Bitcoin and stock markets: a revisit of relationship

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Abstract

The volatility of bitcoin (BTC) and time horizon is the center point for investment decisions. However, attention is not often drawn to the relationship between BTC and equity indices. Thus, the purpose of this paper is to investigate the volatility and time frequency domain of BTC with stock markets.

Keywords Bitcoin, Cryptocurrency, Equity market

Paper type Research paper

1. Introduction

Bitcoin (BTC) as an investment asset (Baur *et al.*, 2018b; Bouri *et al.*, 2017b) has been the center point of attention for investors, international participants, regulators and media after its introduction by Nakamoto (2008). It has become the largest cryptocurrency market of today and the first decentralized digital currency, retaining its position as leader of the cryptocurrency market (Corbet *et al.*, 2018a, 2018b). Although cryptocurrency investors enjoy several benefits such as efficient and advanced payment systems, there are risks that could be destructive to consumers, businesses, financial systems and national security. Thus, there have been mixed views on cryptocurrencies and their future continues to be the major reassurance of their excessive volatility and market values. Exploring this fact is one of the interests of this research which seeks to determine the short and long run volatility of BTC in the complex world of cryptocurrencies which remains unclear for most market participants and scientists. Furthermore, the relationship between BTC and the equity markets is a new concern on which this study is looking into. This is inspired by studies conducted by Baur *et al.* (2018a, 2018b) and Bouri *et al.* (2017a, 2017b) which investigate the relationship of several financial assets, including the more conventional investments such as international equities, bonds and currencies, as well as commodities which can provide useful implications for investors and policymakers. In examining the equity market, we consider a global equity index and pay attention to significant equity markets with major BTC mining in their regions such as Japan, Korea, Singapore, Philippines and Hong Kong. These equity markets are significant for investors in Asia. To find more transparent results, this research excludes the Chinese equity market even though Chinese users are an important group of stakeholders in the BTC market, as the People's Bank of China banned

JEL classification – G12, G14

the use of BTC (Yi *et al.*, 2018) with reference to this point, this study excludes China and leaves investigation on Chinese equity market for future researches. Our study looks at the long run and short run relationship between BTC and five major equity markets separately and tries to answer the causal relationship among those equity markets and BTC in both short and long run. Our final intention in this study is to understand which time horizon the ideal time is to invest in BTC. In doing this, investors may choose to invest in short, medium and long-term investments on BTC. This question opens new windows to BTC investors and provides clearer time horizons, enabling them to identify the most suitable time to invest on BTC. Such is deemed important because the study on time horizon and BTC investment has been largely absent in the literature.

Moreover, we must enhance our partial knowledge of BTC's market integration with other financial assets for several other reasons. First, it influences the structure and implementation of policies to continue financial stability. Second, it stimulates the conclusions of policymakers in nations that are likely to consider BTC as an official digital currency or as portion of their foreign reserves. Third, from asset allocation and risk management perspectives, it has significant influence on investors. As mentioned earlier, studies have been limited in the literature on the relationship between BTC and other economic assets which mostly relies on unconditional correlations. However, in the present study, we offer a broad view of the long and short run relationships between BTC and global equity markets as well as the volatility and time horizon of BTC investment.

Our research contribution arises from three main aspects. First, the application of the long-run and short-run causality and VECM approach allows us to map the long run and short run relationship of five major equity markets. The discussion concerning the relationship between BTC (the largest cryptocurrency) and five important equity markets provides new empirical evidence under different market situations. Second, our findings add to the literature on volatility of cryptocurrencies with respect to BTC by using a rich data and GARCH approach. Based on the existing literature, further development on the volatility of BTC is essential because of the inconclusive findings of different volatility models and differences data. Hence, from the perspective of volatility, there are scopes to be discovered. Finally, our findings uncover a significant question on the time horizon of investment on BTC. Such findings extend our limited understanding of BTC incorporation by revealing a time varying nature of equity markets that seems to challenge the general view in the current empirical literature in which BTC is isolated from the global financial system. Various studies have discovered the relationship between BTC and equity markets; however, the research at hand, disclose the relationship of the two for major Asian countries by using the rich database. Furthermore, investigations of the financial characteristics of BTC (Brandvold *et al.*, 2015; Bouoiyour *et al.*, 2016, for more details) are getting the attention of scholars in the recent time, in this regards, findings of this study in particular, time frequency domain analysis and volatility would shed a light on the institutional investors and participants of stock markets in the major Asian countries. Moreover, the Asian countries are selected because business cycle in those countries may have pattern of dependence across time and frequencies (Kang *et al.*, 2019).

The analysis in this paper is divided into three parts. First, we investigate the volatility behavior of BTC in comparison with five different equity market indices. According to Blau (2017), the high volatility of BTC until 2014 is not related to speculative trading. This is in contradiction to Cheah and Fry (2015) and Cheung *et al.* (2013), who find BTC to build speculative bubbles in the same time frame. In the present study, we aim to investigate the volatility of BTC in the short run and long run by using Multivariate Generalized Autoregressive Conditional Heteroscedasticity (M-GARCH) to further understand the

volatility of BTC by using a database which covers the daily prices of BTC until the end of first quarter of 2019. Second, this paper investigates the long-run and short-run relationship of BTC with five major equity indices by using time series analysis of VECM and Granger causality test. Finally, time frequency domain analysis is conducted by using Wavelet Transform (CWT) to determine the suitable time (short, medium and long term) to invest in different equity indices.

2. Literature review

There is an ever-growing literature examining BTC. In an influential work, Dwyer (2015) shows that the average monthly volatility of BTC is higher than that of gold or a set of foreign currencies while Urquhart (2016) discloses the inefficient returns of BTCs, which is also supported by Nadarajah and Chu (2017) and Bariviera (2017). BTC is an electronic system that eases the allocation of funds between parties. Based on peer-to-peer networking and algorithm, it allows users to make nameless transactions, just like cash, but through the internet and without the need for financial mediators. In this sense, BTC is fully decentralized without the intervention of third parties, such as central banks or government financial agencies (Weber, 2014). In recent time, BTC is subject to various studies. For instance, Katsiampa (2017) investigated the volatility of BTC by implementing different GARCH-type models of volatility which showed the importance of having both short-run and long-run components of the conditional variance. The research concluded that the AR-CGARCH was the most suitable model to study the volatility of BTC. However, this study is challenged by a recent study by Charles and Darné (2019) which claims the absence of a conclusive result for the volatility model of BTC. Furthermore, Conrad et al. (2018) examined the drivers of long-term volatility of BTC and compared them to other asset classes, e.g. gold. The authors found that BTC volatility was distinct compared to other asset classes. Also, researchers like Bariviera (2017) and Nadarajah and Chu (2017) confirmed the inefficiency of BTC. Moreover, Guesmi et al. (2018) examined the joint dynamics of BTC and different financial assets via a multivariate GARCH model. Existing arguments highlight the need for further investigations on this area. Nevertheless, a question yet to be answered in the literature is the relationship between BTC and equity markets. This relationship has received little attention in the existing literature. Cryptocurrencies are considered a new era of research and still need to be investigated according to different perspectives.

BTC and its price dynamics has been the subject of various studies. For instance, Urquhart (2017) shows the significant clustering of BTC prices. Shen et al. (2019) found the significant relationship between the trading volume of BTC and its number of tweets. However, there is another body of literature on the relationship between other financial assets to BTC. For instance, Dyhrberg (2016) investigated the hedging possibilities of BTC, the US dollar and UK stock market and found a similar capability of hedging to gold. Additionally, Bouri et al. (2017a) examined the relationship between gold, global uncertainty and BTC via a quantile regression approach and found that BTC has the capability to be hedged against global uncertainty for short investment horizons and in the bull market regimes. However, in a later study Bouri et al. (2017b), the researchers found limited evidence of hedging capability and safe haven properties for BTC. Following their study, Guesmi et al. (2018) made evident that BTC has some hedging capabilities and diversification benefits against many other safe haven assets. However, Klein, Thu and Walther (2017) conclude that BTC offers no hedging capabilities like gold which also holds for the brad cryptocurrency index (CRIX). On the other hand, Urquhart and Zhang (2019) argue that BTC can be a hedge at an intraday level for the CHF (Swiss Franc), EUR (Euro Currency) and GBP (British Pound Sterling) currencies.

Moreover, hedging property of BTC with regards to the various international stock market indices is been investigated by Garcia-Jorcano and Muela (2020). They used several copula models to investigate the relationship between BTC and international stock indices such as S&P500 (US), STOXX50 (EU), NIKKEI (Japan), CSI300 (Shanghai) and HSI (Hong Kong) and concluded that BTC has hedging properties during normal market conditions. Furthermore, hedging property, safe heaven and diversification characteristics of BTC for five selected countries from three continents of Asia, America and Europe were investigated by Agata Kilber et al. (2019). By using the multivariate stochastic volatility model with dynamic conditional correlation, they conclude that for all market's BTC treated as a safe haven in Venezuela and weak hedge for all the markets of their study.

Hence, the existing literature has presented an inconclusive finding on the capability of BTC hedging against safe haven assets. However, a substantial majority of published papers on the economics of BTC address the issue from an empirical perspective without addressing the relationship between BTC and equity market indexes, as well as the short-run and long-run causality of such relationships (if exist). These are factors yet to be explored clearly in need of discovery.

Ever since the invention of BTC, investors have been concerned about adding BTC to their portfolio of investment. As such, there exist several studies which investigated BTC from the portfolio perspective. However, Platanakis and Urquhart (2018) warn over the risks of having cryptocurrencies in the portfolio which should not be ignored in the decision-making process. In their study, Brière et al. (2015) investigated the performance of portfolio with BTC as part of the portfolio. They used Sharpe ratio of diversified portfolio and found that BTC improves the performance ratio. Also, they found the benefits of diversification by conducting stock-bond portfolio. The fact that BTC is isolated from other financial and economic variables makes it an important diversifier. Nevertheless, the introduction of BTC lines funded by global investment banks enhances accessibility to the BTC market. In particular, the launch of future contracts based on BTC prices in 2017 increased the legality of BTC as an investment and moved it closer to the main screen for financial world. In this regard, Mensi et al. (2019) used wavelet coherence analysis and DCC-GARCH model to investigate the co-movement of BTC and gold futures and find more on the structure of their correlations and they documented the causality and volatility persistence evidences among the BTC and gold futures. Furthermore, wavelet analysis reveals high degree of co-movement across the different frequencies for BTC and gold futures.

Hence, these developments give the signal that BTC should not be isolated by the investment communities (Polasik et al., 2015). Studies by Bouri et al. (2017a) and Bouri et al. (2017b) on BTC's ability to diversify, especially during bear market, reveal the network construction between BTC and equity indices. In their findings, there is a poor relationship between BTC and equities and this relationship is not steady over time and is precious with structural breaks. This weak relation between BTC and other financial assets may be owing to BTC not sharing many common price determinants with those financial assets (Bouoiyour et al., 2016; Kristoufek, 2013). Finally, studies on portfolio diversifications of BTC among Islamic managers were also investigated by Lim and Masih (2017). By using of M-GARCH-DCC, continuous wavelet transforms (CWT) and maximum overlap discrete wavelet transform (MODWT), they found that that BTC and Shari'ah stock indices are lowly and negatively correlated.

In this study, we extend the previously mentioned literature by discovering the long-run and short-run relationship between BTC and a set of global and country equity indexes. Furthermore, the volatility of BTC for the short and long run is examined by using an approach that is different than the existing literature on BTC's volatility, as this study uses a

rich sample from the beginning of BTC until the present. This paper also considers the time horizon of BTC investment from three different horizons of short term, medium and large terms by using an advanced methodology which makes this paper different from the existing studies on BTC.

3. Methodology
3.1 Data collection
We use daily series data from 20 July 2010 until 26 April 2019, the series are collected in USD. Considering the fact this study investigates multi countries, converting the local currencies for BTC makes it difficult; therefore, this study obtains series according to USD from the following sources. The data on BTC and Asian stock indexes was collected from (www.investing.com/) and (www.wsj.com/market-data/quotes/index). We furnish the information regarding the data based on country basis as well as BTC and market index. We further convert the index values using the formula of $R = ln\left[\frac{Vi_t}{Vi_{t-1}}\right]$ where R represents return for BTC index and equity indexes, Vi is current index value, Vi_{t-1} is the previous value, and ln represents natural log. In the calculation of index return, we followed Shuyue Yi et. al (2018) and choose the ending date of the sample because the market capitalization rank of cryptocurrencies is updated on a week-by-week basis. Furthermore, owing to availability of data for multiple countries, this study only investigates the weekday's data for the period of study. Our data is rich in terms of its total number of observations and captures divergence in volatilities and correlation of BTC and Asian markets because of 2013's April meltdown, the Fammed 2013 Bubble, the bankruptcy of Mt. Gox BTC Exchange, the summer sale of 2017, and China's Stern intervention. We excluded days for weekend given the fact of missing data in stock indexes during the analysis period. We opted five Asian emerging economies as these countries show tremendous growth in different types of cryptocurrencies and recorded good momentum in BTC and other assets. The details of indexes used are shown in the table below Table 1:

This paper adopts multiple techniques to investigate the relationship between BTC and equity market returns in selected developed and developing countries. The approached methodology follows the traditional econometric method of VECM in combination with the time-frequency domain analysis via Wavelet techniques. VECM restricts the long run behavior of the endogenous variable to cointegrate while allowing short run adjustment. The cointegrating term is known as an error correction term, as the deviation from long-run

No.	Symbol	Definition
1	BTC	Bitcoin Index
2	JPN	Nikkei 225 Index – Japan
3	KOR	KOSPI – Korea
4	STI	FTSE Straits Times Index – Singapore
5	PHIL	PSEi Index – Philippines
6	HK	Hang Seng Index – Hong Kong

Table 1.
Description of variables

Notes: This table shows further details on the variables chosen in this study. Overall, we have chosen five Asian countries for analysis purposes

equilibrium is corrected gradually through a series of partial short-run adjustments. In this research, VECM approach examines the equilibrium between the price of BTC index and equity market indices for five selected countries. We also use the M-GARCH to identify the changes in correlation and volatilities of BTC and Asian stock markets indices over time together with its directions (positive or negative) and magnitude (stronger or weaker). Following that, we also analyze the time frequency domain using Wavelet investigation and balance its findings through cross-correlation and cross-coherence analysis. Initially, it expresses how the cross-correlation between the two series varies across multiple scales, followed by the time-based evolution of the co-movement between the series along with directional leadership. Thus, the cross-coherence analysis helps us unravel new evidence on whether the higher price of BTC is influencing the prices of selected equity markets or the opposite, for instance, higher equity market prices are happening as a result of increased BTC price. Moreover, as wavelet analysis operates in a time-frequency domain (i.e. time horizon), the significance of the hypothesized interactions and the magnitudes of interactions are also discoverable. In the following sections, we explain in detail the estimations of the three tools.

3.2 Long-run and short-run associations using time series analysis (VECM and Granger causality)
Vector error correction model (VECM) also called restricted VAR, is designed to use non-stationary variables that are known to be cointegrated. VECM restricts the long run behavior of the endogenous variables to converge to their cointegrating relationship while permitting for short-run dynamic adjustment. VECM distinguishes short- and long-term associations in a model. In this content, the lagged structure of error term refers to short term deviation from long term equilibrium. The VECM also enables for Granger causality relations and Error Correction Term. The Granger causality test is also implemented in this research to understand the relationship of the dependent variables and explanatory variable. The general equation for VECM is presented as follows:

$$\Delta X_t = \alpha_t + \Omega X_{t-1} + \sum_{t=1}^{k=1} \gamma_t \Delta X_{t-1} + \varepsilon_t \qquad (1)$$

where X_t is used to denote the chosen endogenous variables for each model and ε_t is disturbance error term. From equation (1), the VECM model for this study can be illustrated as the equation below:

For market index (MI) for each country (i = Japan, Korea, Singapore, Philippines and Hong Kong):

$$\Delta MI_i = \mu_{1t} + \theta_1 (MI - \gamma_0 - \gamma_1 BC)_{t-1} + \sum_{i=1}^{j} \beta_{1,j} \Delta MI_{t-j} + \sum_{i=1}^{j} \beta_{2,j} \Delta BC_{t-j} + \varepsilon_{it} \qquad (2)$$

where MI is market index and BTC refers to BTC price index (BTC) which is the ratio of price and standard deviation of BTC. Causality test is implemented to understand the direction of the relationship between variables. In regression modeling, the

underlying theory will indicate the direction of causality between Y and X, which is in the context of single equation models, is generally from X to Y. Hence, to understand this relationship and its directions, this research applies the Granger causality test.

3.3 Multivariate generalized autoregressive conditional heteroscedasticity (M-GARCH)
Multivariate GARCH-DCC is the modified version of Bollerslev's (1990) constant conditional correlation (CCC-GARCH) as introduced by Engle and Sheppard (2001) and Engle (2002). This research uses MGARCH-DCC to explore two important phenomena; first, to investigate the fluctuations in correlation and volatilities of BTC return and Asian stock market indices over time. Second, to determine the directions and magnitude of existing correlations. MGARCH-DCC eases the assumption of CCC-GARCH on the conditional correlations of series as persistent following the assumption of having positive amount for the time dependent conditional correlation matrix. This assumption is impractical in various empirical investigations. In the process of using MGARCH-DCC, two stages were observed; first, the estimation of standard deviation (SD) from univariate GARCH, and second, using SD to calculate the standardized residuals and correlation matrix. By referring to Engle (2002), the equation for multivariate conditional covariance matrix (H_t) for this research can be written as follows:

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

where D_t = diagonal matrix of conditional time varying, standardized residuals (ε_t) that are obtained from the univariate GARCH models (on-diagonal elements), and R_t = time varying correlation matrix (off-diagonal elements).

The log-likelihood of the above estimator can be written as follows:

$$
\begin{aligned}
L = \ & -\frac{1}{2}\sum_{t=1}^{T}\Big(k\log(2\pi) + 2\log|H_t| + r_t H_t^{-1} r_t\Big) \\
= \ & -\frac{1}{2}\sum_{t=1}^{T}\Big(k\log(2\pi) + 2\log|D_t R_t D_t| + r_t D_t^{-1} R_t^{-1} D_t^{-1} r_t \\
= \ & -\frac{1}{2}\sum_{t=1}^{T}\Big(k\log(2\pi) + 2\log|D_t| + \log\Big(|R_t| + \varepsilon_t R_t^{-1}\varepsilon_t\Big) \tag{4}
\end{aligned}
$$

Here, $\varepsilon_t \sim N(0,R_t)$ are the standardized residuals (ε_t) of their conditional standard deviations.

The conditional variances for any individual asset can be obtained from the univariate GARCH model as follows:

$$h_{it} = \omega_i + \sum_{p=1}^{Pi}\alpha_{ip}r_{it-p}^2 + \sum_{q=1}^{Q1}\beta_{iq}h_{it-p}\ for\ i = 1, 2, 3, \ldots .k \tag{5}$$

where ω_i, α_{ip} and β_{iq} are non-negative and $\sum_{p=1}^{P_i} \alpha_{ip} + \sum_{q=1}^{Q_i} \beta_{iq} < 1$. h_{it} is the estimated conditional variance of individual asset, α_{ip} is the short-run persistence of shocks to return P (the ARCH effects) and β_{iq} is the contribution of shocks to return Q to long-run persistence (the GARCH effects).

Having obtained the conditional variances for any individual asset, the dynamic correlation structure can thus be written as follows:

$$Q = \left(1 - \sum_{m=1}^{M} \alpha_m - \sum_{n=1}^{N} \beta_n\right)\overline{Q} + \sum_{m-1}^{M} \alpha_m(\varepsilon_{t-m}\varepsilon_{t-m}) + \sum_{n-1}^{N} \beta_n Q_{t-n}$$

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}$$

(6)

where $\overline{Q}$ is the unconditional covariance of the standardized residuals (ε_t); and Q* is a diagonal matrix composed of the square root of the diagonal elements of Q_t, which is as follows:

$$Q_t^* = \begin{bmatrix} \sqrt{q_{11}} & 0 & \cdots & 0 \\ 0 & \sqrt{q_{22}} & \cdots & 0 \\ \vdots & \vdots & \vdots & 0 \\ 0 & 0 & \cdots & \sqrt{q_{kk}} \end{bmatrix}$$

(7)

The component of R_t will be $P_{ijt} = \frac{q_{ijt}}{\sqrt{q_{ii}q_{jj}}}$ and the matrix R_t will be positive definite/constant. The K is covariance H_t is positive definite/constant and can be written as $H_t = D_t R_t D_t$. The breakdown of H_t allows separate specification of the conditional volatilities and conditional correlations. For instance, one can use the GARCH (1, 1) model for the variance $\sigma_{i,t-1}^2$, namely:

$$V(r_{it} \mid \Omega_{t-1}) = \sigma_{i,t-1}^2 = \overline{\sigma}_i^2(1 - \lambda_{1i} - \lambda_{2i}) + \lambda_{1i}\sigma_{i,t-2}^2 + \lambda_{2i}r_{i,t-2}^2$$

(8)

where $\overline{\sigma}_i^2$ is the unconditional variance of the asset return, and λ_1 and λ_2 are individual asset volatility parameters. Under the constraint $\lambda_{1i} + \lambda_{2i} = 1$, the unconditional variance ($\overline{\sigma}_i^2$) will be extinct in the above equation. Hence, the Integrated GARCH (I-GARCH) model will be estimated on which discloses that any shocks to the variance are permanent and non-stationarity of the conditional variance.

3.4 Continuous wavelet transform

Researches in finance and economics are witnessing the growth on the usage of wavelet transformation analysis. There are some points on the aspects of wavelet methodology that suit the model of the current study. By implementing wavelet analysis, researchers are able to fetch high quality information confined into a signal in various scales. Because the VECM analysis of this research uses the traditional econometric testing for short and long run relationship between BTC and equity market indices, wavelet testing is placed exclusively to not only perform the robustness check on VECM results,

but to also explore new visions in the time-frequency domain by using cross-correlation and coherency analysis.

Using a wavelet transform requires a restricted waveform expressed as $\Psi(t)W(t)$, called commonly a mother wavelet. While the mother wavelet integrates to zero, its harmonizing normalized counterpart ϕ integrates to 1 and is known as a father wavelet. The former is used for interrogating signals in greater details and is, therefore, more relevant for higher frequency testing. As such, we go on to build a wavelet function by forging a series of plans including mother and father wavelets. We achieve this by transformation and scaling Haar (Daughter) Wavelets, expressed mathematically as:

$$\psi_{s,k}(t) = 2^{j/2}\psi(2^j s - k) \tag{9}$$

$$\phi_{s,k}(t) = \sum_{k=0}^{1}(-1)^k c_k\sqrt{2\psi}(2t - k) \tag{10}$$

In the two equations above, s = 1,..., S, where S and k are scaling and translation parameters and j is dilation index respectively. Also, the wavelet transformation of a signal can be represented as:

$$y(t) = \sum_k \theta_{s,k}\phi_{s,k}(t) + \sum_k d_{s,k}\psi_{s,k}(t) + \sum_k d_{s-1,k}\psi_{s-1,k}(t) + \ldots + \sum_k d_{1,k}\phi_{1,k}(t) \tag{11}$$

the smooth coefficient is $\theta_{s,k} = \int y(t)\phi_{s,k}(t)dt$ and detail coefficient is $d_{s,k} = \int y(t)\psi_{s,k}(t)dt$. Together $\theta_{s,k}$ and $d_{s,k}$ represent how much a particular wavelet function contributes to the overall signal. Following the methodology of Rua and Nunes (2009) and Kristoufek (2013), we have the wavelet Morlet as following;

$$\psi_{u,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right), \varphi(.)L^2 \subset \mathbb{R} \tag{12}$$

At this stage, the cross-wavelet spectrum of BTC returns and equity market indices for individual equity market series are as follow;

$$W^1_{Equity\ indices,\ Returns}(\tau, s) = W_{indices}(\tau, s)W^*_{return}(\tau, s) \tag{13}$$

Accordingly, the cross-wavelet spectrum's cross-coherency is achieved by taking the absolute value of the squares of the smoothed spectrums, as follows:

$$CC^2_{(\tau,s)} = \frac{|S(s^{-1}W_{x,y}(\tau, s)|^2}{S\left(s^{-1}|W_x(\tau, s)|^2\right)S\left(s^{-1}|W_y(\tau, s)|^2\right)} \tag{14}$$

Equation (14) is useful for capturing the degree to which two time-series co-moves across time and frequencies, an improvement over Fourier transforms which deal with frequencies alone. A $CC^2_{(\tau,s)}$ value ranges from 0 to 1, where 0 indicates no co-movement and 1 as perfect strong co-movement.

4. Empirical results and discussion

4.1 Descriptive statistics

Table 2 provides a description of the data used for analysis. The data is described based on mean, maximum, minimum and standard deviation. In terms of mean values, STI index recorded higher mean value followed by BTC, JPN, PHIL, HK and KOR. In terms of maximum values, BTC obtained higher value as compared to others. The same goes for minimum value as well in which BTC recorded minimum values. We can observe that large dispersion occurs at BTC market where the standard deviation is of 0.070157 followed by JPN, HK, PHIL, KOR and STI. The total number of observations are 1,909 because the data collected are in the daily basis mode.

4.2 Long- and short-run associations using time series analysis (VECM and Granger causality)

Several steps were performed, and they include the unit root test, optimal lag selections test as well as cointegration test. In this research, we use augmented Dickey–Fuller (ADF) and the Phillips-Perron (PP) for the test of unit root for BTC and five Asian emerging economies' indices. Table 3 shows the analysis of unit root at level and first difference. The null hypotheses have a unit root which cannot be rejected by both ADF and PP tests. Apparently, after incorporating the first difference, both unit root tests rejected the null hypothesis, concluding that all variables are not stationary at the level basis but it stationary in first difference.

The identification of lag will be more difficult as lag variables incorporate exogenous variable in the system (Ender, 1995). Thus, for lag selection, we use the shortest lag based on Akaike Information Criteria (AIC). We conducted optimal lag selection for the indices of

	BTC	JPN	KOR	STI	PHIL	HK
Mean	0.005874	0.000458	0.000119	6.79E-05	0.000439	0.000199
Maximum	0.515155	0.074262	0.055307	0.048676	0.055419	0.055187
Minimum	−0.470004	−0.111534	−0.085676	−0.056870	−0.095984	−0.080260
Std. Dev.	0.070157	0.013955	0.010066	0.008487	0.011323	0.012315
Obs	1909	1909	1909	1909	1909	1909

Notes: This table illustrates the descriptive statistics of the data used in this study. It consists five elements (i.e. mean, SD = Standard deviation, Min = Minimum value, Max = Maximum value and Obs = Observation). The samples are bitcoin return and Asian Economies Stock Indexes Return

Table 2.
Descriptive statistics

Variables	Level		First difference	
	ADF	PP	ADF	PP
BTC	−2.403547	−2.501709	−14.19600*	−43.72934*
JPN	−2.863470	−2.779592	−45.77698*	−45.80180*
KOR	−3.182944	−3.076102	−43.00685**	−43.06836*
STI	−2.716996	−2.892518	−42.40451*	−42.42439*
PHIL	−2.418378	−2.277534	−43.22455*	−43.36255*
HK	−2.703887	−2.750872	−43.04464*	−43.04038*

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

Table 3.
Unit root tests (ADF
and PP unit root
tests) for BTC and
equity indices

Asian emerging economies. Referring to Table 4, the Asian countries' index lag chosen are: JPN (lag = 3), KOR (lag = 3), STI (lag = 3), PHIL (lag = 4) and HK (lag = 4).

Case in hold, we can observe that each of the series is stationary, and therefore, we can evaluate whether there is the presence of long-run equilibrium or vice versa for model test in this study. To assess the existence of long-run association, we refer to Johansen–Juselius cointegration tests based on trace and maximum eigenvalue analysis. Again, we analyze the cointegration test using the lag selected in Table 4. As per disclosed in the Table 5, the co-integration result shows that all the Asian emerging economies have co-integration at 1% significance level. The trace statistics and maximum eigenvalue postulate the existence of one co-integrating vector, thus confirming that there is a unique co-integrating vector controlling the long-run association between Asian market indices and BTC. These variables are knotted together in the long run, and their eccentricities from the long-run equilibrium path would be rectified. Furthermore, the existence of co-integration also reveals the non-causality among the variables.

Table 6 shows the long-run association of market indices with BTC. All market indices are statistically significant at 5% significance level. Looking at the market index, there seem

	JPN	KOR	STI	PHIL	HK
Akaike Information Criterion (AIC)	−8.186374	−8.844965	−9.183065	−8.603191	−8.434908
Lags	3	3	3	4	4

Table 4.
VAR Lag order selection criteria for equity indices

			t-statistics (5%)	
Markets	Null Hypothesis	Trace		Max Eigen
JPN*	At Most One	803.3344		345.2216
KOR*	At Most One	808.5560		465.6239
STI*	At Most One	762.3281		423.3376
PHIL*	At Most One	694.4797		409.5602
HK*	At Most One	630.5607		346.9450

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

Table 5.
Johansen–Juselius cointegration tests for equity indices

Countries	Asian Markets Index
JPN	JPN = 0.023181 − 62.63207BTC [−22.7723]
KOR	KOR = 0.009627 − 117.6253BTC [−22.8851]
STI	STI = −0.003898 − 27.15635BTC [−20.9501]
PHIL	PHIL = −0.069235 + 145.7809BTC [21.3017]
HK	HK = 0.002984 − 43.45732BTC [−19.3074]

Table 6.
Long-run relationship of market indices and bitcoin

to be a negative relationship between market indices and BTC for JPN, KOR, STI and HK. For example, in the context of JPN, the negative sign of BTC coefficient reveals that when BTC increases by 1%, it will trigger the decreasing number of JPN market index by 37.97% (to quantifying the long-run relationship between BC and the stock index, the error correction speed coefficient has been multiplied by the cointegrating coefficient). The similar discussion is also applied for other Asian countries which have negative association. A high decrease in market index occurs at KOR where a 1% increase in BTC causes a shrink in market index at 4.977%, followed by HK and STI markets. A possible reason to this (i.e. increase in BTC leads to decrease in market for Korea) is because of the strong information technology (IT) infrastructure within the country. Furthermore, the economic slowdown and increase in employment rate in Korea also cause Koreans to look for a better way to invest, especially digitally. On the other hand, we can notice a positive association between BTC and PHIL equity market in the long run. The Philippines is considered a good market for BTC given the fact that the country has an active BTC community and the country has a special economic zone in which foreign crypto exchanges are licensed for operation. Furthermore, the rise of fintech in Philippines also contributes to the rapid development of the BTC market in addition to the equity market. This will have a positive long-term economic impact toward Philippines's financial landscape.

Table 7 discloses information on the ECT for the market indices of each Asian country. ECT basically looks at the speed of adjustment toward long-run equilibrium. All Asian equity markets obtained negative ECT. For simplicity, Japan is selected as sample for discussion. The ECT of Japan's market Index with BTC is −0.006063 (the error correction speed coefficient has been multiplied by the cointegrating coefficient) = 37.97%, meaning that 37.97% of that disequilibrium dissipated before the next period and 62.03% remained. This value is significant at 10%. There may be other factors which this study did not consider augmenting or detract from the disequilibrium in the next period.

We further our investigation to see the dynamic interactions between these variables. In Table 8, we show the result of the pair wise Granger causality with a lag selected in Table 4 which is enough to whiten the noise process. From Table 7, some general findings can be concluded. Most of the equities index do not have any short-run association with the BTC market except for Korea where there is evidence of a short-run association between BTC and Korean index. This supports the idea that BTC investment is suitable for long-term investment instead of short-term. Lee et al.'s (2018) study confirms that BTC and other cryptocurrencies are better options for investment and diversification in the long-term as correlation between cryptocurrencies is lower as compared to other traditional assets.

Countries	ECT
JPN	−0.006063*
KOR	−0.004232*
STI	−0.096677*
PHIL	−0.000736**
HK	−0.023501*
Note: ***, ** and * indicate significance at 1, 5 and 10%, respectively	

Table 7.
Error correction term
(ECT) of market
indices with bitcoin

Countries	Null hypothesis	F-statistics	Prob
JPN	JPN does not Granger Cause BTC	0.80178	0.4928
	BTC does not Granger Cause JPN	0.51775	0.6701
KOR	KOR does not Granger Cause BTC	1.39119	0.2437
	BTC does not Granger Cause KOR	2.14055	0.0932***
STI	STI does not Granger Cause BTC	2.15483	0.0914***
	BTC does not Granger Cause STI	1.17690	0.3171
PHIL	PHIL does not Granger Cause BTC	0.22794	0.9228
	BTC does not Granger Cause PHIL	0.82782	0.5073
HK	HK does not Granger Cause BTC	2.20766	0.0659***
	BTC does not Granger Cause HK	0.73138	0.5705

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

Table 8.
Short-run Granger causality

4.3 Multivariate generalized autoregressive conditional heteroscedasticity (M-GARCH) – dynamic conditional correlation

First, we performed the MGARCH-DCC to analyze the association between BTC and selected Asian equity markets' index. Basically, the MGARCH-DCC improves the volatility modeling by relaxing some of its assumptions, especially in terms of its means and variances of the factors. We show both Gaussian-DCC model and t-DCC model. In addition, there are the plotting of estimated conditional correlations and volatilities as well. The main purpose of showing both analyses is to determine model suitability and appropriation to measure the research objective. Table 9 postulates the value of maximum likelihood (ML) prediction of λ_1 and λ_2 (parameters of volatility) and δ_1 and δ_2 (mean reverting parameters) for each of the return sequences. All the estimated coefficients (λ_1 and λ_2) are less than 1, disclosing that DCCs are following the mean reverting process. This means that BTC and stock indexes do not follow I-GARCH and the estimates of λ_{1i}, $I = 1, 2, 3, 4, 5, 6$ are close to 1, implying a steady volatility decay. Furthermore, all volatility decay structures are

Parameter	Estimate	SE	t-ratio	[Prob]
Lambda1 (λ_1)				
BTC	0.81000	0.023547	34.3989	0.000
JPN	0.81131	0.034595	23.4514	0.000
KOR	0.86167	0.025027	34.4303	0.000
STI	0.93161	0.013535	68.8290	0.000
PHIL	0.76420	0.043385	17.6144	0.000
HK	0.94599	0.009431	100.3046	0.000
Lambda2 (λ_2)				
BTC	0.14338	0.014886	9.6321	0.000
JPN	0.09972	0.015097	6.6055	0.000
KOR	0.06829	0.011193	6.1014	0.000
STI	0.04358	0.007429	5.8664	0.000
PHIL	0.13110	0.019541	6.7091	0.000
HK	0.03284	0.004814	6.8221	0.000
Maximized log-likelihood	33676.9			

Notes: This table reveals statistics of maximum likelihood based on Gaussian-DCC model for Bitcoin and Asian indices. λ_1 and λ_2 are decay factors for variance and covariance, respectively

Table 9.
Maximum likelihood estimates of the Gaussian-DCC model

at the significant level. We also present the analysis of t-DCC model to identify the model suitability (Table 10). The maximum likelihood (ML) of t-DCC postulates that all volatility forecasts are statistically significant, and the estimated values are also close to one. Like Gaussian-DCC model, these ML estimates for t-DCC also indicate gradual volatility decay. The ML value for t-DCC is 34,153.2, higher than 33,676.9 and the degree of freedom for t-DCC is 7.4280, less than 30. Given these facts and based on M-GARCH rules, t-DCC model is more suitable and fit for analysis with the series and fat tails. Thus, the discussion of analysis will be based on Table 9. The sum of estimated coefficients (λ_1 and λ_2) is less than 1 for most of the preferred parameters. For example, $\lambda 1\_$ JPN $+ \lambda 2\_$ JPN (0.79256 + 0.0615 = 0.9714) basically signals that the volatility of JPN Index returns appears to deviate from the IGARCH approach. A similar outcome is also applied for indexes return and shocks to the volatilities for all indexes, which are not tenacious. The lambda totaling of BTC $\lambda 1\_$ BTC $+ \lambda 2\_$ BTC (0.78431 + 0.17795 = 0.96226) still shows that the value is less than 1, meaning that the volatilities also do not follow IGARCH, thus any shocks to the volatilities are not insistent. Let us say the volatility of any asset is obstinate given the shock in the economy; retail and institutional investors could have a chance of losing all their investment money in the long run although they have made short run profit given the uncertainty level in the BTC market. The t-DCC result confirms that the volatilities of BTC and Asian stock indexes are not persistent and would significantly alarm investors on whether the investment is safe for them. This outcome is also consistent with a study done by Rahim and Masih (2016).

Table 11 displays the result of unconditional correlation and volatilities of BTC and Asian stock market indexes. The on-diagonal shows unconditional volatilities while off-diagonal indicates the unconditional correlation of each asset. When the unconditional volatility is closer to 0, the asset thus contains least volatility. However, if the unconditional volatility is close to 1, the asset encounters higher level of volatility, meaning higher risk. To make it clear, we sort the BTC and Asian stock indices from the highest to the lowest volatility (Table 12). Table 11 illustrates the orders of the

Parameter	Estimate	SE	t-ratio	[Prob]
Lambda1 ($\lambda 1$)				
BTC	0.78431	0.022993	34.1113	0.000
JPN	0.79256	0.039047	20.2976	0.000
KOR	0.91799	0.020504	44.7711	0.000
STI	0.92237	0.018229	50.5984	0.000
PHIL	0.82413	0.041149	20.0280	0.000
HK	0.94304	0.012236	77.0736	0.000
Lambda2 ($\lambda 2$)				
BTC	0.17795	0.017206	10.3420	0.000
JPN	0.10090	0.017102	5.9002	0.000
KOR	0.04696	0.009756	4.8137	0.000
STI	0.04475	0.009026	4.9587	0.000
PHIL	0.09367	0.018557	5.0478	0.000
HK	0.03017	0.005528	5.4570	0.000
Maximized log-likelihood	34153.2			
df	7.4280			

Notes: This table reveals statistics of maximum likelihood based on *t*-DCC model for Bitcoin and Asian indices. $\lambda 1$ and $\lambda 2$ are decay factors for variance and covariance, respectively

Table 10.
Maximum likelihood estimates of the
t-DCC model

unconditional volatilities of the five Asian stock indexes with BTC. Interestingly, all the indexes recorded low unconditional volatilities ranging from 0.008534 to 0.014019. The five stock markets are less volatile whenever there is uncertainty in BTC. The BTC logged unconditional volatility of 0.070765 which can be considered as a relatively moderate volatile. STI-Singapore index recorded the lowest volatility is. In the news highlighted by DBS Singapore (2018), Singapore investment encounters less volatility as it offers plenty of diversification opportunities to investors.

Looking at the off-diagonal components in Table 11, we notice that three stock market indexes have negative correlations, namely, KOR, STI and HK. On the other hand, the other two markets (i.e. JPN and PHIL) have a positive correlation. Results of the unconditional correlation in Table are like Table 5 of the long run relationship between BTC and Asian stock indexes. This shows the consistency in our results as predicted by the VECM and t-DCC model. This is except for one Asian country, where we find a positive correlation (BTC and JPN stock index). The Japanese government has legalized (for medium of exchange and investment purposes) the BTC currency and the spillover effect has caused the share price to increase. To illustrate, for small exchange listed firms incorporating BTC as part of their business transaction, the share price tends to increase as BTC prices increase, which coincides with BTC's rally (bitcoin.com, 2017).

Details of the time framework proportion are given in the footnote [1]. As we observe in Figure 1, the co-movements of BTC with Asian stock indexes are unpredictable. However, one thing is very clear, and that is BTC return is more volatile than stock indexes. During the period of 2010 to 2015, we can see that the volatility was not so explosive, but after 2015,

Parameters	BTC	JPN	KOR	STI	PHIL	HK
BTC	0.070765*	–	–	–	–	–
JPN	0.036582	0.014019*	–	–	–	–
KOR	−0.009961	0.133520	0.010106**	–	–	–
STI	−0.027420	0.201950	0.576820	0.008534**	–	–
PHIL	0.009212	0.067884	0.424900	0.418810	0.011383**	–
HK	−0.018871	0.157810	0.622470	0.710420	0.417870	0.012370**

Table 11.
Unconditional correlation and volatility (based on t-DCC model)

Notes: This table shows the unconditional correlation and volatility for Bitcoin and Asian indices based on t-DCC model. The time horizon used in this study was from July 20, 2010 until April 26, 2019 (daily basis data). It involves five Asian countries. The ***, ** and * indicate significance at 1, 5 and 10%, respectively

No.	BTC and Asian indices	Unconditional volatility
1	BTC	0.070765
2	JPN	0.014019
3	HK	0.012370
4	PHIL	0.011383
5	KOR	0.010106
6	STI	0.008534

Table 12.
Ranks of unconditional volatilities of bitcoin and asian indices

Notes: This table shows the rank of unconditional volatilities for Bitcoin and Asian indices based on t-DCC model. The time horizon used in this study was from July 20, 2010 until April 26, 2019 (daily basis data). It involves five Asian countries

Plot of conditional volatilities and correlations

Figure 1.
Conditional
volatilities of bitcoin
with Asian Indices
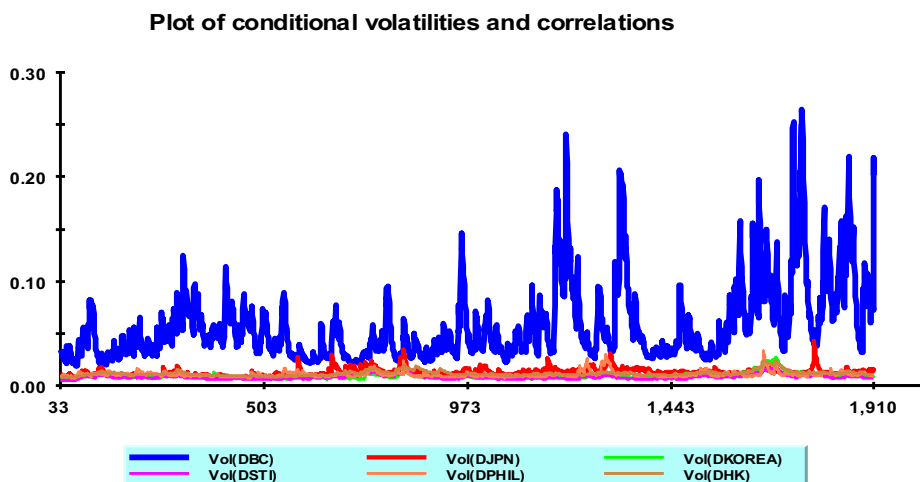
the returns of BTC are tremendously volatile. Forbes (2019) reported that bitcoin is still a very speculative asset and most of the time will follow the "Bart Simpson" pattern in which the price would increase, drop and increase again. The 2013's April meltdown, Fammed 2013 Bubble, bankruptcy of Mt. Gox BTC Exchange, summer sale of 2017, and China's Stern intervention contribute significantly toward these volatiles. A similar sentiment is shared by Cheung *et al.* (2013) and Corbet *et al.* (2018c). Comparatively, stock indexes are less volatile than BTC as revealed in Figure 1. The degree of volatilities for BTC is higher than the stock indexes during the analysis period in terms of the conditional correlation (Figure 2). Looking at the unconditional correlation, the degree of relationship can see from different time horizons. During 2010 and 2011, the correlation between BTC and HK stock index peaked quite significantly while KOR recorded lowest correlation with BTC recording negative value. Other stock indexes observe mixed movement with BTC. For example, from 2010 until 2015, there was inconsistent movement but with the same direction, meaning that the correlations co-move together. JPN recorded strong correlation with BTC, indicated by the blue color line during the analysis period, followed by PHIL. As these two countries actively promote digital currency and cryptocurrency, this could be the main reason contributing to

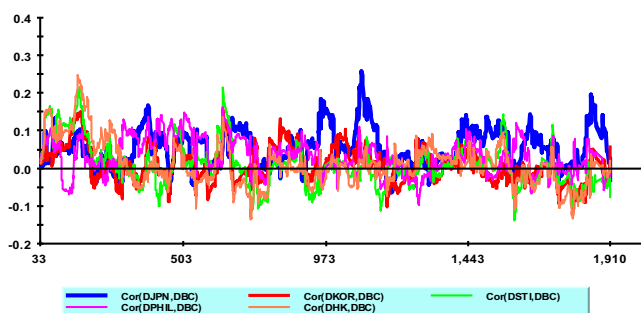**Plot of conditional volatilities and correlations**

Figure 2.
Conditional
correlations of bitcoin
with Asian Indices

this movement. KOR, STI and HK logged inconsistent movement with negative correlation during 2010 until 2019. From 2015 onwards, JPN and BTC correlation shows peak level of correlation. However, for STI, the correlation is most of time in the negative–positive, especially during 2012, 2013, 2014, 2016, 2017 and 2019. As mentioned earlier, STI market offers a quite diversified assets platform for investors which influences this movement. The results of Figure 2 and Table 10 (off-diagonal indicates unconditional correlation of each asset) postulate a similar outcome. Thus, given the correlation between stock indexes and BTC, we can now classify which markets can be considered a safe investment or safe heaven. Generally, in finance, investors tend to opt for the negative correlation as they can diversify investment risk (Jones, 2014). With this concept, the ones to offer a good investment opportunity (safe zone) in the case of heavy volatility in BTC would be STI, HK and KOR. JPN and PHIL may not be considered as a safe zone because of the strong interdependence which would be very risky for investors. However, this is subject to the investors' attitude toward risk factors.

4.4 Time frequency domain using continuous wavelet transform
Before we further discuss the wavelet analysis, we first need to understand their classification prior to making any judgment. Basically, the horizontal line represents the number of years while the vertical line shows the frequency component (scale), with the shorter frequency range closest to the origin of the BTC return fluctuation. Red areas show higher coherency of BTC with stock indexes while blue areas indicate lower co-movement between BTC and stock indexes. Additionally, the black solid silhouettes correspond that the co-movement is statistically significant at 5% given a time and frequency. For example, as we look at the Wavelet Coherence for BTC and JPN, the blue color covers a large proportion of the cone. This means that the time domain co-movement is commonly weak. However, we may notice that the blue area dominates the low scale area (blue color is more prevalent in the higher level of axis y), meaning that the co-movement is more obvious in the long term than it is in the short term. Furthermore, as time progresses, the blue color is less dominant, showing an increase in the co-movement between BTC and JPN. The wavelet phase-difference specifies the dynamic relationship of return or price by looking at the lead-lag association between the paired sets (example: A and B). The arrows set out the lead-lag relationship between the series. If the phase arrow points to the right, this signals that the relationship follows a positive co-movement (in phase: A and B). If the arrow points to the left, the relationship is out of phase (negative co-movement: A and B). If the arrow points down, this implies the price or return of A leads to the price or return of B. If the arrow points up, then B leads A.

4.5 CWT for BTC with Japan, Korea, Singapore, Philippines and Hong Kong
As discussed earlier, the CWT reveals the dominance of blue which covers a large proportion of the cone, showing that the co-movement between BTC and JPN is relatively low. However, as time progresses, we can observe the increasing dominance of red, meaning that the co-movement is getting stronger (short term, medium and long term). These values are statistically significant at 5%. The outcome is quite pragmatic under the scale of 64 to 256. This result is also consistent with the finding revealed in the M-GARCH analysis of the unconditional correlation between BTC and JPN stock index which recorded positive correlation. The lead-lag relationship postulates a positive co-movement between BTC and JPN stock index where most of the arrows point to the right. In other words, the lead-lad relationship between BTC and JPN stock index is within the phase category. If the BTC goes up, then the stock index will also move up. This is consistent with the unconditional

correlation shown by our M-GARCH analysis as well (Figure 3). The CWT for BTC and
KOR indicates quite similar results with BTC and JPN but for this case, the blue color
domain covers the entire cone with little red color areas. This highlights that the degree of
co-movement is very low even though time progresses. The red color can be observed at the
scale of 16 to 64 and 64 to 256 but at minimal level. On the other hand, few arrows are
available and most of the arrows point up when looking at the lead-lag relationship,
meaning that BTC does not lead the KOR stock but the KOR stock index leads the BTC.
This happens in the medium and long periods. This finding is consistent with the M-
GARCH unconditional correlation where the relationship is negative (Figure 4). The
difference is mainly cause by different time horizons involved. As it is very difficult to see
the relationship in the short-term. As time progresses medium term onwards, thus the co-
movement will be strong and the phenomena can be notice in the long-term as well.

Like KOR, the outcome for STI is also more or less similar with blue covering most areas
in the cone. Just a small proportion of red is available under the scale of 64 to 256. This again
shows the degree of co-movement which is very low between BTC and STI. Again, the
wavelet phase difference demonstrates limited arrows that point upward, meaning that the
STI stock index leads the BTC (Figure 5). This can be evidenced at scales of 64 to 256 which
occur at long term.

In terms of the degree of co-movement between BTC and PHIL for short and long scales,
it is very clear that blue dominates over red. However, in the medium scale from 16 to 64, red
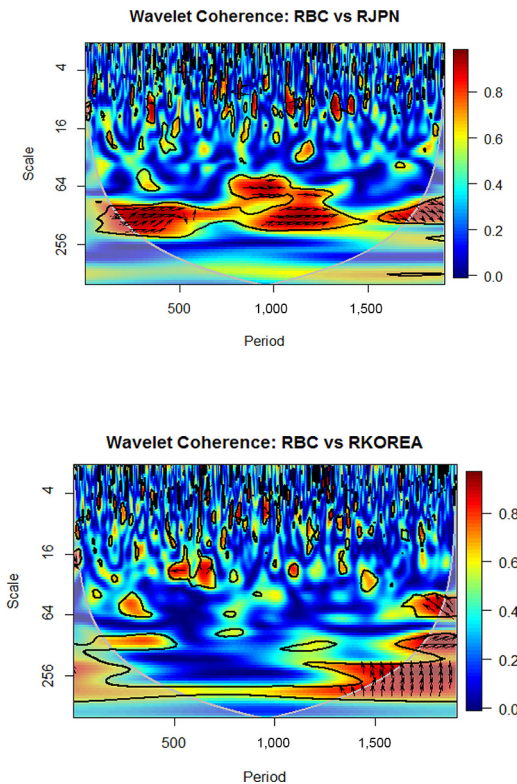

Figure 3.
Continuous Wavelet
Transform (CWT) for
BTC and JPN Stock
Index

Figure 4.
Continuous Wavelet
Transform (CWT) for
BTC and Korea Stock
Index

colors some areas. Moreover, the lead-lag relationship shows the arrows pointing to the left. This is an out of phase relationship as the relationship shows a negative co-movement between BTC and PHIL during the medium term but not in the short and long periods. Finally, for BTC and HK, again blue is dominant, which shows that the co-movement between these two remains low. As time progresses, blue remains a dominant color in the cone. Just a small proportion of red color can be observed inside the cone, which only happens at short and medium scale. A limited number of arrows are available inside the cone which can predict the wavelet phase difference. The arrows are available only at the medium scale, such as 16 to 64. The outcome shows that in the short term, the arrow points to the right while in the long term, the arrow points to the left. Basically, there are in-and-out phases for the lead-lag relationship (Figure 6 and Figure 7).

5. Conclusion
The objective of this paper was to investigate the connection between BTC with Asian Stock Indexes from July 20, 2010 until April 26, 2019 in terms of long and short run relationships, correlations, volatilities and time frequency domains as well as lead-lag analysis. The methods used included VECM and Granger causality, M-GARCH and Wavelet Analysis, respectively. First, based on VECM, all market indexes showed a long-run association with BTC. Four markets recorded negative association and they were JPN, KOR, STI and HK. One market obtained a positive relationship with BTC, which was PHIL. Together with that, the ECT postulated a negative speed of adjustment for all Asian markets considering the

Figure 5.
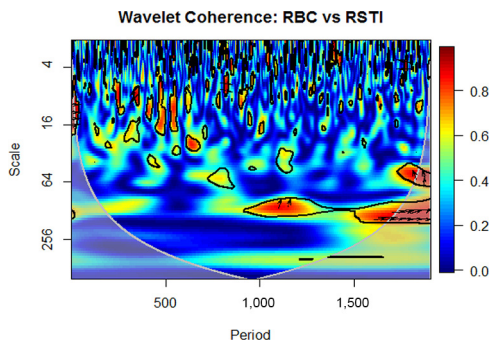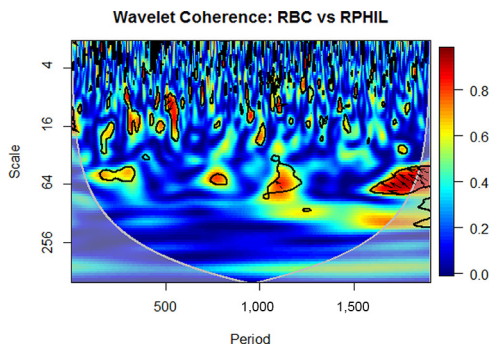Continuous Wavelet Transform (CWT) for BTC and Singapore Stock Index

Figure 6.
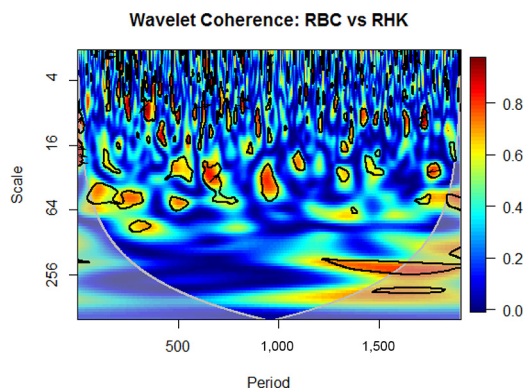Continuous Wavelet Transform (CWT) for BTC and Philippines Stock Index

Wavelet Coherence: RBC vs RHK

change in BTC price. We also observed that in the short-run, only one market had a relationship with BTC movement (i.e. KOR). This reveals that BTC investment is suitable for long term investment rather than short term considering this aspect. Secondly, further econometrics evidence using M-GARCH analysis revealed that most of the Asian markets recorded low-unconditional volatilities with BTC and the only one attained a low value, which was STI. Indirectly, Singapore investment encounters less volatility among other markets. In addition, we also observed that three markets had a negative correlation with BTC (i.e. KOR, STI and HK) while two other markets had positive correlation (i.e. JPN and PHIL). These findings are consistent with the prediction made by VECM. Based on the time-frequency domain analysis using the Wavelet, we observed the following outcomes:

- In the long run, BTC and JPN shared strong co-movement, while the lead-lag predicted a phase category.
- BTC, KOR and STI postulated a similar outcome in which the co-movement between the markets was very low and the lead-lag analysis showed an anti-phase relationship.
- The co-movement between BTC and PHIL existed in the medium scale quite significantly but the lead-lag relationship revealed an out-of-phase category.
- BTC and HK revealed a low co-movement and mixed lead-lag relationship. Our findings have implications for academic and industry practitioners.

Theoretically, our study enriches the existing literature available in the area of cryptocurrency, especially because it uses advanced econometrics techniques. Most of the results are consistent and show the different dimensions about long and short run relationships, volatilities, correlations and time-frequency analysis. We have also used Asian emerging economies which are rarely the subject or focus in the literature as existing studies are more skewed toward the West. As for industry practitioners, we believe the outcomes of this study will be a significant sway for retail and institutional investors to design better strategies on diversifying their stock portfolios with different holding period horizons and dimensions as mentioned above. However, it must be remembered that, not all risks can diversify as markets are still expose to the systematic risks. Future researchers are encouraged to test these phenomena with other developing countries to see if similar patterns are observable as to that of advanced

economies. Comparing Asian countries with developed countries will certainly add value to the existing literature with large data sets.

Note

1. The proportion of time framework used in this study as follows Figure 1:
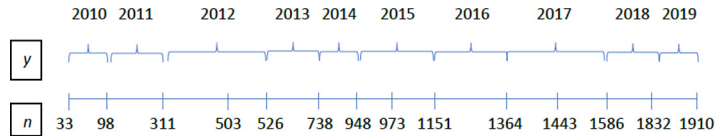
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