IBN HALDUN UNIVERSITY
SCHOOL OF GRADUATE STUDIES
DEPARTMENT OF ECONOMICS

MASTER'S THESIS

INTER- AND INTRA- DYNAMICS OF PRICES AND VOLUMES: BITCOIN AND ETHEREUM IN THE PRE- AND PERI-COVID-19 PERIOD

HAMZA BALINDA

THESIS SUPERVISOR
ASST. PROF. ASAD UL ISLAM KHAN

ISTANBUL, 2023

IBN HALDUN UNIVERSITY
SCHOOL OF GRADUATE STUDIES
DEPARTMENT OF ECONOMICS

MASTER'S THESIS

INTER- AND INTRA- DYNAMICS OF PRICES AND VOLUMES: BITCOIN AND ETHEREUM IN THE PRE- AND PERI-COVID-19 PERIOD

by
HAMZA BALINDA

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

THESIS SUPERVISOR
ASST. PROF. ASAD UL ISLAM KHAN

ISTANBUL, 2023

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.

Thesis Jury Members

Title - Name Surname	Opinion	Signature

This is to confirm that this thesis complies with all the standards set by the School of Graduate Studies of Ibn Haldun University.

Date of Submission Seal/Signature

ACADEMIC HONESTY ATTESTATION

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.

Name Surname:

Signature:

ÖZ

FİYATLAR VE HACİMLER ARASI VE İÇİ DİNAMİKLER: COVID-19 ÖNCESİ VE SONRASI DÖNEMDE BITCOIN VE ETHEREUM

Balinda, Hamza
İktisat Yüksek Lisans Programı
Öğrenci Numarası: 194024005
Open Researcher and Contributor ID (ORC-ID): 0000-0001-6936-4206
Ulusal Tez Merkezi Referans Numarası: 10407951

Tez Danışmanı: Dr. Öğr. Üyesi Asad Ul Islam Khan
Temmuz 2023, 53 Sayfa

Bitcoin ve Ethereum sırasıyla birinci ve ikinci sırada yer alan en iyi iki kripto para birimidir. Bu çalışma Bitcoin fiyatı (BTCP), Ethereum fiyatı (ETHP), Bitcoin hacmi (BTCV) ve Ethereum hacmi (ETHV) arasındaki iç ve dış dinamikleri ve ilişkiyi incelemeyi amaçlamaktadır. Bu çalışmada, COVID-19 pandemisi öncesinde ve sırasında Bitcoin fiyatı (BTCP), Ethereum fiyatı (ETHP), Bitcoin hacmi (BTCV) ve Ethereum hacmi (ETHV) arasındaki uzun dönemli ilişkiyi belirlemek ve pandeminin bu kripto para birimlerinin fiyat ve hacimlerindeki değişiklikler üzerinde herhangi bir etkisi olup olmadığını tespit etmek için Johansen Eşbütünleşme Testi ve Vektör Hata Düzeltme Modeli (VECM) kullanılmıştır. Çalışmada ayrıca coinmarketcap.com'dan Bitcoin fiyatı ve hacmi ile Ethereum fiyatı ve hacmi için 8 Ağustos 2015'ten 1 Mart 2021'de çıkarılan 28 Şubat 2021'e kadar olan günlük veriler kullanılmıştır. COVID-19 salgınının tüm spesifikasyonlar için Bitcoin fiyatı (BTCP), Ethereum fiyatı (ETHP), Bitcoin hacmi (BTCV) ve Ethereum hacmi (ETHV) arasındaki uzun dönemli ilişki üzerinde hiçbir etkisi olmadığını bulduk. Ayrıca, pandeminin Bitcoin ve Ethereum fiyatları üzerinde bir etkisi olmadığını, ancak kısa vadede işlem hacimleri üzerinde bir etkisi olduğunu bulduk. Bitcoin fiyatının Bitcoin işlem hacmi ile pozitif ve Ethereum işlem hacmi ile pozitif ilişkili olduğunu, Ethereum fiyatının ise Bitcoin işlem hacmi ile negatif ve Ethereum işlem hacmi ile pozitif ilişkili olduğunu bulduk. Ayrıca Bitcoin fiyatının Bitcoin işlem hacmi ile pozitif, Ethereum işlem hacmi ile negatif ilişkili olduğunu bulduk. Öte yandan, Ethereum'un fiyatı Bitcoin'in işlem hacmiyle pozitif, Ethereum'un işlem hacmiyle pozitif ilişkilidir.

Anahtar Kelimeler: Bitcoin, COVID-19 Salgını, Ethereum, Fiyat ve Hacim Dinamikleri, VECM.

ABSTRACT

INTER- AND INTRA- DYNAMICS OF PRICES AND VOLUMES: BITCOIN AND ETHEREUM IN THE PRE- AND PERI-COVID-19 PERIOD

Balinda, Hamza
MA in Economics
Student ID: 194024005
Open Researcher and Contributor ID (ORC-ID): 0000-0001-6936-4206
National Thesis Center Referance Number: 10407951

Thesis Advisor: Asst. Prof. Asad Ul Islam Khan
July 2023, 53 Pages

Bitcoin and Ethereum are the top two cryptocurrencies in the first and the second places respectively. This study looks to examine the inter and intra dynamics and relationship between Bitcoin price (BTCP), Ethereum price (ETHP), Bitcoin volume (BTCV) and Ethereum volume (ETHV). This study utilizes the Johansen Cointegration Test as well as the Vector Error Correction Model (VECM) to determine the long-run relationship between Bitcoin price (BTCP), Ethereum price (ETHP), Bitcoin volume (BTCV) and Ethereum volume (ETHV) before and during the COVID-19 pandemic and to determine whether the pandemic has any effect on the changes in prices and volumes of these cryptocurrencies. The study also utilizes daily data extracted from coinmarketcap.com for Bitcoin price and volume as well as for Ethereum price and volume from August 8, 2015 up to February 28, 2021 extracted on March 1, 2021. We find that the COVID-19 pandemic has no effect on the long run relationship between Bitcoin price (BTCP), Ethereum price (ETHP), Bitcoin volume (BTCV) and Ethereum volume (ETHV) for all the specifications. We also find that the pandemic has no effect on the prices of Bitcoin and Ethereum but has an effect on their trading volumes in the short run. We find that the price of Bitcoin is positively related with the Bitcoin trading volume and positively related with the trading volume of Ethereum whereas the Ethereum price is negatively related with the Bitcoin trading volume and positively related with the trading volume of Ethereum. We also find that the price of Bitcoin is positively related with the trading volume of Bitcoin and

negatively related with the trading volume of Ethereum. On the other hand, the price of Ethereum is positively related with trading volume of Bitcoin and positively related with the trading volume of Ethereum.

Keywords: Bitcoin, COVID-19 pandemic, Ethereum, Price and Volume dynamics, VECM.

DEDICATION

This dissertation is dedicated to my family, relatives and friends who have been a great support to me here and in my home country, Uganda. They have assisted me through thick and thin. and their support enabled me to take up the challenges and endure them throughout my academic journey.

ACKNOWLEDGEMENTS

I would like to thank first of all my academic supervisor Asst. Prof. Dr. Asad Ul Islam Khan for his effort and dedication in assisting me at every step of the way and for guiding me through the process without giving up on me. I would also like to appreciate the assistance from my lecturers, classmates and friends regarding topics and subjects that I was not well acquainted with during the period of my Master's studies and thesis writing in general.

Hamza BALINDA

ISTANBUL, 2023

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS AND ABBREVIATIONS

ADF	Augmented Dickey-Fuller
BTCP	Bitcoin Price
BTCV	Bitcoin Volume
CE	Cointegrating Equation
ECT	Error Correction Term
ETHP	Ethereum Price
ETHV	Ethereum Volume
KPSS	Kwiatkowski, Phillips, Schmidt, and Shin
LBTCP	Natural Logarithm of Bitcoin Price
LBTCV	Natural Logarithm of Bitcoin Volume
LETHP	Natural Logarithm of Ethereum Price
LETHV	Natural Logarithm of Ethereum Volume
PND	Pandemic
PP	Phillips-Peron
VECM	Vector Error Correction Model

CHAPTER I

INTRODUCTION

In recent years, there has been development of technology in different sectors including the financial sectors where money is moving to the direction of digitalization. That being said, there has been a launch of cryptocurrencies in the financial market which is considered by some as the future of money. In 2009, the first cryptocurrency, Bitcoin was launched by Satoshi Nakamoto whose identity is unknown to date. The evolution of money before the emergence of cryptocurrencies continues to this day and paved the way for the development of virtual or digital currencies. Digital currencies can be traded and stored via pre-configured software or electronic platforms such as phones or computers, as well as digital wallets. The majority of digital currency transactions take place in full secrecy over the internet, over secure dedicated networks. Although various digital currencies have problems, such as double-spending difficulties, virtual currencies have gained significant acceptance around the world. The growing popularity of virtual currencies has accelerated the adoption and acceptance of cryptocurrencies as a safe and dependable form of money that performs the same functions as fiat currencies. To put it another way, a cryptocurrency is a type of digital or virtual currency that can be used as a medium of exchange or a store of value. For both novice and expert investors, cryptocurrency has moved from peer-to-peer payment systems to financial instruments, store of value assets, safe havens, and hedging choices. The growth of cryptocurrency markets has been exponential and unexplainable. Approximately 5000 cryptocurrencies are presently in use for a variety of purposes, with the number projected to grow in the future. The cryptocurrency market's volatility clustering is unrivalled by any other commodity market. Most major cryptocurrencies' market capitalizations have risen, implying that their prices and trading volumes have risen as well. Cryptocurrencies, unlike other types of digital currencies, are difficult or impossible to counterfeit, and they do not have the issue of double spending during transactions. Blockchain technology underpins the majority of cryptocurrencies. It's a decentralized network with many nodes (computers) that organizes and records transactions similarly to a ledger. As a result, blockchain is known as a public or distributed ledger. There are almost 5,000 different types of cryptocurrencies available today. Each cryptocurrency has its own role, method, and protocol that distinguishes it from the rest. By market capitalization, Bitcoin, XRP, Ethereum, Tether, Bitcoin Cash, Polkadot, Binance Cash, Chainlink, Cardano, and Litecoin are the most valued cryptocurrencies. In September 2020, the total value of all cryptocurrencies was more than $370 billion, according to coinmarketcap.com. Bitcoin continues to reign supreme, with 62 percent of the cryptocurrency industry and a market capitalization of almost $270 billion.

1.1. Bitcoin

Bitcoin is a peer-to-peer payment system that maintains its integrity and functionality mostly through cryptography and Blockchain technology. It's a decentralized, anonymous digital money that's not backed by any government, central authority, or other regulatory body. In terms of market valuation, Bitcoin is the first and largest cryptocurrency. Bitcoin is an internet-based cryptocurrency and digital currency that is alleged to have been created by an unknown programmer or group of programmers known as Satoshi Nakamoto (Greenwood-Evans, Hillard, Harper, & Williams, 2016). Satoshi Nakamoto produced a white paper called "Bitcoin: A Peer-to-Peer Electronic Cash System" in 2009. In this work, he stated that there was no way to make payments through a specific communication channel without the help of a trustworthy third party. He suggested that instead, an electronic payment system based on cryptographic evidence is required, allowing parties to connect directly with one another without the necessity for a Trusted Third Party. He then presented Bitcoin as a solution to fulfil that need. It is accomplished through the use of blockchain, which does away with the requirement of a central authority to verify and approve digital transactions. This is a product that has gotten a lot of attention and has had a lot of support from a lot of different people throughout time.

1.2. Blockchain

A distributed ledger or decentralized database that continuously updates and verifies records of digital transactions is referred to as blockchain. It's a one-time read-only database with immutability, which means that records can't be modified or fabricated because they can't be edited, added, or deleted. Blockchain is accessible to everyone (every node) in the network with relative simplicity. Cryptography is used to record transactions and make them pseudonymous in order to guarantee transaction privacy. Blockchain is a technology that helps to solve the problem of double spending by allowing everyone to validate transactions as they happen. This blockchain confirmation shows that there is an alternative to relying on trusted third parties to validate digital transactions. It's the software that allows Bitcoin and other crypto currencies to function. A number of researchers have drawn parallels between Bitcoin and blockchain and the internet and email (Kolokotronis, Limniotis, Shiaeles, & Griffiths, 2019). Some of the qualities of blockchain are listed below:

- Decentralised: the network is distributed over multiple nodes, with no central authority dictating how the network is used.
- Transparency—through their public keys, everyone in the network has access to the recorded transactions, and as transactions happen, everyone has access to the updated information at the same time. Immutability refers to the fact that transactions on the blockchain cannot be modified, destroyed, or falsified.

1.3. Ethereum

Ethereum is a digital framework that helps programmers to create and deploy decentralized applications, also known as Dapps using an open software architecture based on blockchain technology. Ethereum, like Bitcoin, is based on blockchain technology, and its native currency, Ether, is viewed as a competitor or rival to Bitcoin by some. On a market capitalization basis, Ethereum is the second most valuable cryptocurrency. Ethereum was built primarily to address some of Bitcoin's shortcomings. Ethereum was intended to address many problems of Bitcoin, including its limited functionality and scripting language, according to (Greenwood-Evans et al., 2016). In 2013, Vitalik Buterin, a Russian-Canadian programmer who was engaged in the cryptocurrency community and Bitcoin at the time, produced a white paper which revolutionized the use of blockchain technology to solve this problem. The crypto and Bitcoin communities, according to Buterin, the co-founder of Ethereum, were treating blockchain technology incorrectly and narrowly. He claimed that blockchain applications were only meant to do a limited set of tasks and act as a peer-to-peer digital payment system. Vitalik and his colleagues created Ethereum, a next-generation smart contract and decentralized application platform, to address Bitcoin's severe technological limitations. This eventually made it impossible to create new blockchain-based applications. Unlike Bitcoin, Ethereum enables the creation and operation of smart contracts and decentralized applications (Dapps) without the risk of fraud, third-party meddling, or outside control. A smart contract is a set of rules that govern the exchange of anything of value between parties, such as property, shares, and money. Szabo (1994) was the first to suggest smart contracts, which he defined as "computerized transaction protocols that carry out the terms of a contract." Self-executing contracts are so named because the conditions of the buyer-seller agreement are directly encoded into lines of code. They ensure that all transactions are transparent, traceable, and irreversible. Furthermore, Ethereum is not only a platform but also a programming language based on blockchain technology (solidity). This programing language helps the developers to build and publish decentralized applications. Some other cryptocurrencies were launched and operate using the Ethereum’s blockchain. Ethereum is making its impact thanks to the Decentralized Applications (Dapps) which are being used to create other digital currency protocols and other applications and this is a feature that Bitcoin’s blockchain do not possess at the moment. Smart Contracts and Decentralized Applications are some of the main differences Bitcoin and Ethereum blockchains in terms of their operations. Additionally, Ethereum can be used to represent assets such as USD, gold, corporate stocks, identity and reputation systems, financial derivatives, decentralized file storage, and Decentralized Autonomous Organizations (DAO). Ethereum has the potential to be used to create a wide range of decentralized applications.

1.4. Objectives of the Study

Bitcoin and Ethereum being the top two cryptocurrencies in the first and the second places respectively, this study looks to examine the inter and intra dynamics and relationship between Bitcoin price (BTCP), Ethereum price (ETHP), Bitcoin volume (BTCV) and Ethereum volume (ETHV) before (pre COVID-19) and during the COVID-19 pandemic.

This study aims to:

- Determine the effect of the COVID-19 pandemic on the long-run relationship between Bitcoin price, Bitcoin volume, Ethereum price and Ethereum volume.
- Determine whether the COVID-19 pandemic has any significant effect on the Bitcoin price, Bitcoin volume, Ethereum price and Ethereum volume.
- Determine the link between the price of Bitcoin and the volume of Bitcoin and Ethereum.
- Determine the relationship between the price of Ethereum and the volume of Bitcoin as well as Ethereum.

1.5. Significance of the Study

The increasing popularity of cryptocurrencies in the global market has created interest among people and investors who look forward to expand their gains through various investments. According to Husodo et. al 2020, Bitcoin and Ethereum have proven to possess safe-haven properties for stocks during the COVID-19 pandemic. In some cases, they have been used as payments in digital transactions. Bitcoin and Ethereum being the first and second largest cryptocurrencies respectively, they are important to investors in order to determine the impact of global economic shocks and various studies have been conducted on these two cryptocurrencies because they are known to possess hedging and save haven properties in the market (Husodo et. al 2020; McGee et. al 2020). The increasing prices of Bitcoin and Ethereum is proof of their recognition in the market and worth being considered for a study. This makes our study important to the public eye because it can create interest among the would be investors who might want to deal in these two cryptocurrencies especially with their growing popularity and vitality in the market.

1.6. Motivation of the Study

There was a turn of events as many economies and business sectors were shutting down because of the outbreak of the COVID-19 pandemic in 2020. According to some studies like Husodo et. al 2020, assets like gold, stock markets, or fiat currencies were also affected due to the outbreak. In this situation, investors would look out for assets that could be safe havens in order to protect and secure their markets. However, cryptocurrencies were able to rebound and recover quickly from the economic shock of the COVID-19 pandemic. According to Husodo et. al. 2020, the top two cryptocurrencies, Bitcoin and Ethereum were considered to be safe havens for stocks during this period of the pandemic. Because of this, I have selected and considered these two cryptocurrencies, Bitcoin and Ethereum in my study since they have the largest market capitalization.

CHAPTER II

LITERATURE REVIEW

In the previous chapter, we introduced Bitcoin and Ethereum that we are going to be examining in our study and we also specified the objectives of our study as well as the significance of the study.

In this chapter, we are reviewing and looking at some of the previous studies related to two cryptocurrencies, Bitcoin and Ethereum, and connect them with our study in order to assess and get a better grasp of understanding of our content. The literature review as the focus of this chapter follows below:

A study was conducted by (Mariana, Ekaputra, & Husodo, 2020) to see if Bitcoin and Ethereum may be used as a stock safe haven during the COVID-19 pandemic. They allege that the World Health Organization's declaration of COVID-19 as a pandemic on March 11, 2020, had sent financial markets all over the world into a tailspin as a result of projected worldwide economic recessions in the future years. The authors examine Bitcoin and Ethereum returns during the market shock produced by the COVID-19 pandemic and assess their impact on the market in this situation. The authors used the WHO's declaration of COVID-19 as a pandemic to test Bitcoin and Ethereum as stock safe-havens. Because the US has the greatest economic market and appears to be the worst afflicted by the COVID-19 pandemic, the stock and price indexes used are for the US, in order to create a proxy for the world's most major problem. Because the COVID-19 global epidemic is the first global health event to cause an economic shock since the 2008 Global Financial Crisis and the launch of Bitcoin in 2009, gold, which is considered a safe-haven (Baur and Lucey, 2010), falls in value, setting the stage to see if Bitcoin and Ethereum, the largest and second largest cryptocurrencies, respectively, exhibit short-term safe-haven attributes for stocks. The website Coindesk.com provided data for Ethereum (ETH) and Bitcoin (BTC) while DataStream provided data for gold spot prices and the S&P500. The authors use a short-term monitoring window from July 1, 2019 to April 6, 2020, to control the potential impact of Bitcoin halving on May 12, 2020, (Crawley,2020). To assess the results of previous investigations (Engle, 2002; Corbet et al., 2020; Bouri et al., 2017; Akhtaruzzaman et al., 2020), the authors employ the DCC-GARCH technique. Using the DCC-GARCH technique, the authors investigate the dynamic association between cryptocurrencies, gold, and the S&P500 index (Engle, 2002). According to Aielli (2013), the authors calculate the corrected-DCC (cDCC) and weigh up the results to the DCC results as a robustness test. They adopt the same technique as Baur et al. (2018) and conduct OLS regressions with the Newey-West robust estimator after evaluating the vibrant correlations. They discovered that during the COVID-19 outbreak, volatility increases, and that all returns on Ethereum, Bitcoin, the S&P500 and gold are more irregular than previously. During the pandemic, the bilateral connections between gold and both coins appear to rise, whilst the correlations between the S&P500 and both coins appear to decrease, with the S&P500 and Bitcoin at -0.3790 and the S&P500 and Ethereum at -0.3757, respectively. To see whether the halving of Bitcoin would have an impact on the study's findings, the authors compared Bitcoin and Ethereum returns before and during the pandemic, finding that they have a correlation of 0.8306 and 0.9841, respectively. The high correlation shows that halving Bitcoin would have little effect because Ethereum is not subject to halving. Prior to the pandemic, the dynamic correlations between the S&P500 and gold index are always negative, having a median of -0.2909, and tend to be less negative during the pandemic, having a median of -0.1800. Dynamic correlations between Bitcoin and the S&P500 index varied from -0.0713 to 0.1007 before the outbreak, having a median of -0.0047, but they were significantly more negative after the pandemic, having a median of -0.0393. The dynamic connections between the S&P500 and Ethereum were negative prior to the pandemic, ranging from -0.1259 to 0.1180, with a median of -0.0580, and they remain negative during the outbreak, with a median of -0.0499. Furthermore, the median connection between Ethereum and the S&P500 for the entire period is lower than the median connection between Bitcoin and the S&P500. Second, unlike gold and Bitcoin, dynamic correlations between gold and Ethereum are always favourable prior to the outbreak and are expected to increase during one. Finally, the median correlations between Ethereum and gold were larger than those between Bitcoin and gold during the pandemic. Bitcoin and Ethereum, according to this analysis, are suitable as short-term safe havens since they are positively connected with gold and negatively correlated with the S&P500. Furthermore, because Ethereum has a larger volatility return than Bitcoin, it could be a better safe-haven asset in the event of a stock market correction. The study's authors conclude that the safe-haven qualities of various cryptocurrencies are dependent on market conditions and investment horizons. During major stock market falls, both Ethereum and Bitcoin have proven to be beneficial as short-term safe havens, and investors are urged to buy these coins during market downturns in order to secure a large gain in the future. Another study was undertaken by (Conlon, Corbet, & McGee, 2020) to analyse Tether, Ethereum, and Bitcoin's hotly disputed safe haven attributes from the perspective of international equities index investors. They used daily data from Coinmetrics on the cryptocurrencies Tether, Ethereum, and Bitcoin, as well as their CM reference rates. To isolate the impact of the COVID-19 pandemic, they used the VaR and CVAR techniques from 11 April 2019 to 9 April 2020. According to them, Ethereum and Bitcoin are not found to be a safe haven for worldwide equities markets in general, however Tether has been found to be a safe haven in recent times, particularly during the COVID-19 crisis. In another study by (Feng, Wang, & Zhang, 2018) using a tail risk perspective analysis to see if cryptocurrencies may operate as safe havens, they used daily price data from www.coinmarketcap.com for seven cryptocurrencies, with the data period spanning from August 8, 2015 to August 1, 2017, with the selected cryptocurrencies being Ethereum, Bitcoin, Litecoin, Ripple, Dash, Monero, and NEM, with the ARMA-GARCH-PML-GPD technique. According to them, throughout the sub-period of August 1, 2016 to August 1, 2017, most of the selected cryptocurrencies, which are akin to commodities but not stock indexes, have restricted loss constraints. Meanwhile, left tail correlations are far stronger than right tail correlations across all cryptocurrencies, and tail correlations have been rising since August 2016, indicating significant systemic vulnerabilities. With four stock indices, it was discovered that cryptocurrencies are tail and cross tail independent, implying that part of their safe-haven function is to be a tremendous stock market diversifier, similar to gold, but not enough to be a tail hedging tool, similar to gold.

(Beneki, Koulis, Kyriazis, & Papadamou, 2019) investigated the volatility transmission and hedging properties of Bitcoin and Ethereum in a study. Following the temporary spike in Bitcoin and Ethereum in 2017, the authors contend that cryptocurrencies have become a phenomenon that has piqued the curiosity of the media, as well as government and financial organizations. This is mostly owing to the fact that they have opened up new possibilities in terms of payment methods and the capacity to utilize pseudonyms, as well as a broad range of academic studies in finance and economics, with cryptocurrencies serving as the primary focus. The systematic and comprehensive examination of Bitcoin and Ethereum has piqued the interest of policymakers and investors alike, owing to the problems and opportunities they present. From the launch of Ethereum until June 2018, cryptocurrency aficionados have expressed concerns over which cryptocurrency to invest in, with much speculation about whether Bitcoin will be superseded by Ethereum, making the relationship between the two cryptocurrencies a hot topic. Our research broadens this type of research by looking at any volatility transmission. It focuses on the Ethereum-Bitcoin relationship while accounting for trading volume in each market. The study's Ethereum and Bitcoin pricing and volume dataset comprises daily observations from August 8, 2015, when Ethereum was founded, through June 10, 2018, when Bitcoin was launched, with all values collected from the Coinmarketcap database. The initial differences in natural logarithms are used to calculate Ethereum and Bitcoin returns, as well as trade volumes. A multivariate GARCH framework is utilized to estimate time-varying variances and covariance, and the VECH and diagonal BEKK (Baba, Engle, Kraft, and Kroner) models are among the multivariate GARCH formulations employed in this study. According to the authors, changes in trading volume have a positive impact on each currency's returns, but changes in Bitcoin trading volume have a negative impact on Ethereum returns, despite the fact that this is not possible in terms of Bitcoin returns. Bitcoin returns have a lower level of volatility than Ethereum returns. While focusing on the time-varying conditional correlation between the two cryptocurrencies, the authors detect some noteworthy differences between positive and negative values. This correlation between Ethereum and Bitcoin, in particular, shows positive values during periods of rapid price increases for both cryptocurrencies, and there was a trend toward reduced correlation between the two cryptocurrencies during the second half of the year 2017, when Ethereum and Bitcoin exchange rates to US dollars actually increased, indicating a higher level of competitiveness. Despite this, as the prices of both cryptocurrencies plummeted at the start of 2018, the correlation between them rebounded to a positive position and surged to higher levels than before. The volatility transfer from Ethereum to Bitcoin, according to empirical data, peaks in less than ten days and fades out in more than two weeks, but the inverse effect is significantly smaller. Because shocks take time to price in, the delayed response of Bitcoin volatility to an Ethereum return volatility shock shows market inefficiency. According to the paper, while owning Bitcoin can help investors by offering exceptional gains, it cannot be utilized as a hedge during periods of low demand in the Ethereum and Bitcoin markets. Another study was conducted by (Yousaf & Ali, 2020) to investigate how Litecoin, Ethereum, and Bitcoin performed before and after COVID-19 in terms of return and volatility transmission. They utilized hourly data of Bitcoin, Ethereum, and Litecoin, two sample periods: the pre-COVID-19 period (January 1, 2019 to December 31, 2019) and the COVID-19 period (January 1, 2020 to April 22, 2020).Bittrex is the source of the bitcoin prices, which are in US dollars. According to the VAR-DCC-GARCH approach, during the COVID-19 timeframe, investors should reduce their investments in Bitcoin for BTC/ETH and BTC/LTC portfolios, and Ethereum for ETH/LTC portfolios. In both crisis and non-crisis settings, investors can employ optimum portfolios and hedging ratios to create portfolios that minimize risk exposure. Overall, these findings give useful information on diversification, optimal asset allocation, hedging, and risk management to investors and regulators.

Research was conducted by (Sifat, Mohamad, & Shariff, 2019) to find and assess price leadership between Bitcoin and Ethereum, the top two cryptocurrencies. To arrive at their conclusions, they used a year's worth of hourly and daily data, as well as the VECM, ARMA, ARDL, Granger Causality and Wave Coherence procedures, as well as the VECM, ARDL Granger Causality, ARMA, and Wave Coherence approaches. Overall, the findings imply that using hourly and daily data to exploit Bitcoin and Ethereum price leadership cannot be used to scalp or make a quick profit. Researchers may want to investigate into the price discovery process for BTC and ETH in the future utilizing a larger and more comprehensive dataset. Another study was conducted by (Mensi, Al-Yahyaee, & Kang, 2018) to research on the impacts of structural breaks (SB) on the dual long memory levels, as well as recognizing structural changes in cryptocurrency markets, which included a comparison of Bitcoin and Ethereum price returns. They employed the GARCH, FIGARCH, FIAPARCH, and HYGARCH procedures, as well as daily spot Bitcoin and Ethereum prices from the Coindesk price index website from July 1, 2011 to March 3, 2018, as well as the GARCH, FIGARCH, FIAPARCH, and HYGARCH approaches. According to them, data suggests that

Ethereum and Bitcoin have a dual long memory property, which contradicts market efficiency and random walk theory. Because the markets for Ethereum and Bitcoin are still governed by a central body, they are volatile, which may help investors plan for future volatility and implement hedging methods. In another study, an investigation was undertaken by (Song, Chang, & Song, 2019) to examine the structure of the cryptocurrency market and reduced their linear effects on other cryptocurrencies using a correlation-based agglomerative hierarchical clustering and minimal spanning tree via the Ethereum-Bitcoin filtering mechanism. From December 2017 to March 2018, they used hourly data prices from the Binance exchange API for 76 cryptocurrencies with 24-hour trading time, as well as the Correlation-based clustering and MST techniques, as well as the OLS approach. According to them, the most valued assets on the market are Ethereum and Bitcoin, resulting in a simple cryptocurrency market structure with two clusters. However, because of the two main assets' prominence, it's difficult to see regular patterns among weaker cryptocurrencies. Following the release of rules from several nations, the structure of the bitcoin market has changed.

(Corbet, Lucey, & Yarovaya, 2017) conducted research into the existence and times of Bitcoin and Ethereum pricing bubbles. They used datasets retrieved from previous APIs and the recursive ex ante methods for Bitcoin after July 18,2010 and Ethereum after August 7,2015 to November 9,2017. They argue that there is no evidence of a long-term bubble in the Ethereum or Bitcoin markets. Although there are different short-term time periods in which the price dynamics of both cryptocurrencies are substantially changed, these effects vanish quickly. Another study by (Fry, 2018) focused on developing credible Bitcoin and cryptocurrency bubble models that account for large tails as well as the danger of a catastrophic asset price crash. From January 1, 2015 to January 1, 2018, he projected Ripple and Bitcoin values, Ethereum prices from August 7, 2015 to January 1, 2018, and Bitcoin Cash prices from July 23, 2017 to January 1, 2018. He obtained pricing data from Coinmarketcap.com, a reliable source, using the Robustness approach. He argues that liquidity difficulties are to blame for large tails in the Bitcoin and other cryptocurrency markets. Bubbles aren't required in the case of cryptocurrencies to establish boom–bust patterns. If there is no central regulation, prices may fall to zero. This proves that the Ethereum and Bitcoin bubbles do exist.

(Mensi, Lee, Al-Yahyaee, Sensoy, & Yoon, 2019) investigated high-frequency asymmetric multifractality, weak-form efficiency, and extended memory for Ethereum and Bitcoin in a study. They used data for the Bitcoin and Ethereum exchanges from June 1, 2013 to June 23, 2018, generated from high frequency intraday data acquired from the Bitfinex Exchange at three different intervals (five, ten, and fifteen minutes) and the A-MF-DFA technique. Both markets have asymmetric multifractality, prolonged memory, and structural breaks, according to them. The Bitcoin market is more inefficient in terms of downward, upward, and overall swings. Another study was carried out during the COVID-19 pandemic by (Naeem, Bouri, Peng, Shahzad, & Vo, 2020) to look into asymmetric efficiency and found that the price of cryptocurrency has a lot of asymmetric multifractality. From July 1, 2017 to April 1, 2020, they used high-frequency 1-hour pricing of four major cryptocurrencies: Ethereum (ETH), Ripple (XRP), Bitcoin (BTC) and Litecoin (LTC), as well as the Asymmetric MF-DFA technique for the empirical investigation. According to them, the COVID-19 pandemic had a negative impact on cryptocurrency efficiency. The efficiency of Ethereum and Bitcoin has taken the brunt of the blow. Around March 2020, the efficiency of these major cryptocurrencies rebounded more quickly.

(Cagli, 2018) investigated the price volatility of Bitcoin and seven other cryptocurrencies, including Monero, Ethereum, Ripple, Stellar, Nem Dash, and Litecoin. From September 1, 2015, to January 31, 2018, he used daily data from Coinmarketcap for each coin's price, volume, market capitalization, and circulating supply statistics, as well as the novel explosive process framework of continuous systems with moderately explosive regressors approach. All coins other than Nem, he claims, have explosive behaviour. The explosive cryptocurrencies have considerable pairwise co-movement correlations. All feasible pairings of mined coins are moving in the same direction. Non-mined cryptocurrencies have a negative correlation with other cryptocurrencies. Another study was carried out by (Shi & Chang, 2020) to investigate the major four cryptocurrencies' dynamic information shares: Ethereum (ETH), Ripple (XRP), Bitcoin (BTC) and Litecoin (LTC). They used daily data from Coinmarketcap, including market capitalization, closure price, and dollar trading volume, from January 1, 2016 to December 31, 2019, as well as a time-varying vector error correction model (VECM) technique. Despite its decreasing importance over time, they claim that Bitcoin is still the most important cryptocurrency in the market-level price discovery process. Individual effects of trading volume and market capitalization can explain 20% of changes in Bitcoin information sharing, but only 6% of variations in Ethereum information share. An investigation was conducted by (Mensi, Rehman, Al-Yahyaee, Al-Jarrah, & Kang, 2019) to look into the relationship between Bitcoin and five other significant cryptocurrencies (Ethereum, Monero, Litecoin, Ripple, and Dash), as well as the consequences for portfolio risk. They obtained daily data closing-price information for six major cryptocurrencies from the Coindesk Price Index website, including Ethereum, Bitcoin, Litecoin, Dash, Ripple, and Monero, using cross wavelet transformations and wavelet coherence techniques. According to their investigation, Bitcoin has leading relationships with Ripple, Dash, and Monero, lagging ties with Ethereum, and out of phase movements with Litecoin, indicating co-movements in time frequency space. It examines a number of portfolios to prove that a mixed portfolio (Bitcoin and other cryptocurrencies) offers portfolio managers and investors superior diversification (risk-minimizing portfolio, evenly weighted portfolio, and hedging portfolio). Finally, an Ethereum-Bitcoin (Monero-Bitcoin) hedging portfolio delivers the most risk reductions and hedging efficacy across medium and long term (short term) timelines. Negative risk reductions have different consequences depending on the time horizon.

(Bouraoni, 2019) conducted research in twenty-one emerging countries to identify and focus on the factors that affect Bitcoin transaction volume. He used weekly data on Bitcoin trading volume in twenty-one emerging nations, the price of two altcoins, Ripple and Ethereum, derived from the Thomson Reuters Eikon database, and the VECM and ARDL techniques between August 1, 2015, and June 2, 2018. He argues that in all of the countries studied, access to the banking system has a major impact on local Bitcoin trade activity. Because having bank accounts is still difficult in many developing nations, people are more likely to accept a new decentralized system that operates outside the authority of any government or central bank. The VECM results show a significant and positive relationship between altcoin values (Ethereum, Ripple) and Bitcoin trading volume over time. There is a short-term link between altcoin prices and Bitcoin trading volume, according to ARDL research. Another study was undertaken by (Lahiani, Jeribi, & Jlassi, 2020) to investigate the relationship between BRICS and cryptocurrency stock market returns and stock market returns in developed countries. From January 4, 2016 to December 31, 2019, they used daily data prices for five top cryptocurrencies, five developed country stock market indices (S&P 500, Nasdaq, Nikkei, FTSE, DAX 30), BRICS stock market indices (SSE, RTSI, BSE 30, BVSP, JSE 40), VIX, WTI, and gold prices, as well as the GARCH and a newly developed model-free measure. The data, they say, demonstrates the significance of the S&P 500, Nasdaq, and DAX 30 in predicting stock market success in Brazil, Russia, India, China, South Africa (BRICS) and developed countries. In the BRICS countries, the BVSP is critical for predicting stock market success. Cryptocurrency returns, which are less predictable than stock market returns, are best predicted by the BSE 30 index. The most accurate predictor of stock market and cryptocurrency performance is Ethereum, followed by Bitcoin. The S&P500, Nasdaq, and BVSP all have a considerable impact on projecting stock market outcomes, according to tail dependency. In a subsample analysis, the impact of Bitcoin features in changing the mean and tail dependence between cryptocurrency and stock market returns is demonstrated. For hedge funds, portfolio managers, and investors, our findings have significant policy consequences. An investigation was also carried out by (Palazzi, Junior, & Klotzle, 2020) to check if Bitcoin has a nonlinear link with six currencies denominated in US dollars: the pound sterling, euro, yen, rubble, Swiss franc, and renminbi. They used Bloomberg platform daily closing price data for BTC, GBP,EUR,CNY, RUB, CHF, and JPY between July 2010 and April 2020, translated into log-return form, and a multivariate filter-BEKK-GARCH algorithm. According to them, currencies and bitcoin's return are predictable and interconnected. It demonstrates how the Chinese yuan has an impact on bitcoin's price.

(Noda, 2020) used the adaptive market hypothesis and assessed market efficiency to see if the adaptability of cryptocurrency markets (Ethereum and Bitcoin) will change over time. They used daily Ethereum (ETH) and Bitcoin (BTC) price data from coinmarketcap.com. The datasets for the two cryptocurrencies have distinct start dates: April 28, 2013 for Bitcoin and August 7, 2015 for Ethereum, but the end dates are the same for both cryptocurrencies, which is September 30, 2019, and the GLS-based time-varying AR methodology is used. According to them, the level of market competence varies over time in marketplaces. Bitcoin's market competency has been higher than Ethereum's over the majority of time periods, and a market with robust market liquidity has evolved. The findings support the adaptive market hypothesis for the most entrenched cryptocurrency market. Another research was conducted by

(Subramaniam & Chakraborty, 2019) to see how investor interest affects cryptocurrency pricing. The cryptocurrency markets' arbitrary pricing behaviour and inefficiencies provide an opportunity to research behavioural elements of cryptocurrency prices. From January 2013 to March 2018, they used daily closing values in US dollars for Ethereum, Bitcoin, Litecoin, and Ripple from the Thomson Reuters Datastream database. Because some of these cryptocurrencies were not traded in 2013, the timeframe was determined on a case-by-case basis depending on the availability of data, and the Quantile causality technique was used. They say that the findings demonstrate that investors pay attention to the periodic news cycle and rank cryptocurrencies accordingly (Ethereum and Bitcoin). Only when nascent cryptocurrencies like Ripple perform well can investor interest restrict their pricing. In cryptocurrency prices during expansionary stages and fear selling during periods of bad market performance, the study finds evidence of the attention-induced price pressure hypothesis.

(Grobys, 2021) looked into how hacking incidents in the Bitcoin market impact market volatility. They used data from coinmarketcap.com to compute the worth of Ethereum and Bitcoin. For the sake of this study's main analysis, Bitcoin data was collected from April 28, 2013 to December 31, 2017, whereas Ethereum data was collected from April 7, 2015 to December 31, 2017. In addition, the EGARCH method is used. The data they believe shows a considerable increase in volatility. There are two sorts of effects identified in this study: a delayed effect and a contemporaneous effect. While the immediate effect may be attributed to the hacked exchange's huge rise in uncertainty, the delayed effect could be attributed to the fact that smaller exchanges with fewer security measures are more likely to be hacked than larger exchanges.

Following up on all of the research in the review, I discovered a gap in the literature where they do not address the dynamics of the leading two cryptocurrencies, Ethereum and Bitcoin, before and during the COVID-19 pandemic. In my study, I utilized the Johansen Cointegration Test and the Vector Error Correction Model (VECM) to look into and analyse their link during this period.

CHAPTER III

DATA AND METHODOLOGY

In the previous chapter, we reviewed some literature of previous studies which are connected to our study with the aim of grasping a better understanding of our work. In this chapter, we are looking at the data selection and the methodology for our study. The data set and the methodology are described below as follows:

3.1. Data Description

This study utilizes daily data for the four variables: Bitcoin price (BTCP), Ethereum price (ETHP), Bitcoin volume (BTCV) and Ethereum volume (ETHV) between the period August 8,2015 up to February 28, 2021 from Coinmarketcap.com extracted on March 1,2021 . The data selected consists of 2032 observations and covers a period before and during the COVID-19 pandemic which is also included in this study. In this case, COVID-19 pandemic is considered as a dummy variable which takes up a value 0 for a period before the pandemic and a value 1 for a period during the pandemic.

3.2. Methods

3.2.1. Unit Root Test

– Basic Unit Root Theory

Consider a simple AR(1) process:

$$y_t = \rho y_{t-1} + x_t' \delta + \epsilon_t$$

Where x_t are exogenous regressors that can be either constant or constant and trend, ρ and δ are parameters that need to be estimated, and ϵ_t is assumed to be white noise. If $|\rho| \geq 1$, y is a nonstationary series, and its variance grows exponentially over time, approaching infinity. If $|\rho| < 1$ y is a (trend-) stationary series. Thus, the (trend-) stationarity hypothesis can be tested by determining if the absolute value of ρ is strictly less than one.

– **Augmented Dickey-Fuller (ADF) Test (1979)**

Dickey and Fuller (1979) developed the ADF, which is widely recognized as a ground-breaking work in the field of recognizing and investigating the presence of unit root in time series analysis. The unit root hypothesis is the null hypothesis of the Augmented Dickey-Fuller (ADF) test, while stationarity is the alternative hypothesis. The following are three scenarios:

Testing for unit root (No intercept and No Trend, D0T0)

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

Testing for unit root (Intercept and No trend, D1T0)

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

Testing for unit root (Intercept and Trend, D1T1)

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

Where y_t signifies the value of the variables at the given time period t, β_0 is a constant, $\beta_1 t$ is the deterministic drift and μ_t is the error term. The alternative hypothesis and null hypothesis to be investigated are as follows;

H_0: $\varphi^*= 0$ → time series having a unit root

H$_1$: $\varphi^{*}= 0$ → time series having stationarity

– **Phillips- Peron (PP) Test (1988)**

The Phillip-Peron test, like the Dickey-Fuller test, includes a null hypothesis of unit root and an alternative hypothesis of stationarity. Unlike the Dickey-Fuller test, the Phillip-Peron technique does not use distinguished models to create test statistics, but it is ultimately generated from them. For the model with a constant, the test statistic Z is stated as below: (Arltová & Fedorová, 2016; Pesaran, 2015):

$$Z_{\phi} = \left(\widehat{\phi_T} - 1\right) - \frac{1}{2}\frac{T^2 \times se_{\hat{\phi}}^2}{se_T^2}\left(se_{LT}^2 - se_T^2\right)$$

$$Z_T = \left(\frac{se_T}{se_{LT}}\right) t_{DF} - \frac{1}{2}\left(se_{LT}^2 - se_T^2\right)\frac{1}{se_{LT}}\frac{T \times se_{\hat{\phi}}}{se_T},$$

Where:

$$t_{DF} = \frac{\widehat{\phi_T} - 1}{se_{\hat{\phi}}}, se_T^2 = \frac{1}{T}\sum_{t=1}^{T}\widehat{\varepsilon_t^2}, se_{LT}^2 = se_T^2 + 2\sum_{j=1}^{q}\left(1 - \frac{j}{q+1}\right)\widehat{\gamma_{J,T}}\ and\ \widehat{\gamma_{J,T}} = \frac{1}{T}\sum_{t=j+1}^{T}\widehat{\varepsilon_t}\widehat{\varepsilon_{t-J}}$$

And $\hat{\phi}_T$ is representing the estimated auto regression parameter for the lagged value of the series y_{t-1}, t_{DF} is the Dickey-Fuller test's original test statistics, se_T^2 reflects the unsystematic component variance's Ordinary Least Square estimator, $\widehat{\gamma_{J,T}}$ is the component variance's ML estimator and q is the number of the lags of covariates. $\gamma_{j,T} = 0$ when the residuals do not have a correlation ε_t, for $j > 0, and\ se_{LT}^2 = se_T^2$, the limiting distribution of the test statistic t is thus nondependent on the residual process's autoregressive parameters ε_t (Arltová & Fedorová, 2016).

– Kwiatkowski, Phillips, Schmidt, and Shin Test (KPSS, 1992)

This method was created by Kwiatkowski, Phillips, Schmidt, and Shin (KPSS, 1992) to address the limitations of the Augmented Dickey-Fuller (ADF) test. It is a type of stationarity test in which the null hypothesis is that the time series is stationary, and the alternative hypothesis is that it is not, in which case the time series has unit root. This method, which is based on the idea that time series stationarity occurs around a deterministic trend, computes the sum of a random walk, deterministic trend, and stationary random error or white noise. The following is a description of the model:

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

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

Where $d_t = \sum_{i=0}^{p} \delta_i t^i$, $for\ p = 0{,}1,$ comprising the deterministic elements (trend and constant) of the preceding equations, ε_t are independent and identically distributed (IID) N$(0,\ \sigma_\varepsilon^2), r_t$ is a variance-adjusted random walk $\sigma_u^2\ and\ u_t\ are\ iid\ N(0, \sigma_u^2)$.

The Lagrange Multiplier (LM) test is used in the KPSS the null hypothesis, which states that the random walk has no variance; $H_0: \sigma_u^2 = 0,$ implying that, r_t is constant in contrast to the alternative hypothesis that the random walk has a variance greater than zero; $H_1: \sigma_u^2 > 0$.

The KPSS LM statistic is shown or defined as follows:

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

Where $\sum_{t=1}^{T} \frac{se_t^2}{\widehat{\sigma_t^2}}$ represents the estimated error variance from the regression below:

$$y_t = \alpha + \beta_1 + \varepsilon_t$$

$se_t = \sum_{t=1}^{T} \widehat{\varepsilon_t}\ for\ t = 1, 2, \ldots, T\ and\ \widehat{\sigma_t^2}$ is the residual process variance estimate ε_t from the basic equation. The test's critical values were determined by a simulation approach and are stated in Kwiatkowski, Phillips, Schmidt and Shin, (1992).

3.2.2. Testing for Cointegration

Cointegration is a method that is used to investigate the presence of a long-run relationship among any given time series. A test for cointegration has to be conducted if the time series are not stationary. It is important to analyse non-stationary time series which have varying variances and means over a given time period. If there is evidence of cointegration among any given time series or variables, then an error correction model should also exist among the given times series or variables (Granger 1969).

The presence or absence of Granger causality is determined through cointegration. Cointegration occurs when two or more time series are individually integrated. It does, however, have a weakness in that it does not reveal whether or not they are causally related. To determine the causality's direction, only the Vector Error-Correction Model (VECM), which is generated from long run cointegrating vectors, can be employed. To test if any of the time series are cointegrated, the Johansen (1988) and Johansen & Juselius (1990) methods are utilized.

3.2.3. Johansen Cointergration Test

The Johansen cointegration test is utilized to see if the time series of a model are cointegrated. It is considered to be an improvement of the Engle-Granger test. Applying OLS on the level non-stationary time series can produce spurious results as stated by Granger and Newbold (1974). A test for cointegration, according to Granger (1986), should be used as a pre-test to rule out any false regression circumstances. Unlike the two-step Engle-Granger method, Johansen Cointergration can test for cointegration for two or more time series, each of which is integrated to the order of one shown as I(1). Two or more cointegrating relationships can coexist using this cointegration approach. This test is run with a group object or a VAR object that has been estimated.

Consider a VAR of order p:

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + Bx_t + \epsilon_t$$

Where y_t is a k- vector of non-stationary I(1) variable, A is the k-vector parameter matrix, x_t is a d- vector of deterministic variables, B is the d-vector parameter matrix and ϵ_t is a vector of innovations.

This AR can be rewritten as follows:

$$\Delta y_t = \mu + \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma i \, \Delta y_{t-1} + \epsilon_t$$

Where

$$\Pi = \sum_{i=1}^{p} A_1 - I$$

And

$$\Gamma_i = -\sum\nolimits_{j=i+1}^{p} A_j$$

$\Delta y_t = y_t - y_{t-1}$ is the differencing equation, Π represents the long run coefficient matrices and Γ_i represents the short run dynamics.

This study utilizes the unrestricted linear deterministic trend specification of the Johansen Cointergration Test as it is considered to be more credible. This specification is formulated as stated below:

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

Where the terms associated with $\alpha_1$are the deterministic terms which are 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. The trace test and maximum eigenvalue t-statistics are recommended by Johansen & Juselius (1990) for estimating the number of cointegrating vectors. However, the focus of this research is on the trace test, which is formulated as follows:

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

Where T depicts the sample size, r is the number of cointegrating vectors and λ is the eigenvalues. This null hypothesis of this cointegration approach of at most r cointegrating vectors versus the alternative hypothesis of more than r cointegrating vectors is tested by trace statistics.

3.2.4. Vector Error Correction Model (VECM)

Before we move on to the Vector error-correction model, we must first perform a cointegration test to see whether the variables or time series are cointegrated. This test can be used to determine whether two or more variables have a long-run and short-run relationship. In 1981, Granger established a relationship between error correction models and co-integration. Granger (1987) recommended that if two or more variables are cointegrated, they should also have a suitable error correction model. In order to model the Vector Error Correction Model (VECM), evidence of cointegration among the variables or time series is required, with the total number of cointegrating equations being smaller than the number of variables or time series in the model.

A simple error correction term can be defined by:

$$\varepsilon_t = y_t - \beta x_t$$

Where ε_t depicts the error term from the regression y_t on x_t and β is the cointegration coefficient.

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

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

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

The basic Error Correction Model is converted into Vector Error Correction Model and it is defined as follows:

$$\Delta y_t = \mu + \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma i \, \Delta y_{t-1} + \epsilon_t$$

Where $\Delta y_t = y_t - y_{t-1}$ is the differencing equation, Π represents the long run coefficient matrices and Γ_i represents the short run dynamics.

In our study, we are considering the price and volume dynamics of Bitcoin (BTC) and Ethereum (ETH) before and during the COVID- 19 pandemic. In this case, we take the pandemic as a dummy variable where it has a value 0 for the period before and a value 1 for the period during its declaration as the pandemic. Our model has four time series Bitcoin price (BTCP), Ethereum price (ETHP), Bitcoin volume (BTCV) and Ethereum volume (ETHV) and two cointegrating equations. Therefore, the model is defined as stated below:

– **Before the pandemic**

$$\Delta lbtcp = \alpha_0 + \alpha_1\Delta lethp_{t-1} + \alpha_2\Delta lbtcv_{t-1} + \alpha_3\Delta lethv_{t-1} + \alpha_4\Delta ECT_{t-1} + \mu_{t1}$$

$$\Delta lethp = \beta_0 + \beta_1\Delta lbtcp_{t-1} + \beta_2\Delta lbtcv_{t-1} + \beta_3\Delta lethv_{t-1} + \beta_4\Delta ECT_{t-1} + \mu_{t2}$$

$$\Delta lbtcv = \gamma_0 + \gamma_1\Delta lbtcp_{t-1} + \gamma_2\Delta lethp_{t-1} + \gamma_3\Delta lethv_{t-1} + \gamma_4\Delta ECT_{t-1} + \mu_{t3}$$

$$\Delta lethv = \delta_0 + \delta_1\Delta lbtcp_{t-1} + \delta_2\Delta lethp_{t-1} + \delta_3\Delta lbtcv_{t-1} + \delta_4\Delta ECT_{t-1} + \mu_{t4}$$

– **During the pandemic**

$$\Delta lbtcp = \alpha_0 + \alpha_1 \Delta lethp_{t-1} + \alpha_2 \Delta lbtcv_{t-1} + \alpha_3 \Delta lethv_{t-1} + \alpha_4 \Delta ECT_{t-1} + \lambda PND + \mu_{t1}$$

$$\Delta lethp = \beta_0 + \beta_1 \Delta lbtcp_{t-1} + \beta_2 \Delta lbtcv_{t-1} + \beta_3 \Delta lethv_{t-1} + \beta_4 \Delta ECT_{t-1} + \rho PND + \mu_{t2}$$

$$\Delta lbtcv = \gamma_0 + \gamma_1 \Delta lbtcp_{t-1} + \gamma_2 \Delta lethp_{t-1} + \gamma_3 \Delta lethv_{t-1} + \gamma_4 \Delta ECT_{t-1} + \phi PND + \mu_{t3}$$

$$\Delta lethv = \delta_0 + \delta_1 \Delta lbtcp_{t-1} + \delta_2 \Delta lethp_{t-1} + \delta_3 \Delta lbtcv_{t-1} + \delta_4 \Delta ECT_{t-1} + \omega PND + \mu_{t4}$$

CHAPTER IV

RESULTS AND DISCUSSIONS

In the previous chapter, we looked at the description of the data and methodology which are being used to make analysis in our study. In this chapter, we obtain the results of our analysis and make the necessary discussions about the conclusions to be drawn. In this case, we consider Bitcoin price (BTCP), Ethereum (ETHP), Bitcoin volume (BTCV) and Ethereum volume (ETHV) as our time series as observed in the table below.

4.1. Descriptive Statistics

Table 4.1. Descriptive Statistics Table

Variable	BTCP	ETHP	BTCV	ETHV
Mean	6703.182	258.7122	1.27E+10	5.44E+09
Median	6233.430	185.0500	5.00E+09	1.84E+09
Maximum	57539.94	1960.160	3.51E+11	6.07E+10
Minimum	210.4900	0.434800	12712600	102128.0
Std. Dev.	7594.768	310.3099	1.85E+10	8.11E+09
Skewness	2.963077	2.358623	4.511464	2.562079
Kurtosis	15.31722	10.01064	60.66787	11.42121

The summary of price returns as well as trading volumes of Bitcoin and Ethereum are given in Table above. As seen in the table, due to market manipulation, the values of Bitcoin (BTCP) and Ethereum (ETHP), as well as their trading volumes BTCV and ETHV, grew and peaked around February 2021. Because standard deviation is a proxy for evaluating asset volatility, both Bitcoin price (BTCP) and Ethereum price (ETHP) have relatively large standard deviations, signalling that both assets are highly volatile. Due to Bitcoin's dominance in terms of market capitalization in the crypto market, its mean and maximum values are substantially greater than those of Ethereum. As described in the table above, the price returns and the trading volumes of Bitcoin and Ethereum are relatively volatile. The figures below show how Bitcoin and Ethereum prices and volumes exhibit their volatility behaviour in these given time series.

4.2. Time Series Graphs

Figure 4.1. Bitcoin Prices, 2014-21

Figure 4.1. and Figure 4.2. indicate the trends of Bitcoin prices and Bitcoin trading volume over time respectively. It is observed from the graph that there is a spike in the trading volume and price of Bitcoin between 2017 and 2018. According to a recent analysis of bitcoin transactions from March 2017 to March 2018, big volume trades influenced the price of bitcoin, causing it to climb. The tremendous inflow of investors from large-scale institutions such as investment trusts, pension schemes, and university endowment funds is one of the reasons for the significant price increase. The 2017 hot streak also helped to propel Bitcoin into the mainstream, with analysts debating its value as an asset and a slew of so-called investors and experts making aggressive price predictions. As in the past, Bitcoin's price remained flat over the

following two years, with a resurgence in trading volume and price in June 2019, rekindling hopes of another rally, but it fell again in December 2019.

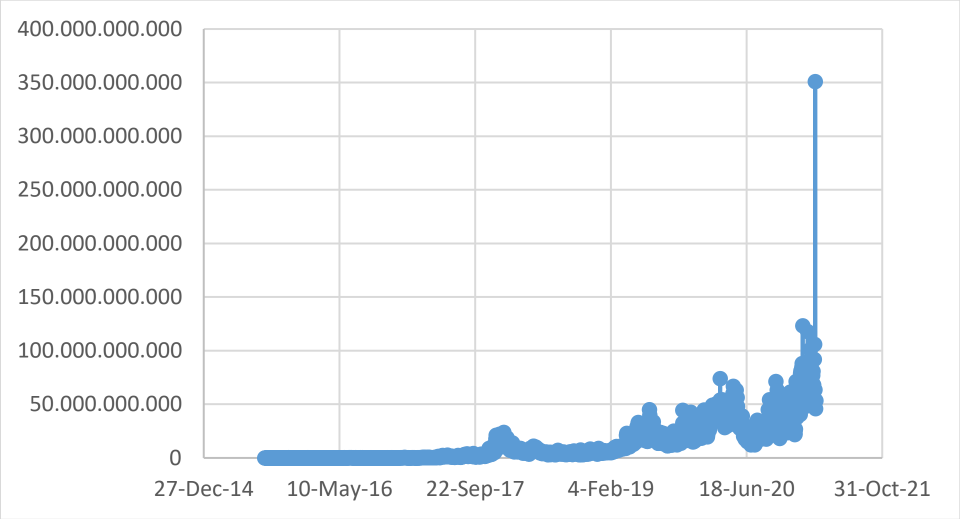

Figure 4.2. Bitcoin Trading Volume

Bitcoin's price didn't start to rise again until 2020, when the economy was shut down due to the pandemic. Investors' anxieties about the global economy were increased by the pandemic shutdown, as well as following government policy, prompting Bitcoin to surge by November 2020. Bitcoin's price surged even more in December 2020, representing a 224 percent increase since the beginning of the year. Bitcoin price reached a new high of almost 40,000 dollars in less than a month around January 2021, but then plummeted back to around 30,000 dollars. Around February 2021, due to some influence in the crypto market, Bitcoin price hit a record high surpassing 57,000 dollars and the price and trading volume spikes are observed and shown in the figures above.

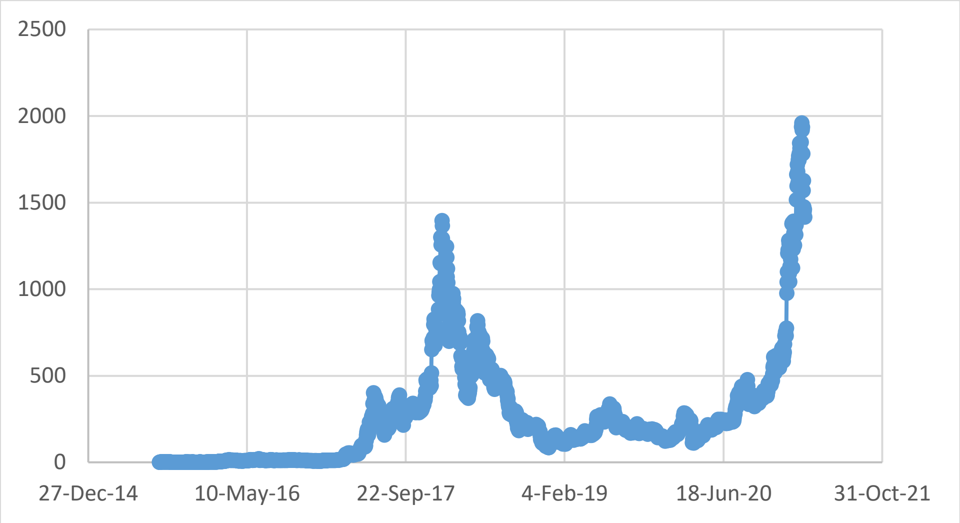

Figure 4.3. Ethereum Prices

Figure 4.3. and Figüre 4.4. show the trends of Ethereum price and Ethereum trading volume over time respectively. Ethereum has huge potential and around 2017, Ethereum price increased and it gained around 10,000% to its value. This is due to the increased demand for ether – the Ethereum network's crypto fuel – as a result of its broader applicability. Developers are doing more and more work as businesses and enterprises focus their attention to decentralized ledger technologies. Ether is a cryptocurrency that clients use to pay developers for services on the Ethereum platform. It also serves as a motivator for programmers who want to create and execute applications on the network. This also in turn creates competition for Bitcoin which may also influence the price rise of Ethereum.

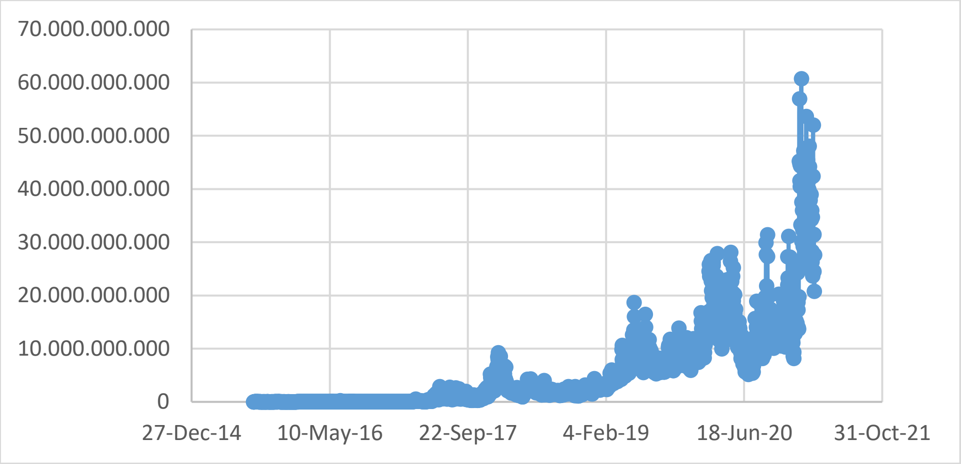

Figure 4.4. Ethereum Trading Volume

Around January 2018, Ethereum price reached a peak due to increased demand by investors there by influencing large trading volumes. It took a downward trend through 2018 by the end of the year, the price had fell beyond imagination due to the decline in the trading volumes. It maintained a steady profile throughout the year 2019. It was not until 2020, that a financial outlook was affected negatively, with the pandemic limiting financial operations especially those of banks that had been switched to digital platforms. Developing countries had little infrastructure in terms of reliable internet connections which could encourage them to participate in digital banking. developers of cryptocurrency saw this as an opportunity for investment. In a silos of positive benefits of Ethereum, investors started relying on this cryptocurrency as a safe haven in periods of economic downturns. Relying on Ethereum exponentially increased trading volumes due to high demand from investors in various countries, which influenced a swift increase in the cryptocurrency market causing a global alarm. This increase in the trading volumes directly influences and causes an increase in the Ethereum price which made it reach a record high.

4.3. Unit Root Tests

Table 4.2. Augmented Dicky Fuller (ADF) Test

UR Test	Specification	At Level			At First Difference			Conclusion
		None	Intercept	Intercept and Trend	None	Intercept	Intercept and Trend	
ADF	BTCP	2.738	-0.624	-1.484	-45.835***	-46.013***	-46.002***	I(1)
	ETHP	1.639	-2.012	-1.706	-46.689***	-43.834***	-43.857***	I(1)
	BTCV	1.652	-1.238	-2.678	-28.508***	-28.581***	-28.577***	I(1)
	ETHV	1.093	-1.417	-2.700	-26.606***	-26.644***	-26.642***	I(1)

Note: '*','**' and '***' indicate the rejection of the null hypothesis of unit root at 10%, 5%, and 1% significance level, respectively.

The null hypothesis of Augmented Intelligence According to Dicky Fuller, the time series have unit root, and stationarity is the alternative explanation. The null hypothesis is accepted for the time series at level and rejected at first difference for all specifications: no intercept and no trend (D0T0), intercept (D1T0), and intercept and trend (D1T1). The time series are unit root at level and stationary at first difference, as denoted by I (1).

Table 4.3. The Phillips-Peron (PP) Test

UR Test	Specification	At Level			At First Difference			Conclusion
		None	Intercept	Intercept and Trend	None	Intercept	Intercept and Trend	
PP	BTCP	2.663	-0.643	-1.529	-45.881***	-46.016***	-46.006***	I(1)
	ETHP	1.459	-1.979	-1.749	-43.904***	-43.968***	-43.986***	I(1)
	BTCV	1.091	-1.485	-6.654***	-77.202***	-79.959***		I(1)
	ETHV	1.163	-1.930	-5.099***	-78.396***	-78.811***		I(1)

Note: '*','**' and '***' indicate the rejection of the null hypothesis of unit root at 10%, 5%, and 1% significance level, respectively.

According to Phillip Peron, the null hypothesis is that the time series have unit root, while the alternative hypothesis is stationarity. The null hypothesis is accepted for all three specifications, no intercept and no trend (D0T0), intercept (D1T0), and intercept and trend (D1T1), except for Bitcoin volume (BTCV) and Ethereum volume (ETHV) under the intercept and trend (D1T1) specification, where it is rejected. For all parameters and time series, the null hypothesis is also rejected at first difference. This means that the BTCV and ETHV time series are stationary at the level for the intercept and trend (D1T1) specification, and at the first difference for all other specifications. In general, I(1) indicates that the time series are unit root at the level and stationary at the first difference.

Table 4.4. Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test

UR Test	Specification	At Level		At First Difference		Conclusion
		Intercept	Intercept and Trend	Intercept	Intercept and Trend	
KPSS	BTCP	4.846***	0.863***	0.128	0.129*	I(1)
	ETHP	3.739***	1.040***	0.325	0.158**	I(1)
	BTCV	5.443***	0.806***	0.031	0.025	I(1)
	ETHV	5.152***	0.889***	0.074	0.018	I(1)

The null hypothesis for the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) time series is that they are stationary, but the alternative hypothesis is that they are unit root. Except for BTCP and ETHP for the intercept and trend (D1T1) specification, where it is likewise rejected, the null hypothesis is rejected for all-time series at level and accepted at first difference. In general, it means that the time series are unit root at the level and stationary at the first difference, resulting in the final remark I(1).

Table 4.5. Johansen Cointegration Test

No of CEs	**Specification**	**Without PND**	**With PND**
None	**Unrestricted linear deterministic trend Specification**	145.4626***	148.5927***
1		39.81316***	41.90532***
2		7.882741	10.33652
3		0.660725	3.098501*
None	**Restricted linear deterministic trend Specification**	201.4321***	229.8706***
1		75.46537***	90.31222***
2		13.78141	14.31661
3		2.678920	3.495369

The table above shows the unrestricted and the restricted linear deterministic trend specifications of the Johansen Cointegration Test. In both specifications, the null hypothesis of two cointegrating equations is not rejected both before and during the pandemic, which depicts that there are two cointegrating equations in our model.

Table 4.6. Normalised Cointegrating Coefficients

Variables	**Specification**	**Without PND**		**With PND**	
		CE1	**CE2**	**CE1**	**CE2**
LBTCP	**Unrestricted linear deterministic trend Specification**	1	-	**1**	-
LETHP		-	1	-	**1**
LBTCV		-0.226*	1.348*	-0.228*	1.288*
LETHV		-0.262**	-1.658**	-0.261**	-1.623**
		CE1	**CE2**	**CE1**	**CE2**
LBTCP	**Restricted linear deterministic trend Specification**	1	-	**1**	-
LETHP		-	**1**	-	**1**
LBTCV		-0.983**	-0.498*	-1.089**	-0.731*
LETHV		0.055	-0.899**	0.043	-0.927**

Note: '*','**' and '***' indicate the rejection of the null hypothesis of unit root at 10%, 5%, and 1% significance level, respectively.

4.4. Johansen Cointegration Test

❖ **Unrestricted Linear Deterministic Trend Specification**

– **Before the pandemic**

Without considering pandemic as exogenous, the price of Bitcoin is positively related with the volume of Bitcoin and significant and positively related with the volume of

Ethereum and also significant. The price of Ethereum is negatively related with volume of Bitcoin and significant and positively related with the volume of Ethereum and also significant.

– During the pandemic

Considering the pandemic as an exogenous again there are two cointegrating vectors and there is cointegration among the four time series. Furthermore, the price of Bitcoin is positively related with the volume of Bitcoin and significant and positively related with the volume of Ethereum and also significant. The price of Ethereum is negatively related with volume of Bitcoin and significant and positively related with the volume of Ethereum and also significant.

Therefore, it can be observed from the results that the pandemic has no effect on the long run relationship between Bitcoin price (BTCP), Ethereum price (ETHP), Bitcoin volume (BTCV) and Ethereum volume (ETHV).

Increase in Bitcoin price causes an increase in the trading volume of Ethereum because if there is high demand for Bitcoin as the main cryptocurrency, it validates the use of other crypto currencies in the market and therefore causing an increase in the demand for Ethereum which is the second largest cryptocurrency, hence high trading volume.

If the price of Ethereum is increasing, that means there is more demand for ether to pay for the smart contracts. Since Bitcoin and Ethereum can be considered as substitutes, and Bitcoin does not have smart contracts in its blockchain technology, the demand for Bitcoin may reduce in favour of Ethereum which in turn may cause a reduction in the Bitcoin trading volume hence symbolizing the negative relationship between Bitcoin volume and Ethereum price.

❖ **Restricted Linear Deterministic Trend Specification**

– **Before the pandemic**

Without considering pandemic as exogenous, the price of Bitcoin is positively related with the volume of Bitcoin and significant and negatively related with the volume of Ethereum but insignificant. The price of Ethereum is positively related with volume of Bitcoin and significant and positively related with the volume of Ethereum and also significant.

– **During the pandemic**

Considering the pandemic as an exogenous again there are two cointegrating vectors and there is cointegration among the four time series. Furthermore, the price of Bitcoin is positively related with the volume of Bitcoin and significant and negatively related with the volume of Ethereum but insignificant. The price of Ethereum is positively related with volume of Bitcoin and significant and positively related with the volume of Ethereum and also significant.

Therefore, it can be observed from the results that the pandemic has no effect on the long run relationship between Bitcoin price (BTCP), Ethereum price (ETHP), Bitcoin volume (BTCV) and Ethereum volume (ETHV).

The increase in Bitcoin price causes a reduction in the trading volume of Ethereum because they are considered as substitutes. This implies that if there is high demand for Bitcoin, there would be less demand for Ethereum, hence low trading volumes (Bitcoin dominance) from the traders' perspective are observed.

If the price of Ethereum is increasing, that means there is more demand for ether to pay for the smart contracts. This symbolizes the validation of cryptocurrencies as a mode of payment. In turn the popularity of crypto currency acceptance for payments increases the demand for other cryptocurrencies, including Bitcoin, since it is the largest cryptocurrency.

Table 4.7. VECM Short-run Dynamics

	D(LBTCP)	D(LETHP)	D(LBTCV)	D(LETHV)
PND	**0.000255**	**0.008882**	**-0.068883**	**-0.153698**
	(0.00297)	**(0.00462)**	**(0.01965)**	**(0.02667)**
	[0.08582]	**[1.92212]**	**[-3.50629]**	**[-5.76337]**

The table above shows the short-run dynamics of the Vector Error Correction Model(VECM) during the COVID-19 pandemic. The results in the table show that the pandemic has no effect on the Bitcoin price (BTCP) and the Ethereum price (ETHP) but has an effect on the Bitcoin volume (BTCV) and Ethereum volume (ETHV). The results 0.08582 of the Bitcoin price and 1.92212 of the Ethereum price are insignificant which means that their prices are not affected and they do not change during the pandemic. The results -3.50629 of the Bitcoin volume and -5.76337 of the Ethereum volume are significant which means that their volumes are affected and the negative sign depicts a decreasing change during the pandemic. The decreasing change is because the trading volumes of Bitcoin and Ethereum decrease since the crypto investors and enthusiasts would not want to sell and trade off their assets and would prefer to hold them as they are considered safe-havens during a market downturn. The decrease in the trading volumes of Bitcoin and Ethereum would not affect their prices as the trade of these assets decreases in the short-run.

Table 4.8. VECM Long-run Dynamics

Variables	**Specification**	**Without PND**		**With PND**	
		CE1	**CE2**	**CE1**	**CE2**
LBTCP	**Restricted linear deterministic trend Specification**	1	-	**1**	**-**
LETHP		**-**	**1**	**-**	**1**
LBTCV		-0.983**	-0.498*	-1.089**	-0.731*
LETHV		0.055	-0.899**	0.043	-0.927**

The table above shows the long-run dynamics of the Vector Error Correction Model (VECM). It shows that the long-run relationship between Bitcoin price (BTCP), Ethereum price (ETHP), Bitcoin volume (BTCV) and Ethereum volume (ETHV), does not change before and during the COVID-19 pandemic. The positive and negative relationship between these assets' prices and volumes remains the same before as well as during the pandemic. This means that the pandemic has no effect on the long-run relationship among these assets' prices and volumes.

4.5. Vector Error Correction Model (VECM)

❖ **Restricted Linear Deterministic Trend Specification**

– **Before the pandemic**

Without considering pandemic as exogenous, the price of Bitcoin is positively related with the volume of Bitcoin and significant and negatively related with the volume of Ethereum but insignificant. The price of Ethereum is positively related with volume of Bitcoin and significant and positively related with the volume of Ethereum and also significant.

– **During the pandemic**

Considering the pandemic as an exogenous again there are two cointegrating vectors and there is cointegration among the four time series. Furthermore, the price of Bitcoin is positively related with the volume of Bitcoin and significant and negatively related with the volume of Ethereum but insignificant. The price of Ethereum is positively related with volume of Bitcoin and significant and positively related with the volume of Ethereum and also significant.

The increase in Bitcoin price causes a reduction in the trading volume of Ethereum because they are considered as substitutes. This implies that if there is high demand for Bitcoin, there would be less demand for Ethereum, hence low trading volumes (Bitcoin dominance) from the traders' perspective.

If the price of Ethereum is increasing, that means there is more demand for ether to pay for the smart contracts. This symbolizes the validation of cryptocurrencies as a mode of payment. In turn the popularity of crypto currency acceptance for payments increases the demand for other cryptocurrencies, including Bitcoin, since it is the largest cryptocurrency.

CHAPTER V

CONCLUSION

In the previous chapter, we analysed and discussed the behaviour of our time series, Bitcoin price (BTCP), Ethereum price (ETHP), Bitcoin Volume (BTCV) as well as Ethereum volume (ETHV). We examined their relationship and how they are linked with one other before and during the COVID-19 pandemic. In summary, we discovered that the COVID-19 pandemic had no effect in the long run relationship among our given time series, Bitcoin price (BTCP), Ethereum price (ETHP), Bitcoin Volume (BTCV) and Ethereum Volume (ETHV). We also found that the pandemic has no effect on the changes in prices of Bitcoin and Ethereum but has an effect on the changes in their trading volumes in the short run.

By considering the unrestricted linear deterministic trend specification ,we found that the price of Bitcoin is positively linked with the trading volume of Bitcoin and positively related with the trading volume of Ethereum which means that an increase in Bitcoin price causes an increase trading volume of Bitcoin as well as that of Ethereum whereas the price of Ethereum is negatively related with the Bitcoin trading volume and positively related with the trading volume of Ethereum which means that a rise in the Ethereum price causes a rise in the trading volume of Ethereum and causes a decline in the Bitcoin trading volume because of the decline in demand for Bitcoin in favour of Ethereum since Bitcoin does not have smart contracts which is present in Ethereum blockchain technology.

By considering the restricted linear deterministic trend specification, we discovered that ,the price of Bitcoin is positively related with the volume of Bitcoin and negatively related with the volume of Ethereum which means that a rise in Bitcoin price causes a rise in the trading volume of Bitcoin and a reduction in the trading volume of Ethereum because they are considered substitutes and if there is high demand for Bitcoin, there is less demand for Ethereum hence low trading volume for Ethereum. On the other hand ,the price of Ethereum is positively related with volume of Bitcoin and positively related with the volume of Ethereum which means that a rise in Ethereum price causes a rise in the trading volume of Ethereum as well as that of Bitcoin because of the validation of cryptocurrencies in economic markets and the increase in demand for cryptocurrencies especially the largest cryptocurrency, Bitcoin, and this depicts the inter and intra dynamics and relationship between them as cryptocurrencies.

– **Policy Recommendations**

It is observed from our study that both Bitcoin and Ethereum can be highly volatile in their prices and trading volumes because of market influence which can affect their demand one way or the other. However, from the investors' perspective and point of view, it would be recommended for investors to consider making some investments in these cryptocurrencies since they are the most dominant in terms of market capitalization and also considering their performance as hedging and safe-haven tools during the COVID-19 pandemic, which would yield big returns in future because they are considered by many as the future of money.

– **Directions for Future Research**

In our study, we have examined the influence of the COVID-19 pandemic on Bitcoin and Ethereum prices and trading volumes. In future research, there is a possibility to examine the effect of other crises like political instability and war, environmental disasters such as earthquakes or floods, on the cryptocurrency market. In this case, we would consider Ethereum and Bitcoin as our proxy of the cryptocurrency market since they are the most dominant in terms of market capitalization.

REFERENCES

Beneki, C., Koulis, A., Kyriazis, N. A., & Papadamou, S. (2019). Investigating volatility transmission and hedging properties between Bitcoin and Ethereum. *Research in International Business and Finance*.

Bouraoni, T. (2019). The drivers of Bitcoin trading volume in selected emerging countries. *The Quarterly Review of Economics and Finance*.

Cagli, E. C. (2018). Explosive behavior in the prices of Bitcoin and altcoins. *Finance Research Letters*.

Conlon, T., Corbet, S., & McGee, R. J. (2020). Are cryptocurrencies a safe haven for equity markets? An international perspective from the COVID-19 pandemic. *Research in International Business and Finance*.

Corbet, S., Lucey, B., & Yarovaya, L. (2017). Datestamping the Bitcoin and Ethereum bubbles. *Finance Research Letters*.

Feng, W., Wang, Y., & Zhang, Z. (2018). Can cryptocurrencies be a safe haven: a tail risk perspective analysis. *Applied Economics*.

Fry, J. (2018). Booms, busts and heavy-tails: The story of Bitcoin and cryptocurrency markets? *Economics Letters*.

Grobys, K. (2021). When the blockchain does not block: on hackings and uncertainty in the cryptocurrency market. *Quantitative Finance*.

Lahiani, A., Jeribi, A., & Jlassi, N. B. (2020). Nonlinear tail dependence in cryptocurrency-stock market returns: The role of Bitcoin futures. *Research in International Business and Finance*.

Mariana, C. D., Ekaputra, I. A., & Husodo, Z. A. (2020). Are Bitcoin and Ethereum safe-havens for stocks during the COVID-19 pandemic? *Finance Research Letters*.

Mensi, W., Al-Yahyaee, K., & Kang, S. H. (2018). Structural breaks and double long memory of cryptocurrency prices: A comparative analysis from Bitcoin and Ethereum. *Finance Research Letters*.

Mensi, W., Lee, Y., Al-Yahyaee, K., Sensoy, A., & Yoon, S. (2019). Intraday downward/upward multifractality and long memory in Bitcoin and Ethereum markets: An asymmetric multifractal detrended fluctuation analysis. *Finance Research Letters*.

Mensi, W., Rehman, M., Al-Yahyaee, K., Al-Jarrah, I., & Kang, S. (2019). Time frequency analysis of the commonalities between Bitcoin and major Cryptocurrencies: Portfolio risk management implications. *The North American Journal of Economics and Finance*.

Naeem, M., Bouri, E., Peng, Z., Shahzad, S. J., & Vo, X. V. (2020). Asymmetric efficiency of cryptocurrencies during COVID19. *Physica A: Statistical Mechanics and its Applications*.

Noda, A. (2020). On the evolution of cryptocurrency market efficiency. *Applied Economics Letters*.

Palazzi, R. B., Junior, G. S., & Klotzle, M. (2020). The dynamic relationship between bitcoin and the foreign exchange market: A nonlinear approach to test causality between bitcoin and currencies. *Finance Research Letters*.

Shi, Y., & Chang, L. (2020). Does Bitcoin dominate the price discovery of the Cryptocurrencies market? A time-varying information share analysis. *Operations Research Letters*.

Sifat, M. I., Mohamad, A., & Shariff, M. B. (2019). Lead-Lag relationship between Bitcoin and Ethereum: Evidence from hourly and daily data. *Research in International Business and Finance*.

Song, J., Chang, W., & Song, J. (2019). Cluster analysis on the structure of the cryptocurrency market via Bitcoin–Ethereum filtering. *Physica A: Statistical Mechanics and its Applications*.

Subramaniam, S., & Chakraborty, M. (2019). Investor Attention and Cryptocurrency Returns: Evidence from Quantile Causality Approach. *Journal of Behavioral Finance*.

Yousaf, I., & Ali, S. (2020). The COVID-19 outbreak and high frequency information transmission between major cryptocurrencies: Evidence from the VAR-DCC-GARCH approach. *Borsa Istanbul Review*.

APPENDIXES

APPENDIX A

Table A.1. Without Considering the Pandemic

Cointegrating Eq:	CointEq1	CointEq2		
LBTCP(-1)	1.000000	0.000000		
LETHP(-1)	0.000000	1.000000		
LBTCV(-1)	-0.982543	-0.497921		
	(0.12104)	(0.20620)		
	[-8.11727]	[-2.41475]		
LETHV(-1)	0.054877	-0.899383		
	(0.07856)	(0.13383)		
	[0.69851]	[-6.72020]		
@TREND(8/08/15)	0.001606	0.003998		
	(0.00030)	(0.00052)		
	[5.30494]	[7.75048]		
C	10.31588	20.37835		
Error Correction:	D(LBTCP)	D(LETHP)	D(LBTCV)	D(LETHV)
CointEq1	-0.009713	-0.001092	0.148640	-0.094461
	(0.00402)	(0.00626)	(0.02662)	(0.03624)
	[-2.41541]	[-0.17455]	[5.58375]	[-2.60678]

Table A.1. (cont.)

CointEq2	0.006394	-0.001844	-0.032314	0.118100
	(0.00232)	(0.00362)	(0.01539)	(0.02094)
	[2.75105]	[-0.50994]	[-2.10034]	[5.63913]
D(LBTCP(-1))	0.007641	-0.064739	0.185465	-0.367449
	(0.02673)	(0.04160)	(0.17696)	(0.24088)
	[0.28585]	[-1.55639]	[1.04808]	[-1.52542]
D(LBTCP(-2))	0.010041	0.049755	0.229985	0.008215
	(0.02662)	(0.04142)	(0.17622)	(0.23989)
	[0.37717]	[1.20113]	[1.30506]	[0.03425]
D(LETHP(-1))	-0.034154	0.038353	0.015068	0.713619
	(0.01739)	(0.02706)	(0.11512)	(0.15671)
	[-1.96394]	[1.41728]	[0.13089]	[4.55373]
D(LETHP(-2))	0.014379	0.008463	0.106667	0.182933
	(0.01738)	(0.02705)	(0.11506)	(0.15662)
	[0.82728]	[0.31290]	[0.92706]	[1.16797]
D(LBTCV(-1))	-0.003541	-0.009345	-0.211421	0.026509
	(0.00460)	(0.00716)	(0.03047)	(0.04148)
	[-0.76925]	[-1.30469]	[-6.93862]	[0.63911]
D(LBTCV(-2))	-0.007425	-0.012626	-0.197851	-0.042854
	(0.00447)	(0.00695)	(0.02956)	(0.04024)
	[-1.66281]	[-1.81721]	[-6.69337]	[-1.06503]
D(LETHV(-1))	0.005643	0.009233	-0.029384	-0.265782
	(0.00346)	(0.00539)	(0.02292)	(0.03120)
	[1.62990]	[1.71383]	[-1.28206]	[-8.51877]

Table A.1. (cont.)

D(LETHV(-2))	0.003866	0.013602	0.007639	-0.158311
	(0.00331)	(0.00515)	(0.02192)	(0.02984)
	[1.16737]	[2.63942]	[0.34844]	[-5.30474]
C	0.002558	0.003576	0.004102	0.005339
	(0.00088)	(0.00138)	(0.00586)	(0.00797)
	[2.89070]	[2.59703]	[0.70011]	[0.66944]
R-squared	0.007907	0.010567	0.136942	0.134232
Adj. R-squared	0.002991	0.005664	0.132665	0.129941
Sum sq. resids	3.172679	7.682002	139.0315	257.6274
S.E. equation	0.039651	0.061699	0.262480	0.357302
F-statistic	1.608388	2.155132	32.01978	31.28775
Log likelihood	3675.376	2778.250	-159.5595	-785.3174
Akaike AIC	-3.612002	-2.727698	0.168122	0.784936
Schwarz SC	-3.581559	-2.697256	0.198564	0.815379
Mean dependent	0.002533	0.003746	0.003865	0.005486
S.D. dependent	0.039710	0.061874	0.281840	0.383055

Determinant resid covariance (dof adj.)	2.03E-08
Determinant resid covariance	1.99E-08
Log likelihood	6475.236
Akaike information criterion	-6.329458
Schwarz criterion	-6.180012
Number of coefficients	54

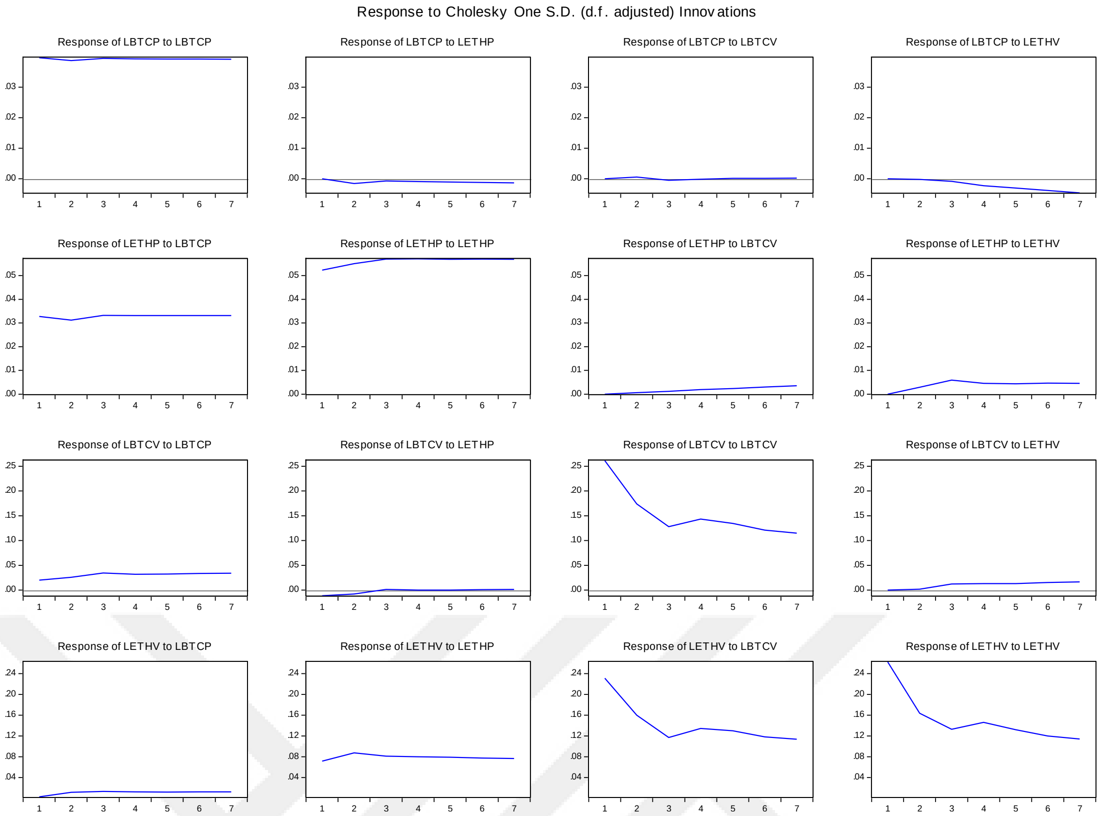

Figure A.1. Impulse Responses I

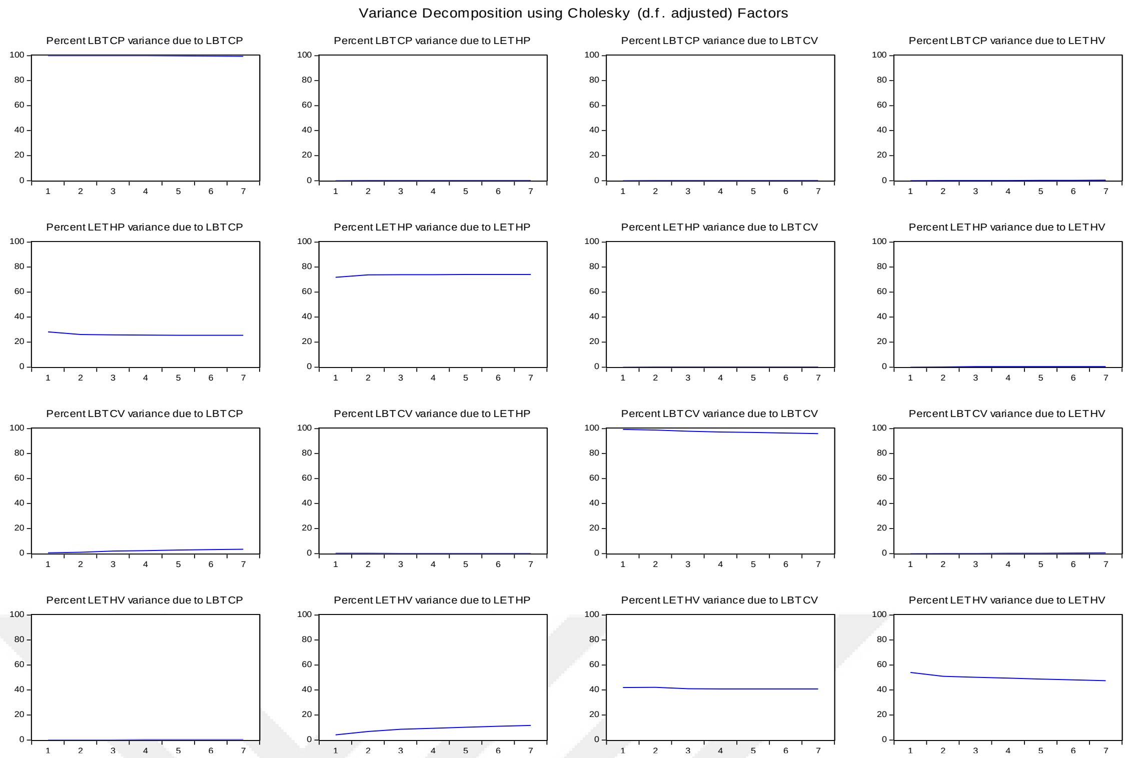

Figure A.2. Variance Decomposition I

Table A.2. Considering the Pandemic

Cointegrating Eq:	CointEq1	CointEq2
LBTCP(-1)	1.000000	0.000000
LETHP(-1)	0.000000	1.000000
LBTCV(-1)	-1.089692	-0.731389
	(0.11895)	(0.19274)
	[-9.16123]	[-3.79478]
LETHV(-1)	0.042884	-0.927138
	(0.07780)	(0.12607)
	[0.55118]	[-7.35403]

Table A.2. (cont.)

@TREND(8/08/15)	0.002449	0.005841		
	(0.00039)	(0.00063)		
	[6.27824]	[9.24055]		
C	12.01136	24.09872		

Error Correction:	D(LBTCP)	D(LETHP)	D(LBTCV)	D(LETHV)
CointEq1	-0.009702	0.001708	0.129715	-0.135643
	(0.00412)	(0.00641)	(0.02726)	(0.03700)
	[-2.35218]	[0.26644]	[4.75847]	[-3.66560]
CointEq2	0.005859	-0.004749	-0.019603	0.146236
	(0.00244)	(0.00379)	(0.01610)	(0.02185)
	[2.40552]	[-1.25433]	[-1.21783]	[6.69246]
D(LBTCP(-1))	0.007912	-0.063626	0.187266	-0.362469
	(0.02673)	(0.04156)	(0.17667)	(0.23983)
	[0.29597]	[-1.53104]	[1.05996]	[-1.51136]
D(LBTCP(-2))	0.010402	0.051529	0.227804	0.004139
	(0.02662)	(0.04139)	(0.17595)	(0.23885)
	[0.39070]	[1.24505]	[1.29471]	[0.01733]
D(LETHP(-1))	-0.033937	0.036399	0.029360	0.744065
	(0.01741)	(0.02706)	(0.11504)	(0.15617)
	[-1.94954]	[1.34511]	[0.25521]	[4.76455]
D(LETHP(-2))	0.014408	0.005386	0.126399	0.225659
	(0.01741)	(0.02707)	(0.11509)	(0.15623)
	[0.82738]	[0.19898]	[1.09830]	[1.44443]

Table A.2. (cont.)

D(LBTCV(-1))	-0.003507	-0.009274	-0.212441	0.024002
	(0.00460)	(0.00716)	(0.03043)	(0.04131)
	[-0.76156]	[-1.29559]	[-6.98092]	[0.58101]
D(LBTCV(-2))	-0.007431	-0.012735	-0.197651	-0.042504
	(0.00447)	(0.00694)	(0.02952)	(0.04007)
	[-1.66368]	[-1.83423]	[-6.69605]	[-1.06077]
D(LETHV(-1))	0.005393	0.007655	-0.022176	-0.249738
	(0.00349)	(0.00542)	(0.02305)	(0.03130)
	[1.54591]	[1.41159]	[-0.96186]	[-7.97972]
D(LETHV(-2))	0.003716	0.012651	0.011873	-0.148922
	(0.00332)	(0.00516)	(0.02195)	(0.02980)
	[1.11885]	[2.44995]	[0.54087]	[-4.99744]
C	0.002513	0.002047	0.015970	0.031829
	(0.00102)	(0.00159)	(0.00676)	(0.00918)
	[2.45690]	[1.28754]	[2.36250]	[3.46857]
PND	0.000255	0.008882	-0.068883	-0.153698
	(0.00297)	(0.00462)	(0.01965)	(0.02667)
	[0.08582]	[1.92212]	[-3.50629]	[-5.76337]
R-squared	0.007890	0.012517	0.139815	0.141896
Adj. R-squared	0.002479	0.007132	0.135123	0.137216
Sum sq. resids	3.172734	7.666860	138.5687	255.3467
S.E. equation	0.039661	0.061653	0.262108	0.355805
F-statistic	1.458229	2.324268	29.80392	30.32104
Log likelihood	3675.359	2780.252	-156.1775	-776.2962
Akaike AIC	-3.610999	-2.728686	0.165774	0.777029
Schwarz SC	-3.577789	-2.695475	0.198984	0.810240

Table A.2. (cont.)

Mean dependent	0.002533	0.003746	0.003865	0.005486
S.D. dependent	0.039710	0.061874	0.281840	0.383055
Determinant resid covariance (dof adj.)		2.00E-08		
Determinant resid covariance		1.96E-08		
Log likelihood		6490.121		
Akaike information criterion		-6.340189		
Schwarz criterion		-6.179673		
Number of coefficients		58		

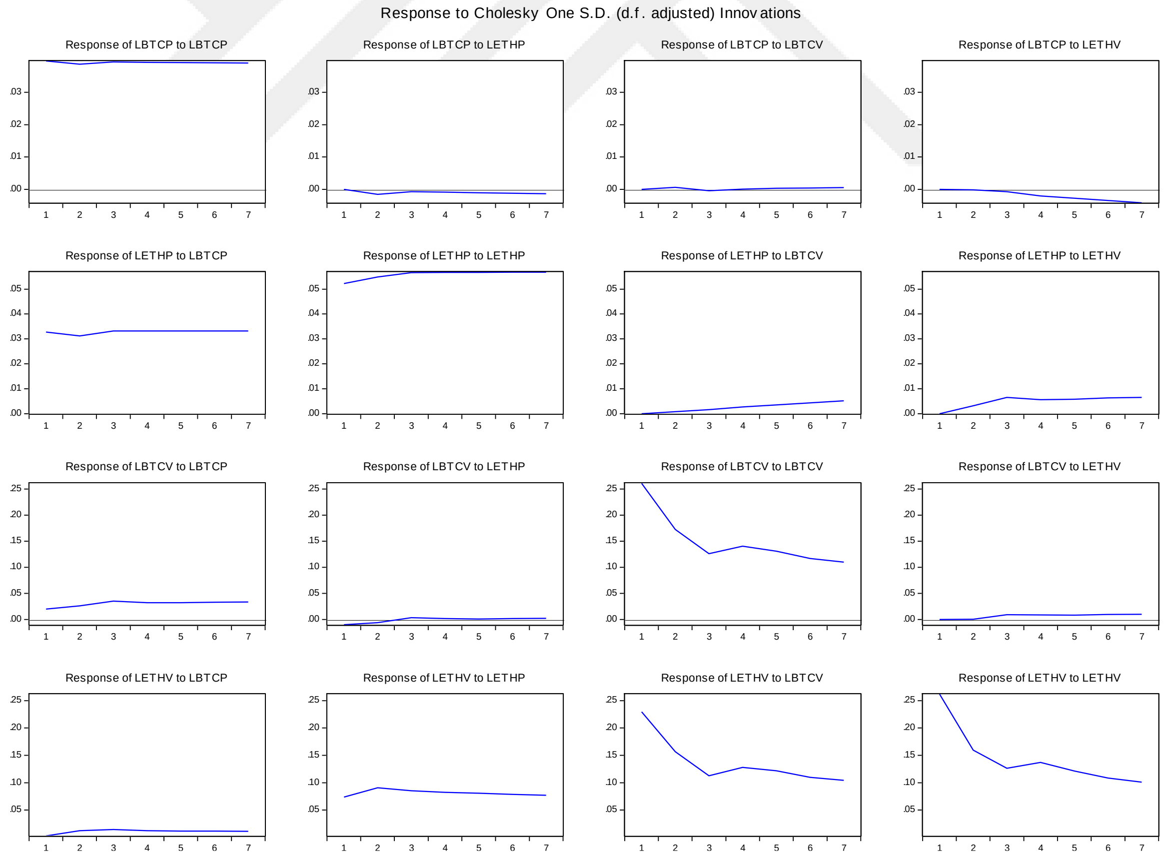

Figure A.3. Impulse Responses II

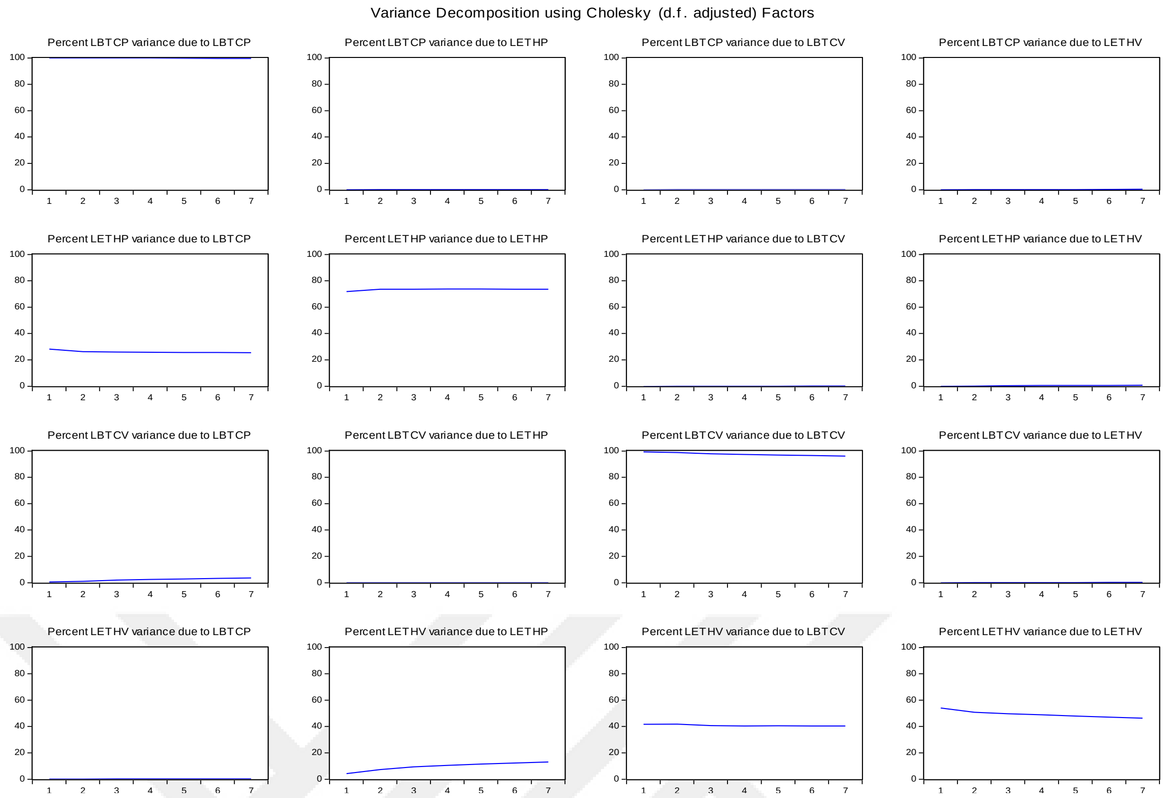

Figure A.4. Variance Decomposition II

CURRICULUM VITAE

Personal Information:

Name - Surname: HAMZA BALINDA

Education:

2013-2018	BSc in Civil Engineering, Anadolu Üniversitesi, Eskişehir, Türkiye
2019-2022	MA in Economics, Ibn Haldun University, Istanbul, Türkiye

Experience:

February - April 2017	Intern at Eskişehir Yapı Denetim Limited Şirketi
March – May 2018	Intern at Eserler Jeoteknik Mimarlık İnşaat Limited Şirketi
2019- 2021	Research Assistant at Ibn Haldun University