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Market efficiency assessment for multiple exchanges of cryptocurrencies

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Abstract

Purpose – This study aims to analyze the efficient market hypothesis (EMH) of cryptocurrencies on multiple platforms by observing whether there is a discrepancy in the levels of efficiency between different exchanges. Additionally, EMH is tested in a multivariate way: whether the prices of the same cryptocurrencies traded on different exchanges are temporally related to each other. ADF and KPSS tests, whereas the vector autoregression model of order p – VAR(p) – for multivariate system.

Findings – Both Bitcoin and Ethereum show efficiency in the weak form on the main platforms in each market alone. However, when estimating a VAR(p) between prices among exchanges, there was evidence of Granger causality between cryptocurrencies in all exchanges, suggesting that EMH is not adequate due to cross information.

Practical implications – It is essential to assess the cryptocurrency market in a multivariate way, not only to favor its maturation process, but also to promote a broad understanding of its inherent risks. Thus, it will be possible to develop financial products that are actively managed in a more sophisticated cryptocurrency market.

Social implications – There is a possibility of performing arbitrage on different exchanges and market assets through cross-exchanges. Thus, emphasizing the need for regulation of exchanges in the digital asset market, as an eventual price manipulation on a single platform can impact others, which generates various distortions.

Originality/value – This study is the first to find evidence of cross-information for the same (and other) cryptocurrencies among different exchanges.

Keywords Cryptocurrencies, Efficient market hypothesis, Vector autoregression

Paper type Research paper

1. Introduction

Recent studies have estimated that there are currently 101 million investors in the cryptocurrency market, which represents a growth of 188% over the last two years. An even larger expansion is expected given the presence of large players in this market, such as Tesla and Paypal, as these assets are showing exponential valuation cycles (Bouri, Shahzad, & Roubaud, 2019).

The trend of adopting cryptocurrencies is not only highlighted among market agents, but also new asset classes have attracted the attention of scholars, who seek to understand the rapid evolution and the dynamics of this market in the past three years (Jeris, Chowdhury, Akter, Frances, & Roy, 2022). Also, Jiang, Li and Wang (2020) showed a significant increase in the literature on cryptocurrencies.

Cryptocurrencies can be financial instruments for both investment and portfolio protection, given the characteristic shortage of digital currency (Anyfantaki, Arvanitis, & Topaloglou, 2021; Dyhrberg, 2016a; Jiang, Wu, Tian, & Nie, 2021). Despite being a recent market with some risks

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and uncertainties from the point of view of liquidity, regulation, access infrastructure for institutional investors, including some criticism regarding cryptocurrencies (Alexander & Heck, 2020; Fujiki, 2020), there are numerous signs of both its institutionalization process (Akyildirim, Corbet, Katsiampa, Kellard, & Sensoy, 2020) and its use as an efficient portfolio diversifier (Sun, Dedahanov, Shin, & Li, 2021) and as hedging instrument (Dyhrberg, 2016b).

In Brazil, the expansion trend of digital asset market expansion trend is also evident. Since the implementation of the Brazilian Federal Revenue Service IN No. 1,888/2019, which makes monthly disclosure of crypto assets transactions above BRL30,000 per month mandatory, between August 2019 and August 2020, more than BRL114 billion were declared [1].

Within the context of regulation and expansion of the crypto asset market, there can be seen evidence of significant growth in investment funds in this class, with more than US$25 billion under management in investment funds around the world [2]. Given its current financial relevance, it is important to understand the efficiency of the cryptocurrency market as the main techniques used for pricing derivative financial instruments rely on the hypothesis of an efficient market (Black & Scholes, 1973).

The efficient markets hypothesis (EMH) is a theory widely used in the current finance literature both to understand the impacts of more recent and unexpected events, such as the COVID-19 pandemic (Choi, 2021), to define the best path analysis for a market (Yamani, 2021), and to understand the behavior of more recent markets such as cryptocurrency market (Yi, Ahn, & Choi, 2022).

Understanding the level of efficiency of crypto asset market is essential for investors to define better strategies for allocating resources in this class of investment, enabling different strategies, ranging from arbitrage (Sensoy, 2019) to the development of diversified portfolios in this class of assets (Liu, 2019). However, unlike stock markets, there is not a single price source for cryptocurrencies due to their decentralized nature and the existence of hundreds of cryptocurrency exchanges [3], with diversity of quotations and variations (Dimpfl & Peter, 2021).

Even though this market may be new, the literature on the subject is prolific and thus allows in-depth analysis of the political and economic uncertainties involved (Alexander & Heck, 2020). There are also many scholars (e.g. Tiwari, Jana, Das, & Roubaud, 2018; Vidal-Tomás & Ibañez, 2018) who seek to analyze and define whether there is an efficient cryptocurrency market. However, Corbet, Lucey, Urquhart, and Yarovaya (2019) show that there is still no consensus on the results. This picture is further aggravated by the existence of multiple databases with real-time variations in asset prices in each of the existing exchanges. Thus, there emerges the need for analyzing the informational divergence between them (Kabašinskas & Šutienė, 2021).

Although EMH is widely used in many different markets (Ţiţan, 2015), there is still a significant theoretical gap in the cryptocurrency market (Jeris *et al.*, 2022). This is precisely the gap we intend to explore. The objective is to analyze the EMH of cryptocurrencies on multiple platforms, by observing whether there is a divergence in the level of efficiency between the different exchanges. Additionally, this analysis is expanded in a multivariate way, by testing whether the prices of the main cryptocurrencies traded on different exchanges are temporally related to each other so that cross information could be evidenced. If this occurs, evidence of possible arbitrage within the cryptocurrency market will remain, which may be useful for regulators to identify divergences between digital asset brokers.

2. Theoretical background

The EMH was proposed by Fama (1970), with the objective of analyzing whether the market returns are predictable or not based on information asymmetry existing in that market. According to this theory, there are three levels of market efficiency: (1) strong efficiency, under which all public or nonpublic information is incorporated into the asset price, (2) semi-strong efficiency in which the price adjusts immediately to public information on the market and (3) weak efficiency, the way in which prices reflect the already existing information.

If the market presents a semi-strong or weak level of efficiency, it is possible to predict its price movements by using past information. Otherwise, its variation follows a random walk. It should be noted how fundamental the EMH is for the finance theory. Black and Scholes (1973) argue that this assumption is necessary for an efficient option pricing. Nevertheless, the modern portfolio theory (Sharpe, 1964) has EMH as one of its pillars, thus reinforcing its validity for the development of an efficient portfolio in any given market.

The study of the EMH has proven to be very relevant for understanding the traditional financial market, being a recurrent theme (Ţiţan, 2015) and recently used for the analysis of major economic events, such as the COVID-19 crisis (Mensi, Sensoy, Vo, & Kang, 2022) and Russia–Ukraine war (Gaio, Stefanelli, Pimenta, Bonacim, & Gatsios, 2022). However, little is known in markets which are still expanding and consolidating, such as cryptocurrencies (Liu, Liang, & Cui, 2020; Mokhtarian & Lindgren, 2017; Wątorek *et al.*, 2021).

The cryptocurrency market is a new topic in literature. Corbet *et al.* (2019) carried out a systematic review and identified the main aspects empirically addressed in the literature on digital asset market: (1) the bubble dynamics for evaluating whether the digital assets market is a speculative bubble, (2) regulation for evaluating the regulatory impacts of this new market, (3) digital crimes for analyzing the use of digital assets for illegal practices, (4) portfolio diversification, evaluating the impact of diversification by including digital assets in a portfolio with traditional assets and, finally, (5) EMH analysis for evaluating the efficiency of the main cryptocurrencies.

There is a lot of recent studies addressing the latter topic (Apopo & Phiri, 2021; Palamalai, Kumar, & Maity, 2020; Tran & Leirvik, 2020). Cryptocurrencies have two major factors making the analysis of EMH difficult. Firstly, as crypto assets are not traded on an integrated basis through a single stock exchange, there is a significant difference in the price of the same asset across different trading platforms (Dimpfl & Peter, 2021). It is important to highlight that there are no specific regulatory requirements for these platforms either, which allows practices such as the manipulation of volumes and data on some platforms that can distort asset prices (Al-Yahyaee, Mensi, Ko, Yoon, & Kang, 2020).

Secondly, the market is fairly new, and it is not even integrated with the traditional financial market. Several aspects of its operation are not yet fully disseminated, especially to regulators (Mokhtarian & Lindgren, 2017), and its benefits to investors are not yet fully known (Anyfantaki *et al.*, 2021). Therefore, all these make this process somewhat similar to that occurred with emerging markets in the 1980s and 1990s (Bekaert & Harvey, 2003), suggesting that it might be a less efficient market.

In terms of methodology, many different techniques have been used to assess EMH. Urquhart (2016) was one of the pioneers in addressing this issue in the crypto asset market. With an autocorrelation test using the Ljung–Box method, he found evidence of weak efficiency in Bitcoin (BTC). Aiming to broaden the EMH analysis, Brauneis and Mestel (2018) used the same technique to assess the EMH for several cryptocurrencies. Other techniques are also applied to investigate this phenomenon, from high-frequency model (Sensoy, 2019) to long-memory models (Caporale, Gil-Alana, & Plastun, 2018), with both finding evidence that the cryptocurrency market is not efficient, as its returns are predictably based on past returns or volatility.

Palamalai *et al.* (2020) performed both parametric (unit root test, multiple variance radius test and GARCH models) and nonparametric tests (Kolmogorov–Smirnov and Runs tests) for the random walk hypothesis, finding evidence that the analyzed cryptocurrencies do not follow the behavior of a random walk. Apopo and Phiri (2021), on the other hand, assessed EMH by using Kwiatkowski–Phillips–Schmidt–Shin (KPSS) model to test the random walk hypothesis, finding strong evidence against the weak efficiency in the cryptocurrency market.

Market efficiency determinants are also addressed in the literature. There is evidence that six major cryptocurrencies have the long memory property and multifractality, i.e., they not only have a long-term dependency structure, but also a heavy-tailed distribution (Al-Yahyaee *et al.*, 2020). Furthermore, increases in liquidity have positive effects, whereas increases in volatility have negative effects on the market efficiency of cryptocurrencies (Sensoy, 2019).

Shocks in volatility can generate externalities on other cryptocurrencies, creating systemic interconnections and possibilities for contagion (Caporale, Kang, Spagnolo, & Spagnolo, 2021). In such a situation, opportunities for price arbitrage increase (Duan, Li, Urquhart, & Ye, 2021), aggravated mainly by the existence of multiple exchanges (Makarov & Schoar, 2020; Shynkevich, 2021). Köppl and Monnet (2007) argue that the existence of multiple exchanges for trading an asset can impair its efficiency, with the most likely hypothesis being the existence of information asymmetry between the exchanges that trade these assets, such as security and liquidity criteria, similar to what happens in the traditional financial market.

Nevertheless, Alexander and Heck (2020) showed that the presence of multiple unregulated exchanges affects the price of BTC on regulated platforms whose practices are against market manipulation. For example, the impact of the price of platforms (e.g., Bitmex, Okex) on the Chicago Mercantile Exchange, thus becoming a roadblock for the creation of exchange-traded funds (ETF) for the asset, as well as the price arbitrage of these futures contracts (Shynkevich, 2021) and the arbitrage between exchanges trading BTC spot and BTC derivatives (Lee, Meslmani, & Switzer, 2020).

Kabašinskas and Šutienė (2021) used graph theory not only to describe the network of cryptocurrencies generating price arbitrage opportunities, but also to determine that cryptocurrency volatility index is the main online arbitrage indicator, which is in line with findings by Sensoy (2019). In fact, Dimpfl and Elshiaty (2020) pointed out that BTC volatility can be derived from other cryptocurrencies. The possibility of arbitrage in the cryptocurrency market tends to grow even more in the coming years, given the advent of decentralized exchanges, new formats for exchange models through smart contracts and even a greater degree of decentralization to the market (Lo & Medda, 2021).

Therefore, the need for investigating the EMH on multiple exchanges becomes evident, while aiming at understanding the arbitrage risk of this market, which would make it impossible to create more robust financial instruments (e.g., ETFs). Moreover, this would not even allow understanding and measuring the risk of new technologies being developed in this market, aside from comprehending the level of maturity of cryptocurrencies.

3. Methodology

3.1 Market efficiency test

To analyze whether there is a divergence in the level of market efficiency in different cryptocurrency trading platforms for the same assets, the random walk hypothesis was evaluated by using unit-root tests, which is in line with Palamalai *et al.* (2020) and Apopo and Phiri (2021).

An asset has statistical independence of R_t returns if this stochastic property is verified:

$$\mathbb{P}\{R_t = R|\mathcal{F}\} = \mathbb{P}\{R_t = R\}, \tag{1}$$

where $\mathcal{F}$ represents natural filtration, the left-hand side of Equation (1) represents the probability that the return assumes any value conditional on prior knowledge of the past return trajectory. The right-hand side represents the unconditional return probability over time. Fama (1970) generalized the random walk model using the probability density function for future return $R_{j,t+1}$:

$$f(R_{j,t+1}|\Omega_t) = f(R_{j,t+1}), \tag{2}$$

where Ω_t is the complete set of historical returns information available up to time t, and f is the time-invariant probability density function. By using the theory of expected returns (Fama, 1970), the statistical representation of the weak efficiency of a market is obtained as:

$$\mathbb{E}(Rj, t+1|\Omega_t) = \mathbb{E}(R_{j,t+1}) \tag{3}$$

where $\mathbb{E}(.)$ is the expectancy operator. If this equation is true, then it is not possible to use past information to form expectations about future returns. Assuming that returns can be written in the form of a first-order autoregressive process, AR(1), then asset returns would be:

$$R_t = \rho R_{t-1} + e_t, t = 1, 2, \ldots, T, e_t \sim N(0, \sigma^2). \tag{4}$$

Thus, if the AR(1) model of the time series of returns on asset R_t presents $\rho < 1$, then future returns are predictable and will not show market efficiency in the weak form. Otherwise, if $\rho = 1$ the series is a random walk: a purely random and unpredictable process.

3.1.1 Augmented Dickey–Fuller Test (ADF). Following the argument, it is worth noting that some time series have more complex structures, so that a test using an AR model is not adequate to determine the level of efficiency of a market. Therefore, it is necessary to use a more robust EMH test. For that, Dickey and Fuller (1979) proposed the ADF test, which considers three distinct approaches for the unit-root test. All approaches are derived from Equation (5):

$$\Delta R_t = \alpha + \beta t + \gamma R_{t-1} + \sum_{i=1}^{p-1} \Delta R_{t-i} + e_t \tag{5}$$

where Δ is the difference operator. The main interest is the γ. If $\gamma \neq 0$, then it is concluded that the series does not have a unit root and the market will not show efficiency in the weak form. When $\gamma = 0$, then the series is a random walk, thus being necessary to evaluate the parameters α and β. If $\alpha = 0$, there is no drift. On the other hand, if $\beta = 0$, the series does not have a deterministic trend.

3.1.2 Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. Also widely used to assess EMH, the KPSS test is a complement to the ADF test, as its null hypothesis establishes that the series is stationary. Equations (6) and (7) define the test:

$$y_t = \varepsilon_t + r_t + e_t \tag{6}$$

$$r_t = r_{t-1} + u_t \tag{7}$$

where r_t is a random walk, with the initial value r_0 known, $u_t \sim N(0, \sigma^2)$, i.i.d. (Kwiatkowski, Phillips, Schmidt, & Shin, 1992). The asymptotic distribution of the statistic is derived under the null hypothesis with general conditions on the stationary error, and the hypothesis test is based on the LM statistic. The null hypothesis is $\varepsilon_t = 0$.

3.2 Multivariate model

The structure of a vector autoregression model of order p – VAR(p) – can be described as follows:

$$\widetilde{X}_t = \phi_0 + \phi_1 \widetilde{X}_{t-1} + \ldots + \phi_p \widetilde{X}_{t-p} + a_t, \tag{8}$$

where $a_t \sim RB(0, \Sigma)$, $\phi_0 = (\phi_{10}, \ldots, \phi_{n0})'$ is a $n \times 1$ vector of constants and ϕ_k are $n \times n$ constant matrices, with elements $\phi_{ij}^{(k)}$, $i, j = 1, \ldots, n, k = 1, \ldots, p$.

$\phi(B)\widetilde{X}_t = \phi_0 + a_t$, where $\phi(B) = I_n - \phi_1 B - \ldots - \phi_p B^p$ is the VAR operator of order p, or an $n \times n$ matrix polynomial in B, with I_n representing the n-th order identity matrix. The process $\widetilde{X}_t$ is stationary, i.e., it has constant mean and $\mathbb{E}(\widetilde{X}_{t+\tau}\widetilde{X}_t)$ independent of t, if the solutions:

$$\left|I_n - \phi_1 B - \ldots - \phi_p B^p\right| = 0 \tag{9}$$

are outside the unit circle. As the solutions of Equation (9) are the matrices' inverses of the eigenvalues ϕ_k, $k = 1, \ldots, p$, an equivalent condition is that all the eigenvalues of the matrices ϕ_k, $k = 1, \ldots, p$, are less than one (Morettin, 2011).

The matrices' coefficients ϕ_k, $k = 1, \ldots, p$ are estimated. If the variables involved are in logarithmic form, the coefficients are interpreted as the elasticities of the present in relation to the past.

3.2.1 Model order selection. There are several ways to select the lag order of VAR(p) models. The simplest way is to sequentially adjust VAR models with increased time lag ($k = 1, \ldots, p$) and test the significance of matrix's coefficients. The hypotheses to be tested are:

$$\begin{cases} H_0: \ \phi_k = 0 \\ H_A: \ \phi_k \neq 0 \end{cases} \tag{10}$$

for every $k = 1, \ldots, p$.

Another way to identify the optimal order p of a VAR model is by using some information criterion. In this study, two of them are used:

$$\text{AIC(k)} = \ln(|\widehat{\Sigma}_k|) + 2kn^2/T \text{ (Akaike)} \tag{11}$$

$$\text{BIC(k)} = \ln(|\widehat{\Sigma}_k|) + kn^2 \ln T/T \text{ (Schwarz)} \tag{12}$$

Their rationale is to choose the VAR(k) model in such a way that the forecast error made is minimized, but this does not include so many parameters which makes the model too difficult to explain.

3.2.2 Granger's causality. In multivariate systems involving time series, Granger (1969) defines causality as predictability. An X variable causes another Y variable, with respect to a given set of information (which includes X and Y), whether the present of Y can be predicted more efficiently by using past values of X when compared to not using them, considering any and all other information available, including the own past of Y. It is important to highlight that this definition does not require linearity of the system. If so, the projections are said to be linear.

Let $\{A_t, t = 0, \pm 1, \pm 2, \ldots\}$ be the relevant information set up to time t, containing at least X_t e Y_t. It is defined as:

$$\overline{A}_t = \{A_s : s < t\}, \ \overline{\overline{A}}_t = \{A_s : s \leq t\} \tag{13}$$

and analogous definitions for $\overline{X}_t$, $\overline{Y}_t$, $\overline{\overline{X}}_t$ e $\overline{\overline{Y}}_t$. Also, let $P_t(Y|B)$ be the least mean squared error (MSE) predictor of Y_t, by using the set of information B and $\sigma^2(Y|B)$ the corresponding MSE of the predictor.

Definition 1. It is said that:

(1) $X_t \rightarrow Y_t$: X_t *causes* Y_t in the Granger sense if:

$$\sigma^2(Y_t|\overline{A}_t) < \sigma^2(Y_t|\overline{A}_t - \overline{X}_t), \tag{14}$$

i.e., Y_t can be better predicted by using all available information, including the past values of Y_t and X_t. It is also denoted that X_t is exogenous or antecedent to Y_t.

(2) $X_t \to Y_t$: X_t instantly causes Y_t in the Granger sense if:

$$\sigma^2(Y_t|A_t, \overline{\overline{X}}_t) < \sigma^2(Y_t|\overline{A}_t), \tag{15}$$

that is, the present value of Y_t is better predicted if the present value of X_t is included. It is easy to see that if $X_t \to Y_t$ then $Y_t \to X_t$.

(3) There is a feedback relationship ($X_t \leftrightarrow Y_t$), if $X_t \to Y_t$ and $Y_t \to X_t$.

(4) There is unidirectional causality from X_t to Y_t if $X_t \to Y_t$ and there is no feedback.

Morettin (2011) reports different methods to operationalize Granger's definitions of causality. However, in this study, the VAR(p) representation of the multivariate series $\widetilde{X}$ is used, considering Proposition 1.

Proposition 1. The optimal predictor of Y_t based on $\overline{\overline{X}}_t$ is equal to the optimal predictor of Y_t based on $\overline{\overline{Y}}_t$ if and only if:

$$\phi_{jk,i} = 0, i = 1, 2, \ldots, p; j, k = 1, 2, \ldots, n, j \neq k \tag{16}$$

The Proposition 1 is linked to the concept of prediction. If the series X_t does not help to reduce the projected MSE of another series Y_t, then the matrix parameter linking X_t to Y_t in the VAR model is statistically insignificant. In this way, the concept of Granger causality is related to multivariate time series models.

4. Data analysis

4.1 Databases

To check for divergence across databases of different exchanges in the cryptocurrency market, data from the three main brokers in the cryptocurrency market were used: Binance, the largest broker in volume (US$3.6tn in the 2021 second quarter); Coinbase, the leading US brokerage, with a volume of US$0.46tn in the same period [4]; Kraken, in addition to the CoinMarketCap data aggregator, it is the main cryptocurrency market with around 200 million daily visits [5]. Data on price and volume were extracted from the respective APIs. The selection of these databases is in line with the literature used to understand the cryptocurrency market (Vidal-Tomás, 2022).

Thus, the daily variation in the BTC and Ethereum (ETH) prices in the same period were analyzed, as they are the main cryptocurrencies in terms of market value. The BTC-USD and ETH-USD were chosen because they are the only two assets listed in the Chicago Mercantile Exchange (CME), and have a strong derivative structure (Chi & Hao, 2021) besides representing about 60% of the crypto-asset market value. The period of analysis is between September 12, 2019–August 20, 2021, with 4,563 observations of nine time series. The start date was chosen to ensure that all selected databases have complete data, with a start limit from ETH and provided by Kraken.

It is important to highlight that the cryptocurrencies market does not close. Therefore, the assets' closing quotation was considered at 00:00 UTC. However, the database used for the analyses of EMH and the multivariate model, covers only working days, as S&P500 is also used as a control variable, and whose data were gathered from the Federal Reserve Bank of St. Louis' website.

4.2 Descriptive analyses

Initially, it is presented the daily returns of assets. The objective is to verify whether there is any discrepancy between the databases regarding variation in asset prices and volatilities as well as any correlation between BTC-USD and ETH-USD regarding price fluctuations.

From Figure 1, there does not seem to be any conflicting behavior in the analyzed databases of the BTC-USD or ETH-USD ratio, all of them showing similar daily returns and very similar volatility behavior.

One can see that when there are market volatility peaks (Figure 1), this behavior is a little out of line with the CoinMarketCap series in relation to the other series.

4.3 Analysis of time-series stationarity

After a descriptive analysis, the EMH was verified in the time series by using ADF and KPSS tests, both implemented in the R software. The results for the BTC-USD and ETH-USD time series on different exchanges are shown in Table 1.

From Table 1, one can see that all null hypotheses were rejected after ADF tests on all databases. Thus, there is evidence of stationarity in both BTC-USD and ETH-USD time series. The KPSS test results indicated the same conclusion: there is evidence to say that both BTC-USD and ETH-USD time series are efficient in their weak form.

The results also suggest that there may be a divergent behavior of the CoinMarketCap databases in relation to Binance, to a greater degree, and Coinbase and Kraken, to a lesser degree, given the small difference found in the estimates of ADF and KPSS tests. However, although the ADF and KPSS tests indicate stationarity, nothing can be said about cross information between databases or about cryptocurrencies. This is important as information from the past value of one time series could be used to predict the behavior of other time series. This assessment is made in the next section.

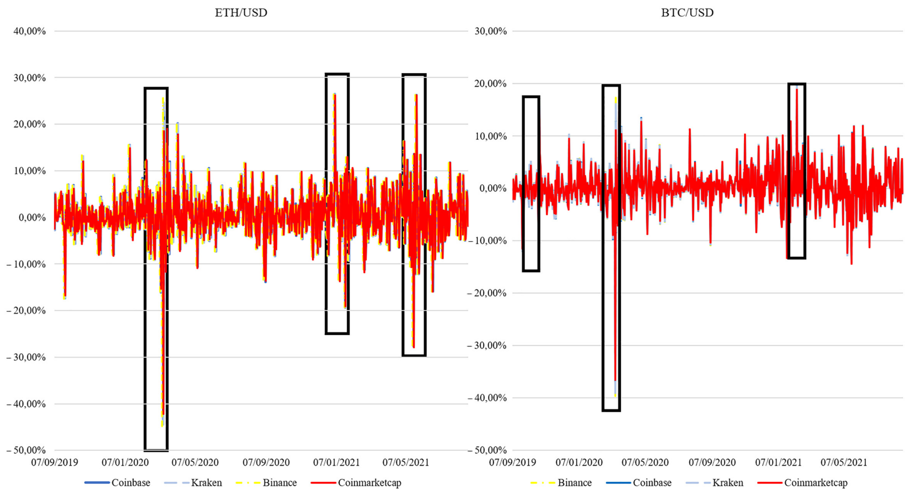

Figure 1.
ETH/USD and BTC-USD daily returns

EMH test		ADF				KPSS						
Exchange/asset	*ADF*	*Lag order*	*p-value*	Hypothesis	KPSS	*Lag order*	*p-value*	Hypothesis	DF-GLS	*Lag order*	*1% Critical Value*	Hypothesis
Coinbase BTC-USD	−8.0303	7	<0.001	Stationary	0.23687	6	<0.001	Stationary	−7.1762	7	−2.57	Stationary
Kraken BTC-USD	−8.0367	7	<0.001	Stationary	0.23667	6	<0.001	Stationary	−4.8502	7	−2.57	Stationary
Binance BTC-USD	−8.0454	7	<0.001	Stationary	0.23632	6	<0.001	Stationary	−4.9164	7	−2.57	Stationary
CoinMarketCap BTC-USD	−7.9206	7	<0.001	Stationary	0.24067	6	<0.001	Stationary	−5.0000	7	−2.57	Stationary
Coinbase ETH-USD	−7.9093	7	<0.001	Stationary	0.17497	6	<0.001	Stationary	−5.1866	7	−2.57	Stationary
Kraken ETH-USD	−7.9304	7	<0.001	Stationary	0.17441	6	<0.001	Stationary	−7.0833	7	−2.57	Stationary
Binance ETH-USD	−7.7032	7	<0.001	Stationary	0.17073	6	<0.001	Stationary	−6.9282	7	−2.57	Stationary
CoinMarketCap ETH-USD	−7.8394	7	<0.001	Stationary	0.17587	6	<0.001	Stationary	−7.3798	7	−2.57	Stationary

Table 1. HME test results for log (BTC-USD) and log (ETH-USD) for different exchanges

4.4 Multivariate model estimation

The VAR(p) model aims to estimate the Granger causality between the exchanges, so that one can verify whether there is evidence of cross information between the databases. Furthermore, to assess whether there is interference of the traditional market on the returns of the chosen cryptocurrencies, the S&P500 time series, one of the main financial market indices, was included in the model as a control variable.

To properly fit the model, several methods were used to select the ideal order to find the most parsimonious one. Bayesian Information Criterion (BIC) indicates VAR(2) as the most suitable model (BIC $= -92.391$), whereas Hannan-Quinn (HQ) indicates a VAR(3) model (HQ $= -93.350$), and Akaike Information Criterion (AIC) suggests a VAR(6) model (AIC $= -94.546$). BIC is a more parsimonious model selection criterion because it is an asymptotically consistent estimator, whereas HQ and AIC work best for small samples (Morettin, 2011). Thus, we opted to estimate a VAR(2) model, whose results are shown in Table 2, including estimated parameters and their respective significance levels.

The coefficients' stability of the estimated model over time was verified by using the OLS-CUSUM test (Figure 2), which consists of summing the recursive residuals calculated iteratively from sequential data of subsamples (Ploberger & Kramer, 1992).

One can see that the VAR(2) system is stable, i.e., it has converging means and controlled variances, in all dimensions, in addition to having all the memories captured adequately.

With regard to the results presented in Table 2, one can verify the significance of several estimated parameters. Thus, it can be said that the returns of some cryptocurrencies traded on some exchanges over the past yield (in the Granger's sense) other returns in other databases. The interrelationships verified between these exchanges create market inefficiencies, meaning that the past information on a crypto-asset exchange is useful to predict the same crypto asset on another exchange. It is also possible to use prior information on a crypto-asset exchange to predict the returns of another crypto asset on the same exchange.

It is interesting to emphasize that BTC-USD on Kraken is more highly related to BTC-USD on Binance compared to other databases. On the other hand, S&P500 proved to be of little relevance for predicting the behavior of asset returns, which reinforces the consensus that the cryptocurrency market is poorly related to the North American capital market.

5. Final remarks

We aimed to test the hypothesis that the prices traded for different crypto assets on a given exchange could affect the price of the same crypto asset on another exchange, which would make the cryptocurrency market inefficient. Initially, each dimension was evaluated alone and showed evidence of market efficiency in its weak form, both through KPSS and ADF tests. This evidence is in line with the most recent results in the literature (Apopo & Phiri, 2021; Palamalai *et al.*, 2020).

However, when evaluating the problem of other exchanges in multiple dimensions, it was found evidence that the market is not efficient because the interrelationships between these exchanges present causality in the Granger sense. These results expand the literature, which is mostly focused on the crypto asset market analysis in a single dimension. Therefore, it is essential to assess the cryptocurrency market in a multivariate way, not only to favor its maturation process, but also to promote a broad understanding of its inherent risks. In this way, it would be possible to develop financial products that are actively managed in a more sophisticated cryptocurrency market, such as ETF.

Moreover, light is shed on the possibility of arbitrage on different exchanges and market assets through cross-databases. Thus, the need for some regulation of exchanges in the digital asset market should be emphasized, since any manipulation of asset prices in a single platform can impact others, generating several distortions. For future research,

Table 2. VAR(2) model parameter estimates

Explanatory variable	Dependent variable S&P 500	BNB BTC	COIN BTC	Kraken BTC	CMC BTC	BNB ETH	COIN ETH	Kraken ETH	CMC ETH
S&P 500 L1	−0.175***	−0.031	−0.032	−0.029	−0.034	0.087	0.092	0.149	0.093
BNB BTC L1	0.382	4.152	4.611	4.682	4.220	9.556**	9.752**	4.485	8.982**
COIN BTC L1	0.754	7.114*	6.374	7.112*	6.415	8.094	8.348	7.372	7.817
Kraken BTC L1	−1.293	−11.106***	−10.822	−11.614***	−9.980***	−16.999***	−17.403***	−12.773***	−16.194***
CMC BTC L1	0.137	−0.151	−0.149	−0.166	−0.629	−0.712	−0.761	0.810	−0.657
BNB ETH L1	2.338***	2.177	2.091	2.090	2.347	5.264*	6.010**	5.873**	6.335**
COIN ETH L1	−2.072***	−2.765	−2.669	−2.678	−2.920	−5.996*	−6.769**	−5.695*	−6.527**
Kraken ETH L1	0.001	−0.043	−0.0431	−0.045	−0.046	−0.086	−0.087	−0.456***	−0.090
CMC ETH L1	−0.254	0.528	0.517	0.528	0.515	0.731	0.760	0.402	0.200
S&P 500 L2	0.131***	−0.131	−0.120	−0.124	−0.070	0.004	−0.005	−0.011	0.038
BNB BTC L2	3.123***	10.226***	10.404***	10.471***	9.426***	15.340***	15.551***	6.792	14.539***
COIN BTC L2	−1.819	−1.150	−1.544	−1.136	−1.259	−6.163	−6.007	−3.858	−5.881
Kraken BTC L2	−0.863	−8.876**	−8.675**	−9.130**	−7.831**	−9.487*	−9.774**	−2.914	−8.961*
CMC BTC L2	−0.450	−0.204	−0.190	−0.209	−0.340	0.276	0.195	−0.214	0.262
BNB ETH L2	0.3792	4.456*	4.464*	4.445*	4.615**	6.390**	6.714**	4.275	6.837**
COIN ETH L2	−0.698	−4.519*	−4.513*	−4.509*	−4.558*	−6.468**	−6.851**	−4.290	−6.648**
Kraken ETH L2	0.0218	0.054	0.0538	0.053	0.053	0.024	0.024	−0.213***	0.029
CMC ETH L2	0.332	0.125	0.110	0.129	0.009	0.270	0.331	0.600	0.010
Constant	0.001	0.003	0.003	0.003	0.003	0.005*	0.005*	0.004	0.005*

Note(s): "***" significant at 1%, "**" significant at 5% and "*", significant at 10%, L1: lag of 1 period, L2: lag of 2 periods. CMC – CoinMarketCap, COIN – Coinbase, BNB – Binance, BTC – BTC-USD, ETH – ETH-USD, S&P500 – S&P500 (USD)

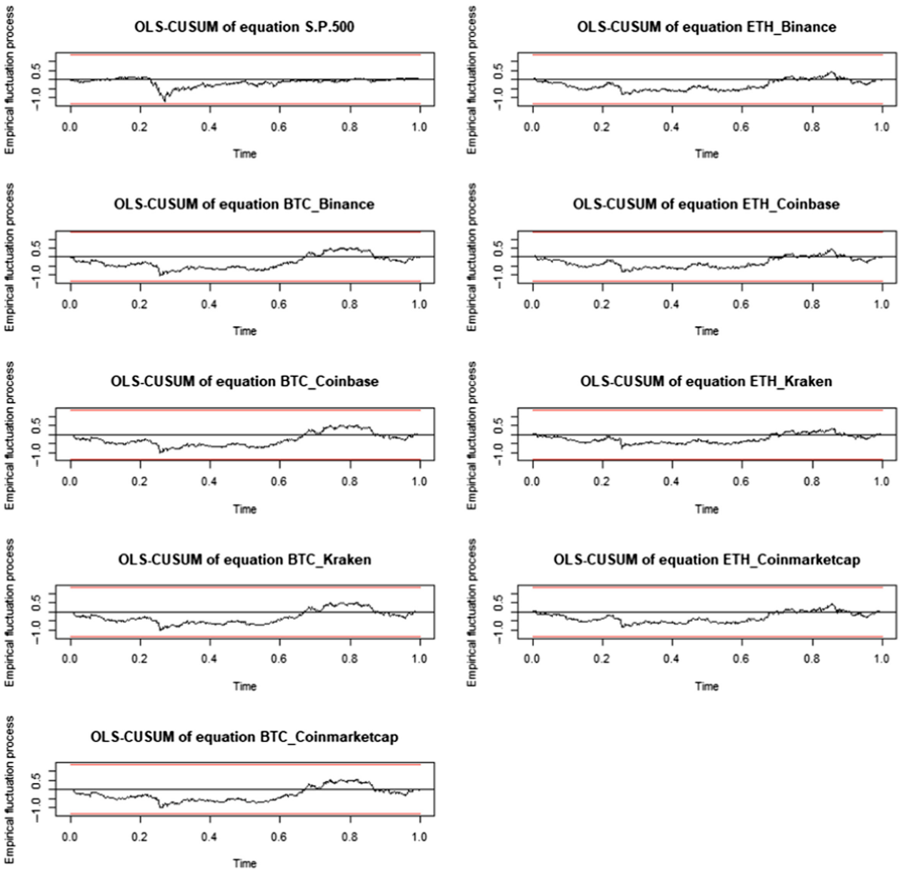

Figure 2.
OLS-CUSUM test for the model

it is suggested that models using a methodological framework with high frequency data and event studies should be used to explain the causes of abrupt shifts which are still typical of this segment.

Notes

1. https://receita.economia.gov.br/orientacao/tributaria/declaracoes-e-demonstrativos/criptoativos/criptoativos-dados-abertos.pdf
2. https://cryptofundresearch.com/cryptocurrency-funds-overview-infographic/
3. https://coinmarketcap.com/currencies/bitcoin/markets/
4. https://image.tokeninsight.com/levelPdf/TokenInsight_2021_Q2_Crypto_Trading_Industry_Report(1)_2.pdf
5. https://www.similarweb.com/website/coinmarketcap.com/

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