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Bitcoin-Altcoin Price Synchronization Hypothesis: Evidence from Recent Data

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Abstract The study investigates the bitcoin-altcoin price synchronization hypothesis using cointegrating test and VEC Granger Causality/Block Exogeneity Test approaches on the daily data of bitcoin and ten selected alternative coins (altcoins) between August 8, 2015 and December 31, 2018. The data is structurally divided into three distinct periods which are; August 8, 2015 to December 31, 2016; January 1, 2017 to December 31, 2017 and January 1, 2018 to December 31, 2018. The study establishes pure price separation between the altcoin and bitcoin in 2015-2016, price synchronization between bitcoin and each of the selected altcoin in 2017 and dominant altcoin-to-bitcoin price formation in 2018. The study concludes that cryptocurrency buyers are more sensitive in 2018 to the features and quality of project each coin promotes, unlike the indiscriminating choices which dominated cryptocurrency world during the 2017 boom.

Keywords: *Bitcoin, Altcoin, price synchronization, price formation*

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1. Introduction

Cryptocurrency advances in popularity, recognitions and acceptability on daily basis across the world, Baur, Hong, & Lee [1]. In the early days of cryptocurrency emergence, when bitcoin was the sole coin in circulation, less was the prediction that it would grow and advance to the level accorded it in the global financial system within the last three years. However, when the cryptocurrencies began to gain momentum and when other alternative coins, such as litecoin, ripple, ethereum among others emerged, attention is shifted to the potential revolutionary impact of the new innovations. Given the supremacy of bitcoin in the committee of cryptocurrencies, Urquhart [2], it was not surprising when some studies predicated the success and acceptability of other coins largely on the performances of bitcoin. Until in the recent time, investors in alternative coin (Altcoin)[1] must first purchase bitcoin using fiat currency and then convert to the coin of choice. Thus, it may be unclear to decide on why the price of bitcoin kept increasing in certain period and the nature of price relationship between altcoin and bitcoin. However, Bouri, Lau, Lucey & Roubaud [3] argued that altcoin and bitcoin are interrelated when examined within the frameworks of certain characteristics which include the price and volume of transactions. There are many possibilities when scouting for the nature of price relationships between altcoins and bitcoin. First, if the cryptocurrency users are interested in coins other than bitcoin, they might of necessity purchase bitcoin, especially when the direct fiat currency pairs are minimal in cryptocurrency exchange platform, which might therefore force bitcoin price upward. In this case, ‘altcoin-to-bitcoin price formation’ prevails. More also, some users, as a result of high price of bitcoin might settle for coin with relatively low price, in expectation of price rally along the bitcoin trend. This might usher in ‘bitcoin-to-altcoin price formation’. Other option is for investor to assumed all cryptocurrencies as identical and thus, randomly choose among the available options, especially as it was in the early development of cryptocurrency. This could be referred as ‘bitcoin-altcoin price separation’. However, the bitcoin-altcoin price separation could also occur when users are growing versatile in knowing the importance of development in the blockchain technology, such that each cryptocurrency is handled on its merit and usefulness, without necessarily purchasing altcoins using bitcoin. The last option is when investor engages in speculative game, in which, investment is interchanged between bitcoin and altcoin or between one altcoin and another altcoin, such that, when price of one increases, the investor sells off and takes advantage of the low price alternative on a continuous basis [4]. Such price relationship could be tagged ‘bitcoin-altcoin price synchronization or cryptocurrency price synchronisation’. Pavel, d'Artis & Miroslava, [5] while examining the bitcoin and altcoin markets, confirmed that in a specified period, bitcoin and altcoin markets were interdependent.

In the early stage, cryptocurrency users found it difficult to differentiate bitcoin from other altcoins, such

[1] Altcoin is the general name for all cryptocurrencies excluding the bitcoin.

that, other coins were perceived as replica of bitcoin or minor modification of it. However, as the studies, researches and innovations in the blockchain technology increase, the huge potential of the technology were uncovered and several projects with unique developmental target sprang up and began to attract the interest of many people across the globe. The enlightenment and interest in the blockchain technology gives each coin individual unique identity and recognition, which were distinct from the laissez-faire notion that all coins originated from bitcoin protocols. More also, direct fiat conversion to other coins also gives several altcoins distinct attention and identity independent of bitcoin.

In statistical term, if the causal effects run through bitcoin prices to altcoins, the popularity of bitcoin remains the shield on the price performance of the altcoins, thus, the trend of speculative purchase of all cryptocurrencies remain on the classical track of bitcoin performance. Meanwhile, if bidirectional causality runs between bitcoin and altcoins, the investors and cryptocurrency users react to cryptocurrency as a single entity, such that, a negative or positive shock to one is taken as response to all. The absence of causal effect is an evidence that users are growing versatile in knowing the importance of growing development in the blockchain technology, such that, each cryptocurrency is handled on its merit and usefulness.

2. Literature Reviews

In the work of Pavel, d'Artis & Miroslava [5], the interdependencies between bitcoin and altcoin markets in the short- and long-run were examined and it was confirmed that bitcoin and altcoin markets are interdependent. It was specifically established that bitcoin-altcoin price relationship is significantly stronger in the short-run than in the long-run. More specifically, Cagli [4] investigates explosive behavior in the prices of Bitcoin and seven other altcoins which include Ethereum, Ripple, Litecoin, Stellar, Nem, Dash, and Monero using the new ‘explosive process framework’ of Chen et al. [6] and found that all cryptocurrencies other than Nem exhibit explosive behavior and reveal significant pairwise co-movement relationships among the explosive cryptocurrencies.

In a related study, Bouri et al [3] examined Granger causality from trading volume to the returns and volatility in the cryptocurrency market via a copula-quantile causality approach. Using daily data of seven leading cryptocurrencies (Bitcoin, Ripple, Ethereum, Litecoin, Nem, Dash, and Stellar), they found that trading volume Granger causes extreme negative and positive returns of all cryptocurrencies under study. However, they established that volume Granger causes return volatility for only three cryptocurrencies (Litecoin, NEM, and Dash) when the volatility is low. Cryptocurrencies in many cases, exhibit common characteristic in their behavioural pattern. Brauneis & Mestel [7] performed various tests on efficiency of several cryptocurrencies and additionally link efficiency to measures of liquidity and conclude that cryptocurrencies become less predictable or inefficient as liquidity increases.

Yi, Xu & Wang [8] used spillover index approach and its variants to examine both static and dynamic volatility connectedness among eight typical cryptocurrencies and found that their connectedness fluctuates cyclically and has shown an obvious rise trend since the end of 20 16. In the variance decomposition framework, they further constructed a volatility connectedness network linking 52 cryptocurrencies using the LASSO-VAR for estimating high dimensional VARs and found that the 52 cryptocurrencies are tightly interconnected and what they referred as “mega-cap” cryptocurrencies are more likely to propagate volatility shocks to others. However, they argued that some unnoticeable cryptocurrencies such as Maidsafe coin are also significant net-transmitters of volatility connectedness and even have larger contribution of volatility spillovers.

Meanwhile, in an earlier work of Grinberg [9], it was identified that bitcoin performance in terms of usage and demand depends on its competition with at least two classes of products; products that facilitate internet-based commerce, and gold-backed currencies. He posited that bitcoin is unlikely to make significant headway in the traditional ecommerce market because consumers generally do not care about the kind of anonymity that it provides, traditional settings prefer to compare prices of most goods and services in a currency they are familiar with, and are keen to fraud protection (which bitcoin lacks). However, they argued that bitcoin might be much competitive in the micropayment and virtual world markets, where consumers care less about pricing in a familiar currency. The expectation was that Bitcoin might likely be attractive to those who like gold-backed currencies because its value depends on the availability of a limited resources, such as virtual features rather than discretionary actions by central bankers.

Barber, Boyen, Shi and Uzun [10] pitched the tent of bitcoin pricing around the superiority of the virtual currency over other class of e-cash. They posited that, the stronger the features of the bitcoin the higher its adoption and higher the pricing. In the study, it was identified that bitcoin become widely accepted because of its decentralized features, predictable rate of its supply over time, its divisibility like any other fiat currencies, its versatility, openness, and vibrancy. More also, they argued that its transaction irreversibility is appealing to merchants who are concerned about credit-card fraud and chargebacks. In addition, they identified that low fee of bitcoin transaction also contributes to its wide acceptance. In the work of Ciaian, Rajcaniova & Kancs [11], it was demonstrated that market forces and bitcoin attractiveness for investors and users have a significant impact on bitcoin price but with variation over time. However, their estimates do not support previous findings that macro financial developments drive bitcoin price in the long run. Unfortunately, most of the set back of bitcoin is the scamming roles of the middle men who patronize themselves as the frontline in its dissemination and managements [12].

Studies frequently confirms the speculative nature of bitcoin, regardless of other factors which are responsible for its performances. Bouoiyour, Selmi, and Tiwari [13] confirms the extremely speculative nature of Bitcoin without neglecting its usefulness for economic reasons, such as trade transactions. The study identified Chinese market index and hash rates as critical to the validation of the bitcoin speculative nature. The study of Bouoiyour et al [13] was confirmed in the later work of Kristoufek [14] which further conclude that bitcoin forms a unique asset possessing properties of a standard financial asset and a speculative one. In the same way Blau [15] examined price dynamic and speculative trading in bitcoin. He founds that bitcoin is volatile and the volatility is attributed to speculative trading. It implies the price dynamic of bitcoin was predicated on the investors' or users' speculation, rather than the nature of altcoin attributes.

3. Scope and Data Sources

Time series daily data on bitcoin and ten selected altcoins prices (Ethereum, Litecoin, Dash, Doge, IOTA, Nem, Neo, Stellar, Ripple and Tron) between August 8, 2015 and December 31, 2018 were collected from cryptocompared daily database online. August 8, 2015 was the time limit for the latest of five selected old coins, while five more recent coins were also selected. All the included coins are among the top rated cryptocurrencies, in terms of their capitalisation. More also, a mix of coins with various features such as blockchain protocols, underlining projects, daily trading volumes, quantity of coins in circulation, time of creation and price variation among other features were considered. All were considered in a bid to select representative altcoin with strong credibility.

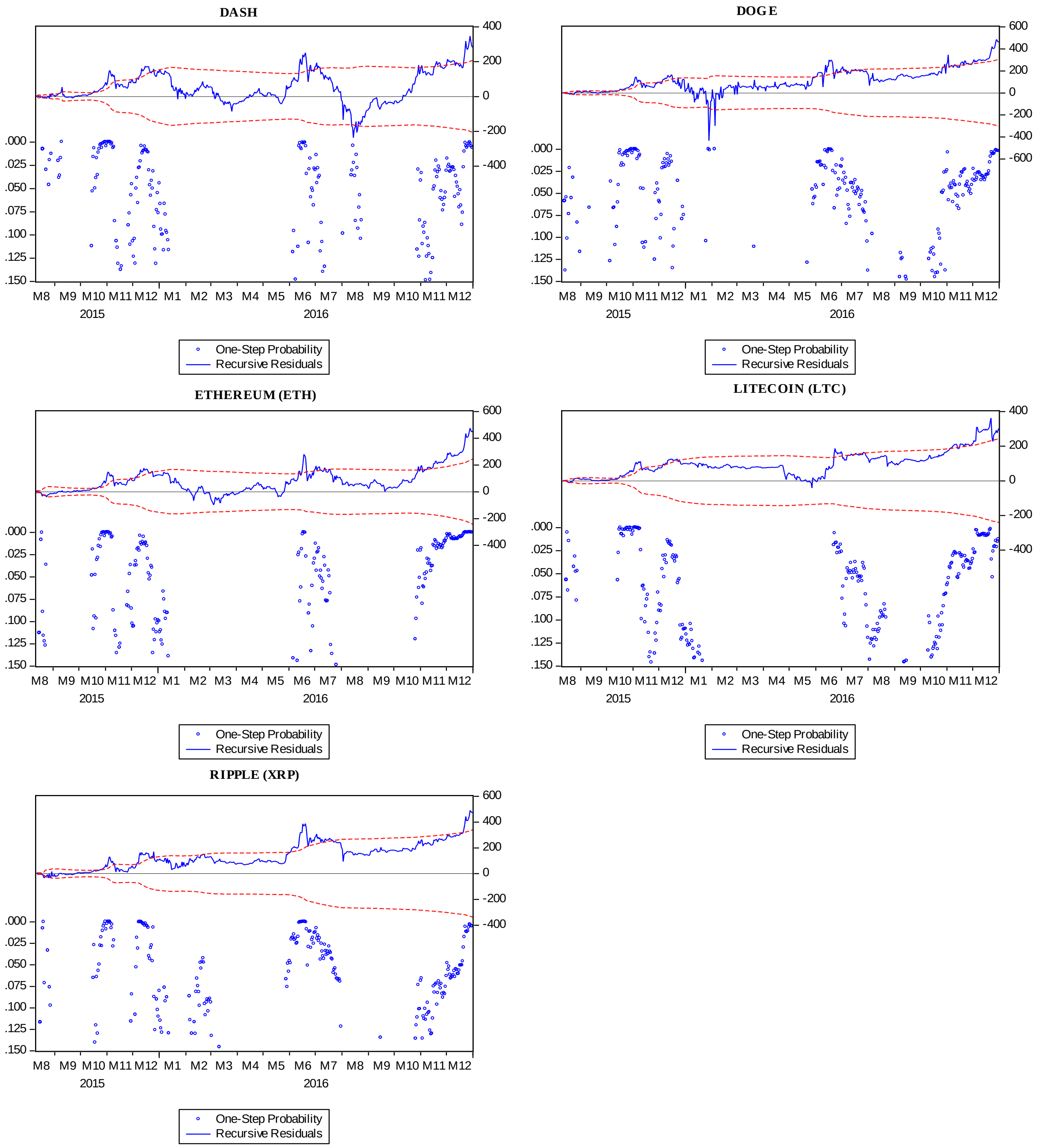

Figure 1. One-Step Forecast (2015-2016)

3.1. Recursive Residual Tests for Structural Breaks

To test for structural breaks in variables, the recursive test for stability was conducted using one-step forecast test to identify where the break(s) exist. It is a method augmenting CUSUM test which is based on the cumulative sum of the recursive residuals suggested by Brown, Durbin, and Evans [16]. CUSUM plots the cumulative sum together with 5% critical lines. Parameter instability is found if the cumulative sum goes outside the area between the two critical lines. As such, movement of the sample outside the critical lines suggests coefficient instability. The one-step forecast helps in identifying the periods when the instability sets in the data series. The one-step forecast tests results on bitcoin and selected alternative coins are presented in Figure 1 to Figure 5 covering the periods, 2015-16, 2017 and 2018 sub-grouping. The essence of the recursive residual test is to account appropriately for the structural breaks in the course of the data analysis.

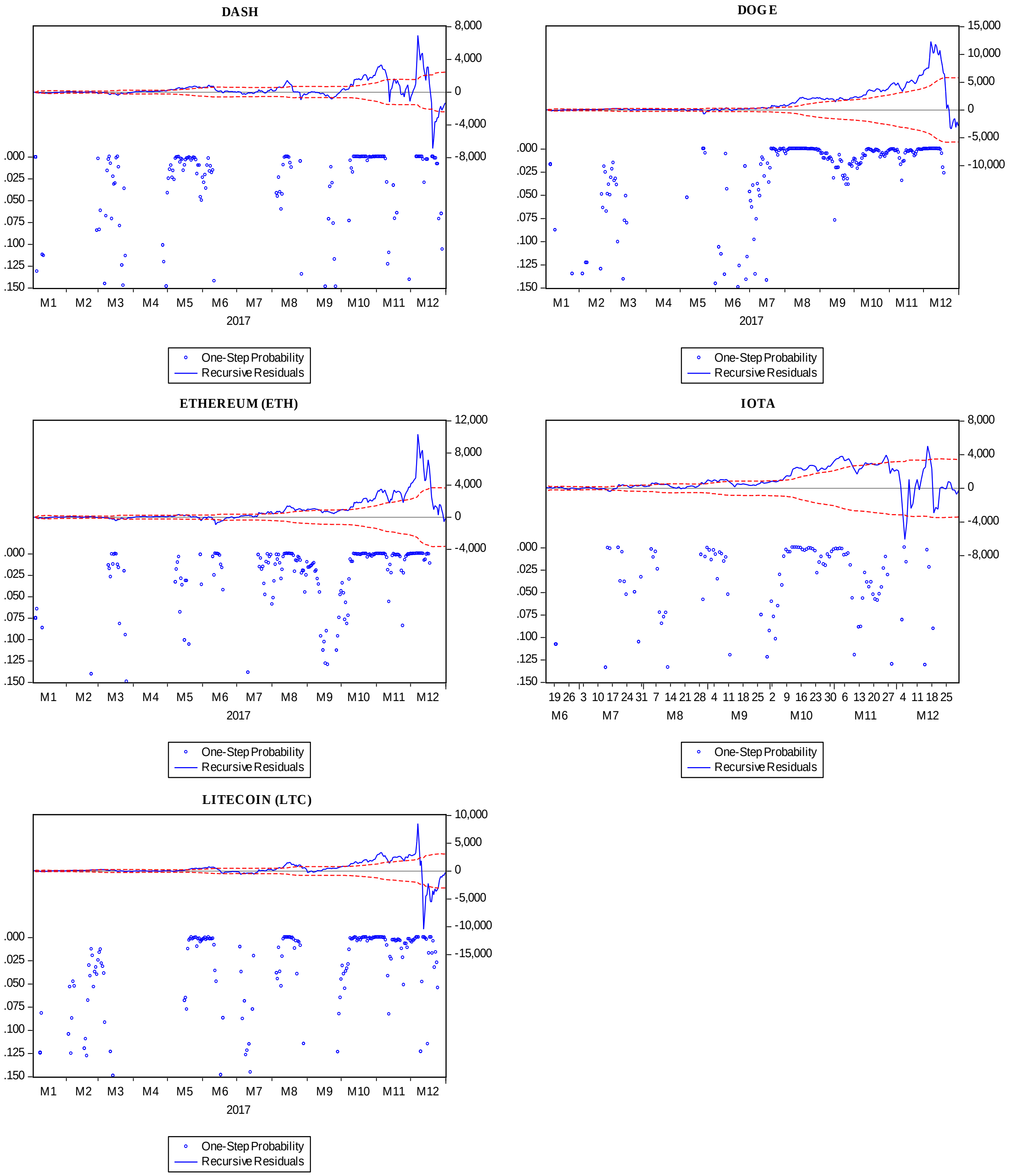

Figure 2. One-Step Forecast (2017)

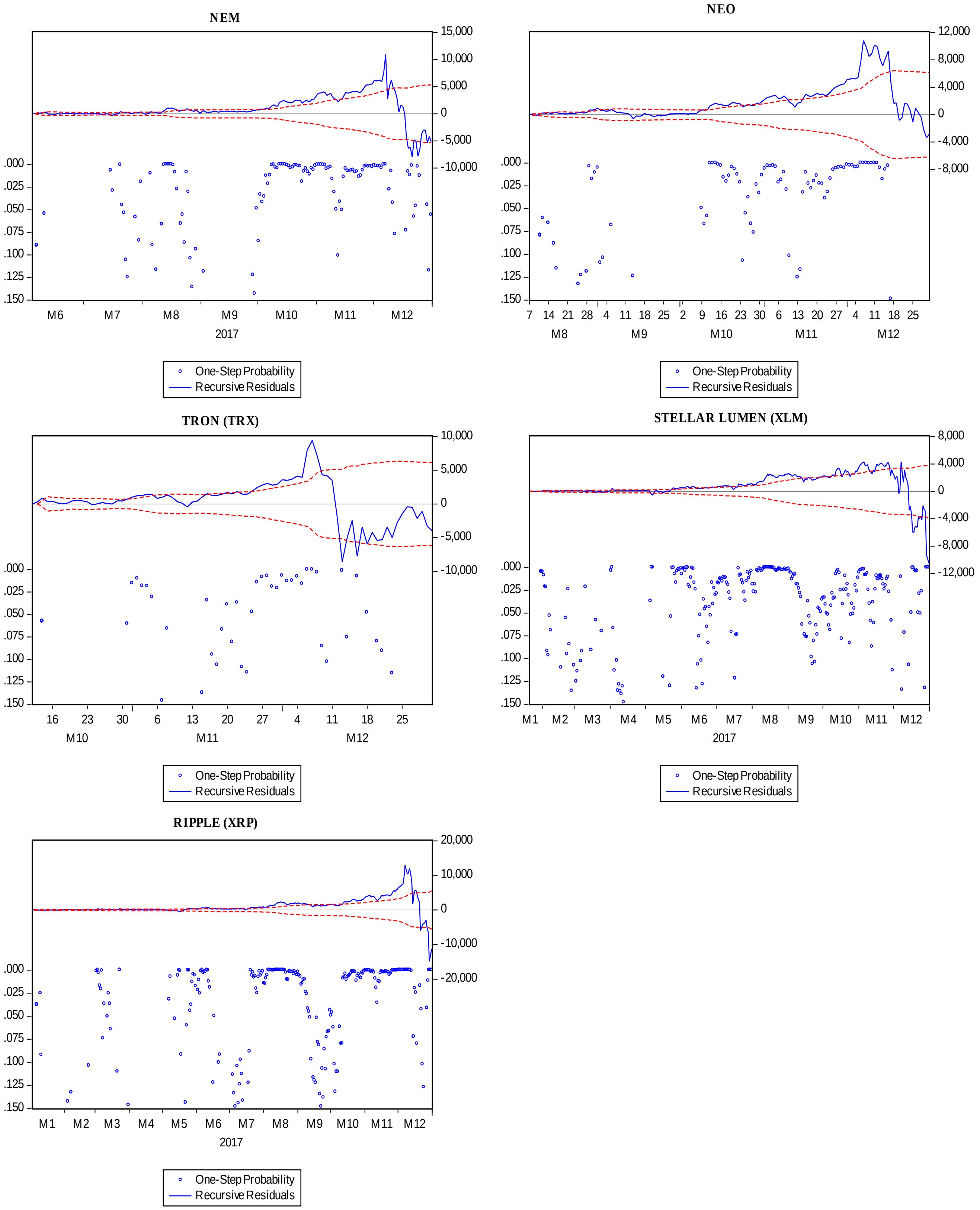

Figure 3. One-Step Forecast (2017)

3.2. Recursive Residual Test (2015-2016)

The one-step forecast tests on the variables shows relative stability with few points of instability and divergence of the trend outside the 5% boundary. The out of boundary points supports variance instability, which is an indication of existence of structural breaks in in the period. Only five of the eleven selected cryptocurrencies were in existence during the period. It is observed that, the relatively new emergence of the cryptocurrencies during the period allow a level of stability within the cryptocurrency space. However, it is obvious in the figure that all the variables exhibit high level of instability towards the last months of 2016 in preparation for the cryptocurrency boom which emerged in the early months of 2017.

3.3. Recursive Residual Test (2017)

The cryptocurrency world experienced an unprecedented boom in 2017, especially in the second half of the year. The cryptocurrency price instability in 2017 was obvious across board. As presented in the Figure 2 and Figure 3, the selected cryptocurrencies exhibited identical pattern of instability. In the early year of 2017, the prices were relatively low compared to the explosion experienced in the later period of the year. However, IOTA, TRON and NEO are relatively stable compared to others.

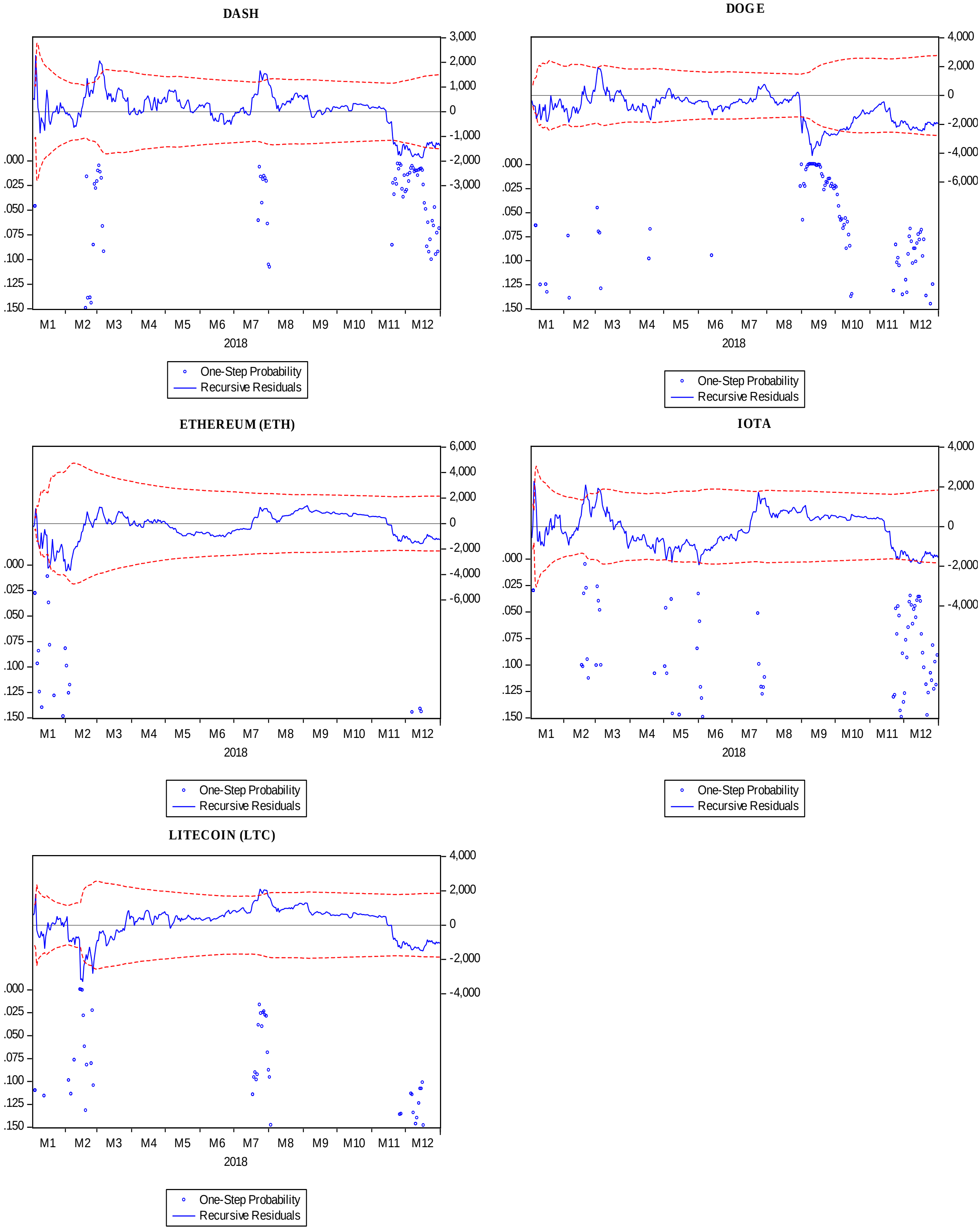

Figure 4. One-Step Forecast (2018)

3.4. Recursive Residual Test (2018)

The cryptocurrency boom of 2017 was brought to halt and subsequently price retrogression set-in in 2018. It is not out of place to attribute the crash and relative stability of cryptocurrency prices in 2018 to the regulatory crackdown in many cryptocurrency leading countries of the world. As presented in Figure 4 and Figure 5, the prices were relatively stable compared to both the 2015-16 and 2017 sub-grouping periods. Meanwhile the stability pattern is deviating out of boundary towards the end of 2018. It is much obvious in DASH, NEM and RIPPLE. This might be pointing to possible new price pattern in 2019.

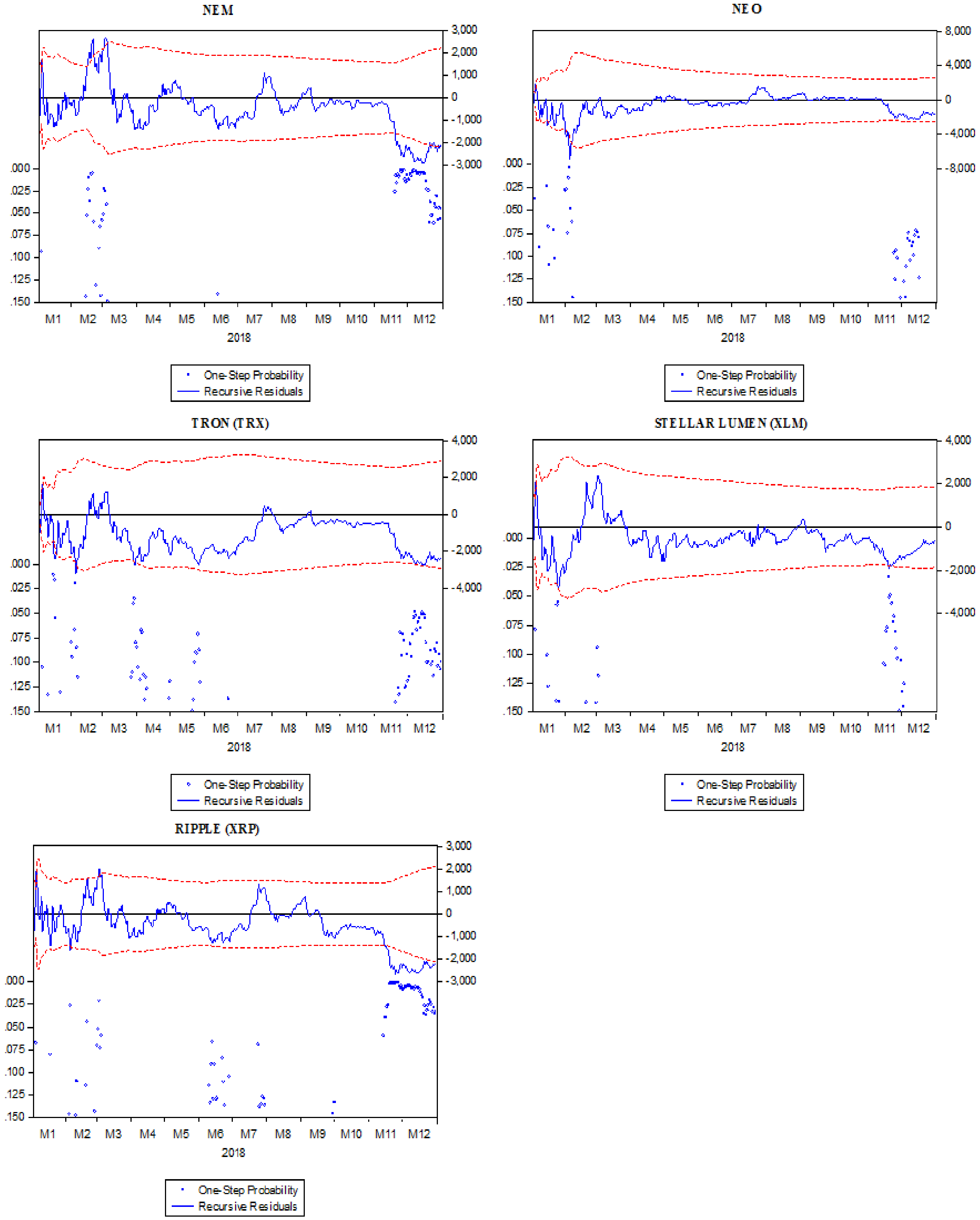

Figure 5. One-Step Forecast (2018)

The Econometric Model

This paper adopts Granger Causality/Block Exogeneity test between the bitcoin (BTC) and selected altcoins (ALT) within VAR structure.

In the bi-variate VAR describing variable x and y, y does not granger cause x if the coefficient matrix $\emptyset_J$ are lower triangular for all values of J:

$$\begin{pmatrix} x_t \\ y_t \end{pmatrix} = \begin{pmatrix} \propto_1 \\ \propto_2 \end{pmatrix} + \begin{pmatrix} \varnothing_{11}^1 & 0 \\ \varnothing_{21}^1 & \varnothing_{22}^1 \end{pmatrix} \begin{pmatrix} x_{t-1} \\ y_{t-1} \end{pmatrix} + \begin{pmatrix} \varnothing_{11}^2 & 0 \\ \varnothing_{21}^2 & \varnothing_{22}^2 \end{pmatrix} \begin{pmatrix} x_{t-2} \\ y_{t-2} \end{pmatrix} + \ldots\ldots\ldots + \begin{pmatrix} \varnothing_{11}^\rho & 0 \\ \varnothing_{21}^\rho & \varnothing_{22}^\rho \end{pmatrix} \begin{pmatrix} x_{t-\rho} \\ y_{t-\rho} \end{pmatrix} + \begin{pmatrix} \mu_{1t} \\ \mu_{2t} \end{pmatrix}. \quad (1)$$

From the first row of the above system, the optimal one-period ahead forecast of x does not depend on lagged value of y but on its own lagged values, that is;

If

$$E\left(x_{t+1} | x_t, x_{t-1}, \ldots\ldots, y_t, y_{t-1} \ldots..\right) = \propto_1 + \varnothing_{11}^1 x_t + \varnothing_{11}^2 x_{t-1} + \ldots + \varnothing_{11}^\rho x_{t-\rho+1}. \quad (2)$$

To implement the test, having the knowledge that the variables are integrated of order 1, the optimal lag length ρ suggested by various criteria is adopted and eq. 3 below is estimated within the Vector Error Correction structure:

$$W_t = \left(BTC_t, ALT_t\right)'. \quad (3)$$

The W_t is the column vector of the variables. Explicitly:

$$\begin{aligned} \Delta BTC_t &= \alpha_1 + a_1 \Delta BTC_{t-1} + a_2 \Delta BTC_{t-2} \\ &+ \ldots\ldots + a_p \Delta BTC_{t-\rho} + b_1 \Delta ALT_{t-1} \\ &+ b_2 \Delta ALT_{t-2} + \ldots\ldots + b_p \Delta ALT_{t-\rho} \\ &- \gamma_{BTC} \left(BTC_{t-1} - \alpha_0 - \alpha_1 ALT_{t-1}\right) + \varepsilon^{BTC}{}_t \end{aligned} \quad (4)$$

$$\begin{aligned} \Delta ALT_t &= \alpha_2 + a_1 \Delta ALT_{t-1} + a_2 \Delta ALT_{t-2} + \ldots\ldots + a_p \Delta ALT_{t-\rho} \\ &+ b_1 \Delta BTC_{t-1} + b_2 \Delta BTC_{t-2} + \ldots\ldots + b_p \Delta BTC_{t-\rho} \\ &- \gamma_{ALT} \left(BTC_{t-1} - \alpha_0 - \alpha_1 ALT_{t-1}\right) + \varepsilon^{ALT}{}_t \end{aligned} \quad (5)$$

Where $BTC_t = \alpha_0 + \alpha_1 ALT_t$ is the long-run co-integrating relationship between the two variables and γ_{BTC} and γ_{ALT} are the error correction parameters that measure how BTC and ALT react to deviations from long-run equilibrium.

Eq. (4) and (5) shows that the optimal one-period-ahead forecast of BTC_t (ALT_t) does not depends on lagged values of ALT_t(BTC_t), but its own lagged values.

For possible pairs of BTC_t and ALT_t , ρ is the optimal lag length adopted. Reported F-Statistic are the Wald-statistic for the joint hypothesis

$$b_1 = b_2 = \ldots\ldots = b_\rho = 0. \quad (6)$$

The null hypothesis in eq. (6) states thatALT_t(BTC_t), does not granger cause REV_t (EXP_t) in equation (4) and (5) respectively.

If any of the coefficient b_i ; i = 1,2......ρ is significantly different from zero, null hypothesis (6) is rejected in either or both cases in eq. (4) and (5). In case any of coefficient b_i is significantly different from zero in both equation (4) and (5), then bi-directional causality holds.

3.5. Estimation and Analysis

3.5.1. Unit root Test

To avoid spurious findings in the analyses, it is necessary to ensure that time series data are stationary. If the data are trending, trend removal is required [17]. The most common trend removal or de-trending procedure is first differencing of data. First differencing is appropriate for I(1) time series. Unit root tests are used to determine if trending data should be first differenced or be differenced at higher order to transform data to be stationary. In the current case, as characterized by any other financial data, cryptocurrency prices are extremely volatile which make them prone to instability as earlier revealed in the recursive residual test. Thus, in a bid to account for the structural break attributed to the cryptocurrency data, break-point unit root test is carried out on each of the variables and the results are presented in Table 1.

In Table 1, three different set of data are presented under various designated periods. All data in 2015-2016 are not stationary at level I(0) except DOGE, but they are all stationary at first difference I (1) when tested with intercept and with incept and trend. The case is different for the 2017 data. As presented, NEM and TRX are stationary at levels when tested with intercept only, while BTC, IOT and LTC in addition to TRX are stationary at level when tested with intercept and trend. However, they are all stationary when tested at first difference I(1). Like the case in 2017, NEM and TRX data are both stationary at level I(0) when tested with incept only in 2018 data. However, when tested with intercept and trend, ETH, NEO, XLM and XRP in addition to NEM and TRX are stationary. Meanwhile, all the variables are stationary at first difference I(1).

3.5.2. Cointegration Test

It is evident in the unit root tests that variables are integrated of order one I(1). Theoretically, if non-stationary time series data have the same order of integration and there is linear combination of the series, it is referred as being cointegrated [18]. Cointegration means that time series data move together in the long run, which implies the error term from the linear combination of time series quantifies the deviation of the series from their common long-run relationship and can be used to predict their future values [19]. Cointegration analysis is employed to examine possible long run relationship between the variables. In this study, Johansen technique test for cointegration among the variables is employed. The results of ‘trace statistic’ and ‘maximum eigenvalue test’ as proposed by Johansen [20] are presented in Table 2.

The pairwise cointegration tests between the BTC and each of the selected altcoins as presented in Table 2 show that most of the variables in 2015 are not cointegrated based on trace and maximum Eigen value tests. Basically, only BTC-DOGE and BTC-LTC exhibit a weakly cointegrating relationship, while others exhibit no evidence of cointegration. It could be inferred through the cointegrating results that bitcoin and altcoins were not co-move in the long-run during the period. Consequently, there might not be causality between the pairs of cryptocurrencies during the period. Unlike the results presented for 2015-2016, the cointegrating results for various cryptocurrency pairs in 2017 exhibit at least one cointegrating equation for each of the pairs. In other words, there are sufficient evidence to conclude a long-run co-movement between the BTC and selected altcoin in 2017. The case is the same in 2018, all the pairs exhibit at least one cointegrating equation.

Table 1. Breakpoint Unit Root Tests on Bitcoin (BTC) & Selected Alternative Coins (ALTCOIN)

Variable	Coverage					
	2015-2016		2017		2018	
	Level	1st diff.	Level	1st diff.	Level	1st diff.
With intercept only						
BTC	-1.1184	-23.6514*	-1.63027	-14.5375*	-2.9163	-20.4777*
DASH	-2.5707	-32.3623*	-0.6034	-14.5013*	-3.2606	-22.4126*
DOGE	-5.1441*	-18.8873*	-2.2245	-19.0705*	-3.2631	-16.4883*
ETH	-4.298	-25.6782*	-1.6835	-20.3298*	-3.4394	-19.1146*
IOTA	n.a	n.a	-8.1726	-14.9580*	-4.14	-21.3051*
LTC	-4.3972	-22.1399*	-4.5111	-10.2729*	-3.3106	-22.1784*
NEM	n.a	n.a	-5.6971*	-22.7143*	-5.6428*	-20.1692*
NEO	n.a	n.a	-4.1588	-12.8075*	-3.9751	-21.2794*
TRX	n.a	n.a	-9.8419*	-3.734	-5.0305*	-18.2000*
XLM	n.a	n.a	-0.2893	-10.6366*	-4.6922	-22.1018*
XRP	-3.5945	-26.5989*	-0.069	-5.1682*	-3.5279	-17.3710*
With Intercept and Trend						
BTC	-3.1775	-23.7926*	-6.9775*	-12.2194*	-4.9029	-20.6139*
DASH	-3.9699	-32.4913*	-4.4361	-13.4131*	-5.1897	-22.2944*
DOGE	-5.7883*	-19.0835*	-2.3778	-18.9344*	-4.9587	-16.6159*
ETH	-4.4206	-25.7122*	-4.1678	-19.9913*	-6.8917*	-19.9740*
IOTA	n.a	n.a	-7.5595*	-15.2047*	-4.2505	-21.5399*
LTC	-4.6874	-22.1657*	-6.9566*	-17.6923*	-4.7553	-22.1533*
NEM	n.a	n.a	-5.2284	-23.4148*	-10.1909*	-20.9894*
NEO	n.a	n.a	-3.9392	-12.5671*	-6.1166*	-21.9513*
TRX	n.a	n.a	-7.7369*	-7.2460*	-8.7927*	-18.4931*
XLM	n.a	n.a	-3.5405	-10.5823*	-6.4514*	-22.0594*
XRP	-3.6158	-26.5631*	-2.4914	-5.7346*	-6.2748*	-17.4006*

n.a - not available during the period, *Indicate rejection of the null hypothesis of non-stationary at 1%, and **indicates stationary at 5% critical values.

Table 2. Trace and Maximum Eigen Value Cointegration Test between Bitcoin (BTC) and Each of the Selected Alternative Coins (Altcoins)

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

	Trace Test						Max. Eigen Value Test					
	0			1			0			1		
	2015	2017	2018	2015	2017	2018	2015	2017	2018	2015	2017	2018
BTC & DASH	5.4052	46.2266*	23.1210*	0.618	0.4867	7.7272*	4.7872	45.7399*	15.3938*	0.618	0.4867	7.7272*
BTC & DOGE	25.31194*	36.8203*	19.2313*	0.5501	12.0516*	8.2999*	24.7618*	24.7687*	10.9314*	0.55	12.0516*	8.2999*
BTC & ETH	3.1053	15.1807*	28.8798*	0.0846	1.1809	4.1387*	3.0207	13.9998*	24.7411*	0.085	1.1809	4.1387*
BTC & IOTA	n.a	23.6568*	20.5305*	n.a	2.7003	5.1799*	n.a	20.9565*	15.3507*	n.a	2.7003	5.1799*
BTC & LTC	20.5574*	38.7669*	16.2300*	0.8189	1.0971	2.1742	19.7385*	37.6698*	14.0558*	0.819	1.0971	2.1742
BTC & NEM	n.a	42.4163*	36.4179*	n.a	9.6367*	2.5942	n.a	32.7796*	33.8237*	n.a	9.6367*	2.5942
BTC & NEO	n.a	12.3178	21.1188*	n.a	5.8409*	2.8208	n.a	6.4769	18.2981*	n.a	5.8409*	2.8208
BTC & TRX	n.a	20.5856*	37.3753*	n.a	8.4083*	8.5921*	n.a	12.1772	28.7832*	n.a	8.4083*	8.5921*
BTC & XLM	n.a	40.2951*	27.2976*	n.a	12.7039*	5.6484*	n.a	27.5912*	21.6492*	n.a	12.7039*	5.6484*
BTC & XRP	9.5629	47.9802*	57.7981*	0.2708	13.0189*	2.2289	9.2921	34.9612*	55.5692*	0.271	13.0189*	2.2289

*Rejection of the hypothesis at 5% significance level for both the Trace and Maximum Eigen Value Tests. **MacKinnon-Haug-Michelis (1999) *p*-values; n.a-not available during the period

Table 3. VEC Granger Causality/Block Exogeneity Test between Bitcoin (BTC) and Each of the Selected Alternative Coins (Altcoins)

	BTC → ALTCOIN						ALTCOIN → BTC					
	DF	2015	DF	2017	DF	2018	DF	2015	DF	2017	DF	2018
BTC & DASH	2	0.4396	7	58.7424*	7	31.2665*	2	1.4519	7	85.3159*	7	43.9968*
BTC & DOGE	5	2.0626	5	52.9467*	1	5.4654*	5	2.9817	5	114.9366*	1	1.1398
BTC & ETH	1	1.6309	3	9.1975*	1	7.2988*	1	2.8474	3	38.6581*	1	0.0009
BTC & IOTA	n.a	n.a	1	5.9305*	7	16.4106*	n.a	n.a	1	0.8093	7	24.6853*
BTC & LTC	1	2.8166	8	248.9885*	7	5.368	1	0.1164	8	81.972*	7	19.3569*
BTC & NEM	n.a	n.a	2	11.0295*	1	6.0985*	n.a	n.a	2	33.8955*	1	1.7628
BTC & NEO	n.a	n.a	6	14.9513*	1	3.0757	n.a	n.a	6	12.5075	1	4.8834*
BTC & TRX	n.a	n.a	8	31.5987*	4	7.907	n.a	n.a	8	18.1199*	4	39.3571*
BTC & XLM	n.a	n.a	8	20.6366*	2	2.7454	n.a	n.a	8	99.0506*	2	22.6065*
BTC & XRP	3	2.6501	8	87.4506*	3	23.6471*	3	4.0794	8	169.1895*	3	32.9009*

*Rejection of the null hypothesis of no causality at 5% significance level; n.a - not available during the period.

Table 4. Summary of VEC Granger Causality Test between Bitcoin (BTC) and Each of the Selected Alternative Coins (Altcoins)

2015-16		2017			2018		
BTC & DASH	N.C	BTC	↔	DASH	BTC	↔	DASH
BTC & DOGE	N.C	BTC	↔	DOGE	BTC	↔	XRP
BTC & ETH	N.C	BTC	↔	ETH	BTC	↔	IOTA
BTC & IOTA	n.a	BTC	↔	IOTA	BTC	→	DOGE
BTC & LTC	N.C	BTC	↔	LTC	BTC	→	ETH
BTC & NEM	n.a	BTC	↔	NEM	BTC	→	NEM
BTC & NEO	n.a	BTC	↔	TRX	BTC	←	LTC
BTC & TRX	n.a	BTC	↔	XLM	BTC	←	NEO
BTC & XLM	n.a	BTC	↔	XRP	BTC	←	TRX
BTC & XRP	N.C	BTC	→	NEO	BTC	←	XLM

N.C - No Causality; n.a - not available during the period; → one directional causality; ↔ bidirectional causality

2.5.3. VEC Granger/ Block Exogeneity Test

In causality test, when non-stationary variables of order 1, that is I(1) are cointegrated, the choice of lag length plays critical role. In this study, given several pairs of variables involved, different lag order is selected based on each pair. The lag order selected by various criteria are reported alongside the causality test result in Table 3. The results of causality test presented in Table 3 covers the three separate periods of the study.

There is no causal relationship between the Altcoin and BTC during 2015-2016. In other words, neither BTC nor any of the selected altcoin could predict one another which implies pure bitcoin-altcoin price separation in 2015-2016. However, in 2017, all the pairs exhibit bi-directional causality except NEO with unidirectional causality running from BTC to NEO. In other words, 2017 is characterized with bitcoin-altcoin price synchronization. In 2018, three different patterns are observable, some pairs which include DASH, XRP and IOTA have bi-directional causality with BTC (bitcoin-altcoin price synchronization); DOGE, ETH and NEM exhibit unidirectional causality which run from BTC to each of the Altcoin (bitcoin-to-Altcoin price formation), while LTC, NEO, TRX and XLM have unidirectional causality with BTC which run from altcoin to bitcoin (altcoin-to-bitcoin price formation). The summary is presented in Table 4.

4. Discussion of Results and Policy Implications

In 2015-2016, cryptocurrency was at the relatively early stage of development with few people having proper understanding of the potential and efficacy of blockchain technology. Most of the people who participated in cryptocurrency investment could only make little or no difference between bitcoin and alternative coins in existence, they were seen as vehicle of investment and also as an alternative medium of exchange. It is however not surprising the decision of each cryptocurrency holders to purchase bitcoin or any other alternative coin is independent of price of one another. Meanwhile, taking inventory of various cryptocurrencies in 2015-2016, most of them were built on bitcoin protocol. For instance, litecoin (LTC) and DASH were built on bitcoin protocol with the main purpose of using each of them as a medium of exchange for goods and services. DOGE was also built on litecoin protocol to serve as medium of exchange. However, Ethereum (ETH) and Ripple (XRP) are project coins. In each case ethereum serves dual-purpose of medium of exchange and platform for other cryptocurrency related projects, while XRP is financial project aimed at enhancing transnational money transfer services. In short, the identity of each coin were hidden in the early period, thus there were no lines of demarcation on how the cryptocurrency users perceived the purpose of each coin.

In the later period of the cryptocurrency development, which entered limelight in 2017, the acceptability and adoption of cryptocurrency especially bitcoin improved which led to surge in its price. The euphoria of expanded faith in bitcoin triggered the cryptocurrency world and pool large crowd into seeing investment in the cryptographic network as a profitable venture. It could be argued using this study that most of the mammoth crowd cryptocurrency users blindly invest their money into any of the available coins based on the speculative move on the potential increase in prices such that whenever bitcoin price increases, the altcoin prices would follow suit. Meanwhile, as the price of an altcoin increases, the investors quickly jump on bitcoin with further expectation of price rise. It is obvious the cryptocurrency users were not purchasing coins based on the fundamental characteristic of the project underlining its formation. In other words, project coins and bitcoin based protocol were not being treated separately.

The 2018 regulatory crackdown on the cryptocurrency world reduced speculative bubble, and provide each investor opportunity to screen each coin based on their merit and the project being promoted. It was not surprising many unwholesome coins were down played to pave the ways for sophisticated ones. It is therefore not surprising the price predictability shifts were based on the feature of each coin. Meanwhile, Bitcoin still maintain its dominance, given that its price is assisting substantially in predicting the price of many other altcoins, especially most of the coins based on the bitcoin protocol with main purpose of usage as medium of exchange, such as, DASH and DOGE, and coin built on related protocol such as NEM, IOTA and ETH. However, and interestingly, all the specific project based coins could assist in predicting the bitcoin prices in the period. Interpretatively, the users of project based coins such as NEO, XLM, TRX, XRP and even IOTA took purchasing decision based on the merit of coin, which eventually inform the price of the bitcoin itself, especially due to limited opportunity to effect direct fiat currency exchange. Some of the project coin especially those with relatively longer period of existence, such as XRP and IOTA maintained bidirectional causal relationship with bitcoin, while the relatively new project coins such as XLM, TRX and NEO are picking their prices without any prior consideration of the price of bitcoin.

It could be concluded therefore that, the cryptocurrency users have started investing in the coins based on the underlining merit and purpose each coin serves, unlike the generalist approaches that dominated the cryptocurrency space in 2017 and preceding years.

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