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THE RELATIONSHIP BETWEEN BITCOIN, ETHEREUM AND NFT MARKET

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The Relationship Between Bitcoin, Ethereum and NFT Market

Bitcoin, Ethereum ve NFT Piyasası Arasındaki İlişki

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ABBREVIATIONS

NFT: Non Fungible Token

BTC: Bitcoin

ETH: Ether

MANA: Mana

CHZ: Chiliz

VECM: Vector Error Correction Model

VAR: Vector Autoregression

ADF: Augmented Dickey-Fuller

DeFi: Decentralized Finance

DApp: Decentralized Application

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ABSTRACT

The popularity of NFT tokens has started to spread to the masses as the NFT market has grown tremendously from the beginning of 2021. This study examines the relationship between the NFT market and Bitcoin and Ethereum through Chiliz, MANA and THETA. In the study, the relationship between the prices of Bitcoin, Ethereum prices and the prices of three different elements of the NFT market with high market capitalization is examined on the basis of interrelationships. Using daily data between January 2020 and June 2022, short-term dynamic Granger causality of Ethereum on Bitcoin, Granger causality of THETA on Ethereum and Granger causality of THETA on MANA are shown. However no effects of Bitcoin on Ethereum, MANA, Chiliz and THETA can be shown. The results suggest that THETA may have a causal effect both on Ethereum, which is the second largest actor in the cryptocurrency market, and on the MANA token, which is one of the important representatives of the NFT market. From this point of view, it can be said that THETA contains preliminary information about the NFT and cryptocurrency markets.

ÖZET

NFT piyasasının 2021'in başından itibaren muazzam bir şekilde büyümesiyle NFT'nin popülaritesi kitlelere yayılmaya başladı. Bu çalışma, Chiliz, MANA ve THETA aracılığıyla NFT piyasası ile Bitcoin ve Ethereum arasındaki ilişkiyi incelemektedir. Çalışmada Bitcoin, Ethereum fiyatları ile NFT piyasasının yüksek hacimde işlem gören üç farklı tokenının fiyatları arasındaki ilişki, karşılıklı ilişkiler temelinde incelenmektedir. Ocak 2020 ile Haziran 2022 arasındaki günlük veriler kullanılarak, Bitcoin üzerinde Ethereum'un kısa vadeli Granger nedenselliği, Ethereum üzerinde THETA'nın Granger nedenselliği ve MANA üzerinde THETA'nın Granger nedenselliği tespit edilmiştir. Ancak Bitcoin'in Ethereum, MANA, Chiliz ve THETA üzerinde herhangi bir etkisi gösterilememektedir. Sonuçlar, THETA'nın hem kripto para piyasasının en büyük ikinci aktörü olan Ethereum üzerinde hem de NFT pazarının önemli temsilcilerinden biri olan MANA token üzerinde nedensel bir etkiye sahip olduğunu göstermektedir. Bu açıdan bakıldığında THETA'nın NFT ve kripto para piyasaları hakkında ön bilgiler içerdiği söylenebilir.

INTRODUCTION

The NFT market begins to attract enormous public attention, especially from the early part of 2021. Jack Dorsey's first tweet to sell for $2.9 million as NFT (Valuables, 2021), and the platform which is a virtual multiverse called Decentraland made a worldwide impact. In addition to this many digital art producers start to sell their works as a digital asset which is called NFT. Thanks to smart contracts, NFTs give property rights to individuals, especially in digital products and works. NFT trades can be made in certain NFT markets, digital platforms such as gaming and multiverse.

NFT exchange is done utilizing digital coins such as cryptocurrency or NFT tokens used in NFT trading. After the rapid growth of the NFT market and its wide recognition, platforms where NFT creativity is at a high level have released their own NFT tokens in order to create their own ecosystems. Although these tokens use Ethereum blockchain technology like ETH coin, their pricing in the market is differentiated from coins in accordance with the law of supply and demand, and at the same time, the risks they carry differ from cryptocurrencies based on their standard deviations (Aharon & Demir, 2021).

Blockchain technology has a creative feature for the NFT market, just as it does for the cryptocurrency market. NFTs are first derived from smart contracts of the Ethereum ecosystem. In this respect, NFTs are a part of the Ethereum ecosystem and therefore have a direct link with it (Wood, 2014). Although the infrastructure of both cryptocurrencies and NFTs is based on blockchain technology, the two markets are quite different from each other (Ante, 2021a).

The aim of this study is to analyze the interrelation between NFT and cryptocurrency market in a different point of view by using Vector Error Correction Model (VECM) utilized in Ante's (2021c) study. In the mentioned study the analysis is done by using Bitcoin, Ethereum prices and the number of NFT wallets and NFT sales to interrelate the two markets. The point of view of this study is to examine the relation between the two markets by using the NFT trading token and coins along with Bitcoin, Ethereum prices.

The contribution of this study to the limited literature is that these two markets are based on indicator tokens and coins with high market capitalization and large number of observations. The current literature examines the relationship between the NFT market and the cryptocurrency market through different variables representing the NFT market and cryptocurrency prices. This study, on the other hand, aims to obtain a more consistent conclusion by analyzing the relationship between both markets over cryptocurrencies along with tokens and coins representing the NFT market, and comparing them with previous studies.

The organization of this thesis is as follows: In chapter one an introduction to blockchain and fundamentals of NFT is given, in chapter two a thorough literature review on cryptocurrency market and on the growing field of NFT market interrelations is presented, in chapter three the information on data collection, the proposed methodology, summary on important statistical tests about our dataset and information about the model, Vector Error Correction Model (VECM), which is used in the thesis are presented, in chapter four the findings of the analysis are explained along with output of the statistical test results and in the last chapter conclusion remarks and comparative analyzes of the findings of recent literature are presented.

1. FUNDAMENTALS of NFTs

1.1. BLOCKCHAIN TECHNOLOGY

Blockchain, in a nutshell, is a kind of immutable ledger developed to record and share peer-to-peer transactional information processes across any network. Especially in the period after the 2008 financial crisis, decentralized structures begin to attract the attention of masses of people. Blockchain technology, which claims to form the basis of trust-based economic relations, also attracts great public attention. (Glaser, 2017). Blockchain technology, which became famous as the underlying technology of Bitcoin (Beckand & Müller-Bloch, 2017), also has the feature of eliminating the service provided by various intermediary institutions (Tapscott & Tapscott, 2016).

The results of the 2008 financial crisis and especially the attitudes and behaviors of the Fed (Federal Reserve) and the ECB (European Central Bank) throughout the crisis damaged the trust in central financial institutions (Varma, 2019). The concept of centralization, especially the loss of reputation of central institutions in the financial field, and the loss of trust of people in such financial institutions due to their biased behavior have made structures with decentralized systems more attractive by world.

Blockchain technology now continues to expand in many other application areas (Wörner et al., 2016). Through the blockchain technology, the information about the assets subject to this transaction information becomes available for monitoring (Fauziah et al., 2020). The asset referred to here can be both a tangible asset (house, car, financial asset, land) or an intangible asset (patent, intellectual property, license right, brand ownership). It is possible to monitor and track all kinds of things that have a certain value, payments, accounts, the production process of an institution on a blockchain network. The fact that the information on the blockchain can be monitored by the community of that network or by everyone ensures that the blockchain technology gains a decentralized feature.

This emerging concept of decentralization also paves the way for decentralized applications (DApps) on the internet. The working principle of DApps is based on operating on a distributed network. In this way, DApps work independently of any central authority in accordance with the performance of their users' devices. The increase in the number of users stands out as a factor that increases the working performance of DApps. The fact that DApps work on a distributed network with an open source system brings many advantages such as protecting user privacy and avoiding censorship. However, they are more disadvantageous than traditional applications because with a centralized architecture updating and development of applications are much easier. Although the emergence of DApps is affected by the rise of peer-to-peer (P2P) networks, DApps find their real use cases with the emergence of blockchain technology. The most important factor that enables the spread of blockchain technology is undoubtedly Bitcoin.

Satoshi Nakamoto's famous paper in 2008 presents Bitcoin as decentralized money and blockchain technology (Vujičić et al., 2018). Satoshi describes a system that computes the proof of transactions chronologically and records these transactions in a peer-to-peer distributed network (Nakamoto, 2008). This working principle is called proof of work (PoW). The rise of the concept of decentralization in the internet environment is parallel with the rise of blockchain technology that emerged through Bitcoin.

Ethereum, on the other hand, highlights the shortcomings of the working principle of the Bitcoin blockchain, and offers a blockchain with a new working principle to these problems (Buterin, 2014). In this context, although the blockchain that Ethereum offers is basically similar to the Bitcoin blockchain, the main differences are that the Ethereum blockchain also includes the transaction list and the latest status information (Vujičić et al., 2018). This working principle of the Ethereum blockchain is called proof of stake (PoS). Ethereum has a platform called ERC20 Token standard, on which smart contracts can be built. With this feature, various tokens in the crypto market can also be located on the Ethereum blockchain. Chiliz and MANA used in our study are also ERC20 tokens and are located on the Ethereum network.

The working principle of the Ethereum blockchain is not only important for its own coin Ether and but also important for other tokens defined on Ethereum blockchain. Because of its features, the Ethereum blockchain offers faster programming. As a result, decentralized applications (DApps) meet the infrastructure they need in the Ethereum blockchain. For this reason, many of the decentralized applications (DApps) operate on top of the Ethereum network. As of today, 2970 of 4073 DApps in total are built using the Ethereum blockchain. The main ones are the Tether DApp (DeFi), the Decentraland DApp (property) which is used in our study, the ChainLink DApp (security) that connects smart contracts to real-life data, payments and events and ensures the security of these data, and the OpenSea DApp (marketplace) that enables peer-to-peer NFT trading.

1.2. BRIEF SUMMARY OF NON FUNGIBLE TOKENS

NFTs (Non Fungible Tokens) are items that are "non fungible", that is, unique and represented by blockchain technology, as can be guessed from the name. So unlike the interchangeability of money or cryptocurrencies (one Bitcoin can replace another Bitcoin fully or one can split one Bitcoin), NFTs are not interchangeable (Wang et al., 2021). In this respect, each NFT has its own unique value and its originality comes from its uniqueness. For example, let's take an artist's painting. Although many copies of an artist's painting can be made and replicas of that painting are also circulating in the market, the original of the painting has a different value from other copies. And that painting cannot be used by dividing it into parts. What makes the painting valuable is its form as it is produced, and its originality gives the painting an intrinsic value. Just as individuals and institutions can own the original of a painting/work/thing in the physical world, owning NFTs gives individuals the right to own the original of a work in the digital world (Ante, 2021b; Dowling, 2021a). All kinds of artifacts/things that are known to be original in the physical world appear as NFT in the digital environment. In the digital world, any artifact/thing gains a "unique" feature by being stored as data in the digital ledger in blockchain technology.

Most NFTs represent a digital asset written on smart contracts using Ethereum blockchain technology. These contracts contain information for items such as artwork in digital media (such as music, painting, film), game item, collection, a parcel in a virtual world created, represented by NFT. These data stored in the blockchain include information such as who the creator of that item is, who owns that item (property right), the amount of commission that will be paid to the creator of the item in case of resale of that item.

The exchange of NFTs takes place through cryptocurrencies and tokens, in this respect, NFTs have the feature of being an answer to how cryptocurrencies can be used in practice. Many NFTs are traded with Ethereum, with the effect of the Ethereum blockchain technology it uses. NFTs, whose emergence dates back to 2015, gained their popularity when people saw them as a digital investment tool. Of course, the reason why NFTs are seen by people as a digital investment tool lies in the normalization process of cryptocurrencies for people and as a result, the reputation that the blockchain technology framework has gained for people. However, the fact that NFTs attracted the attention of the masses, especially in the first quarter of 2021, and the tremendous rapid growth of the NFT market has accelerated the increase in the use of NFTs of their own NFT coins in the market and the exchange of NFTs through these coins.

1.1.1. MANA

With the massive growth of the NFT market, the variety of NFT tradable marketplaces is growing rapidly and the rise of tokens that make NFT trading possible. The following section describes the three different NFT tokens used in this study as they are used for trading in NFT markets.

Decentraland, which was founded by Ari Meilich and Esteban Ordano in 2015 and evolved into a three-dimensional virtual universe in 2017, is one of the most prominent structures in the emerging NFT market. The parcels of this virtual universe and the houses, roads, clothes, etc. figures in it are built in NFT form by means of blockchain technology (Ordano et al., 2017). Decentraland offers the ownership rights of the parcels of its virtual world to its users through a token called LAND token (Dowling, 2021a).. Pricing of LAND tokens is done through another token, the MANA token. For this reason, with the popularity of Decentraland, one of the biggest players in the dramatically rising NFT market, MANA token is also in demand by users. Thanks to its organic relation with the NFT market and its fungible feature unlike the LAND token, the MANA token has been used in our study both because it is a good representative of the NFT market and for easy tracking of price movements.

The MANA token is a token belonging to the Ethereum ecosystem, as it is built on top of the Ethereum blockchain. This organic connection of MANA token with Ethereum is also important for examining the relationship between the NFT market and the cryptocurrency market. In this respect, the MANA token, which is used as a variable in our study, also contributes to the existing literature in which the relationship between the NFT market and cryptocurrencies is researched.

1.1.2. CHILIZ

The growth of the NFT market is not limited to the emergence of new concepts in digital environments. At the same time, figures and communities of the traditional world are moved to this digital world. For example, sports entertainment institutions such as world-famous football clubs and basketball clubs can enter the NFT market through fan tokens. Clubs offer fan tokens that give fans the right to vote in decision-making about the club, the right to buy tickets and various special content in order to improve their bond with their fans (Kienle, 2021). In this way, world-famous clubs take their place in the digital world enabled by blockchain technology, increasing their visibility both in the token market and in the NFT market worldwide. Although fan tokens are fungible unlike NFTs, they share common features with NFTs in terms of their intrinsic value (voting right, priority in purchasing tickets), and fan tokens are included in use cases of NFTs (Parham & Breitinger, 2022).

The biggest actor in the fan token market, "socios.com", makes fan token trading possible with the coin named Chiliz (CHZ) (Vidal-Tomás, 2022). Just like in Decentraland, LAND tokens can be traded with the MANA token, so fan tokens can be traded with CHZ. CHZ is sort of what BTC is to the cryptocurrency market for the fan token market (Kienle, 2021). In this respect, CHZ has a good signal about the NFT-enabled fan token market and is one of the reasons we used CHZ prices in our study.

The entry of many football clubs such as world-famous and highly prestigious FC Barcelona, Juventus, Paris Saint-Germain and Atletico de Madrid into the fan token market, as well as the special opportunities they offer to their fan token holders, ensure that this market rises rapidly (Parham & Breitinger, 2022).

1.1.3. THETA

THETA network is a software that is established to create a decentralized video streaming platform on the internet with blockchain technology. The THETA network enables the proper transmission of high-quality videos using available computing resources of the users. According to THETA network founders and the advisory board, existing content delivery networks (CDN) have limited technical infrastructure due to their centralized nature (Barman et al., 2020). Development speed of CDN infrastructure cannot satisfy the requirements imposed by the increasing supply of high quality live streams due to the constraints of the centralized structure. For this reason, blockchain technology, which has a distributed structure, is offered by THETA Network as a solution. Unlike the other elements (MANA and CHZ), THETA network provides this activity through its own blockchain technology. The THETA network operates with the THETA coin and a cryptocurrency called TFUEL. In our study, THETA coin prices are used.

2. LITERATURE REVIEW

With the increase in users' interest in NFTs, academic research in this field gains momentum. NFTs start to be seen as digital financial assets for individuals, especially in the fields of digital art, music, game items, collections and metaverse. The fact that users see NFTs as digital financial investment instruments, apart from dealing with the technology and technical infrastructure behind NFTs, accelerates academic studies examining NFT pricing, returns and their interrelationship with other both digital and common financial assets and investment instruments.

Like other cryptocurrencies and tokens, NFTs, whose infrastructure is based on blockchain and smart contracts, have a different intrinsic nature from other cryptocurrencies due to their intrinsic value-carrying properties (Ante, 2021b). It is very difficult to detect this intrinsic value of NFTs in the NFT market, which is still in its early stages (Dowling, 2021a). It is observed that it tends to display an inefficent outlook, like every newly emerging market, which is in its early stage.

Nadini et al. (2021) maps the financial aspects of NFTs in terms of sales numbers and traded volume, taking into account different projects, different stakeholders, and other characteristics with a general framework. The pricing aspect of NFTs with a digital financial asset feature, which is considered worthy of investigation, is examined by Dowling (2021a) for the pricing of Decentraland, an NFT project that enables parcel trading in a blockchain-based virtual reality. Decentraland plays an important role in the NFTs being noticed by the wider masses and expanding the NFT market. For example, the world-famous Swedish-based retail clothing company H&M opened its shop on the metaverse for the first time, allowing its customers to shop in three dimensions in the virtual world.

Bitcoin is the most important actor in terms of market capitalization of the cryptocurrency market based on the blockchain software architecture, followed by Ethereum in terms of market capitalization. Moreover since the Ethereum blockchain constitutes the technological infrastructure of most NFTs, Ethereum also has a significant impact for NFTs. NFTs are naturally closely related to the cryptocurrency market due to their general technological infrastructure such as utilization of blockchain. Furthermore, NFTs that are traded in NFT markets such as Opensea, Rarible and Decentraland use Ethereum blockchain (Ante, 2021a).

The uses of tokens, especially tokens with Ethereum infrastructure technology, as means of payment while purchasing NFT, increases the possibility of a relationship between the cryptocurrency market and NFT market. This study will also investigate whether there is a causal relationship between the prices of Bitcoin and Ethereum, and the prices of certain NFT token and coins which are selected based on available historical data and high market capitalization. Considering Bitcoin's indisputable impact on other cryptocurrencies, it is not enough to examine Ethereum's relationship to NFT token and coins alone.

With its property of being the cryptocurrency market leader of Bitcoin, it seems likely to have the power to affect the NFT market if there is a relationship between cyrptocurrency and NFT market (Kumar and Ajaz, 2019). Moreover Bitcoin has a very high volatility transmission effect to other cryptocurrencies (Moratis, 2021). From this perspective, it is undeniable that Bitcoin might be also an important explanatory variable for the NFT market, as it is a case in which Bitcoin is associated with many other financial asset markets. Particularly Bitcoin is one of the most researched elements of the world of cryptocurrencies, and its impact on other cryptocurrencies is seen as the most likely.

Koutmos (2018) examines the return and volatility spillover on 18 major cryptocurrencies and identifies Bitcoin as the dominant contributor to the return and volatility spillover. Furthermore Kyriazis (2019) determines that cryptocurrencies with high market capitalization such as Ethereum, Litecoin and Ripple also have a close relationship with Bitcoin and that they are highly affected by the spillover effect of Bitcoin. Considering that the volatility of the cryptocurrency market is quite high, it is clear that there is a necessity to analyze the price movements of Bitcoin in order to analyze the prices of any of cryptocurrencies or tokens, which are relatively new compared to cryptocurrencies and at the same time the majority of transactions are carried out on the basis of the ethereum blockchain.

Shen et al. (2019) reveal that Bitcoin has a causal effect on Ethereum, ripple, and litecoin, and that even Ethereum prices are affected by lagged Bitcoin prices. Aysan et al. (2021) in their long-term research covering the 2021 pre-pandemic and pandemic period, obtained strong findings on the relationship of Bitcoin with altcoins. Strong signals that Bitcoin has an impact on the cryptocurrency market raise the possibility that it also has an impact for NFT tokens, which are built on the blockchain technology that forms the infrastructure of cryptocurrencies.

Moreover, in a study with Bitcoin and altcoins, the co-movements of Bitcoin-Dash and Ethereum-Dash pairs are determined, and findings are presented regarding the separate effects of Bitcoin and Ethereum on booming cryptocurrencies (Cagli et al., 2019). There appears to be interdependencies and long-term relationships between Bitcoin and other cryptocurrencies. The positive and negative changes in Bitcoin returns have a high permanent effect on the returns of other cryptocurrencies (Gonzalez et al., 2020). From a different perspective, Bitcoin prices also seem to interact with traditional financial instruments and commodity markets.

In the context of the process after the emergence of Bitcoin, the interaction of cryptocurrencies with traditional financial investment instruments, their interconnectedness with commodity prices and the stock market also come to the fore. Jareño et al., (2020) find that the VIX and STLFSI stress indices can have a statistically significant and negative effect on Bitcoin returns, and also find a statistically significant positive relationship with Bitcoin and gold returns with the Non-Linear ARDL approach.

During the economic instability which is created by the Covid-19 pandemic, a strong interdependence relationship between cryptocurrencies and oil is observed in both the short and long term (Jareño et al., 2021). Ghorbel and Jeribi (2021) using the BEKK-GARCH (1,1) model, determine that there is a volatility spillover between cryptocurrencies, stock index, oil and gold markets. They also find that the current conditional volatility of stock indices (S&P500, Nasdaq, and VIX), gold and oil not only depends on their past volatility, but also on the past volatility of cryptocurrencies. This interconnectedness and causality relationship that cryptocurrencies establish even with the instruments of the real economy may indicate that it also affects the NFT market, which is an ecosystem in the subset of blockchain technology.

Cryptocurrencies also have interrelations with the foreign exchange market, which has money features like itself. Raza et al. (2022) research with nine different foreign exchange currencies and selected cryptocurrencies, find that there is a positive relationship between cryptocurrencies and foreign exchange currencies. As can be seen, cryptocurrencies establish interrelations even with traditional financial instruments such as common financial assets, commodity markets and developing country currencies.

Although the NFT market is still in a emerging stage, it may be affected by the changes in the cryptocurrency market, as well as by the changes in the common financial asset market, which affect the financial investment decisions of individuals, both due to its digital financial assets and its location on blockchain technology. The NFT market also creates new opportunities for individuals who want to diversify their financial investments. Aharon and Demir (2021) states that NFTs have a weak relationship with other asset classes, and shocks in other asset classes have a limited effect on NFTs. According to these findings, NFTs give the signal that they can be important as a risk-reducing factor and attract attention by investors in portfolio diversification. Yousaf and Yarovaya (2022), on the other hand, states that it is not possible to predict the course of the NFT market from the usual financial products such as oil, gold, stock market index, since the prices of the NFT market are not affected much by classical financial investment instruments.

Findings that Bitcoin is interdependent and interrelated with other cryptocurrencies, stocks, foreign exchange, and most variables in the real economy strengthen the possibility that Bitcoin has a broad spectrum of influence. Bitcoin, one of the most important elements of blockchain technology, can also have an impact on NFTs which are also built on blockchain technology. The fact that many different NFTs are based on the Ethereum blockchain strengthens the possibility that Ethereum might be an important element for the NFT market Also, because many NFTs are built on top of the Ethereum blockchain, Ethereum has an organic link to the NFT market. There is also considerable amount of research showing that Ethereum has a relationship with Bitcoin.

NFTs attract a wide audience and they are perceived as a digital asset, so they are also considered as a financial asset by investors. These reasons create the factors to be investigated that underlie the pricing behavior of NFTs. In this context, there is a rapidly growing academic literature that studies the pricing behavior of NFTs and which factors their prices are related to. It is suggested that the best indicator for estimating the prices of NFTs is the past prices of NFTs, but also that the unique features of NFTs – such as their visual properties – are helpful in estimating NFT prices (Nadini et al., 2021).

Past prices are one of the important features that are used in price prediction for most financial instruments. This finding is in line with the notion that NFTs have intrinsic value of their own, as they are treated as a unique digital asset. Considering that Bitcoin and Ethereum are the two most important elements using blockchain technology, it can be expected that the majority of the relationships detected in the cryptocurrency market can be found for the NFT market which is built on the Ethereum blockchain.

Aalborg et al. (2019) do not find any relationships between Bitcoin returns and trading volume in their research with using Bitcoin's price, volatility, and trading volume. In contrast, for the NFT market, Wang et al. (2022), examine the relationship between the returns of NFT and the trading volume and they mention that there is a negative relationship between the trading volume and NFT returns in the short run for CryptoPunks. They further state that the high turnover of the NFT token negatively affects the price of the NFT token.

From this point of view, it is observed that the NFT market -perhaps because it is in the growth phase- differs from the appearance of the cryptocurrencies market, which is in a more mature period. Dowling (2021b) studies with wavelet coherence analysis and detect that there is a low-level spillover between three different NFT markets, Decentraland, CryptoPunks, AxieInfinity and Bitcoin, but for the same method that he concludes that there is a co-movement for these two different markets. The low spillover effect is detected between the NFT market and Bitcoin, which is the indicative element of cryptocurrencies, with this pioneering study is one of the first findings that NFTs are independent from the cryptocurrency market. Karim et al. (2022) examine that risk transmission for the blockchain market and they find that risk spillovers in the blockchain market have a strong disconnection with NFTs. And they also state that NFTs can be a good alternative option as a portfolio diversification tool in the blockchain market. NFTs are closely watched by investors due to their organic connection with the cryptocurrency market. Investors with investments in the digital platform will shape the investment decision-making process according to how NFTs relate to the cryptocurrency market. The findings that NFTs have an inverse relationship with cryptocurrencies or that they do not establish any relationships between them. The findings also include the possibility that NFTs may be seen as a risk aversion tool or a risk reducing tool by investors. It should be emphasized that academic studies can shape and contribute to the investment decision-making process.

The relationship between NFT market and cryptocurrency market is among the issues that arouse curiosity about the two important actors of the blockchain market, for the investors of the digital world and for the academics. In a study of behavioral price determination research of NFTs with the hedonic pricing model, it is concluded that the prices of NFTs are not a simple derivative of classical cryptocurrencies (Horky et al., 2022). However, the detected co-movement contains signals that both markets are in a mutual relationship. The fact that the NFT market is much smaller in terms of market capitalization compared to the cryptocurrency market gives rise to the expectation that the interaction between the two markets should be from the larger market to the smaller market (Bhattarai, 2020).

In one of the most recent studies, Ante (2021c) obtains findings that Bitcoin and Ethereum cryptocurrencies affect the NFT market, while the NFT market has no effect on Bitcoin and Ethereum cryptocurrencies. He studies with NFT sales, NFT wallets, Bitcoin and Ethereum prices using the vector error correction model (VECM). These findings are consistent with Dowling's (2021b) findings that NFT pricing patterns are related to Bitcoin and Etherum prices (co-movement).

3. DATA AND METHODOLOGY

In this section, general information about the data used in the study is given and also we explain the model chosen by our study, why that model is chosen, and under what conditions this model can be studied. In addition, various statistical tests are performed with our data set and the results of these tests are presented.

3.1. DATA COLLECTION

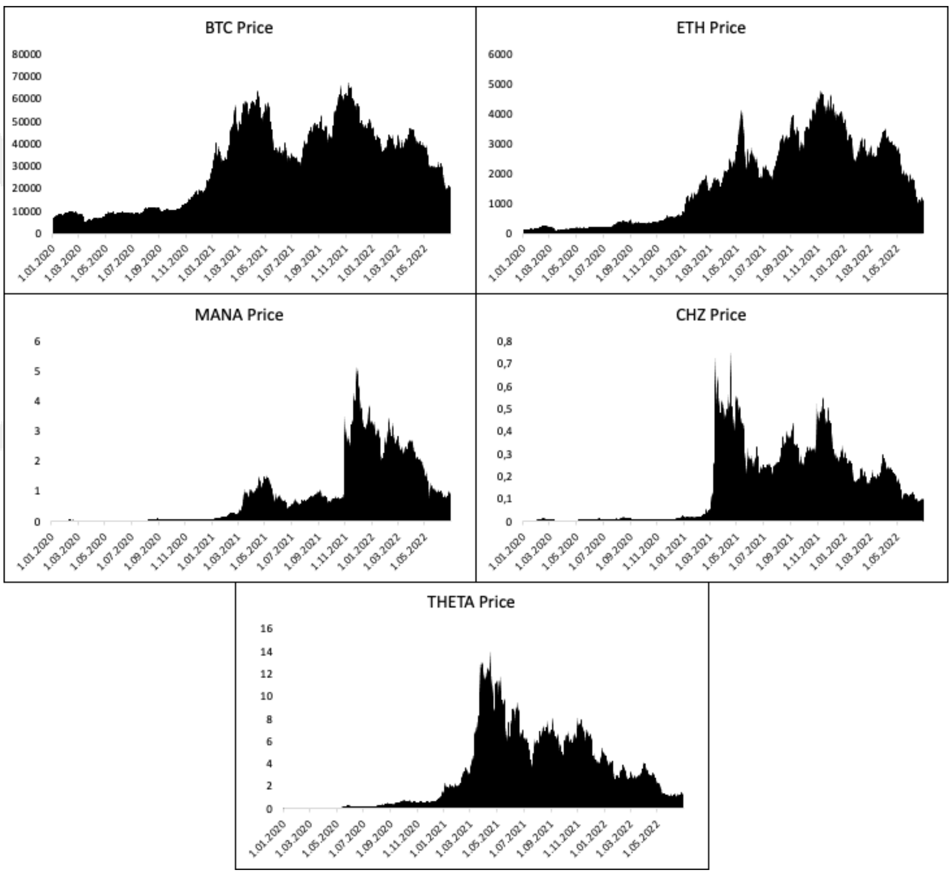
This study covers Bitcoin (BTC), Ether (ETH), Chiliz (CHZ), Decentraland (MANA) and THETA (THETA) prices between 01.01.2020 - 30.06.2022. There are 912 daily observations for each variable in our data set. All coin and token prices data are collected from the website "coingecko.com".

In parallel with the Dowling (2021a) study, these two coins (BTC & ETH) are chosen because all of the selected NFT tokens in our study use the Ethereum blockchain infrastructure and Bitcoin is the most significant actor in the cryptocurrency market. The MANA and THETA tokens, on the other hand, are chosen because of the large number of observations in the examined period.

Furthermore, MANA token is also used in Dowling (2021b) study which examines the relationship between NFT and cryptocurrency markets, therefore we have a chance to compare our results with it. The CHZ token, on the other hand, has been variably included in this study as it is the most widely used token in the rapidly growing fan token market (Vidal-Tomás, 2022).

In Figure 1 below, the behaviour of raw data of BTC, ETH, MANA, CHZ, THETA prices are shown for the specified time period (01.01.2020 - 30.06.2022).

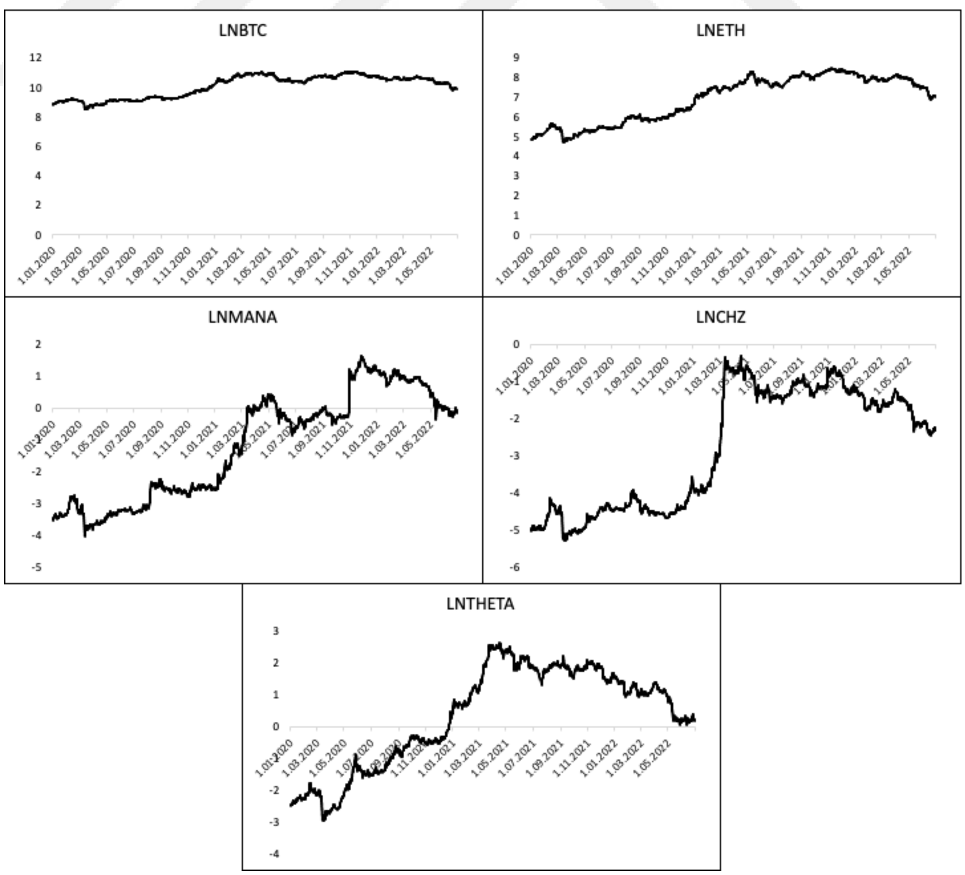
Figure 1. Price Data



As can be seen, immediately after the dates 01.03.2021 and 01.11.2021, there are tremendous increases especially in the price of CHZ and MANA while in the price of THETA shows increases only after 01.03.2021. In this timeframe, upward movements are also observed in BTC and ETH prices. This situation increases the possibility of a cointegration between our multivariate time series. If the data set in our study is non-stationary at the level (I(0)) and stationary at the first difference (I(1)), cointegration test will be performed on the data set. If our multivariate time series also has at least one cointegration at the level, then our data set becomes suitable for constructing a Vector Error Correction Model (VECM).

Our study uses BTC, ETH, MANA, CHZ and THETA prices and we have to check whether there is a long-term relationship between them and/or the dynamic relationship between them in the short run. To examine this, we first transform our dataset by the natural logarithm to linearize it. The natural logarithm transformation of our dataset is as shown below.

Figure 2. Price Data with Natural Logarithm



In Figure 2, the log-transformed data of BTC, ETH, CHZ, MANA and THETA prices with natural logarithms is shown graphically. Unlike raw data, prices can be seen in a more linear pattern. The fluctuations and trends in price over the time period have become smoother. In this way, cointegration and lag length criteria tests will be more appropriately applied to our data set. Log-transformation data is a standard approach in Vector Autoregressive Models (VAR Model) and therefore also in Cointegrated VAR Models (VECM) especially in data used in economics and finance (Mayr & Ulbricht 2015).

Table 1 presents raw data, log-transformation and log-difference descriptive statistics for BTC, ETH, CHZ, MANA and THETA prices. According to the raw data and log-transform data set in the monitored time period, BTC has the highest mean in terms of price, while it has the lowest mean of return (log difference). BTC, which has the highest standard deviation according to the raw data set, has the lowest standard deviation when the data set is linearized (log-series).

In addition, in terms of return (log difference), BTC still has the lowest standard deviation. With a skewness value of 0.08 in the BTC raw data set, it is understood that it has a distribution with larger numbers, albeit at a very low rate. But after the log-transformation, the skewness becomes -0.42, indicating that BTC has become shaped in the log-price distribution as the number of bigger numbers are more in the distribution based on its mean.

Table 1. Descriptive statistics for the raw data, log-transformed data

	Mean	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum
Raw Series							
BTC	30776.29	33930.19	18217.94	-1.38	0.08	5032.50	67617.02
ETH	1748.09	1788.52	1388.41	-1.23	0.33	110.60	4815.00
MANA	0.92	0.60	1.12	1.10	1.40	0.02	5.20
CHZ	0.16	0.11	0.17	-0.38	0.79	0.01	0.75
THETA	3.31	2.26	3.35	0.15	0.99	0.05	14.10
Log Series							
LNBTC	10.10	10.43	0.75	-1.41	-0.42	8.52	11.12
LNETH	6.95	7.49	1.16	-1.42	-0.40	4.71	8.48
LNMANA	-1.16	-0.52	1.67	-1.52	-0.06	-4.00	1.65
LNCHZ	-2.77	-2.17	1.62	-1.74	-0.10	-5.26	-0.28
LNTHETA	0.35	0.81	1.57	-1.11	-0.46	-2.92	2.65
Log Differences							
D(LNBTC)	0.001	0.002	0.040	16.663	-1.477	-0.434	0.176
D(LNETH)	0.002	0.004	0.053	16.085	-1.569	-0.563	0.219
D(LNMANA)	0.004	0.003	0.084	21.966	1.330	-0.654	0.923
D(LNCHZ)	0.003	0.002	0.080	18.650	0.609	-0.692	0.726
D(LNTHETA)	0.003	0.004	0.074	8.451	-0.950	-0.629	0.260

A similar situation seems to be valid for ETH as well. The skewness value of ETH, which was 0.33 in the raw data set, decreased to -0.40 after the data set was linearized. Remarkably, this situation is same for other tokens too. MANA, CHZ and THETA have positive skewness values in raw data series but all they have negative skewness values when they are transformed into log series. They have larger number of smaller values than their means in the raw series while having larger number of bigger values than their means in the log series.

In the log differences series (return of the tokens and coins) BTC, ETH and THETA have negative skewness values but MANA and CHZ have positive skewness values. It is understood that more of the observations in the return distributions of BTC, ETH and THETA are larger than their mean. However, MANA and CHZ return distributions contain a larger number of smaller values than their mean.

Another striking point is that the prices of MANA, CHZ and THETA tokens have higher standard deviations in their log-transformations and returns (log differences) than BTC and ETC coins. However, in terms of returns, it is another remarkable situation that tokens have a higher mean than coins.

3.2. CORRELATION MATRIX

The correlation coefficient is a coefficient that takes a value between -1 and 1. The sign of the coefficient contains information about the direction of the relationship. If the sign takes a negative value, it is understood that there is an inverse relationship between the variables, and if it takes a positive value, there is a positive relationship between the variables. When the correlation coefficient approaches -1 and 1, it means that the strength of the relationship increases. As can be seen in Table 2, the high correlation coefficients between the natural logarithms of the prices of our variables (since they are close to 1) indicate that there is a positive and strong relationship between our variables.

Table 2. Log-transform price, Correlation Matrix

	LNBTC	***LNETH***	***LNMANA***	***LNCHZ***	***LNTHETA***
LNBTC					
LNETH	0,97				
LNMANA	0,90	0,95			
LNCHZ	0,92	0,94	0,94		
LNTHETA	0,96	0,95	0,87	0,92	

In Table 3, the correlation coefficients between our variables are given by log-difference. We can also read this matrix as the correlation coefficients between BTC, ETH, CHZ, MANA and THETA returns, since the log-difference is also the returns of our variables. As seen in Table 3, there is a positive and relationship between the returns of our variables, just like the natural logarithm of their prices.

However, the strength of these relationships is not as strong as the relationship between the prices of our variables. In addition, the level of strength of the relationship existed in our variables change according to the price analysis when the returns are examined. Although the correlation between BTC and ETH is lower than when analyzed according to returns, it is noteworthy that it continues to be of high strength with a high correlation coefficient as evidence of the existence of a positive relationship between them.

Table 3. Log-Differences, Correlation Matrix.

	D(LNBTC)	***D(LNETH)***	***D(LNMANA)***	***D(LNCHZ)***	***D(LNTHETA)***
D(LNBTC)					
D(LNETH)	0,83				
D(LNMANA)	0,55	0,57			
D(LNCHZ)	0,54	0,56	0,64		
D(LNTHETA)	0,63	0,62	0,54	0,59	

3.3. LAG ORDER SELECTION

The optimal lag length is extremely important in order to avoid the inconsistency problem that will arise as a result of the lag length chosen by the model differs from the actual lag length (Braun and Mittnik, 1993). In order for the model to work in the most realistic way, it is a necessity to select the lag length according to certain criteria in terms of statistical technique.

Choosing the lag length too long causes the coefficients included in the model to be overestimated, the problem of multicollinearity, and serial correlation in the error terms, which is another important problem for the model, on the contrary, choosing the lag length too short causes the degrees of freedom of the model to decrease. The decrease in the degree of freedom causes the model to be less descriptive statistically (Stock & Watson 2015).

Considering these two different situations, it is understood that the lag length selection should be determined at the most optimal point for any econometric model, in order to avoid the problems that both of the above-mentioned situations may cause, in order to ensure the consistency of the model.

In Vector Autoregressive Models (VAR), lag order selection model is a common approach in the literature to determine the optimal lag length (Stock & Watson 2015). Optimal lag length determination is made with the help of indicator information criteria such as Akaike's Information Criterion (AIC), Final Prediction Error (FPE), Schwarz Information Criterion (SC), Hannan Quinn Information Criterion (HQ).

Table 4. Lag Length Criterian Statistical Results

VAR Lag Order Selection Criteria						
Endogenous variables: LNBTC LNETH LNCHZ LNMANA LNTHETA						
Exogenous variables: C						
Lag	**LogL**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	-2749.140	NA	0.000305	6.093231	6.119818	6.103385
1	7385.267	20134.29	5.89e-14	-16.27271	-16.11320*	-16.21179*
2	7410.429	49.71251	5.89e-14	-16.27307*	-15.98062	-16.16138
3	7424.870	28.37018	6.03e-14	-16.24971	-15.82433	-16.08725
4	7443.079	35.57198	6.12e-14	-16.23469	-15.67637	-16.02145
5	7469.556	51.43078	6.10e-14	-16.23795	-15.54671	-15.97395
6	7491.718	42.80399	6.14e-14	-16.23168	-15.40750	-15.91690
7	7503.924	23.43997	6.32e-14	-16.20337	-15.24626	-15.83783
8	7524.930	40.10709*	6.38e-14	-16.19454	-15.10449	-15.77822
***significant at 5% level**						

In Table 4, the suggested optimal lag lengths for the model are shown according to different information criteria. The recommended optimal lag length according to SC and HQ criteria is one, while the recommended optimal lag length according to FPE and AIC is two. The optimal lag length selected for the model is determined as two in line with the AIC's recommendation.

In the empirical study examining the relationship between the NFT market, BTC and ETH price, the optimal lag length is determined by AIC (Ante, 2021c). Our study also examines the relationship between these two markets. In this context, we determine the optimal lag length for our model with the same information criterion (AIC) in order to contribute to previous studies and be able to make a consistent comparison.

Symmetrical lags determined in determining lag length in VAR model studies is a general trend according to the literature (Ozcicek and McMillin, 1999). What is meant by the symmetrical lag length here is that all variables in the model have the same lag length. Therefore, we use symmetric lag length in our model and assume the lag lengths of all variables are the same.

3.4. UNIT ROOT TEST

When studying regression with time series data, the stationarity of the data gains importance for the predictive power of the model. When working with non-stationary data, fundamental differences emerge between past data and future data. In this case, the model loses its power to predict future data from past data due to non-stationary time series.

Beyond that, non-stationary data, due to their trends, may seem like there is a relationship between them, although there is actually no relationship between them. This raises the problem of the possibility of spurious regression. To avoid this possibility, the time series used in the model should be stationary. Augmented Dickey Fuller (ADF) test is used to test the stationarity of the data.

The ADF test tests that the variable has a unit root (non-stationary) in the null hypothesis, and that the variable is stationary in the alternative hypothesis. We test the natural logarithms of the prices of our variables, which we have made our data set more linear, one by one and separately (LNBTC, LNETH, LNCHZ, LNMANA and LNTHETA) with the ADF test to see if they are stationary.

Table 5. Unit Root Test for LNBTC at Level.

Null Hypothesis: LNBTC has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag=20)			
		t-Stats	**Prob.***
Augmented Dickey-Fuller test statistic		-1.609368	0.4774
Test critical values:	**1% level**	-3.437306	
	5% level	-2.864500	
	10% level	-2.568399	
*MacKinnon (1996) one-sided p-values			

In Table 5, the results of the ADF test performed to test the stationarity of LNBTC at the level are given. As can be seen, the null hypothesis cannot be rejected at all 10%, 5%, and 1% significance levels. As can be seen from the 0.4774 p-value, the failure to reject the null hypothesis means that LNBTC is not stationary in level.

Table 6. Unit Root Test for LNETH at Level

Null Hypothesis: LNETH has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag=20)			
		t-Stats	**Prob.***
Augmented Dickey-Fuller test statistic		-1.856834	0.3530
Test critical values:	**1% level**	-3.437306	
	5% level	-2.864500	
	10% level	-2.568399	
*MacKinnon (1996) one-sided p-values			

Table 6 presents the ADF test results for LNETH at the level. Because of its p-value of 0.3530 for LNETH, the non-stationary null hypothesis could not be rejected for any significance level. As a result, LNETH is also non-stationary for all significance levels at the level.

BTC and ETH, the two largest coins of the cryptocurrency market in terms of market capitalization, have a non-stationary characteristic in the examined time period. Considering that the time series, like the prices of traditional investment products and macroeconomic variables, are non-stationary at the level, this is an expected situation.

Table 7. Unit Root Test for LNCHZ at Level.

Null Hypothesis: LNCHZ has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag=20			
		t-Stats	**Prob.***
Augmented Dickey-Fuller test statistic		-1.329983	0.6173
Test critical values:	**1% level**	-3.437306	
	5% level	-2.864500	
	10% level	-2.568399	
*MacKinnon (1996) one-sided p-values			

ADF test statistics for LNCHZ are given in Table 7. Since the p-value is 0.6173, the null hypothesis cannot be rejected for the 10%, 5% and 1% significance levels for LNCHZ, LNCHZ is also non-stationary at level.

Table 8. Unit Root Test for LNMANA at Level.

Null Hypothesis: LNMANA has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag=20)			
		t-Stats	**Prob.***
Augmented Dickey-Fuller test statistic		-1.277812	0.6417
Test critical values:	**1% level**	-3.437306	
	5% level	-2.864500	
	10% level	-2.568399	
*MacKinnon (1996) one-sided p-values			

The statistical results of the ADF test for LNMANA at level are finally given in Table 8. A p-value of 0.6417 means that the null hypothesis cannot be rejected at any significance level for LNMANA as well. Thus, it is understood that the natural logarithms of the prices of MANA are non-stationary at the level.

Table 9. Unit Root Test for LNTHETA at Level.

Null Hypothesis: LNTHETA has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag=20)			
		t-Stats	**Prob.***
Augmented Dickey-Fuller test statistic		-1.820256	0.3708
Test critical values:	**1% level**	-3.437306	
	5% level	-2.864500	
	10% level	-2.568399	
*MacKinnon (1996) one-sided p-values			

Finally, since the ADF test statistic's p-value is 0.37 according to the test statistics in Table 9, the hypothesis that LNTHETA prices also have a unit root is not rejected. As a result, LNTHETA is also non-stationary at the level.

It is seen that all the variables we used in our study are non-stationary at the level. For this reason, we test the stationarity of our variables at the first difference. In order to create VECM with our variables, it is necessary to determine the level at which our variables are stationary. If our variables are not stationary in their first differences, stationarity tests are performed on the second differences and on the third differences, respectively, until they become stationary.

Table 10. Unit Root Test for LNBTC at First Difference

Null Hypothesis: D(LNBTC) has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag=20)			
		t-Stats	**Prob.***
Augmented Dickey-Fuller test statistic		-32.00	0
Test critical values:	**1% level**	-3.437314	
	5% level	-2.864503	
	10% level	-2.568401	
*MacKinnon (1996) one-sided p-values			

ADF test statistics at first differences of LNBTC are given in Table 9. The hypothesis that first differences of LNBTC are non-stationary at all significance levels is rejected. Although LNBTC is not stationary at the level, it is stationary at the first difference.

Table 11. Unit Root Test for LNETH at First Difference

Null Hypothesis: D(LNETH) has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag=20)			
		t-Stats	**Prob.***
Augmented Dickey-Fuller test statistic		-32.76052	0.00000
Test critical values:	**1% level**	-3.437314	
	5% level	-2.864503	
	10% level	-2.568401	
*MacKinnon (1996) one-sided p-values			

ADF test results applied to the first differences of LNETH are as in Table 10. Since the p-value is 0, the null hypothesis that LNETH is assumed to be non-stationary at the first differences is rejected. Therefore, at their first difference, LNETH (I(1)) is also stationary.

Table 12. Unit Root Test for LNCHZ at First Difference

Null Hypothesis: D(LNCHZ) has a unit root			
Exogenous: Constant			
Lag Length: 3 (Automatic - based on SIC, maxlag=20)			
		t-Stats	**Prob.***
Augmented Dickey-Fuller test statistic		-12.55216	0.0000
Test critical values:	**1% level**	-3.437338	
	5% level	-2.864514	
	10% level	-2.568407	
*MacKinnon (1996) one-sided p-values			

According to ADF test statistics, as seen in Table 11, the hypothesis that LNCHZ is also non-stationary at all significance levels in the first difference is rejected. From this point of view, it can be said that LNCHZ is stationary at its first difference (I(1)).

Table 13. Unit Root Test for LNMANA at First Difference

Null Hypothesis: D(LNMANA) has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag=20)			
		t-Stats	**Prob.***
Augmented Dickey-Fuller test statistic		-29.12482	0.0000
Test critical values:	**1% level**	-3.437314	
	5% level	-2.864503	
	10% level	-2.568401	
*MacKinnon (1996) one-sided p-values			

The ADF test results in the first differences of LNMANA are as in Table 12. The fact that the null hypothesis can be rejected for each significance level shows that LNMANA is also stationary at first difference (I(1)).

Table 14. Unit Root Test for LNTHETA at First Difference

Null Hypothesis: D(LNTHETA) has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag=20)			
		t-Stats	**Prob.***
Augmented Dickey-Fuller test statistic		-32.68000	0
Test critical values:	**1% level**	-3.437314	
	5% level	-2.864503	
	10% level	-2.568401	

As can be seen in Table 14, unit root test statistics for the first difference of LNTHETA show that LNTHETA is stationary for the first difference. Since the p-value is 0 in the ADF test, it is determined that LNTHETA is stationary at first differences I(1) and thus all our variables are stationary at first differences.

After detecting that all our variables are stationary at their first difference, we check whether there is cointegration between our variables for compliance for VECM.

3.5. COINTEGRATION TEST

In order to construct a Vector Error Correction Model (VECM), there must be at least one cointegration between the variables that proves a long-term relationship between our variables. For this reason, it is necessary to check the cointegration equations in the equation system.

For the VAR model estimation with unit root variables, the cointegration equations of the variables should be checked. The situation that the variables have trends in the same direction in parallel with time indicates that they have a high probability of having a common trend (Stock & Watson, 2015). The fact that at least some of the variables have a common trend indicates the existence of cointegration in the system of equations and therefore there is one or more long-term relationships within the system of equations.

The presence of cointegration in the equation system is an indication that the short-term effects of a particular variable in the time series will reflect on other variables in the long run. The absence of any cointegration in the system of equations allows a standard VAR model to examine the short-run effects of variables, which can be estimated by their first difference. However, in the presence of cointegration in which the variables are made stationary from non-stationary, the use of the standard VAR model has been viewed with suspicion since it ignores the information of long-term effects and does not include them in the model (Engle & Granger, 1987).

At this point, the Vector Error Correction Model (VECM), which creates a model by taking into account the cointegration equations and unit roots, appears. Determining the number of cointegration in the equation system is a prerequisite for VEC model estimation. The determination of the number of cointegration in the equation systems is made with the Johansen cointegration test.

Table 15. Johansen Cointegration Test.

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	Critical Value	Prob.*
None	0.032933	68.66807	69.81889	0.0615*
At most 1	0.015856	38.22751	47.85613	0.2922
At most 2	0.015107	23.69866	29.79707	0.2135
At most 3	0.005929	9.861823	15.49471	0.2915
At most 4	0.004891	4.456427	3.841465	0.0348**
* rejection of the hypothesis at %10 , ** rejection of the hypothesis at %5				

Table 13 shows the results of the Johansen Cointegration Test that we performed on our variables. While the hypothesis of at least one cointegration can be rejected at the 10% significance level, it is able to be understood that at least one cointegration is existed and so there is a long-term relationship.

We find that our variables have a unit root and also contain at least one cointegration equation. In this way, we see that our variables are suitable for estimating VECM.

3.6. VECTOR ERROR CORRECTION MODEL (VECM)

The Vector Error Correction Model is a restricted Var model that enables the cointegration between the variables to converge mainly to this long-term equilibrium of the variables. VECM converges variables to their long-run relationships by adding an error correction term to the model. The general formula of VECM with two different variables is as follows.

$\Delta y_t = a_0 + a_1\Delta y_{t-1} + a_2\Delta y_{t-2} + ... + a_{p-1}\Delta y_{t-p-1} + b_1\Delta x_{t-1} + b_2\Delta x_{t-2} + \ldots + b_{p-1}\Delta x_{t-p-1} - \lambda ect_{t-1} + u_t$

Where;

$\Delta y_t = y_t - y_{t-1}$

$\Delta x_t = x_t - x_{t-1}$

λ is the speed of adjustment, the rate at which the long-run relationship turns into a short-term dynamic effect,

ect is error correction term, which contains the information of the long-run relationship arising from cointegration.

u_t is the error term.

The error correction term (ect) is the long-term relationship information resulting from cointegration calculated by OLS regression. The general formula for a bivariate system can be represented as:

$ect_{t-1} = y_{t-1} - c_0 - c_1x_{t-1}$

Where, long run relationship equation as follows.

$y_{t-1} = c_0 + c_1x_{t-1}$

The error correction term is derived from the long run equation. In this way, it explains how the deviations from the long-run equilibrium in the previous period affect the dependent variable in the short run. The coefficient of the error correction term (λ), on the other hand, indicates how fast the dependent variable converges to the long-run equilibrium. This is why the coefficient of this term is called "speed of adjustment".

The negative value of this coefficient (λ) in the VECM equation means that the system converges towards the long-term equilibrium. From this point of view, negative value of this coefficient is good news for the model.

Vector Error Correction Model (VECM) is made possible by taking the first difference of a standard Vector Autoregressive Model (VAR). Therefore, the optimal lag length (p) for the variables, which is found by first establishing the VAR model, means that one lag is lost for the VECM performed with the first differences of the variables. Therefore, the optimal lag length for VECM should be (p - 1).

3.7. GRANGER CAUSALITY TEST

Granger (1969) presented a causality hypothesis test that tests whether the data of one of any two different time series variables can be used to predict the other. The results that are significant from this hypothesis test imply the Granger causality of one variable to the other variable. Granger causality implies that historical data for one variable can be used to predict the other variable. However, this causality determination, which implies that one variable affects the other variable, does not imply that the only effect factor of the variable exposed to Granger causality is the influencing variable.

Engle and Granger (1987) imply that in a system of equations where cointegration exists, there must be short-run Granger causality in at least one direction. It has also been studied that the systems of equations in which cointegration exists already show a Granger causality and therefore there is no need to apply a Granger causality test (Toda & Phillips, 1993). In this way, causality in the VECM model can be tested from the t-statistics of the coefficients. However, Belloumi (2009) also found cases where cointegration is present and Granger causality does not exist.

The VAR model and VECM's Granger causality testing methods are different. While the null hypothesis is tested according to F-statistics in VAR, it is tested according to the chi-square distribution in VECM. Because VECM treats data as stationary. In addition, considering that VECM makes one less lag estimation, Granger causality testing is applied to the first difference of the relevant coefficient.

3.8. IMPULSE RESPONSE FUNCTION

Impulse response functions examine the external shock relationship between two different endogenous variables. The effect of a sudden change in the standard deviation of an endogenous variable on other variables is measured with these functions (Lütkepohl, 2005). IRFs are graphs that show how other variables respond to the impulse created by one variable over time.

4. FINDINGS

4.1. COINTEGRATING EQUATION

As shown in Table 4 above, the optimal lag length found by estimating the VAR model with LNBTC, LNETH, LNCHZ, LNMANA and LNTHETA in our data set is 2 according to AIC.

As can be seen from Table 5 - Table 8, all of our variables are non-stationary in their level values. However, all of our variables are stationary, as can be seen from Table 9 and Table 12, based on their first differences. Therefore, all of our variables become integrated I(1) at their first difference.

Table 13 shows that the equation system created by our variables contains at least one cointegration equations at 10% significance level, according to the trace statistics.

These features make our dataset suitable for performing Vector Error Correction Model (VECM). Since VECM is performed on the first differences in which our data is stationary, the optimal lag length suitable for VECM will be 1 less than the optimal lag length suitable for the VAR model. Therefore, the rank will be 2-1=1 when estimating the VECM.

Table 16. Cointegrating Equation. (Long-run relationship)

Vector Error Correction Estimates	
Sample (adjusted): 1/03/2020 6/30/2022	
Included observations: 910	
Standard errors in ( ) & t-statistics in [ ]	
Cointegrating Eq:	*CointEq1*
LBTC(-1)	1
LNETH(-1)	-0.555419
Std. Errors	0.13988
T Stats	-3.97073
LNCHZ(-1)	-0.017449
Std. Errors	0.07050
T Stats	-0.24750
LNMANA(-1)	0.006949
Std. Errors	0.07623
T Stats	-0.09116
LNTHETA(-1)	-0.062934
Std. Errors	0.07475
T Stats	-0.84191
C	-6.255853

The first cointegration equation results given by the VECM estimation as a result of the existence of at least one cointegrating equation obtained from the Johansen cointegration test results are given in Table 14.

If the error correction term (ect) is written here;

$$ECTt_{t-1} = LNBTC_{t-1} - 0.56LNETH_{t-1} - 0.02LNCHZ_{t-1} + 0.01LNMANA_{t-1} - 0.06LNTHETA_{t-1}$$

$$\qquad\qquad (0.14) \qquad\qquad (0.07) \qquad\qquad (0.08) \qquad\qquad (0.07)$$

However, the coefficients of LNCHZ and LNMANA in the error correction term were insignificant according to T-Stat at 10% significance level. Therefore, the hypothesis that they do not show a long-term causal relationship cannot be rejected.

Or the long run relationship equation can be written as;

$$LNBTC_{t-1} = 0.56LNETH_{t-1} + 0.02LNCHZ_{t-1} - 0.01LNMANA_{t-1} + 0.06LNTHETA_{t-1}$$

$$\qquad\qquad (0.14) \qquad\qquad (0.07) \qquad\qquad (0.08) \qquad\qquad (0.07)$$

According to the results, it is only the LNETH coefficient that has significance at the 5% significance level ($T\ Stats^* > T\ Stats_{0.05}$) in the cointegrating equation, which also shows the long-term relationship in the system of equations. Therefore, the long-term relationship exists only between LNBTC and LNETH.

In line with these test statistics results, a 1 percentage point increase in the price of ETH will result in an increase of 0.56 percentage points on average in the price of ETH in the long run, all else being constant.

4.2. VECTOR ERROR CORRECTION MODEL (VECM)

The Vector Error Correction Model is performed with a lag length of 1, which is the optimal lag length for this model for our variables. 5 different short-term equations are obtained. The output of this system of equations is given in Table 15 as follows.

Table 17. VECM Matrix

Dependent Variables	Independent Variables						
	Constant	*ect*	*D(LNBTC(-1))*	*D(LNETH(-1))*	*D(LNCHZ(-1))*	*D(LNMANA(-1))*	*D(LNTHETA(-1))*
D(LNBTC)	0.01869	0.01869	0.063726	-0.088565	0.016158	-0.014661	-0.031721
D(LNETH)	0.00267	0.04055	0.045997	-0.062426	-0.011802	-0.006960	-0.056280
D(LNCHZ)	0.00324	0.07725	0.160388	-0.115467	-0.026747	-0.007299	-0.033384
D(LNMANA)	0.00381	0.05489	-0.015118	-0.148551	0.037686	0.098729	-0.090563
D(LNTHETA)	0.00326	0.05690	0.129218	-0.125303	-0.026322	0.047316	-0.097861

Looking at Table 17, it is seen that the error correction term (ect) takes positive values in all equations. Therefore, it can be said that all of the dependent variables, that is, the change in the logarithms of the prices of the variables, have an positive relationship with the cointegration equation. From this point of view, it is possible to say that the variables in the system of equations diverge towards the long-term equilibrium. In other words, the established system seems not to reach equilibrium in the long run.

The direction and strength of the interrelationships of the endogenous variables can be seen through the coefficients shown in Table 15. However, in order to detect the existence of the relationship between each variable and other variables, it is necessary to find Granger causality of the variables relative to each other. The coefficients showing the direction and strength of the relationship between dependent and independent variables given in Table 15 can only become significant if this precondition is accepted. Failure to detect Granger causality causes inability to detect causality from the independent variable to the dependent variable, and therefore the coefficients showing the strength of the relationship between the relevant dependent and independent variable in Table 15 are not taken into account.

4.3. GRANGER CAUSALITY FOR VECM

The VEC Granger Causality/Block Exogeneity Wald Tests results are presented in Table 15 to look at the short-term dynamic effects of endogenous variables in VECM on each other. In order to examine the short-term causality effects of each variable in the Vector Error Correction Model (VECM) on each other separately, the coefficients in all equations were tested separately with the Granger causality test.

Table 18. VEC Granger Causality/Block Exogeneity Wald Tests

Null Hypotheses	p-values	Test
D(LNETH) does not Granger causality on D(LNBTC)	0.0594*	REJECT
D(LNCHZ) does not Granger causality on D(LNBTC)	0.4941	Do Not Reject
D(LNMANA) does not Granger causality on D(LNBTC)	0.5061	Do Not Reject
D(LNTHETA) does not Granger causality on D(LNBTC)	0.2057	Do Not Reject
D(LNBTC) does not Granger causality on D(LNETH)	0.5762	Do Not Reject
D(LNCHZ) does not Granger causality on D(LNETH)	0.7061	Do Not Reject
D(LNMANA) does not Granger causality on D(LNETH)	0.8116	Do Not Reject
D(LNTHETA) does not Granger causality on D(LNETH)	0.0900*	REJECT
D(LNBTC) does not Granger causality on D(LNCHZ)	0.1941	Do Not Reject
D(LNETH) does not Granger causality on D(LNCHZ)	0.2162	Do Not Reject
D(LNMANA) does not Granger causality on D(LNCHZ)	0.8677	Do Not Reject
D(LNTHETA) does not Granger causality on D(LNCHZ)	0.5028	Do Not Reject
D(LNBTC) does not Granger causality on D(LNMANA)	0.9072	Do Not Reject
D(LNETH) does not Granger causality on D(LNMANA)	0.1296	Do Not Reject
D(LNCHZ) does not Granger causality on D(LNMANA)	0.4447	Do Not Reject
D(LNTHETA) does not Granger causality on D(LNMANA)	0.0833*	REJECT
D(LNBTC) does not Granger causality on D(LNTHETA)	0.2613	Do Not Reject
D(LNETH) does not Granger causality on D(LNTHETA)	0.1496	Do Not Reject
D(LNCHZ) does not Granger causality on D(LNTHETA)	0.5474	Do Not Reject
D(LNMANA)does not Granger causality on D(LNTHETA)	0.2463	Do Not Reject
******significant at 1%, **significant at 5%, *significant at 10%***		

As seen in Table 18, the null hypothesis of "Granger no causality" on BTC price changes of ETH price changes is rejected at the 10% significance level. Therefore, there is Granger causality over the BTC price of the ETH price in the short run. The coefficient of the independent variable D(LNETH) is significant in the equation where the dependent variable is D(LNBTC) in the Estimated Vector Error Correction Model (VECM).

Again, in the light of the results in Table 15, the null hypothesis of "No Granger causality" of the changes in the THETA price on the ETH price changes is rejected at 10% significance level. Therefore, it can be implied that there is Granger causality on the ETH price of the THETA price in the short run. In VECM, the coefficient of the independent variable D(LNTHETA) in the equation where the dependent variable is D(LNETH) becomes significant.

Finally, when the price changes of THETA are examined whether there is Granger causality on the price changes of MANA, the "No Granger causality" hypothesis at 10% significance level is rejected. It can be stated in parallel with these data that the independent variable D(LNTHETA) has a Granger causality in the short run on the dependent variable D(LNMANA).

From Table 15, in the equation where the dependent variable is Bitcoin logarithm prices change (D(LNBTC)), it is seen that the coefficient of lagged change of Ether logarithm prices is -0.089. It can be said that 1 percentage point change in Ether price in parallel with the relationship from LNETH prices, which has Granger causality to LNBTC in the short term, will cause the Bitcoin price to decrease by 0.089 percentage points on average in the next period ceteris paribus.

Also, from Table 15, the equation D(LNETH), where the dependent variable is the change logarithm prices of the ETH, can be obtained. In this equation, the coefficient of lagged logarithm prices of Ether for which Granger causality is determined from THETA to ETH is calculated as -0.056. In other words, it can be stated that 1 percentage point change in the price of THETA will cause a change of -0.056 percentage points in the ETH price on average in the next period when the other things are constant.

Finally, as can be seen from Table 15, the equation of the dependent variable MANA price change (D(LNMANA)) shows the coefficient of the independent variable THETA price change (D(LNTHETA)) as -0.09. Therefore, everything else being equal, it can be said that 1 percentage point increase in THETA price change in the previous period will cause an average of 0.09 percentage points decrease in MANA price in the next period.

4.4. VECTOR AUTOREGRESSIVE MODEL (VAR)

Table 19 shows the outputs of the VAR model established with our variables. The VAR model is set up with an optimal lag value of 2 lags. For this reason, there are more dependent variables in the equations established for each independent variable compared to VECM. For the VAR model established with the same variables, whether there is a causal relationship between the variables is also tested for the VAR model.

Table 19. VAR Matrix

Independent Variables	Dependent Variables				
	LNBTC	*LNETH*	*LNCHZ*	*LNMANA*	*LNTHETA*
Constant	-0.055759	- 0.118075	-0.579729	-0.471778	-0.346771
LNBTC(-1)	1.061531	0.074815	0.217710	0.021976	0.171279
LNBTC(-2)	-0.054653	-0.045879	-0.144439	0.023838	-0.120683
LNETH(-1)	-0.093678	0.911606	-0.143479	-0.160926	-0.150123
LNETH(-2)	0.089220	0.062160	0.117659	0.161837	0.126119
LNCHZ(-1)	0.015341	-0.011101	0.967677	0.036828	-0.025633
LNCHZ(-2)	-0.020892	0.007413	0.024968	-0.033341	0.024145
LNMANA(-1)	-0.012207	-0.003373	-0.008013	1.089823	0.048436
LNMANA(-2)	0.010938	0.004733	0.004468	-0.106791	-0.051516
LNTHETA(-1)	-0.031321	-0.057419	-0.035598	-0.092164	0.895614
LNTHETA(-2)	0.036555	0.063878	0.030160	0.082659	0.099442

4.5. GRANGER CAUSALITY FOR VAR

For the VAR model, it is determined that no other variable in the model has Granger causality on BTC. For ETH, it was rejected that BTC at 5% significance level and THETA at 10% significance level do not have Granger causality. From this point of view, it can be said that BTC and THETA have Granger causality on ETH. It is understood that ETH has Granger causality on CHZ at 10% significance level and BTC at 1% significance level. While the hypothesis that BTC does not have Granger causality on MANA is rejected at 10% significance level, the hypothesis that BTC does not have Granger causality on THETA is rejected at 1% significance level, and the hypothesis that ETH does not have Granger causality on THETA is rejected at 10% significance level.

One of the most striking points in the outputs of the VAR model here is that unlike the VECM analysis, BTC has Granger causality on all other variables. In addition, Granger causality of THETA on ETH is determined in the VAR model. In both models, it is found that there is a causality from THETA to ETH between these two variables.

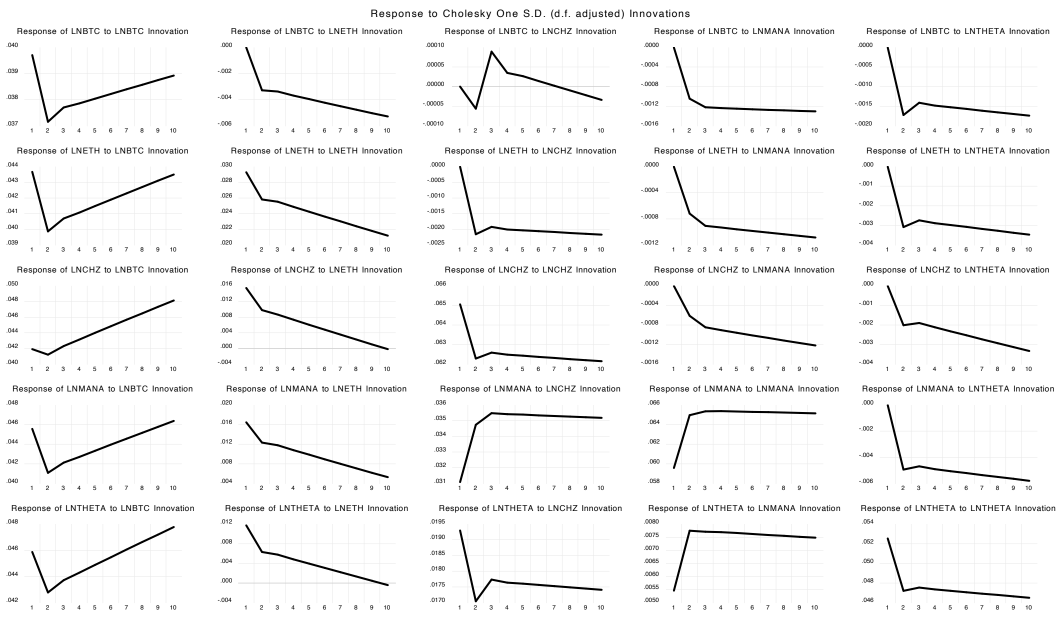
Table 20. VAR Granger Causality/Block Exogeneity Wald Tests

Null Hypotheses	p-values	Test
D(LNETH) does not Granger causality on D(LNBTC)	0.1294	Do Not Reject
D(LNCHZ) does not Granger causality on D(LNBTC)	0.1591	Do Not Reject
D(LNMANA) does not Granger causality on D(LNBTC)	0.8155	Do Not Reject
D(LNTHETA) does not Granger causality on D(LNBTC)	0.1539	Do Not Reject
D(LNBTC) does not Granger causality on D(LNETH)	0.0416**	REJECT
D(LNCHZ) does not Granger causality on D(LNETH)	0.6483	Do Not Reject
D(LNMANA) does not Granger causality on D(LNETH)	0.9470	Do Not Reject
D(LNTHETA) does not Granger causality on D(LNETH)	0.0847*	REJECT
D(LNBTC) does not Granger causality on D(LNCHZ)	0.0001***	REJECT
D(LNETH) does not Granger causality on D(LNCHZ)	0.0963*	REJECT
D(LNMANA) does not Granger causality on D(LNCHZ)	0.8672	Do Not Reject
D(LNTHETA) does not Granger causality on D(LNCHZ)	0.6068	Do Not Reject
D(LNBTC) does not Granger causality on D(LNMANA)	0.0504**	REJECT
D(LNETH) does not Granger causality on D(LNMANA)	0.2560	Do Not Reject
D(LNCHZ) does not Granger causality on D(LNMANA)	0.6734	Do Not Reject
D(LNTHETA) does not Granger causality on D(LNMANA)	0.1108	Do Not Reject
D(LNBTC) does not Granger causality on D(LNTHETA)	0.0049***	REJECT
D(LNETH) does not Granger causality on D(LNTHETA)	0.0734*	REJECT
D(LNCHZ) does not Granger causality on D(LNTHETA)	0.8233	Do Not Reject
D(LNMANA)does not Granger causality on D(LNTHETA)	0.4182	Do Not Reject
****significant at 1%, **significant at 5%, *significant at 10%*		

4.6. IMPULSE RESPONSE FUNCTIONS

The impulse response functions of the variables in the VEC model are given in Figure 3.

Figure 3. Impulse Response Functions



The standard deviation shock increase in BTC prices has a positive effect on the ETH price in the short run. Although this effect is around 0.043% at the beginning of the time period, it decreases rapidly firstly to 0.040% and continues to increase permanently.

The standard deviation shock increase in the ETH price has a negative effect on the BTC prices. Although there is no effect at the beginning of the period, it is clear that the standard deviation increase in the ETH price after the second time frame has an increasing negative effect on Bitcoin prices.

Considering the impulse response functions of the standard deviation increase shock in the price of BTC, it is seen that the price of BTC has a positive effect on the prices of all variables . In addition, it can be said that this effect increases as time progresses.

The standard deviation shock in the CHZ token price has a mixed effect on other variables. While CHZ prices have a negative effect on ETH prices, this effect continues to increase at a decreasing rate as time passes and this effect stabilizes around -0.0025% over time. The effect of the CHZ token price on the Bitcoin price is negative at the beginning of the time period and then the effect that turns to positive but again it starts to show a continuous decrease and it starts to take negative values again with time. The effect of standard deviation shock in CHZ prices on MANA reaches its maximum by leaping at the beginning of the time period, and then starts to decrease slowly, becoming permanent in the monitored time period and converging to 0.035%. And finally, CHZ prices affect Theta prices positively. However this effect fluctuates at the beginning of period, it becomes stable around %0.0174.

When we look at the MANA, the standard deviation shocks in its price have a negative effect on BTC, ETH and CHZ especially at the beginning of the time period. All these negative effects becomes higher with decreasing rate at the beginning of the period and they becomes stable towards the end of the monitored time period. The increase of standard deviation in MANA has positive effect on THETA. This effect reaches its peak at the second period of followed time period and then it becomes stable at higher level than initial.

CONCLUSION

In this study, BTC, which is the locomotive of the cryptocurrency market, and ETH, which is the coin of the Ethereum ecosystem, are discussed and the relationship of the cryptocurrency market with the NFT market is examined. In terms of the representation of the NFT market, the prices of the three important actors of the NFT market, CHZ, MANA and THETA are used. CHZ and MANA are part of the Ethereum ecosystem through their use of the ETH blockchain. The aim of the study is to contribute to the emerging literature examining the relationships between the NFT market and the cryptocurrency market.

Despite the high correlation coefficients between all the variables included in the model, no effect of any tokens or coins which are used in the NFT market on BTC. At the same time, there is no short-term effect of BTC on any of the variables. This finding for BTC, the coin with the largest market capitalization of the cryptocurrency market, differs from most studies in the current literature.

However, it is found that THETA provides Granger causality on ETH prices in the short run. Therefore, it can be said that the NFT market has Granger causality on the cryptocurrency market. This detection leads to a different finding than Ante's (2021c) research that states that NFT market has no causality effect on cryptocurrency market. In addition, the NFT market itself gives a Granger causality. Short-term Granger causality of THETA on MANA is also detected.

In line with the results of our research, as in the NFT market, short-term Granger causality between the two elements in the cryptocurrency market from ETH prices to

BTC prices is also detected. ETH prices are detected within the scope of short-term causality in our findings. These findings are in line with the findings of Dowling (2021a) as a result of wavelet consistency analysis between these two markets and Ante's (2021c) findings with VECM for these two markets.

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