoin community, several altcoins experience a significant surge in overall value. Litecoin starts signalling Segregated Witness activation (https://coindesk.com/litecoin-jump-70-market-cap-100-million/ accessed on 31st May 2018). Japan's MUFG's banking arm The Bank of Tokyo-Mitsubishi UFJ (BTMU) publicly announces that it is joining Ripple's Global Payments Steering Group (GPSG), an interbank group for global payments system that is based on distributed financial technology (https://cointelegraph.com/news/ripple-price-surge-continues-altcoin-takes-advantage-of-bitcoin-scaling-troubles/ accessed on 31st May 2018).
8/5/2017	Presentation of the Stellar Consensus Protocol at the Interdisciplinary Centre for Security, Reliability and Trust (wwwde.uni.lu/snt/news_events accessed on 31st May 2018).

16/7/2017	Bitcoin's miners start signalling for the controversial scaling proposal Segwit2x earlier (https://www.coindesk.com/bip91-begins-bitcoins-miners-signal-segwit2x-scaling-proposal-early/ accessed on 31st May 2018).
15/9/2017	Chinese authorities shut down China-based cryptocurrency exchanges (https://www.coindesk.com/document-lists-closure-steps-for-chinas-bitcoin-exchanges/ accessed on 31st May 2018).
10/12/2017	CBOE Bitcoin futures are launched (https://www.theguardian.com/business/live/2017/dec/11/bitcoin-price-futures-trading-begins-cryptocurrency-business-live/ accessed on 31st May 2018).
16/1/2018	Bitconnect announces it shuts down its operation after regulators from Texas and North Carolina issued a cease and desist order against it as it was suspected of being fraudulent (https://www.bloomberg.com/news/articles/2018-01-16/bitconnect-closes-exchange-as-states-warn-of-unregulated-sales/ accessed on 31st May 2018).
5/2/2018	Several major US and UK banks ban customers from purchasing cryptocurrencies using credit cards (https://www.businessinsider.com/bitcoin-ethereum-ripple-price-buying-cryptocurrencies-uk-banks-2018-2/ accessed on 31st May 2018).