

**IBN HALDUN UNIVERSITY
SCHOOL OF GRADUATE STUDIES
DEPARTMENT OF ECONOMICS**

MASTER THESIS

**PRICE AND VOLUME DYNAMICS: THE CASE OF
CRYPTOCURRENCY MARKETS BEFORE AND
DURING COVID-19 PANDEMIC**

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**THESIS SUPERVISOR
ASST PROF. ASAD UL ISLAM KHAN**

ISTANBUL, 2021

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CRYPTOCURRENCY MARKETS BEFORE AND
DURING THE COVID-19 PANDEMIC**

by

WILLIAM BWANDO

**A thesis submitted to the School of Graduate Studies in partial
fulfilment of the requirements for the degree of Master of Arts in
Economics**

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ASST PROF. ASAD UL ISLAM KHAN

ISTANBUL, 2021

APPROVAL PAGE

This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Arts in Economics

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I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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ÖZ

FİYAT VE HACİM DİNAMİKLERİ: COVID-19 PANDEMİSİ ÖNCESİNDE VE SIRASINDA KRİPTO PARA PİYASALARININ ÖRNEĞİ

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Alternatif bir para kaynağı olarak kripto para birimlerinin ortaya çıkışı, 21. yüzyılın en büyük fenomenlerinden biri olarak adlandırılmıştır. Yıllar geçtikçe, kripto para birimleri geleneksel finansal sistemi büyük ölçüde kesintiye uğrattı ve devrimi için bir katalizör görevi görmeye devam ediyor. Bununla birlikte, kripto para birimleri sefalet ve tartışmalardan arınmış değildir. Bu çalışma, bu tür gizemlerden birini keşfetmeyi ve araştırmayı amaçlamaktadır. Bu çalışmanın ana odak noktası, COVID-19 pandemisinin kripto piyasalarındaki fiyat ve hacim dinamikleri üzerindeki etkisini ampirik olarak araştırmaktır. Çalışma iki veri örneğinden yararlanmaktadır ancak bu örnekler ayrı ayrı ve bağımsız olarak analiz edilmektedir. İlk veri örneği, 7 Kasım 2020 itibariyle piyasa değeri açısından İlk Beş Kripto Para Biriminden oluşmaktadır. Bu para birimleri BITCOIN, ETHEREUM, XRP, BINANCE COIN ve LITECOIN'dir. İkinci veri örneği, 7 Kasım 2020 itibariyle ilk 40 kripto para birimi arasında yer alan Alt Beş Kripto Para Biriminden oluşur. Bunlar FTX TOKEN, HUOBI TOKEN, FILECOIN, DASH ve DECREED'dir. İlk Beş Kripto Para Birimi arasındaki veriler 2014 ile 2021 arasında, en Alt Beş Kripto Para Birimi arasındaki veriler ise 2018 ile 2021 arasında değişmektedir. Her iki örnekteki tüm kripto para birimleri 1. sıraya entegre edilmiştir, yani I (1). Johansen Eşbütünleşme Testi ve Vektör Hata Düzeltme modeli, bu çalışma kapsamında kripto para birimleri arasındaki fiyat-hacim ilişkilerinin kurulmasında çalışmanın benimsediği temel istatistiksel yöntemdir.

Çalışma, pandemi öncesi veya pandemi dönemi olup olmadığına bakılmaksızın, kripto pazarındaki fiyat ve hacim dinamikleri arasında uzun vadeli ve uzun vadeli ilişkilere dair güçlü kanıtlar buldu. Bu çalışmanın bulguları, kripto piyasası tüccarları, yatırımcıları ve portföy yöneticileri için herhangi bir yatırım kararı vermeden önce, diğer altcoinlerin fiyatlarını ve hacimlerini büyük ölçüde etkilediğinden, Bitcoin'in fiyat dinamiklerini ve işlem hacimlerini dikkate almanın kritik olduğunu ima ediyor.

Anahtar Kelimeler: Kripto para birimleri, Johansen Eşbütünleşme, VECM, COVID-19



ABSTRACT

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The emergence of cryptocurrencies as an alternative source of currency has been dubbed as one of the greatest phenomenon of the 21st century. Over the years, cryptocurrencies have grossly interrupted the traditional financial system and continues to act as a catalyst for its revolution. However, the cryptocurrencies has not been free from misery and controversies. This study aims to explore and investigate one of such misteries. The main focus of this study is to explore and investigate empirically the impact of COVID-19 pandemic on the price and volume dynamics in the crypto markets. The study make use of two data samples but these samples are analysed seperately and independently. The first sample consist of Top Five Cryptocurrencies in terms of market capitalization (BITCOIN, ETHEREUM, XRP, BINANCE COIN and LITECOIN) as at 7 November 2020. The second one is made up of the Bottom Five Cryptocurrencies among the top 40 cryptocurrencies (FTX TOKEN, HUOBI TOKEN, FILECOIN, DASH and DECREED) as at 7 November 2020 again. The data among the Top Five Cryptocurrencies ranges from 2014 to 2021 and the data among the Bottom Five Cryptocurrencies ranges from 2018 to 2021. All the cryptocurrencies in both samples are integrated at order 1 i.e. $I(1)$. Johansen Cointegration Test and Vector Error Correction model are the main statistical method adopted by the study. The study has found strong evidence of intra and inter long run relationships among the price and volume dynamics within the crypto market irrespective of whether it is pre-pandemic or pandemic period. The findings of this

study imply that it is critical for crypto market traders, investors and portfolio managers, before making any investment decision must consider the dynamics of the price and trading volumes of BITCOIN as they hugely impact the prices and volumes of other altcoins.

Keywords: Cryptocurrencies, Johansen Cointegration, VECM, COVID-19



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William Bwando

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LIST OF SYMBOLS AND ABBREVIATIONS

ADF	Augmented Dickey-Fuller
COVID	Coronavirus Disease
ECM	Error Correction Model
ERS	Elliot, Rothenberg and Stock
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
KPSS	Kwiatkowski-Phillips-Schmidt-Shin
VAR	Vector Autoregression
VECM	Vector Error Correction Model



CHAPTER I

INTRODUCTION

If one goes down memory lane, we can think of a time when in order to meet their imminent daily needs and wants humanity had been subjected to trading with one another. Trading has been a tradition that dates back to the time of creation of humankind as trading was and continues to be a survival strategy. Down the centuries, trade has taken many forms and shapes and it continues to evolve as time progresses. The history of trade has evolved from bartering to the use of commodity money to the adoption of fiat (paper) money and now into digital currencies over the past 10,000 years.

The first form of trade was bartering. This is believed to have been practiced around 9000BC and it involved the direct exchange of goods and services between two or more parties without the use of other mediums of exchange such as money. This means of exchange to some extent played a pivotal role in facilitating trade at the time only for its success to be undermined by some of its limitations such as the double coincident of wants. This concept asserts that for bartering to take place, both parties the seller and buyers have to agree and show a willingness to sell and buy each other's commodities. This made trading very slow, inefficient and in some instances insurmountable.

After this, some other forms of medium of exchange were adopted. This includes the commodity money, which gained traction during the Bronze Age of 3000BC. Commodity money was comprised of valuable objects such as salt, cowry gold, silver, bronze, shells, cattle and others which were widely accepted as currency. As a result of direct response to the limitations of commodity currency, other forms of currency followed such as paper money, which is believed to have been first established in 700BC by Tang Dynasty in China. The efficiency and effectiveness of using paper money was spread around the world, especially by explorers and trader, and other communities adopted their own form of paper money. Subsequently, over the years

other forms of paper money were also established and one of the most common among them was the Gold Standard system from 1933 to 1971.

The Gold Standard system in its early years was phenomenal in engendering long term price stability and as well easing international trade by providing a platform for trading using a fixed exchange. This system like the other systems before it had its own problems. One of such problems was the unequal distribution of gold deposits across different country. Countries with large untapped gold deposits such as United States of America, Australia, South Africa and Russia were at an advantage compared to other countries. After being confronted with a number of problems and controversies the Gold Standard system was finally abolished in 1971. This opened a new chapter for currencies as the currency evolution continued.

The evolution of currencies continues up to date and has given birth to one of the most phenomenal developments of the 21st century which is the establishment of virtual currencies. These are digital currencies in electronic form that can be stored and transacted through a dedicated software or electronic platforms e.g. mobile phones, computer applications or designated electronic wallets. The transaction involving digital currencies is internet based through secured dedicated networks and as well as in privacy.

The popularity of virtual currencies have accelerated the acceptance and recognition of cryptocurrencies as a safe and credible form of currency that enjoys the same functions as that of traditional currencies. A cryptocurrency is a form of virtual and digital currency that can be accepted as a means of exchange or as a store of value. Magro, (2016), described cryptocurrencies as a peer-to-peer encrypted network that facilitates virtual barter. Throughout the years cryptocurrencies have evolved in their functionality from just been a peer to peer payment system into investment instruments, store of value asset as well as hedging options for both prospective and adept investors. The growth of cryptocurrency markets have been exponential and unprecedented. Currently, there are over 5000 cyptocurrencies serving different purposes (protocols) and the number is expected to raise.

However, the cryptocurrency market has not been free from misery and controversies. The volatility clustering within the cryptocurrency market is unparralled to any other commodity market. The market capitalisation of most of the top cryptocurrencies has

been soaring and this means simultaneously both the price and traded volumes of these currencies has been ascending. This has been the nature of most of these cryptocurrencies since the time they gained traction. Nevertheless, WHO declared COVID-19 as a global pandemic on 11 March , 2020 and like any other commodity markets the crypto market has its own reaction to the external economic shock induced by this pandemic. This has resulted in the change in behaviour of the price and volume relationship in many commodity markets including within the cryptocurrency market.

1.1 What are Cryptocurrencies?

A cryptocurrency is a form of virtual and digital currency that can be accepted as a means of exchange or as a store of value. The currency is secured by cryptographic technology which verify transactions as well as controlling the creation of new units of cryptocurrency. Magro (2016), described crypto-currencies as an encrypted, peer-to-peer network for facilitating digital barter. Unlike other forms of digital currency this makes it nearly impossible to counterfeit or to face the problem of double spending when transacting using cryptocurrency.

Most cryptocurrencies are blockchain technology based. This is a decentralized network that is spread across many nodes (computers) within the network that manages and records the transactions like a ledger. This is the reason blockchain is referred to as a distributed or public ledger. As to date there are more than five thousand different type of cryptocurrencies. Each cryptocurrency has a special function, mechanism and protocol that makes it different from the other. According to CoinMarketCap the total value of all cryptocurrencies as of November 2020 was more than \$370 billion. Bitcoin is still dominating with 62% of the total market share and a total value of \$270 billion.

1.2 History of Cryptocurrencies

The technical foundations of cryptocurrency dates back as early as 1980s. This was when American cryptographer named David Chaum released an article titled “Untraceable Electronic Mail, Return Addresses and Digital Pseudonyms”. In his article he introduced a blinding algorithm that can be used for information encryption. The algorithm was for securing information between parties involved in the mail. He also described a way to use public cryptography to hide the participants and the contents of

an electronic mail communication. This development laid the groundwork for future electronic currency transfers.

Ever since the emergence of internet there were some attempts to introduce a currency native to the internet. A number of entrepreneurs attempted to create digital platforms for exchanging currency during the 90s technology boom, this involved systems like Beenz, DigiCash, Flooz and PayPal being introduced to the market. However, most of these systems of digital currency failed to make it through due to a number of challenges and hindrances such as fraud, financial problems, legal disputes and even disagreements between companies' employees and their employers.

These systems of digital currency had their own problems. One such problem was the double spending problem. Digital currency users might try to buy two goods using the same unit of digital currency thereby double spending the units which they own. This problem was solved by the concept of centralisation. In this concept a Trusted Third Party (usually financial intermediaries) were used to verify each transaction before approving and confirming it in order to avert the problem of double spending.

However, this centralisation concept also had its indigenous problems chiefly among them being the issue of how much you can trust the Trusted Third Party? Scammers and other stakeholders could target the central authority to corrupt and control it. Moreover, the Trusted Third Party because of the technology at the time delayed the verification of the transactions making the transactions to take many days before they can be approved. This slowing down process affected businesses. Moreover, because of the commission paid to the Trusted Third Party the transaction through the third party became more expensive to conduct.

Then, in the 2009, an pseudonymous programmer or a group of programmers under the name Satoshi Nakamoto solved the double spending problem in a different way than before. He introduced BITCOIN which he described as a peer-to-peer electronic cash system. This is a digital currency powered by a blockchain. This is a chain of blocks of transaction strung together in a digital ledger. This means that it doesn't need a Trusted Third Party to validate the transactions but the network does that itself. To achieve this momentous work, the blockchain uses a combination of cryptography, P2P networking and economic incentive. The success of Bitcoin has resulted in the creation of many altcoins (cryptocurrencies created after BITCOIN) some

following the BITCOIN protocols whilst other developing entirely different mechanisms from BITCOIN. Currently there are more than five thousand cryptocurrencies. Examples of some of them are BITCOIN, ETHEREUM, TETHER, XRP, BITCOIN CASH, BINANCE COIN, CHAINLINK and LITECOIN.

1.3 What is a Blockchain?

A blockchain is a distributed ledger or decentralised database. This is a ledger that continuously update and verify records of digital transactions. It is a once read only database with characters of immutability where records can not be edited, added or deleted. This means that the records cannot be changed or forged.

Blockchain is available to everyone within the network to access with much easy. In order to maintain the transactions' privacy, cryptography is used in recording the transactions making them pseudonymous. Blockchain technology helps in solving the double spending problem since everyone will have access to confirm the transactions as they happen. This confirmation through blockchain exhibits it as an alternative to trusted parties in verifying digital transactions. This is a technology that enables BITCOIN and other crypto currencies to operate. The relationship between BITCOIN and Blockchain has been compared to what the internet is to the email by many academicians such as Kolokotronis, Limniotis, Shiaeles, and Griffiths. Blockchain includes some of the following characteristics:

Decentralised- the network is spread across different nodes and there is no central authority that dictates the application of the network.

Transparency- the recorded transactions are accessible to everyone within the network through their public keys. As transactions happen everyone can access the updated information concurrently.

Immutability- this means that the transactions on the blockchain can never be edited, deleted, changed and forged.

1.4 Cryptocurrencies Under the Study

The study makes use of two data samples but these samples are analysed separately and independently. The first sample consist of the **Top Five Cryptocurrencies** in terms of market capitalization (BITCOIN, ETHEREUM, XRP, BINANCE COIN and

LITECOIN) as at 7 November 2020. The second one is made up of the **Bottom Five Cryptocurrencies** among the top 40 cryptocurrencies (FTX TOKEN, HUOBI TOKEN, FILECOIN, DASH and DECRED) again as at 7 November 2020. The main reason for using two data samples independently is to do a more robust analysis that provides the behavior patterns (dynamics) of cryptocurrencies that are within different levels (dominant and non-dominant) of the crypto markets.

The top five cryptocurrencies consist of more than 80% of the total market share in the crypto market. This means they dictate much of the behaviors of other cryptocurrencies (altcoins). They act as a microcosm of the crypto market and by including these currencies in the study it gives an idea of how the crypto markets as a whole reacts to external shocks. The bottom five cryptocurrencies gives an idea of how non influential or non-dominant cryptocurrencies react to external shocks in the cryptocurrency market. Studying both samples gives a better perspective and more information of the crypto market than focusing on only one sample. Below is some brief information of the Top Five Cryptocurrencies used in this study.

BITCOIN- Greenwood-Evans et al. (2016) defined BITCOIN as a cryptocurrency and a digital currency, native to the internet invented by an individual or a group of individuals under the alias Satoshi Nakamoto. Unlike physical transactions, digital transactions are prone to a double spending problem. Fraudulent users might attempt to buy more than one good with the same unit of digital currency. This makes digital transaction too reliant on financial institutions and other financial intermediaries as Trusted Third Parties. Their duty is to verify transactions and to ensure that there is no double spending of digital currency. The reliance on Trusted Third Parties means all the digital transactions have to go through these trusted parties before they are verified and approved makes these transaction painfully slow and expensive to conduct. Satoshi Nakamoto, (2009) proposed BITCOIN as an alternative which is not reliant on the trusted parties to verify and approve digital transactions. This is achieved through the use of blockchain mechanism which replaces the central authorities in verifying and approving digital transactions. This is a technology that has taken the world by storm and has earned over the years much following from different stakeholders.

ETHEREUM- This is a blockchain mechanism based digital currency that was developed on an open software platform that enables developers to build and deploy decentralised applications also known as Dapps. Just like BITCOIN, ETHEREUM

also depend on Blockchain technology in its operations. Its native currency is called Ether. It was created mainly to satisfy some of the limitations of BITCOIN. Greenwood-Evans et al., (2016), argued that ethereum was developed in order to tackle several limitations of the BITCOIN such as limited functions and its scripting language. To address this scenario, in 2013, a Russian-Canadian programmer at the time very active in the BITCOIN and the crypto community named Vitalik Buterin, released a white paper that changed the application of blockchain technology. Buterin, (2014) and his team developed ETHEREUM. Unlike BITCOIN, ETHEREUM enables smart contracts and Distributed Applications (DApps) to be built and run without any fraud, outside control or interference from a third party

RIPPLE- Ripple also known as Ripple Transaction Protocol or Ripple Protocol is a technology that acts as both a cryptocurrency and a digital payment network for mainly international financial transactions. It is a real time gross settlement system currency exchange and remittance network. The native currency of Ripple is called XRP and was released in the year 2012. This currency was co-founded by Chris Larsen and Jed McCaleb under the Ripple Labs (a blockchain business entity). It was initially meant to stand as an alternative to SWIFT and other legacy financial networks such as VISA, Paypal and Western Union

BINANCE COIN- This is an altcoin issued by the world biggest cryptocurrency exchange Binance and it trades with the BNB symbol. Binance coin was firstly made available to the public on 25th July 2017 after it was launched on the Ethereum blockchain as an ERC-20 token. According to some sources just getting listed on Binance Exchange can give a cryptocurrency a temporary boost of 80% in market value. This explains how this exchange market has much influence in the cryptocurrency ecosystem. The BINANCE COIN act as vehicle that fuels Binance exchange operations and its ecosystem. It supports multiple utilities on the Binance ecosystem which include paying trading fees, paying exchange fees and paying listing fees.

LITECOIN- This currency is one of the oldest cryptocurrencies and it was launched in 2011 shortly after the launch of BITCOIN in 2009. Like BITCOIN it is a peer to peer digital currency. The differences between LITECOIN and BITCOIN are relatively very small. They both rely on Blockchain technology and at the same time they both

use Proof of Work (PoW). Due to many similarities between the two, LITECOIN is often referred to as a silver to BITCOIN's gold. Their relationship resembles that of a silver and gold. LITECOIN being the silver and BITCOIN as the gold.

The **Bottom Five Cryptocurrencies** among the top 40 cryptocurrencies selected for the study are described in brief as below:

FTX TOKEN- This is the native cryptocurrency token of the crypto derivatives trading platform FTX. This trading platform was launched on 8 May 2019. FTX trading platform was launched by some of the largest crypto traders as a direct response to their frustrations over issues within most mainstream crypto exchanges. This includes issues such as clawback prevention and a centralized collateral pool.

HUOBI TOKEN- This is a token native to the cryptocurrency exchange HUOBI Global (Seychelles based but China founded) and is based on the ETHEREUM blockchain. It was first launched in January 2018. The HUOBI TOKEN fuels the operations of the Huobi exchange and its ecosystem.

FILECOIN- This project was launched in 2017 as a decentralized storage system whose main objective is to store people's important information. This is a product of Protocol Labs. It is regarded as both a cryptocurrency and a digital payment system. The protocol makes use of blockchain mechanism when registering new deals and transactions

DASH- This is a blockchain based cryptocurrency that offers peer to peer payment solutions. This currency was forked out of BITCOIN and LITECOIN in order to offer faster and cheaper transactions than both BITCOIN and LITECOIN. It was launched in January 2014 as XCOIN. Shortly afterwards it changed its name to DARKCOIN but later on rebranded in 2015 as DASH.

DECRED- This is also a blockchain based cryptocurrency launched in February 2016. Its protocol is made up of two consensus models that is Proof of Work (PoW) which has 60% share, Proof of Stake (PoS) which constitutes 30% shares and the remaining 10% share is used to fund the development of the protocol. DECRED protocol facilitates open governance, enhance community interactions as well as acting as an ideal platform for funding policies.

1.5 Objectives of the Study

The general scope of this study is to systematically investigate and explore the long and short run impact of COVID 19 pandemic on the crypto market's price and volume relationship dynamics. The study looks at the price and volume interactions of the cryptocurrencies before and during the COVID-19 pandemic. The research is serving and focusing on the following specific objectives:

- Determining the intra price-volume dynamics within a cryptocurrency e.g. within BITCOIN market pre-pandemic and during COVID pandemic period
- Determining the inter price-volume dynamics across cryptocurrency market before and during the Covid-19 pandemic.
- Investigating COVID 19 pandemic impact on the prices and trading volumes of cryptocurrencies.

The study is divided into five chapters and each chapter focuses on a certain aspect of the study. The first chapter is the introductory chapter that gives the background of the study. This is followed by the Literature Review which consist of the preliminary work done before on the subject of this research question. The third chapter explain the statistical methods used in the course of this study. The fourth chapter shows the results and the analysis of the results obtained from the study. The final chapter is the conclusion which summarizes and give brief information about all the stages that the study has undertaken as well as giving necessary recommendations needed.

CHAPTER II

LITERATURE REVIEW

Since their inception, cryptocurrency markets have managed to gain traction among both researchers and investors. The last decade has witnessed and continues to witness an unprecedented boom in the cryptocurrency landscape. This has made cryptocurrency market behaviors to be one of the topical issues on both economic and political fronts. As a result, this popularity has exacerbated much research in this field and more robust research are currently underway. Cryptocurrency markets unlike traditional markets are very dynamic in nature. Available literature attests to the significant research done before but however, more research is needed as the field remains underexplored. The general objective of this study lies in filling some of these literature gaps.

The popularity of cryptocurrencies has also drawn academic attention. Preliminary academic intervention on this subject mainly focused on expounding the whole concept, that is the mechanisms and protocols behind cryptocurrencies. Studies by Peters et al. (2015) ElBahrawy et al. (2017), Gandal et al. (2018), Farrell (2015) and Böhme et al. (2015) are some of the early studies that focused on giving an overview on the subject of cryptocurrencies especially BITCOIN, elucidating its mechanisms and components.

Subsequently, empirical studies regarding the cryptocurrency market have also been conducted over the years. Yi et al. (2018) explored the dynamic and static volatility changes among cryptocurrencies. Katsiampa (2019) examined the volatility dynamics of five major cryptocurrencies namely BITCOIN, LITECOIN, RIPPLE, ETHER and STELLA. Bouri et al. (2020) examined the time-varying measurement of volatility connectedness involving 15 cryptocurrencies. In another study, Conrad et al. (2018) extracted the long and short-term volatility components of cryptocurrencies using the GARCH-MIDAS model.

Supplementary empirical studies on the cryptocurrency market focused on the relations between cryptocurrencies and other assets such as Gold prices ,Oil prices and other Stock indexes. Okorie & Lin (2020) examined the volatility connectedness between crude oil and cryptocurrency prices. Owusu Junior et al. (2020) using returns series of gold and 8 cryptocurrencies explored and compared both their symmetric and asymmetric dependency structure. Kurka (2019), Chemkha et al. (2020), Andrada-Félix et al. (2020) and Baumöhl (2019) conducted different studies investigating the volatility connectedness between cryptocurrencies and major fiat currencies such as Euro, Japanese Yen and US Dollars.

2.1 Empirical Research on Price-Volume Relationship

Market equilibrium is when there is stability between market price and trading volumes . Price-volume dynamics represent the reactions and adjustments of market players in an event of an economic shock (positive or negative). The first studies about price-volume relations is traced back to Osborne (1959) when he attempted to model stock prices change as a diffusion process within variance dependent on a number of transactions (Karpoff, 1987).

Early empirical price-volume relations examinations were conducted by Granger and Morgensten (Karpoff, 1987). In the 1970s two stock market theoretical models for price-volume relationship interpretation were proposed. These two theories are the Sequential Information Arrival Model (Copeland, 1976) and the Mixture of Distributions Hypothesis (MDH) (Epps, 1978).

2.2 Sequential Information Arrival Model (Copeland, 1976)

This hypothesis was firstly propounded by Copeland, (1976) and was later developed by Jennings et. al. (1981) and then improved by Starks (1995). The sequential information arrival hypothesis assumes that new information is sequential in terms of buyers and sellers in the stock market.

The basis of this theory is that at the beginning the market buyers and sellers are at an equilibrium since they have the same set of market information and have the same market expectations and make their decisions based on that information. However, when new information emerges the dissemination of that information is in such a way that the market players (buyers and sellers) never receiver that information

simultaneously. The players that receives the information first will change its expectations in accordance to the new information received. Once this happens there is asymmetric information and no more equilibrium in the market. Equilibrium will be only achieved again when the new information finally reaches the other player. This sequency of receiving information determines the equilibrium of both price and volume in the market.

2.3 The Mixture of Distributions Hypothesis (MDH) (Epps, 1978).

This theory was developed as a result of works of different researches such as Clark (1973), Epps and Epps (1976), Harris (1986) and Anderson (1996). The mixture of distribution hypothesis (MDH) indicates the existence of a positive correlation between asset price and trading volume (Yamak, Yamak, & Samut, 2019).

Gallant, Rossi, and Tauchen (1992) cites by studying the joint dynamics of price and trading volumes more can be learned which can not be achieved by analyzing them in a univariate form. Karpoff (1987) gave the following as four main important factors of studying the price-volume relationship:

- it gives intuition of the financial market structure
- it is ideal for studies that involving price and volume data from which to draw inferences
- the relation is critical to the debate over empirical distribution of speculative prices
- price-volume relationship dynamics have remarkable implication for research into future markets

2.4 Empirical Research on the Price-Volume Relationship in the Cryptocurrency Market

The price-volume relationship in the cryptocurrency landscape has been a topic of discussion for some time. A plethora of empirical studies has been conducted over the years on this subject in order to determine the nature, direction, and dynamic nature of this relationship. Gemici and Polat (2019) examined the relationship between price and trading volume in the BITCOIN market using both symmetric and asymmetric causality tests as well as cointegration tests. Their study found that the BITCOIN price and volume are strongly cointegrated.

Sapuric et al. (2020) conducted a study investigating the relationship between BITCOIN returns, volatility, and volume by applying some asymmetric GARCH modeling techniques (EGARCH). Their results show the existence of a positive and significant relationship between BITCOIN volume and volatility. Yamak et al. (2019) explored the causal relationship between BITCOIN Price, volatility, and trading volume. Their study adopted the EGARCH model, the Toda-Yamamoto causality test, and the Granger causality test. According to the results from this study, there is a strong trading volume to the price volatility causal relationship.

Aalborg et al. (2019) applied Vector Autoregression (VAR) models when there were trying to found out what can explain the price, volatility and trading volume of BITCOIN. The study looks at the possible variables that can explain and predict the return, volatility and trading volume of BITCOIN. The results of the study show that trading volume can help in predicting volatility. However, both trade volume and volatility could not be established predictors of BITCOIN returns. Motivated by this study Balcilar et al. (2017) using BITCOIN, RIPPLE, ETHEREUM, LITECOIN, NEM, DASH, and STELLER empirically examined the predictability power trade volume, returns, and volatility in the cryptocurrency market. Their study used the Copula-quantile causality approach and the results show that trading volume causes extreme negative and positive returns of all cryptocurrencies under study.

Another strand of literature focused on the multifractal nature of the price-volume relationship. Ardalankia, Osoolian, Haven, and Jafari (2020) focused on scaling features of price–volume cross-correlation. Their study adopted the Multifractal Detrended Cross-correlation Analysis (MF-DXA) method. The results of this study imply that price and trading volume relationship to be multifractal. Stosic et al. (2019) examined the multifractal behavior of price and volume changes in the cryptocurrency market. The study was based on 50 cryptocurrencies and it employed the Multifractal detrended fluctuation analysis (MF-DFA). The results of this study indicate that price changes are more complex than volume changes.

In a similar fashion, Zhang et al. (2018) did a study on the Multifractal Detrended Cross-Correlation Analysis (MF-DCCA) of the BITCOIN markets return-volume. The results show that nonlinear dependency and multifractal cross-correlations in the return-volume relationship are found. Another study that looked at the multifractal nature of the price-volume relationship was conducted by Alaoui et al. (2019) in his

study about multifractal cross correlation of BITCOIN price–volume. The study also adopted the Multifractal Detrended Cross-Correlations Analysis (MF-DCCA). Results of their study show that changes in BITCOIN prices and changes in trading volume mutually interact in a nonlinear way and also multifractality was found to be present and significant.

Additionally, Yarovaya and Zięba (2020) explored the intraday volume-return nexus in cryptocurrency markets. In this study the 30 most traded cryptocurrencies from the April of 2013 to June 2019 were considered and the Granger causality test was employed. The study managed to identify significant bidirectional causalities between trading volume and returns at high-frequency intervals. However, those linkages were disappearing with increased frequencies of data. The findings confirm the leading position of the BITCOIN trading volume in the cryptocurrency price formation.

Despite the flourishing literature concerning the price-trade volume relationship in the cryptocurrency market, the dynamics of this relationship has been underexplored and remain scarcely examined. Like any commodity market, the cryptocurrency market also reacts to economic shocks. Covid-19 ignited economic shock that has some effects on the global economy and this study seeks to empirically explore and analyze the price-volume dynamics within the cryptocurrency market before and during the Covid-19 pandemic. This is the academic contribution from this study.

CHAPTER III

METHODOLOGY

The chapter above has shown that there has been no much preliminary substantive studies that seeks to explore the dynamic behavior of price-volume relations in the crypto markets. This section consist of the methodology that this study will adopt as it investigates, explores and detects the price-volume relationship dynamics in the crypto currency market.

3.1 Data Definitions and Source

The first thing in the construction of a model that help analyze the dynamics of price-volume relations is to decide which strategic variables to include in the model. The study adopts two categories of cryptocurrencies in order to have a more robust approach to the investigations of the price-volume relationship dynamics in the cryptocurrency market prior and during COVID-19 pandemic. The first category is made up to Five Top Cryptocurrencies in terms of market capitalization as at 7 November 2020. These currencies are BITCOIN, ETHEREUM, XRP, BINANCE COIN and LITECOIN. The second category consist of the Bottom Five Cryptocurrencies among the top 40 cryptocurrencies in accordance to their market capitalization as at 7 November 2020. These currencies are FTX TOKEN, HUOBI TOKEN, FILECOIN, DASH and DECRED.

The prices and volume of cryptocurrencies in both categories are extracted from <https://coinmarketcap.com/> . The data among the Top Five Cryptocurrencies ranges from 2014 to 2021 and the data among the Bottom Five cryptocurrencies ranges from 2018 to 2021. To avoid the problems of scale and for simplicity reasons the data is converted into natural logs.

Table 3.1: Cryptocurrencies Under Study

Top Five Currencies	Abbreviation	Bottom Five Currencies	Abbreviation
BITCOIN PRICE	lnbp	FTX TOKEN PRICE	lnftxp
BITCOIN VOLUME	lnbv	FTX TOKEN VOLUME	lnftxv
ETHEREUM PRICE	lnep	HUOBI TOKEN PRICE	lnhtp
ETHEREUM VOLUME	lnev	HUOBI TOKEN VOLUME	lnhtv
XRP PRICE	lnxp	FILECOIN PRICE	lnfcp
XRP VOLUME	lnxv	FILECOIN VOLUME	lnfcv
BINANCE COIN PRICE	lnbnp	DASH PRICE	ln dp
BINANCE COIN VOLUME	lnbnv	DASH VOLUME	ln dv
LITECOIN PRICE	lnlp	DECRED PRICE	ln drp
LITECOIN VOLUME	lnlv	DECRED VOLUME	ln drv

3.2 Descriptive Statistics

After obtaining the data the next step is to apply the descriptive analysis on the price and volume values of the cryptocurrencies in question. Descriptive analyses is important for a number of purposes. It summarize the characteristics of a data sample. It is useful for giving a brief information about the relations and interactions within a data sample. More so, it can be used for data cleaning before the main data analysis. Before further analysis various data errors can be identified using descriptive statistic tools. There are two kinds of descriptive analysis. These are measure of central tendency and measure of dispersion or variation. The measure of central tendency consists of statistical parameters such as the mean, median and mode whereas the measure of dispersion is made up of statistical parameters such inter-quarter range and standard deviation.

3.3 Test for Stationarity

Unit root tests test is used to determine whether a time series data is non-stationary in nature and possess a unit root. It test whether the mean and variance changes over time in a time series data. This is very important in preventing spurious regression that results from the use of non-stationary data. A stationary series is a series that comprise of constant mean, constant variance and constant auto-covariance. In order to come up with more robust results and to see whether they do not conform or support each other's results, this study adopts three different approaches of testing for stationarity. These approaches are Augmented Dickey-Fuller (ADF,1979), Kwiatkowski, Phillips, Schmidt, and Shin, (KPSS, 1992) and Elliott, Rothenberg, and Stock, (ERS, 1996)

3.3.1 Augmented Dickey-Fuller (ADF,1979)

This was developed by Dickey-Fuller (1979) and is one the pioneering work in the field of detecting and investigating the unit root presence in the time series data. The Augmented Dickey-Fuller (ADF) test null hypothesis states that the time series has unit root whereas the alternative hypothesis say that the time series data is stationary. It has three versions which are as follows:

- Unit Root Test (None)

$$\Delta y_t = \varphi^* y_{t-1} + \sum_{i=1}^{p-1} \varphi^i y_{t-1} + \mu_t$$

The ADF test statistic is calculated by subtracting y_{t-1} from both sides of the equations as demonstrated below:

$$y_t - y_{t-1} = \phi_1 y_{t-1} - y_{t-1} + \varepsilon_t$$

$$\Delta y_t = (\phi_t - 1) y_{t-1} + \varepsilon_t$$

Let $\delta = \phi_1 - 1$. and the test statistic can be defined as:

$$t_{DF} \frac{\widehat{\phi}_1 - 1}{se_{\widehat{\phi}_1}}$$

Where $se_{\hat{\phi}_1}$ represents the standard error estimate, $se_{\hat{\phi}_1}$ is the OLS estimate of ϕ_t . This test statistic follows a Dickey-Fuller distribution under the null hypothesis and the critical values are obtained by simulation, as shown in D. Dickey (1976) and Fuller (1976).

- Unit Root Test with Constant

$$\Delta y_t = \beta_0 + \varphi^* y_{t-1} + \sum_{i=1}^{p-1} \varphi^i y_{t-1} + \mu_t$$

- Unit Root Test with Constant and Deterministic trend

$$\Delta y_t = \beta_0 + \beta_1 t + \varphi^* y_{t-1} + \sum_{i=1}^{p-1} \varphi^i y_{t-1} + \mu_t$$

Where y_t denotes the variable's value at the time period t , β_0 is a constant term, $\beta_1 t$ is the deterministic trend and μ_t is the error term.

The null hypothesis that is to be examined is as follows:

$$H_0 : \varphi^* = 0 \rightarrow \text{series has a Unit Root}$$

$$H_1 : \varphi^* < 0 \rightarrow \text{series is Stationary}$$

3.3.2 Elliot, Rothenberg and Stock Point Optimal (ERS, 1996)

The ERS test is based on trending data before establishing the test equation, and it is suggested to be superior to other tests, especially if the time series have unknown mean and linear trend. This test was proposed by Elliot, Rothenberg, and Stock (1996). It is regarded as a modified version of the ADF tests and its purpose is to increase the power of these tests. The null hypothesis of this test is states that the time series has unit root whereas the alternative hypothesis is that the time series data is stationary.

The Elliot, Rothenberg and Stock (ERS) Point Optimal test is derived from the quasi-differencing regression as defined below.

$$d\left(\frac{y_t}{\alpha}\right) = d\left(\frac{x_t}{\alpha}\right)' \delta(\alpha) + \varepsilon_t$$

Where $d\left(\frac{y_t}{\alpha}\right)$ and $d\left(\frac{x_t}{\alpha}\right)$ are quasi-differenced data for y_t and x_t respectively $\delta(\alpha)$ denotes the OLS estimation of this regression and ε_t has an independent and identically distributed (iid).

The test statistic for ERS test is

$$Pt = \frac{SSR(\bar{\alpha}) - \bar{\alpha}(SSR)(1)}{f_0}$$

Where $SSR(a)$ is the sum of squared residuals function, where f_0 is an estimator of the residual spectrum frequency zero

The null hypothesis of the ERS point optimal test is:

$H_0 : \alpha = 1$ *The null hypothesis*

$H_1 : \alpha = \bar{\alpha}$ *The alternative hypothesis*

3.3.3 Kwiatkowski, Phillips, Schmidt, and Shin (KPSS, 1992)

This approach was developed by Kwiatkowski, Phillips, Schmidt and Shin, (1992) . It is an alternative for test for stationarity and its null hypothesis is that the time series is stationary whereas its alternative hypothesis is that the time series is not stationary. This technique is based on the notion that the stationarity of the time series occurs around a deterministic trend and is calculated as the sum of a random walk, deterministic trend and stationary random error or white noise

This test follows a Lagrange multiplier test. Its test statistic is calculated firstly by regressing the depended variable y_t on either constant or constant and time trend t depending with the specifications used in the test. The model is as follows:

$$y_t = d_t + r_t + \varepsilon_t,$$

$$r_t = r_{t-1} + u_t,$$

Where $d_t = \sum_{i=0}^p \delta_i t^i$, for $p = 0,1$, contains within it the deterministic parts of the above equations (trend and constant), ε_t are iid $N(0, \sigma_\varepsilon^2)$, r_t is a random walk having a variance σ_u^2 and u_t are iid $N(0, \sigma_u^2)$.

Moreover, KPSS relies on Lagrange Multiplier (LM) test with a null hypothesis that, the random walk has a variance of zero; $H_0: \sigma_u^2 = 0$, meaning that, r_t is constant, against the alternative; $H_1: \sigma_u^2 > 0$.

The KPSS LM statistic is given as follows:

$$KPSS LM = \sum_{t=1}^T \frac{se_t^2}{\widehat{\sigma_t^2}}$$

Where $se_t = \sum_{t=1}^T \widehat{\varepsilon}_t$, $t = 1, 2, \dots, T$ and $\widehat{\sigma_t^2}$ is the variance estimate of residual process ε_t from the initial equation. The critical values for the test were derived via simulation process.

3.4 Test for Cointegration

The unit root tests are used to determine if the time series data are stationary or not. If time series time variables are found to be non-stationary at their level, it means they are integrated (of order one) and their first differences are stationary. Granger, (1980) cited that if these variables are integrated, this means there exist a stable long run relationship among them. For instance, if BITCOIN price is cointegrated with BITCOIN volume then any increase in BITCOIN price will have empirical impact on BITCOIN trade volumes. This study follows the Johansen co-integration as the test for cointegration among the cryptocurrencies in the study

3.5 Johansen Cointegration Test

The Johansen co-integration test is used to test the co-integration between the variables in a model. It was developed to be and is considered as an improvement over the Engle-Granger test. Granger, (1980) suggested that a test for cointegration is a pre-test to avoid situations of spurious regression. Engle and Granger (1987) assert that it may not be easy to determine whether a set of variables are cointegrated or not before estimating a multivariate dynamic model such as a Johansen Cointegration Test.

Unlike two-step Engle-Granger, Johansen Cointegration has the capacity for testing for cointegration of two or more time series. Johansen test has also an advantage in that it considers all the time series in the model as endogenous, unlike other techniques available in the literature which only treats one time series as endogenous variable and considers the rest as exogenous variables. This means Johansen cointegration approach

allows two or more cointegrating relationships to co-exist. This test is a derivation or is performed using an estimated VAR object.

Consider VAR of order k :

$$y_t = \beta_1 y_{t-1} + \beta_2 y_{t-2} + \dots + \beta_k y_{t-k} + \mu_t$$

Where y_t is a k -vector of non-stationary I(1) variables, β_k is the coefficient matrices of each lag and μ_t is the white noise disturbance term. By adding the error correcting components the above equation is converted into Vector Error Correction Model (VECM) as follows:

$$\Delta y_t = \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \dots + \Gamma_{k-1} \Delta y_{t-(k-1)} + \mu_t$$

Where $\Delta y_t = y_t - y_{t-1}$ is the differencing equation, k is the number of lags and the two matrices $\Pi = (\sum_{i=1}^k B_i) - I_g$ and $\Gamma_i = (\sum_{j=1}^i B_j) - I_g$. Where Π represents the long run coefficient matrices, Γ_i constitute of short term dynamics and " g " denotes the number of variables in the model.

This study adopts the 3rd specification of the Johansen Cointegration Test which is more theoretically plausible and it is formulated as follows:

$$H_1(r): \Pi y_{t-1} + Bx_t = \alpha(\beta' y_{t-1} + \rho_0) + \alpha_1 \gamma_0$$

Where terms associated with α_1 are the deterministic terms outside the cointegrating relations, γ_0 are also deterministic terms within the cointegration relations and $\alpha(\beta' y_{t-1} + \rho_0)$ is the cointegrating equation

Johansen and Juselius, (1990) forwarded the trace test and the maximum eigenvalue statistics in making the inference of the number of cointegrating vectors. However in this study I am using the trace test as it is more powerful than maximum eigenvalue test as cited by Lutkepohl, Saikonnen, Trenkler, (2000). The trace test is formulated as:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^n \ln(1 - \lambda_i)$$

Where T is the sample size, r is the number of cointegrating vectors and λ is the eigenvalues. The sequentially tested set of Johansen null and alternative hypotheses are as follows:

$$H_0: r = 0 \text{ versus } H_1: 0 < r \leq g$$

$$H_0: r = 1 \text{ versus } H_1: 1 < r \leq g$$

$$H_0: r = 2 \text{ versus } H_1: 2 < r \leq g$$

$$H_0: r = g - 1 \text{ versus } H_1: r = g$$

Where r denotes the number of cointegrating vectors under the relevant null hypothesis. However, if the first null hypothesis is rejected such as $H_0: r=1$ and the second $H_0: r = 1$ cannot be rejected then we can conclude that there is one cointegrating vector. The same goes for more than one cointegrating vectors.

3.6 Vector Error Correction Model (VECM)

If cointegration between time series variable has been established by the Johansen Cointegration Test as above, the next step is to model a Vector Error Correction Model (VECM). This is a restricted VAR that is designed for use with cointegrated non stationary data. The Vector error-correction model is useful for distinguishing the short-run and long-run relationship and interactions between two or more variables. Granger, (1980) insinuated that if cointegration exist between two or more variables, then a valid error correction model should also exist between those variables. In order for VECM to be formed there is need to first have evidence of cointegration among the variables involved in a model.

The basic Error Correction Model (ECM) is defined as:

$$\Delta y_t = \alpha \varepsilon_{t-1} + \gamma \Delta x_t + \mu_t$$

Where μ_t is an independent and identically distributed (iid) and the first difference of y_t can be explained by the lagged ε_{t-1} and Δx_t

This basic Error Correction Model (ECM) can be expanded after adding the error correcting components as follows into a Vector Error Correction Model (VECM).

$$\Delta y_t = \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \Gamma_{k-1} \Delta y_{t-(k-1)} + \mu_t$$

Where $\Delta y_t = y_t - y_{t-1}$ is the differencing equation, k is the number of lags and the two matrices $\Pi = (\sum_{i=1}^k B_i) - I_g$ and $\Gamma_i = (\sum_{j=1}^i B_j) - I_g$. Where Π represents the long run coefficient matrices, Γ_i constitute of short term dynamics and " g " denotes the number of variables in the model.

3.7 Impact of COVID 19 Pandemic

This study seeks to capture the effect of COVID 19 pandemic on the price and trading volume relationships within the cryptocurrency market. In this study, I make use of two types of models. The first model looks how the price and volume dynamics are if COVID 19 pandemic is not considered whereas the second model tries to detect the price and trade volume dynamics when COVID 19 pandemic is taken into account.

In order to capture the impact of COVID 19 pandemic on the dynamics of the price volume relations, COVID dummy variable is added to the second model (where COVID 19 is considered) as an exogenous variable. This helps in establishing and detecting the effects of COVID 19 pandemic. Gallant, Rossi, & Tauchen (1992) cites by studying the joint dynamics of price and trading volumes more can be learned which can not be achieved by analyzing them in a univariate form. The importance of this study is that it is essential for understanding the cryptocurrency markets and more so it helps in preparing for future economic shocks with the same impact as that of COVID 19 pandemic.

For the purpose of this study the Vector Error Correction Models (VECM) are extended to the following equations:

VECM for top 5 without COVID 19 pandemic

$$\begin{aligned} \Delta \ln bp = & \alpha_0 + \alpha_1 \Delta \ln ep_{t-1} + \alpha_2 \Delta \ln xp_{t-1} + \alpha_3 \Delta \ln bnp_{t-1} + \alpha_4 \Delta \ln lp_{t-1} + \alpha_5 \Delta \ln bv_{t-1} \\ & + \alpha_6 \Delta \ln ev_{t-1} + \alpha_7 \Delta \ln xv_{t-1} + \alpha_8 \Delta \ln bnv_{t-1} + \alpha_9 \Delta \ln lv_{t-1} + \alpha_{10} ECT_{t-1} \\ & + \mu_{t1} \end{aligned}$$

$$\begin{aligned}\Delta \ln ep &= \beta_0 + \beta_1 \Delta \ln bp_{t-1} + \beta_2 \Delta \ln xp_{t-1} + \beta_3 \Delta \ln bnp_{t-1} + \beta_4 \Delta \ln lp_{t-1} + \beta_5 \Delta \ln bv_{t-1} \\ &\quad + \beta_6 \Delta \ln ev_{t-1} + \beta_7 \Delta \ln xv_{t-1} + \beta_8 \Delta \ln bnv_{t-1} + \beta_9 \Delta \ln lv_{t-1} + \beta_{10} ECT_{t-1} \\ &\quad + \mu_{t2}\end{aligned}$$

$$\begin{aligned}\Delta \ln xp &= \gamma_0 + \gamma_1 \Delta \ln bp_{t-1} + \gamma_2 \Delta \ln ep_{t-1} + \gamma_3 \Delta \ln bnp_{t-1} + \gamma_4 \Delta \ln lp_{t-1} + \gamma_5 \Delta \ln bv_{t-1} \\ &\quad + \gamma_6 \Delta \ln ev_{t-1} + \gamma_7 \Delta \ln xv_{t-1} + \gamma_8 \Delta \ln bnv_{t-1} + \gamma_9 \Delta \ln lv_{t-1} + \gamma_{10} ECT_{t-1} \\ &\quad + \mu_{t3}\end{aligned}$$

$$\begin{aligned}\Delta \ln bnp &= \delta_0 + \delta_1 \Delta \ln bp_{t-1} + \delta_2 \Delta \ln ep_{t-1} + \delta_3 \Delta \ln xp_{t-1} + \delta_4 \Delta \ln lp_{t-1} + \delta_5 \Delta \ln bv_{t-1} \\ &\quad + \delta_6 \Delta \ln ev_{t-1} + \delta_7 \Delta \ln xv_{t-1} + \delta_8 \Delta \ln bnv_{t-1} + \delta_9 \Delta \ln lv_{t-1} + \delta_{10} ECT_{t-1} \\ &\quad + \mu_{t4}\end{aligned}$$

$$\begin{aligned}\Delta \ln lp &= \varphi_0 + \varphi_1 \Delta \ln bp_{t-1} + \varphi_2 \Delta \ln ep_{t-1} + \varphi_3 \Delta \ln xp_{t-1} + \varphi_4 \Delta \ln bnp_{t-1} + \varphi_5 \Delta \ln bv_{t-1} \\ &\quad + \varphi_6 \Delta \ln ev_{t-1} + \varphi_7 \Delta \ln xv_{t-1} + \varphi_8 \Delta \ln bnv_{t-1} + \varphi_9 \Delta \ln lv_{t-1} + \varphi_{10} ECT_{t-1} \\ &\quad + \mu_{t5}\end{aligned}$$

VECM for top 5 with COVID 19 pandemic

$$\begin{aligned}\Delta \ln bp &= \alpha_0 + \alpha_1 \Delta \ln ep_{t-1} + \alpha_2 \Delta \ln xp_{t-1} + \alpha_3 \Delta \ln bnp_{t-1} + \alpha_4 \Delta \ln lp_{t-1} + \alpha_5 \Delta \ln bv_{t-1} \\ &\quad + \alpha_6 \Delta \ln ev_{t-1} + \alpha_7 \Delta \ln xv_{t-1} + \alpha_8 \Delta \ln bnv_{t-1} + \alpha_9 \Delta \ln lv_{t-1} + \alpha_{10} ECT_{t-1} \\ &\quad + \theta_1 COVID_t + \mu_{t1}\end{aligned}$$

$$\begin{aligned}\Delta \ln ep &= \beta_0 + \beta_1 \Delta \ln bp_{t-1} + \beta_2 \Delta \ln xp_{t-1} + \beta_3 \Delta \ln bnp_{t-1} + \beta_4 \Delta \ln lp_{t-1} + \beta_5 \Delta \ln bv_{t-1} \\ &\quad + \beta_6 \Delta \ln ev_{t-1} + \beta_7 \Delta \ln xv_{t-1} + \beta_8 \Delta \ln bnv_{t-1} + \beta_9 \Delta \ln lv_{t-1} + \beta_{10} ECT_{t-1} \\ &\quad + \theta_2 COVID_t + \mu_{t2}\end{aligned}$$

$$\begin{aligned}\Delta \ln xp &= \gamma_0 + \gamma_1 \Delta \ln bp_{t-1} + \gamma_2 \Delta \ln ep_{t-1} + \gamma_3 \Delta \ln bnp_{t-1} + \gamma_4 \Delta \ln lp_{t-1} + \gamma_5 \Delta \ln bv_{t-1} \\ &\quad + \gamma_6 \Delta \ln ev_{t-1} + \gamma_7 \Delta \ln xv_{t-1} + \gamma_8 \Delta \ln bnv_{t-1} + \gamma_9 \Delta \ln lv_{t-1} + \gamma_{10} ECT_{t-1} \\ &\quad + \theta_3 COVID_t + \mu_{t3}\end{aligned}$$

$$\begin{aligned}\Delta \ln bnp &= \delta_0 + \delta_1 \Delta \ln bp_{t-1} + \delta_2 \Delta \ln ep_{t-1} + \delta_3 \Delta \ln xp_{t-1} + \delta_4 \Delta \ln lp_{t-1} + \delta_5 \Delta \ln bv_{t-1} \\ &\quad + \delta_6 \Delta \ln ev_{t-1} + \delta_7 \Delta \ln xv_{t-1} + \delta_8 \Delta \ln bnv_{t-1} + \delta_9 \Delta \ln lv_{t-1} + \delta_{10} ECT_{t-1} \\ &\quad + \theta_4 COVID_t + \mu_{t4}\end{aligned}$$

$$\begin{aligned}\Delta \ln lp &= \varphi_0 + \varphi_1 \Delta \ln bp_{t-1} + \varphi_2 \Delta \ln ep_{t-1} + \varphi_3 \Delta \ln xp_{t-1} + \varphi_4 \Delta \ln bnp_{t-1} + \varphi_5 \Delta \ln bv_{t-1} \\ &\quad + \varphi_6 \Delta \ln ev_{t-1} + \varphi_7 \Delta \ln xv_{t-1} + \varphi_8 \Delta \ln bnv_{t-1} + \varphi_9 \Delta \ln lv_{t-1} + \varphi_{10} ECT_{t-1} \\ &\quad + \theta_5 COVID_t + \mu_{t5}\end{aligned}$$

Where $\ln bp$ and $\ln bv$ are the natural logs of BITCOIN price and volume respectively, $\ln ep$ and $\ln ev$ are the natural logs of ETHEREUM price and volume, $\ln xp$ and $\ln xv$ are the natural logs of XRP price and volume, $\ln bnp$ and $\ln bnv$ are the natural logs of BINANCE COIN price and volume, and $\ln lp$ and $\ln lv$ are the natural logs of LITECOIN price and volume. $COVID$ represents the time period during the COVID

19 pandemic, ECT is the error correctional term and μ_t is the white noise disturbance term.

VECM for bottom 5 without COVID 19 pandemic

$$\begin{aligned}
\Delta lnftxp &= \alpha_0 + \alpha_1 \Delta lnhtp_{t-1} + \alpha_2 \Delta lnfcpt_{-1} + \alpha_3 \Delta lndp_{t-1} + \alpha_4 \Delta lndrp_{t-1} \\
&\quad + \alpha_5 \Delta lnftxv_{t-1} + \alpha_6 \Delta lnhtv_{t-1} + \alpha_7 \Delta lnfcv_{t-1} + \alpha_8 \Delta lndv_{t-1} \\
&\quad + \alpha_9 \Delta lndrv_{t-1} + \alpha_{10} ECT_{t-1} + \mu_{t1} \\
\Delta lnhtp &= \beta_0 + \beta_1 \Delta lnftxp_{t-1} + \beta_2 \Delta lnfcpt_{-1} + \beta_3 \Delta lndp_{t-1} + \beta_4 \Delta lndrp_{t-1} \\
&\quad + \beta_5 \Delta lnftxv_{t-1} + \beta_6 \Delta lnhtv_{t-1} + \beta_7 \Delta lnfcv_{t-1} + \beta_8 \Delta lndv_{t-1} \\
&\quad + \beta_9 \Delta lndrv_{t-1} + \beta_{10} ECT_{t-1} + \mu_{t2} \\
\Delta lnfcpt &= \gamma_0 + \gamma_1 \Delta lnftxp_{t-1} + \gamma_2 \Delta lnhtp_{t-1} + \gamma_3 \Delta lndp_{t-1} + \gamma_4 \Delta lndrv_{t-1} \\
&\quad + \gamma_5 \Delta lnftxv_{t-1} + \gamma_6 \Delta lnhtv_{t-1} + \gamma_7 \Delta lnfcv_{t-1} + \gamma_8 \Delta lndv_{t-1} \\
&\quad + \gamma_9 \Delta lndrv_{t-1} + \gamma_{10} ECT_{t-1} + \mu_{t3} \\
\Delta lndp &= \delta_0 + \delta_1 \Delta lnftxp_{t-1} + \delta_2 \Delta lnhtp_{t-1} + \delta_3 \Delta lnfcpt_{-1} + \delta_4 \Delta lndrp_{t-1} \\
&\quad + \delta_5 \Delta lnftxv_{t-1} + \delta_6 \Delta lnhtv_{t-1} + \delta_7 \Delta lnfcv_{t-1} + \delta_8 \Delta lndv_{t-1} \\
&\quad + \delta_9 \Delta lndrv_{t-1} + \delta_{10} ECT_{t-1} + \mu_{t4} \\
\Delta lndrp &= \varphi_0 + \varphi_1 \Delta lnftxp_{t-1} + \varphi_2 \Delta lnhtp_{t-1} + \varphi_3 \Delta lnfcpt_{-1} + \varphi_4 \Delta lndp_{t-1} \\
&\quad + \varphi_5 \Delta lnftxv_{t-1} + \varphi_6 \Delta lnhtv_{t-1} + \varphi_7 \Delta lnfcv_{t-1} + \varphi_8 \Delta lndv_{t-1} \\
&\quad + \varphi_9 \Delta lndrv_{t-1} + \varphi_{10} ECT_{t-1} + \mu_{t5}
\end{aligned}$$

VECM for bottom 5 with COVID 19 pandemic

$$\begin{aligned}
\Delta lnftxp &= \beta_0 + \beta_1 \Delta lnhtp_{t-1} + \beta_2 \Delta lnfcpt_{-1} + \beta_3 \Delta lndp_{t-1} + \beta_4 \Delta lndrp_{t-1} \\
&\quad + \beta_5 \Delta lnftxv_{t-1} + \beta_6 \Delta lnhtv_{t-1} + \beta_7 \Delta lnfcv_{t-1} + \beta_8 \Delta lndv_{t-1} \\
&\quad + \beta_9 \Delta lndrv_{t-1} + \beta_{10} ECT_{t-1} + \theta_1 COVID + \mu_{t1} \\
\Delta lnhtp &= \beta_0 + \beta_1 \Delta lnftxp_{t-1} + \beta_2 \Delta lnfcpt_{-1} + \beta_3 \Delta lndp_{t-1} + \beta_4 \Delta lndrp_{t-1} \\
&\quad + \beta_5 \Delta lnftxv_{t-1} + \beta_6 \Delta lnhtv_{t-1} + \beta_7 \Delta lnfcv_{t-1} + \beta_8 \Delta lndv_{t-1} \\
&\quad + \beta_9 \Delta lndrv_{t-1} + \beta_{10} ECT_{t-1} + \theta_2 COVID + \mu_{t2} \\
\Delta lnfcpt &= \gamma_0 + \gamma_1 \Delta lnftxp_{t-1} + \gamma_2 \Delta lnhtp_{t-1} + \gamma_3 \Delta lndp_{t-1} + \gamma_4 \Delta lndrv_{t-1} \\
&\quad + \gamma_5 \Delta lnftxv_{t-1} + \gamma_6 \Delta lnhtv_{t-1} + \gamma_7 \Delta lnfcv_{t-1} + \gamma_8 \Delta lndv_{t-1} \\
&\quad + \gamma_9 \Delta lndrv_{t-1} + \gamma_{10} ECT_{t-1} + \theta_3 COVID + \mu_{t3} \\
\Delta lndp &= \delta_0 + \delta_1 \Delta lnftxp_{t-1} + \delta_2 \Delta lnhtp_{t-1} + \delta_3 \Delta lnfcpt_{-1} + \delta_4 \Delta lndrp_{t-1} \\
&\quad + \delta_5 \Delta lnftxv_{t-1} + \delta_6 \Delta lnhtv_{t-1} + \delta_7 \Delta lnfcv_{t-1} + \delta_8 \Delta lndv_{t-1} \\
&\quad + \delta_9 \Delta lndrv_{t-1} + \delta_{10} ECT_{t-1} + \theta_4 COVID + \mu_{t4}
\end{aligned}$$

$$\begin{aligned}\Delta \ln drp = & \varphi_0 + \varphi_1 \Delta \ln ftxp_{t-1} + \varphi_2 \Delta \ln ht p_{t-1} + \varphi_3 \Delta \ln fcp_{t-1} + \varphi_4 \Delta \ln dp_{t-1} \\ & + \varphi_5 \Delta \ln ftxv_{t-1} + \varphi_6 \Delta \ln ht v_{t-1} + \varphi_7 \Delta \ln fcv_{t-1} + \varphi_8 \Delta \ln dv_{t-1} \\ & + \varphi_9 \Delta \ln drv_{t-1} + \varphi_{10} ECT_{t-1} + \theta_5 COVID + \mu_{t5}\end{aligned}$$

Where $\ln ftxp$ and $\ln ftxv$ are the natural logs of FTX TOKEN price and volume respectively, $\ln ht p$ and $\ln ht v$ are the natural logs of HUOBI TOKEN price and volume, $\ln fcp$ and $\ln fcv$ are the natural logs of FILECOIN price and volume, $\ln dp$ and $\ln dv$ are the natural logs of DASH price and volume, and $\ln drp$ and $\ln drv$ are the natural logs of LITECOIN price and volume. $COVID$ represents the time period of COVID 19 pandemic, ECT is the error correctional term and μ_t is the white noise disturbance term

3.8 Variance Decomposition

These VECM models were introduced by Christopher A. Sims, (1980) and have been in use since among the economist and econometricians as an alternative to classical simultaneous equations. Sims, criticized the way classical simultaneous equations were specified and also questioned the exogeneity assumption that is commonly used in modeling simultaneous equations.

Variance decomposition analysis also known as forecast error variance decomposition is an important tools regarding the causal relationship of variables beyond the in-sample period. It forecast errors and relationships among variables. These models give the proportion of the movement of a variable due to the shock to itself and the shock to other variables. According to Bessler, (1985), variance decomposition can be termed as causality tests outside the estimation time period. The variance decompositions are obtained from the Moving Average (MA) model derived from an unrestricted VAR model.

VAR models bear the form:

$$y_t = A_1 y_{t-1} + \dots + A_p y_{t-p} + \mu_t$$

Where y_t denotes a $k * 1$ vector of endogenous variables that are non-stationary I(1), the A 's are $k * 1$ parameter matrices, p is the lag order and μ_t represents a $k * 1$ vector of white noise. In the VAR model above all variables are endogenous and it is difficult to disentangle the relations between the variables directly from the co-

efficient matrices. Therefore variance decomposition model are a special tool that helps solve this problem and also helps in the interpretation of VAR models.

In order to achieve that a h steps ahead forecast or briefly h -step forecast at origin t can be added to the VAR Model above. This convert VAR Model into an equation as demonstrated below

$$y_{t+h|t} = A_1 y_{t+h-1|t} + \dots + A_p y_{t+h-p|t}$$

Where $y_{t+j|t} = y_{t+j}$ for $j \leq 0$. Then forecast turns out to be :

$$y_{t+h} - y_{t+h|t} = \mu_{t+h} + \sum_{i=1}^{h-1} \Phi_i \mu_{t+h-i}$$

Here Φ_i' is the coefficient of the power series expansion

Variance decomposition helps in determining how much of variability in the dependent variable is lagged by its own variance. Additionally, it also shows which independent variables is stronger in explaining the variability in the dependent variables over time.

CHAPTER IV

RESULTS AND DISCUSSION

The previous chapter looked at the statistical methods undertaken in this study in order to establish the price and volume relationship dynamics in the cryptocurrency market. This chapter consist of the results those statistical analysis. It consist firstly of descriptive statistics analysis, which is then followed by unit root test results, Cointegration test results, the results of the Vector Error Correctional (VECM) and finally the variance decomposition.

4.1 Descriptive Statistics

This section consists of the descriptive statistics of the data set of the prices and volumes of the cryptocurrencies that are under study in this research. Descriptive statistics give brief information about the data at hand and at times helps in data cleaning. According to the descriptive statistics Table 4.1 below BITCOIN price and volume have the highest mean among the price and volume variables respectively. Moreover, BITCOIN price has the highest maximum price than the prices of other cryptocurrencies whereas XRP price has the minimum price. Among the volumes BITCOIN volume has the highest maximum volume and BINANCE COIN has the lowest minimum volume. BITCOIN price has also the highest standard deviation compared to others. This translates that BITCOIN price is the most volatile currency compared to others currencies under this study.

Table 4.1: Descriptive Statistics for Top Five Cryptocurrencies

	BP	EP	XP	BNCP	LTC P	BV	EV	XV	LTCV	BNCV
Mean	9315	357. 8	0.40	16.54	81.4 3	1.85E+1 0	7.94E+0 9	1.87E +09	2.31E+0 9	2.04E+0 8
Median	8244.6	256. 01	0.30	15.28	60.6 4	1.47E+1 0	6.07E+0 9	1.12E +09	1.98E+0 9	1.72E+0 8
Maximum	40797. 6	1718 .6	3.38	67.84	358. 34	1.23E+1 1	6.07E+1 0	3.50E +10	1.80E+1 0	1.43E+0 9
Minimum	3154.9	84.3 1	0.14	0.45	23.4 6	7.68E+0 8	2.54E+0 8	20566 500	517862 00	9284.00 0
Std. Dev.	5770.3	270. 70	0.33	9.88	51.9 4	1.63E+1 0	8.11E+0 9	3.10E +09	2.29E+0 9	1.86E+0 8

Table 4.1: (cont.)

Skewness	2.85	1.92	4.29	0.71	2.01	1.562	2.26	5.087	1.933	1.415
Kurtosis	12.99	6.83	28.37	3.69	7.61	6.52	10.32	36.75	9.062	6.35
Jarque-Bera	6997.7	1558	37989	132	1980	1172	3926	65744	2736	1017
Observations	1270	1270	1270	1270	1270	1270	1270	1270	1270	1270

According to the descriptive statistic Table 4. below DASH price and volume have the highest mean among the price and volume variables respectively. Additionally, DASH price has the highest maximum price and its volume has the highest maximum volume. FTX TOKEN price has the lowest price and FILECOIN volume has the lowest volume. DASH price and volume are the most volatile among the rest since they have the highest value of the standard deviation.

Table 4.2: Descriptive Statistics for Bottom Five Cryptocurrencies

	FTXP	HTP	FCP	DP	DRP	FTXV	HTV	FCV	DV	DRV
Mean	3.268	4.041	12.866	80.277	20.202	8102832	1.64E+08	58472996	6.35E+08	33759100
Median	2.89	4.07	6.27	74.54	16.88	4308038.	1.26E+08	10890409	4.23E+08	15912047
Maximum	14.84	8.11	59.26	148.38	79.72	1.01E+08	1.30E+09	7.13E+08	1.41E+10	1.47E+08
Minimum	1.15	2.4	2.43	39.87	9.3	510850	51315132	51124	1.37E+08	1918527
Std. Dev.	2.11	0.78	9.92	19.94	11.64	11152537	1.20E+08	98184152	1.24E+09	38388421
Skewness	2.56	0.80	0.82	0.55	2.72	3.89	3.75	2.35	9.41	1.37
Kurtosis	10.56	6.007	2.90	3.18	10.47	22.55	26.62	9.39	98.15	3.34
Jarque-Bera	1804	252	58	28	1849	9574	13281	1360	203437.4	164
Observations	519	519	519	519	519	519	519	519	519	519

4.2 Time Series Graphs

Top Five Cryptocurrencies

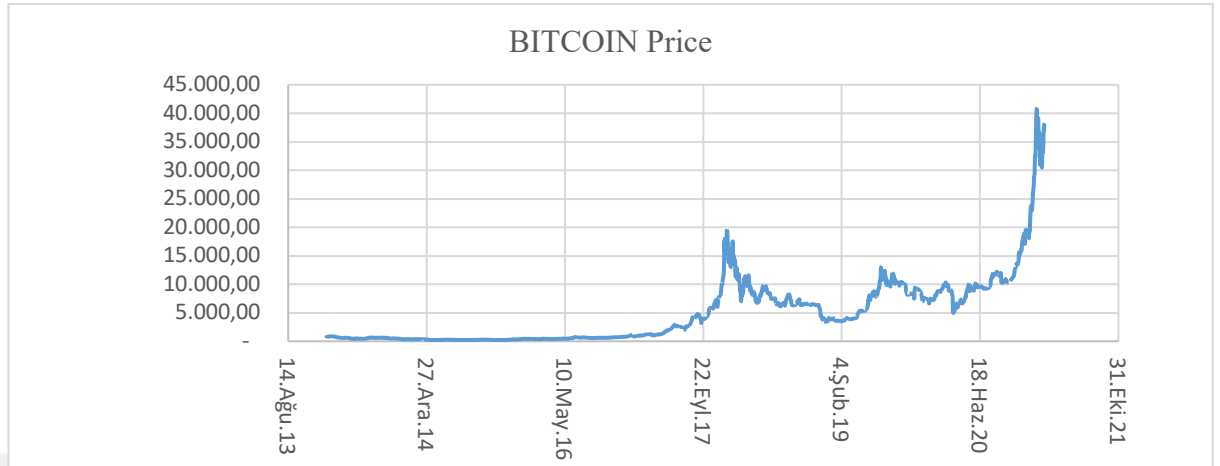


Figure 4.1: BITCOIN Price

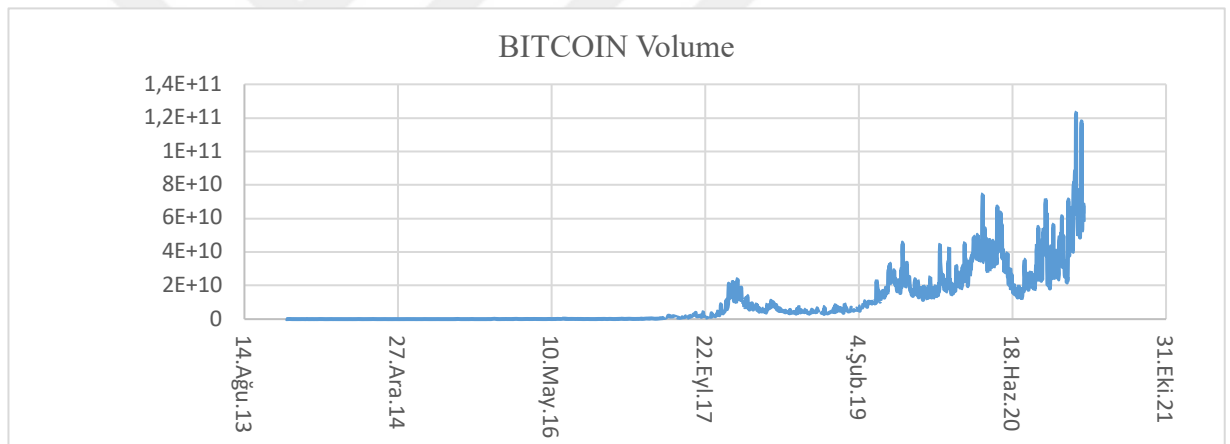


Figure 4.2: BITCOIN Volume

BITCOIN was launched in 2009 but gained the mainstream recognition in 2013 when it started experiencing steady increase in both price and trade volume. Since it started trading BITCOIN price and volume has been stable until the 2014 Mt GOX hack which affected it negatively as both the prices and volumes decreased. In 2017 because of the “crypto bull run” both BITCOIN price and trading volumes increased exponentially. In 2018 both price and volume of BITCON had a sharp decrease as a result of the 2018 crypto crash also known as the Great Crypto Crash. By 2019, the both the price and volume returned some form of stability and followed the same trajectory until 2020 (COVID 19 pandemic) when the price and volumes persistently increased.



Figure 4.3: ETHEREUM Price

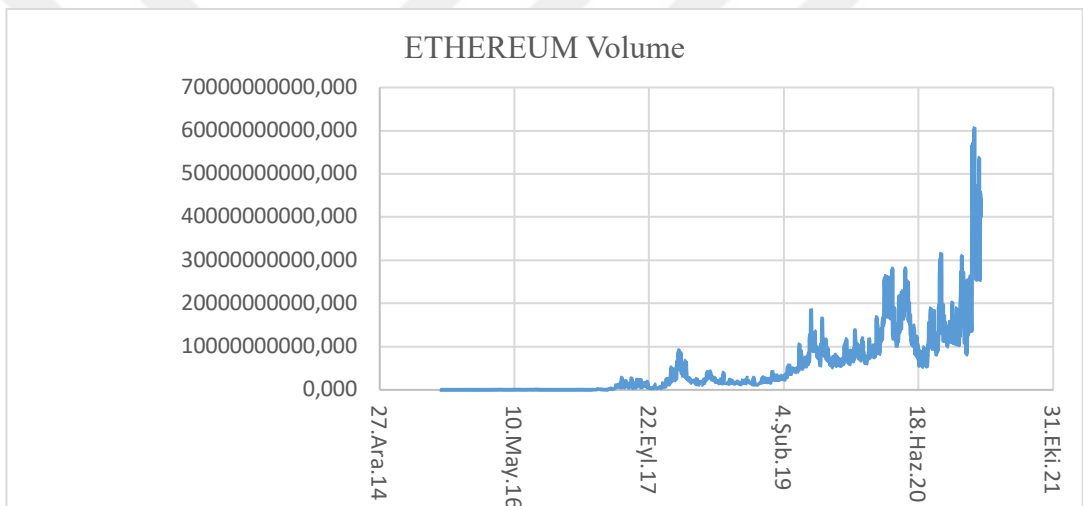


Figure 4.4: ETHEREUM Volume

The ETHEREUM blockchain was launched in 2015 and started trading immediately. In 2017 just like BITCOIN, the prices and volumes of ETHEREUM benefited from the crypto bull run and its popularity increased and resulted in increase in both of its prices and volumes. However, in 2018 the “2018 crypto crash” resulted in the downward spiral of ETHEREUM’s price and volume. Since 2019 after recovering from the crypto crash, ETHEREUM has been enjoying stable increase in price and volumes until 2020 (COVID 19 Pandemic) when it had a sharp increase in both values.

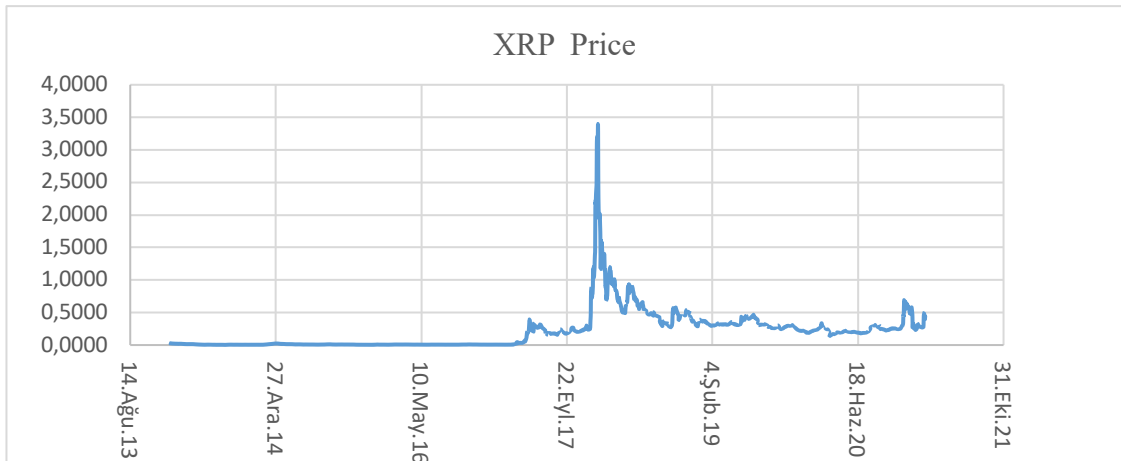


Figure 4.5: XRP Price

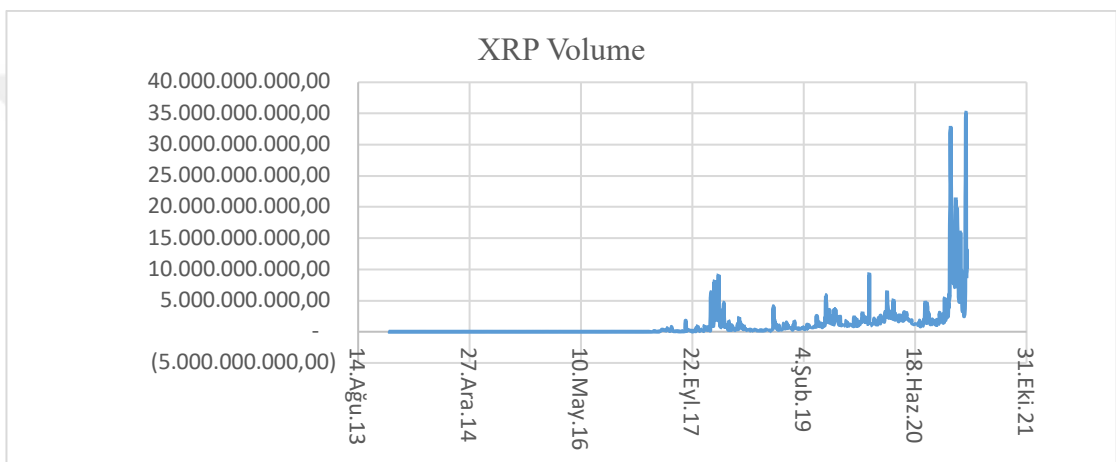


Figure 4.6: XRP Volume

XRP was released in the year 2012. Since its inception its prices and volumes have been stable until the cryptocurrency bubble between 2017 and 2018. In 2017 when there was a crypto bull run its prices and volumes increased and in 2018 when there was a crypto crash the price and volumes sharply decreased. Since 2019 after recovering from the crypto crash, the prices have been stable but the volumes have continued to rise.

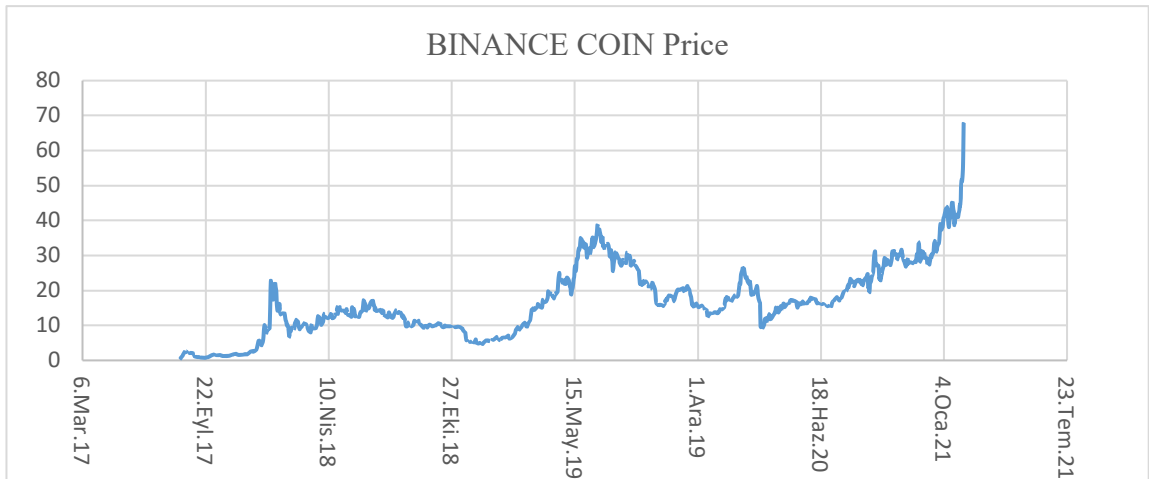


Figure 4.7: BINANCE COIN Price

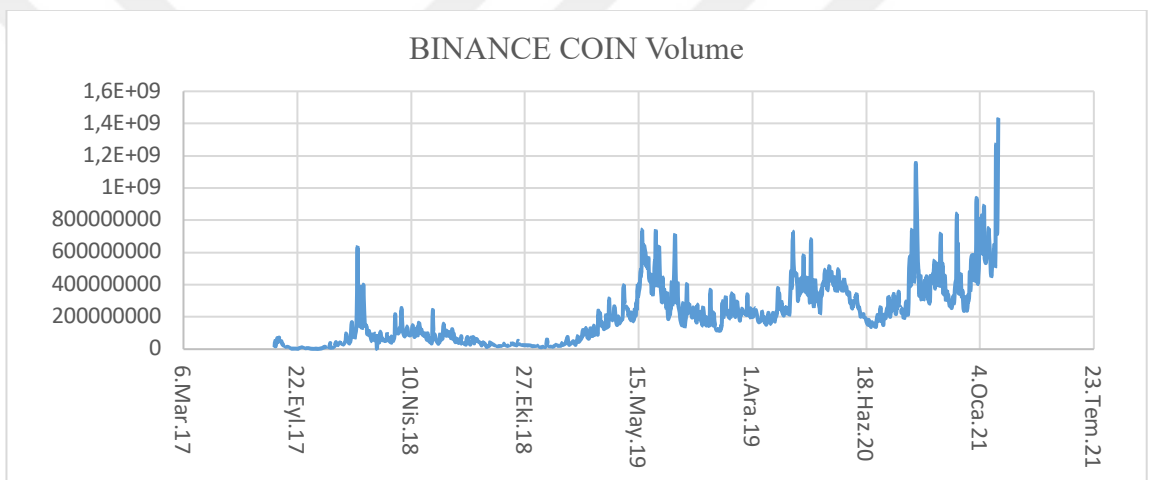


Figure 4.8: BINANCE COIN Volume

BINANCE COIN was firstly made available to the public on 25th July 2017 and was launched on the ETHEREUM blockchain as an ERC-20 token. It was launched shortly before the 2017 crypto bull run period and immediately enjoyed persistent price and volume increases. However, like other cryptocurrencies it was not spared by the 2018 crypto crash which resulted in the fall of its price and volumes. In 2019, it managed to recover from the crash but again since 2020 (COVID 19 pandemic period) both price and volume values have increasing consistently.



Figure 4.9: LITECOIN Price

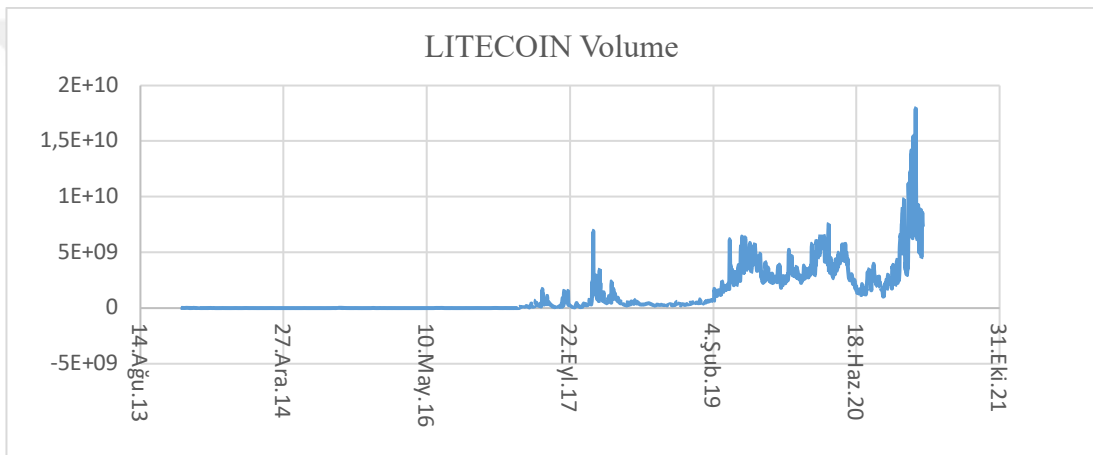


Figure 4.10: LITECOIN Volume

LITECOIN is one of the oldest cryptocurrencies that was launched in 2011 shortly after the launch of BITCOIN in 2009. Since its inception its prices and volumes have been stable until the cryptocurrency bubble between 2017 and 2018. In 2017 when there was a crypto bull run its prices and volumes increased and in 2018 when there was a crypto crash the price and volumes sharply decreased. In 2019 the currency recovered until 2020 (COVID19 pandemic) when it has been experiencing continuous increase in both its price and volume.

Bottom Five Cryptocurrencies

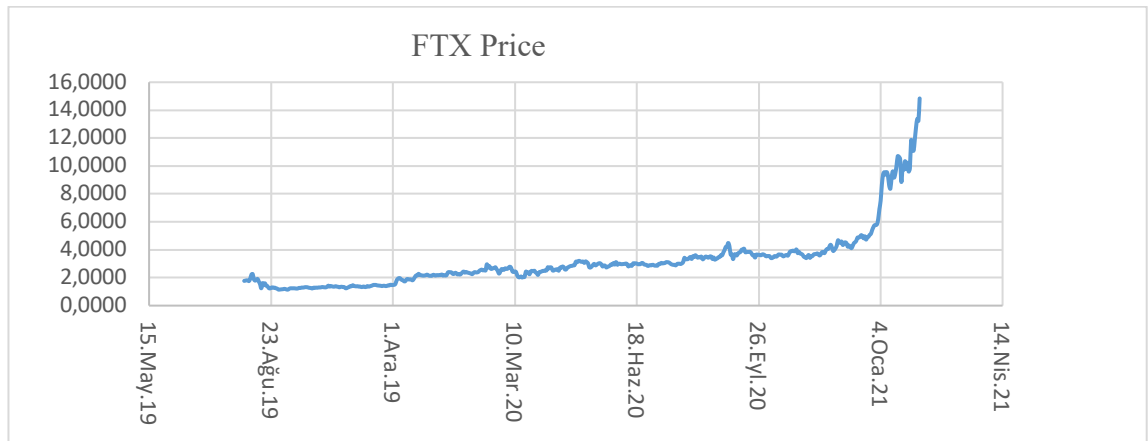


Figure 4.11: FTX TOKEN Price

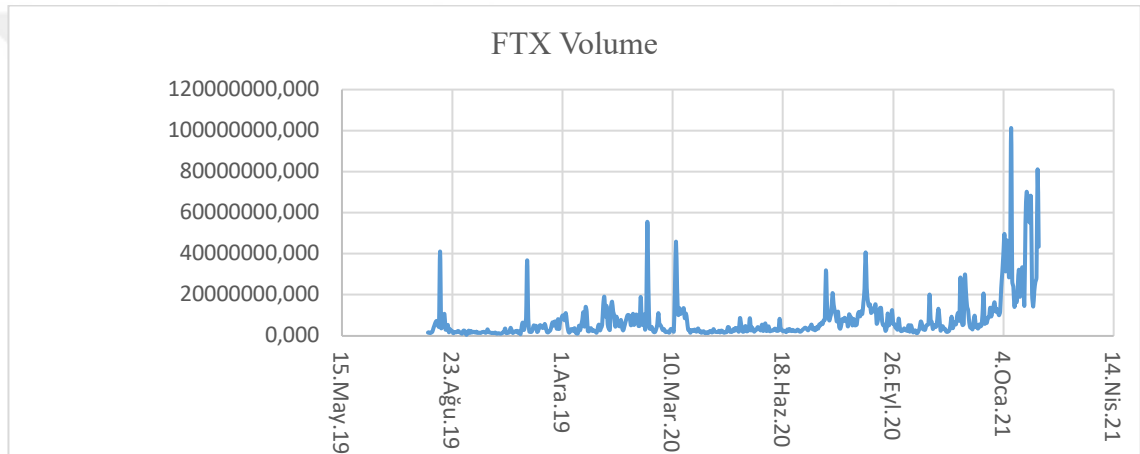


Figure 4.12: FTX TOKEN Volume

FTX TOKEN is the native cryptocurrency token of the crypto derivatives trading platform FTX that was launched on 8 May 2019. This price of this currency has been rising steady since it started trading. However, since the beginning of 2020 the price level of this currency have been rising sharply. This increase can be attributed to the cryptocurrency boom of 2020. As for the FTX TOKEN volume its values have been highly volatile since its inception and continues to be the same.

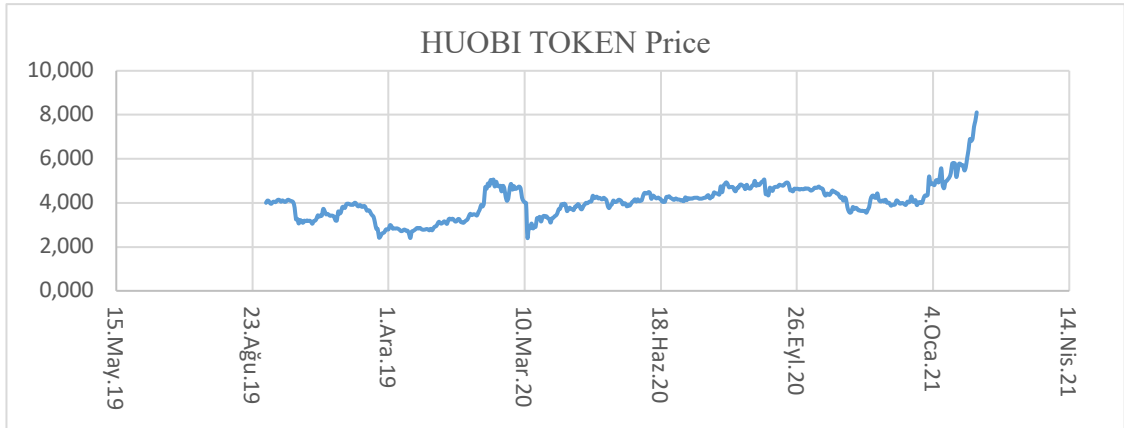


Figure 4.13: HUOBI TOKEN Price

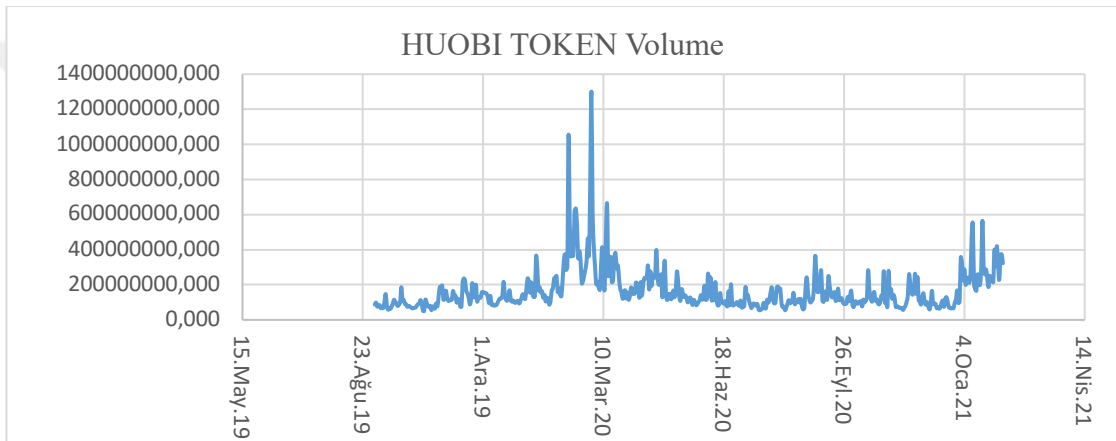


Figure 4.14: HUOBI TOKEN Volume

HUOBI TOKEN is a token native to the cryptocurrency exchange Huobi Global and is based on the ETHEREUM blockchain. It was first launched in January 2018. From 2019 to 2020 its price has been fluctuating steadily. Since 2020 there is a spike in its prices and it continues to increase. As for its volumes, there have been always more volatile than its price and they have reached its maximum in March 2020.

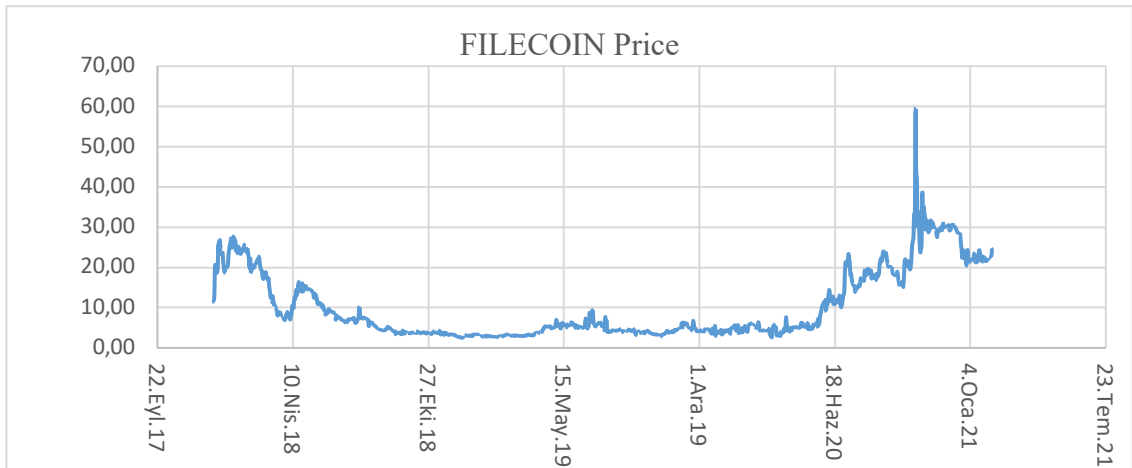


Figure 4.15: FILECOIN Price

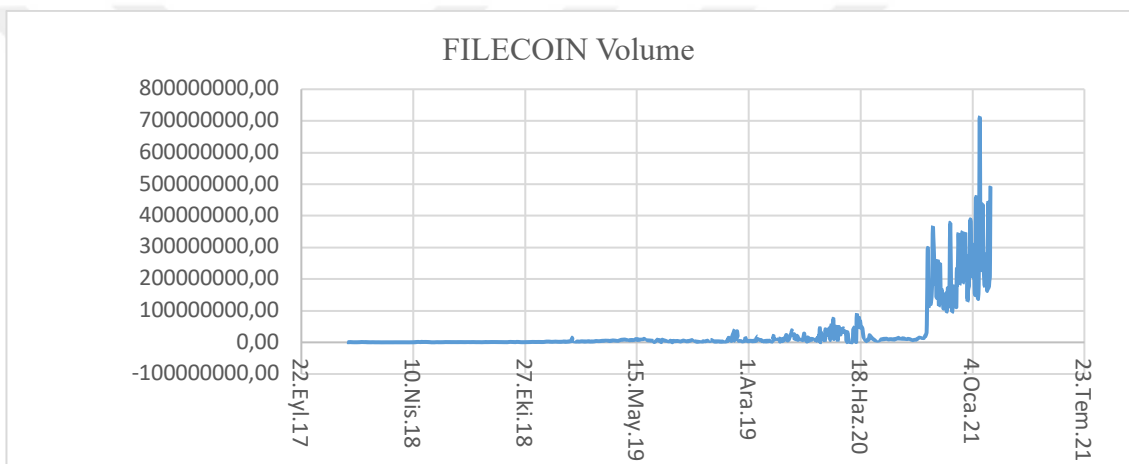


Figure 4.16: FILECOIN Volume

This currency is a product of a project that started in 2017. Immediately after the launch, the FILECOIN was an immediate beneficiary of crypto bull run as its prices increased rapidly only for that increment of prices to be undermined by the 2018 crypto crash that made its prices to fall. After the crypto crash over the years the price has been increasing systematically but the increase since 2020 (COVID 19 pandemic period) has been sharper and more persistent. Its volumes have been steady over time but also started to increase more exponentially since 2020.



Figure 4.17: DASH Price

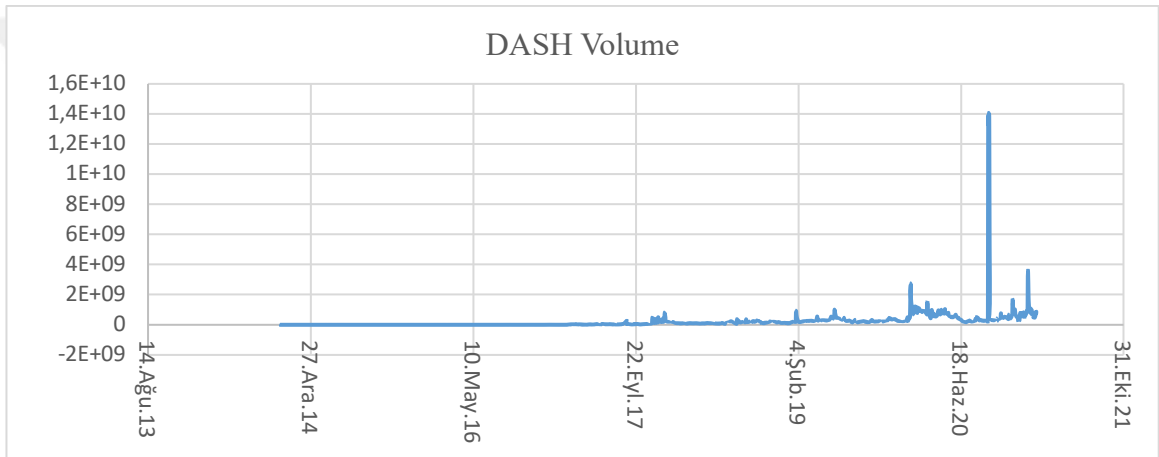


Figure 4.18: DASH Volume

DASH was launched in 2014 as a fork of BITCOIN and LITECOIN. Since its introduction its prices and volumes have been stable until the cryptocurrency bubble between 2017 and 2018. In 2017 as a result of the 2017 crypto bull run its prices and volumes increased and in 2018 due the 2018 crypto crash the price and volumes sharply decreased. Since the crypto crash its prices have recovered but have not yet managed to repeat the values of 2017. As for the volume, it has been more stable than the price and has reached its peak in September 2020.



Figure 4.19: DECREED Price

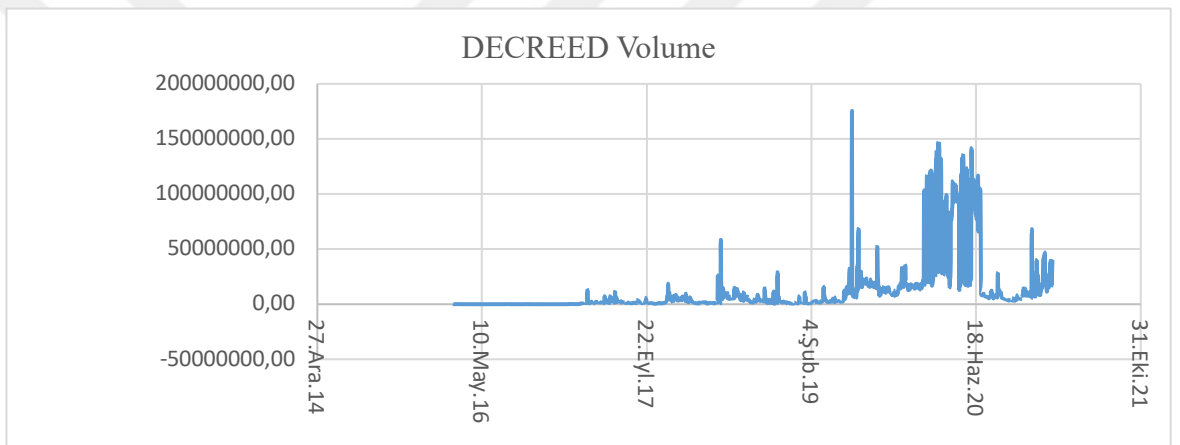


Figure 4.20: DECREED Volume

DECREED was launched in February 2016. Like other cryptocurrencies in 2017, due to the 2017 crypto bull run, its prices increased rapidly but in 2018 because of the crypto crash the prices fall again. After the crypto crash, it managed to recover and since then its prices had been following a steadier trajectory until 2020 when there was a crypto boom which resulted in the increase of its prices. As for its volume there have been always more volatile than its price and they have reached its maximum in June 2019.

4.3 Unit Root Tests

This section contains the results of the unit root test conducted on the time series variables of the Top Five Cryptocurrencies (prices and volumes) relevant to this study. In this study three techniques for testing the unit root were adopted. These techniques

are Augmented Dickey-Fuller (ADF) test, ERS Optimal Point test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test and. The main reason for using different techniques is to arrive at a more robust conclusion which is being concluded by three tests but not one. Augmented Dickey-Fuller (ADF) and ERS Optimal Point test have the null hypothesis that states that the time series has a unit root and the alternative hypothesis is that the time series is stationary, whereas Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test conducts a test whereby the null hypothesis is that the data series is stationary against the alternative that says it is non-stationary. The following are the unit root test results of the Top Five Cryptocurrencies:

4.3.1 Augmented Dickey-Fuller Test Results for Top Five Cryptocurrencies:

The result from Table 4. show that all the top five cryptocurrencies under this study with the exception of LITECOIN volume cannot reject the null hypothesis at level. Therefore, it can be concluded that at the level the rest of the series except LITECOIN volume have a unit root. At level LITECOIN volume is stationary at 5% level of significance. However, at first difference all cryptocurrencies in this category are stationary at a 1% level of significance. This translates that all series under consideration in this category are concluded as integrated of order 1, i.e., I(1).

4.3.2 ERS Optimal Point Test Results for Top Five Top Five Cryptocurrencies:

The null hypothesis of ERS Optimal Point test indicates that all the series in top five cannot be rejected except for XRP price, BINANCE COIN volume and LITECOIN volume. This means that except these three at the level all series have a unit root. At level XRP price, BINANCE COIN volume and LITECOIN volume are all stationary at 5% level of significance. Nevertheless, at first difference all series in this category are stationary at 1% level of significance. This means that all series in this category appear to be integrated to order one I(1).

4.3.3 Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test Results for Top Five Cryptocurrencies:

Having a null hypothesis of stationary the results of Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test shows that the null hypothesis is rejected a 1% significant level in all series in this category. However, at first difference, the null hypothesis cannot be rejected for all series except for BITCOIN price, ETHEREUM price and BINANCE COIN price. This results again indicate that cryptocurrencies in this category are concluded as integrated of order 1, time series.

Table 4.3: Unit Root Test Results for Top Five Cryptocurrencies

Test	Price & Volume Time Series	Top Five Cryptocurrencies						Conclusion
		At Level			First Difference			
		None	Constant	Trend	None	Constant	Trend	
Augmented Dicky Fuller (ADF) Test	BP	2.05	0.604	-2.074	-51.8***	-51.877***	-51.923***	I(1)
	BV	1.552	-0.43	-3.018	-13.94***	-14.040***	-14.046***	I(1)
	EP	0.949	-1.612	-1.876	-7.59***	-7.795***	-7.810***	I(1)
	EV	1.568	-1.655	-2.478	-11.39***	-11.547***	-11.567***	I(1)
	XP	-1.04	-0.929	-2.358	-14.92***	-14.933***	-14.941***	I(1)
	XV	1.525	-0.938	-2.619	-12.56***	-12.682***	-12.679***	I(1)
	BNCP	0.840	-2.093	-2.702	-10.60***	-10.674***	-10.651***	I(1)
	BNCV	0.416	-1.707	-3.242*	-24.37***	-25.373***	-25.363***	I(1)
	LTCP	0.343	-0.459	-2.371	-51.49***	-51.489***	-51.522***	I(1)
LTCV	0.331	-1.216	-4.16***	-23.88***	-23.897***	-23.903***	I(1)	
ERS Point Optimal	BP		66.27	42.558		0.023***	0.071***	I(1)
	BV		12.001	13.855		0.645***	1.497***	I(1)
	EP		187.73	55.42		0.070***	0.115***	I(1)
	EV		55.074	8.784		0.12***	0.568***	I(1)
Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test	XP		16.43	25.525		0.014***	0.053***	I(1)
	XV		9.945	4.474**		0.265***	0.976***	I(1)
	BCP		90.557	36.102		4.059*	4.354**	I(1)
	EV		5.097***	0.874***		0.063	0.02	I(1)
	XP		4.717***	0.596***		0.127	0.113	I(1)

Table 4.3: cont.

	XV		5.890***	0.49***		0.019	0.018	I(1)
	BCP		2.360***	0.314***		0.235	0.124**	I(1)
	BCV		2.882***	0.15***		0.051	0.041	I(1)
	LTCP		4.236***	0.542***		0.338	0.197	I(1)
	LTCV		5.645***	0.566***		0.159	0.086	I(1)

Note: ***, ** and * show the null hypothesis rejection at 1%, 5% and 10% significance level respectively.

4.3.4 Augmented Dickey-Fuller Test Results for Bottom Five Cryptocurrencies:

The Augmented Dickey-Fuller test results of the Bottom Five Cryptocurrencies show that at level, the null hypothesis cannot be rejected in all series under observation with the exception of HUOBI TOKEN volume and FILECOIN volume. Therefore, it can be concluded that at the level the remaining series has a unit root. At level HUOBI TOKEN volume is stationary at 10% level of significance and FILECOIN volume is stationary at 5% level of significance. However, at first difference all series in this category are stationary at a 1% level of significance. This means that all series under consideration in this category are concluded as integrated of order 1, i.e., I(1).

4.3.5 ERS Optimal Point Test Results for Bottom Five Currencies:

The results of the ERS Optimal Point test indicate that all the series in this category cannot be rejected except for three series (FTX volume, FILECOIN volume and DECRED volume). At level FTX volume, FILECOIN volume and DECRED volume are all stationary at 5% level of significance. At first difference, the results indicate that all series in this category are stationary at 1% level of significance. This means that all series in this category appear to be integrated to order one, I(1).

4.3.6 Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test Results for Bottom Five Currencies:

Having null hypothesis of stationary the results of KPSS shows that the null hypothesis is rejected at 1% significant level in all series under this test. At first difference, the null hypothesis cannot be rejected for all series except for HUOBI TOKEN volume and DASH price. This means that again all series in this category are concluded as integrated of order 1.

Table 4.4: Unit Root Test Results for Bottom Five Cryptocurrencies

Test	Price & Volume Time Series	Bottom Five Cryptocurrencies						Conclusion
		At Level			First Difference			
		None	Constant	Trend	None	Constant	Trend	
Augmented Dickey Fuller (ADF Test)	FTXP	0.281	-1.076	-1.720	-11.023***	-11.018***	-11.237***	I(1)
	FTXV	0.379	-2.568	-2.983	-17.363***	-17.354***	-17.343***	I(1)
	HTP	0.61	-1.114	-2.633	-10.25***	-10.277***	-10.366***	I(1)
	HTV	0.397	-3.4	-3.408*	-12.325***	-12.327***	-12.315***	I(1)
	FCP	-0.397	-1.206	-1.848	-9.969***	-9.964***	-10.204***	I(1)
	FCV	0.99	-0.896	-3.919**	-10.35***	-10.409***	-10.429***	I(1)
	DP	0.471	-1.158	-0.940	-20.084***	-20.119***	-20.134***	I(1)
	DV	0.963	-1.195	-2.802	-18.419***	18.463***	-18.462***	I(1)
	DRP	0.605	-1.332	-1.355	-17.921***	-17.978***	-17.976***	I(1)
	DRV	0.698	-1.311	-2.725	-15.173***	-15.202***	-15.196***	I(1)
ERS Optimal Point	FTXP		13.567	39.105		0.16***	0.343***	I(1)
	FTXV		1.735	4.357*		0.176***	0.652***	I(1)
	HTP		5.677	10.476		0.105***	0.001***	I(1)
	DP		59.358	35.758		0.026***	0.094***	I(1)
	DV		17.148	8.38		0.278***	0.689***	I(1)
	DRP		65.583	41.14		0.134***	0.191***	I(1)
	DRV		4.601	5.28**		0.596***	1.142***	I(1)
Kwiatkowski-Phillips-Schmidt-Shin	FTXP		0.676**	0.495***		0.456*	0.032	I(1)
	FTXV		0.423*	0.314***		0.083	0.053	I(1)
	HTP		1.587***	0.092*		0.187	0.059	I(1)
	HTV		0.252**	0.271***		0.134	0.128*	I(1)

Table 4.4: cont.

	FCP		1.149***	0.893***		0.249	0.041	I(1)
	FCV		3.587***	0.221***		0.065	0.033	I(1)
	DP		3.804***	1.144***		0.237	0.152*	I(1)
	DV		5.495***	0.959***		0.117	0.120	I(1)
	DRP		2.083***	0.956***		0.224	0.173	I(1)
	DRV		4.179***	0.477**		0.038	0.04	I(1)

Note: ***, ** and * show the null hypothesis rejection at 1%, 5% and 10% significance level respectively.

4.4 Johansen Cointegration Test Results

The unit root test results have shown that all the series under this study are integrated of order one I(1). This is a good sign as it satisfies one of the conditions needed when conducting a Johansen Cointegration to determine the long run relationship among the series (cryptocurrencies) within the scope of this study. However, before conducting any cointegration technique an appropriate or optimal lag length has to be determined. Too small or over parameterized lag length can lead to model misspecification as cited by Wooldridge, (2009). The Johansen Cointegration test was conducted using the 3rd specification of the Johansen Cointegration Test which is more theoretically plausible. However the results of this 3rd specification of the Johansen Cointegration Test are not much different from other specifications.

Table below shows that the optimal lag length for unrestricted VAR model and AIC and SC are the information criteria used but the study adopts a more parsimonious approach in order to minimize information criteria by selecting Schwarz Criteria (SC) which gives a much lower lag length.

Table 4.5: Lag Length Criteria for Top Five Cryptocurrencies

Top Five Cryptocurrencies								
Without COVID as Exogenous					With COVID as Exogenous			
Lag Length	0	1	2	3	0	1	2	3
Schwarz SC	9.443	-18.908*	-18.71	-18.49	7.975	-18.884*	-18.68	-18.448
Akaike AIC	9.402	-19.36	-19.57	-19.75*	7.893	-19.373	-19.58	-19.75*

Table 4.6: Lag Length Criteria for Bottom Five Cryptocurrencies

Bottom Five Cryptocurrencies								
Without COVID as Exogenous					With COVID as Exogenous			
Lag Length	0	1	2	3	0	1	2	3
Schwarz SC	-1.006	-20.355*	-19.678	-18.770	-2.388	-20.290*	-19.6	-18.68
Akaike AIC	-1.090	-21.271	-21.427*	-21.352	-2.555	-21.289	-21.43*	-21.34

Table 4.7. and Table 4.8. show the results of the Johansen cointegration test for both Top Five Cryptocurrencies and Bottom Five Cryptocurrencies respectively. The number of cointegrating vectors under the hypothesis is denoted by r . The results of the Top Five Cryptocurrencies (both without COVID as exogenous and with COVID as exogenous variable) show that it has 6 cointegrating vectors at 1% significance level. However, to get more information and a better perspective of the cointegration among these series 5 cointegration equations are used in this study. As for the Bottom Five Cryptocurrencies show that its series (both without COVID as exogenous and with COVID as exogenous variable) have 4 cointegration vectors at 5% level of significance.

Table 4.7 Unrestricted Cointegration Test for Top Five Cryptocurrencies

Top 5 Cryptocurrencies (<i>Trace Test Statistic</i>)					
		Without COVID as Exogenous		With COVID as Exogenous	
Null Hypothesis	Alternative Hypothesis	Trace Test Stat	Prob	Trace Test Stat	Prob
$r = 0$	$r > 0$	785.2387***	0.0000	808.7395***	0.0001

Table 4.7 cont.

$r \leq 1$	$r > 1$	540.8758***	0.0001	563.1673***	0.0001
$r \leq 2$	$r > 2$	349.2551***	0.0000	368.4653***	0.0000
$r \leq 3$	$r > 3$	195.4133***	0.0000	207.9041***	0.0000
$r \leq 4$	$r > 4$	126.2052***	0.0001	138.5610***	0.0000
$r \leq 5$	$r > 5$	79.23365***	0.0073	85.01597***	0.0019
$r \leq 6$	$r > 6$	47.66430*	0.0521	46.72144*	0.0636
$r \leq 7$	$r > 7$	20.51234	0.3888	15.70361	0.7329

Note: ***, ** and * show the null hypothesis rejection at 1%, 5% and 10% significance level respectively

Table 4.8: Unrestricted Cointegration Test for Bottom Five Cryptocurrencies

Bottom Five Cryptocurrencies (Trace Test Statistic)					
		Without COVID as Exogenous		With COVID as Exogenous	
Null Hypothesis	Alternative Hypothesis	Trace Test Stat	Prob	Trace Test Stat	Prob
$r = 0$	$r > 0$	382.2863***	0.0000	401.2038***	0.0000
$r \leq 1$	$r > 1$	275.3480***	0.0000	286.8777***	0.0000
$r \leq 2$	$r > 2$	194.2767***	0.0002	205.6086***	0.0000
$r \leq 3$	$r > 3$	135.2316**	0.0113	144.1825***	0.0022
$r \leq 4$	$r > 4$	79.80568	0.3711	88.63302	0.1397
$r \leq 5$	$r > 5$	48.22261	0.7128	53.07110	0.5021
$r \leq 6$	$r > 6$	30.10739	0.7135	33.70601	0.5180

Note: ***, ** and * show the null hypothesis rejection at 1%, 5% and 10% significance level respectively

4.5 Vector Error Correction Model (VECM) Results

The long-run relationship between the top five cryptocurrencies under this study are demonstrated by the Cointegrating Vectors (CV). The long run coefficients of the Top Five Cryptocurrencies are tabulated on Table below after imposition of the Johansen normalization restrictions. According to the results on Table the volumes of BITCOIN, ETHEREUM and LITECOIN are statistically crucial in the determination of the closing price of BITCOIN when COVID 19 pandemic is not taken into account. However, when COVID 19 pandemic is considered the volumes of BITCOIN, ETHEREUM, XRP and LITECOIN are all statistically crucial for the closing price of BITCOIN. These results are in line with the findings of Sapuric et al. (2020), Yamak et al. (2019) and Gemici & Polat (2019) in their respective studies

For the closing price of ETHEREUM when the COVID 19 pandemic is excluded, the trading volumes of BITCOIN, ETHEREUM, BINANCE COIN and LITECOIN are statistically crucial. With the inclusion of COVID 19 pandemic the trading volumes of BITCOIN, ETHEREUM, XRP and LITECOIN are statistically crucial for the closing price of ETHEREUM. As for the closing price of XRP, the volumes of four cryptocurrencies (ETHEREUM, XRP, BINANCE COIN AND LITECOIN are statistically crucial when the COVID 19 pandemic is not considered. However, when the pandemic is taken into account, the trading volumes of five cryptocurrencies (BITCOIN, ETHEREUM, XRP, BINANCE COIN AND LITECOIN are statistically crucial.

When not considering COVID 19 pandemic volumes of three cryptocurrencies (BITCOIN, XRP and BINANCE COIN) are significantly impacting the closing price of BINANCE COIN. However when the pandemic is considered, the trading volumes of BITCOIN, ETHEREUM, XRP, BINANCE COIN and LITECOIN all have statistically significant effect on the closing price of BINANCE COIN. Before taking COVID 19 pandemic into account, volume of BITCOIN, ETHEREUM, BINANCE COIN and LITECOIN have a crucial effect on the closing price of LITECOIN. When COVID 19 pandemic is finally taken into account the volume of the same four cryptocurrencies (BITCOIN, ETHEREUM, BINANCE COIN and LITECOIN) maintained their significance in explaining the closing price of LITECOIN. The results of the intra and inter relationship between the prices and volumes of the top five cryptocurrencies have shown some form of resilience against the shock induced by COVID 19 pandemic. This bears the results same as the study by Aysan, Ul, & Khan (2021)

Table 4.9 Normalized Cointegration Coefficients for Top Five Cryptocurrencies

	Top 5 Cryptocurrencies									
	Without COVID					With COVID				
	CV1	CV2	CV3	CV4	CV5	CV1	CV2	CV3	CV4	CV5
BP	1					1				
EP		1					1			
XP			1					1		
BNP				1					1	
LTP					1					1
BV	-4.4*** (0.498)	-7.6*** (0.999)	0.118 (0.234)	1.7*** (0.335)	-4.3*** (0.57)	-7.6*** (1.028)	-12*** (1.73)	-0.7*** (0.24)	0.6*** (0.24)	-7.56*** (1.03)

Table 4.9 cont.

EV	3.3*** (0.467)	5.9*** (0.935)	1.7*** (0.221)	-0.412 (0.313)	4.9*** (0.53)	2.01** (0.96)	4.4*** (1.62)	1.7*** (0.22)	-0.9*** (0.23)	4.06*** (0.96)
XV	-0.17 (0.193)	0.23 (0.388)	-1.0*** (0.09)	-0.9*** (0.13)	-0.13 (0.22)	0.82** (0.39)	1.5*** (0.66)	-0.9*** (0.089)	-0.5*** (0.09)	0.72 (0.39)
BNV	-0.361 (0.184)	-1.4*** (0.369)	-0.9*** (0.09)	-0.7*** (0.123)	-1.4*** (0.21)	-0.075 (0.37)	-0.99 (0.63)	-0.8*** (0.09)	-0.6*** (0.08)	-1.09** (0.37)
LTC	0.98*** (0.25)	2.5*** (0.5)	0.3*** (0.12)	0.23 (0.17)	0.8*** (0.28)	3.4*** (0.54)	5.6*** (0.921)	0.7*** (0.12)	0.6*** (0.12)	2.9*** (0.55)

Note: ***, ** and * show the coefficient significance 1%, 5% and 10% significance level respectively. Standard errors are shown in parenthesis

The study further explores the short-run impact of the COVID 19 pandemic on both closing prices and trading volumes of all the Top Five Cryptocurrencies under the study. The results on Table indicate that COVID 19 pandemic has a statistically significant positive short-run impact on trading volumes of all cryptocurrencies considered for the study (BITCOIN, ETHEREUM, XRP, BINANCE COIN and LITECOIN). The negative economic shock induced by COVID 19 pandemic on traditional investment instruments (stocks, bonds, and cash) has been overwhelming, subsequently cryptocurrencies have posed as an alternative form of saving money or investments.

As cryptocurrencies have shown a characteristic of resilience against any form of external economic shock (COVID 19 pandemic), both experienced and aspirant investors have turned to cryptocurrencies as an alternative to the traditional investment assets. This has exacerbated the acceptance of many cryptocurrencies as either a form of currency or an investment option. Consequently, because of these dynamics the volumes of any cryptocurrencies have been increasing at unparalleled mode. However, as for the impact of COVID 19 pandemic on the closing prices of the Top Five Cryptocurrencies no statistically significant impact could be established.

Table 4.10 : Short-Run Impact of COVID 19 Pandemic on Top Five Cryptocurrencies

Top 5 Cryptocurrencies									
BP	EP	XP	BNP	LTP	BV	EV	XV	BNV	LTC
0.0019 (0.004)	0.0032 (0.005)	0.0077 (0.006)	-0.005 (0.006)	-0.0051 (0.006)	0.09*** (0.019)	0.05*** (0.021)	0.145*** (0.034)	0.100*** (0.038)	0.067*** (0.024)

Note: ***, ** and * show the coefficient significance 1%, 5% and 10% significance level respectively. Standard errors are shown in parenthesis

The long run coefficients of the Bottom Five Cryptocurrencies are tabulated on Table below after imposing the Johansen normalization restrictions. According to the results on the table the volumes of FILECOIN, DASH and DECRED have a significant effect on the closing price of FTX TOKEN when COVID 19 pandemic is excluded. However, when the pandemic is considered, the volumes of four cryptocurrencies (FTX TOKEN, FILECOIN, DASH and DECRED) are statistically crucial in the closing price of FTX TOKEN. For the closing price of HUOBI TOKEN when the COVID 19 pandemic is not taken into consideration, the trading volumes of FTX TOKEN, HUOBI TOKEN, DASH and DECRED are statistically crucial. When COVID 19 pandemic is taken into consideration the HUOBI TOKEN, FILECOIN, DASH and DECRED trading volumes are statistically crucial for the closing price of HUOBI TOKEN.

When not considering COVID 19 pandemic volumes of three cryptocurrencies (FTX TOKEN, FILECOIN and DASH) are significantly impacting the closing price of FILECOIN. However when the pandemic is considered, all the trading volumes of FTX TOKEN, HUOBI TOKEN, FILECOIN, DASH and DECRED have statistically significant effect on the closing price of FILECOIN. Before taking COVID 19 pandemic into account, volume of FILECOIN, DASH and DECRED have a crucial effect on the closing price of DASH. Nevertheless, when COVID 19 pandemic is finally taken into account the volume of the same three cryptocurrencies (FILECOIN, DASH and DECRED) maintained their significance in explaining the closing price of LITECOIN.

Table 4.11: Normalized Cointegration Coefficients for Bottom Five Cryptocurrencies

Bottom Five Cryptocurrencies								
	Without COVID				With COVID			
	CV1	CV2	CV3	CV4	CV1	CV2	CV3	CV4
FTXP	1				1			
HTP		1				1		
FCP			1				1	
DP				1				1
DRP								
FTXV	-0.106 (1.04)	21.1*** (5.27)	45.93*** (6.22)	12.44 (7.85)	-0.57 (1.10)	6.88 (5.53)	38.15*** (5.72)	7.38 (8.58)
HTV	-0.003 (0.03)	-1.2*** (0.19)	0.31 (0.22)	0.14 (0.282)	0.008 (0.03)	-0.83*** (0.19)	0.46*** (0.20)	0.23 (0.30)

Table 4.11 cont.

FCV	0.04*** (0.01)	0.09 (0.04)	-0.55*** (0.063)	0.29*** (0.08)	0.05*** (0.013)	0.28*** (0.07)	-0.426*** (0.068)	0.38*** (0.102)
DV	-0.18*** (0.03)	-0.54*** (0.15)	-1.07*** (0.18)	-1.63*** (0.22)	-0.19*** (0.03)	-0.56*** (0.16)	-1.082*** (0.16)	-1.67*** (0.25)
DRV	0.08*** (0.02)	0.3*** (0.08)	0.21 (0.095)	0.39*** (0.12)	0.08*** (0.02)	0.37*** (0.09)	0.26*** (0.085)	0.44*** (0.13)

Note: ***, ** and * show the coefficient significance 1%, 5% and 10% significance level respectively. Standard errors are shown in parenthesis

The study also investigated the short-run impact of COVID 19 pandemic on the closing prices and trading volumes of all the Bottom Five Cryptocurrencies under this study. According to the results shown on Table below COVID 19 pandemic did not have a statistically significant impact on all the trading volumes of all these cryptocurrencies except on HUOBI TOKEN volume. Since, HUOBI TOKEN is a native currency of Huobi Crypto Exchange, its trading volumes are mostly reliant on the reputation of the Huobi Crypto Exchange. In July 2020 (same period as COVID 19), the Chinese police arrested a criminal gang that was involved in selling fake HUOBI TOKEN. Few months later the Chief Operating Officer (COO) of Huobi Crypto Exchange Zhu Jiawei was arrested on charges of money laundering by the Chinese authorities. All this developments one after the other affected the reputation of both Huobi Crypto Exchange and HUOBI TOKEN. In the same period the Huobi Crypto Exchange market lots its customers (especially the risk averse ones) and later few transactions were recorded. This had a direct impact on the volumes of HUOBI TOKKEN.

Table 4.12: Short-Run Impact of COVID 19 Pandemic on Bottom Five Cryptocurrencies

Bottom Five Cryptocurrencies									
FTXP	HTP	FCP	DP	DRP	FTXV	HTV	FCV	DV	DRV
0.00042 (0.0015)	0.0022 (0.0049)	0.0056 (0.014)	0.003 (0.007)	0.0063 (0.007)	0.00139 (0.001)	-0.13*** (0.038)	-0.089 (0.098)	-0.048 (0.036)	0.0008 (0.058)

Note: ***, ** and * show the coefficient significance 1%, 5% and 10% significance level respectively. Standard errors are shown in parenthesis.

4.6 Variance Decomposition

In this section we decompose each cryptocurrency's variance attributed to a shock in itself or other cryptocurrencies in order to investigate the interrelationships among the Top Five Cryptocurrencies in this study when COVID 19 pandemic is taken into account. According to the results, it is evident that the variation of closing price BITCOIN due to itself is very high almost 100%. More so, the amount of variation attributed to closing prices of BITCOIN in closing prices of other cryptocurrencies (ETHEREUM, XRP, BINANCE COIN and LITECOIN) is very high averaging at almost 45%.

As for to the variation of the closing price of ETHEREUM on itself is fairly high approximately at 40% and also the attribution of its variance in the closing price of XRP, BINANCE COIN and LITECOIN is also fairly significant averaging at around 10%. However, the results show that the variation of the closing prices of XRP, BINANCE COIN and LITECOIN due to themselves respectively is high but their influence is very low on other cryptocurrencies. The results indicate that closing price of BITCOIN followed by ETHEREUM have a significant amount of influence in the variation of closing prices of itself and other cryptocurrencies.

One the other side of the coin, the variation in the trading volume of BITCOIN in itself is around 80%. Accordingly, BITCOIN trading volume has a significant amount of the variation on the trade volume of ETHEREUM, XRP, BINANCE COIN and LITECOIN. The trading volume of ETHEREUM has also a significant impact on the variation in itself and also in other cryptocurrencies such as XRP, BINANCE COIN and LITECOIN.

The trading volumes of the remaining cryptocurrencies (XRP, BINANCE COIN and LITECOIN) have significant portions of variation in themselves respectively but their influence in the variation of other cryptocurrencies is not very significant. However, the results suggest that trading volume of BITCOIN followed by ETHEREUM have a more significant amount of influence than the trading volumes of other cryptocurrencies (XRP, BINANCE COIN and LITECOIN) in the variation of trading volume of itself and other cryptocurrencies.

FILECOIN's closing price variance on itself is very high at 95% but also like HUOBI TOKEN, its variance on the closing prices of other currencies is very low and inconsequential.

Furthermore, the results show that the variation of the closing prices of DASH and DECREED due to themselves respectively is high (around 50% and 60% respectively) but their influence is very low on other cryptocurrencies. The results indicate that the closing price of FTX TOKEN has the most significant (when compared to others) amount of influence in the variation of closing prices of itself and other cryptocurrencies.

As for the variance of the trading volume of FTX TOKEN on itself is around 80%. However, FTX TOKEN trading volume has a significant amount of the variance on the trade volume of HUOBI TOKEN (30%), FILECOIN (10%), DASH (10%) and DECRED (5%). The trading volume of HUOBI TOKEN has also a significant impact on the variation in itself at approximately 60% but very low on other cryptocurrencies.

The results conclude that the trading volumes of the other Bottom Five Cryptocurrencies (FILECOIN, DASH and DECREED) have significant portion of variation on themselves respectively but their influence on the variation of other cryptocurrencies is not much significant. However, the results suggest that trading volume of FTX TOKEN has a more significant amount of influence than the trading volumes of other cryptocurrencies (XRP, BINANCE COIN and LITECOIN) in the variation of trading volume of itself and other cryptocurrencies. This makes it the most influential among them.

Variance Decomposition using Cholesky (d.f. adjusted) Factors

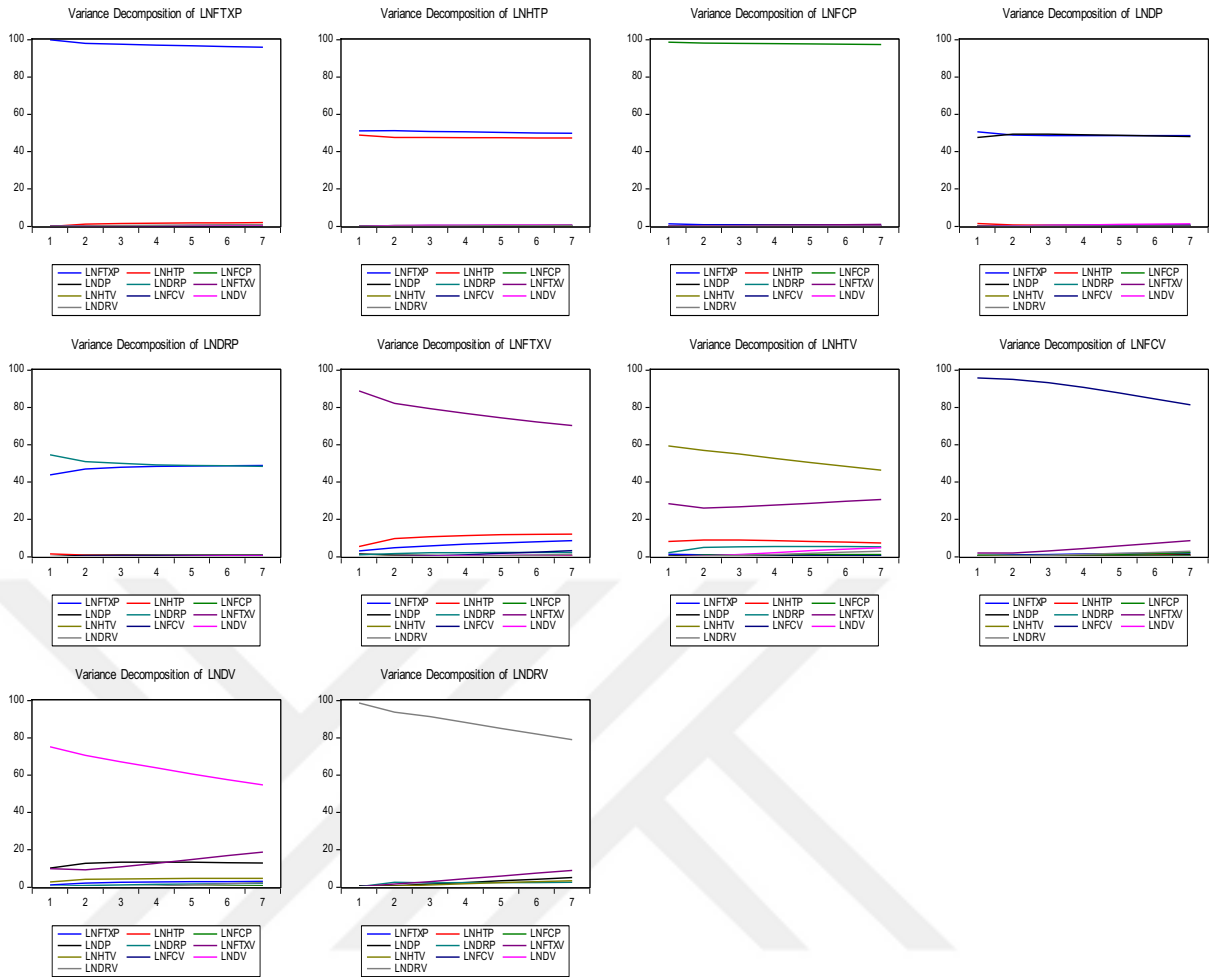


Figure 4.22: Variance Decomposition of Bottom Five Cryptocurrencies

CHAPTER V

CONCLUSION

The previous chapters showed different stages in the exploration of the dynamic relationship between the price and volume within the cryptocurrency market. Understanding the relationship between price and volume is an important step toward understanding the dynamics of any market whether it's a commodity market or stock market. Gallant, Rossi, and Tauchen (1992) cite that by studying the joint dynamics of price and trading volumes more can be learned which can not be achieved by analyzing them in their univariate form.

In a nutshell, the prime objective of this research work is to investigate the dynamic nature of price-volume relationship within the cryptocurrency market. The study investigates the impact of COVID 19 pandemic on the relationship between price and trading volume within the cryptocurrency market. The study uses different time periods i.e. before and during COVID-19 pandemic as a benchmark to explore the impact of COVID 19 pandemic in this relationship by comparing the price and volume behavior within these two periods. The main goal is to study, compare and contrast the behavioral patterns of the cryptocurrency market price-volume relationship within these to specific periods with the aim to ascertain the impact of COVID 19.

In order to get more robust results and a better perspective of the nature of the price-volume relationship the study is divided into two categories. The first category is made up of the Top Five Cryptocurrencies in terms of market capitalization as at 7 November 2020. These currencies are BITCOIN, ETHEREUM, XRP, BINANCE COIN and LITECOIN. The second category consists of the Bottom Five Cryptocurrencies among the top 40 cryptocurrencies and again in accordance to their market capitalization. These currencies are FTX TOKEN, HUOBI TOKEN, FILECOIN, DASH and DECRED. Daily data of the price and volume values was extracted from <https://coinmarketcap.com/>.

In this study three techniques for testing the unit root were adopted. These techniques are Augmented Dickey-Fuller (ADF) test, Kwiatkowski-Phillips-Schmidt-Shin

(KPSS) test and ERS Optimal Point test. The main reason for using different techniques is to arrive at a more robust conclusion which is being concluded by three tests rather than one. The unit root tests results show that all cryptocurrencies in both categories are concluded as integrated of order 1, time series.

After concluding the series as integrated of order 1, the next step is to do the cointegration tests in order to determine the long run relationship within the data series. For that purpose, Johansen cointegration test was adopted and cointegration vectors were detected in both categories which gave us the incentive to proceed to Vector Error Correctional Model (VECM). The Vector Correction Model (VECM) acts as the main model of this study as it gives both the long run and short run relationship among our variables of interest.

According to the results of this study the volumes of BITCOIN, ETHEREUM and LITECOIN are statistically crucial in the determination of the closing price of BITCOIN when COVID 19 pandemic period is excluded. However, when the COVID 19 pandemic period is included the volumes of BITCOIN, ETHEREUM, XRP and LITECOIN are all statistically crucial for the closing price of BITCOIN. The study has found strong evidence of intra and inter long run relationships between the price and volume dynamics among the Top Five cryptocurrencies irrespective of whether it is pre-pandemic or pandemic period. These results are in line with the results from the studies by Sapuric et al. (2020), Yamak et al. (2019) and Gemici & Polat (2019).

Among the bottom Five Cryptocurrencies the VECM results show that the volumes of FILECOIN, DASH and DECREED have a significant effect on the closing price of FTX TOKEN when COVID-19 pandemic is not taken into consideration. However, when the pandemic is taken into account, the volumes of four cryptocurrencies (FTX TOKEN, FILECOIN, DASH and DECRED) are statistically crucial in the closing price of FTX TOKEN. The study has also found strong evidence of intra and inter long run relationships between the price and volume dynamics among the Bottom Five cryptocurrencies irrespective of whether it is pre-pandemic or pandemic period

In conclusion, the study has shown that the COVID-19 pandemic had some impact on the price and volume dynamics in the cryptocurrency market. The pre-pandemic or

pandemic period price and volume dynamic fluctuations have shown how the COVID 19 influenced these changes. It is evident that the economic shock induced by the COVID 19 had the capacity to change the price and volume dynamics in the cryptocurrency market. The findings of this study show that crypto market traders, investors and portfolio managers, before making any investment decision must consider the dynamics of the price and trading volumes of BITCOIN as they hugely impact the prices and volumes of other cryptocurrency. Moreover, the findings help future crypto investors in forecasting the price and volume dynamics of cryptocurrency especially confronted with an external shock capable of causing a financial crisis. It also help investors in designing effective and efficient trading strategies in the crypto market such as portfolio diversification.

Further studies are required to continue exploring the price-volume relations in the cryptocurrency markets after the COVID 19 pandemic. This is to measure the ripple effects of COVID 19 pandemic on this relation or the aftermaths of COVID 19 pandemic. Future studies can focus on the dynamics of the same relationship as this study but using other categories of cryptocurrencies or using other time periods. Additional studies are needed to explore the same relationship focusing on specific geographical area for example focusing on a certain country or region. This will prepare investors and other stakeholders to prepare against future financial crisis that might have an impact on the cryptocurrency market.

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