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Time-varying dynamic conditional correlation between stock and cryptocurrency markets using the copula-ADCC-EGARCH model

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HIGHLIGHTS

- This study examines the time-varying asymmetric correlations between cryptocurrency and US stock markets.
- A copula-ADCC-EGARCH model is effectively utilized to capture the asymmetric relationship.
- Litecoin is the most effective hedge asset against the risk of US stock market.

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ABSTRACT

This study examines the time-varying correlations between six cryptocurrency and S&P 500 index markets using a copula-ADCC-EGARCH model. The increasing influence and usage of cryptocurrencies has led the notion in which it is regarded as risky assets. In order to maximize returns on investment, there must be hedging options to protect investors against potential risks. From empirical analysis, we find the overall time-varying correlations are very low, indicating that cryptocurrency serves as a hedge asset against the risk of S&P 500 stock market. We also show that volatilities respond more to negative shock as compared to positive shock in both markets. Furthermore, we identify Litecoin to be the most effective hedge asset against risk of S&P 500 index. Thus, we conclude that the cryptocurrency might be one of important elements in portfolio diversification.

1. Introduction

In recent years, the increasing prominence of cryptocurrencies[1] in the global financial system cannot be ignored.[2] As such, policymakers and academics have devoted more energy in trying to understand the dynamics and functionality

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[1] Other commonly used nomenclatures are digital currencies and virtual currencies. They are used inter-changeably in this study. Among the available proxies include Bitcoin, Ethereum, Litecoin, Ripple, Bitcoin Cash, Stellar, Cardano, Monero, Dash among others. However, Bitcoin accounts for 80% of the market capitalization [1].

[2] Between 2016 and 2017, there was about 1300% increment in the price of Bitcoin, with a market capitalization of about US$215 billion [2].

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of this financial series. In fact, cryptocurrencies offer several advantages as an innovative and efficient payment tool that helps develop into an alternative global monetary system [3]. Bitcoin, the most recognized and valuable of the cryptocurrencies available globally (https://coinmarketcap.com/coins/views/all/), possesses the characteristics of both a limited stock and inelasticity of supply in the short run [4]. This property of scarcity is one reason Bitcoin has been argued to be synthetic commodity money, as well as its sharing an absence of intrinsic value with fiat money [5]. Assuming its potential as synthetic commodity money, Weber [6] explores the possibility of a global Bitcoin standard. Furthermore, cryptocurrencies have been viewed as an alternative asset or diversification option by investors to reduce the exposed risk of their portfolios. Despite the major impact of cryptocurrencies, so far, they remain volatile and interdependent [7]. Therefore, the correlations of cryptocurrency are essential in determining diversification investment opportunities, assessing optimal hedging strategies, and preventing contagion effects. According to the overview of the literature, cryptocurrencies are associated with several macroeconomic variables and financial assets. Prior studies include commodity prices and Bitcoin [8–11] and Bitcoin and exchange rate [12–14]. The linkage between cryptocurrencies and stock markets has produced two strands of the literature. The first strand posits the strong relationship between the cryptocurrencies and stock markets (see [2,15,16]). The second strand of the literature concluded that there is a weak relationship between them [17–22]. Therefore, it can be concluded that this literature is not only immature but also not conclusive.

In this paper, we consider the role of cryptocurrency as the diversified portfolio investment to reduce the risk of stock market. Since cryptocurrencies have become an important investment asset in the financial mainstream, their prices and returns are invariably tied to the risk tolerances that support other traditional financial assets [23,24]. Having hedging options would be helpful for investors to minimize risks and thus yield maximum possible returns [25]. The literature on cryptocurrencies has focused analysing the role of bitcoin from portfolio investors' perspective, such as a safe haven asset, or a hedge against the risk of financial investments [26–28]. For example, bitcoin serves as a hedge against equities [15,29], currencies [14], and commodities [30] as well as a safe haven against financial assets [31,32].

Based on the foregoing discussion, the primary objective of this paper is to examine the time-varying correlations and conditional volatilities between the cryptocurrency and S&P 500 index returns. In particular, we investigate the hedge role of cryptocurrency against the risk of stock market using a copula-asymmetric dynamic conditional correlation (ADDC)-EGARCH model.

We contribute to the extant literature by examining the structure of time-varying conditional correlation between the cryptocurrency and stock markets using the copula-ADCC-EGARCH model. This copula-ADDC-EGARCH model allows us to capture both the time-varying nature and asymmetry of the cross-movement of volatilities between cryptocurrency and stock markets. We observe low time-varying correlations which is close to zero, indicating that cryptocurrency serves as a hedge asset against the risk of S&P 500 stock market. Furthermore, we calculate hedging ratios between six cryptocurrencies and S&P 500 index return pairs to investigate the diversification and hedging properties of cryptocurrency markets. According to our results, we found a time-varying low correlation, indicating that the cryptocurrency serves as a hedge asset against the risk of S&P 500 stock market. We identify that Litecoin is the most effective hedge investment against the risk of S&P 500 stock market.

The rest of the paper is structured as follows. Section 2 explains data and methodology. Section 3 discusses the empirical results. The final section presents some concluding remarks.

2. Data and methodology

2.1. Data

We employ the prices of S&P 500 index and six cryptocurrencies, namely, Ripple, Dash, Stellar, Litecoin, Ethereum, and Bitcoin, respectively. The daily closing prices span from 7 August 2015–15 June 2018. All cryptocurrency data were extracted from the website of the Coindesk Price index and daily S&P 500 index prices were sourced from the Thomson Reuters DataStream database. We compute the continuously compounded daily returns by taking the difference in the logarithms of two consecutive prices (index).

Table 1 presents the descriptive statistics of the return series. The summary statistics show the daily average returns are positive for all sample series over the sample period. The unconditional volatility (standard deviation) is the highest for Stellar and the lowest for S&P 500 index returns. Furthermore, all returns series are asymmetric and leptokurtic, as indicated by skewness and kurtosis. According to the Jarque–Bera test, the null of normal distributions applies for all return series. A close inspection on the linear correlation shows that S&P 500 returns are highly correlated with Dash, while the pair of S&P 500 and Ethererum shows the lowest level of correlation.

Fig. 1 shows the correlation between six cryptocurrencies and S&P 500 index returns with different rolling windows (25-day, 50-day, 100-day, and 150-day). In the shorter time window, the correlation coefficients widely oscillate around zero and show no pattern. As increase in longer time windows, we can see a clear and smooth correlation pattern and a much lower correlation between US stock and cryptocurrency markets than for shorter time window. This finding indicates that S&P 500 index provides a possible diversification benefit for cryptocurrency investors.

Table 1
Descriptive statistics.

	S&P 500	Ripple	Dash	Stellar	Litecoin	Ethereum	Bitcoin
Mean	0.00040	0.00581	0.00607	0.00634	0.00435	0.00719	0.00436
Maximum	0.03829	0.75083	0.39189	1.2992	0.53988	0.51083	0.22512
Minimum	−0.0418	−0.5474	−0.3283	−0.4296	−0.3951	−1.3635	−0.2387
Std. Dev.	0.00834	0.08715	0.06695	0.10971	0.06996	0.10153	0.04756
Skewness	−0.68925	2.1573	0.45652	3.2441	1.6928	−2.8495	−0.16528
Kurtosis	7.1477	19.807	7.5676	34.731	15.196	47.722	4.6176
Jarque–Bera	573.10***	9032.3***	650.90***	31469.***	5568.1***	69295.***	642.95***
P-value	[0.0000]	(0.0000)	[0.0000]	(0.0000)	[0.0000]	[0.0000]	[0.0000]
Correlations		0.05307	0.12205	0.04187	0.05895	0.00298	0.04992

Notes: Jarque–Bera statistics test for normality. The asterisk *** denotes the rejection of the null hypothesis at the 1% significance level.

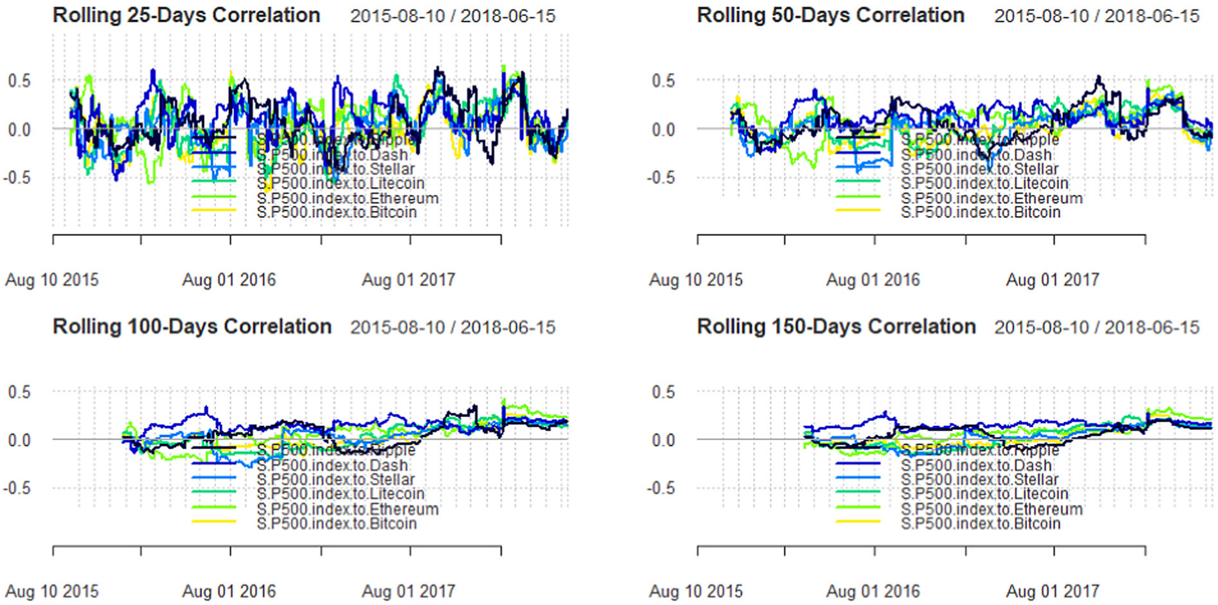

Fig. 1. Correlations between S&P 500 and cryptocurrency markets.

2.2. Copula-ADCC-EGARCH model

We initially use the DCC-EGARCH framework, which will be enhanced by considering some improvements such as the asymmetries and copulas. These enhancements will lead us to the proposed copula-ADCC-EGARCH model, which solves the mentioned problems.

In order to examine the DCC structure between the cryptocurrency and stock markets, we first estimate the ARMA-exponential GARCH (EGARCH) model of Nelson [33], which allows to capture asymmetry in volatility. We presume that the index return is expressed by an autoregressive moving average (ARMA (1, 1)) model as follows:

$$r_t = \mu + \xi_1 r_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1}, \quad t \in N \text{ with } \varepsilon_t = H_t^{1/2} z_t, \tag{1}$$

where H_t is the conditional covariance matrix of r_t and z_t follows the normal distribution. We estimate univariate EGARCH model. The expressions for h are univariate EGARCH models (H is a diagonal matrix). For the EGARCH (1, 1) processes as specified in Eq. (2).

$$ln\left(h_{i,t}\right) = \omega_i + \beta_i ln\left(h_{i,t-1}\right) + \gamma_i \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \alpha_i \left[\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}}\right], \tag{2}$$

The EGARCH specification ensures that the conditional variances are always positive and no restrictions on coefficients need to be imposed. For $\gamma > 0$, negative shocks will obviously have a bigger impact on future volatility than positive shocks of the same magnitude.

Now, we obtain the dynamic correlations using the conditional variance–covariance matrix, H_t, can be written as:

$$H_t = D_t^{1/2} R_t D_t^{1/2}, \tag{3}$$

Table 2
Empirical results from the copula–DCC–EGARCH model.

	Ripple	Dash	Stellar	Litecoin	Ethereum	Bitcoin	S&P500
μ	0.0036***	0.0041***	0.0010**	0.0024***	0.0029	0.0027***	0.0003***
	(0.0007)	(0.0010)	(0.0023)	(0.0006)	(0.0030)	(0.0012)	(0.0001)
AR(1)	0.9598***	−0.9259***	0.2131***	0.2642***	0.0894***	−0.8879***	−0.0154***
	(0.0072)	(0.0188)	(0.0432)	(0.0182)	(0.0276)	(0.0143)	(0.0023)
MA(1)	−0.9458***	0.8911***	−0.2883***	−0.3574***	−0.1087***	0.8723***	−0.0857***
	(0.0001)	(0.0231)	(0.0306)	(0.0274)	(0.0264)	(0.0159)	(0.0109)
ω	−0.0460***	−0.2958**	−0.6692**	−0.1381***	−0.6408***	−0.1669	−0.5587
	(0.0028)	(0.1560)	(0.3865)	(0.0167)	(0.2258)	(0.1903)	(0.0872)
α_1	0.0997***	0.0269	0.0511***	0.0967***	0.0029***	0.1111***	−0.1990***
	(0.0172)	(0.0333)	(0.0560)	(0.0397)	(0.0405)	(0.0310)	(0.0311)
β_1	0.9920	0.9470***	0.8625***	0.9761***	0.8727***	0.9737***	0.9439
	(0.000)	(0.0278)	(0.0808)	(0.0017)	(0.0449)	(0.0313)	(0.0090)
γ_1	0.0530***	0.2433***	0.4625***	0.2591	0.3850***	0.3701***	0.2283***
	(0.0024)	(0.0918)	(0.1503)	(0.0693)	(0.0744)	(0.1657)	(0.0426)
skew	0.4015***	0.1765	0.3632***	0.1962***	0.1381	−0.1083	−0.1294***
	(0.0530)	(0.0672)	(0.0764)	(0.0667)	(0.1007)	(0.0963)	(0.0649)
shape	0.2558***	0.6630***	0.3029***	0.1823***	0.3755***	0.2915***	0.9960***
	(0.0645)	(0.1475)	(0.0702)	(0.0474)	(0.1105)	(0.0652)	(0.3422)
$dcca_1$	0.0263***						
	(0.0063)						
$dccb_1$	0.9628***						
	(0.0135)						
mshape	11.873***						
	(1.5102)						
Information criteria							
Akaike	−27.031						
Bayes	−26.589						
Shibata	−27.048						
Hannan–Quinn	−26.861						

Notes: The asterisks *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

where R_t is the 2×2 time-varying correlation matrix, while the diagonal matrix of the conditional variances is given by $D_t = diag\left(h_{i,t}, \ldots, h_{n,t}\right)$. [34] models the right-hand side of Eq. (4) rather than H_t directly by proposing the following dynamic correlation structure:

$$R_t = diag\,(Q_t)^{-1/2}\, Q_t diag\,(Q_t)^{-1/2}\,, Q_t \qquad = \left[q_{ii,t}\right] = (1 - dcca_1 - dccb_1)\, S + dcca_1 u_{t-1}u'_{t-1} + dccb_1 Q_{t-1}, \tag{4}$$

where Q_t defines the covariance matrix of the standardized residuals $u_t = \left(u_{i,t}, \ldots, u_{k,t}\right)$. $S = Cov\left(u_t u'_t\right) = E\left(u_t u'_t\right)$ is the 2×2 unconditional covariance matrix of u_t, and $dcca_1$ and $dccb_1$ are non-negative scalars and $dcca_1 + dccb_1 < 1$. The residuals of u_t follow joint distribution with a skew Student-t distribution.[3]

In order to estimate asymmetries in volatility, we apply the ADDC model of [36] which modifies the DCC model described by Eqs. (4) and (5) as:

$$Q_t = \left(\overline{P} - A'\overline{P}A - B'\overline{P}B - G'\overline{N}G\right) + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + G'k_{t-1}k'_{t-1}G + B'Q_{t-1}B, \tag{5}$$

where, $\overline{N}$ and G are the unconditional correlation matrices, $k_t = I\left[u_t < 0\right]$ is equal to 1, and 0 otherwise. In the ADCC (1, 1) model, the matrices A, B, and G is measured by scalars (a, b, and g). To secure the positive definite constraint of Q_t, the intercept, $\overline{P} - A'\overline{P}A - B'\overline{P}B - G'\overline{N}G$ must be positive semi-definite and the initial covariance matrix Q_0 positive definite.

We employ the copula method to capture the extreme dependence and co-movement between six cryptocurrencies and stock market index. To estimate the copula and marginal density parameters, we apply Sklar's theorem [37], which asserts a joint distribution $F_{XY}\left(x, y\right)$ of two random variables X and Y can be expressed as:

$$F_{XY}\left(x, y\right) = C\left(u, v\right) \tag{6}$$

where $C\left(u, v\right)$ for $u = F_X\left(x\right)$ and $v = F_Y\left(y\right)$ is a bivariate copula function with uniform marginal distributions. It is uniquely determined for the ranks $RanF_X \times RanF_Y$ when the margins are continuous. In addition, the joint probability density $f_{XY}\left(x, y\right)$ can be obtained from the copula density, $c\left(u, v\right)$ as:

$$f_{XY}\left(x, y\right) = c\left(u, v\right) f_X\left(x\right) f_Y\left(y\right) \tag{7}$$

[3] See the further details on the skew Student-t distribution [35].

Table 3
Empirical results from copula–ADCC–EGARCH model.

	Ripple	Dash	Stellar	Litecoin	Ethereum	Bitcoin	S&P500
μ	0.0036***	0.0041***	0.0010	0.0023***	0.0029	0.0027***	0.0004***
	(0.0007)	(0.0010)	(0.0023)	(0.0005)	(0.0030)	(0.0012)	(0.0001)
AR(1)	0.9598***	−0.9259***	0.2131***	0.2642***	0.0894***	−0.8879***	−0.0154***
	(0.0073)	(0.0188)	(0.0429)	(0.0181)	(0.0276)	(0.0143)	(0.0023)
MA(1)	−0.9458***	0.8911***	−0.2883***	−0.3574***	−0.1087***	0.8723***	−0.0857***
	(0.0001)	(0.0231)	(0.0306)	(0.0273)	(0.0264)	(0.0159)	(0.0109)
ω	−0.0460***	−0.2958***	−0.6692**	−0.1381***	−0.6408***	−0.1669	−0.5587***
	(0.0028)	(0.1560)	(0.3868)	(0.0166)	(0.2260)	(0.1903)	(0.0871)
α_1	0.0997***	0.0269	0.0511	0.0967**	0.00290	0.1111***	−0.1991***
	(0.0172)	(0.0332)	(0.0555)	(0.0399)	(0.0402)	(0.0311)	(0.0311)
β_1	0.9920***	0.9470***	0.8625***	0.9761***	0.8727**	0.9737***	0.9439***
	(0.0001)	(0.0279)	(0.0808)	(0.0017)	(0.0449)	(0.0313)	(0.0090)
γ_1	0.0530***	0.2433***	0.4625***	0.2591***	0.3850***	0.3701***	0.2283***
	(0.0024)	(0.0917)	(0.1501)	(0.0695)	(0.0745)	(0.1653)	(0.0425)
skew	0.4015***	0.1765	0.3632***	0.1962***	0.1381	−0.1083	−0.1294**
	(0.0530)	(0.0666)	(0.0753)	(0.0667)	(0.0999)	(0.0960)	(0.0649)
shape	0.2558***	0.6630***	0.3029***	0.1823***	0.3755***	0.2915***	0.9960***
	(0.0646)	(0.1476)	(0.0702)	(0.0474)	(0.1098)	(0.0653)	(0.3420)
$dcca_1$	0.0205***						
	(0.0055)						
$dccb_1$	0.9550***						
	(0.0228)						
$dccg_1$	0.0293**						
	(0.0123)						
mshape	11.8984***						
	(1.6012)						
Information criteria							
Akaike	−27.065						
Bayes	−26.615						
Shibata	−27.082						
Hannan–Quinn	−26.891						

See Table 2.

where $c(u, v) = \partial^2 C(u, v) / \partial u \partial v$, and $f_X(x) f_Y(y)$ are the marginal densities of the X and Y variables. In order to model the conditional correlation and dependence, simultaneously, it is necessary to construct the joint CDF of residuals from the first stage of DCC approach and use them to complete the second stage of DCC model.[4]

3. Empirical results

Tables 2 and 3 report the estimates between six cryptocurrencies and US stock markets using a copula-DCC-EGARCH and copula-ADDC-EGARCH models, respectively.[5] Results indicate the ARCH and GARCH values are significant and the sum of the alpha (α_i) and beta (β_i) values are statistically significant in the conditional volatility of each market. This finding implies that volatility seems to be more dependent of previous shocks (α_i) and conditional variances (β_i). The leverage effect coefficient (γ_1) is positive and statistically significant at the 1% level for all markets, suggesting that negative shocks have a greater impact on the conditional volatility than positive shocks of the same magnitude. The significance of *skew* and *shape* indicates the skewed Student-t distribution is the best fit for the residuals based on the DCC and ADCC models.

As shown in Tables 2 and 3, all $dcca_1$ coefficients are positive and significant, underlying the importance of shocks between the cryptocurrency and US stock markets. Likewise, all $dccb_1$parameter are significant and very close to one, confirming the higher persistence of volatility between cryptocurrency and US stock markets. It is worth noting that the significance of the parameters $dcca_1$ and $dccb_1$ confirms the appropriateness of the copula-ADCC-EGARCH model. We also show that the copula-ADCC-EGARCH model is a useful to capture the asymmetry due to the significance of $dccg_1$. The joint distribution coefficient of *mshape* shows the best fit of the copula-ADCC-EGARCH based on student-t copula, i.e., the best fit for both marginal distributions and joint distribution. Due to the lowest values of information criteria (Akaike, Bayes, Shibata, and Hannan–Quinn), The copula-ADCC-EGARCH model is a better for modelling time-varying conditional variances of cryptocurrency and US stock markets

Fig. 2 exhibits the dynamic conditional correlation and estimated conditional volatility between S&P 500 index and six cryptocurrency returns, which obtained from the copula-ADCC-EGARCH model. As shown in Figs, the copula-ADCC-EGARCH model is a useful tool to capture the market instability and the events that affect the volatilities of both

4 For more details, see [38].

5 We have estimated the bivariate copula-DCC-EGARCH and copula-ADDC-EGARCH models between each S&P 500 and cryptocurrency pair. To save our space, we do not report these results, making them available on demand.

Table 4
The results of hedge ratio—based on the copula-ADCC-EGARCH model.

Series pairs	Hedge ratio
S&P 500/Ripple	−0.01154
S&P 500/Dash	0.011364
S&P 500/Stellar	−0.01221
S&P 500/Litecoin	0.002075
S&P 500/Ethereum	−0.00299
S&P 500/Bitcoin	−0.0113

cryptocurrencies and S&P 500. For example, most cryptocurrencies show higher conditional volatility than S&P 500. Interestingly, the conditional volatilities of cryptocurrency exhibit several distinct spikes in 2017–2018, corresponding to the emergence of hard fork, China banning cryptocurrency trading, and the announcement of Bitcoin futures trading in the CME Group Inc. Likewise, the ratios of Cryptocurrency*/S&P 500* show that the most cryptocurrencies are more volatile (risker) than S&P 500, while the highest peak is observed in 2017. In addition, the correlation coefficients are not constant, but vary greatly with time change in the pairwise cases of S&P 500 index and cryptocurrency markets, meaning that investors frequently change their portfolio structure. More importantly, we observe low time-varying correlations which is close to zero, indicating that cryptocurrency serves as a hedge asset against the risk of S&P 500 stock market. Thus, the dynamic conditional correlations reveal that investors adjust their portfolio structure accordingly. It is also important to compute hedge ratios, which are of concern to investors and portfolio managers.

Now, we consider the hedge ratios of Kroner and Sultan [39] to minimize the risk of this portfolio. We measure how much a long position (buy) of one dollar in the S&P 500 index should be hedged by a short position (sell) of βdollar in the cryptocurrency markets, where β is given by:

$$\beta = \frac{h^{Stock,Cypto}}{h^{Cypto}}, \tag{8}$$

where h^{Cypto}, and $h^{Stock,Cypto}$ are the conditional volatility of each cryptocurrency returns, and the conditional covariance between each cryptocurrency returns and the S&P 500 index returns.

Table 3 summarizes the values of the hedge ratios between cryptocurrency markets based on the copula-ADCC-EGARCH model. As shown in Table 3, the highest average hedge ratio (the most expensive hedge) is observed between S&P 500 and Dash (0.011364). This value indicates that a long position (buy) in the S&P 500 stock market should be shorted (sold) by a 1.1% portion of investment in the Dash market. In contrast, the lowest value of the hedge ratio in the S&P 500 (long)-Litecoin (short) pair is 0.002075, indicating that the Litecoin is the most effective hedge asset against the risk of S&P 500 stock market. (See Table 4.)

4. Conclusion

The paper is motivated by the recently increase in the influence and usage of cryptocurrencies as investment assets. Even though the literature on cryptocurrencies is in its embryonic state, existing studies have only ignored the risk elements accompanying cryptocurrencies an as "Stub" asset. Thus, we examine the correlation between cryptocurrencies and stock returns, while accounting for time varying dynamic conditional features and the role of asymmetry.

Our empirical results show the existence of asymmetric volatility and weak positive correlations between each cryptocurrency and S&P 500 pair. This finding indicates that volatilities respond more to negative shocks rather than positive shocks in both cryptocurrency and stock markets. The overall time-varying correlations is very low, indicating that cryptocurrency serves as a hedge asset against the risk of S&P 500 stock market. However, the sharp increase in correlation in 2017 is observed to be related to the emergence of hard fork, China banning cryptocurrency trading, and the announcement of Bitcoin futures trading in the CME Group Inc Furthermore, with respect to the diversification and hedging properties of the cryptocurrency markets, we found that Litecoin is the most effective hedge asset against the risk of S&P 500 stock market.

Our findings provide two important implications for portfolio investors. First, the asymmetry volatility offers better information for portfolio diversification by indicating which market is better for short or long-term investment. Second, the cryptocurrency plays the role of hedge asset against the risk of stock market, which provides a guideline on designing optimal portfolio and diversification benefits in the stock-currency portfolio. Thus, we conclude that the cryptocurrency might be one of important elements in portfolio diversification. Following Corbet et al. [23], it would be interesting that future study examines the role of cryptocurrency to hedge against other financial assets such as, currency, bond, and uncertainty.

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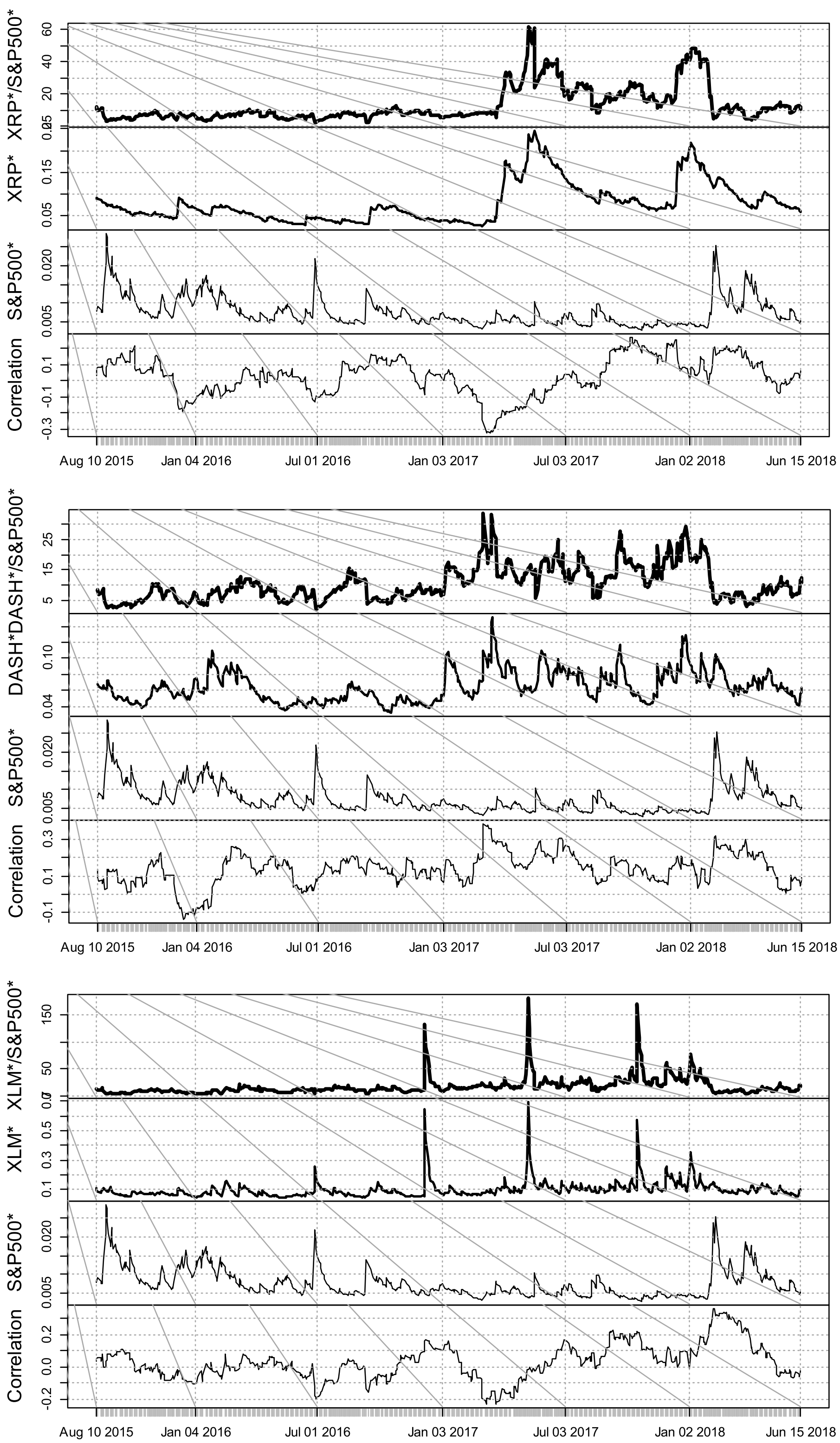

Fig. 2. Conditional volatility and correlation between S&P 500 and cryptocurrencies. Notes: * denotes conditional volatility series. Cryptocurrency*/S&P 500* presents the ratio of volatilities between each cryptocurrency and S&P 500.

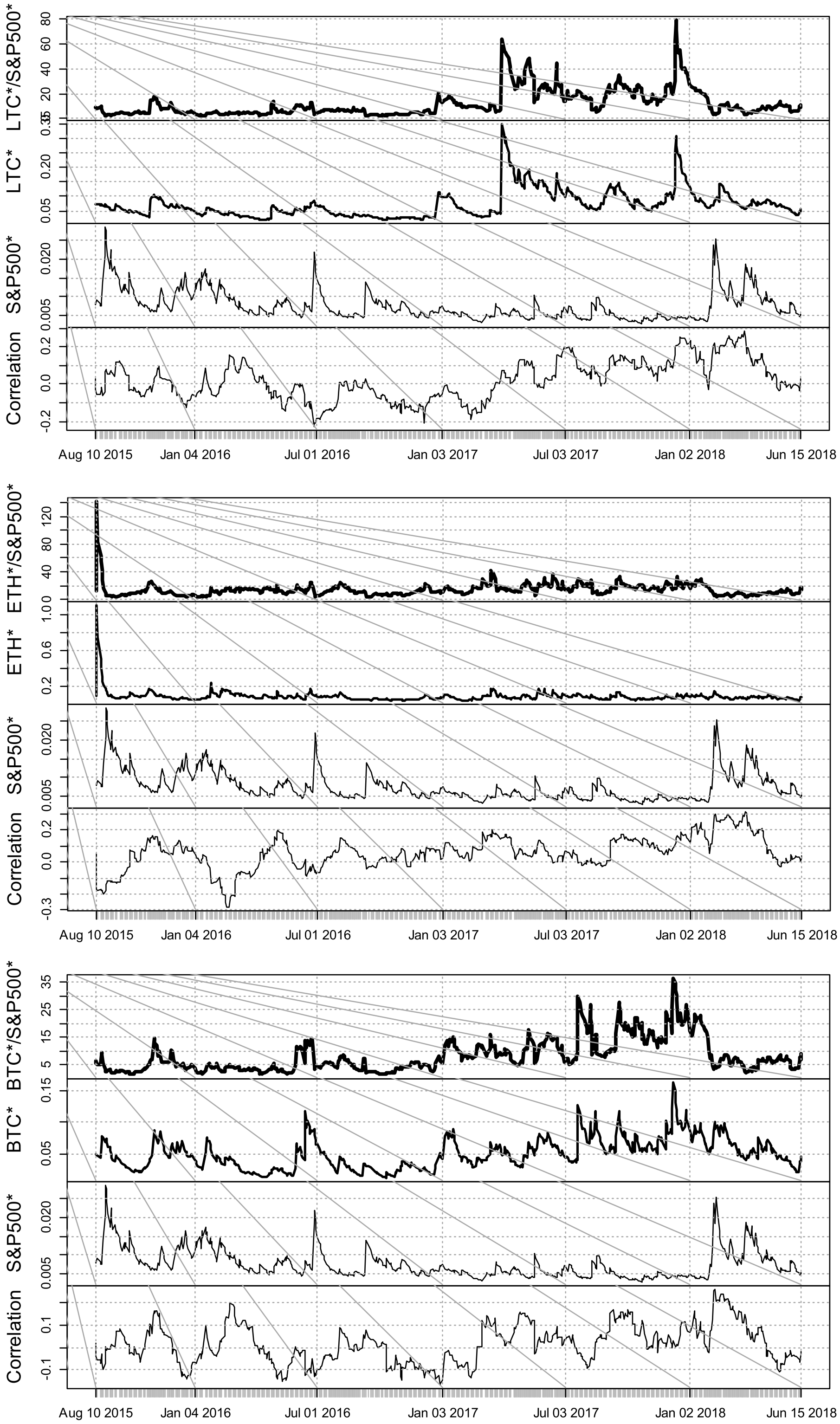

Fig. 2. (*continued*).

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