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Volatility Spillovers and Correlation Between Cryptocurrencies and Asian Equity Market

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ABSTRACT

Although, the growth in the cryptocurrency market slowed down after the meteoric rise in late 2017, the market is still enjoying steady capital inflow. This has made the study of market dynamics between the cryptocurrencies and equity market indispensable. In this paper, the study of the volatility spillovers and correlation between the two has been undertaken by considering five Asian stock indices and four cryptocurrencies ranging from November 2014 to December 2018, to cover three phenomena-Leverage effect, Volatility spillovers and Time varying correlation using EGARCH, Diagonal BEKK and DCC tests respectively. Firstly, the EGARCH test reveals the absence of leverage effect in the returns of cryptocurenices. Secondly, the multivariate GARCH test shows, out of all the cryptocurrencies taken, the past innovations in Bitcoin affect the future volatility of the equity market returns the most. Lastly, the DCC model reveals evidence of time varying correlation between the markets and Bitcoin.

Keywords: Cryptocurrencies, Asian Equity Market, Volatility Spillovers, Dynamic Conditional Correlation
JEL Classifications: G12, G14, G17, C15, C32

1. INTRODUCTION

All existing research considers only the Bitcoin dynamics, while other cryptocurrencies are not muxh exposed, research on bitcoin is also in limited quantity, which makes it impossible to draw conclusions on the cryptocurrencies market. About the market dynamics between the Asian equity market and cryptocurrencies, little is known. With the recent introduction of financial derivatives related to these coins, these insights become increasingly important as the coins are establishing a position within the regulated markets. This study attempts to fill the gap by considering the other cryptocurrencies as well. The sample consists of five stock indices (S&PBSE500 [India stock exchange], (PSE) [Philippines stock exchange], SGX [Singapore stock exchange], HNX [Vietnam stock exchange], and BUR [Malaysia stock exchange]) with four cryptocurrencies (Bitcoin, DASH, Litecoin, and Monero), in order to be able to draw conclusions. This study covers three well known phenomena in a bivariate setting, whose presence comes from stocks, making it possible to see the potential dynamics between cryptocurrencies and the equity market. A reason for taking India with the other Asian markets is to do a comparative study of two different economies, one where the cryptocurrencies is not a legal tender and another where it is legal.

The following phenomena are being covered:
1. Volatility spillovers
2. Leverage effect
3. Time varying correlation.

For volatility spillovers, Diagonal BEKK model is applied; leverage effects are studied using the EGARCH model and DCC model is applied to study the time varying correlation.

2. LITERATURE REVIEW

Bitcoin has not significantly attracted the focus of economic and financial researchers, although it has been of interest in law and computer science for a long time. Firstly, we account the study of Klashorst (2008), as the elusive inventor of bitcoin. Bitcoin was originally presented as a purely peer-to-peer version of electronic cash that allows online payments directly from one party to another without undergoing any monitoring. There is debate among the economists because of the sharp spike in bitcoin price, and its huge volatility from time to time. Some papers have concentrated on the characteristics of cryptocurrencies following different forms of money and other well-known assets; among others Barber et al. (2012), Grinberg (2011), Glaser et al. (2014). Wu and Pandey (2014), and Whelan (2013). Grinberg (2011) showed that bitcoin has a relative advantage to make micropayments. Although, Wu and Pandey (2014) found that bitcoin should be regarded as a very illiquid financial asset as it does not have the key attributes of a currency. Whelan (2013) argues that bitcoin might be similar to dollar. The main difference is that on one hand the dollar is backed by a government entity and on the other hand bitcoin is created and managed by non-government entities. The users' intentions to participate in the Bitcoin ecosystems is given by Glaser et al. (2014), who found that new users, rather than trading Bitcoin as a means of paying for goods or services, tend to trade Bitcoin on a speculative investment intention basis. Yermack (2015) claimed that Bitcoins trading style demonstrates characteristics similar to stock trading as it resembles speculative investments. Other papers have focussed on the price formation of cryptocurrencies; among others van Wijk (2013), Dyhrberg (2015a). These authors argued that the price of Bitcoin is determined by several factors such as investor's speculative behavior, demand–supply fundamentals, and global financial indicators related to equity markets, foreign exchange rate, crude oil and gold. Ali et al. (2014) includes other factors that influence the value of crypto currencies, such as transaction costs or relative benefits, risk-return trade-offs, and habit formation. Briere et al. (2013) provide evidence that Bitcoin could be suitable for diversification.

The researchers conclude that as Bitcoin correlates negatively with most of the analyzed stock market indices, it delivers high diversification benefits as it. More recently, Gangwal (2017) wrote about the effect of including Bitcoin to the portfolio of an international investor. The author argued that adding Bitcoin to portfolios always yields a diversification benefit, by using mean-variance analysis. Therefore, Bitcoin's return offsets its volatility risk. Because of the non-normal nature of Bitcoin return, Eisel et al. (2015) adopted a Conditional Value-at-Risk framework (CVaR). The results obtained indicate that an investment in Bitcoin increased the CVaR of a portfolio. Even then, the additional risk is compensated by high return. Dyhrberg (2015b) further extended this by exploring the financial asset capabilities of bitcoin using the Generalized Auroregressive Conditional Heteroskedasticity (GARCH) model. Results obtained showed that Bitcoins have a few aspects similar to gold and the dollar which indicates the hedging capabilities of Bitcoin and its advantages as a medium of exchange. The asymmetric GARCH shows that bitcoin may be useful in risk management and ideal for risk-averse investors in anticipation of negative shocks to the market. Overall, it can be concluded that Bitcoin can be considered as an entity between a fiat currency and a commodity as it has a place in the financial markets and also in portfolio management.

On the contrary, Baur et al. (2018), using the same sample and econometric models of Dyhrberg (2015), displayed that Bitcoin shows different return, volatility and correlation characteristics compared to gold and the US dollar. Baur et al. (2015) argued that Bitcoin is a actually a hybrid between conventional currencies and precious metals. They also showed the role of Bitcoin as a helpful diversifier and an investment. Bouri et al. (2017) assessed the ability of Bitcoin to act as a hedge, or diversifier against daily movements in commodities. Through the use of an Asymmetric Dynamic Conditional Correlation (DCC) model, results show that Bitcoin is an important hedge and also a safe-haven against movements of commodity indices. Also, Bouoiyour and Selmi (2015) provide insightful evidence that Bitcoin may be used for economic reasons using financial indicators, global macroeconomic and technical drivers. This study contributes to adding onto the existing studies on Bitcoins by assessing interwovenness within the cryptocurrency market and the Bitcoin price changes, also the volatility of traditional asset classes by utilizing the spillover index approach.

3. METHODOLOGY

3.1. Data

Derived from daily closing prices, this study considers various cross-sectional market dynamics based on log returns. Data regarding the stock indices and the cryptocurrencies is extracted from Bloomberg. Modelling and programming is done in EViews and Rstudio.

3.2. Sample Construction

The sample consists of five Asian stock indices and four cryptocurrencies, as presented in Table 1, and covers a period ranging from November 2014 to December 2018. The five Asian stock indices are selected based on their geographical

Table 1: Profile of the Asian markets and cryptocurrencies

Markets	Launch date	Market cap (April 2018)	No. of listings
S&PBSE (India stock exchange)	July 09, 1875	US$2.1 trillion	500
PSE (Philippines stock exchange)	August 08, 1927	$ 253.59 Billion	323
SGX (Singapore stock exchange)	December 01, 1999	$692.21 Billion	776
HNX (Vietnam stock exchange)	July 2000	128.34 billion USD	396
BUR (Malaysia stock exchange)	1964	$397.39 Billion	801
BTC (Bitcoin)	Started trading in 2009	$276 Billion	-
LTC (Litecoin)	Started trading in 2011	$15 Billion	-
DASH	Started trading in 2014	$10 Billion	-
XMR (Monero)	Started trading in 2013	$7 Billion	-

If $\gamma<0$, negative shocks increase the volatility more than positive. If $\gamma>0$, positive shocks increase the volatility more than negative presence compositions, and liquidity; and the fact that they are all developing economies. It is important to assess general market dynamics by taking stocks representing a range of sectors. The reason for choosing India along with the other economies is to also look at the comparison of an economy where cryptocurrency is legal and another where it isn't.

3.3. EGARCH Model

The first model able to incorporate the asymmetric volatility (Nelson, 1991) was the EGARCH model. As per the empirical studies, as compared to the conventional GARCH model, the EGARCH provides a more accurate result.

(Brooks, 2014) The EGARCH variance equation having a normal distribution is given below. It indicates that incorporating the asymmetric volatility gives a more adequate result.

$$\text{Ln}(\sigma t\ 2) = \omega + \beta \ln(\sigma t{-}1\ 2) + \gamma \times ut{-}1/\sqrt{\sigma t{-}1\ 2} + \alpha\ [|\ ut{-}1\ |/\sqrt{\sigma t{-}1\ 2} - \sqrt{2/\pi}] \quad (1)$$

Where, ω = Intercept for the variance, β = Coefficient for the log GARCH term, $ln(\sigma t{-}1\ 2)$ = Log GARCH term, γ = Scale of the asymmetric volatility, $\gamma \times ut{-}1/\sqrt{\sigma t{-}1\ 2}$ = Last period's standardized shock, $[|\ ut{-}1\ |/\sqrt{\sigma t{-}1\ 2} - \sqrt{2/\pi}]$ = Parameter taking into account the absolute value of latest period's volatility shock that replaces the usual ARCH term. Through the variable gamma (γ), the model captures the asymmetric volatility. The size of the asymmetric volatility is determined by the sign of the gamma and shows if the asymmetric volatility is positive or negative:

If $\gamma = 0$, symmetry is there which means no asymmetric volatility.

Even if the parameters are negative, the variance will still be positive since the model uses the log of the variance ($\sigma t\ 2$). Hence, the model is not subject to the non-negativity constraints.

3.4. Diagonal BEKK

First, the following mean equations are estimated for each market's own returns and the returns of other markets lagged one period:

$$RT = \alpha + DRT - 1 + \rho * PCH(X) + \sigma\, PCH(Y) \quad (2)$$

Where, $PCH(X)$ = % change in X and $PCH(Y)$ = % change in Y indexes.

Diagonal BEKK methodology is used to assess the volatility spillover effects between the five markets. Diagonal BEKK is a multivariate GARCH model that permits the explicit and dynamic parametrization of conditional covariances by reducing the number of parameters estimated. This is done by restricting the parameter matrices to be diagonal. It also addresses the difficulty faced with VECH by making sure the conditional covariance matrix is always positive.

The general diagonal BEKK Equation is given by:

$$H_t = C\,0C + A\,0\,(E_t{-}1\ E0\ t{-}1)A + B\,0\,(H_t{-}1)B \quad (3)$$

Where, $H_t = n \times n$ conditional variance-covariance matrix, C = upper triangular matrix of parameters, $E_{t-1} = n \times 1$ disturbance vector, and A and $B = n \times n$ diagonal parameter matrices respectively. A trivariate Diagonal BEKK model can be described as follows. Let be Ω an 3×3 matrix and equal to the $C0C$. The $C0C$ matrix equals:

$$\Omega = C'C$$

$$= \begin{vmatrix} c_{11} & 0 & 0 \\ c_{12} & c_{22} & 0 \\ c_{13} & c_{23} & c_{33} \end{vmatrix} \begin{vmatrix} c_{11} & c_{12} & c_{13} \\ 0 & c_{22} & c_{23} \\ 0 & 0 & c_{33} \end{vmatrix}$$

$$= \begin{vmatrix} c_{11}^2 & c11c12 & c11c13 \\ c_{11}c_{12} & c12^2 c22^2 & c12c13 + c22c23 \\ c_{11}c_{13} & c12c13 + c22c23 & c13^2 c23^3 c33 \end{vmatrix} \quad (4)$$

The H_t matrix can be represented as:

$$H_t = \begin{vmatrix} h_{11,t} & h_{12,t} & h_{13,t} \\ h_{21,t} & h_{22,t} & h_{23,t} \\ h_{31,t} & h_{32,t} & h_{33,t} \end{vmatrix} \quad (5)$$

So, the equation becomes:

$$\begin{vmatrix} h_{11,t} & h_{12,t} & h_{13,t} \\ h_{21,t} & h_{22,t} & h_{23,t} \\ h_{31,t} & h_{32,t} & h_{33,t} \end{vmatrix} = \begin{vmatrix} \Omega_{11,t} & \Omega_{12,t} & \Omega_{13,t} \\ \Omega_{21,t} & \Omega_{22,t} & \Omega_{23,t} \\ \Omega_{31,t} & \Omega_{32,t} & \Omega_{33,t} \end{vmatrix} + \begin{vmatrix} a_{11} & 0 & 0 \\ 0 & a_{22} & 0 \\ 0 & 0 & a_{33} \end{vmatrix}$$
$$\begin{vmatrix} u_{1,t-1} \\ u_{2,t-1} \\ u_{3,t-1} \end{vmatrix} \begin{vmatrix} u_{1,t-1} \\ u_{2,t-1} \\ u_{3,t-1} \end{vmatrix} \begin{vmatrix} a_{11} & 0 & 0 \\ 0 & a_{22} & 0 \\ 0 & 0 & a_{33} \end{vmatrix} + \begin{vmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{vmatrix}$$
$$\begin{vmatrix} h_{11,t-1} & h_{12,t-1} & h_{13,t-1} \\ h_{21,t-1} & h_{22,t-1} & h_{23,t-1} \\ h_{31,t-1} & h_{32,t-1} & h_{33,t-1} \end{vmatrix} \begin{vmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{vmatrix} \quad (6)$$

All conditional variance and covariance equation are given as:

$$h_{11,t} = \Omega_{11} + a_{11}^2 u_{1,t-1}^2 + b_{11}^2 h_{11,t-1} \quad (7)$$

$$h_{12,t} = \Omega_{12} + a_{11}a_{12}u_{1,t-1}u_{2,t-1} + b_{11}b_{22}h_{12,t-1} \quad (8)$$

$$h_{13,t} = \Omega_{13} + a_{11}a_{33}u_{1,t-1}u_{3,t-1} + b_{11}b_{33}h_{13,t-1} \quad (9)$$

$$h_{22,t} = \Omega_{22} + a_{22}^2 u_{2,t-1}^2 + b_{22}^2 h_{22,t-1} \quad (10)$$

$$h_{23,t} = \Omega_{23} + a_{22}a_{23}u_{2,t-1}u_{3,t-1} + b_{22}b_{23}h_{23,t-1} \quad (11)$$

$$h_{33,t} = \Omega_{33} + a_{33}^2 u_{3,t-1}^2 + b_{33}^2 h_{33,t-1} \quad (12)$$

The parameters of the multivariate GARCH models of any of the above specifications are estimated by maximizing the log-likelihood function under the assumption of conditional normality:

$$l(\theta) = -\frac{TN}{2} - \frac{1}{2}\sum_{t=1}^{T}(log\left|H_t\right| + H_{t-1}^{-1}) \quad (13)$$

Here we employ a 5-variate Diagonal BEKK Specification. With a system of five equations, the conditional mean and variance-covariances are estimated simultaneously.

3.5. Dynamic Conditional Correlation

Engle (2002) gave the DCC model set up that can be expressed as the following:

$$H_t = D_t R_t D_t = \rho_{ijt}\sqrt{h_{iit}h_{jjt}} \tag{14}$$

Where, H_t = conditional variance co-variance matrix, $R_t = n \times n$ conditional correlation matrix and the matrices Dt and Rt are computed as follows:

$$D_t = diag(h_{11t}^{\frac{1}{2}},\dots,h_{nnt}^{\frac{1}{2}}) \tag{15}$$

Where, hiit is taken as a univariate GARCH (1,1) process;

$$R_t = (diagQ_t)^{-1/2} Q_t (diagQ_t)^{-1/2} \tag{16}$$

The conditional correlation coefficient ρ_{ij} between two markets i and j is calculated as:

$$\rho_{ij} = \frac{(1-\alpha-\beta)\bar{q}_{ij} + \alpha u_{i,t-1}u_{j,t-1} + \beta q_{ij,t-1}}{\left((1-\alpha-\beta)\bar{q}_{ii} + \alpha u_{i,t-1}^2 + \beta_{q_{ii,t-1}}\right)^{1/2}\left((1-\alpha-\beta)\bar{q}_{jj} + \alpha u_{j,t-1}^2 + \beta_{q_{jj,t-1}}\right)^{1/2}} \tag{17}$$

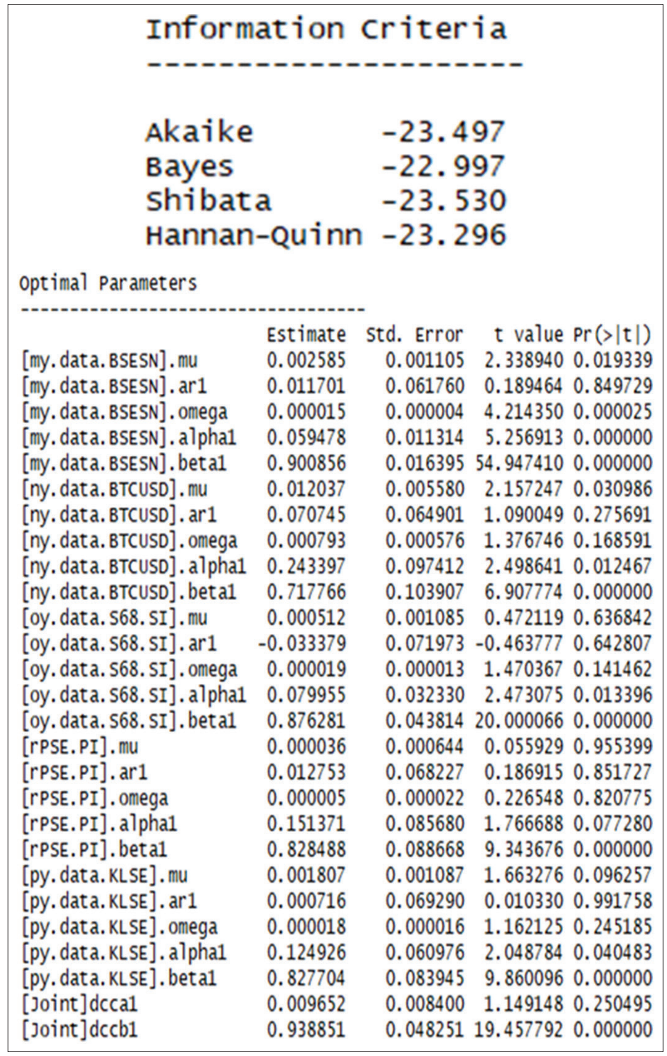
Where ρ_{ij} = Element located in the ith row and jth column of the symmetric positive matrix Q_t.

4. DATA ANALYSIS

4.1. Descriptive Statistics

From Table 2 can be inferred that all markets have positive returns on average, with the stock indices and the cryptocurrencies substantially above zero. The standard deviations, which highlight the extremely volatile nature of cryptocurrencies,

Figure 1: Dynamic conditional correlation model results



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Information Criteria
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Akaike       -23.497
Bayes        -22.997
Shibata      -23.530
Hannan-Quinn -23.296

Optimal Parameters
------------------------------------
                          Estimate  Std. Error  t value Pr(>|t|)
[my.data.BSESN].mu        0.002585  0.001105  2.338940 0.019339
[my.data.BSESN].ar1       0.011701  0.061760  0.189464 0.849729
[my.data.BSESN].omega     0.000015  0.000004  4.214350 0.000025
[my.data.BSESN].alpha1    0.059478  0.011314  5.256913 0.000000
[my.data.BSESN].beta1     0.900856  0.016395 54.947410 0.000000
[ny.data.BTCUSD].mu       0.012037  0.005580  2.157247 0.030986
[ny.data.BTCUSD].ar1      0.070745  0.064901  1.090049 0.275691
[ny.data.BTCUSD].omega    0.000793  0.000576  1.376746 0.168591
[ny.data.BTCUSD].alpha1   0.243397  0.097412  2.498641 0.012467
[ny.data.BTCUSD].beta1    0.717766  0.103907  6.907774 0.000000
[oy.data.S68.SI].mu       0.000512  0.001085  0.472119 0.636842
[oy.data.S68.SI].ar1     -0.033379  0.071973 -0.463777 0.642807
[oy.data.S68.SI].omega    0.000019  0.000013  1.470367 0.141462
[oy.data.S68.SI].alpha1   0.079955  0.032330  2.473075 0.013396
[oy.data.S68.SI].beta1    0.876281  0.043814 20.000066 0.000000
[rPSE.PI].mu              0.000036  0.000644  0.055929 0.955399
[rPSE.PI].ar1             0.012753  0.068227  0.186915 0.851727
[rPSE.PI].omega           0.000005  0.000022  0.226548 0.820775
[rPSE.PI].alpha1          0.151371  0.085680  1.766688 0.077280
[rPSE.PI].beta1           0.828488  0.088668  9.343676 0.000000
[py.data.KLSE].mu         0.001807  0.001087  1.663276 0.096257
[py.data.KLSE].ar1        0.000716  0.069290  0.010330 0.991758
[py.data.KLSE].omega      0.000018  0.000016  1.162125 0.245185
[py.data.KLSE].alpha1     0.124926  0.060976  2.048784 0.040483
[py.data.KLSE].beta1      0.827704  0.083945  9.860096 0.000000
[Joint]dcca1              0.009652  0.008400  1.149148 0.250495
[Joint]dccb1              0.938851  0.048251 19.457792 0.000000
```

Table 2: Descriptive statistics

Statistic	SPBSE500 (India stock exchange)	PSE (Philippines stock exchange)	SGX (Singaporestock exchange)	HNX (Vietnam stock exchange)	BUR (Malaysia stock exchange)	BTC Bitcoin	LTC Litecoin	XMR Monero	DASH
Mean	11722.81	263	7.45	91.61	1751	1403.7	28.64	62.80	153.90
Std dev	2143.235	39.7	0.37	15.29	78.79	2698.72	46.15	92.12	234.2
Skewness	0.069525	−0.29	0.70	0.993	−0.069	4.12	2.43	1.78	2.2
Kurtosis	2.137159	2.66	3.83	3.129	1.865	2.024	9.09	5.688	8.07
Prob ARCH-LM	0	0	0	0	0	0	0	0	0
Prob Jarque Bera	0	0	0	0	0	0	0	0	0
Prob ADF	0	0	0	0	0	0	0	0	0

Table 3: EGARCH results

Coefficients	Bitcoin		Litecoin		DASH		Monero	
Prob. Chi-square	0.0000		0.0214		0.0000		0.0004	
	Coefficient	Probability	Coefficient	Probability	Coefficient	Probability	Coefficient	Probability
C(2)	0.0275	0.352	−1.0267	0.000	−0.3526	0.000	−1.4868	0.000
C(3)	−0.0935	0.032	0.2947	0.000	0.3949	0.000	0.3822	0.000
C(4)	0.1580	0.000	0.1127	0.010	−0.0010	0.977	0.2126	0.004
C(5)	0.9908	0.000	0.7920	0.000	0.9823	0.000	0.6121	0.000

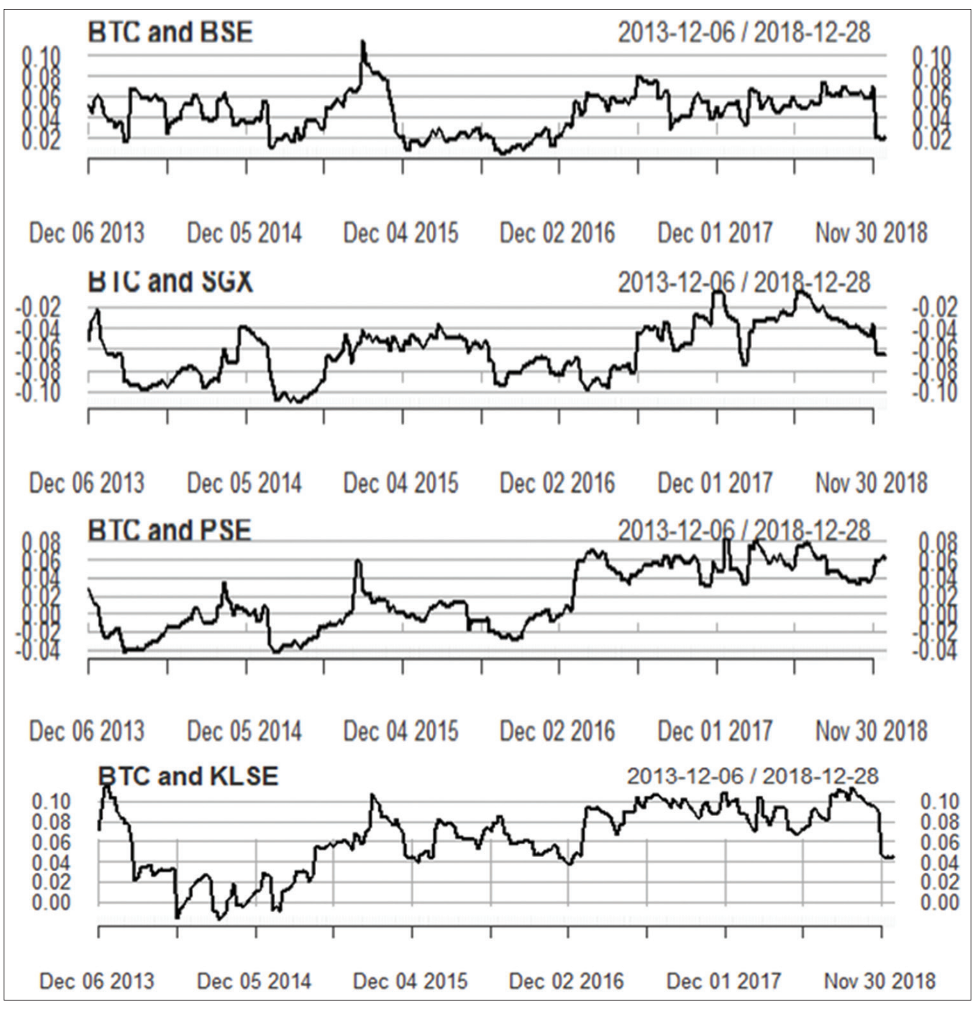
exhibit similar comparison. Furthermore, SGX (Singapore stock exchange) and BUR (Malayasia stock exchange) exhibit negative skewness, whereas the other markets show positive skewness. Negative skewness means that the chance of having a negative daily return is larger than having a positive daily return, and positive skewness means the opposite. Kurtosis gives the description of the shape of the probability distribution and measures the tailedness. A result of infrequent extreme deviations, higher kurtosis is clearly visible in the statistics of DASH, LTC (Litecoin), and XMR (Monero).

The statistics that follow provide the test results of: (1) Engle's ARCH test; (2) Jarque-Bera test; and (3) the augmented Dickey-Fuller test. The first test is for autocorrelation, the second test is for having a normal distribution, and the third is for having a unit root which implies a pattern/trend that is unpredictable. All three tests should be rejected in order to perform autoregressive modeling.

Table 3 provides the parameter estimations of the univariate EGARCH model for the Asian stock indices and cryptocurrencies. The different coefficients denote different effects: C(2) Is the constant, C(3) is the impact of magnitude of shock or ARCH effect or spillover effect, C(4) is the impact of sign of the shock and C(5) is the GARCH effect showing persistence of past volatility. Since leverage effect is the focus here, only values of parameter C4 are considered. Keeping in line with previous studies, for all the stock indices except HNX (Vietnam stock exchange) and PSE (Philippines stock exchange), coefficient of C4 is economical negative and significant. Hence, the presence of an asymmetric leverage effect in these assets seems quite possible. The indices are composed of actual stocks which have underlying economic fundamentals. Hence, it seems possible that the mechanical leveraging effect works similarly for both actual stocks and stock indices. Because of the lack of these economic fundamentals, this reasoning does not apply for cryptocurrencies though. The results show the presence of an asymmetric leverage effect seems not possible in the times series of BTC (Bitcoin), DASH, LTC (Litecoin), and XMR (Monero). A possible explanation could be the prospect theory that explains the significant positive coefficients of LTC (Litecoin), XMR (Monero), and BTC (Bitcoin), which could indicate the strong risk taking or return chasing behavior in the cryptocurrency market as a positive leverage coefficient shows a stronger impact of positive return shocks on volatility.

The diagnostic tests are applied on the residuals in each case to check the appropriateness of the model. The test for autocorrelation showed no serial correlation among the residuals, which is desirable; the test for normality showed a normal

Figure 2: Graphs of dynamic conditional correlations



distribution of the residuals which is desirable and the test for ARCH effects showed no ARCH effects in the residuals which is also desirable. All the three tests were performed for all the datasets and the results revealed that our EGARCH model was applied properly.

4.2. Diagonal BEKK

To effectively capture the volatility and cross volatility among the five Asian stock markets and the cryptocurrencies, the conditional variance-covariance equations are obtained, and we can see that most coefficients are statistically significant (Figures 1 and 2). The conditional variances-covariances implied by the Diagonal BEKK specification are presented in Table 4.

Table 4 shows a statistically significant covariation in shocks which depends more on its lags than on past errors. Common to the respective markets, market shocks are influenced by past information. Own-volatility spillovers (ARCH effects) are positive and significant for all five Asian markets exchanges and the four cryptocurrencies. The spillover effect is higher for Philippines (0.4), Malaysia (0.2) and Vietnam (0.2) than for India (0.08), and Singapore (0.06); and for BTC (0.6) and DASH (0.23) are higher than XMR (0.11) and LTC (0.12). The coefficients show the volatility persistence of each market in terms of its own past errors. As for cross-volatility effects, past innovations in Bitcoin have greatest influence on the future volatility of the Asian developing market returns. In the case of Bitcoin, DASH has the greatest influence on its future volatility.

The cross-volatility spillovers are greater than own-volatility spillovers in all markets except for Philippines. Therefore, we can say that Bitcoin has the greatest effect on the Asian market than the other cryptocurrencies.

The lagged own-volatility persistence (GARCH effects) is India (0.8652), Philippines (0.5138), Malaysia (0.8189), Singapore (0.9264), Vietnam (0.3740), Bitcoin (0.7330), Litecoin (0.8279), Monero (0.7117), and DASH (0.7576). These results suggest that Singapore derives more of its volatility persistence from within the domestic market, while Vietnam derives more of its volatility persistence from outside the domestic market. Moreover, the own volatility spillover effects for five exchanges do not remain within

Table 4: Diagonal Bekk results

Variance-covariance representation: GARCH = M + A1*RESID(-1)*RESID(-1)'*A1 + B1*GARCH(-1)*B1 COV1_2 = M(1,2) + A1(1,1)*A1(2,2)*RESID1(-1)*RESID2(-1) + B1(1,1)*B1(2,2)*COV1_2(−1)		
	Own-volatility spillovers	Own-volatility persistence
	A1*RESID(−1)*RESID(−1)'*A1	B1*GARCH(−1)*B1
India	0.0792	0.8652
Philippines	0.4010	0.5138
Malaysia	0.1591	0.8189
Singapore	0.0593	0.9263
Vietnam	0.2112	0.3740
Bitcoin	0.2605	0.7330
Litecoin	0.1156	0.8279
DASH	0.1052	0.7117
Monero	0.2315	0.7576
	Cross-volatility spillovers	Cross-volatility persistence
	A1(1,1)*A1(2,2)*RESID1(−1)*RESID2(−1)	B1(1,1)*B1(2,2)*COV1_2(−1)
India-Bitcoin	0.1436	0.7964
India-Litecoin	0.0957	0.8463
India-DASH	0.0913	0.7847
India-Monero	0.1354	0.8096
Philippines-Bitcoin	0.3232	0.6137
Philippines-Litecoin	0.2153	0.6522
Philippines-DASH	0.2054	0.6047
Philippines-Monero	0.3047	0.6239
Malaysia-Bitcoin	0.2036	0.7747
Malaysia-Litecoin	0.1356	0.8234
Malaysia-DASH	0.1294	0.7634
Malaysia -Monero	0.1919	0.7876
Singapore-Bitcoin	0.1243	0.8240
Singapore -Litecoin	0.0828	0.8757
Singapore-DASH	0.0790	0.8119
Singapore-Monero	0.1171	0.8377
Vietnam-Bitcoin	0.2346	0.5235
Vietnam-Litecoin	0.1563	0.5564
Vietnam-DASH	0.1491	0.5159
Vietnam-Monero	0.2211	0.5323

a close range. Each emerging market faces a different risk-return profile and level of vulnerability to outside conditions is further implied by this. For India the lagged cross-volatility persistence ranges from 0.84644 (Litecoin) to 0.7964 (Bitcoin), and in Philippines it goes from 0.6522 (Litecoin) to 0.6047 (Monero). In Malayisa the cross-volatility persistence varies between 0.8234 (Litecoin) and 0.7634 (Monero), while in Singapore it goes from 0.8757 (Litecoin) to 0.8120 (Monero), and in Vietnam from 0.5564 (Litecoin) to 0.5159 (Monero). Hence, in terms of cross-volatility persistence, the least influential market is Vietnam while the most influential would appear to be Singapore. Past volatility shocks in Litecoin have the greatest influence on the future volatility of Singapore. Moreover, the order of influence does not depend on the size nor the market cap which is also corroborated by the past study done by Klashorst (2018). The lagged covariance influence on future covariance is found positive for all pairs and coefficients range from 0.5159 (Litecoin-Vietnam) to 0.8757 (Litecoin-Singapore). The analysis implies that the magnitude of cross volatility persistence is not directly linked to legality of the cryptocurrency by the government. It could be due to the level of integration of the market to the rest of the world. The plots given by the BEKK Model, for the conditional variances-covariances are shown below. It is suggested that an extremely volatile trend for the period studied is displayed by the co-movements of the stock markets.

Finally, the Ljung-Box Q statistics from Portmanteau tests for Autocorrelation show no autocorrelation in the standardized residuals. Therefore, the conditional mean return equations are correctly specified with the diagonal BEKK GARCH model.

4.3. Dynamic Conditional Correlation

The results of DCC model applied to test for dynamic conditional correlation between the Asian markets and Bitcoin as shown in Figure 1, reflects the changing pattern of the dependence or influence of volatility of one price on the other. GARCH (1, 1) parameters are highly significant which implies time varying variance-covariance process and gives evidence to use bivariate GARCH modeling for the data taken. The persistence of volatility is achieved by (alpha+beta) which is less than unity which shows that the unconditional variance is not infinite. The estimated ARCH parameter (DCC α) in the conditional correlation is small and positive while the GARCH parameter (DCC β) is relatively large which shows that persistence in the time varying correlation is high. The results show evidence of dynamic time varying correlation between the markets and Bitcoin.

Figure 2 First graph shows the correlation between Bitcoin and BSE (Bombay stock exchange), correlations are positive in the range of 0.06 except for 2015 when they reach 0.1 and in 2016 when they drop to 0.02, and the end of the sample when they are again about 0.02. The second graph shows the correlation between Bitcoin and SGX (Singapore stock exchange), correlations are negative throughout signaling that there isn't much correlation between the two. The third graph shows the correlation between Bitcoin and PSE (Philippines stock exchange), correlations are generally of brief periods in 2013, 2014, and the end of the sample when they are about 0.06. The fourth graph shows the correlation between Bitcoin and KLSE (Malaysia stock exchange), correlations are positive in the range of 0.04-0.1 except for 2014 when they reach 0.

5. CONCLUSION

With the recent introduction of various financial derivatives related to cryptocurrencies, the digital coins are slowly taking a position within the regulated markets. It seems to be a matter of time before cryptocurrencies like BTC (Bitcoin), DASH, LTC (Litecoin), and XMR (Monero) are regarded as mature financial products. About the market dynamics between the Asian equity market and cryptocurrencies, little is known. This study examines the market dynamics between these four cryptocurrencies and five Asian stock indices, which allows us to draw conclusions. Similar studies have not been done yet which give us many new insights.

This study has paved way to the following findings. Firstly, presence of one-way volatility spillovers in the direction from the BTC (Bitcoin) to the equity market is found according to the the empirical results obtained. As it possibly can be explained by BTC's dominant position, the observed impact of BTC (Bitcoin) on the volatility of its peers seems more rational, making it an important benchmark for most cryptocurrency investors.

Secondly, the results provide no evidence for the presence of a traditional asymmetric leverage effect in the data of cryptocurrencies which is also corroborated by previous research done. As the coins do not have economic fundamentals, the rational leveraging mechanism does not come into the picture. However, the results provide evidence for an opposite effect, suggesting more irrational behavior such as risk taking in the cryptocurrency market.

Thirdly, this study gives the importance of modeling time varying correlation involving stock indices and cryptocurrencies for portfolio management, since the actual correlation between the different assets fluctuates heavily and requires frequently adjusted portfolio weights. Our results are keeping with the study by Klaskorst (2018) which is proof of the robustness of our study.

Last but not least, this study could be improved in the following ways. Firstly, other developed markets could be studied to examine all the effects beside the markets taken into consideration. Secondly, the study can be enhanced by dividing the sample in to two sub-samples: pre-reformation and post-reformation of the Southeast Asian market.

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