Exploring the Dynamic Relationships between Cryptocurrencies and Stock Markets in the ASEAN-5

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ABSTRACT

This research examines the dynamic linkage between four major cryptocurrencies—Bitcoin, Ethereum, Ripple, and Litecoin—and stock markets in ASEAN-5. The findings revealed that first, linkage testing, in the long run using Engle and Granger co-integration, provided evidence of a relationship among all cryptocurrencies with the stock markets in ASEAN-5, with the exception of Malaysia. Secondly, using the dynamic conditional correlation model, the results showed that time-varying patterns of short-run correlations were found in all relationships. Moreover, the Litecoin linkage with ASEAN-5 markets fluctuated significantly. Further, Bitcoin's dynamic linkage with the stock markets showed a very high correlation from 2013 to 2015, and then became close to stable until January 2020. Finally, this paper tested the determinants of the linkage cryptocurrencies with financial market factors, consisting of GOLD, CRUDE, FX, and INT. The empirical results showed that GOLD and INT did not affect the degree of linkage with the stock market or cryptocurrency, although both CRUDE and FX impacted it. As for recommendations and policy implications, the cryptocurrencies demonstrated a dynamic linkage with stock markets and exhibited extreme volatility, and therefore the five countries should prepare a policy or regular information regarding cryptocurrencies for investors or policymakers. On the other hand, investors should focus on indicators such as foreign exchange rates and crude oil prices prior to trading.

Keywords: Cryptocurrency, Dynamic Conditional Correlation, Stock Market

Introduction

In recent years, the analysis of cryptocurrency has gained increasing popularity in both academic research and the financial system as a whole. The concept of Bitcoin was introduced by (Nakamoto, 2008), embodying the high-security technology Blockchain. The

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cryptocurrency quickly became an important aspect of the global financial market (Gajardo, Kristjanpoller, & Minutolo, 2018, pp 195-205). Not only Bitcoin, but other cyptocurrencies have been introduced to the digital currency market such as Ethereum, Ripple and Litecoin; sharing in Bitcoin's market capitalisation. At the time of writing, capitalisation in the cryptocurrency market has reached approximately 262 billion U.S. dollars. Accordingly, it is not surprising that cryptocurrency provides a new alternative financial digital asset for investors, creating a tremendous opportunity for maximising returns.

Therefore, in response to this new digital finance innovation, we address the issue of how cryptocurrencies can be correlated with the stock market and established asset classes to benefit investors in portfolio diversification. If the results show linkage with the stock market, cryptocurrency represents a good opportunity for investors.

Moreover, stock market integration can be found in many regions such as the US, Europe or ASEAN. For example, ASEAN investors typically allocate more of their portfolio investment to other markets than developed countries within the region, although sometimes they choose to invest in their own region rather than going global (French, & Poterba, 1991). This result shows that the behaviour of investors tends towards diversifying their portfolios into many markets.

Generally, previous studies focus on the price returns and volatility of cryptocurrencies (Conrad, Custovic et al. 2018; Klein, Thu et al. 2018; Walther, Klein et al. 2019). To enhance digital assets, this research contributes to the dynamic linkage between cryptocurrency and the stock market to aid crypto-investors in creating strategies that may involve combining leading cryptocurrencies within their portfolios. The factors affecting each cross-correlation are also identified. Generally, cryptocurrency is popular in developed rather than developing countries. In recent years, Asia has experienced a high rate of economic growth following the establishment of the ASEAN Economic Community (AEC) in 2015. Consequently, investors wishing to seek higher returns and the opportunity for portfolio diversification invested in the new economic region.

Given the pattern, the aim of this paper is to examine the linkage between cryptocurrency and the ASEAN stock market using data from its five original members, consisting of Thailand, Malaysia, Singapore, Indonesia and the Philippines. This paper uses both daily and monthly data to test for long-run and short-run relationships, respectively. Because this data can be clearly separated the results.

The four major cryptocurrencies are studied in this research: Bitcoin, Etheruem, Ripple and Litecoin, following the work of Catania, Grassi, & Ravazzolo, (2018). The external macroeconomic factors which may affect this association are then identified for each country, namely gold price, crude oil price, foreign exchange rate and interest rate. Moreover, the multivariate GARCH through dynamic conditional correlation generalised autoregressive conditional heteroscedasticity (DCC-GARCH) model of (Engle 2002) is used in this paper for testing short- run relationship. The advantage of this model is that it allows conditional correlation to vary over time, with the assumption that more than one factor is the source of volatility shock.

The remaining parts of this paper are organised as follows. Section 2 provides the literature review. Methodology is reported in sections 3. Section 4 presents the empirical results from the cointegration and dynamic conditional correlation model. Finally, the conclusion and implications are discussed in section 5.

Research Objective

This paper studied the linkage between cryptocurrency: Bitcoin, Ethereum, Ripple and Litecoin and the ASEAN stock market using data from its five original members, consisting of Thailand, Malaysia, Singapore, Indonesia and the Philippines.

Scope of Research

The monthly data represented the short-run linkage, which estimated by multivatiate GARCH through dynamic conditional correlation (DCC) technique. The cointegration technique was used to test in the long- run linkage, which collected by daily data. The period of data started from April 2013 to January 2020.

Literature Review

The literature review is divided into two parts: 1) a review of the returns and volatilities in cryptocurrency to study the behaviour and trends; 2) a review of the relationship between cryptocurrency and other factors.

Firstly, previous research shows that cryptocurrencies are highly volatile (Catania, Grassi et al. 2018; Conrad, Custovic et al. 2018; Akyildirim, Corbet et al. 2020; Walther, Klein et al. 2019). For example, Walther, Klein et al. (2019) reported that the volatility of cryptocurrencies is shown to be driven by the global business cycle rather than country-specific economic or financial variables. When cryptocurrency sharply increases in volatility, investors fear the effect, as indicated by both the United States and European financial markets (Akyildirim & Corbet et al. 2020). Specifically, Bitcoin has experienced huge growth and price volatility, compared to regular stock assets on the financial market. Furthermore, investors must be aware of such volatility when choosing cryptocurrency for investment. Katsiampa (2017) estimated the volatility of Bitcoin through a GARCH family comparison, finding that Bitcoin has both a short and long-run component of conditional variance. Moreover, Chu, Chan et al. (2017); Corbet (2018) found that Ethereum, Ripple and Litecoin prices all became highly volatile. Also, the behaviour and trend of cryptocurrencies confirmed such fluctuations.

Secondly, the primary research paper by Klein & Thu et al. (2018) identified the different property features of Bitcoin such as assets and linkage to equity markets, reporting that Bitcoin and gold have different characteristics. Gajardo, Kristjanpoller et al. (2018) showed the linkage between Bitcoin and crude oil, gold and the Dow Jones stock index. Moreover, Bitcoin demonstrated a different relationship with commodities and the stock market index. Regarding the effect of major macroeconomic factors on crypto, (Corbet, Larkin et al. 2018) examined GDP, unemployment, retail sales and durable goods. Their results indicated that durable goods and unemployment had a significant effect on Bitcoin, while other factors did not. Moreover, Corbet, McHugh et al. (2017) showed that monetary policy announcements on the interest rate by the Federal Open Market Committee in the US affected Bitcoin returns. While Conrad, Custovic et al. (2018) indicated that S&P 500 volatility had a positive and significant effect on long-term Bitcoin volatility. In the stock market, Prukumpai & Sethapromote (2018) reported that the equity market in the ASEAN-5; Indonesia, Malaysia, the Philippines, Singapore and Thailand showed long-run integration.

Previous papers using the model is a generalized autoregressive conditional heteroskedasticity (GARCH) to test the volatility of cryptocurrency. Since this paper estimates the time-varying conditional correlation linkage among cryptocurrencies and stock markets, a suitable model must be employed to explain the data. Modern research studies tend to choose the multivariate GARCH (MGARCH) model, first proposed by (Bollerslev, Engle et al. 1988) to explain stock market correlation. One part of MGARCH, namely the DCC-GARCH model introduced by (Engle, 2002), is used in this study to explain the direct conditional correlation among stock markets.

Research Methodology

In this study, we focus on Bitcoin, Ethereum, Ripple and Litecoin and ASEAN-5 stock markets in term of returns. The return of Bitcoin and Litecoin started data in April 2013, Ethereum started in August 2015 and Ripple started at August 2013. All cryptocurrencies and stock markets were examined both in the long- and short-run. A cointegration technique is used to test in the long- run linkage, while the short-run is estimated by using multivatiate GARCH through dynamic conditional correlation (DCC) technique introduced by (Engle, 2002)

First, cointegration technique tested in the equation (1). If the movement of these returns showed a common stochastic trend over long-term horizons. The cointegration implied cryptocurrency and the stock market has linkage.

$$Y_{1,t} = \beta_1 + \beta_2 R_{1,t} + \varepsilon_t \tag{1}$$

Which $Y_{1,t}$ is the market index and $R_{1,t}$ is the cryptocurrency price. When testing the variable show non-stationary by OLS will lead to a spurious relationship. The cointegration that introduced by (Engle and Granger, 1987) explained the method by choosing the residual ε_t of the results from non-stationary variable to test the long-run relationship. The two series were cointegrated when the Augmented Dickey Fuller (ADF) test showed the stationary property of the residual; however, these results not reported whether crypto linkage with stock market how to become.

Second, the DCC investigated the short-run relationship between cryptocurrency and the stock market. DCC estimation is the multivariate GARCH model that is the second step from GARCH. The DCC estimated the conditional variance for each series and conditional covariance between series. The correlation estimator showed in equation (2)

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \tag{2}$$

In equation (2) $\rho_{ij,t}$ and $q_{ij,t}$ represented the time-varying conditional correlation and covariance, respectively. $q_{ii,t}$ and $q_{jj,t}$ are the pair-wise conditional variances for each series. A pair of each cross correlations were used to measure the degree of short-run co-movement between crypto and stock market.

Third, we added the trend regressions are estimated to confirm the statistical pattern of the time-varying correlations which showed in the equation (3)

$$\rho_{ij,t} = \delta_{i.0} + \delta_{i,1}\text{Trend}_t + \vartheta_t \tag{3}$$

Last, determinants of behavior linkage with crypto and stock market, the panel data regression was used to measure for determinant factors. We chose four major financial assets: gold price (GOLD), crude oil price (CRUDE), foreign exchange rate (FX) and interest rate (INT) that represented the coupon bond, which estimated in the equation (4)

$$\rho_{ij,t} = \gamma_{i.0} + \gamma_{i,1}X_{ij,t} + \mu_t \tag{4}$$

Where $\rho_{ij,t}$ is the conditional correlation and $X_{ij,t}$ is the matrix of determinant factors, including GOLD, CRUDE, FX and INT. This result will report in the last section of empirical results.

Empirical Results

Data

The recording of daily data on cryptocurrencies commenced at different times: Bitcoin (BTC) and Litecoin (LTC) data became available on 28 April 2013, while Ethereum (ETH) data recording began on 7 August 2015 and Ripple (XRP) on 4 August 2015. All data has been recorded to the end of January 2020. Data on cryptocurrency price has been collected from the website: coinmarketcap.com. The BTC, ETH, XRP and LTC prices are shown in Figure 1.

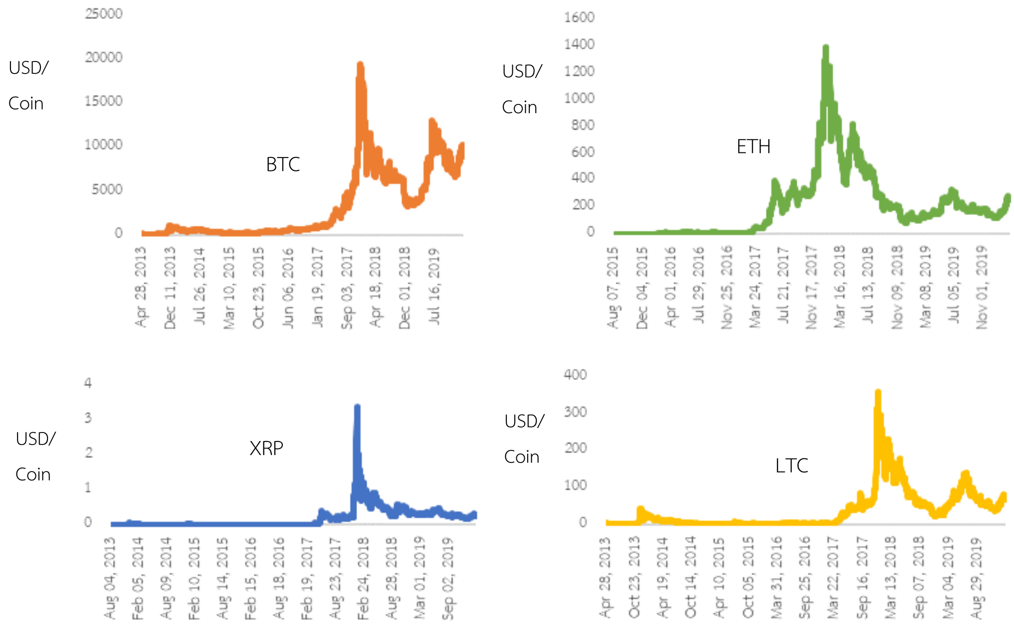

Figure 1 Cryptocurrencies' Price
Source: Authors' Study

And, the daily stock index data of ASEAN-5 (Indonesia: IND), Malaysia (MYS), the Philippines (PHI), Singapore (SGP) and Thailand (THA) collected from Datastream. GOLD, CRUDE, FX and INT prices collected from the CEIC statistic database. All variables were in the natural logarithm.

Table 1 shows the descriptive statistics for returns on four cryptocurrencies and five stock markets. The ETH is high risk and provides high returns of 35.6533 (SD) and 14.6622 (mean), respectively. The average returns for BTC, XRP and LTC range from 0.2% for BTC to 0.4% for XRP, but the risk measured by SD is shown at around 4.26 for BTC to 8.1997 for XRP. The average daily market returns from April 2013 to January 2020 are around -0.0003% for SGP to 0.0097% for IND. However, the stat showing the highest risk (SD) is PHI; while, the lowest risk is shown in the MYS market.

Table 1 Descript Statistics for the Rate of Return in Long- run Relationship

	BTC	ETH	XRP	LTC	IND	MYS	PHI	SGP	THA
Mean	0.2621	14.6622	0.4387	0.3290	0.0097	-0.0034	0.0056	-0.0003	0.0001
Median	0.1810	0.6626	-0.2661	-0.0401	0.0000	0.0000	0.0000	0.0000	0.0000
Maximum	42.9680	283.704	179.3669	129.0954	4.6486	3.3780	5.6983	2.6916	4.5859
Minimum	-23.3713	0.0631	-46.0047	-40.1857	-5.5844	-3.1850	-6.7499	-4.2955	-5.2313
SD	4.2600	35.6533	8.1997	7.0170	0.7782	0.4621	0.8578	0.5966	0.6904

Source: Authors' Study

Unit root testing is shown in Table 2, measured using the Augmented Dickey Fuller (ADF) test and Phillips-Perron (PP) with a null hypothesis of non-stationarity confirmed under two alternative models: with constant (w/c) and with constant and trend (w/c+t). The results report unit roots at level for all variables, except XRP for the w/c and w/c+t. However, the results at first difference show a 1% level of significance for all variables.

Table 2 The Results of Unit Root Test Using the ADF and PP Test in Long-run Relationship

	BTC	ETH	XRP	LTC	IND	MYS	PHI	SGD	THA
At-Level		ADF t-stat							
w/c	-0.82	-1.35	-3.95*	-0.89	-1.51	-1.66	-2.50	-2.27	-1.98
w/c+t	-1.56	-0.90	-4.68*	-1.67	-3.07	-2.58	-3.25	-2.31	-2.64
At First Difference		ADF t-stat							
w/c	-49.93***	-43.41***	-11.21***	-48.83***	-48.06***	-47.93***	-49.53***	-48.44***	-50.23***
w/c+t	-49.92***	-43.48***	-11.21***	-48.82***	-48.05***	-47.94***	-49.52***	-48.43***	-50.22***
At-Level		PP t-stat							
w/c	-0.87	-1.36	-3.77*	-1.01	-1.33	-1.75	-2.31	-2.55	-1.97
w/c+t	-1.71	-0.92	-4.42*	-1.83	-2.85	-2.69	-3.04	-2.58	-2.66
At First Difference		PP t-stat							
w/c	-49.82***	-43.08***	-45.93***	-49.03***	-48.55***	-47.95***	-49.89***	-48.68***	-50.23***
w/c+t	-49.81***	-43.20***	-45.92***	-49.02***	-48.54***	-47.96***	-49.88***	-48.67***	-50.22***

Note: *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively.
Source: Authors' Study

The following section presents the results, divided into four parts.

1) Results of the Long Run Relationship from Cointegration tests

The long-run relationship between four cryptocurrencies and five stock markets were examined using the Engle and Granger (1987) cointegration test. The results show that all cryptocurrencies are linked with the ASEAN-5 stock market, except MYS and the BTC-SGP pairing; as shown in Table 3. Although the BTC shows a long-run relationship with IND, PHI and THA, the MYS and SGP does not effect. Malaysia is the only country unrelated in the long run with all cryptocurrencies.

Table 3 Results of the Long Run Relationship from Cointegration Tests

	IND		MYS		PHI		SGP		THA	
	coeff	t-stat	coeff	t-stat	coeff	t-stat	coeff	t-stat	coeff	t-stat
C	0.0000	-0.3417	0.0000	-0.3402	0.0000	-0.2370	0.0000	-0.3675	0.0000	-0.3402
BTC	-0.0080	-3.1917	-0.0036	-1.8876	-0.0078	-3.0931	-0.0046	-2.4940	-0.0036	-1.8876
ADF	-3.1917**		-1.8876		-3.0931**		-2.4940		-3.0012**	
C	0.0000	-0.0868	0.0000	-0.7148	0.0000	-0.3645	0.0000	-0.5233	0.0000	-0.4876
ETR	-0.0138	-3.3692	-0.0043	-1.5246	-0.0172	-3.7813	-0.0157	-3.9351	-0.0116	-2.8500
ADF	-3.3692**		-1.5246		-3.7813***		-3.9351***		-2.8500*	
C	0.0000	0.4648	0.0000	-0.6937	0.0000	0.1763	0.0000	-0.1399	0.0000	0.1302
XRP	-0.0088	-3.5045	-0.0030	-1.6068	-0.0088	-3.3264	-0.0065	-2.8088	-0.0116	-3.8811
ADF	-3.5045***		-1.6068		-3.3264**		-2.8088*		-3.8811***	
C	0.0000	-0.0330	0.0000	-0.4619	0.0000	-0.0699	0.0000	-0.3392	0.0000	-0.4496
LTC	-0.0058	-2.7588	-0.0031	-1.6856	-0.0066	-2.8598	-0.0051	-2.5816	-0.0062	-2.7357
ADF	-2.7588*		-1.6856		-2.8598*		-2.5816*		-2.7357*	

Notes: The critical values are from Mackinnon (2010); the numbers in parentheses indicate the probability of failing to reject null hypothesis. ***, **, and * indicate the significance level at 10%, 5%, and 1%, respectively.

Source: Authors' Study

2) Results of the Short Run Relationship from Correlation Tests

Table 4 shows the descriptive statistics for returns on four cryptocurrencies and five stock markets. The ETH is high risk and provides high returns of 0.3822 (SD) and 0.0902 (mean), respectively. The average monthly market returns from April 2013 to January 2020 are around --0.0014% for MYS to 0.0020% for IND. However, the stat showing the highest risk (SD) is PHI; while, the lowest risk is shown in the MYS market.

Table 4 Descriptive Statistics for the Rate of Return in Short-run Relation

	BTC	ETH	XRP	LTC	IND	MYS	PHI	SGP	THA
Mean	0.0506	0.0902	0.0489	0.0310	0.0020	-0.0014	0.0002	-0.0008	-0.0007
Median	0.0283	-0.0288	-0.0551	-0.0446	0.0068	0.0024	0.0030	0.0043	0.0022
Maximum	1.2461	1.1122	1.8378	1.6463	0.0656	0.0534	0.0849	0.0717	0.0664
Minimum	-0.3741	-0.4388	-0.7007	-0.5715	-0.0944	-0.0719	-0.0888	-0.0921	-0.0949
SD	0.2338	0.3822	0.4202	0.3533	0.0337	0.0232	0.0383	0.0355	0.0366

Source: Authors' Study

Before estimation, the ADF and PP are employed to check whether the series contains unit roots. The result in the table 5 reveals that all factors are stationary, and is therefore used in subsequent analysis.

Table 5 Descriptive Statistics for the Rate of Return in Monthly Data

	BTC	ETH	XRP	LTC	IND	MYS	PHI	SGP	THA
ADF test with/ c	-6.019***	-4.781***	-6.276***	-6.060***	-8.044***	-8.834***	-8.674***	-11.314***	-8.540***
ADF test with/ c+t	-5.988***	-5.098***	-6.232***	-6.021***	-7.990***	-8.863***	-8.620***	-11.253***	-8.478***
PP test With/c	-6.033***	-4.758***	-5.469***	-5.948***	-8.041***	-8.962***	-8.673***	-11.310***	-8.530***
PP test With c+t	-6.001***	-5.062***	-5.414***	-5.906***	-7.987***	-9.028***	-8.618***	-11.248***	-8.466***

Note: *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively. With/c and with c+t stand for with constant and with constant plus trend, respectively.
Source: Authors' Study

The short-run co-movement between cryptocurrencies and ASEAN-5 returns, tested using monthly data covering the same period as for long-run testing. Table 6 shows a static correlation between four cryptocurrencies and five countries. All cross-correlation pairs are significant at the 1% level, indicating a short-run linkage. The BTC and LTC are shown to have a negative relationship with IND, PHI and THA, while others have a positive relationship. The ETR has a positive relationship with all countries. Whereas XRP has a positive relationship with all countries, except THA.

Table 6 Static Correlation between BTC, ETR, XRP, LTC and ASEAN-5

	IND	MYS	PHI	SGP	THA
BTC	-0.0349	0.1130	-0.0959	0.0032	-0.0542
ETR	0.2588	0.1768	0.2657	0.0944	0.2607
XRP	0.1322	0.1331	0.0354	0.0808	-0.0619
LTC	-0.0425	0.1209	-0.0655	0.0347	-0.0952

Note: The numbers are the static correlations coefficient.
Source: Authors' Study

Moreover, the linkage co-movement examined by dynamic conditional correlation (DCC) to allow for time-varying characteristics, which showed in the Figure 2 – 5.

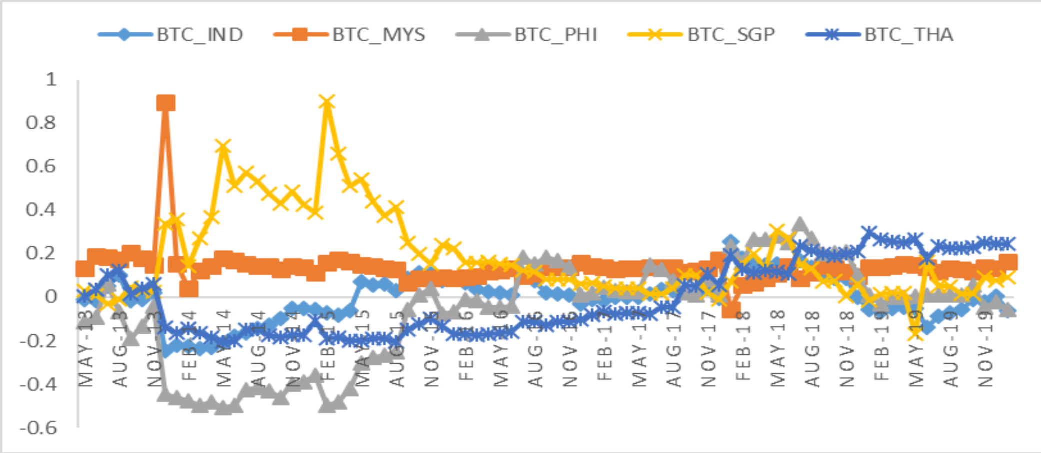

Figure 2 The Dynamic Conditional Correlation: BTC and ASEAN-5
Source: Authors' Study

Figure 2 shows the linkage between BTC and five countries, indicating a relationship between BTC and stock market changes over time. Consistent with the static correlation, the first time Bitcoin started trading in the market, high fluctuations in the ASEAN-5 market were observed for around three years (2013–2015), subsequently showing stability and correlation with five countries. When focusing on the BTC linkage, MYS and SGP show positive signs. Moreover, BTC and SGP markets were highest at 0.9 in February 2015, and BTC and MYS markets were highest at 0.9 in December 2013. However, for BTC and PHI co-movement in the negative zone, the results are the lowest at 0.5 for the period from November 2013 to February 2015. From 2016 to January 2020, BTC shows close linkage with five countries.

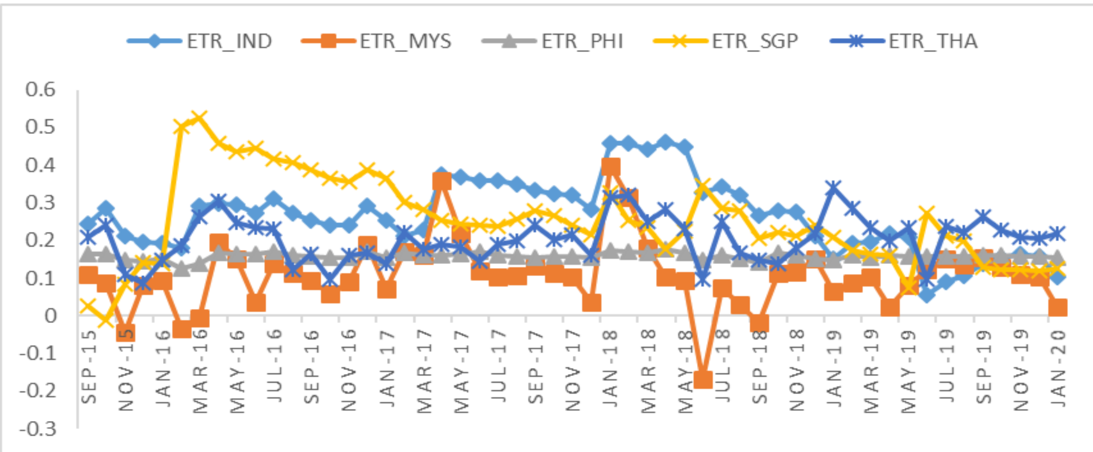

Figure 3 The Dynamic Conditional Correlation: ETR and ASEAN-5
Source: Authors' Study

Figure 3 shows a linkage between ETR and five countries, all of which have time-varying relationships. The results are very volatile because ETR was introduced as a new cryptocurrency for investment in September 2015. All correlations are shown to be in the positive range, except for the pairing of ETR and MYS, exhibiting a big drop at 0.2 in June 2018 because the price of ETR decreased by around 26% in one month. These patterns suggest that this cryptocurrency remains volatile for investment purposes.

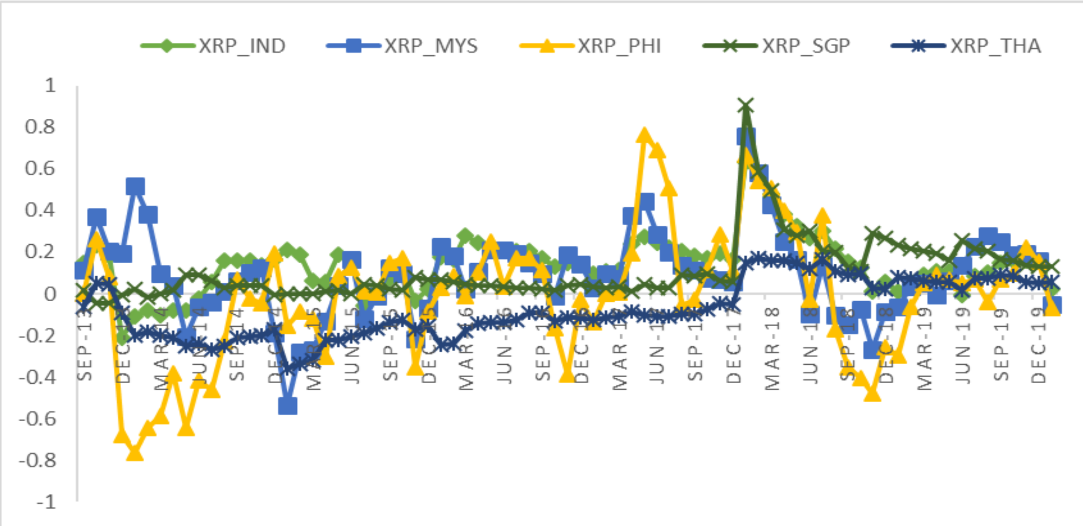

Figure 4 The Dynamic Conditional Correlation: XRP and ASEAN-5
Source: Authors' Study

In Figure 4, the time-varying correlation between XRP and ASEAN-5 stocks demonstrate a fluctuating pattern in certain periods. A large jump can be observed in two periods. Firstly, in September 2013, the fluctuation was caused by the introduction of a new cryptocurrency, and during the other period (January 2018), the very high fluctuation was caused by the three pairings of XRP_SGP, XRP_MYS and XRP_PHI. The highest correlation of 0.8. occurred in around December 2017 when XRP produced significantly increased returns of 262% in one month. The dynamic correlation of XRP continues to remain volatile.

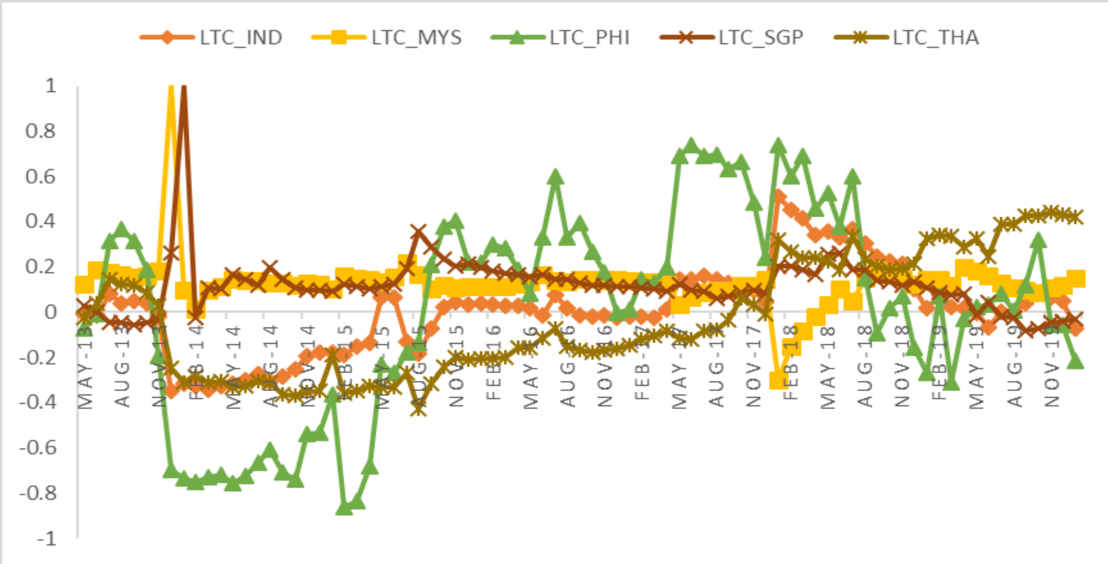

Figure 5 The Dynamic Conditional Correlation: LTC and ASEAN-5
Source: Authors' Study

Figure 5 shows that the LTC cryptocurrency, although introduced during the same period as BTC is less popular. This is because LTC fluctuates considerably, especially in the Philippines (PH). During the big jump covering November 2013 to February 2014, LTC_MYS and LTC_SGP show a positive relationship close to one since the price increased from 10 to 26 dollars per coin in one month. These results showed a positive linkage between MYS and SGP while the relationship between IND, PHI and THA was in the negative range. This outcome indicates that the behavior exhibited by LTC in MYS and SGP differs from that of IND, PHI and THA. In the dynamic time-varying of LTC, PHI is shown to have the highest co-movement. Consequently, investors should be made aware that LTC is extremely volatile.

3) Result of the Trend Regression

Table 7 confirms the changing patterns of correlation over time. The results show both positive and negative trends between the BTC and ASEAN-5 stock markets. The ETR exhibits significant negative trend in IND and SGP while others are insignificant. The XRP shows a positive significant trend in all countries, except MYS. The LTC shows a significant positive trend in IND, PHI and THA but a significant negative trend in MYS.

Table 7 The Trend Regression

	IND		MYS		PHI		SGP		THA	
	coeff	t-stat	coeff	t-stat	coeff	t-stat	coeff	t-stat	coeff	t-stat
C	-0.0612	-2.8242	0.1757	8.8078	-0.3334	-8.6220	0.3497	9.0143	-0.2157	-8.7338
BTC	0.0014***	3.0763	-0.0009**	-2.1875	0.0067***	7.9741	-0.0041***	-4.9507	0.0052***	9.7852
R^2	0.1070		0.0571		0.4459		0.2368		0.5479	
C	0.3150	12.4350	0.1051	4.2452	0.1576	63.0566	0.3312	11.1863	0.1811	11.4878
ETR	-0.0019**	0.0268	0.0001	0.1314	0.0000	0.3856	-0.0030***	-3.1173	0.0009	1.6611
R^2	0.0926		0.0003		0.0029		0.1600		0.0513	
C	0.0732	2.4346	0.0573	1.2445	-0.1888	-2.8615	-0.0324	-1.1654	-0.2529	-12.4825
XRP	0.0018***	2.6417	0.0009	0.9050	0.0048***	3.1960	0.0036***	5.7632	0.0046***	10.0946
R^2	0.0851		0.0108		0.1199		0.3069		0.5760	
C	-0.1778	-5.2187	0.1765	6.7456	-0.3134	-3.4980	0.1597	5.4725	-0.3617	-9.6256
LTC	0.0047***	6.3852	-0.0012**	-2.1922	0.0084***	4.3513	-0.0010	-1.5974	0.0083***	10.2836
R^2	0.3404		0.0573		0.1933		0.0313		0.5724	

Note: ***, **, and * indicate the significance level at 10%, 5%, and 1%, respectively.
Source: Authors' Study

4) Result of determinants of behavior linkage with BTC, ETR, XRP, LTC and ASEAN-5

The panel regression results are estimated using the fixed-effect method because the numbers of independent variables are larger than the cross-section unit. Thus, the random effect is rejected, making the fixed effect the appropriate model. This estimation includes time trend variables (TREND) in the model to control the increasing trends in cryptocurrency linkage with the stock market. Table 8 presents the determinant behavior results of this linkage.

The results show that GOLD is insignificant in all cryptocurrency correlations. Hence, linking cryptocurrency with the stock market had no effect on gold. This finding is consistent with the research of (Klein, Thu et al. 2018). The CRUDE variable was found to have a positive significant relationship with ETR, but its relationship with others was insignificant. Furthermore, changes in CRUDE affects investment in ETR for ASEAN-5 stock markets. The FX factor exhibits a positive significant relationship with BTC and LTC. Hence, appreciation or depreciation in domestic currency affects investment in BTC and LTC. Finally, the INT variable is insignificant for all cryptocurrencies. However, the correlation confirmed that all cryptocurrencies and stock markets show dynamic co-movement during the period of study, with the results indicating significance in the trend variable. Thus, cryptocurrencies are shown as clear determinants of the different relationships between financial assets such as GOLD, CRUDE, FX and INT.

Table 8 Result of Determinants of Behavior Linkage with BTC, ETR, XRP, LTC and ASEAN-5

	BTC	ETR	XRP	LTC
C	-0.0258	0.2222	-0.0735	-0.1151
GOLD	-0.2054	0.0271	-0.1259	-0.0185
CRUDE	0.0480	0.1159*	0.1390	0.1764
FX	0.8114*	-0.0245	0.1579	1.2209*
INT	2.9259	1.9890	-5.1577	0.1287
TREND	0.0018***	(-0.0009)***	0.0033***	0.0041***
Adjust R^2	0.2781	0.3505	0.2440	0.1600
F-test for Fixed Effect	18.0814 (0.0000)	16.5275 (0.0000)	14.5924 (0.0000)	9.4464 (0.0000)

Note: ***, **, and * indicate the significance level at 10%, 5%, and 1%, respectively.
Source: Authors' Study

The empirical results confirm that for financial assets such as GOLD, CRUDE, FX and INT, certain factors determine the degree of cryptocurrency linkage. GOLD and INT do not affect the degree of linkage between stock markets and cryptocurrencies. While CRUDE was found to impact only on ETR; although FX affected the linkage between BTC, LTC and the ASEAN-5 stock markets.

Conclusion

This research investigates the relationship between four cryptocurrencies, namely Bitcoin, Ethereum, Ripple and Litecoin, and the five stock markets of Indonesia, Malaysia, the Philippines, Singapore and Thailand. The data covered the period from April 2013 to January 2020. Linkage testing, in the long run, was estimated using the cointegration test, and examined by a correlation test in the short run. The factors determining the degree of linkage between cryptocurrencies and ASEAN-5 stock markets were estimated using panel regression. The findings of this study are concluded in three parts.

Firstly, in the long-run relationship, all cryptocurrencies were found to be associated with ASEAN-5 stock markets, except Malaysia. Secondly, the short-run relationship test using the DCC model showed that cryptocurrencies and stock markets show a dynamic time-varying movement over the period of study. Litecoin was shown to have the highest volatility with Malaysia, the Philippines and Singapore. The dynamic linkage of Bitcoin with the stock markets showed very high correlation from around 2013 to 2015 but remained stable until January 2020. Finally, the empirical results show that the degree of linkage depends on the crude price when investing in Ethereum. Moreover, the FX factor affected the determinants of Bitcoin and Litecoin. However, gold price and interest rate changes do not impact on the degree of cryptocurrency determination and stock market integration.

Recommendations and Policy Implications

As for recommendations and policy implications, cryptocurrencies show a dynamic linkage with stock markets and significant volatility. Therefore, the five countries in this study should plan for the cryptocurrency exchange to be regulated for investors or policymakers beginning to see investment prospects. The long-run and short-run relationships between cryptocurrencies and stock markets exhibit time-varying patterns. Therefore, cryptocurrencies can offer investors portfolio diversification. Furthermore, investors should be encouraged to monitor indicators such as foreign exchange rates and crude oil prices.

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