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Market efficiency of the cryptocurrencies: Some new evidence based on price–volume relationship

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Abstract

Cryptocurrencies have emerged as an important investment avenue in the past few years. Investors are increasingly interested in these currencies amid surging financial returns. In this context, understanding market efficiency of cryptocurrency has become very crucial for investors and academicians. The price–volume framework is a popular approach in financial economics to understand the market efficiency of stocks in the stock markets. Therefore, this article examines the market efficiency of cryptocurrencies through price–volume framework to understand whether crypto market is predictable. Towards this objective, data on both return and trading volume (TV) of the top eight cryptocurrencies are used for the period 8 August 2015–20 October 2022. As an empirical method, both linear and non-linear causality models are used to validate the hypothesis. Our results confirm that TV cannot predict the cryptocurrencies' return, thereby validating the market efficiency hypothesis. Furthermore, we divide the sample according to the structural break period. The result from the post-break period analysis also confirms the presence of market efficiency in the recent period for all currencies, barring XRP, XMR and DASH.

KEYWORDS

cryptocurrencies, efficient market hypothesis, non-linear causality, structural break

1 | INTRODUCTION

Over a decade, virtual currencies have created a new identity in the global financial market. Unlike the centralized payment method, they have emerged as a new investment avenue and digital payment system among the investors, industry people, and researchers. Bitcoin (BTC) is the first decentralized cryptocurrency to be introduced by Satoshi Nakamoto in 2009. After that, 20,000+ cryptocurrencies have emerged in the market, either as a replica or substitute to Bitcoin. Bitcoin has dominated the cryptocurrency market with highest market capitalization.[1] Bitcoin being a cryptocurrency is backed by blockchain technology. This technology is also followed by other cryptocurrencies.

The cryptocurrency market is highly volatile (Bouoiyour et al., 2014; Bouri et al., 2018; Cheah & Fry, 2015; Ciaian et al., 2016; Hu et al., 2019; Le Tran & Leirvik, 2020; Pelster et al., 2019), where the total market cap of all currencies is about near $250 billion (during the time of writing). To take advantage of these fluctuations, investors are trying to predict future prices. It is only possible if they can predict the cryptocurrencies, thereby proving market inefficiencies. So, researchers are examining the efficiency of cryptocurrencies through the efficient market hypothesis (EMH) theory. The EMH states that a market is said to be efficient if all information is available and fully reflected in the market (Fama, 1970). It has three forms, the weak, semi and strong form of efficiency. The weak form of efficiency is the most highlighted one used by the researchers, which states that the present and future stock returns cannot be estimated based on past prices information.

The first set of literature on EMH is shown in the studies of Bitcoin, where, some studies observed that Bitcoin is efficient as the weak efficiency market hypothesis is validated in case of Bitcoin (Nadarajah & Chu, 2017; Sensoy, 2019; Tiwari et al., 2018). But others (Al-Yahyaee et al., 2018; Cheah et al., 2018; Corbet et al., 2020; Jiang et al., 2018; Kristoufek, 2018; Noda, 2020) argued that Bitcoin market is not efficient, and people can predict the future price of Bitcoin. While Urquhart (2016) finds evidence of the inefficiency of Bitcoin for the full sample period from 1 August 2010 to 31 July 2016, but the split sample from 1 August 2013 to 31 July 2016 confirms the efficiency of Bitcoin. Similarly, Bariviera (2017) says that the EMH is time-dependent, as their study period from 2011 to 2014 states that Bitcoin returns are inefficient, but after that, the market is efficient. Another set of literature test the same EMH property on Bitcoin, as well as some related cryptocurrencies (Caporale et al., 2018; Charfeddine & Maouchi, 2019) and some, also check on the major cryptocurrencies(Hu et al., 2019). Where, Caporale et al. (2018) apply the EMH on Bitcoin, Ripple, Litecoin and Dash. Zhang et al. (2018) examine 12 cryptocurrencies, and their study signs that these currencies are inefficient in the market. On the other hand, Hu et al. (2019) revisit the EMH for 31 top cryptocurrencies by using the panel unit root test and conclude that all cryptocurrencies are not following the weak form of EMH concept.

All the above studies have taken only the information about the past prices or returns of Bitcoin as well as other cryptocurrencies to examine the EMH. But none of the literature looks at the dynamic angles of 'price–volume' relationships for examining EMH. They have neglected the trading volume (TV) angle while estimating the efficiency properties of the cryptocurrency. As Hiemstra and Jones (1994) have rightly pointed out that we can learn more about the stock market through studying the joint dynamics of stock prices and TV than by focusing only on the univariate dynamics of stock prices. Therefore, understanding the movement in the prices of cryptocurrencies requires analysis of joint interaction of its prices and TV. There are several explanations for the existence of price–volume relationship which can be borrowed from financial literature. First, the sequential information arrival models of Copeland (1976) explain that there is a positive relationship between stock price and its volume. The model shows that the arrival of new information into the market is disseminated to investors which gets reflected in prices through TV, thus concluding that lagged TV can help predict stock returns. Second, the mixture of distributions models (MDH) of Clark (1973) provides an explanation arguing that the arrival of new information into the market revises the trader's reservation prices of stocks, thereby establishing a strong correlation between prices and volume. Therefore, we infer TV as an important factor for understanding the behaviour of return of cryptocurrencies. Studies by Balcilar et al. (2017); Kurihara and Fukushima (2017); Sahoo et al. (2019) and Shen et al. (2019) on the price–volume relationship on Bitcoin, have opened the source for whole cryptocurrencies to check their efficiency. In light of the above, the present study adopts the price–volume framework to check the market efficiency property of cryptocurrencies. This approach helps for a better understanding of the movements of prices of the cryptocurrency market.

Cryptocurrencies have emerged as an important investment avenue in the past few years. Investors are increasingly interested in these currencies owing to the surge in its financial returns. In this context, predicting the price movement of these currencies has become very crucial for investors and academicians. Prior studies have failed to address the market efficiency of cryptocurrencies using the price–volume relationship framework. Therefore, we attempt to examine the EMH in cryptocurrency market. Our contribution to the literature is threefold. First, to our best knowledge, this is the first study to explore the market efficiency hypothesis of the cryptocurrencies through the price–volume relationship of Bitcoin as well as seven other different cryptocurrencies. Second, we examine the possibilities of both the linear and non-linear relationship between prices and volume in the cryptocurrency market with the help of linear Toda and Yamamoto (1995) (hereafter TYM) and non-linear Diks and Panchenko (2006) (hereafter D-P) causality models. The D-P non-linear causality test helps reveal the non-linear relationship exiting between cryptocurrencies' returns and their volume which the traditional test fails. Furthermore, D-P test solves the problem of not allowing conditional distribution to vary with an increasing sample size encountered by Hiemstra and Jones (1994). Third, to correct for any biases in the results due to structural break, we divide the sample into pre-break and post-break periods based on Bai and Perron (2003) test. The presence of structural break in the movement of cryptocurrencies' market may undermine the empirical inference about the market behaviour.

The rest of the article as follows. Section 2, presents the review of literature. Section 3 describes the data and construction of variables. Section 4 employees the relevant methodology used for the study. Section 5 discusses the empirical finding and finally, Section 6 provides discussion, and concluding remarks are given in the end.

2 | LITERATURE REVIEW

The testing of EMH for cryptocurrencies relies heavily from the EMH developed by Fama (1970) in the context of financial market. The reason being that in the last few years cryptocurrencies have grabbed the attention of many investors who treat them as financial instruments. Investors are closely following the developments in crypto market. Therefore, many researchers have tried to examine the market efficiency theory in the context of crypto market. Some of the relevant and recent studies are discussed as follows.

Bouoiyour et al. (2014) examine the causal relationship between price, transaction volume and investor's attractiveness on Bitcoin with the help of Granger causality. They use the daily data period from December 2010 to June 2014. The result revealed that the high volatility of Bitcoin price is due to the attractiveness of the users in the short and long period. Urquhart (2016) analyse the informational efficiency of Bitcoin market by adopting daily data during the period from 1 August 2010 to 31 July 2016. The findings of the full sample show that Bitcoin returns are predictable and consider that the market is inefficient. He also examines the recent sub-sample period from 1 August 2013 to 31 July 2016, where the result shows that Bitcoin is efficient, and we cannot predict the market. Furthermore, a similar data period is also examined by Nadarajah and Chu (2017) to know the efficiency in the Bitcoin market. They use the similar test adopted by Urquhart (2016), where the findings show that the Bitcoin market is efficient in weak form for all sample cases. This demonstrates that in the Bitcoin market, no abnormal gains can be made. Bariviera (2017) examines the dependency of Bitcoin return and volatility for 18 August 2011 to 15 February 2017. He uses the Hurst exponent model by using detrended fluctuation analysis (DFA) to examine Bitcoin market efficiency. The result reveals that EMH is time-dependent, as their study period from 2011 to 2014 observed that Bitcoin returns are inefficient, but after that, the market is efficient. Kurihara and Fukushima (2017) investigate the market efficiency of Bitcoin price and transaction volume by taking the daily return price of Bitcoin. They use the robust least squares model for the estimation process. The findings of their study show that Bitcoin market is not efficient, but its transaction volume is efficient. Balcilar et al. (2017) examine the causal linkage of Bitcoin return and transaction volume with quantile regression approach from 19 December 2011 to 25 April 2016. The causality in quantile test regression reveals that Bitcoin transaction volume can predict returns. Sahoo et al. (2019) observe the non-linear price volume relationship of Bitcoin market from 17 August 2010 to 16 April 2017. The results of non-linear causality analysis over the complete sample period and sub-sample period reveal that there are non-linear feedbacks between Bitcoin TV and returns.

Similarly, Corbet et al. (2018) analyses the time and frequency domain relationship of the top three cryptocurrencies with other financial assets. The findings suggest that investors can benefit by diversifying in the short-horizon where time variation creates external shocks to the cryptocurrency market. Alvarez-Ramirez et al. (2018) investigate the Bitcoin market's informational efficiency covering the period 30 June 2013 to 3 June 2017. They use DFA to check the long-range correlation of Bitcoin returns. The study finds that Bitcoin returns are not uniformly efficient since they exhibit periods of efficiency up to certain periods and periods of inefficiency due to anti-persistence price trends. Furthermore, similar techniques have been applied by Tiwari et al. (2018) to examine the long-range dependence and informational efficiency of Bitcoin market from 18 July 2010 to 16 June 2017. The result reveals that Bitcoin market is efficient for the whole sample period, with an exception for sub-sample starting from April–August 2013 to August–November 2016. Khuntia and Pattanayak (2018) use the adaptive market hypothesis (AMH) to forecast Bitcoin market returns from 18 July 2010 to 21 December 2017. For the predictability of Bitcoin returns, they use the martingale difference hypothesis (MDH). The findings reveal that inefficiency exists in the early sub-period of the research, between August 2011 to August 2012 and December 2013 to December 2014. However, efficiency is seen from middle 2012 to the end of 2013. So, they argue that efficiency of Bitcoin market is time-dependent. Al-Yahyaee et al. (2018) investigate Bitcoin's market efficiency compared with other alternative assets such as gold, equity and forex market under the period 18 July 2010 to 31 October 2017. They use the multifractal detracted fluctuation analysis method and find Bitcoin to be less efficient than other assets.

In addition, Aggarwal (2019) studies the Bitcoin market from 2010 to 2018, with the help of unit root and ARCH test. He does not find any support to the EMH for Bitcoin returns. Sensoy (2019) observe the time-varying weak-form efficiency of Bitcoin prices through US dollar (BTC-USD) and Euro (BTC-EUR) by using permutation entropy. He finds that BTC-USD and BTC-EUR market is more informationally efficient, where, BTC-USD is more efficient than BTC-EUR. Köchling et al. (2019) examine the EMH of Bitcoin covering the period 10 August 2017 to 10 April 2018 just before the starting of Bitcoin future and after that period. They use several efficiency tests to examine the efficiency of Bitcoin. The majority of tests proved that the Bitcoin market is inefficient before starting future trade, but after that, the market is efficient by following a weak-form efficient market. El Alaoui et al. (2019) use a multifractal detrended cross-correlation study to look at the non-linear relationship between Bitcoin price and TV from 17 July 2010 to 2 May 2018. The results show that the Bitcoin price and trading sequence have a multifractal non-linear relationship. They said that the Bitcoin market is inefficient and the price can be easily predictable through trading strategy. Kyriazis (2019) observes the pricing behaviour of cryptocurrencies through the EMH. He admits that EMH is not work in cryptocurrencies but speculation is feasible via trading.

Many studies examine the efficiency of the cryptocurrencies market (Bouri et al., 2018; Cagli, 2018; Hu et al., 2019; Zhang et al., 2018), where they find that Bitcoin and crypto returns do not follow the random walk hypothesis, means the market is not efficient. Bouri et al. (2018) observes the causal linkage between TV and returns of cryptocurrencies for seven major cryptocurrencies. They use the quantile regression method to estimate the nexus between returns and TV. The finding proves that TV Granger causes returns on all the seven currencies examined. They conclude that no efficiency is detected in cryptocurrency markets. However, Zhang et al. (2018) analyse daily data of Bitcoin and other eight cryptocurrencies for the period 28 April 2013 to 30 April 2018. They use a battery of efficiency test along with GARCH and GJR method to know the efficiency of cryptocurrencies. The result shows that all the cryptocurrencies have conveyed inefficient markets. Cagli (2018) examines the explosive behaviour of Bitcoin and other seven cryptocurrencies such as Ethereum, Litecoin, Ripple, Nem, Stellar, Monero and Dash. He finds that except NEM, all cryptocurrencies have exhibited explosive behaviour and there are significant co-movement relationships among them. Hu et al. (2019) apply the top 31 market-cap cryptocurrency's daily closing price using various panel tests. The result of their study suggests that 'the weak form of efficient market hypothesis' does not hold for top-ranked cryptocurrencies. This shows that cryptocurrencies are not efficient.

Some recent studies also examine the role of the cryptocurrency market and their efficiency hypothesis. Eom (2020) examines the bubble effect of cryptocurrencies by analysing the price and TV of cryptocurrencies with the Bitcoin data from Korea and the US. The study finds that high TV creates and increases the speculative bubble of Bitcoin. It shows that bubbles tend to grow due to the uncertainty and high trading market volume of Bitcoin. Similarly, Shu and Zhu (2020) also observe that high-frequency trading data can effectively detect bubbles in the Bitcoin market and help predict the price of Bitcoin. Bedi and Nashier (2020) analyse the diversification capabilities of Bitcoin for a global portfolio spread across six asset classes with US Dollar, Pound, Euro, Japanese Yen and Chinese Yuan. The results suggest that portfolios denominated in Japanese Yen, Chinese Yuan and US Dollar account for a larger proportion of optimum Bitcoin investment and have better risk-adjusted returns due to Bitcoin investment. They observe that the results reveal a significant gap in Bitcoin trading rates across national currencies from a portfolio theory viewpoint. Corbet et al. (2020) investigate the link between Kodak, cryptocurrency and stock market index returns spans from 22 November 2017 to 21 February 2018. They use generalized autoregressive conditional heteroscedasticity (GARCH) and dynamic conditional correlations GARCH methodologies for the estimation process. The finding shows that before the announcement of Kodakcoin, there is a significant relationship between Kodak, stock indices and Bitcoin returns. Nevertheless, after the announcement of Kodakcoin, the nexus between Kodak and stock indices weakens, where Bitcoin shows a healthy nexus. Gil-Alana et al. (2020) investigate the cointegration properties of six major cryptocurrencies and the stock market indices. They discovered that neither six cryptocurrencies nor cryptocurrencies and stock indices had any cointegration. They conclude that cryptocurrencies are unrelated to mainstream finance and economic assets. Noda (2020) examines the degree of market efficiency of cryptocurrencies using the generalized least squares based on the time-varying model. the result shows that the efficiency of cryptocurrencies is time-invariant and the Bitcon's market efficiency is higher than other cryptos like Ethereum over most periods. The result supports the AMH.

3 | DATA AND VARIABLES DESCRIPTION

Daily data of the top eight cryptocurrencies' closing price and total volume of trading (VT) have been collected from coinmarketcap.com. It is a website that tracks the average of all prices from different related markets of all cryptocurrencies. The reason for considering top eight currencies is that these currencies hold top share in terms of market capitalization in the cryptocurrency market. Currencies with smaller market capitalization tend to have data constraints and contribute insignificantly to any new development in market activities. In addition, there are many currencies with smaller capitalization that are not listed in the major trading exchanges and some cases they get delisted from currency exchanges. The inclusion of such currencies will only provide artificially inflated reported volumes. To avoid such abnormality, we have taken only those currencies which are frequently traded and have major share in the crypto market. Furthermore, we have taken a common time period for eight currencies where the TV is comparable across the currencies except NEM. To take care of any kind of heterogeneity in the TV across currencies, we have used time series analysis for individual currencies. By doing this we have ruled out the possibility of biased view of efficiency. We have targeted the long period data and the data period is pertaining from 8 August 2015 to 20 October 2022. Data for all the cryptocurrencies are not available in an equal period. The time series data for each currency are available disproportionately. Since we are dealing with a multi-currency analysis, we have taken a common time period to make the analysis unbiased by having an appropriate comparison. We have taken a common time period that is 8 August 2015 for which data for all currencies are available thereafter. All variables are in US dollar. Based on the availability of data we have taken the top eight cryptocurrencies, that is, Bitcoin (BTC), Ripple (XRP), Ethereum (ETH), Litecoin (LTC), Stellar (XLM), Monero (XMR), Dash (DASH) and Nem (XEM). All cryptocurrencies' closing price is converted to a series of log returns and the TV is taken as the log of change in VT. Here, we have taken relative volume as a measure of TV of cryptocurrencies. Though market capitalization can be useful in understanding the cryptocurrency market behaviours, the inclusion of it will cause inconsistency in the estimation. The attributable factors for such inconsistency could be multicollinearity problems or overlapping issues in the data. For example, spot prices of currencies are a part of the market capitalization of any cryptocurrencies. So, inclusion of market capitalization will be overlapping with return series which also exclusively measures spot prices of currencies.

The returns on cryptocurrencies (R_t) and trading volume (TV_t) are calculated as follows:

$$R_t = \mathrm{Ln}\left(P_t/P_{t-1}\right) * 100 \text{ and } \mathrm{TV}_t = \mathrm{Ln}\left(\mathrm{VT}_t/\mathrm{VT}_{t-1}\right) * 100. \tag{1}$$

4 | EMPIRICAL METHODOLOGY

4.1 | Linear Granger causality

In a bivariate VAR model, we employ the linear TYM as well as the non-linear D-P test to examine the

TABLE 1 Unit root test result of log returns and trading volume

Unit root test		ADF	Intercept and trend PP	KPSS
BTC	Returns	−52.68*** (0.00)	−52.68*** (0.00)	0.083
	Trading volume	−20.59*** (0.00)	−94.14*** (0.00)	0.015
ETH	Returns	−50.64*** (0.00)	−50.72*** (0.00)	0.114
	Trading volume	−20.36*** (0.00)	−79.38*** (0.00)	0.004
XRP	Returns	−33.64*** (0.00)	−52.82*** (0.00)	0.057
	Trading volume	−31.09*** (0.00)	−74.43*** (0.00)	0.017
LTC	Returns	−52.23*** (0.00)	−52.23*** (0.00)	0.081
	Trading volume	−31.78*** (0.00)	−91.72*** (0.00)	0.058
XLM	Returns	−49.13*** (0.00)	−49.18*** (0.00)	0.078
	Trading volume	−29.65*** (0.00)	−106.01*** (0.00)	0.032
XMR	Returns	−55.64*** (0.00)	−55.46*** (0.00)	0.074
	Trading volume	−32.29*** (0.00)	−105.17*** (0.00)	0.019
DASH	Returns	−53.95*** (0.00)	−53.91*** (0.00)	0.080
	Trading volume	−24.84*** (0.00)	−127.48*** (0.00)	0.041
NEM	Returns	−55.24*** (0.00)	−55.12*** (0.00)	0.113
	Trading volume	−23.92*** (0.00)	−132.78*** (0.00)	0.031
Critical values	1%	−3.96	−3.96	0.216
	5%	−3.41	−3.41	0.146
	10%	3.12	3.12	0.119

Note: The table shows the ADF, PP and KPSS tests for the stationarity of log returns and traded volume of eight major cryptocurrencies. Sample period of the study based on daily data from 8 August 2015 to 20 October 2022.

***indicates rejection of null hypothesis of non-stationarity at 1% level, p-values are in the parenthesis.

TABLE 2 Toda–Yamamoto linear causality of log returns and trading volume (full period)

TYM	Return does not Granger cause volume	Volume does not Granger cause returns
Causality direction	$R \rightarrow V$	$V \rightarrow R$
BTC	81.54*** (0.00)	18.54 (0.55)
ETH	90.04*** (0.00)	28.61 (0.19)
XRP	118.70*** (0.00)	41.36*** (0.02)
LTC	68.73*** (0.00)	14.62 (0.33)
XLM	130.24*** (0.00)	22.28 (0.27)
XMR	87.75*** (0.00)	18.45 (0.14)
DASH	55.45*** (0.00)	14.21 (0.22)
NEM	114.21*** (0.00)	36.53** (0.00)

Note: The table shows the Toda–Yamamoto causality result in log returns, trading volume of eight cryptocurrencies. Sample period of the study based on daily data from 8 August 2015 to 20 October 2022.
***, ** denotes significant at 1%, and 5%, level. R and V denotes Returns and Trading volume, p-values are in the parenthesis.

dynamic link between cryptocurrencies return and TV. We have taken the linear TYM test over traditional Granger's (1969) causality, as TYM has the advantage of modified Wald Chi-square test and can be expressed as:

$$R_t = \alpha_0 + \sum_{i=1}^{k+d_{\max}} a_{1i} R_{t-i} + \sum_{i=1}^{k+d_{\max}} \delta_{1i}\,\mathrm{TV}_{t-i} + \mu_{1t}, \tag{2}$$

$$\mathrm{TV}_t = \beta_0 + \sum_{i=1}^{k+d_{\max}} \beta_{1i}\mathrm{TV}_{t-i} + \sum_{j=1}^{k+d_{\max}} \emptyset_{1i} R_{t-j} + \mu_{2t}, \tag{3}$$

where μ_{1t} and μ_{2t} are two residuals of the models. Now we can test market efficiency through this causality test. This model tells us whether lagged TV can be helpful to predict returns on cryptocurrencies. If, past values of TV cannot significantly predict returns then the EMH hold in the cryptocurrency market. It means, whatever information flows into market is distributed to all traders and the possibility of arbitrage in trading is eliminated. The absence of asymmetrical information about the market causes prices to reflect all the information available in the market and there is no scope for traders or investors to predict the future movement in prices. Mathematically, if crypto market is efficient then $\delta_{1i} \neq 0$, for i = 1, 2, 3…k. In other words, 'TV' Granger cause 'R'. If reverse is happening, then $\emptyset_{1i} \neq 0$, for i = 1, 2, 3,…k. The model follows a seemingly unrelated regression testing procedure and the optimal lag is based on Schwarz information criterion.

4.2 | Non-linear Granger causality

It is shown that the traditional non-linear causality test is not able to capture non-linear predictive power due to its low power (Diks & Panchenko, 2006). So, this study employs a non-parametric test of non-linear causality developed by Diks and Panchenko (2006) (hereafter, D-P test). This test being nonparametric has an advantage over the parametric causality methods. The D-P test argues that Hiemstra and Jones (1994) test is not compatible with Granger's definition of causality and it is prone to over rejection problems as it does not allow conditional distribution to vary as the sample size increases. So, to avoid over rejection problem, D-P have proposed a non-parametric test to capture the non-linear causal relationship between two variables. The D–P test can be specified as follows. In Granger causality test, X is said to be not causing Y if the past and present value of X variable does not contain additional information about future value of Y. The null hypothesis of no Granger causality is specified as follows:

$$H_0 : Y_{t+1}| \left(X_t^{l_x}; Y_t^{l_y}\right) \sim Y_{t+1}|Y_t^{l_y}, \tag{4}$$

where $X_t^{l_x} = (X_{t+1}\text{.........}X_t)$ and $Y_t^{l_y} = (Y_{t+1}\text{.........}Y_t)$ are two delay vectors and $(l_x\, l_y \geq 1)$ are the lag length of X and Y variables. The $\sim$ indicates the uniformity in distribution. Assuming $Z_t = Y_{t+1}$ and $l_x = l_y = 1$, the joint probability density function $f_{X,Y,Z\,(x,\,y,\,z)}$ of $W_t = \left(X_t^{l_x}, Y_t^{l_y}, Z_t\right)$ can be obtained in the following relationship:

$$\frac{f_{X,Y,Z\,(x,\,y,\,z)}}{f_Y\,(y)} = \frac{f_{X,Y\,(x,\,y)}}{f_Y\,(y)} * \frac{f_{Y,Z\,(y,\,z)}}{f_Y\,(y)}. \tag{5}$$

Equation (5) shows that X and Z are independent of each other conditioning upon $Y = y$ for each fixed value of y. Thus, the revised null hypothesis can take the following form:

$$q \equiv \left[f_{X,Y,Z}(X,\ Y,\ Z) f_Y\,(Y) - f_{X,Y}(X,\ Y) f_{Y,z}(Y,\ Z)\right] = 0. \tag{6}$$

Then following Diks and Panchenko (2006) let $\widehat{f}_w(W_i)$ be a local density estimator of a d_w- variate random vector W at W_i defined by $\widehat{f}_w(W_i) = (2\varepsilon_n)^{-d_w} (n-1)^{-1} \sum_{j,j \neq i} I_{ij}^W$, where $I_{ij}^W = I\left(\left\| W_i - W_j \right\| < \varepsilon_n\right)$ with I (.), the indicator function and ε_n, the bandwidth dependent upon sample size. Given this estimator, the test statistics is a scaled sample version of q in Equation (6):

TABLE 3 Diks–Panchenko non-linear Granger causality result of cryptocurrencies' returns, trading volume (full period)

Lag $L_x = L_y$	BTC	ETH	XRP	LTC	XLM	XMR	DASH	NEM
Return does not cause Volume								
1	2.15*** (0.01)	3.01*** (0.00)	2.62*** (0.00)	0.59 (0.27)	5.59*** (0.00)	2.69*** (0.00)	2.09*** (0.01)	2.88*** (0.00)
2	1.21 (0.11)	1.82** (0.03)	2.53*** (0.00)	0.53 (0.29)	4.46*** (0.00)	2.43*** (0.00)	1.56** (0.05)	2.50*** (0.00)
3	1.28* (0.09)	1.78** (0.03)	2.33*** (0.00)	0.22 (0.41)	4.38*** (0.00)	1.51* (0.06)	1.40* (0.07)	2.04** (0.02)
4	0.97 (0.16)	1.85** (0.03)	1.68** (0.04)	0.03 (0.48)	3.66*** (0.00)	0.27 (0.39)	1.47* (0.06)	1.91** (0.02)
5	1.19 (0.11)	1.69** (0.04)	1.18 (0.11)	−0.21 (0.58)	2.66*** (0.00)	0.28 (0.38)	1.70** (0.04)	1.20 (0.11)
Volume does not cause Returns								
1	−0.46 (0.67)	1.11 (0.13)	3.32*** (0.00)	−0.81 (0.79)	0.55 (0.28)	1.47* (0.07)	0.01 (0.49)	1.18 (0.11)
2	−1.82 (0.96)	1.26* (0.10)	2.09*** (0.01)	−2.31 (0.98)	0.46 (0.31)	2.60*** (0.08)	−0.31 (0.62)	1.17 (0.11)
3	−1.65 (0.95)	0.97 (0.16)	1.31* (0.09)	−2.51 (0.99)	0.81 (0.20)	1.32* (0.09)	−0.28 (0.61)	0.34 (0.36)
4	−2.53 (0.99)	−0.22 (0.58)	0.70 (0.23)	−3.34 (0.99)	−0.28 (0.38)	0.16 (0.43)	−0.95 (0.83)	0.12 (0.45)
5	−1.91 (0.97)	−0.68 (0.75)	0.82 (0.20)	−3.04 (0.99)	−0.34 (0.63)	0.45 (0.32)	−1.19 (0.88)	0.27 (0.39)

Note: The table shows Diks and Panchenko (2006) non-linear Granger causality result in log returns, trading volume of eight cryptocurrencies. Sample period of the study based on daily data from 8 August 2015 to 20 October 2022. The causality test is conducted using an epsilon value of 1 and 1.5 for all five lags. L_x and L_y represent lags of the variables.

***, **, * denotes significant at 1%, 5%, and 10% level.

$$T_n(\varepsilon_n) = \frac{n-1}{n(n-2)} \sum_i \widehat{f_{XYZ}}(X_i, Y_i, Z_i)\widehat{f_Y}(Y_i) - \widehat{f_{X,Y}}(X_i, Y_i)\widehat{f_{Y,Z}}(Y_i, Z_i).$$

For $l_x = l_y = 1$ when $\varepsilon_n = cn^{-\beta}\left(C > 0, \beta \in \left(\frac{1}{4}, \frac{1}{3}\right)\right)$.

TABLE 4 Bai–Perron structural break test

Variables	Structural break
BTC	12/17/2017
ETH	1/13/2018
XRP	3/18/2017
LTC	No break found
XLM	No break found
XMR	12/21/2017
DASH	12/21/2017
NEM	1/08/2018

Note: Based on Bai and Perron (2003) structural break test.

Diks and Panchenko (2006) verified that this test statistics 'C' follows an asymptotic distribution of the form;

$$\sqrt{n}\frac{S_n(\varepsilon_n) - q}{S_n} \xrightarrow{D} N(0,1), \tag{7}$$

where $\xrightarrow{D}$ indicates convergence of asymptotic variance of $T_n(.)$. The test statistic in Equation (7) is applied to VAR residual where linear predictive components are removed to check the remaining predictive power of one variable for another variable.

5 | EMPIRICAL ANALYSIS

5.1 | Linear causality test results

Before testing Toda and Yamamoto (1995) linear causality, a battery of unit root tests is used as a preliminary check to confirm the order of integration of the time

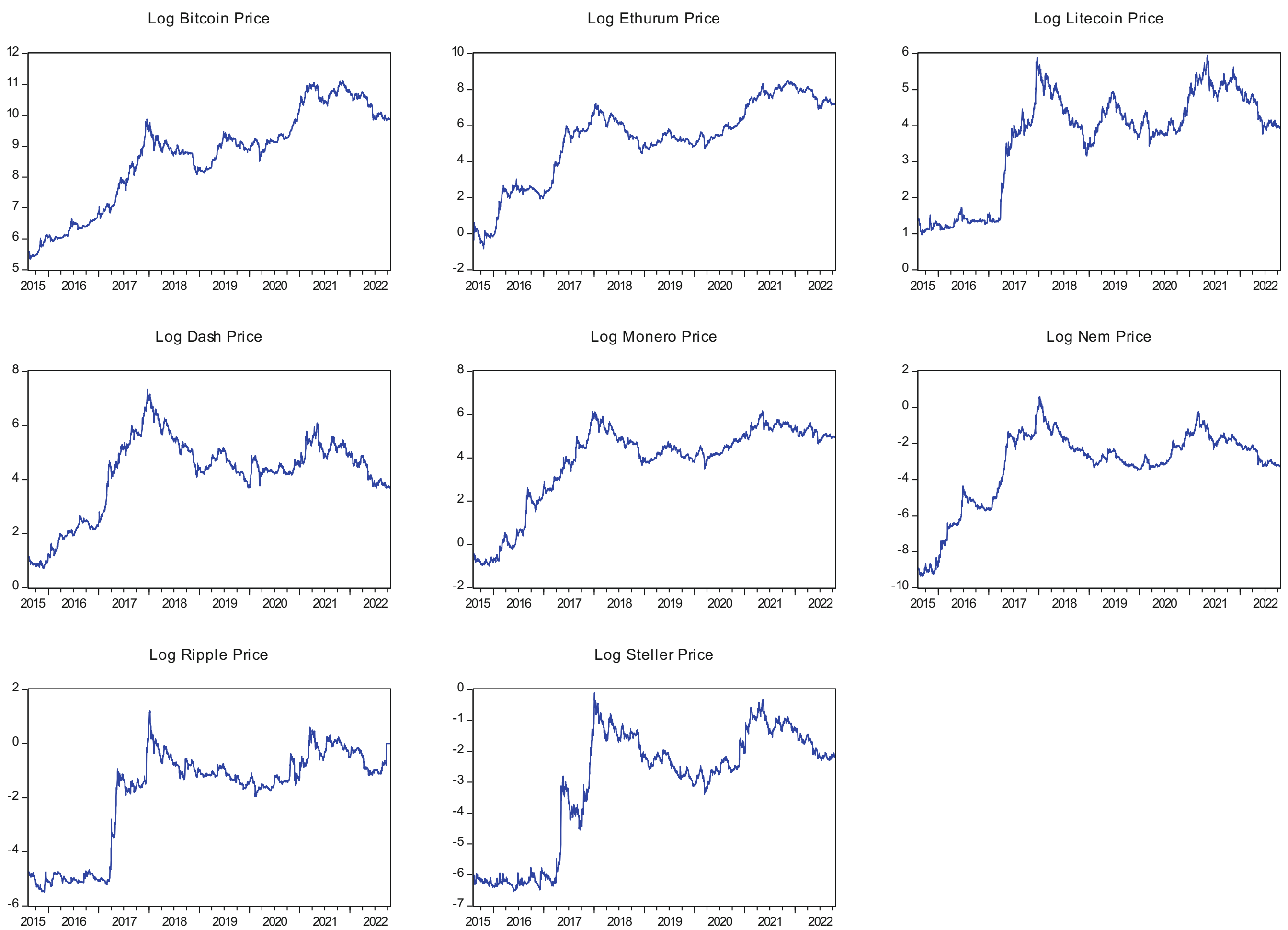

FIGURE 1 Plots of cryptocurrencies. The figure represents the log price trend of cryptocurrencies from 8 August 2015 to 10 October 2022. [Colour figure can be viewed at wileyonlinelibrary.com]

series data. Table 1 shows the results of Dickey and Fuller (1979), Phillips and Perron (1988) and Kwiatkowski et al. (1992). All the tests confirm that returns and TV of cryptocurrencies are stationary at the level [$I(0)$].

Table 2 presents the Toda–Yamamoto linear causality test. The result indicates that returns of cryptocurrencies cannot be predicted with the help of past information on TV. The null hypothesis of 'volume does not Granger cause return' cannot be rejected even at 10%, suggesting that the cryptocurrency market is informationally efficient. However, two currencies XRP and NEM confirm that market is still inefficient and the return can be predicted using past movement in the TV. On the other hand, return helps in predicting future TV. The null of all eight cryptocurrencies 'returns do not Granger cause volume' is rejected at 1%.

TABLE 5 Toda–Yamamoto linear causality of log returns and trading volume (break period)

TYM	Returns does not Granger cause Volume	Volume does not Granger cause Returns
Causality direction	$R \rightarrow V$	$V \rightarrow R$
BTC	42.93*** (0.00)	17.66 (0.60)
ETH	53.48*** (0.00)	18.93 (0.16)
XRP	121.35*** (0.00)	55.75*** (0.00)
LTC	NA	NA
XLM	NA	NA
XMR	37.33*** (0.00)	17.57 (0.17)
DASH	48.34*** (0.06)	7.27 (0.77)
NEM	65.26*** (0.00)	28.41*** (0.000)

Note: The table shows the Toda–Yamamoto causality result in log returns, trading volume of eight cryptocurrencies after the break period. *** denotes significant at 1%, level. R and V denotes Returns and Trading volume. NA indicates no structural break found for the said currency.
***denotes significance at 1%, level in table 5.

5.2 | Non-linear Granger causality

Through the BDS test, we find the presence of non-linear behaviour of cryptocurrencies. Table 3 presents the D–P non-linear Granger causality result of the top eight cryptocurrencies. The result also depicts same findings-majority of cryptocurrencies follow EMH. With an exception of XRP and XMR which do not follow the EMH as their TV can predict returns. This empirical evidence can be explained by following facts. Unlike traditional assets like shares traded in a stock market, cryptocurrencies are subject to additional risks such as regulatory changes, fraud and price manipulation via hacking. Furthermore, bubbles in the crypto market have led to speculations among investors, leading to change in mean and variance levels over time. As a result, we have witnessed different levels of volatilities episodes during different periods. This may have possibly caused non-linearity in the relationship between return and volume of cryptocurrencies.

Since cryptocurrency market might have undergone structural changes, we estimate Bai and Perron (2003) structural break test and calculate the market efficiency of the cryptocurrency return in the post-break period. Results reported in Table 4 shows that all the cryptocurrencies' break

TABLE 6 Diks–Panchenko non-linear Granger causality result of Cryptocurrencies' returns, trading volume (break period)

Lag $L_x = L_y$	BTC	ETH	XRP	LTC	Steller	XMR	DASH	NEM
Returns does not cause Volume								
1	3.39* (0.09)	2.64*** (0.00)	4.14*** (0.00)	–	–	1.92** (0.02)	3.70*** (0.00)	0.96 (0.16)
2	2.67*** (0.00)	2.03** (0.02)	3.68*** (0.00)	–	–	1.96** (0.02)	2.96*** (0.00)	0.65 (0.25)
3	2.63*** (0.00)	1.61** (0.05)	3.30*** (0.00)	–	–	0.75 (0.22)	2.13*** (0.01)	1.10 (0.13)
4	2.28*** (0.01)	1.46* (0.07)	2.54*** (0.00)	–	–	0.17 (0.43)	2.29*** (0.01)	0.87 (0.18)
5	2.32*** (0.01)	1.25* (0.10)	2.09*** (0.01)	–	–	0.47 (0.31)	2.70*** (0.00)	0.04 (0.48)
Volume does not cause Returns								
1	0.77 (0.21)	1.46* (0.07)	5.01*** (0.00)	–	–	1.15 (0.12)	1.94** (0.02)	−0.22 (0.59)
2	−0.23 (0.59)	1.22 (0.11)	3.78*** (0.00)	–	–	(0.01)	1.60** (0.05)	0.43 (0.33)
3	−0.07 (0.52)	0.76 (0.22)	2.93*** (0.00)	–	–	1.48* (0.06)	1.17 (0.11)	0.10 (0.45)
4	−0.59 (0.72)	−0.06 (0.52)	2.28*** (0.01)	–	–	0.37 (0.35)	0.83 (0.23)	−0.68 (0.75)
5	−0.46 (0.67)	0.08 (0.46)	2.28*** (0.01)	–	–	0.65 (0.25)	0.76 (0.22)	−0.38 (0.64)

Note: The table shows Diks and Panchenko (2006) non-linear Granger causality result in log returns, trading volume of eight cryptocurrencies after the break period. The causality test is conducted using an epsilon value of 1 and 1.5 for all five lags. L_x and L_y represent lags of the variables.
***, **, * denotes significant at 1%, 5%, and 10% level.

dates are different coinciding with the actual trend value of those currencies (see Figure 1). LTC and Steller (XMR) do not show any structural break given the sample period.

The market efficiency of cryptocurrency return is checked in the post-break period (see Tables 5 and 6). In case linear TYM test the result indicates that except XRP and NEM all currencies are informational efficient as volume cannot predict returns. On the other hand, in case of non-linear D-P causality test, the result reveals that some cases like XRP, XMR and DASH are not efficient as volume is able to predict returns. So, these currencies are fully absorbing the market information. As cryptocurrencies' prices adjust quickly to the arrival of new public information, an investor cannot benefit over and above the market by trading on that new information. We also find that, in the case of non-linear D-P causality test, past returns help in predicting the volume of major cryptocurrencies.

6 | DISCUSSION

From the above analysis we find that Bitcoin and other cryptocurrencies are informationally efficient as their TVs are unable to predict the returns. The whole sample result of linear and non-linear causal relation from TV to returns exhibits that the market is efficient in case of BTC, ETH, LTC, XLM, DASH and NEM. It suggests that the currency reflects all the available information in the market, thus past movements in the TV are irrelevant for predicting future prices of cryptocurrencies. As market becomes more efficient, the opportunity for arbitrage trading declines. Therefore, future price changes can only be the result of new information becoming available. Based on this result, the investing decision cannot ensure profit above normal level. This supports the early findings of Shen et al. (2019) and Tiwari et al. (2018) that Bitcoin return cannot be predictable. Furthermore, from a structural break analysis, we find that three cryptocurrencies, that is, XRP, XMR and DASH are showing a significant non-linear relationship from TV to return in the post-break period. Thus, it suggests that these cryptocurrencies are informationally inefficient. This result supports the findings of Kurihara and Fukushima (2017) and Hu et al. (2019). The overall study shows that majority of cryptocurrencies are following the 'efficient market hypothesis'.

7 | CONCLUSION

We examine the EMH of cryptocurrencies in a dynamic angle by uncovering the significant role of TV in predicting return of the cryptocurrency market. We examine the linear TYM and non-linear D-P Granger causality test of full sample period. Both analyses confirm that majority of the currencies follow the EMH and fail to predict the return. Furthermore, when we considered structural break analysis, the result confirms a similar finding for most cryptocurrencies. However, in the post-break analysis we observed that EMH is time specific, as some currencies (XRP, XMR and DASH) show EMH is not valid for crypto market.

This finding has important practical implications for the investors in the crypto market. Our result intends to provide practitioners and investors with additional insights on the role of cryptocurrency TV in its future return prediction. As market becomes more efficient, the opportunity for arbitrage trading declines. Therefore, future price changes can only be the result of new information becoming available. Based on this result, the investing decision cannot ensure profit above normal level. In other words, investors can make an investment strategy focused on undervalued stocks to appropriately predict the movement in the cryptocurrency market.

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CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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ENDNOTE

[1] Based on Coinmarketcap.com database.

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