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RESEARCH PAPER

Cryptocurrency Market Efficiency: Does Distributed Ledger Technology Matter?

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Abstract

In recent years, due to its use in transactions with encrypted assets, distributed ledger technology has attracted the attention of the financial sector on the one hand. On the other hand, the expansion of the projects has the potential to increase the efficiency, transparency, speed, and flexibility of financial transactions underlying infrastructure processes. The present article aims to calculate the efficiency of various modes of this technology. Calculating and examining the efficiency of financial markets are remarkably effective in choosing the investors' strategy. There are several methods to calculate efficiency. In the present study, the method of analyzing Multi Fractal Detrended Fluctuation Analysis (MFDFA) has been implemented to calculate such an efficiency. Hence, different forms of distributed ledger technology have been investigated including: "Blockchain" and "Directed Acyclic Graph (DAG)". The DAG technology itself is classified into two modes: 1. Tangle and 2. Hashgraph. To calculate Blockchain efficiency, the hourly data from September 2019 to November 2022 were utilized for Bitcoin (BTC) and Ethereum (ETH) cryptocurrencies. For Tangle technology, Iota cryptocurrencies were used, and for Hashgraph technology, Fantom (FTM) and Hederahashgraph (HBAR) cryptocurrencies were implemented. The results reveal that the distributed ledger technology of cryptocurrencies influences their efficiency. Hashgraph technology (the cutting-edge type of distributed ledger) proves the highest efficiency compared to other technologies.

Keywords: Cryptocurrencies, Distributed Ledger Technology, Efficiency, Multi Fractal Detrended Fluctuation Analysis.
JEL Classification: C02, C15, G14.

1. Introduction

Distributed ledger technology is a decentralized information storage space. Cryptocurrencies, on the other hand, are a means of financial transactions and exchanges on the distributed ledger technology. The historical records and the transactions of cryptocurrencies are written and maintained in a distributed ledger technology. While cryptocurrencies are utilized as exchange tools, distributed ledger technology is used in a variety of areas such as supply chain, health, retail, etc. Simply put, if we consider distributed ledger technology as a banking system of a given country, cryptocurrencies are the money in circulation in that banking system. In the distributed ledger technology, the data is distributed in several copies and exactly indexed the same among the participants. Each participant has a copy of all the information in this ledger. In traditionally distributed general offices, all participants have complete trust in each other and work together to maintain and stabilize the data. Nevertheless, in the new and virtualized form of distributed ledger technology, the participating parties do not trust each other, and there may even be a conflict of interest. Accordingly, there must be a collective mechanism for the approval of the books by all participants called the “consensus mechanism”. In other words, all changes made to the distributed ledger technology are not introduced by a central body; nevertheless, it is conducted by a consensus of the parties and following a set of rules and procedures accepted by all participants (Ugarate, 2018).

The distributed ledger technology has various forms, among which we can mention Blockchain and Dag. The Dag technology itself is classified into two modes: Tangle and Hashgraph. The main strength of the Blockchain is its oversimplification, which is its sequence. In fact, when a block is extracted and approved by all participants, the extracted block becomes immutable and the next block is built on it. However, this process is too slow for different forms of distributed ledger technology to be created (Schueffel, 2017). It should be noted that most cryptocurrencies on the cryptocurrency market use Blockchain technology. All distributed ledger technology models are shown in the Figure (1).

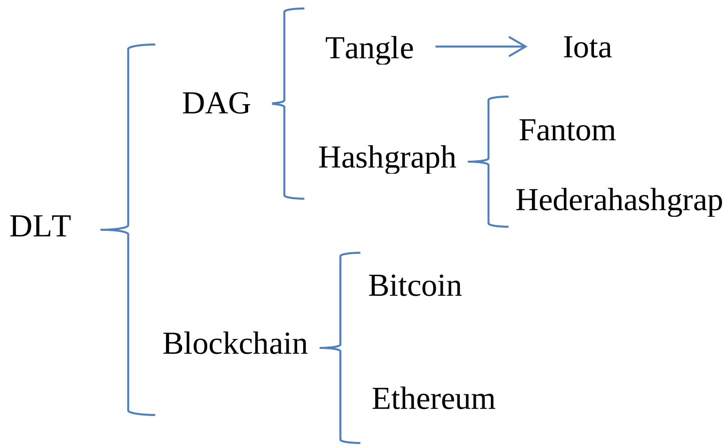

Figure 1. DLT Category
Source: Research finding.

Tangle technology fails to use blocks in the conventional sense, in which a previous transaction must record two previous transactions. In Tangle the transaction fee is lost and the transaction fee is the same as the confirmation of all previous transactions. The remarkable thing about this technology is that by doing so, Tangle integrates the transaction construction process through the consensus mechanism process. Currently, the only cryptocurrency to use this technology is the Iota cryptocurrency, which is active in the field of Internet of Things (Popov, 2018).

Hashgaraph technology implements a completely different method called "gossiping" mechanism to share information and the consensus mechanism. A network participant is required to share all of its information including transactions with several other randomly selected network participants. Next participant then combines the information received with the information from other participants and adds new information to it. This collection of information is then passed on to the next randomly selected participants until all participants become aware of all the information available. The hash technology is extremely quick. Among all cryptocurrencies that use this technology, we can mention Fantom cryptocurrencies and Hederahashgraph cryptocurrencies (Jia, 2017).

Blockchain and Dag generally record transactions decentrally in a distributed ledger technology; however, there are some differences as listed below:

1- Structure: Blockchain is a distributed ledger technology whose blocks are made by miners or network nodes. This way, information on the history of transactions is recorded in the blocks, and then nodes are validated and later added to the main chain as immutable information. Nonetheless, Dag technology is a network of individual transactions, each of which is linked to several previous transactions. Simply put, a person must approve two or more previous transactions to confirm their transaction on the Dag network.

2- Consensus: In the Blockchain network, a consensus mechanism is deployed to show agreement on miners or nodes in order to approve and validate the transactions. All nodes in the network are required to implement. Moreover, in Dag technology, the validation of transactions is performed by network users. In fact, network users play the role of both miners and network nodes.

3- Scalability: Increasing the volume of transactions on the Blockchain platform (especially Blockchains using the proof-of-work mechanism) requires an increase in computational power and an increase in energy consumption. Evidently, with high volumes of transactions, the transaction fee increases sharply due to the scalability of the network. Dag technology solves Blockchain problems such as scalability and high transaction fees, there are other challenges though. The low volume of transactions on the Dag platform makes the network vulnerable to attacks. The implementation of these central coordinators causes the project to move away from the decentralized state, which is the basis of the distributed ledger technology to move towards centralization. In general, Dag projects have so far failed to maintain high levels of decentralization (Bencic et al., 2018).

As mentioned earlier, both Blockchain and Dag technologies have a set of features that are lacking in the other, and neither has reached its full maturity. The transition from evolution to adulthood. Every project in the cryptocurrency market objective must implement one of these two technologies and choose the one that is most compatible with the proposed project according to its purpose and objective. For this objective, a series of features of the opposite technology must be passed in order to use the features of technology to achieve the final objective of the project. The arrangement and chain formation of Blockchain, Tangle and Hshgraph is shown in Figure (2).

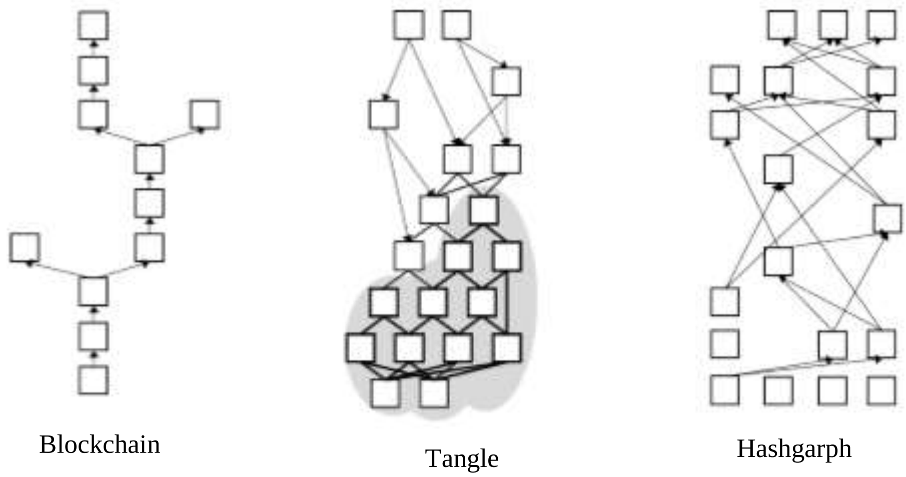

Figure 2. The Sequence of Block Placement and Chain Formation
Source: Schueffel (2017).

One of the key features of financial markets is market efficiency. The efficient markets hypothesis has been proposed and emphasized as the main foundation of financial economics. Efficient market is the information in the market as reflected in a completely transparent way by the prices. In order for financial markets to be able to function properly and be able to attract and allocate financial resources appropriately, “Efficiency” is their main requirement and the necessary condition for the efficiency of financial markets that is the rapid and complete reflection of new information in prices. Cryptocurrency market price growth in recent years has attracted the attention of traders, investors, governments, and legislators. The trade volume in this market has grown exponentially and with the increase in available liquidity, prices have increased too. Since cryptocurrency market is a fledgling market, the amount of liquidity in the market is much less than the amount of liquidity in the commodity, gold and stock markets of the world. This, by itself, generally leads to speculative behavior in this market. However, with the passage of time, the globalization of this market and the concern of the public, the amount of liquidity in the market has grown sharply in the past few years. The greater the amount of liquidity in the market, the less speculative behaviors and unreasonable fluctuations will be (Tran and Leirvik, 2019). Market efficiency of cryptocurrencies are addressed in studies such as Tran and Leirvik, 2019; Zhang et al., 2020; Mnif et al., 2020; Kakinaka and Umeno, 2021; Apopo and Phiri, 2021; Ghazani and Jafari, 2021.

The main hypothesis of the present study is as follows: “the type of distributed ledger technology could influence the efficiency of the cryptocurrency market because price behavior and price fluctuations in the cryptocurrency market would be influenced by various factors. One of the most significant and effective factors is the project discussion and the final objective of the project. As mentioned, one of the factors that makes a project in the cryptocurrency market reached its final objective is the right choice of technology used. If the technological projects of the distributed ledger technology are chosen correctly and are on the path of growth to achieve their final objective, the fluctuations and price growths of the cryptocurrencies related to that project will also be meaningful and naturally more efficient.

Therefore, in this study, the calculation of the efficiency of different forms of distributed ledger technology has been investigated. For this purpose, two cryptocurrencies, Bitcoin and Ethereum, which have the highest market values, respectively, have been utilized to calculate the efficiency of Blockchain. Iota has been used to calculate the efficiency of Tangle technology. So far, Iota is the only cryptocurrency that uses Tangel technology. Finally, to calculate and evaluate the efficiency of the Hashgraph technology, Fantom and Hederahashgraph are on the agenda. The present study differs from other studies in these fields:

1- Studies that have examined the efficiency of cryptocurrencies have not paid attention to the structure of the chain (Blockchain or Dag) and have selected only cryptocurrencies based on ranking and market cap.

2- In this study, the efficiency has been investigated at a deeper level, and the efficiency of the structure of cryptocurrencies (Blockchain, Dag) has been compared with each other.

3- In this study, the MFDFA method was used to calculate the efficiency. The criteria used in this method are criteria (ED, DME, DMEE, ME) that have not been used simultaneously in any of the other studies that have used the method to calculate efficiency.

4- The data used in Essen is the hourly data method from the date of September 2019 to November 2022. During this period, the market size of cryptocurrencies is at a high level and the results obtained are more remarkable.

This article is organized this way: following the introduction, related studies are presented. Then, the research methodology is introduced. After that, the empirical results are stated and at the end, the discussion and conclusion are presented.

2. Literature Review

The field of Blockchains and cryptocurrencies is an emerging field that is rapidly evolving, and new Blockchains and cryptocurrencies are constantly being introduced that use verified technologies and consensus mechanisms. Because of this, studies conducted in this field are quickly invalidated since the cryptocurrencies examined in these studies may be discarded by their competitors and not considered by market participants. For this reason, reviewing and calculating the efficiency of new cryptocurrencies can always be appealing to investors and may lead to various studies on the effectiveness of the cryptocurrency market. These studies have implemented various methods to calculate the market efficiency of cryptocurrencies. Tran and Leirvik 2019 used Market Inefficiency (AMIM) method to calculate the efficiency of BTC, ETH and XRP cryptocurrencies. Zhang et al. (2020) utilized DFA method to calculate the efficiency of BTC and ETH cryptocurrencies. Apopo and Phiri (2021) employed Random walk method for calculating BTC and ETH. Ghazani and Jafari (2021) took the rolling window method to evaluate the market efficiency of cryptocurrencies. It is noteworthy that, although all of these studies have examined the efficiency of the cryptocurrency market based on different approaches, they have all concluded that the cryptocurrency market is an inefficient market; however, this inefficiency is decreasing over time. In fact, as the market value of cryptocurrencies and market capitalization increase, more reasonable price fluctuations, more stable growth and price movements, as well as less speculative behavior in the market would lead to the inefficiency of the market.

The methods used to calculate the efficiency have limitations that is why the MFDFA method is preferred. One of the capabilities of this method is that cryptocurrencies can be ranked based on their degree of inefficiency. The MFDFA method has recently been considered to calculate the cryptocurrency market efficiency. Zhang et al. (2018) have examined the efficiency of BTC, ETH, XRP, and XMR cryptocurrencies in the period 2013 to 2019. Mnif et al. (2020) examined the efficiency of BTC, ETH, and XRP cryptocurrencies for the period before and after the outbreak of COVID-19. Kakinaka and Umeno (2021) have examined the efficiency of BTC and ETH cryptocurrencies in the pre- and post-Covid-19 periods in the short, mid and long term. The remarkable thing about all these studies is that in line with previous studies that used different methods, these studies have shown the inefficiency of the cryptocurrency market, which decrease over time. A summary of the studies is reported in Table 1.

In studies by Mnif et al. (2020), Zhang et al. (2018), and Kakinaka and Umeno (2021), the data are used during a period when the market value of cryptocurrencies is low and, consequently, when the market value is low, the field of speculation increases, and the market is at a decreasing level of efficiency. Now, with time and the increasing concern of the public and the investors to the cryptocurrency market, the amount of capital available in the market has increased. In consequence, different results can be obtained by considering fresh data. Another noteworthy point in the above studies is that in none of the cases, a good classification of cryptocurrencies is provided. To compare the cryptocurrency market efficiency with the Dow Jones index, Zhang et al. (2018) used a weight-value index including 9 cryptocurrencies, Bitcoin Ethereum, Litecin, Dash, XRP, XLM, NEM, XMR and XVG. As it is known, the efficiency of the cryptocurrencies has not been calculated separately, and only the index efficiency that consists of them has been examined. Only the ED criterion has been utilized to calculate the efficiency. Moreover, the studied data were collected from 2013 to 2018, during which the market value of cryptocurrencies was low and the possibility of speculation in this market was very high. Mnif et al. (2020) calculated the efficiency for Bitcoin, Ethereum, Ripple, Litecoin, and Binance coin (BNB) cryptocurrencies from 2013 to 2021. In this research, only the multi-fractal properties of cryptocurrencies have been investigated to evaluate the efficiency. None of the efficiency calculation criteria have been used though. Kakinaka and Umeno (2021) implemented an asymmetric multi-fractured decoupling fluctuation analysis (AMFDFA) method and have only examined the efficiency of Bitcoin and Ethereum cryptocurrencies in the period 2019 to 2021. The duration of the epidemic was afflicted by Covid-19. In this regard, as in the previous study, only the multi-fractal properties of these two ciphers were investigated and none of the efficiency calculation criteria was considered. However, in the present study, unlike the above studies, a new classification is used to calculate the efficiency of cryptocurrencies. In fact, the efficiency of various modes of distributed ledger technology has been investigated. This study examines the efficiency in a more fundamental way and on a deeper layer.

Table 1. A Summary of the Related Studies

Authors (year)	Methodology	Crypto Currencies	Main Result
Zhang et al. (2018)	MFDFA	BTC, ETH,XRP,XLM,NEM LTC,DASH,XMR,XVG	The inefficiency of all the cryptocurrencies tested has been confirmed
Tran and Leirvik (2019)	AMIM [1]	BTC,ETH,XRP,LTC,EOS	The amount of liquidity in the cryptocurrency bar is small, and this causes speculative behavior in the market and confirms market inefficiency.
Mnif et al. (2020)	MFDFA	BTC,ETH,XRP,LTC,BNB	All cryptocurrencies increase efficiency after Covid-19
Zhang et al. (2020)	DFA	BTC,ETH,LTC	All 3 cryptocurrencies are inefficient in the uptrend and downtrend markets
Apopo and Phiri (2021)	Random Walk	BTC,ETH,BCH,LTC,XRP	The inefficiency of the ciphers has been confirmed but this inefficiency is decreasing over time
Kakinaka and Umeno (2021)	MFDFA	BTC,ETH	In the short term, Covid-19 has increased the performance of cryptocurrencies but has been ineffective in the long run.
Ghazani and Jafari (2021)	Rolling Window	Bitcoin, gold and oil	Gold, oil and bitcoin have the lowest inefficiencies, respectively

3. Methodology

Various studies have shown that financial markets have certain characteristics (such as fat tails, long-term correlations, volatility clustering, fractals/multifractals and chaos), which are not compatible with the two hypotheses of random walk and efficient market. Therefore, market movements must be explained by a stronger logic than the efficient market hypothesis. In this regard, the fractal market

[1]. Adjusted Market Inefficiency Magnitude (AMIM)

hypothesis was proposed by Peters (1994). The fractal market hypothesis is less restrictive than the other two hypotheses; For example, it considers the possibility of heterogeneous behavior of investors (Aslam et al., 2020). Fractal theory can be used to describe the Scale invariance property. Of course, the existence of scale invariance property has been confirmed by methods such as Rescaled Range Analysis (R/S), Levy Stable Distribution and Detrended Fluctuation Analysis (DFA). But due to the limitations of these methods in analyzing the scaling behavior of probability distributions in financial time series, it is possible to use the method of Multifractal Detrended Fluctuation Analysis (MF-DFA). This method was presented by Kantelhardt et al. (2002) (Yuan et al., 2009).

DFA is introduced by Peng et al. (1994). In the DFA technique, the time series with length N is divided into (N/s) equal parts and the average function of the detrended fluctuation is expressed as Equation (1):

$$\langle F^2(s)\rangle \sim s^H \tag{1}$$

where H is the Hurst Exponent. Kantelhardt et al. (2002) generalized the DFA method to MF-DFA, which makes it possible to identify the multi-fractal behavior of the data. They performed the MF-DFA technique in five steps as follows:

In the first stage, we would specify the profile:

For this purpose, time series $x(i)$with length N and average $\bar{x}$ is considered and the profile is calculated as Equation (2):

$$\mathrm{y(i)} = \sum_{k=1}^{i} |x(k) - \bar{x}| \qquad \mathrm{i} = 1, 2, \ldots, \mathrm{N} \tag{2}$$

In the second stage, we divide the profile y(i) into $\mathrm{int}(\frac{\mathrm{N}}{\mathrm{s}}) \equiv \mathrm{N_s}$ part with length s that would not overlap.

Since in most cases the length of the time series is not an exact multiple of the time scales, a small portion of the end of the profile remains. Therefore, in order not to ignore this part of the time series, the division process is performed once again from the end of the time series. So finally, 2 N_s of parts are obtained.

In the third stage, we calculate the local trend of each of the 2 $\mathrm{N_s}$ parts using the fitting of the least squares of the time series and determining the variance as in Equation (3):

$$F^2(\upsilon, s) \equiv \frac{1}{s}\sum_{i=1}^{s}\{y[(\upsilon - 1)s + i] - y_\upsilon(i)\}^2 \tag{3}$$

This variance is calculated for each part υ of the time series such that υ = 1,…, N_s . The variance for υ = $N_s + 1, \ldots, 2N_s$ is also calculated as Equation (4):

$$F^2(\upsilon, s) \equiv \frac{1}{s}\sum_{i=1}^{s}\{y[N-(\upsilon-N_s)s+i]-y_{\upsilon}(i)\}^2 \tag{4}$$

where y_{υ} is a polynomial fitted to the υ part.
In the forth stage, averaging the whole parts to calculate the qth order fluctuation function:

$$F_q(s) \equiv \left\{\frac{1}{2\mathrm{N_s}}\sum_{\upsilon=1}^{2\mathrm{N_s}}[\mathrm{F}^2(\upsilon, \mathrm{s})]^{\mathrm{q}/2}\right\}^{1/\mathrm{q}} \tag{5}$$

In the fifth stage,we determine the scaling behavior of the fluctuation function by analyzing the logarithmic-logarithmic curve $F_q(s)$ in terms of s for different values of q. For this purpose, the fluctuation function is written as Equation (6),

$$F_q(s) \sim s^{H_q} \tag{6}$$

$H_q$is the generalized Hurst exponent. If the logarithm-logarithmic curve $F_q(s)$ is plotted in terms of s for different values of q, the slope of the regression line is the generalized Hurst exponent. If H_q is dependent on s, the series in question has multi-fractal properties; otherwise, it will be single-fractal. H_q, is just one of several types of scaling components used to parameterize a time series with a multi-fractal structure. The usual method in MF-DFA literature is to use H_q, the Scaling Exponent,$\tau(q)$, beas calculated in Equation (7):

$$\tau(q) = qH_q - 1 \tag{7}$$

Then τ (q) becomes the Singularity Exponent of the order q, i.e. $h(q)$ and the Singularity Spectrum of the order q, i.e. $D(q)$ (Kantelhardt et al., 2002):

$$h(q) = \frac{d\tau(q)}{dq} \tag{8}$$

$$D(q) = q\frac{d\tau(q)}{dq} - \tau(q) \tag{9}$$

The MF-DFA technique has been widely implemented to identify long-term autocorrelation in financial markets such as stock markets, foreign exchange markets, and gold markets (Zhuang et al., 2015). The correlation function is expressed based on Hurst exponent as Equation (10):

$$C = 2^{(2h-1)} - 1 \tag{10}$$

If the Hurst exponent is equal to 0.5, the correlation is equal to zero. If the Hurst exponent is equal to 1, the correlation coefficient will also be 1, which indicates a completely positive correlation. If the Hurst exponent is between 0 and 0.5, there is anti-correlation behavior. This means that if the time series in the previous period are high, they will most likely be low in the next period. When the Hurst exponent is between 0.5 and 1, the time series is correlated and has long-term memory at all-time scales. For instance, daily price changes are related to future daily price changes. Moreover, weekly price changes are related to future weekly price changes (Nowruzzadeh and Jafari, 2005).

Weak efficiency dynamics of financial markets can also be identified using the generalized Hurst exponent. For a weak efficient market, all types of volatility must have a random walk behavior. In other words, the Hurst exponent of a different order q must be equal to 0.5. Accordingly, several different criteria have been used to calculate inefficiency in different studies. A simple criterion that has been widely used is Equation (11) (Zhuang et al., 2015):

$$ED = |h(q = 2) - 0.5| \tag{11}$$

A higher value of ED indicates a larger deviation of the second-order Hurst exponent from 0.5. Hurst exponent is a measure of the long-term correlation and fractality of the time series. If a series is random and unrelated, the Hurst exponent value will be 0.5, and the ED value will be zero. Consequently, the higher the ED value, the more inefficient the market.

Since the second-order Hurst exponent cannot account for all-time series fluctuations, another criterion would be used to calculate inefficiencies based on different values of the Hurst exponent at different orders:

$$DME = \frac{1}{q_{max} - q_{min} + 1} \sum_{q=q_{min}}^{q_{mqx}} ED(q) \tag{12}$$

For an efficient market, the DME value, like ED, will be zero. Another similar criterion (Equation 13) is introduced which considers only the characteristics of large and small fluctuations:

$$DMEE = \frac{1}{2}[ED(q_{min}) + ED(q_{max})] \tag{13}$$

Finally, another criterion that is widely used is the Equation (14):

$$ME = \frac{1}{2}(|h_{min}(q) - 0.5| + |h_{max}(q) - 0.5|) \tag{14}$$

The fractal dimension is another way to parameterize the multifractal structure. Fractal dimension D_F is a measure of the roughness of the time series and is considered as a measure of the local memory of the time series. The value of the fractal domain is between 1 and 2. In general, D = 1.5 is true for a random series with no local trend or no local anticorrelation. For a low fractal dimension D < 1.5, the series is locally less rough and thus resembles a local persistence. But, a high fractal dimension D > 1.5 is characteristic for coarser series with local anti-persistence.

There are different algorithms to calculate the fractal domain. In the present research, we use Higuchi's algorithm following a Wawrzaszek et al. (2022). In this method, several new time series are constructed by subsampling of the time series $X(t)$ with size N:Type equation here.

$$X_k^m: X(m), X(m+k), X(m+2k), \dots, X\left(m+\left[\frac{N-m}{k}\right].k\right) \quad \text{m=1,2,…,k} \tag{15}$$

where m and k show initial time and interval, respectively. The length of curve X_k^m is defined as Equation (16):

$$L^m(k) = \sum_{i=1}^{[\frac{N-m}{k}]} |X(m+ik) - X(m+(i-1)k)| \frac{N-1}{\left[\frac{N-m}{k}\right].k^2} \tag{16}$$

Higuchi defined $\langle L(k) \rangle$ as the average value of $L^m(k)$ over all m that shows curve length over time interval k. If $\langle L(k) \rangle \sim k^{-D_F}$, then the curve is a fractal with fractal dimension D_F.

4. Empirical Result

4.1 Data

In this research, the efficiency of the distributed ledger technology has been investigated and then calculated. To this end, the cryptocurrencies with the highest market value for each technology are examined. Bitcoin and Ethereum cryptocurrencies are considered for Blockchain technology, Iota cryptocurrencies are used for Tangle technology, and Hederahashgraph and Fantom cryptocurrencies are used for Hashgraph technology. The first cryptocurrency to be explored was Bitcoin, which initially played the role of a transfer and was used as a means of payment, but because of its Blockchain consensus mechanism, transactions were very slow and a high commission is done. Because of this, its nature changed from a payment role to an asset for value storing. The second cryptocurrency under consideration is the native cryptocurrency of Ethereum. Ethereum Blockchain is a platform for writing and implementing smart contracts and decentralized applications. The Ethereum Blockchain Consensus Mechanism, like Bitcoin, is a proof of work mechanism[1]. The next cryptocurrency is Iota. This cryptocurrency operates in the field of Internet of Things. It requires constant communication and a very high speed of operation. Accordingly, it needs a platform that bears very low transaction costs along with high speed. Yes, this Iota foundation uses Tangle technology.

Fantom and Headerahashgraph cryptocurrencies distribute ledger technology ciphers that underlie other decentralized applications and smart contracts. Using cryptographic technology, these cryptocurrencies endeavor to improve Blockchain performance in terms of scalability and the reduction of transaction costs. It should be noted that the Fantom processor engine[2] is fully compatible with the Ethereum Blockchain processor engine[3] so that projects mounted on the Ethereum platform can be easily copied by copying data "Start your own project" on the Fantom platform, "Start your project on this platform and also enjoy the benefits of this platform".

Due to the inconsistency of price information and the inconsistency of the date of Blockchains formation, the information and data under study are hourly from September 2019 to November 2022. The data used in this study are taken from the investing.com statistical database. To analyze the selected markets and calculate efficiency, price return as $r_t = Log\left(\frac{p_t}{p_{t-1}}\right)$has been used. The following is a graph of price fluctuations of the examined cryptocurrencies in the daily range.

As can be witnessed from examining the price charts of cryptocurrencies, Bitcoin is the market leader, and the size of cryptocurrencies will increase or decrease the price following Bitcoin.

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[1]. It should be noted that Ethereum is changing its Blockchain and migrating to the Ethereum 2 Blockchain platform. Ethereum's new Blockchain consensus mechanism is proof of stake. Among its advantages over the proof-of-work mechanism are higher speeds and very low transaction fees.

[2] EVM Compatible

[3] Ethereum Virtual Machine (EVM)

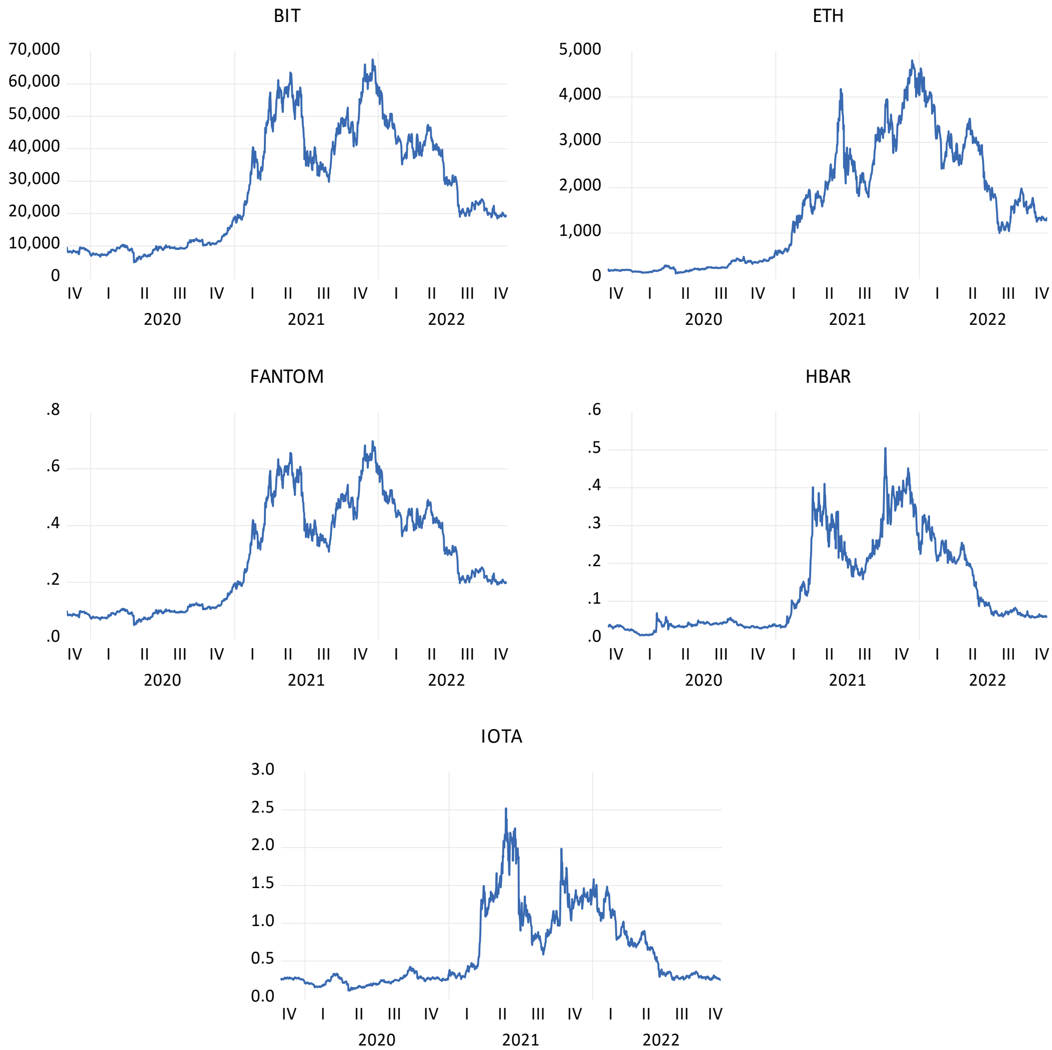


Figure 3. Daily Data Graph of Bitcoin, Ethereum, Fantom, Hederahashgraph and Iota
Source: Research finding.

However, it should be noted that these price changes are not simultaneous and continuous with the increase in the price of Bitcoin. There is a term in the cryptocurrency market titled "Altcoin season", in which when Bitcoins begin to rise in price, altcoins are usually in a price slump. Nonetheless, once the bitcoin price rises and the price stabilizes, investors and traders begin to save their profits, which is due to the price movement of Bitcoin, and move to purchase Altcoins. They move. Usually in the Altcoin season, Ethereum first experiences price growth, and after the Ethereum price rises and the price stagnates, it is high time for other Altcoins on the market to rise in price, which usually raise the experience of staggering prices and fluctuations. The main feature of the Altcoins season is these high price fluctuations and growths (Ivan, 2021).

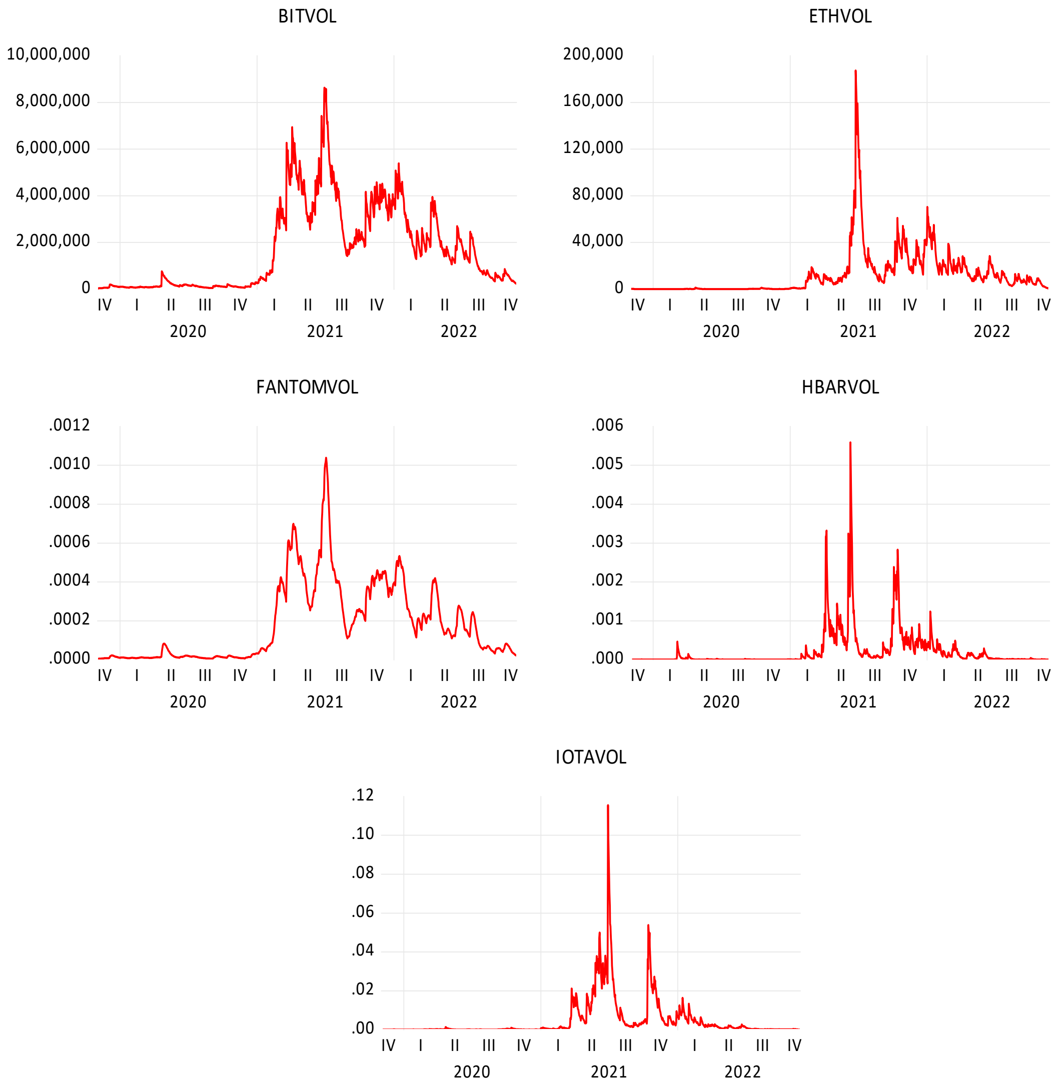


Figure 4. Estimated conditional variance[1] graph of Bitcoin, Ethereum, Fantom, Hederahashgraph and Iota

Source: Research finding.

[1]. Using GARCH model

The cryptocurrency market reacts to news like any other financial market; hence, the intensity of reactions varies depending on the significance of the news. As the cryptocurrency price charts demonstrate they were in a severe price slump before 2020, and even in December 2019, the market panicked due to the outbreak of Covid-19 and experienced a sharp drop in prices. However later, the price gradually began to recover and the price growth of the cryptocurrency market began. In addition to the news and information on the market, the growth of cryptocurrencies depends on other factors such as the strength of the project team, the growth of the project, the community behavior of the project and finally the behavior of the project whales.

As it is clear from figure 4, Bitcoin is the market leader. In fact, every price fluctuation that other cryptocurrencies do is dependent on the price fluctuations of Bitcoin. The difference is that the fluctuations in other cryptocurrencies are more than Bitcoin, which is the cause of this phenomenon of the market value of cryptocurrencies. The lower the market cap of a cryptocurrency, the more potential there is for extreme price behavior and volatility, and thus the incentive to speculate. As shown in Figure 4, from the middle of 2020, according to the macroeconomic conditions, the desire to invest in the cryptocurrency market increased, which in turn caused an increase in the price of cryptocurrencies. After that, in 2022, with the emergence of inflation at the macro level and the need for the Federal Reserve and central banks to increase interest rates, the degree of riskiness of the market increased significantly, and funds began to leave the market, and the cryptocurrency market Entered the recession phase.

4.2 Descriptive Statistics of Data

Table (2) presents the descriptive statistics of the studied cryptocurrencies. As you can see, the average performance of (FTM) and (ETH) cryptocurrencies is higher than that of other cryptocurrencies. Based on the results obtained, IOTA has the lowest average yield among other cryptocurrencies under study, while, Bitcoin (BTC) had an acceptable average. The lowest value (-14.532) is related to Fantom (FTM) and the highest maximum value (22.563) is related to Iota (IOTA), which also reveals the volatile price behavior of these cryptocurrencies.

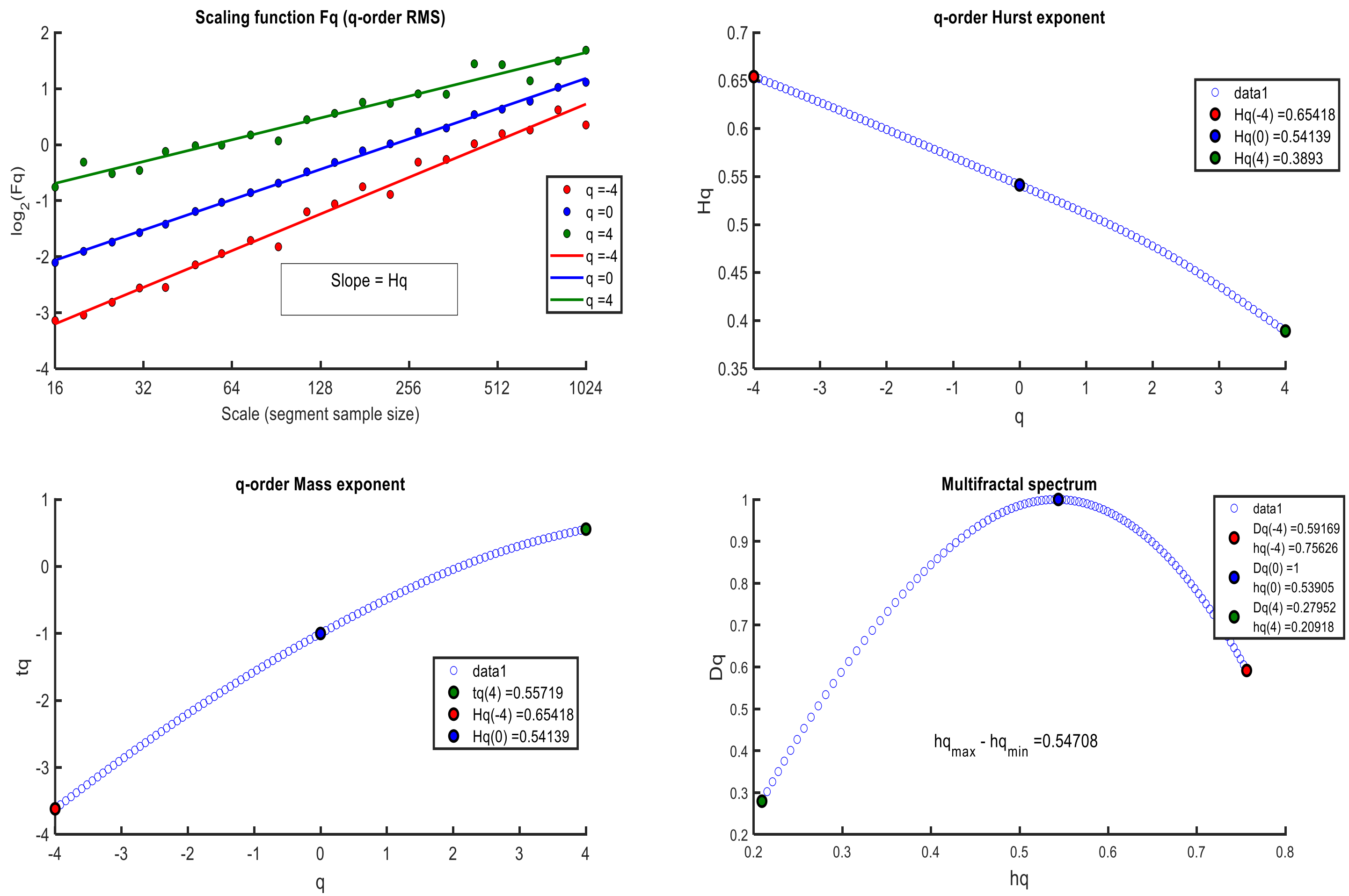
Table 2. Descriptive Statistics of Data

	BTC	ETH	IOTA	HBAR	FTM
Average	0.003157	0.00572	0.00242	0.00367	0.01127
Maximum	6.9608	6.0725	6.7674	22.563	17.6954
Minimum	-8.7307	-10.1674	-13.201	-11.2704	-14.5432

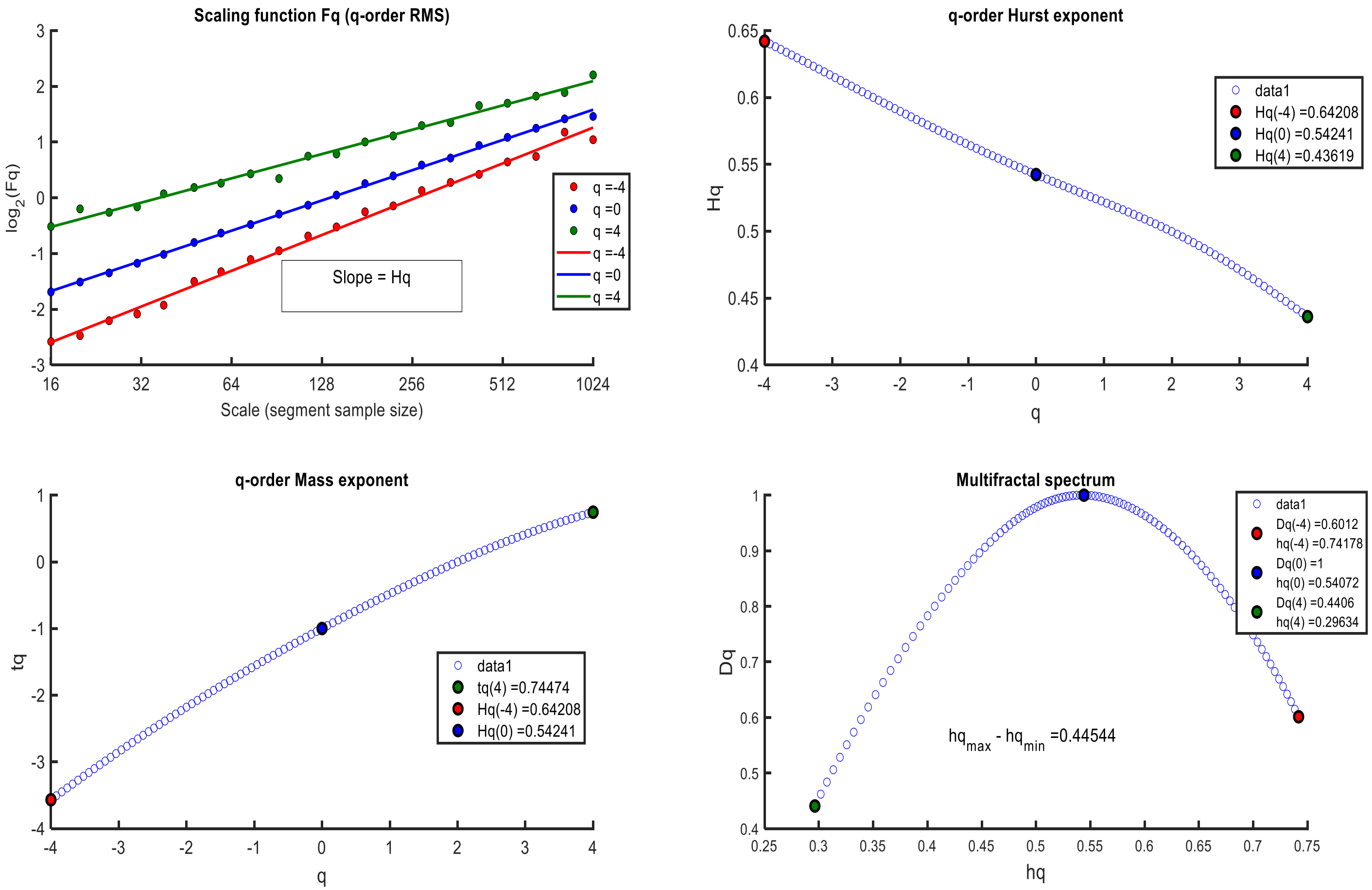
Source: Research finding.

4.3 Multi Fractal Detrended Fluctuation Analysis

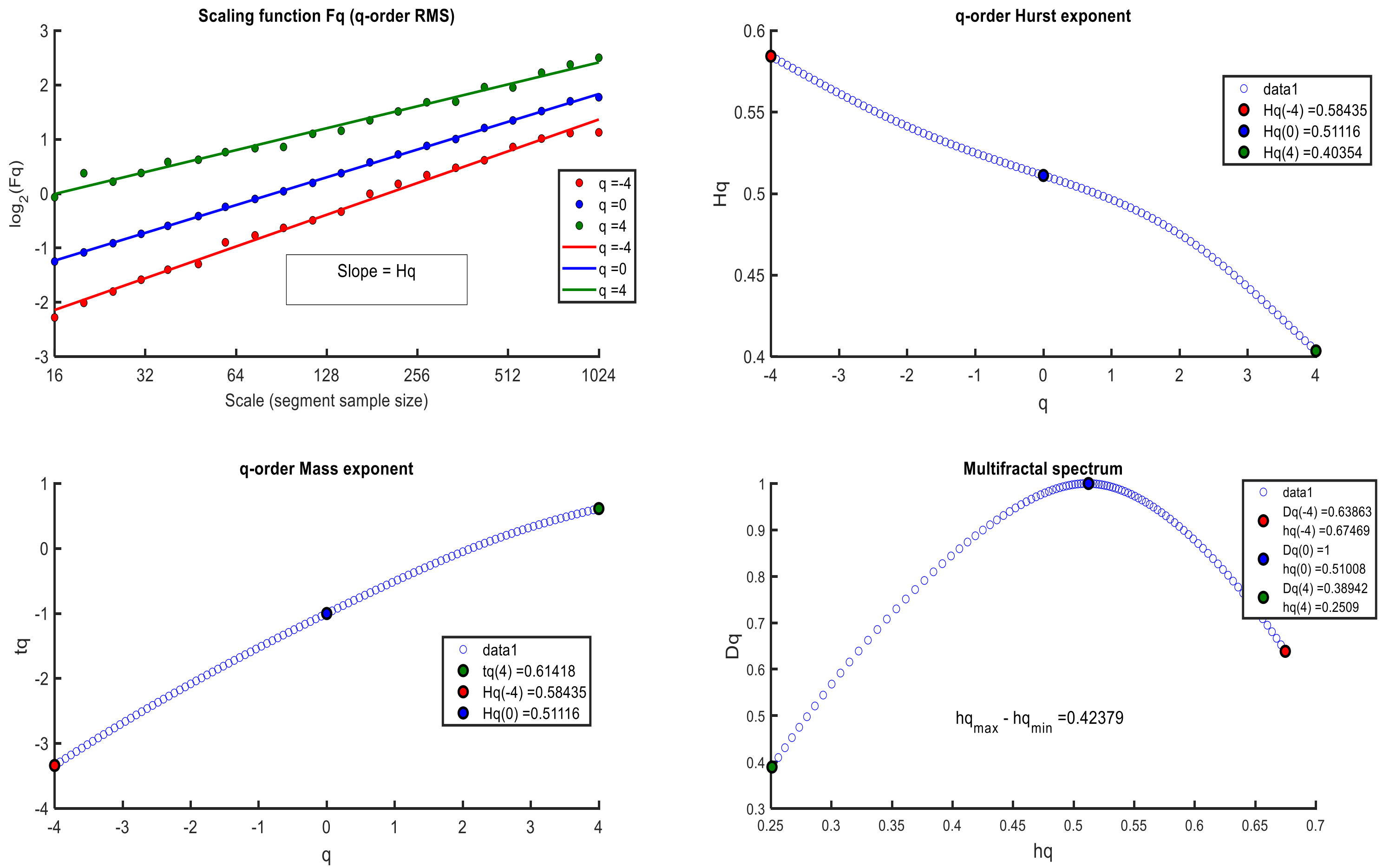
Multi Fractal Detrended fluctuations are analyzed for cryptocurrencies: Bitcoin, Ethereum, Fantom, Hederahashgraph, and Iota. The results obtained are as Figure 5 (A- E):


Scaling function Fq (q-order RMS)
log2(Fq)
Scale (segment sample size)
Slope = Hq
q =-4
q =0
q =4
q-order Hurst exponent
Hq
q
data1
Hq(-4) =0.65418
Hq(0) =0.54139
Hq(4) =0.3893
q-order Mass exponent
tq
q
data1
tq(4) =0.55719
Hq(-4) =0.65418
Hq(0) =0.54139
Multifractal spectrum
Dq
hq
data1
Dq(-4) =0.59169
hq(-4) =0.75626
Dq(0) =1
hq(0) =0.53905
Dq(4) =0.27952
hq(4) =0.20918
hqmax - hqmin =0.54708

A. Bitcoin

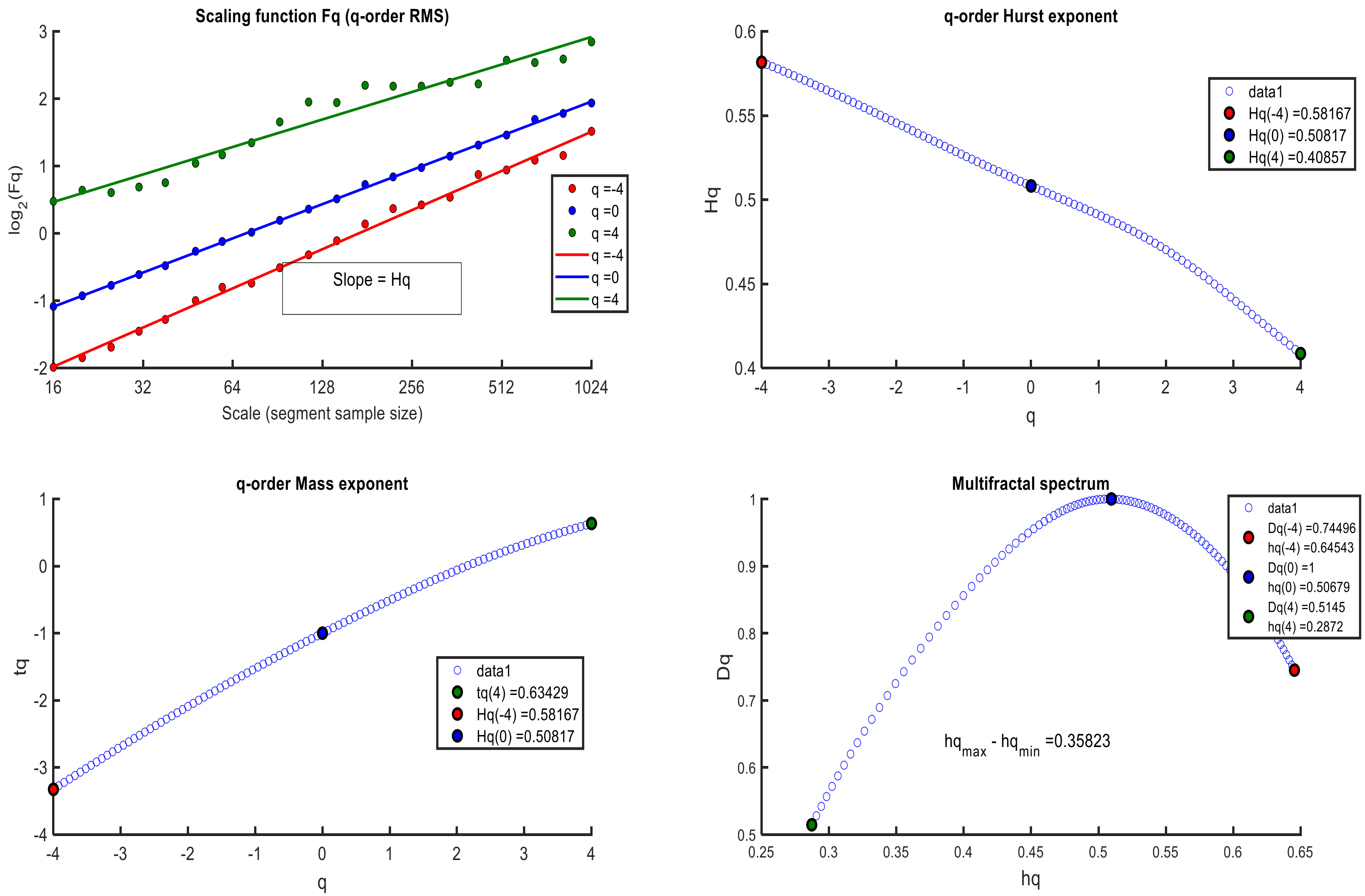

Scaling function Fq (q-order RMS)
log2(Fq)
Scale (segment sample size)
q =-4
q =0
q =4
Slope = Hq
q-order Hurst exponent
Hq
q
data1
Hq(-4) =0.64208
Hq(0) =0.54241
Hq(4) =0.43619
q-order Mass exponent
tq
q
data1
tq(4) =0.74474
Hq(-4) =0.64208
Hq(0) =0.54241
Multifractal spectrum
Dq
hq
data1
Dq(-4) =0.6012
hq(-4) =0.74178
Dq(0) =1
hq(0) =0.54072
Dq(4) =0.4406
hq(4) =0.29634
hqmax - hqmin =0.44544

B. Ethereum

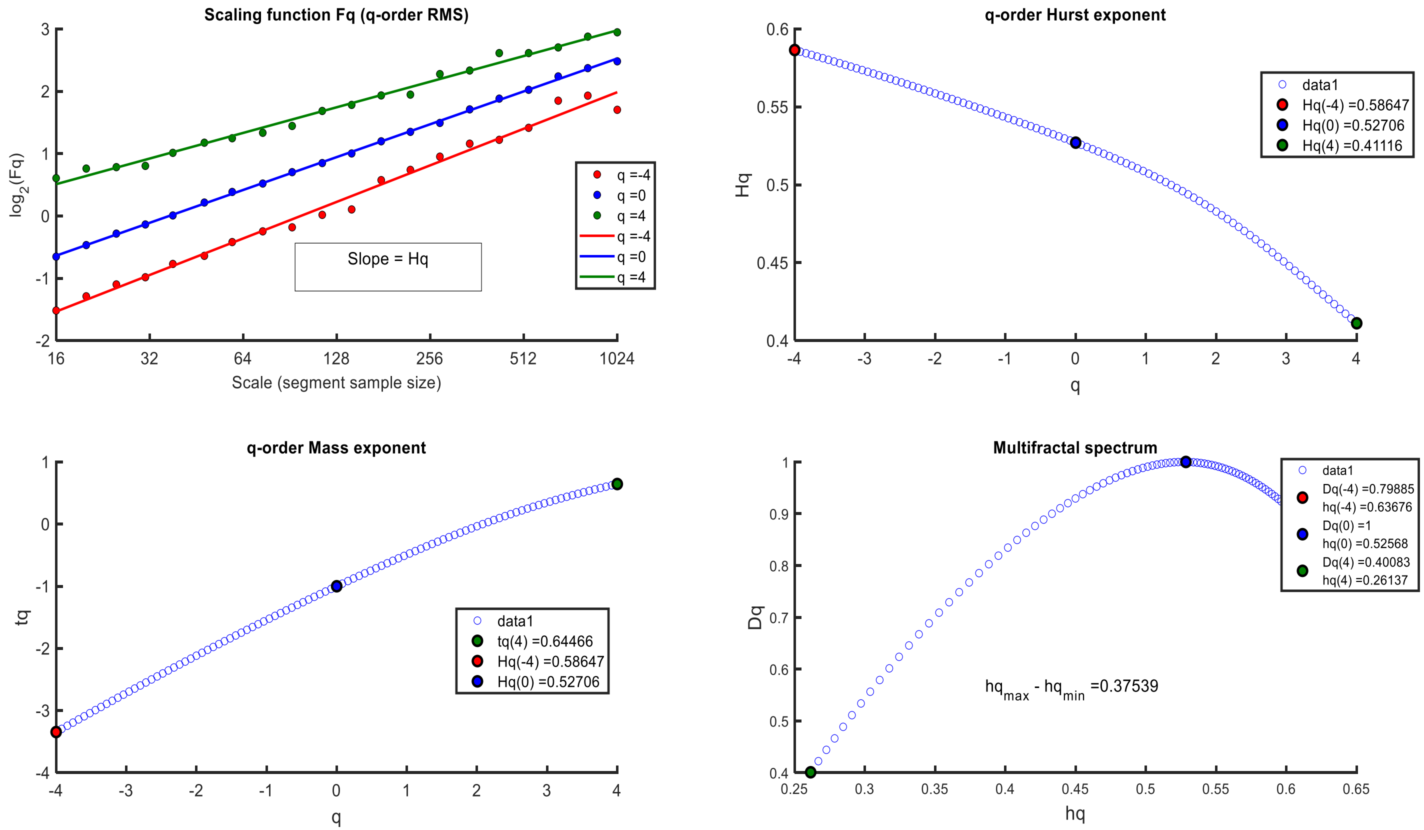


Scaling function Fq (q-order RMS)
log2(Fq)
Scale (segment sample size)
Slope = Hq
q =-4
q =0
q =4
q-order Hurst exponent
Hq
q
data1
Hq(-4) =0.58435
Hq(0) =0.51116
Hq(4) =0.40354
q-order Mass exponent
tq
q
data1
tq(4) =0.61418
Hq(-4) =0.58435
Hq(0) =0.51116
Multifractal spectrum
Dq
hq
data1
Dq(-4) =0.63863
hq(-4) =0.67469
Dq(0) =1
hq(0) =0.51008
Dq(4) =0.38942
hq(4) =0.2509
hqmax - hqmin =0.42379

C. Iota



D. Hederahashgraph



E. Fantom

Figure 5. Bitcoin (A), Ethereum (B), Iota (C), Hederahashgraph (D), Fantom (E)

Source: Research finding.

Note: 1- The right, top and right bottom diagrams demonstrate the generalized Hurst exponent diagram in terms of order q and multi-fractal spectrum widths, respectively. 2-The diagrams on the left, top and bottom are also graphs of the scaling function in terms of scale, the slope of which exhibits the Hurst exponent, and the bottom diagram of the scaled exponent τ (q) in terms of different orders q.

If the multi-fractal spectrum is a continuous, convex and asymmetric cipher, it can be stated that the time series is multi-fractal in nature. The multi-fractal time series also bears a wide spectrum range, while the single-fractal time series and the white noise series have a very small spectrum range (Hou et al., 2018). Examining the shapes of the cryptocurrencies, one can witness that all the cryptocurrencies in question have multi-fractal properties. In the present study to follow the study by Mnif et al., (2020), the values of q are set between 4- and 4. Table (3) reports the values of the Hurst exponent generalized in different orders and the width of the multi-fractal spectrum for the cryptocurrencies studied.

Table 3. Generalized Hurst Exponent at Different Degrees Q and Width of Multi-Fractal Spectrum

Different ranks q	BTC	ETH	FTM	HBAR	IOTA
-4	0.2562	0.2417	0.1367	0.1454	0.1746
-3	0.2088	0.194	0.1142	0.118	0.1258
-2	0.155	0.1401	0.0878	0.0835	0.0769
-1	0.0986	0.088	0.0587	0.0449	0.0393
0	0.039	0.0407	0.0256	0.0067	0.01
1	0.0189	0.0018	0.013	0.0263	0.0202
2	0.0947	0.0483	0.0744	0.0783	0.0766
3	0.1983	0.1245	0.1589	0.1545	0.167
4	0.2909	0.2037	0.2387	0.2128	0.2491
Spectrum width	0.54708	0.4454	0.3753	0.3582	0.4237

Source: Research finding.

The points taken from Table (3) are:

1. The values of the second-order Hurst exponent are close to zero for all the ciphers examined, thus, all the ciphers examined according to the ED criterion (indicating the deviation of the second-order Hurst exponent from 0.5) display unstable behavior in long-term correlation. They have a fractal time series, in which small and large oscillations are repeated one after the other.
2. Another point to be deduced from the table is the values of the range of cryptocurrencies. As it turns out, the values of the bandwidth are large values indicating the multi-fractal properties of these cryptocurrencies. Consequently, the more multi-fractal features, the less developed the market and the more

inefficiency. The bandwidth values in the ME criterion have also been used which will be examined in the following section.

3. The generalized Hurst exponent for all cryptocurrencies decreases first with increasing order q and then starts to increase. This phenomenon indicates that in large fluctuations, the correlation increases with increasing order q. Thereupon, larger oscillations are more correlated than smaller ones.

Table 4 shows the calculations related to the fractal dimension. It can be seen that the value of the fractal dimension is greater than 1.5, so all the investigated cryptocurrencies have a local anti-persistence behavior.

Table 4. Fractal Dimension

Crypto	**BTC**	**ETH**	**FTM**	**HBAR**	**IOTA**
DF	1.897	1.931	1.907	1.901	1.903

Source: Research finding.

4.4 Calculation of the Efficiency of Cryptocurrencies

Considering the data obtained in Table (2), three indicators ME, DME and DMEE, which are efficiency calculation indicators, have been estimated, and the values related to each are reported in Table (5).

Table 5. Inefficiency Values of the Studied Cryptocurrencies based on Different Criteria

Mesure Of Ineffiecncy	**BTC**	**ETH**	**FTM**	**HBAR**	**IOTA**
DME	0.151	0.120	0.100	0.096	0.104
DMEE	0.203	0.181	0.118	0.121	0.139
ME	0.273	0.222	0.187	0.179	0.211
Inefficiency Ranking Based on DME	1	2	4	5	3
Inefficiency Ranking Based on DMEE	1	2	5	5	3
Inefficiency Ranking Based on ME	1	2	4	5	3

Source: Research finding.

It can be discussed that based on all three criteria ME, DME, DMEE and the results obtained from Table (4), Bitcoin (BTC) and Ethereum (ETH) were the most inefficient cryptocurrencies, respectively. In addition, according to the above-mentioned criteria, DME, DMEE and ME, Fantom (FTM) and Hederahashgraph (HBAR) ciphers have the least inefficiencies. IOTA coders also have the third highest inefficiency based on all 3 criteria.

5. Discussion and Conclusion

In the preset study, the efficiency of the cryptocurrency market has been examined from another view, and in fact, the efficiency of the distributed ledger technologies has been investigated. The generalized analysis is based on the programming language and code in 2 modes: Blockchain, which uses programming language 0 and 1, and Dag, which uses programming language -1, 0, 1. The dag itself has 2 modes: Tangle and Hashgraph. To evaluate the efficiency of the distributed ledger technology, hourly price data of Bitcoin, Ethereum, Hederahashgraph, Fantom and Iota cryptocurrencies were considered. Fantom and Headerhashgraph ciphers represented the Hash technology. Price data for the years 2019 to 2022 are addressed to help analyze the present trends.

Time series are now utilized to calculate efficiency, which are complex series, and their analysis requires complex tools. The data reveal small and large fluctuations in which the data behavior in each of these fluctuations may be different from each other. One of the most widely implemented techniques for analyzing financial markets today is the multi-fractal de-trend analysis technique. Using this technique, Hurst's exponent has been calculated for each of the cryptos and the efficiency has been obtained based on it. In addition, fractal dimension has also been calculated.

The results demonstrate that all ciphers studied have a wide multi-fractal spectrum, which indicates the multi-fractal properties present in them. In other words, the cryptocurrency markets are inefficient. This result is consistent with studies of Zhang et al. (2018), Tran and Leirvik (2019), Zhang et al. (2020), and Apopo and Phiri (2021).

Furthermore, the calculation of efficiency using the proposed criteria reveals that Bitcoin and Ethereum, as representatives of Blockchain technology, are the most inefficient cryptocurrencies. This result was not far from the mind, because as mentioned, Blockchain has a number of disadvantages and drawbacks such as scalability, high transaction costs, etc. Hence, new technologies have endeavored to solve such problems. Based on the criteria calculated, Iota is the second most inefficient as the representative of Tangle technology. One of the reasons for Iota to come in second place was technology, which serves as a bridge to Blockchain excellence toward Hashgraph technology. According to the obtained results, Fantom and Hederahashgraph ciphers exhibited the least inefficiencies. These cryptocurrencies have been studied as representatives of Hashgraph technology. Hashgraph technology can be considered the cutting-edge type of distributed ledger technology at present, and it is logical to consider it the highest efficient technology compared to other cases.

Despite the investigation and the calculation of the efficiency of distributed ledger technologies, it should be noted that to invest in a technology, one should not solely pay attention to the efficiency criterion. Investing is a complex phenomenon and should be duly considered along with other influential factors.

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