Czech University of Life Sciences Prague
Faculty of Economics and Management
Department of Economics

Master's Thesis

Cryptocurrencies

Eng.Canberk Sengul

2024 CZU Prague

CZECH UNIVERSITY OF LIFE SCIENCES PRAGUE

Faculty of Economics and Management

DIPLOMA THESIS ASSIGNMENT

Eng. Canberk Şengül

Economics and Management

Thesis title

Cryptocurrencies

Objectives of thesis

The main goal of the thesis is determine the impact of the Cryptocurrencies on Modern Economic Markets/Exchanges.
To maintain that goal the theoretical question are;
-What is the theory behind Cryptocurrencies?
-What are the risks of investing into Cryptocurrencies?
-What is the effect of Blockchain on global market?
After explaining these theoretical questions second goal is to explain the practical part;
-How Cryptocurrencies are deployed (ERC20 Tokens)?
-Smart wallets and Smart Contracts technology.
-The correlation of cryptocurrencies among each other and stock markets.
Practical part will be more effective about explaining the impact and the security of Cryptocurrencies on Markets/Exchanges.
The thesis will achieve conclusions and analytical approaches about impacts of Cryptocurrencies after these specific objectives.

Methodology

To achieve the thesis goal, explaining the theoretical approach will focus on literature reviews. To determine the impact thesis will review stock prices and cryptocurrency prices on monthly and weekly basis after 2018. The collection of data will help to calculate the correlation between cryptocurrencies.

The practical section will start with to deploy Cryptocurrencies (ERC20) on Solidity software. Thesis also explain transaction between wallets with hash algorithm.

The proposed extent of the thesis

60 – 80 pages

Keywords

ERC20 , Ethereum , Bitcoin , SmartContracts , Blockchain

Recommended information sources

Ab Diaries , (2022) , ”Blockchain, Cryptocurrency and Decentralized Finance Investing 2022” , ISBN: 1803073357
David Kuo Chuen Lee , Li Guo , Yu Wang , (2017) , ”Cryptocurrency: A New Investment Opportunity?” , https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2994097
Jitendra Chittoda , (2019) , ”Mastering Blockchain Programming with Solidity” , ISBN-13: 978-1839218262 , ISBN-10: 1839218266
Lin William Cong , (2017) , ”Blockchain Disruption and Smart Contracts” , https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2985764
Marc Pilkington , (2016) , ”Blockchain Technology: Principles and Applications” , https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2662660
Max Raskin , (2016) , ”The Law and Legality of Smart Contracts” , https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2959166
Saifedean Ammous , (2018) , ”The Bitcoin Standard: The Decentralized Alternative to Central Banking” , ISBN-13: 978-1119473862
Sinclair Davidson, Primavera De Filippi, Jason Potts , (2016) , ”Economics of Blockchain” , https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2744751
Usman W. Chohan, (2020) , ”DeFi and the Future of Finance” , https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3711777
Yhlas Sovbetov , (2018) , ”Factors Influencing Cryptocurrency Prices: Evidence from Bitcoin, Ethereum, Dash, Litcoin, and Monero” , https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3125347

Expected date of thesis defence

2022/23 SS – FEM

The Diploma Thesis Supervisor

Ing. Tomáš Maier, Ph.D.

Supervising department

Department of Economics

Electronic approval: 16. 6. 2022

prof. Ing. Miroslav Svatoš, CSc.

Head of department

Electronic approval: 2. 11. 2022

doc. Ing. Tomáš Šubrt, Ph.D.

Dean

Prague on 10. 11. 2023

Declaration

I declare that I have worked on my master's thesis titled “Effects of the Cryptocurrencies on Modern Markets and Exchanges” by myself and I have used only the sources mentioned at the end of the thesis. As the author of the master's thesis, I declare that the thesis does not break any copyrights.

In Prague on 30/11/2023 ______________________________

Canberk Sengul

Acknowledgment

I would like to thank Tomáš Maier, for his cooperation and supervising this research also my family, for their support during my work on this thesis.

Cryptocurrencies

Abstract

This research is focused on the price causalities and correlations of Bitcoin, Ethereum and TSLA (Tesla Stock Prices) in selected period between 2 January 2018 and 31 December 2021. Price data collected with 1009 observations for each variable. The main goal of the thesis is to examine and analyze Bitcoin and Ethereum prices effects on Tesla Stock prices. In the practical part causalities and correlations will be calculated in the selected period to analyze those data by using EViews and SW Gretl programmes.

The main procedure in the practical part of research will be based on Toda-Yamamoto causality test and econometric model by using Ordinary Least Square Method, where selected variables are TSLA, Bitcoin and Ethereum.

The main aim of the research is to evaluate a relationship between prices for selected period to examine impacts of cryptocurrencies on modern markets and exchanges and assist investors when creating a portfolio.

Keywords: Cryptocurrency, Bitcoin, Ethereum, Tesla, Stock, Causality, Correlation, OLSM, Diversification, Portfolio Analysis

Kryptoměny

Abstraktní

Diplomová práce se zabývá cenovou kauzalitou a korelací Bitcoinu, Etherea a TSLA (cena akcií Tesla) v období mezi 2. lednem 2018 a 31. prosincem 2021. Cenové údaje pro tyto kryptoměny byly shromážděné za 1009 období. Hlavním cílem práce je prozkoumat a vyhodnotit vliv ceny Bitcoinu a Etherea na cenu akcií Tesla. V praktické části jsou vypočítané korelace a kauzality ve zvoleném období pomocí EViews a SW Gretl.

Hlavní metoda v praktické části je založena na Toda-Yamamotově testu kauzality a na ekonometrickém modelu odhadnutém pomocí metody nejmenších čtverců, kde jsou vybranými proměnnými ceny TSLA, Bitcoinu a Etherea.

Hlavním cílem výzkumu je vyhodnotit vztah mezi cenami za vybrané období, prozkoumat dopady kryptoměn na moderní trhy a burzy a pomoci investorům při vytváření portfolia.

Klíčová slova: Kryptoměna, Bitcoin, Ethereum, Tesla, Akcie, Kauzalita, Korelace, OLSM, Diverzifikace, Analýza portfolia

Table of Contents

List of Figures

List of Tables

List of Equations and Formulas

List of Abbreviations

BTC – Bitcoin

ETH – Ethereum

TSLA – Tesla Stock

AIC – Akaike Information Criterion

VAR - Vector Autoregressive Models

1 Introduction

Cryptocurrency phrase has entered the literature of the world with an article written about Bitcoin and published on the internet by Satoshi Nakamoto in 2008. Cryptocurrencies, which gradually entered our daily lives with Bitcoin, have been accepted by everyone with the published protocol. It is clear that the popularization of cryptocurrencies and the protocol it contains will change the world financial system.

The world has changed nowadays as a result of computers, internet developments and new methods and arrangements, such online purchasing and payments have been made possible. Ultimately, cryptocurrencies have established itself in the financial sector, led by Bitcoin. There are 21,844 cryptocurrencies in use as November 2022 but not all of them are active or useful. There are 9314 cryptocurrencies are active once inactive cryptocurrencies excluded.

Cryptocurrency, which developed a reputation for itself with bitcoin today, is getting popular in the financial world. Money is always defined as having three basic characteristics (unit of account, store of value, and medium of exchange) (Wandhöfer, 2017). Cryptocurrencies, on the other hand, completely change this perception.

Stocks are one of the most important investment tools of investors. For this reason, estimating the future prices of stocks is important for investors and offers high return opportunities. However, there are many macroeconomic and financial factors that affect stock prices.

In this thesis, which examines the interaction of cryptocurrencies with modern markets; It is aimed to bring a new study to the literature by taking the most important cryptocurrencies with the highest market value in the crypto money market, by measuring their interactions on Tesla stock prices, the relationship between each other, the values that emerge as a result of this relationship, and their effects and reactions according to the data.

2 Objectives and Methodology

2.1 Objectives

The aim of the study is to examine relations between cryptocurrencies and stock prices for portfolio diversification to assist investors. In the thesis TSLA, Bitcoin and Ethereum were selected for comparison for the period of 2 January 2018 and 31 December 2021.

Selected time period is ends in December 2021 cause of increased popularity of cryptocurrencies in that time period. Tesla stock prices has been affected by Elon Musk's various comments and $1.5 billion of Tesla stocks purchased by Tesla in February 2021.

For these purposes, objectives are determined as below.

- To examine causalities between Bitcoin, Ethereum and TSLA between 2 January 2018-31 December 2021.
- To forecast Tesla stock price for future investments
- To identify differences between cryptocurrency and stock investments.

2.2 Methodology

In this Research daily highest prices for Bitcoin, Ethereum and stock prices for TSLA collected between 2 January 2018 and 31 December 2021. Data will be used to determine results firstly TODA-YAMAMOTO test will be done to observe and verify whether is one time series is useful for forecasting another.

Research hypothesis for Toda-Yamamoto test as following.

$\boldsymbol{H_0}$: equals to 0 and x_t does not cause y_t

$\boldsymbol{H_A}$: not equal to 0 and x_t does cause y_t

Nowadays investors have different type of assets in their portfolios. If prices of assets affect each other on positive or negative way understanding and using this research method will assist the investor.

Based on these explanations the hypothesis proposed as below;

$$\boldsymbol{H_0}: TSLA\ prices\ affected\ by\ cryptocurrencies$$

$$\boldsymbol{H_a}: TSLA\ prices\ are\ not\ affected\ by\ cryptocurrencies$$

The research model assumes that TSLA stock prices affected by Ethereum and Bitcoin prices. The research model created as below;

$$T_t = X + \gamma_1 E_t + \gamma_2 B_2 + \epsilon$$

$$\begin{aligned} B_t &= Bitcoin\ price \\ X &= constant \\ E_t &= Ethereum\ price \\ T_t &= TSLA\ price \\ \epsilon &= error\ term \end{aligned}$$

Equation 1: Econometric Model

Model will be analyzed for the selected time series with Ordinary Least Square Method (OLSM) to forecast TSLA stock prices.

VAR (Vector Autoregressive Models) analysis is a type of analysis that researchers use very often. However, hypothesis tests are not valid in cases where the variables analyzed with VAR are not stationary (if they contain a unit root). After the VAR analysis is done with the series that are stationary (without unit root), the F statistic is used according to the Granger Causality test. However, according to Toda-Yamamoto (1995), if there is cointegration between the variables, the F statistic may not comply with the standard distribution and it may lose its validity.

Toda–Yamamoto (1995) states that these pre-tests may cause problems in reaching a healthy result, therefore it is necessary to create a “k + $dmax$” VAR model. Where k the optimal lag length, $dmax$ the maximum integration degrees of the series.

Toda-Yamamoto is basically [k+(dmax)]. Wald test is applied to the first k of the coefficients matrix by estimating the first-order Vector autoregression (VAR) model. The test has an asymptotic (chi-square) distribution with k degrees of freedom (Adriana, 2014).

k: max lag length

dmax: max integration level

The success of the prediction depends on the correct determination of the lag length of the system and the degree of integration of the series (Çil Yavuz, 2006). The VAR model developed by Toda-Yamamoto (1995) is applied with the following equations;

$$\boldsymbol{Y_t} = \mu_1 + \sum_{i=1}^{k+dmax} \alpha_{1i} y_{t-i} + \sum_{i=1}^{k+dmax} \beta_{1j}\, x_{t-i} + \varepsilon_{1t}$$

$$\boldsymbol{X_t} = \mu_2 + \sum_{i=1}^{k+dmax} \alpha_{2i} x_{t-i} + \sum_{i=1}^{k+dmax} \beta_{2j}\, y_{t-i} + \varepsilon_{2t}$$

Equation 2: Var Model for Toda-Yamamoto Test

The maximum degree of integration (dmax) of the variables is a factor that needs to be considered in this test shouldn't be greater than the appropriate lag number for the model k. If not, this test cannot be used.

3 Literature Review

3.1 Cryptocurrencies

3.1.1 Cryptocurrency

Cryptocurrencies are digital currencies that allow safe transactions in encrypted form and create additional electronic money supply. Cryptocurrencies have existed as a phenomenon with an alternative currency structure. Cryptocurrencies are decentralized. The control of this structure is carried out by the database to the related transactions ledgers (Blockchain, etc.). The amount and supply of money in circulation, in what form and when it will be put into circulation are determined during the establishment of the crypto money system. This also means that the money supply cannot be increased. In the crypto money system, there is no control mechanism such as the Central Bank or an institution or person that carries out basic banking transactions. (Ankenbrand, Bieri, 2018)

3.1.2 Comparison between Cryptocurrency and Stock Markets

In his research Nga Vu make comparison between cryptocurrencies and a long-established investment such as stocks. Cryptocurrencies deployed in 2009 and in early January 2021 daily transactions has reach to 400,000. On the other hand, stocks have been around for a long time. In 1661 in Amsterdam, the first stock exchange created. Nowadays New York Stock Exchange has an average 2.4 billion shares traded every day.

Price volatility and stability for cryptocurrency still very new and not stable yet. The character of the market is fragile since prices heavily effected by investors. Stock exchanges has more stable market and large trading volumes.

Cryptocurrencies still not accepted by most international laws, stock exchanges are controlled and ruled by state management and law.

Trading times and fees for cryptocurrencies are more effective for investors. Cryptocurrency exchanges have lower costs than stock exchanges. However, stock exchanges are strictly regulated and there are exchange fees and broker cuts. Stock trading only possible from Monday to Friday and has opening and closing times but cryptocurrencies can be traded 24/7. (Nga Vu, 2022)

3.1.3 Comparison between Bitcoin and Ethereum

The main differences between Ethereum and Bitcoin are:

• Each block addition time is 15 seconds in Ethereum and 10 minutes in Bitcoin. This indicates that transactions will be confirmed more quickly.

• Every four years, the amount of Bitcoin obtained from mining is cut in half. When the total amount of Bitcoin produced reaches 21 million. In Ethereum, this figure is 18 million and the limit is one year. This makes it easier for Ethereum to be used in trades and traded in different places.

• In terms of mining systems, Bitcoin varies according to the number of systems you have or your processing power. Therefore, there is a more unfair situation. In Ethereum, which uses a system called an egalitarian Application Specific Integrated Circuit (ASIC) with graphics cards, a balance is maintained between manufacturers in this way.

• Bitcoin is seen more as "digital gold" as its value reaches astronomical dimensions. Ethereum, on the other hand, is considered as a "digital currency" in a sense.

• The fact that Ethereum is programmable is the main difference between the two cryptocurrencies. Compared to the money (information) produced, Blockchain technology requires more.

• Bitcoin's software base remains very slow for changes to be implemented. Because of the image of the first cryptocurrency, many of the investors turned to Bitcoin. Like Bitcoin, the Proof of Work system is also used in Ethereum mining. The difference from Bitcoin Mining is a little bit different from Bitcoin mining, as it performs proof-of-work using memory called Ethash. Unlike the computational power of proof of work (POW) system, this system requires memory and processor. The increase in Ethereum is limited to 18 million Ether per year. (Zmaznev ,2017)

3.1.4 Cryptocurrencies Used on Research

3.1.4.1 Bitcoin

Bitcoin is a decentralized digital currency. The Blockchain technology was used to create Bitcoin, which then started developing in this manner. Each transaction is stored by nodes in their own systems (ledgers). Through a procedure known as "mining," the history of each matching move made in the ledger is documented and blocks are added. It is an open payment system that anybody, anywhere may access, does not require centralized control. (S. Doğantekin, 2018)

The abbreviation of Bitcoin currency is known as “BTC”. In Bitcoin, which can be divided up to 8 digits, it can be used with the smallest unit such as 0.00000001. “Satoshi” is the name given to the 8th digit Bitcoin unit. 100 million Satoshi means 1 BTC (Çarkacıoğlu, 2016). The reading of the fractional parts of Bitcoin is as follows:

“1 BTC = 1 Bitcoin”,

“0.01 BTC = 1 centiBitcoin”,

“0.001 BTC = 1 milliBitcoin”,

“0.000 001 BTC = 1 microBitcoin”,

“0.00000001 BTC = 1 Satoshi”.

The supply of Bitcoin is capped at 21 million BTC. 1 BTC is worth $46219.5 USD as of 31 December 2021.

When the price changes analyzed of Bitcoin on Figure 1 gradually increase can be observed between 2018 and 2021 with 1009 observations. Bitcoin has reached all time high price in time interval between 2018-2021 is 67,527.90 USD in October 2021 while all time low 4,826 USD in May 2019. Bitcoin price increased %1475 in 3 years which is a remarkable increase.

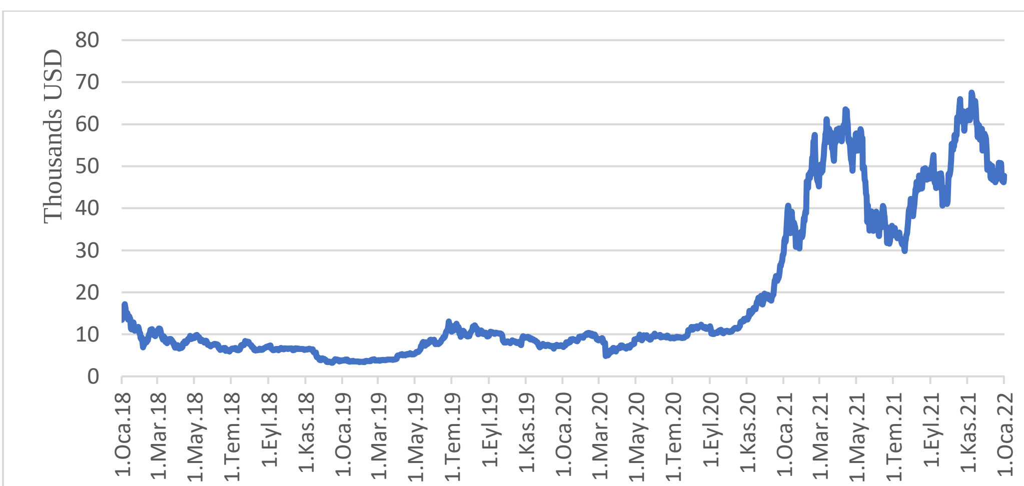

Figure 1: Bitcoin Price Changes between 2018-2021 (Source: coinmarketcap.com)

3.1.4.2 Ethereum

Ethereum was first announced by Vitalik Buterin in 2013 with a whitepaper. Buterin, along with other co-founders, funded the project in an online public crowdsale in the summer of 2014 and officially launched the blockchain on July 30, 2015. Ethereum is an altcoin that helps contract and execute by redesigning the blockchain mechanism. The currency in the Ethereum protocol is Ether. Ethereum helps create and execute highly complex contracts (Antonopoulos, 2014).

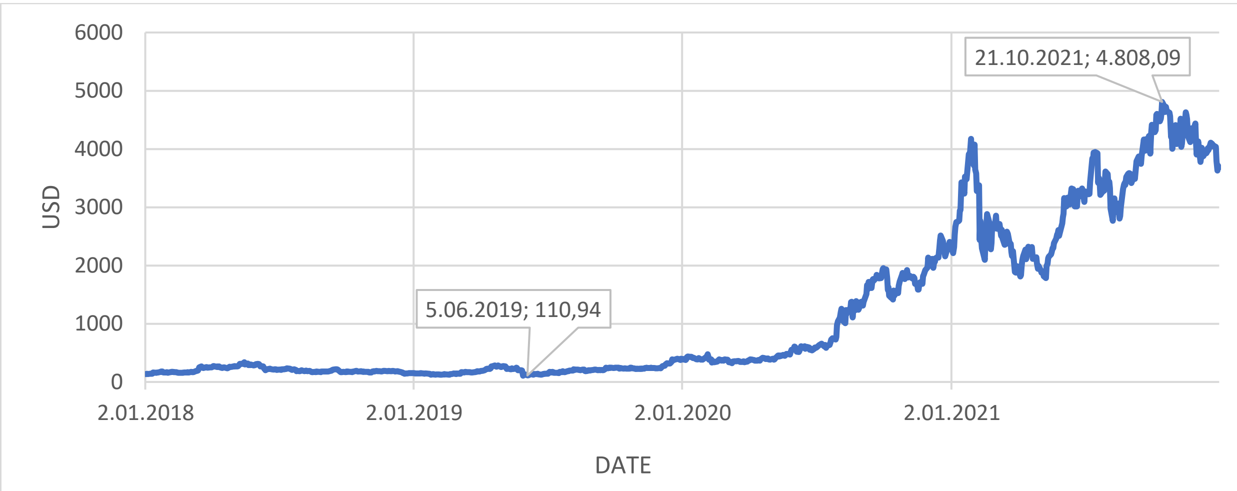

Figure 2: Ethereum Price Changes between 2018-2021 (Source: coinmarketcap.com)

When the price changes analyzed of Ethereum on Figure 2 gradually increase except fluctuations can be observed between 2018 and 2021 with 1009 observations. Ethereum has reached all time high price in time interval between 2018-2021 is 4808,09 USD in October 2021 while all time low 110,94 USD in May 2019. Ethereum price increased %4.233,95 in 3 years which is a remarkable increase. Ethereum and Bitcoin shows similar behavior with price fluctations between 2018-2021 and it can be observed on Figure 1 and 2.

Between 2018 and 2019 bear market can be observed on Ethereum like other cryptocurrencies. Prices was low compared to early 2018 which this period was marked by regulations and slow down in the initial coin offering markets.

3.1.5 Cryptocurrency Markets

To fully understand and display all of the characteristics of cryptocurrency markets, it is ideal to compare and contrast them with traditional stock markets. Because stock markets have been around for a longer time, it is simpler to evaluate their properties and potentially make predictions about the relatively new cryptocurrency markets.

The first distinction is that cryptocurrencies are attracting a larger number of international investors, whereas stocks are typically connected and traded within the countries in which they are incorporated. As noted previously, cryptocurrency markets are less resistant to price manipulation due to a lack of regulations.

As an example, unlike stocks, there is a limited supply of Bitcoin. Mining will end once there are 21 million bitcoins in circulation as mentioned before. Because stocks could be issued at any time, the number of stocks is effectively unlimited under corporate finance rules. The limited supply of certain cryptocurrencies may indicate greater future demand, which may encourage investors to invest in such digital assets in the hope of large potential future earnings.

Because of the high volatility of cryptocurrencies, investors are looking for immediate and simple profits. In the stock market, the process is a little slower and requires more patience. The global crypto market is currently worth $1.149 trillion USD. Bitcoin (BTC), Ethereum (ETH), Tether (USDT), Binance Coin (BNB), Cardano (ADA), Dogecoin (DOGE), XRP (XRP), USD Coin (USDC), Polkadot (DOT) currently have the highest market capitalizations. (Coinmarketcap)

Cryptocurrency markets-exchanges by 24-hour trading volumes in 2 January 2018 and 31 December 2021 for top 5 exchanges shown on Figure 3 and 4.

Crypto Exchange	24 Hour Trading Volume(2.1.2018)	24 Hour Trading Volume(31.12.2021)	Growth
Binance	$3,327,509,023	$55,726,442,119	1574.72%
Bittrue	$59,711,038	$2,899,462,631	4755.82%
Uniswap	$114,315	$422,819,608	369772%
Tidex	$4,286,136	$551,270,806	12761.70%
Coincheck	$17,363,774	$107,987,017	521.91%

Figure 3: Cryptocurrency Exchange Markets Trading Volumes

Volatility: High growth rates shown for cryptocurrency exchange markets can also show market volatility. Cryptocurrencies specifically known for their price changes and high volatility. Trading volume is one of the results and cause of volatility.

Scalability: Trading volume increase also effect scalability of the exchanges. Capability of completing larger volume trades without decreasing investors performance on market or exchange is crucial especially in a market that well known for its volatility.

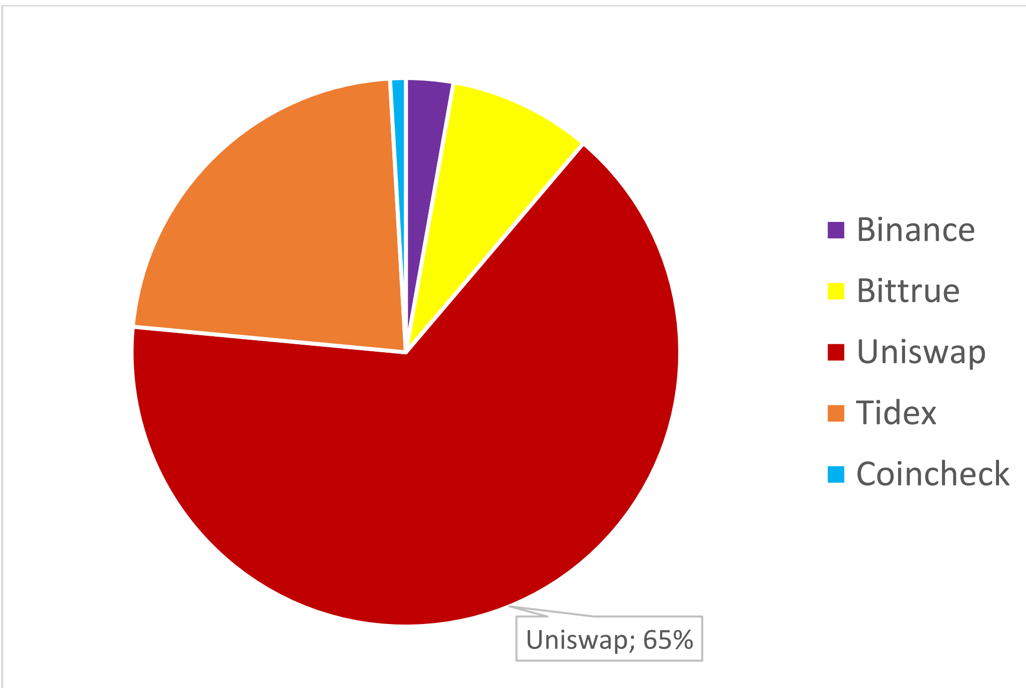

Figure 4: Growth of Trading Volume of Cryptomarkets-Exchanges

Trading volume differences between 2018 and 2021 will explain us some key and crucial indicators for cryptocurrency markets.

Market Liquidity: Trading volumes also can be mentioned as market liquidity and activity. High volume of trade as shown on above table shows that these markets are highly liquid, able to complete quick trades with less risks and impact.

3.1.5.1 Total Cryptocurrency Market Cap

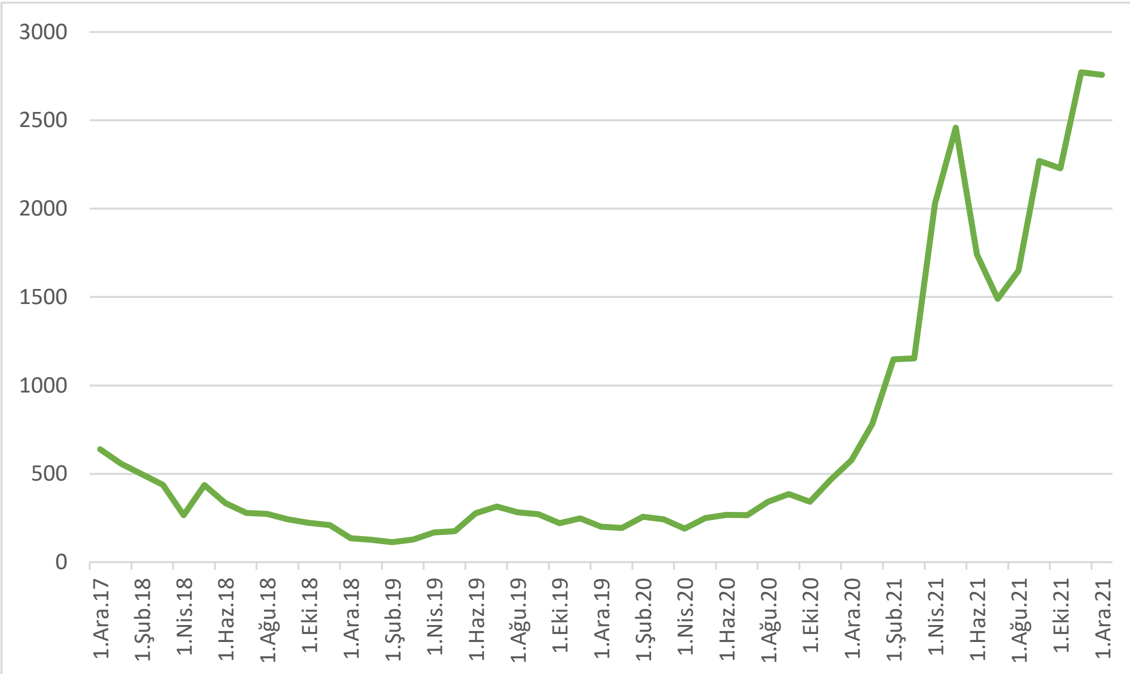

Figure 5: Total Cryptocurrency Market Cap (Billion $)

Market capitalization was the market price of a share or common stock multiplied by the number of shares outstanding (Berk & DeMarzo, 2014). Where 24 hours of trading volume increases Market Cap is increased respectively can be observed on Figure 5.

Bitcoin has the biggest market share on cryptocurrency market with %55, Ethereum following with %22. Market Cap for cryptocurrencies without Bitcoin is 631 billion USD. Bitcoins currently market cap more than all other crypto currency market shares and its 538 billion USD. Marketcaps of selected cryptocurrencies shown on Figure 6 and Table 1.

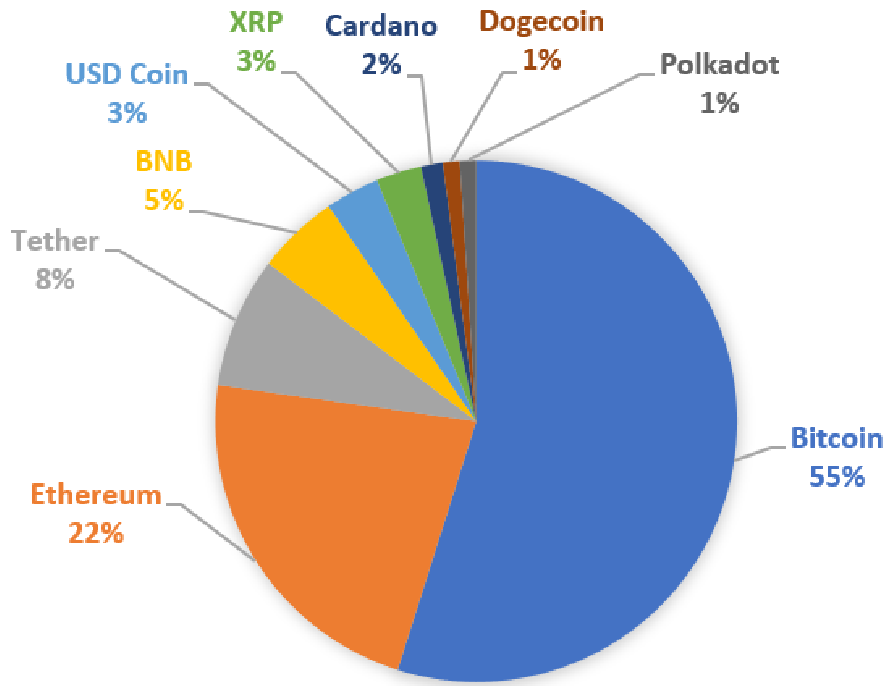

Figure 6: Cryptocurrency Market Cap Percentages

Pie chart above shows the percentages of the largest market capitalization of selected 9 cryptocurrencies.

Bitcoin has the largest percentage and dominate the market which is consistent as most-well known cryptocurrency.

Ethereum's significant share shows that also domination on the market but still less than half of Bitcoin's market cap.

Stable Coins as Tether and USD Coin fixed to the value of the US dollar to reduce volatility in the market. They have noticeable shares at %8 and %3. Investors use that coins for the need of more reliable investment choices.

Altcoins as BNB, XRP, Cardano, Dogecoin and Polkadot are appeal to investors searches for alternative investments because of their unique functionalities and technological developments.

Cryptocurrency	Marketcap(USD)
Bitcoin	$538,249,741,261
Ethereum	$219,175,872,653
Tether	$79,678,790,020
BNB	$49,900,320,973
USD Coin	$32,852,785,154
XRP	$27,536,586,868
Cardano	$13,324,262,465
Dogecoin	$10,289,811,573
Polkadot	$9,840,209,255

Table 1:Cryptocurrency Market cap 2023

Market cap for cryptocurrencies represents the total value of all the coins that has been created or mined. Total market cap calculated by multiplying the current amount of coins with exact value.

It also shows that market share or with another word market dominance. As shown on pie chart for cryptocurrency market cap Bitcoin has %55 of market share which explains more than half of the market value is provided by Bitcoin. Domination of Bitcoin shown above explains that Bitcoin price will influence market cap of the cryptocurrencies by creating trends and measuring the market rankings.

3.2 Stocks and Stock Markets

3.2.1 Stock Markets

The buying and selling of precious papers in unorganized marketplaces had previously occurred in large commercial centers. In addition, the debts of the French and English Kingdoms in Europe for bonds and bills began in the 14th and 15th centuries. Thus, professional groups such as merchants, intermediaries and bankers, who bought and sold these precious papers, were formed. In 1553, the first public stock issuance was made in London on behalf of Muscouyy Company (History of London Stock Exchange Group). The stock exchange, which was the first to buy and sell precious papers, was established in Amsterdam in 1611.

In many countries, trading of stocks or other precious papers began in unorganized markets and before the establishment of stock exchanges. The main reason for the establishment of private and public stock exchanges is the need to organize unorganized markets in a center. (Kemp, 1982)

Some of the economic reasons for the gathering of stock exchanges under one roof are as follows.

1- To create a permanent, continuous and stable market for public debts in public stock exchanges.

2- In an organized market, transactions are carried out with a centralized system, thereby reducing the costs required for these transactions by savers and investors.

3- To maintain the earnings of institutions such as intermediaries and traders engaged in the purchase and sale of securities, in return for their services.

Classification of the stock exchanges according to their establishment processes below.

1- In general, they are stock markets that are formed either by the public organization of the trading system or by the institutionalization of intermediaries in a self-developed trading center. These stock exchanges developed in the international trade centers, firstly with the foreign exchange markets, then with the commercial papers and the beginning of the industrial revolution and the formation of partnerships with joint stock company capital for production.

2- Since the 16th century, the efficiency of the states in the economic field has started to increase. As a result, stock exchanges were established by public administrators because of the need for a stable second-hand market for public securities issuances.

3- Exchanges formed by the purchase and sale of the stocks of companies engaged in the production and trade of mines and raw materials in the countries where the major trade centers have colonial connections.

4- In developing countries, stock exchanges established by the state for the purpose of directing savings to financial instruments and accelerating capital accumulation. (Spray ,1964)

3.2.2 Various Stock Indexes in World

When the stock markets around the world are analyzed, it is seen that there are important stock markets such as America, Europe, Middle East, Asia/Pacific and African stock markets. One of the important stock exchanges in terms of stock market history is the London Stock Exchange and the other is the New York Stock Exchange. While the London Stock Exchange becomes the oldest stock exchange in Europe, the New York Stock Exchange is the world's largest stock exchange in terms of trading volume.

There are not only these two stock exchanges, but also various countries in the world have their own stock exchanges and investors carry out their transactions. In the context of Asia/Pacific, Shanghai and Nikkei are important stock markets; In the European stock market, Dax and FTSE 100 are noteworthy stock exchanges. When the American stock market is analyzed, it includes indices such as DOW (Dow Jones Index), S&P 500 (Standard and Poor's 500 Index) and NASDAQ.

3.2.2.1 Standard & Poor’s 500

This index consists of the stocks of the 500 companies with the highest value in America. The companies that are the strongest in terms of both profitability and market share according to their sectors are included in this 500. This index, which includes many well-known companies such as Tesla, Facebook and Amazon, has a large share in the stock market. Profit and loss payments in the Forex market are made in dollars (S&P 500). The S&P 500 index, which is one of the most traded indices in the world, causes investors to take positions according to the decline or rise of this index. In addition, transactions can be made in foreign futures markets without any swap costs in this index (S&P 500 Index Transactions).

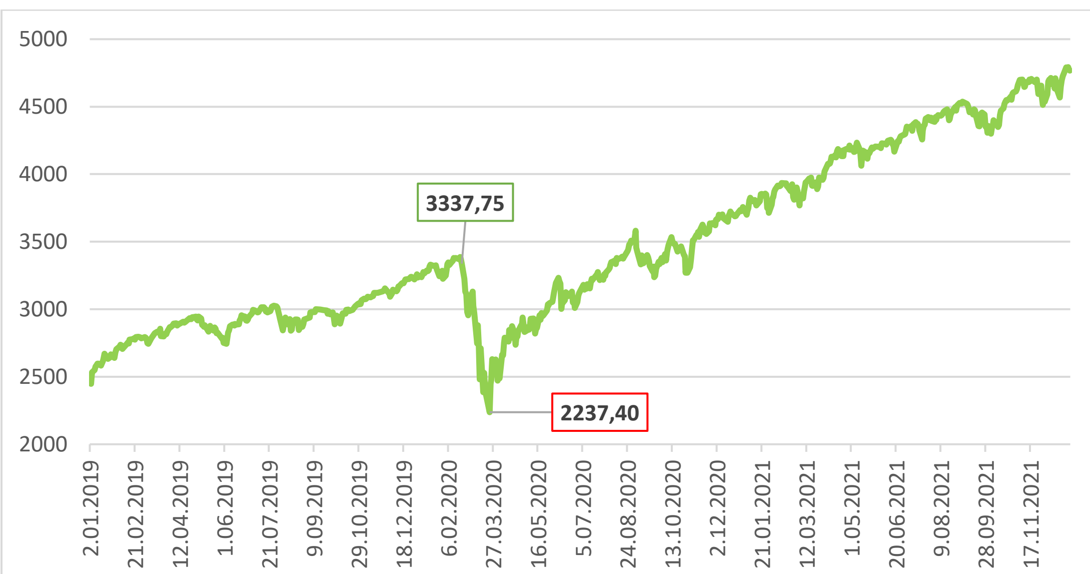

Figure 7: Change of S&P 500 Index between 2018-2021(USD) (Source: https://www.macrotrends.net/)

Change of S&P 500 Index between 2018 and 2021 period analyze shows us critical peaks and troughs to interpret outputs.

Bull Markets: Bull Markets commonly described as a period of the when large stock market indexes are intent to increase and eventually reaching new highest points. Upward movements represent on the graph conditions are convenient for Bull Market.

Bear Markets: Represents sharp decreases investment prices in a specific time frame. As can bee seen on Figure 7. From 6 February 2020 S&P 500 Index triggered by COVID-19 pandemic due to economic uncertainty and caused to Bear Market and it lasted until 27 March 2020.

S&P 500 Market Cap reached all time low in time interval 2018-2021 is 40.5 billion USD in December 2021, while all time high 114 billion USD. S&P 500 Market Cap increase %35.5 between 2018 and 2021 shown on Figure 7.

3.2.2.2 NASDAQ 100

The Nasdaq 100 index consists of the top 100 non-financial local or foreign companies traded on the Nasdaq by market capitalization. The index includes very large and diverse industry sub-branches such as biotechnology, computer hardware, telecommunications, and software. Shares of investment companies are not included in the index. To be included in the Nasdaq 100 index, companies must meet at least the following criteria (NASDAQ)

NASDAQ 100 index shown on Figure 8. When the change in graph analyzed price fluctuations can be observed. It is seen that NASDAQ 100 and S&P 500 show similar behavior in same time interval.

Figure 8: Change of NASDAQ100 Index between 2018-2021(Thousands USD) (Source: https://www.macrotrends.net/)

Index general trend is upwards as same as S&P 500 Bull Market corresponds for the investors. However sharp decrease observed in between 2020 December and 2020 March. Nasdaq100 effected by global pandemic which had widespread economic impacts caused high volatility and short-term buy and sells in global stock market. After the decrease of index Nasdaq100 recovered rapidly and continued to grow. It shows that strong market resilience.

From graph interpretation also can be mentioned that resistance level and support level of the index. Resistance level is where the price is start increasing again and support level is where market movement stop decreasing. Both levels has been shown on Figure 9. Resistance level as 9718,73 USD and Support Level as 6994,29 USD.

3.2.2.3 New York Stock Exchange

US stock market: It is the leader among the world's leading stock markets in terms of its infrastructure, institutions and size. The basis of the US markets is based on the Securities Act of 1933 and the Exchange Act of 1934. In the USA, the Securities and Exchange Commission (SEC) regulates and supervises the functioning of the markets as a legal authority. US stock markets consist of national exchanges and other organized markets. national stock markets; These are the stock exchanges such as the New York Stock Exchange (NYSE) and the American Stock

Exchange (AMEX), where the listing conditions and operating mechanisms are different from each other, where domestic and foreign securities are traded. The New York Stock Exchange (NYSE) is the largest and most developed stock market in the USA and the world, founded on March 8, 1817, but its foundations date back to 1792. It is the market with the strictest quotation conditions among the stock markets. It is very selective about the companies that will be traded in its markets. (Weo, 2013)

Largest stock exchange operator for 2021 in trillion USD shown on Table 2.

Stock Exchange Operator	**Market Capitalization (in trillion USD)**
NYSE , United States	22.77
Shanghai Stock Exchange	6.74
Euronext	6.06
Japan Exchange Group	5.38
Shenzhen Stock Exchange	4.7

Table 2: Largest Stock Exchange Operator Worldwide

New York Stock Exchange (NYSE), has the highest market capitalization with 22.77 trillion USD. It shows that NYSE is the most dominant stock exchange that contains significant aggregation of corporate finance and investment trade.

Shanghai Stock Exchange, ranked as second between five biggest stock exchange over the world. This shows that China's impact and role on global economy and size of the domestic stock market.

Euronext is operating multiple exchanges across Europe and combined market cap is calculated as 6.06 trillion USD in 2021.

Japan Exchange Group with a market capitalization of 5.38 trillion USD, aggregate value of listed companies in Japan.

Shenzhen Stock Exchange is the second Chinese stock market in five biggest stock exchange markets with 4.7 trillion USD.

High market cap for a stock market as NYSE reflects a large number of company stocks with significant values indicates that in stock market ecosystem NYSE ruling considerably amount of corporate finance and investment activities. It also shows that United States position as a leading economic power with a significant impact on global markets.

Market caps of these exchanges can be affected with different factors as well as economic policies, global competitiveness and trade regulations.

Lastly, market cap of a stock exchange can show that the economic health of a country that it represents as it tied with also investors decision taking.

3.2.2 Stock Used on Research

3.2.2.1 TSLA – Tesla Stock

Tesla, Inc. engages in the design, development, manufacture, and sale of fully electric vehicles and energy generation and storage systems. The company operates through the following segments: Automotive and Energy Generation and Storage. The Automotive segment includes the design, development, manufacture, sale, and lease of electric vehicles as well as sales of automotive regulatory credits. Shares of Tesla, initial public offering took place in June 2010, were offered on the New York stock exchange at $17. (Wall Street Journal – Markets)

TSLA stock prices change has been shown on Figure 12 TSLA stock prices have increased from 2018 to the end of 2021 except price fluctuations. TSLA stock prices, which were 21.37 USD on January 2, 2018, became 352.26 USD on December 31, 2021. Also, TSLA stock prices all time low price in time interval between 2018-2021 is shown on Figure 10 as 11.93 USD while all time high price is 407.36 USD. TSLA stock prices has shown similar behavior with Bitcoin in the same interval can be observed with comparison Figure 1 and 9.

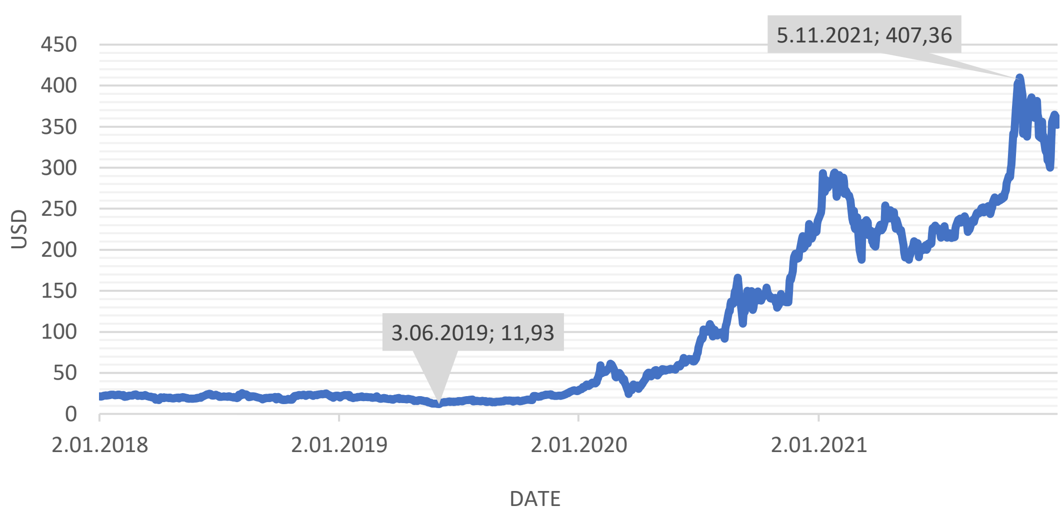

Figure 9: TSLA Stock Prices Change Between 2018-2021 (source: macrotrends.com)

Tesla’s stock for significant time period was in a bull market. Expectation of future growth in the electric vehicle market and positive investor opinion contributed to this increase. In other words Tesla's stock price was greatly impacted by changes in government policies regarding electric vehicles, change perspectives in battery technology, and the company's entry into new markets.

TSLA Market Cap reached all time low in time interval 2018-2021 is 32.77 billion USD in May 2018, while all time high 1205.39 billion USD shown on Figure 10. TSLA Market Cap increase %3.580,19 between 2018 and 2021.

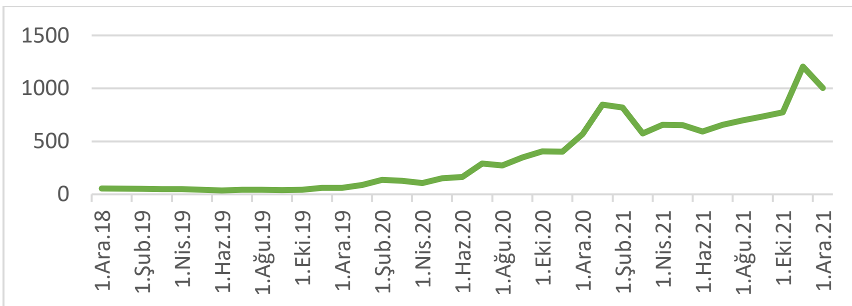

Figure 10: TSLA(NASDAQ) Market Cap Chart between 2January2018-31December2021. (Source: https://www.macrotrends.net/)

3.2.2.2 Effects of TSLA stock prices on Cryptocurrencies

Tesla purchased $1.5 billion in Bitcoin in January 2021. They stated in their filing to the SEC (Securities and Exchange Commission) that they included Bitcoin in their portfolio for diversification and future maximization of cash returns.

Another reason for such investment is to demonstrate and draw attention to the fact that they will begin to accept Bitcoin payments in exchange for their products. This would place Tesla at the forefront of the revolution, as the first major automaker to accept cryptocurrencies. When they decide to accept payments in cryptocurrencies, the $1.5 billion worth Bitcoin they have already purchased will provide them with instant liquidity.

When Tesla announced that they had invested in this particular digital currency, Bitcoin's price reached an all-time high. They described this move as a potential game changer, believing in their ability to cause a ripple effect across multiple corporations all over the world, and that such public investment could mean a significant change for potential future Bitcoin and cryptocurrency use. (Mandić ,2021)

3.3 Blockchain

3.3.1 Blockchain Technology

In the blockchain system, transactions are kept in blocks and these blocks are linked together to form a chain. Blocks created within the framework of certain rules are written to the system. The block is then propagated and added to all distributed ledgers. In creating a new block, the summary of the previous block is taken and the second block is produced and added to the chain. This structure is continued with a structure that connects all the blocks and continues with the summary of the previous block. When a transaction occurs, it is broadcast over the existing network and a block is created by verifying this transaction with encryption algorithms. Each node included in the system keeps its record by confirming this transaction made by any two people in the system. In this way, the block is verified, after which this information can never be changed or deleted. Each block continues to be added by being chained together. So another user can never change them.

3.3.1.1. Public Blockchain

Anyone can join a blockchain network that is open to new members. This technology is thought of as a fully independent, decentralized blockchain system. The platforms and programming languages that Ethereum and Bitcoin offer allow for the use of smart contracts and allow developers to publish distributed apps as examples of this structure. (Mukhopadhyay, Skjellum, Hambolu, Oakley, Yu, Brooks, 2016)

3.3.1.2 Private Blockchain

Only authorized users are able to connect to the network in a private blockchain system. According to I. C. Lin and T. C. Liao on their work in 2017, network consensus participation can be defined either publicly or privately. These systems are referred to as partially permission-requiring systems if those who are authorized in the private blockchain system and who settle in the system enter the consensus structure without permission. In these networks, the rules can be changed and transactions can be rolled back if necessary. It is employed to set up unique systems, save expenses, and boost efficiencies. Eris Industries, a shared software database provider that uses blockchain technology, and Multichain an open-source distributed database provider for financial transactions, are two examples of this system. (Wan ,Max, 2019)

3.3.1.3 Consortium Blockchain

Blockchain networks that are part of a consortium are seen as a hybrid of public and private blockchain networks. It is a system that the node may have been pre-selected by the relevant authority. Both public and private data can be found in this blockchain. A limited number of nodes can have access to read and write data on a consortium blockchain. Institutions or groups that band together, work together, and attempt to create new models can take advantage of this circumstance. The biggest example of this chain type is IBM's Hyperledger project. (Wan,Max,2019)

3.3.2 Smart Contracts

Smart contracts developed by Szabo (1997) are referred to as a crypto protocol between parties. Smart contracts also have significant advantages in terms of cybersecurity (Lone and Naaz, 2021). Smart contracts are contracts that are based on blockchain technology and entering into as soon as predetermined contract conditions are met.

The first practical use of smart contracts on a blockchain was seen on the Ethereum protocol, which came into our lives in 2015. The Ethereum Virtual Machine (EVM), the fundamental innovation of the Ethereum protocol, is software that runs on all nodes in the Ethereum network and is the building block of a distributed virtual computer. This distributed virtual computer is capable of operating smart contracts coded by users. Today, there are tens of blockchain protocols with the ability to run smart contracts and tens of thousands of smart contracts running on these protocols.

Smart contracts allow to automatically change and update the ownership of digitized assets stored on the blockchain network under certain conditions. These automatic transactions are encoded as functions within the smart contract.

Each function operated within the smart contract living on the blockchain will need a processing power and storage capacity on the Ethereum virtual machine of each peer with an Ethereum node on the network. In order to ensure scalability and sustainability in the blockchain network and prevent abuse of the protocol, users are charged a fee called GAS for the operation of smart contracts. (Lone and Naaz, 2021).

3.4 Cryptocurrency Price Factors and Overview

There are four factors that influence cryptocurrency prices on market according to (Poyser, 2017). Three of them are external factor as Crypto market, Macro-financial and Political. There is one internal factor that it is Supply & Demand.

Cryptocurrency Price			
Internal Factor	**External Factors**		
Supply & Demand	**Crypto Market**	**Macro-Financial**	**Political**
Transaction Cost	Attractiveness	***Stock Markets***	Legalization
Reward System	Market Trend	Exchange Rate	Restrictions
Mining Difficulty(Hash Rate)	Speculations	Gold Price	
Coins Circulation		Interest Rate	
Forks(Rule Changes)			

Table 3. Factors that Affect Cryptocurrency Prices : (SOVBETOV , 2018)

Supply & Demand is the basic economic principle defines the price of good or service. For cryptocurrencies supply mostly limited like Bitcoin's 21 million cap. Demand is very depending on numerous factors as investors opinions.

Transaction cost is the fee when transferring cryptocurrencies which can impact attractiveness of investors. If cost is too high valued it can affect the demand negatively.

Reward system refers to rewards offered like Bitcoin block rewards for mining or validating the transactions on the network.

Mining difficulty is the measure of how difficult to found a new block in the blockchain. If it gets more harder it requires more technical power which affects speed and the cost of currency.

Coins Circulation is the total number of coins in active use which can be exchange and influence the price. Greater number of coins needs high liquidity to keep currency value at some level.

Forks(Rule Changes) when cryptocurrency change its protocol it can change the prices due to uncertainty.

Crypto Market overall performance can impact specific cryptocurrencies. Bull or bear market trends can lead price movements.

Attractiveness is how cryptocurrency is appealing to its investors which could be impacted by technology or market movements.

Market Trends are general trends in trading volumes and price movements.

Speculations could be created by some group, company or investor that affect the prices up or down which can Dogecoin can be an example of that where Elon Musk affected.

Stock Markets as will be shown in this thesis can influence cryptocurrency prices where investors mostly see crypto is great alternative of traditional market.

Exchange Rate, Gold Price and Interest Rates movements can affect investor behavior on the cryptocurrency.

Legalization and Restrictions are government decisions that can affect cryptocurrency prices.

3.5 Risks and Opportunities of Cryptocurrencies

The increasing popularity of cryptocurrencies raises several questions and concerns about the viability of future integration of virtual currencies into the monetary and financial systems, particularly in the absence of legislation and regulatory standards (Avdeychik & Capozzi, 2018).

Because of their ability to circumvent existing regulatory schemes and challenge government supervision of monetary policy, Alonso & Luis mentioned on their research cryptocurrencies are associated with illegal activities. Similarly, cryptocurrencies are regarded as the world's largest unregulated markets.

Despite the fact that cryptocurrencies rely on the highly secured features enabled by blockchain technology, users are not immune to hacking, fraud, theft, and privacy breaches. Cybercriminals have already successfully targeted exchanges and stolen thousands of cryptocurrency. For example, over 40 thefts have occurred in bitcoin's short history, including a few incidents in which the stolen value of bitcoin exceeded USD 1 million (Bunjaku et al., 2017). Concerns about security remain a major issue in the handling and storage of cryptocurrencies. Hackers may connect directly to a user's wallet and steal cryptocurrency units.

3.6 Portfolio Analysis and Diversification

Investors want to maximize total return while taking risk into account. The idea of a portfolio evolved with the intention of reducing risk. Because the poor performance of one investment instrument can be easily offset by the strong performance of another investment instrument, investing in a portfolio rather than one asset may be less risky. (Küçükbay & Araz, 2016).

In terms of portfolio management and selection, there are two main approaches. The first of these is the strategy known as "conventional portfolio management," which is founded on straightforward diversification and relies on the portfolio manager's observations rather than objective research. The fundamental principle of traditional portfolio management is to reduce risk by diversifying the types of assets in the portfolio while maintaining an arbitrary viewpoint. Due to its simplicity of use, traditional portfolio management is still widely utilized today. The second is the strategy known as "modern portfolio management," which was pioneered by Harry Markowitz in 1952 and is based on mathematical and statistical principles. (Korkmaz, Aydn, & Sayilgan, 2013).

In their study titled "Assessment of Cryptocurrencies as an Asset Class by Their Characteristics," which was published in Investment Management and Financial Innovations in 2018, Thomas Ankenbrand and Denis Bieri emphasized the significance of diversification as an investment tool if cryptocurrencies are accepted as assets. The study first looked at the properties of cryptocurrencies before analyzing cryptocurrency and other asset portfolios built using numerical techniques (Ankenbrand & Bieri, 2018). Although cryptocurrencies are thought to have minimal correlation with traditional assets and high volatility, they are nonetheless seen as a promising alternative for investment diversification despite their limited trading volume.

According to Markowitz, the concept of “Effective Limit” is in question in choosing the optimum portfolio. The geometric place of the curve formed by bringing together portfolios with the lowest risk at a certain return level or the highest return at a certain risk level is called the effective limit (Markowitz, 1952). In the Efficient Frontier concept, investment clusters are created that include portfolios with the lowest risk levels for each rate of return, since the level of risk that each investor can accept is different. Investors are required to choose the portfolio that has the most suitable conditions at a certain risk or return level from the set of effective portfolios created according to the Average Variance Model.

4 Practical Part

4.1 TODA-YAMAMOTO CAUSALITY TEST

The stages of the Toda-Yamamoto (1995) causality test are presented below.

Step 1. Whether there is a causal relationship between the series, the maximum degrees of integration should be determined using the unit root test (Augmented Dickey Fuller). In this way, the value of '$dmax$' is decided.

Step 2. The VAR model should be established and the appropriate max lag length 'k' should be determined. At this stage, there should be no autocorrelation in the VAR model residues and the characteristic roots of the VAR model should be in the unit circle.

Step 3. After k and $dmax$ are determined, the lags of the variables up to (k + $dmax$) should be added to the VAR model as exogenous variables.

Step 4. The causality test is applied to the VAR model to be obtained. But here, Wald test is applied to test the hypotheses given below. Here, the Wald test statistic has the distribution X^2_{k+dmax} (chi-square).

$$\boldsymbol{H_0}\text{:}\ \ \boldsymbol{C(i) = C(i+1) = \cdots = C(k+dmax) = 0}$$

$$\boldsymbol{H_A}\text{:}\ \ \textbf{at least 1 of them is different from zero}$$

Equation 3: Formulating Hypothesis According to Research

For the test in question, two values must be calculated before the test. Calculation of Dmax and k values was done with the help of a program called EVIEWS.

4.1.1 Determining the appropriate lag length (k)

On EVIEWS program, prices of every variable have been imported. Bitcoin, Ethereum and TSLA prices has been chosen as endogenous variables between 2 January 2018 and 31 December 2021. Lag intervals changed to 1 8 and VAR order selection criteria table created on Figure 35.

Calculation output shown on Figure 14. Akaike Information Criterion shown with AIC, Schwarz Information Criterion shown with SC and Hannan-Quinn Information Criterion shown with HQ. Var order selection criteria for this research has been chosen as Akaike Information Criterion to prevent autocorrelation. Lags are added until autocorrelation disappears since small lags could cause an autocorrelation.

Lower AIC values indicate a better-fitting model, and a model with a delta-AIC (the difference between the two AIC values being compared) greater than -2 is considered considerably better than the model to which it is being compared.

Akaike's Final Prediction Error (FPE) criterion measures model quality by simulating the model's performance on a different data set. This criterion can be used to compare several different models after they have been computed. The most accurate model, according to Akaike's theory, has the smallest FPE.

When the same data set is used for both model estimation and validation, the fit always improves as the model order and, thus, the flexibility of the model structure increase.

VAR Lag order selection Criteria shown on Figure 14 shows the AIC lowest value is 34.3378 and FPE $1.64e^{11}$. Since both values are the lowest on the table shown on Figure 11 is 7th lag , appropriate lag length (k) is determined as 7.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-23682,96	NA	7,52E+16	47,37193	47,38665	47,37752
1	-17183,9	12946,12	1,73E+11	34,39181	34,4507	34,41419
2	-17167,37	32,8466	1,71E+11	34,37673	34,47979	34,4159
3	-17153,67	27,11494	1,69E+11	34,36734	34,51457	34,4233
4	-17143,98	19,13159	1,69E+11	34,36596	34,55736	34,4387
5	-17133,36	20,89465	1,68E+11	34,36272	34,5983	34,45226
6	-17120,01	26,2061	1,67E+11	34,35401	34,63375	34,46033
7*	-17102,9	33,45308	1,64E+11*	34,3378*	34,66172	34,46091
8	-17094,14	17,09305	1,64E+11	34,33827	34,70636	34,47817
*	indicates lag order selected by the criterion					
LR:	sequential modified LR test statistic (each test at 5% level)					
FPE:	Final prediction error					
AIC:	Akaike information criterion					
SC:	Schwarz information criterion					
HQ:	Hannan-Quinn information criterion					

Figure 11: Calculation of appropriate lag length(k)

4.1.2 Determining the maximum degree of integration(dmax)

In order to determine the Dmax , unit root tests of Bitcoin, Ethereum and TSLA prices were completed one by one. The purpose of the Unit Root Tests is to find the dmax of each variable and to select the largest one as the maximum degree of integration value of the study.

Augmented Dickey-Fuller test was used as test type for unit root test. Augmented Dickey-Fuller (ADF) is an extended version of the Dickey Fuller test. To eliminate the autocorrelation problem, the test was expanded by including the lagged values of the dependent variable in the current model. The ADF test adds a lagged difference term (k) to the equation.

4.1.3 Augmented Dickey-Fuller Unit Root Test on TSLA

Null hypothesis has been created as TSLA has a unit root. To accept that hypothesis Probability Absolute Value should be higher than 0.05 and smaller than t-statistic absolute critical table values. Unit root tests outputs could be I(0), I(1), I(2) for Level, 1st difference and 2nd difference. Unit root test has been applied for TSLA stock prices.

Probability Absolute value 0.9938 is bigger than 0.05 and t-statistic smaller than critical table values as shown on Figure 12. Null hypothesis is accepted and TSLA has a unit root.

Null Hypothesis	TSLA_TESLA_ has a unit root
Exogenous	Constant
Lag Length	0 (Automatic - based on AIC, maxlag=21)
Augmented Dickey-Fuller test statistic	
t-Statistic	0.786933
Prob.*	0.9938
Test critical values:	
1% level	-3.436.623
5% level	-2.864.199
10% level	-2.568.238
Augmented Dickey-Fuller Test Equation	
Dependent Variable	D(TSLA_TESLA_)
Method	Least Squares

Figure 12: Augmented Dickey-Fuller Test Level-Intercept for TSLA

Testing on Level-1st Difference level as shown on Figure 16, Null hypothesis TSLA has a unit root is rejected. TSLA dmax value is calculated as I(1)=1.

Null Hypothesis	D(TSLA_TESLA_) has a unit root
Exogenous	Constant
Lag Length	0 (Automatic - based on AIC, maxlag=21)
Augmented Dickey-Fuller test statistic	
t-Statistic	-3.187.433
Prob.*	0.0000
Test critical values:	
1% level	-3.436.631
5% level	-2.864.202
10% level	-2.568.239
Augmented Dickey-Fuller Test Equation	
Dependent Variable	D(TSLA_TESLA_,2)
Method	Least Squares

Figure 13: Augmented Dickey-Fuller Test 1st difference-intercept TSLA

First difference is statistical technique used in time series analysis. It applies to make non-stationary series to stationary. Stationarity is crucial for statistical techniques as it implies that the statistical properties such as mean, variance and autocorrelation are constant over time.

Mathematically if we have time series as Y_t (where t represents the different time points) the first differenced series calculated as ;

$$\Delta Y_t = Y_t - Y_{t-1}$$

Many time series especially financial and economic ones have upward and downward times also seasonality. First differencing helps to remove this characteristics and make time series more likely to be stationary.

In summary, first differencing is a crucial step in time series analysis especially if the time series is non-stationary. It is a step that often comes first for more complex analysis and modeling as in this work.

4.1.4 Augmented Dickey-Fuller Unit Root Test on Bitcoin

Null hypothesis has been created as Bitcoin has a unit root. To accept that hypothesis Probability Absolute Value should be higher than 0.05 and smaller than t-statistic table values.

Augmented Dickey-Fuller Unit Root Test for Bitcoin on Level and Intercept outputs has shown Bitcoin has a root on I(0) and hypothesis is accepted and Bitcoin has a Unit Root.

Null Hypothesis	BITCOIN has a unit root
Exogenous	Constant
Lag Length	20 (Automatic - based on AIC, maxlag=21)
Augmented Dickey-Fuller test statistic	
t-Statistic	-0.927574
Prob.*	0.7797
Test critical values:	
1% level	-3.436.756
5% level	-2.864.257
10% level	-2.568.269
Augmented Dickey-Fuller Test Equation	
Dependent Variable	D(BITCOIN)
Method	Least Squares

Figure 14: Augmented Dickey-Fuller Test level-intercept for Bitcoin

Null hypothesis for the test decided as BITCOIN has a unit root in other words Bitcoin price series is non-stationary. If the null hypothesis not rejected it shows that time series has stochastic trend in other words highly correlated.

Lag length selected as 20 based on Akaike Information Criterion (AIC) which shows number of the lengths used in ADF regression. Lags are been added to test to account for serial correlation in the error terms which calculates relationship between variables current value and past values. If variable serially correlated it shows that time series is not random.

Test value of -0.927574 is the actual test statistic from the ADF test. Comparing this value with critical values helps to determine whether null hypothesis will be rejected or not. Critical values at significance level of 0.01, 0.05 and 0.10 are lower than test value.

P-value of 0.7797 is higher than significance levels which indicates null hypothesis is true and not rejected.

In summary, there is no proof to reject null hypothesis and Bitcoin has a unit root also it is non-stationary on the time frame. Non-stationary series shows us that the mean and variance of the model changing over time which is common for stock prices in this case cryptocurrency prices.

Null Hypothesis	D(BITCOIN) has a unit root
Exogenous	Constant
Lag Length	19 (Automatic - based on AIC, maxlag=21)
Augmented Dickey-Fuller test statistic	
t-Statistic	-6.866.575
Prob.*	0.0000
Test critical values:	
1% level	-3.436.756
5% level	-2.864.257
10% level	-2.568.269
Augmented Dickey-Fuller Test Equation	
Dependent Variable	D(BITCOIN,2)
Method	Least Squares

Figure 15: Augmented Dickey-Fuller Test 1st difference-Intercept for Bitcoin

Augmented Dickey-Fuller Unit Root Test for Bitcoin on Level and 1st difference outputs has shown Bitcoin has not a root on I(1) and hypothesis is rejected. As a result of this dmax for Bitcoin has been calculated as I(1) = 1.

4.1.5 Augmented Dickey-Fuller Unit Root Test on Ethereum

Null hypothesis has been created as Bitcoin has a unit root. To accept that hypothesis Probability Absolute Value should be higher than 0.05 and smaller than t-statistic table values. Test statistics of ADF tests for Level-Intercept shown on Figure 35 1st difference-Intercept on Figure 36.Ethereum and dmax value found as I(1) since 1st difference level null hypothesis rejected as shown on Figure 16.

Null Hypothesis	ETHEREUM has a unit root
Exogenous	Constant
Lag Length	17 (Automatic - based on AIC, maxlag=21)
Augmented Dickey-Fuller test statistic	
t-Statistic	-0.042187
Prob.*	0.9534
Test critical values:	
1% level	-3.436.736
5% level	-2.864.248
10% level	-2.568.264
Augmented Dickey-Fuller Test Equation	
Dependent Variable	D(ETHEREUM)
Method	Least Squares

Figure 16: Augmented Dickey-Fuller Test Level-Intercept for Ethereum

Null hypothesis of the Augmented Dickey-Fuller Unit Root Test is ETHEREUM has a unit root which can be said that this time series is non-stationary. Non-stationary time series statistical properties such as mean and variance changes over time which can make the statistical model unpredictable and can affect the validity of model.

Lag length of 17 means that the number of lagged changes in the series. Its determined based on the Akaike Information Criterion with a maximum lag of 21.

Augmented Dickey-Fuller test statistic is -0.042187 and comparing with the critical values on %1, %5, %10 levels to determine if the null hypothesis can be rejected. More negative t-statistic value means stronger proof against the null hypothesis.

P value of 0.9534 is significantly higher than common thresholds as 0.01, 0.05 and 0.10 which shows that null hypothesis cannot be rejected.

In summary, Augmented Dickey-Fuller test shows that on added particular model and data, there is no strong proof to reject null hypothesis in other words Ethereum has a unit root.

Null Hypothesis	D(ETHEREUM) has a unit root
Exogenous	Constant
Lag Length	16 (Automatic - based on AIC, maxlag=21)
Augmented Dickey-Fuller test statistic	
t-Statistic	-8.277.661
Prob.*	0.0000
Test critical values:	
1% level	-3.436.736
5% level	-2.864.248
10% level	-2.568.264
Augmented Dickey-Fuller Test Equation	
Dependent Variable	D(ETHEREUM,2)
Method	Least Squares

Figure 17: Augmented Dickey-Fuller Test 1st difference-Intercept for Ethereum

Null hypothesis of this test is Ethereum has a unit root in other words time series is non-stationary.Lag length for the test has been automatically selected as 16 and it means that ADF test equation considers past 16 observations of the time series to correct autocorrelation when testing of unit root.

P-Value of the test is 0.0000 or could be a small number rounded to 0. P-Value 0 shows that on this test that null hypothesis can be rejected.

According to the unit root test results given, all variables become stationary at the 1st difference. According to this result, dmax was determined as “1”.

In summary, the ADF test results suggest that these financial time series (BITCOIN, TSLA, ETHEREUM) are non-stationary in their levels but become stationary when first differenced once, which is typical for many financial time series. This finding is crucial for subsequent analysis, such as cointegration tests or modeling using Vector Autoregression models, which require stationary data.

BITCOIN = TSLA = ETHEREUM = I(1) = 1

k+dmax = 8

4.1.6 TODA-YAMAMOTO CAUSALITY TEST for TSLA

According to the results, the maximum lag length k was determined as "7" according to the Akaike Information Criteria (AIC). Based on the unit root test and lag length results, the Wald test was applied by making an 8^{th} degree VAR model estimation from the k+(dmax) formula. Lag Intervals has been chosen as 1 8 since the model is 8^{th} degree.

The seemingly unrelated regression was chosen as the estimation method to eliminate the correlation of the residues between the equations.

Three VAR equation has been created to test null hypothesis.

The below equation for Tesla's stock prices is a linear combination of its past values up to 8 lags, also the past values of Bitcoin and Ethereum as well as up to 8 lags. The coefficients named C(N) represents estimates how each past value affects the current value of Tesla's stock price.

TSLA_TESLA_ = C(1)*TSLA_TESLA_(-1) + C(2)*TSLA_TESLA_(-2) + C(3)*TSLA_TESLA_(-3) + C(4)*TSLA_TESLA_(-4) + C(5)*TSLA_TESLA_(-5) + C(6)*TSLA_TESLA_(-6) + C(7)*TSLA_TESLA_(-7) + C(8)*TSLA_TESLA_(-8) + C(9)*BITCOIN(-1) + C(10)*BITCOIN(-2) + C(11)*BITCOIN(-3) + C(12)*BITCOIN(-4) + C(13)*BITCOIN(-5) + C(14)*BITCOIN(-6) + C(15)*BITCOIN(-7) + C(16)*BITCOIN(-8) + C(17)*ETHEREUM(-1) + C(18)*ETHEREUM(-2) + C(19)*ETHEREUM(-3) + C(20)*ETHEREUM(-4) + C(21)*ETHEREUM(-5) + C(22)*ETHEREUM(-6) + C(23)*ETHEREUM(-7) + C(24)*ETHEREUM(-8) + C(25)

Equation 4: VAR Equation for TSLA

Current value of Tesla stock prices has been shown as TSLA_TESLA and model is aim to predict this value by using lagged also named as past values. TSLA_TESLA(-1) to (-8) are shown as past 8 prices of Tesla stock prices. Same values added to model for also Bitcoin and Ethereum. C(25) is a constant added to model as an error term.

BITCOIN(-1) to BITCOIN(-8): Shows that the lagged values of Bitcoin's price, from one time period ago to eight periods ago. The inclusion of Bitcoin suggests that the model considers the influence of Bitcoin's price on Tesla's stock price.

ETHEREUM(-1) to ETHEREUM(-8): Similarly, these terms are the lagged values of Ethereum's price, shows that Ethereum's price movement is also considered as a potential predictor for Tesla's stock price.

In summary, this VAR model predicts the Tesla's stock price based on past values of itself also Bitcoin and Ethereum. The effectiveness of this model depends on the accuracy that estimated coefficients and the underlying assumptions that past values of these variables are useful in predicting the future price of Tesla stock price.

VAR model has been applied for all three variables prices.

R -Squared	0,997523
Adjusted R-Squared	0,997462
S.E. Of Regression	5,329392

Figure 18: Test Statistics TODA-YAMAMOTO CAUSALITY TEST for Tesla Stock

R Squared value of 0.997523 shows that model explains almost all of the variability of the dependent variable around its mean. It suggests that very good fit of the model to the historical data.

The dependent variable's variability around its mean is almost entirely explained by the model, as indicated by the R Squared value of 0.997523, shows a very high relationship between the model and the historical data. The model shows a strong correlation between the prices of Bitcoin and Ethereum as well as Tesla's stock and past values of itself. This means that changes in the prices of Ethereum and Bitcoin may be important signs of changes in the value of Tesla's stock prices.

Overall, model seems there is a strong relationship between Tesla's stock prices and past values of itself with Bitcoin and Ethereum prices.

4.1.6.1 Wald Test for TSLA and Bitcoin

$\boldsymbol{H_0}$: C(9)=C(10)=C(11)=C(12)=C(13)=C(14)=C(15)=C(16)=0

$\boldsymbol{H_A}$: at least 1 of them is different from zero

Equation 5:Wald Test Hypothesis for TSLA to Bitcoin

Test statistics	Value	df	Probability
Chi-Square	29,5716	8	0,0003

Normalized Restriction (= 0)	Value	Std. Err.
C(9)	-0.000134	0.000201
C(10)	0.000493	0.000284
C(11)	-0.000714	0.000287
C(12)	0.000276	0.000291
C(13)	-0.000223	0.000291
C(14)	0.000509	0.000292
C(15)	-0.000154	0.000293
C(16)	5.53E-05	0.000205

Figure 19: Wald Test for TSLA to Bitcoin

Coefficients C(9) to C(16) represents specific sights of the relationship between Tesla stock and Bitcoin prices. The values indicates the strength and sensitivity of the relationship which Tesla causality to Bitcoin.

Where C(9), C(11), C(13) and C(15) has negative influence, C(10), C(12), C(14) and C(16) has positive influence. As deeper comments with example of C(10) ;

C(10): 0.000493 with standard error 0.000284 suggest that there is a certain degree of positive influence of Tesla stock price on Bitcoin price though the influence is small.

Probability determined as 0.0003 shown on Figure 19. To test hypothesis real probability calculated with Excel formula: =CHISQ.DIST(29.5716,8,FALSE) = 0.000102.

0.000102 < 0.05, H_0 rejected, $TSLA_t$ does cause BTC_t

4.1.6.2 Wald Test for TSLA and Ethereum

$$\boldsymbol{H_0}: \text{ C(17)=C(18)=C(19)=C(20)=C(21)=C(22)=C(23)=C(24)=0}$$

$$\boldsymbol{H_A}: \text{ at least 1 of them is different from zero}$$

Equation 6:Wald Test Hypothesis for TSLA to Ethereum

Test statistics	Value	df	Probability
Chi-Square	15,98218	8	0,0426

Normalized Restriction (= 0)	Value	Std. Err.
C(17)	-0,000628	0,002679
C(18)	0,001508	0,003674
C(19)	0,004007	0,00366
C(20)	-0,00573	0,003656
C(21)	0,003291	0,003666
C(22)	-0,004353	0,00369
C(23)	0,005434	0,003748
C(24)	-0,001818	0,00273

Figure 20: Wald Test for TSLA to Ethereum

Coefficients C(17) to C(24) represents specific sights of the relationship between Tesla stock and Ethereum prices. The values indicates the strength and sensitivity of the relationship which Tesla causality to Ethereum.

Where C(17), C(20), C(22) and C(24) has negative influence, C(18), C(19), C(21) and C(23) has positive influence. As deeper comments with example of C(17) ;

C(21): 0.003291 with standard error 0.003666 suggest that there is a certain degree of negative influence of Tesla stock price on Ethereum price though the influence is small.

Probability determined as 0.0426 shown on Figure 20. To test hypothesis real probability calculated with Excel formula: =CHISQ.DIST(15.98218,8,FALSE) = 0.014393.

0.014393< 0.05, H_0 rejected, ETH_t does cause $TSLA_t$

4.1.7 TODA-YAMAMOTO CAUSALITY TEST for Bitcoin

Below equation will be used to determine causality from Ethereum and TSLA to Bitcoin. Equations shown below.

The below equation for Bitcoin prices is a linear combination of its past values up to 8 lags, also the past values of Tesla stock and Ethereum as well as up to 8 lags. The coefficients named C(N) represents estimates how each past value affects the current value of Bitcoin price.

BITCOIN = C(26)*TSLA_TESLA_(-1) + C(27)*TSLA_TESLA_(-2) + C(28)*TSLA_TESLA_(-3) + C(29)*TSLA_TESLA_(-4) + C(30)*TSLA_TESLA_(-5) + C(31)*TSLA_TESLA_(-6) + C(32)*TSLA_TESLA_(-7) + C(33)*TSLA_TESLA_(-8) + C(34)*BITCOIN(-1) + C(35)*BITCOIN(-2) + C(36)*BITCOIN(-3) + C(37)*BITCOIN(-4) + C(38)*BITCOIN(-5) + C(39)*BITCOIN(-6) + C(40)*BITCOIN(-7) + C(41)*BITCOIN(-8) + C(42)*ETHEREUM(-1) + C(43)*ETHEREUM(-2) + C(44)*ETHEREUM(-3) + C(45)*ETHEREUM(-4) + C(46)*ETHEREUM(-5) + C(47)*ETHEREUM(-6) + C(48)*ETHEREUM(-7) + C(49)*ETHEREUM(-8) + C(50)

Equation 7: VAR Equation for Bitcoin

R -Squared	0,996361
Adjusted R-Squared	0,996271
S.E. Of Regression	1169,968

Figure 21: Test Statistics TODA-YAMAMOTO CAUSALITY TEST for Bitcoin

R Squared value of 0.996361 shows that model explains almost all of the variability of the dependent variable around its mean. It suggests that very good fit of the model to the historical data.

Overall, model seems there is a strong relationship between Bitcoin prices and past values of itself with Tesla stock and Ethereum prices.

4.1.7.1 Wald Test for Bitcoin and TSLA

$\boldsymbol{H_0}$: C(26)=C(27)=C(28)=C(29)=C(30)=C(31)=C(32)=C(33)=0

$\boldsymbol{H_A}$: at least 1 of them is different from zero

Equation 8:Wald Test Hypothesis for Bitcoin to TSLA

Test statistics	**Value**	**df**	**Probability**
Chi-Square	19,74408	8	0,0113

Normalized Restriction (= 0)	**Value**	**Std. Err.**
C(26)	2,569617	6,940669
C(27)	16,22142	9,59215
C(28)	-33,8479	9,598804
C(29)	4,514427	9,659358
C(30)	6,647385	9,66068
C(31)	-3,838762	9,641965
C(32)	4,769358	9,636304
C(33)	4,838096	7,0008

Figure 22: Wald Test for Bitcoin to TSLA

Coefficients C(26) to C(33) represents specific sights of the relationship between Tesla stock and Ethereum prices. The values indicates the strength and sensitivity of the relationship which Bitcoin causality to Tesla Stock.

Where C(28) and C(31) has negative influence, C(26), C(27), C(29), C(30), C(32) and C(33) has positive influence. As deeper comments with example of C(28) ;

C(28): -33,8479 with standard error 9,598804 suggest that there is a certain degree of negative influence of Bitcoin price on Tesla stock price where the influence is too high.

According to calculations shown on Figure 22 Probability determined as 0.0113. To test hypothesis real probability calculated with Excel formula: =CHISQ.DIST(19.74408,8,FALSE) = 0.004137.

0.004137< 0.05, H_0 rejected, $TSLA_t$ does cause BTC_t

4.1.7.2 Wald Test for Bitcoin and Ethereum

$$\boldsymbol{H_0}: \text{ C(42)=C(43)=C(44)=C(45)=C(46)=C(47)=C(48)=C(49)=0}$$

$$\boldsymbol{H_A}: \text{ at least 1 of them is different from zero}$$

Equation 9:Wald Test Hypothesis for Bitcoin to Ethereum

Test statistics	**Value**	**df**	**Probability**
Chi-Square	54,47083	8	0

Normalized Restriction (= 0)	**Value**	**Std. Err.**
C(42)	-2,272481	0,58805
C(43)	2,07111	0,806469
C(44)	-0,85237	0,803563
C(45)	1,439865	0,802505
C(46)	-1,84497	0,804874
C(47)	2,809034	0,809979
C(48)	-2,91724	0,822809
C(49)	1,274740	0,599417

Figure 23: Wald Test for Bitcoin to Ethereum

Coefficients C(42) to C(49) represents specific sights of the relationship between Tesla stock and Ethereum prices. The values indicates the strength and sensitivity of the relationship which Bitcoin causality to Ethereum.

Where C(42), C(44), C(46), C(48) has negative influence, C(43), C(45), C(47) and C(49) has positive influence. As deeper comments with example of C(47) ;

C(47): 2,809034 with standard error 0,809979 suggest that there is a certain degree of positive influence of Bitcoin price on Ethereum price which is lower than Bitcoin to Tesla stock price.

According to calculations shown on Figure 23 Probability determined as 0. Since probably is zero, real probability will be 0.

0.0< 0.05, H_0 rejected, ETH_t does cause BTC_t

4.1.8 TODA-YAMAMOTO CAUSALITY TEST for Ethereum

Below equation will be used to determine causality from Bitcoin and TSLA to Ethereum. Equations shown on Figure 24.

The below equation for Ethereum prices is a linear combination of its past values up to 8 lags, also the past values of Tesla stock and Bitcoin as well as up to 8 lags. The coefficients named C(N) represents estimates how each past value affects the current value of Ethereum price.

ETHEREUM = C(51)*TSLA_TESLA_(-1) + C(52)*TSLA_TESLA_(-2) + C(53)*TSLA_TESLA_(-3) + C(54)*TSLA_TESLA_(-4) + C(55)*TSLA_TESLA_(-5) + C(56)*TSLA_TESLA_(-6) + C(57)*TSLA_TESLA_(-7) + C(58)*TSLA_TESLA_(-8) + C(59)*BITCOIN(-1) + C(60)*BITCOIN(-2) + C(61)*BITCOIN(-3) + C(62)*BITCOIN(-4) + C(63)*BITCOIN(-5) + C(64)*BITCOIN(-6) + C(65)*BITCOIN(-7) + C(66)*BITCOIN(-8) + C(67)*ETHEREUM(-1) + C(68)*ETHEREUM(-2) + C(69)*ETHEREUM(-3) + C(70)*ETHEREUM(-4) + C(71)*ETHEREUM(-5) + C(72)*ETHEREUM(-6) + C(73)*ETHEREUM(-7) + C(74)*ETHEREUM(-8) + C(75)

Equation 10:VAR Equation for Ethereum

R -Squared	0,995944
Adjusted R-Squared	0,995844
S.E. Of Regression	88,05684

Figure 24: Test Statistics TODA-YAMAMOTO CAUSALITY TEST for Ethereum

R Squared value of 0.995944 shows that model explains almost all of the variability of the dependent variable around its mean. It suggests that very good fit of the model to the historical data.

Overall, model seems there is a strong relationship between Ethereum prices and past values of itself with Tesla stock and Bitcoin prices.

4.1.8.1 Wald Test for Ethereum and TSLA

$$\boldsymbol{H_0}: \text{C(51)=C(52)=C(53)=C(54)=C(55)=C(56)=C(57)=C(58)=0}$$

$$\boldsymbol{H_A}: \text{ at least 1 of them is different from zero}$$

Equation 11:Wald Test Hypothesis for Ethereum to TSLA

Test statistics	**Value**	**df**	**Probability**
Chi-Square	17,92172	8	0,0218

Normalized Restriction (= 0)	**Value**	**Std. Err.**
C(51)	0,689277	0,522385
C(52)	0,03751	0,721947
C(53)	-1,82952	0,722448
C(54)	0,301407	0,727005
C(55)	0,589825	0,727105
C(56)	0,719307	0,725696
C(57)	0,061363	0,72527
C(58)	-0,299968	0,526911

Figure 25: Wald Test for Ethereum to TSLA

Coefficients C(51) to C(58) represents specific sights of the relationship between Etherum and Tesla stock prices. The values indicates the strength and sensitivity of the relationship which Ethereum causality to Tesla stock.

Where C(53) and C(58)has negative influence, C(51), C(52), C(54), C(55), C(56) and C(57) has positive influence. As deeper comments with example of C(56) ;

C(56): 0,719307 with standard error 0,725696 suggest that there is a certain degree of positive influence of Ethereum price on Tesla stock price.

According to calculations shown on Figure 25 Probability determined as 0.0218. To test hypothesis real probability calculated with Excel formula: =CHISQ.DIST(17.92172,8,FALSE) = 0.007695.

0.007695< 0.05, H_0 rejected, $TSLA_t$ does cause ETH_t

4.1.8.2 Wald Test for Ethereum and Bitcoin

$\boldsymbol{H_0}$: C(59)=C(60)=C(61)=C(62)=C(63)=C(64)=C(65)=C(66)=0

$\boldsymbol{H_A}$: at least 1 of them is different from zero

Equation 12:Wald Test Hypothesis for Ethereum to Bitcoin

Test statistics	**Value**	**df**	**Probability**
Chi-Square	54,98731	8	0

Normalized Restriction (= 0)	**Value**	**Std. Err.**
C(59)	0,009557	0,003318
C(60)	-0,01954	0,004697
C(61)	0,018461	0,004745
C(62)	-0,01092	0,004801
C(63)	0,016212	0,004807
C(64)	-0,019926	0,004818
C(65)	0,008172	0,004841
C(66)	-0,000099	0,003386

Figure 26: Wald Test for Ethereum to Bitcoin

Coefficients C(59) to C(66) represents specific sights of the relationship between Etherum and Bitcoin prices. The values indicates the strength and sensitivity of the relationship which Ethereum causality to Bitcoin.

Where C(60), C(62), C(64) and C(66) has negative influence, C(59), C(61), C(63) and C(65) has positive influence. As deeper comments with example of C(63) ;

C(63): 0,018461 with standard error 0,004745 suggest that there is a certain degree of positive influence of Ethereum price on Bitcoin price.

According to calculations shown on Figure 26 Probability determined as 0. Since probably is zero, real probability will be 0.

0.0< 0.05, H_0 rejected, BTC_t does cause ETH_t

TODA-YAMAMOTO CAUSALITY TEST outputs for TSLA, Bitcoin and Ethereum shown on Table 4.

Dependent Variable	**Independent Variable**	**dmax**	**k**	**Test Statistic**	**P Value**	**Causality**
TSLA	BTC	1	8	29.5716	0.000102	BTC -> TSLA
	ETH	1	8	15.98218	0.014393	ETH -> TSLA
BTC	TSLA	1	8	19.74408	0.011300	TSLA -> BTC
	ETH	1	8	54.47083	0.000000	ETH -> BTC
ETH	TSLA	1	8	17.92172	0.007695	TSLA -> ETH
	BTC	1	8	54.98731	0.000000	BTC -> ETH

Table 4 : TODA-YAMAMOTO CAUSALITY TEST outputs

TSLA and BTC: The test statistic is 29.5716 with a p-value of 0.000102. Since the p-value is less than 0.05, it suggests that there is a statistically significant causality from Bitcoin (BTC) to Tesla (TSLA) stock prices.

TSLA and ETH: The test statistic is 15.98218 with a p-value of 0.014393. This indicates a statistically significant causality from Ethereum (ETH) to Tesla (TSLA) stock prices, although the evidence is weaker compared to the BTC to TSLA causality given the higher p-value.

BTC and TSLA: The test statistic is 19.74408 with a p-value of 0.011300. This suggests that there is a statistically significant causality from Tesla (TSLA) stock prices to Bitcoin (BTC), although this causality is not as strong as the reverse (BTC to TSLA).

BTC and ETH: The test statistic is 54.47083 with a p-value of 0.000000. This indicates a very strong causality from Ethereum (ETH) to Bitcoin (BTC), with the p-value being practically zero, which strongly rejects the null hypothesis of no causality.

ETH and TSLA: The test statistic is 17.92172 with a p-value of 0.007695. This indicates a statistically significant causality from Tesla (TSLA) to Ethereum (ETH), suggesting that TSLA stock prices can predict ETH prices.

ETH and BTC: Again, the test statistic is very high at 54.98731 with a p-value of 0.000000, indicating a very strong causality from Bitcoin (BTC) to Ethereum (ETH), similar to the reverse causality mentioned earlier.

In conclusion, the findings point to a strong causal relationship—one way or the other—between the prices of Bitcoin and Ethereum and the stock price of Tesla. Furthermore, the findings show that there is a strong bidirectional causal relationship between Ethereum and Bitcoin. This could imply that changes in the price of Tesla stock can predict changes in the prices of Ethereum and Bitcoin in the future, and vice versa. Moreover, the findings imply that there is a strong correlation between the prices of Ethereum and Bitcoin.

4.2 Correlation Analysis

As a result of the causality test, it was observed that TSLA prices were affected by BTC and ETH prices. In the last part of the study, price estimation will be made with the correlation coefficients calculated. Correlation Matrix was calculated in EVIEWS and GRETL programs and the same results were obtained.

Table 5 shows the Correlation Matrix created with Gretl, and Table 6 shows the Correlation Matrix created with EVIEWS.

Correlation Coefficients, Using observations 02-01-2018 and 31-12-2021			
%5 Critical Value(two-tailed) = 0,0618 for n=1008			
Gretl Output			
	TSLA	Bitcoin	Ethereum
TSLA	1	0,9103	0,966
Bitcoin		1	0,9211
Ethereum			1

Table 5: Correlation Matrix for TSLA,Bitcoin and Ethereum by Gretl

Eviews Output			
	TSLA	Bitcoin	Ethereum
TSLA	1	0,910345	0,966022
Bitcoin		1	0,921087
Ethereum			1

Table 6:Correlation Matrix for TSLA,Bitcoin and Ethereum by Eviews

As shown on the Table 5 and Table 6 TSLA, Bitcoin and Ethereum prices examined as highly correlated.

Ordinary Least Square method has been used for model calculation. TSLA prices chosen as dependent variable, Bitcoin and Ethereum chosen as independent variables. Ordinary Least Square method estimated on Gretl and outputs shown on Table 7.

	Coefficient	Std. Error	T-ratio	P-value
const	546.625	146.232	3.738	0.0002
Bitcoin	0.000747290	0.000112970	6.615	6.03e-011 ***
Ethereum	0.0651315	0.00158721	41.04	5.37e-217 ***
Mean dependent var: 99.08813			Adjusted R-squared: 0.935858	
S.D. dependent var: 105.5875			F(2, 1005): 7347.303	
Sum squared resid: 718673.3			P-value (F): 0.000000	
S.E. of regression: 26.74131			Log-likelihood: -4741.287	
R-squared: 0.935986			Akaike criterion: 9488.574	
rho: 0.950851			Schwarz criterion: 9503.321	
Durbin-Watson: 0.104909			Hannan-Quinn: 9494.177	

Table 7: Ordinary Least Square Method outputs for TSLA

Regarding to calculations made on Table 5 and Table 7 research outputs show TSLA prices are positively correlated with Bitcoin and Ethereum Prices. That means if Bitcoin and Ethereum prices are increases TSLA stock prices will increase respectively. Model for estimating TSLA prices shown below.

$$T_t = 5.46625 + \ 0.0651315E_t + \ 0.000747290B_2 + \epsilon$$

$$B_t \ = Bitcoin\ price$$

$$X \ \ = constant$$

$$E_t \ = Ethereum\ price$$

$$T_t \ = TSLA\ price$$

$$\epsilon \ \ = error\ term$$

Equation 13: Economic Model Interpretation with Outputs

4.2.1 Interpretation of Correlation Analysis

$$T_t = 5.46625 + \ 0.0651315E_t + \ 0.000747290B_2 + \epsilon$$

Intercept the value of 5.46625. This value represents the expected value of tesla stock price when Ethereum and Bitcoin prices are zero. However, since in practical scenarios cryptocurrency prices cannot be zero therefore this theoretical intercept is not a meaningful interpretation of the model context.

For every one USD increase in Ethereum prices Tesla stock price is expected to increase 0.0651315 USD while Bitcoin price is constant. This shows a positive relationship between Ethereum and Tesla stock prices. As an investment pattern where investors can see Tesla and Ethereum prices are related investment funds.

For every one USD increase in Bitcoin prices Tesla stock prices expected to increase 0.000747290 USD while Ethereum price is constant. Coefficient of Bitcoin is smaller than Ethereum's shows that Tesla stock price is less affected by the changes in Bitcoin prices.

Adjusted R-Squared shows the accuracy of the model which is calculated %93.5. The R Squared value measures the proportion of variability in the dependent variable which is Tesla stock price that can be explained by the independent variables which is Ethereum and Bitcoin prices in the model. Where Adjusted R-Squared is closed to %100 shows that model explain very high proportion of the variability of Tesla stock price.

5 Results and Discussion

In this study, the causality relationship between Bitcoin, Ethereum crypto money prices and TSLA stock prices, which stand out at the point of market value, was included in the analysis at daily frequency between 02.01.2018 and 31.12.2021. According to the results of Toda Yamamoto causality analysis, it has been determined that cryptocurrencies and TSLA stock prices are related to each other. For the investor, this situation increases the risk to be exposed when a portfolio is created with cryptocurrencies and stocks that move in a similar direction. Building a portfolio with Bitcoin, Ethereum and TSLA can increase the risk to be exposed, given the relationship between these assets, and a diversification with crypto assets compared to traditional tools can be a dysfunctional choice for hedging.

Correlation analysis of cryptocurrencies and stocks, which was observed to have a causality between them as a result of the Toda-Yamamoto test, was performed. Correlation coefficients showed as TSLA, Bitcoin and Ethereum prices have positive correlation and effect their prices in the same way meaning that if Bitcoin prices increase TSLA prices will increase, if Ethereum prices increase TSLA prices will increase. Significant correlation between TSLA and cryptocurrencies, can be influenced by public figures like Elon Musk. His actions and statements shows growing impact of individuals on financial market in the age of social media.

Ethereum's strong correlation with TSLA compared to Bitcoin cause might be its underlying technology. Ethereum blockchain support smart contracts and decentralized systems similar with Tesla's innovative and technology centered business model.

The study also points where traditional and modern financial markets and alternative assets such as cryptocurrencies becoming highly interconnected. This trend in near future could redefine global financial market strategies, investment strategies and risk management.

Investing and having these assets on the same portfolio could cause big income or big loss meaning risk level is very high. The risk and loss will be reduced if these assets are not kept in the same portfolio.

On the study shown rapid changes in the cryptocurrency market, dynamic portfolio allocation methods might become more popular. Investors could take benefits from this trends and mix their investments in response of the market movements.

Investor could potentially follow and analyze Tesla stock prices over time by using this model. However, it is essential to approach this kind of models with caution since correlation does not imply causation and cryptocurrency market famous for its volatility. It is also vital to understand model does not accounting for different parameters as technological improvements, market conditions, regulations that could impact relationship between variables over time.

It is very important for investors, who act according to the logic of diversification, to consider the impact of the prominent assets in the crypto money market. The increasing risk appetite, with cryptocurrencies affecting the whole world and financial markets, has directed the attention of investors to the crypto money market, and there have been great increases in both volume and market value.

Examining complex relationship between traditional stocks and cryptocurrencies shows and provides an insight look about how the financial markets are changing. This research represents a critical conversation about comprehending and negotiating the complexity of investment environment increasingly impacted by digital innovations and globally connected markets since traditional investment strategies may not fully capture the nuances of cryptocurrency markets. There is a growing need for innovative investment approaches that adaptive to rapid changes, volatile environment and unique character of cryptocurrencies.

In conclusion, the study serves a guidance to investors and stakeholders through the undiscovered approaches of a rapidly changing financial movements. It calls for a re-evaluate the traditional investment strategies by showing the face of digital assets. The relationship between Bitcoin, Ethereum and stock prices as proven by Tesla stock prices, is not just a trend but future harbinger of more interactive and technology driven finance. This future demands adaptability, innovative thinking and proactive approach to understand and gain leverage from synergies between digital and traditional financial markets.

6 Appendix

R-squared	0.000616	Mean dependent var	0.328590
Adjusted R-squared	-0.000379	S.D. dependent var	5.423413
S.E. of regression	5.424439	Akaike info criterion	6.221690
Sum squared resid	29571.66	Schwarz criterion	6.231451
Log likelihood	-3130.621	Hannan-Quinn criter.	6.225399
F-statistic	0.619263	Durbin-Watson stat	2.015638
Prob(F-statistic)	0.431507		

Figure 27: Test Statistics ADF Level-Intercept TSLA

R-squared	0.502964	Mean dependent var	-0.004274
Adjusted R-squared	0.502469	S.D. dependent var	7.696330
S.E. of regression	5.428676	Akaike info criterion	6.223254
Sum squared resid	29588.40	Schwarz criterion	6.233022
Log likelihood	-3128.297	Hannan-Quinn criter.	6.226965
F-statistic	1015.973	Durbin-Watson stat	1.998955
Prob(F-statistic)	0.000000		

Figure 28: Test Statistics ADF 1st difference-Intercept TSLA

R-squared	0.041497	Mean dependent var	41.51824
Adjusted R-squared	0.020638	S.D. dependent var	1210.477
S.E. of regression	1197.921	Akaike info criterion	17.03660
Sum squared resid	1.38E+09	Schwarz criterion	17.14570
Log likelihood	-8385.562	Hannan-Quinn criter.	17.07809
F-statistic	1.989421	Durbin-Watson stat	1.995682
Prob(F-statistic)	0.005148		

Figure 29: Test Statistics ADF Level-Intercept Bitcoin

R-squared	0.543346	Mean dependent var	-0.891692
Adjusted R-squared	0.533892	S.D. dependent var	1754.500
S.E. of regression	1197.835	Akaike info criterion	17.03547
Sum squared resid	1.39E+09	Schwarz criterion	17.13961
Log likelihood	-8386.002	Hannan-Quinn criter.	17.07507
F-statistic	57.46937	Durbin-Watson stat	1.995500
Prob(F-statistic)	0.000000		

Figure 30: Test Statistics ADF 1st difference-Intercept Bitcoin

R-squared	0.076205	Mean dependent var	3.549192
Adjusted R-squared	0.059080	S.D. dependent var	92.76430
S.E. of regression	89.98235	Akaike info criterion	11.85611
Sum squared resid	7862015.	Schwarz criterion	11.95011
Log likelihood	-5849.774	Hannan-Quinn criter.	11.89185
F-statistic	4.449918	Durbin-Watson stat	1.998779
Prob(F-statistic)	0.000000		

Figure 31: Statistics ADF Level-Intercept Ethereum

R-squared	0.592848	Mean dependent var	-0.018960
Adjusted R-squared	0.585727	S.D. dependent var	139.7304
S.E. of regression	89.93613	Akaike info criterion	11.85409
Sum squared resid	7862029.	Schwarz criterion	11.94314
Log likelihood	-5849.775	Hannan-Quinn criter.	11.88795
F-statistic	83.25375	Durbin-Watson stat	1.998766
Prob(F-statistic)	0.000000		

Figure 32: Test Statistics ADF 1st difference-Intercept Ethereum

7 References

Adriana, D. (2014). Revisiting the relationship between un employment rates and shadow economy. A Toda-Yamamoto approach for the case of Romania. Procedia Economics and Finance, 227-236

Alexander, G. J., W. P. Sharpe ve J. V. Bailey (1993), Fundamentals of Investments, Prentice Hall, New Jersey.

Ankenbrand, T., & Bieri, D. (2018). Assessment of cryptocurrencies as an asset class by their Investment. Management and Financial Innovations, 15(3), 169-181.

Antonopoulos A.M., (2014), Mastering Bitcoin, ISBN-13 : 978-1449374044

Avdeychik, V., & Capozzi, J. (2018). SEC's Division of Investment Management Voices Concerns Over Registered Funds Investing in Cryptocurrencies and Cryptocurrency Related Products.

Baran, Paul. (1964). "On Distributed Communications Networks." IEEE Transactions on Communications Systems 12(1):1–9.

Baur D.G., Dimpfl T., Kuck K. (2016), Bitcoin, gold and the US dollar – A replication and extension, Finance Research Letters, Page 103-110

Baur, D.G., Dimpfl, T. (2018), Asymmetric volatility in crypto-currencies, Economic Letters, Page : 1–15.

Bunjaku, F., Gorgieva-Trajkovska, O., & Miteva-Kacarski, E. (2017). Cryptocurrencies–Advantages and Disadvantages. Journal of Economics

Claeys, Gregory; Demertzis, Maria; Efstathiou, Konstantinos (2018) : Cryptocurrencies and monetary policy, Bruegel Policy Contribution, No. 2018/10, Bruegel, Brussels

Corbeta S, Luceyb B, Peatc M ve Vigned S. (2018), Bitcoin Futures- What use are they?, Page 23-27

Cil Yavuz, N. (2006). TÜRKİYE'DE TURİZM GELİRLERİNİNEKONOMİK BÜYÜMEYE ETKİSİNİN TESTİ : YAPISAL KIRILMA VE NEDENSELLİK ANALİZİ. , 165-171

David E.Spray , (1964) , The Principal Stock Exchanges of the World--Their Operation, Structure and Development , ASIN : B000TYMN2U

Dyhrberg, A.H. (2016). Hedging capabilities of bitcoin. Is it the virtual gold? FinanceResearch Letters. Page 139-144.

Dyhrberg A.H. (2016), Bitcoin, gold and the dollar - A GARCH volatility analysis,Finance Research Letters, Page 85-92

Egor Zmaznev , (2017) , BITCOIN AND ETHEREUM EVOLUTION , https://core.ac.uk/download/pdf/161423052.pdf

G. Greenspan.(2018) Blockchains vs centralized databases, https://www.multichain.com/blog/2016/03/blockchains-vs-centralized-databases/

Güven V. ve Şahinöz E , (June 2018)., Blokzincir, Kripto Paralar, Bitcoin, Satoshi Dünyayı Değiştiriyor,

I. C. Lin, T. C. Liao(2017), "A Survey of Blockchain Security Issues and Challenges", IJ Network Security, 19(5), 653-659.

Joseph Sterling Grah (2008) HASH FUNCTIONS IN CRYPTOGRAPHY Master of sciencethesis https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=020c30b5391c6f9e4d5e683c158284b2e123e0d7

Küçükbay, F., & Araz, C. (2016). Portfolio Selection Problem: A Comparison of Fuzzy Goal Programming and Linear Physical Programming. An International Journal of Optimization and Control: Theories & Applications, 6(2), 121-128. doi:DOI: 10.11121/ijocta.01.2016.00284

Korkmaz, T., Aydın, N., & Sayılgan, G. (2013). Portföy Yönetimi. (M. Başar, Dü.) Eskisehir

L. Kemp , (1982) , A Guide to World Money and Capital Markets

Lone, A.H. ve Naaz, R. (2021). Applicability of Block chain smart contracts in securing Internet and IoT:A systematic literature review.

Mandić Adam (2021) , Effects of cryptocurrencies on financial markets , https://repozitorij.efzg.unizg.hr/islandora/object/efzg%3A7239/datastream/PDF/view

M. Pilkington.(2018) Blockchain Technology: Principles andApplications. Research Handbook on Digital Transformations,https://ssrn.com/abstract=2662660,

Nakamoto, S. (2008), Bitcoin: A Peer-to-Peer Electronic Cash System, Journal for General Philosophy of Science, https://bitcoin.org/bitcoin.pdf

NUNES, B. S. R. (2017), Virtual currency: a cointegration analysis between bitcoin prices and economic and financial data. Lizbon:ISCTE-IUL, 2017. Master Thesis. http://hdl.handle.net/10071/16078.

Poyser, O. (2017). Exploring the determinants of Bitcoin's price: an application of Bayesian Structural Time Series. Dissertation.

Szabo, N. (1997). Smart Contracts: Formalizing and Securing Relationships on Public Networks

T.Wan,H.Max,(2019)Bitcoin:Fact.Fiction.Future,https://www2.deloitte.com/insights/us/en/topics/emergingtechnologies/bitcoin-fact-fiction-future.html, 04.01.2019.

Thi Ngoc Nga Vu, (2022) , The Impact of Cryptocurrency on Traditional Financial Markets , https://www.theseus.fi/bitstream/handle/10024/753871/Vu_Nga.pdf?sequence=2

U. Mukhopadhyay, A. Skjellum, O. Hambolu, J. Oakley, L. Yu, R. Brooks,(2016), "A brief survey of Cryptocurrency systems", 2016 14th Annual Conference on Privacy, Security and Trust (PST), 745– 752

Victoria L Lemieux , (2017). Blockchain and distributed ledgers as trusted recordkeeping systems: An archival theoretic evaluation framework. In Future Technologies Conference (FTC), pages 1–11,

Wall Street Journal : https://www.wsj.com/market-data/quotes/TSLA/company-people

Yiğitbaşı Ş. ve Atabey A(2006), Mikro İktisat

Yhlas Sovbetov (2018)Factors Influencing Cryptocurrency Prices: Evidence from Bitcoin, Ethereum, Dash, Litcoin, and Monero : https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3125347

WEO (2013); http: //www.world-exchanges.org/, Word Federation Of Exchanges