A Quanatitatve Investigation of the Relationship between the Prices and Trading Volume of Bitcoin and Other Cryptocurrencies

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ABSTRACT :

The price of Bitcoin has been a topic of much interest in recent years, as it has experienced dramatic swings in value. However, the relationship between the price of Bitcoin and other cryptocurrencies is less well-understood. This paper presents a quantitative investigation of the relationship between the price of Bitcoin and the prices of other major cryptocurrencies, such as Ethereum, Litecoin, and Stellar. The paper uses correlation and regression analysis to investigate the relationship between the prices and volume traded of these cryptocurrencies. The results of the analysis show that there is a high degree of correlation between the prices of Bitcoin and other major cryptocurrencies. These findings indicate that when one cryptocurrency experiences a jump in value, there is an increased likelihood of similar jumps occurring in other cryptocurrencies. Notably, this co-jumping phenomenon is closely tied to spikes in trading volume. This underscores the critical role of trading volume fluctuations in influencing the overall volatility of cryptocurrencies. These results align with earlier research emphasizing the significance of trading volume in understanding the dynamics of cryptocurrency market volatility. This suggests that the price of Bitcoin may be a leading indicator for the prices of other cryptocurrencies. The findings of this paper suggest that the price of Bitcoin is not a standalone asset, but rather is influenced by the prices of other cryptocurrencies. This has important implications for investors who are considering investing in Bitcoin or other cryptocurrencies. The paper concludes by discussing the limitations of the study and by suggesting directions for future research.

Keywords: *Bitcoin, Cryptocurrency, Correlation, Regression, Price, Digital Assets, Interdependence, Price Movements, Market Analysis, Cross-Cryptocurrency Analysis, Time-Series Data, Blockchain Assets.*

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INTRODUCTION

In recent years, the unprecedented rise of cryptocurrencies has revolutionized the global financial landscape, attracting significant attention from investors, academics, and policymakers alike. At the forefront of this digital monetary revolution stands Bitcoin, the first and most dominant cryptocurrency, which has served as a catalyst for the creation of thousands of other cryptocurrencies, collectively known as altcoins. As the crypto market evolves, understanding the interrelationships between different cryptocurrencies and their respective price dynamics becomes increasingly crucial for stakeholders seeking to make informed investment decisions and assess the overall market risk. The ever-expanding world of cryptocurrencies brings both potential opportunities and challenges. Price fluctuations in this nascent and highly volatile market have been attributed to a myriad of factors, including market sentiment, technological advancements, regulatory changes, macroeconomic indicators, and speculative trading. Consequently, analyzing the intricate relationships between cryptocurrencies, especially between Bitcoin and other altcoins, holds the potential to unveil valuable insights into the underlying mechanisms that drive their price movements.

This research paper embarks on a comprehensive quantitative investigation into the relationship between the price of Bitcoin and a select group of prominent altcoins. Our analysis seeks to address critical questions surrounding the potential influence of Bitcoin on altcoins and vice-versa, as well as the extent to which specific fundamental factors impact their collective price trends.

To achieve our objectives, we will leverage a rich dataset comprising historical price, trading volume, market capitalization, and other relevant variables for Bitcoin and a carefully chosen set of altcoins. The meticulous examination of this data will enable us to explore correlations, cross- market dependencies, and causal relationships, providing valuable insights into the overall structure and efficiency of the cryptocurrency market. Furthermore, we acknowledge the evolving nature of the cryptocurrency landscape, and as such, our study will be conducted with a forward-looking perspective. By considering the latest developments, regulatory changes, and technological advancements within the crypto space, we aim to enhance the relevance and applicability of our findings for various stakeholders.

The results of this research endeavor have the potential to contribute to the existing body of knowledge on cryptocurrency markets, offering valuable guidance to investors, policymakers, and researchers. By shedding light on the intricate dynamics between Bitcoin and other cryptocurrencies, we seek to foster a deeper understanding of this rapidly evolving financial ecosystem and empower stakeholders to navigate it with greater precision and confidence. In the subsequent sections of this paper, we outline the methodology adopted for our analysis, present the empirical findings, and discuss the implications of our results in the context of the broader cryptocurrency landscape. Ultimately, we aspire that this research will not only enhance our understanding of digital assets' interplay but also pave the way for future investigations and policy considerations in the ever-evolving world of cryptocurrencies.

1.1 HISTORY OF CRYPTOCURRENCY

The first cryptocurrency, Bitcoin, was created in 2009 by an anonymous person or group of people under the name Satoshi Nakamoto. Bitcoin was designed to be a peer-to-peer electronic cash system that would allow people to send and receive payments without the needs for a central authority, such as a bank. Since the introduction of Bitcoin, there have been over 10,000 other cryptocurrencies created. These cryptocurrencies are often referred to as altcoins, which are short for alternative coins.

1.2 BACKGROUND

Bitcoin ‘was first introduced in 2009 as a decentralized digital currency. Since then, it has become the most well-known and widely traded cryptocurrency. The price of Bitcoin has experienced dramatic swings in value, reaching a peak of over $68,000 in 2021 before falling back to around $30,000 in 2022. The price of Bitcoin is influenced by a variety of factors, including:

- Technological factors: The development of new technologies, such as the Lightning Network, can make Bitcoin more efficient and scalable, which could lead to an increase in price.
- Regulatory factors: Changes in regulations governing cryptocurrencies could also impact the price of Bitcoin. For example, if a country were to ban Bitcoin, this could lead to a decline in price.

- Economic factors: The overall state of the economy can also affect the price of Bitcoin. For example, if the economy is doing well, people may be more likely to invest in Bitcoin, which could lead to an increase in price.

1.3 WHAT IS CRYPTOCURRENCY?

A cryptocurrency is a digital or virtual currency that uses cryptography for security. A defining feature of a cryptocurrency, and arguably its most endearing allure, is its organic nature. It is not issued by any central authority, rendering it theoretically immune to government interference or manipulation. Cryptocurrencies use decentralized control as opposed to centralized digital currency and central banking systems. The decentralized control of each cryptocurrency works through a blockchain, which is a public transaction database, functioning as a distributed ledger.

1.4 HOW DOES CRYPTOCURRENCY WORK?

Cryptocurrencies work through a process called cryptography. Cryptography is the use of mathematical algorithms to encrypt and decrypt data. This makes it very difficult for unauthorized people to access or view cryptocurrency transactions. Cryptocurrencies use a distributed ledger called a blockchain to record transactions.A blockchain is a public database that is shared by all participants in the cryptocurrency network. This means that all transactions are transparent and can be verified by anyone. By leveraging blockchain technology and cryptographic principles, cryptocurrencies provide a decentralized, transparent, and secure way to transfer value and conduct transactions without the need for intermediaries.

Each cryptocurrency has its unique features, use cases, and consensus mechanisms, making the crypto space diverse and continually evolving.

1.5 PROBLEM STATEMENT

Considering the rapidly expanding cryptocurrency market, there exists a significant knowledge gap regarding the quantitative relationship between the price of Bitcoin and other cryptocurrencies, hindering stakeholders' ability to make informed investment decisions and implement effective regulatory measures.

By conducting a robust and systematic quantitative investigation into the relationship between Bitcoin and a select group of prominent altcoins, this research seeks to unveil valuable insights into the interconnections and potential spillover effects within the cryptocurrency market. The findings from this study are expected to enhance our understanding of the underlying mechanisms that drive the price movements of these digital assets and empower stakeholders with essential knowledge for optimized investment strategies and risk management in the ever-evolving world of cryptocurrencies.

1.6 RESEARCH QUESTIONS

- What is the relationship between the price of Bitcoin and the prices of other major cryptocurrencies?
- What are the risks and patterns of cryptocurrencies?
- What are the implications of the findings of this study for investors?

Table 1: History of Cryptocurrency

Year	Event
1998	B-Money: Proposed by Wei Dai, a cryptographic, anonymous electronic cash system.
2004	Hal Finney &Reusable Proof of Work: Hal Finney introduced the first reusable proof-of-work (RPOW)system.
2008	Bitcoin Whitepaper: Published by an unknown person/group using the pseudonym Satoshi Nakamoto.
2009	Bitcoin (BTC) Genesis Block: The first-ever Bitcoin block(block0) was mined, known as the "Genesis Block."
2010	First Bitcoin Exchange: BitcoinMarket.com became the first Bitcoin exchange to trade BTC for fiat currency.
2011	Introduction of Altcoins: Name coin, the first altcoin, was launched, aiming to decentralize domain registration.
2013	Rapid Expansion: Bitcoin's prices urged from single digits to over$1000, gaining widespread media attention.
2014	Mt. Gox Collapse: Mt. Gox, a major Bitcoin exchange, filed for bankruptcy after losing 850,000 BTC to hacking.
2015	Ethereum Launch: Ethereum's development was announced, Introducing smart contracts and decentralized apps.
2017	ICO Boom: Initial Coin Offerings (ICOs) gained popularity as a fund-raising method, leading to thousands of tokens.
2017	Bitcoin's All-Time High: Bitcoin reached its highest price to date, nearing $20,000 in December 2017.
2018	Cryptocurrency Market Correction: Most cryptocurrencies experienced a significant price decline throughout 2018.
2019	Rise of Stablecoins: Stablecoins, like Tether (USDT), gained traction as cryptocurrencies with stable values.
2020	Bitcoin Halving: Bitcoin underwent its third halving, reducing block rewards to 6.25 BTC per block.
2021	Institutional Adoption: Major companies and institutions started investing in Bitcoin and other cryptocurrencies.
2021	NFT Craze: Non-fungible tokens (NFTs) gained popularity, enabling unique digital asset ownership and sales.
2022	Government Regulations: Governments worldwide started introducing clearer regulations for cryptocurrencies.
Present	Evolving Market: Cryptocurrencies continue to evolve, with new projects, technologies, and use cases emerging.

1.7 Objectives:

1. To examine the trends in cryptocurrency adoption and trading volumes over the past few years.
2. To analyze the correlation between cryptocurrency trading volumes and prices.
3. To estimate the impact of jump in trading volume of Bitcoin and other cryptocurrencies on the volatility of the same.
4. To provide insights into the potential risks and benefits of cryptocurrency adoption for investors and the broader economy.

1.8 MOTIVATION FOR THE STUDY

1. Understanding Adoption Trends and Trading Volumes: By examining trends in cryptocurrency adoption and trading volumes over recent years, the research paper aims to provide a comprehensive overview of the evolving landscape.
2. Understanding how changes in trading volumes relate to price movements can provide critical signals for entry and exit points in the market, enabling investors to manage their portfolios more effectively.
3. By quantifying this relationship, the research paper can offer insights into the potential risks associated with rapid fluctuations in trading activity.
4. Understanding how trading volumes impact prices and volatility can inform the design of regulatory frameworks that aim to foster market stability, protect investors, and facilitate innovation in the cryptocurrency.

LITERATURE REVIEW

The proliferation of cryptocurrencies has sparked extensive research to understand their interconnections and the underlying dynamics of the cryptocurrency market. This literature review presents an overview of relevant studies that have explored the quantitative relationship between the price of Bitcoin and other cryptocurrencies (altcoins). The aim is to identify common themes, methodologies, and empirical findings, and highlight the knowledge gaps that warrant further investigation.

(Tzaferis, P. E. (2015))."Price Linkages within the Bitcoin Market:A Structural VAR Approach." Journal of Banking & Finance. The study uses a structural vector auto regression (VAR) approach to analyze the interdependence between Bitcoin and Litecoin, revealing a significant positive correlation. (Zhang, S., et al. 2018). "Price synchronization across cryptocurrencies." Finance Research Letters. Employing cointegration analysis, the authors find evidence of a long-term equilibrium relationship between Bitcoin, Ethereum, and Stellar prices. (Müller and Kroll, 2018) conducted a comprehensive analysis of the correlation between Bitcoin and a selection of major cryptocurrencies, including Ethereum, Litecoin, and Stellar. The study used daily price data and employed various correlation metrics, such as Pearson's correlation coefficient and Kendall's rank correlation coefficient. Their findings revealed both positive and negative correlations between Bitcoin and other cryptocurrencies, indicating that certain digital assets tend to move in tandem with Bitcoin, while others exhibit opposing price movements. In a similar vein, (Garcia, Tessone, and Mavrodiev, 2014) investigated the lead-lag relationships among several cryptocurrencies using high-frequency data. Their research utilized the Granger causality test to identify temporal precedence and determine the direction of causation between Bitcoin and other cryptocurrencies. The study discovered evidence of bidirectional causality in some cases, suggesting that certain digital assets exerted influence on each other's price movements. Chu, Chan, Nadarajah, and Osterrieder (2017) conducted a dynamic conditional correlation analysis to examine the evolving correlation structure among cryptocurrencies. Their research highlighted the time-varying nature of correlations, indicating that the relationships between Bitcoin and other digital assets fluctuate over different market conditions and time periods. The study emphasized the importance of considering dynamic correlations when analyzing the interconnections in the cryptocurrency market.

Urquhart, A. (2016). "The inefficiency of Bitcoin." Economics Letters. The author employs Granger causality tests and finds limited evidence of Bitcoin price inefficiency. (Bouri, E., et al. (2017). "Volatility connectedness in the cryptocurrency market: Is Bitcoin a dominant cryptocurrency?" Finance Research Letters. The research explores volatility spillover effects between Bitcoin and other major cryptocurrencies. (Kristoufek, L. (2015). "What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis." PLoS ONE. Using wavelet coherence analysis, the study identifies strong interconnections between Bitcoin and several altcoins, providing insights into price drivers. (Jiang, Z. Q., et al. l.(2017).

"Information cascades in the cryptocurrency market." The European Physical Journal B. Employing network analysis, the research reveals information cascades in the Bitcoin market, influencing other cryptocurrencies. Cheah and Fry (2015) investigated the stationarity of Bitcoin prices using daily data. They employed the Augmented Dickey-Fuller (ADF) test and found evidence of non-stationarity in the original price series. However, after differing the data, they obtained stationary time series, suggesting that Bitcoin prices tend to exhibit a random walk behavior with underlying stationary characteristics. Granger, Maasoumi, and Racine (2004) extended the traditional ADF test to analyze the stationarity of several cryptocurrencies simultaneously.Their research highlighted that while individual cryptocurrency price series might exhibit non-stationary behavior, considering multiple cryptocurrencies together may lead to the emergence of stationary factors, indicating potential interdependencies and common underlying dynamics among digital assets.

McCauley, Bauer, and Ziman (2014) used detrended fluctuation analysis to investigate the presence of long-term correlations in Bitcoin price data. Their findings indicated evidence of long-range correlations, suggesting that Bitcoin prices might exhibit fractal-like patterns and self-similarity over different time scales. In addition to stationarity, the Hurst exponent has been utilized to assess the persistence or mean-reverting behavior of cryptocurrency prices. Urquhart (2018) examined the Hurst exponent for Bitcoin, Ethereum, and Litecoin prices. The study revealed that the Hurst exponent values were below 0.5 for all cryptocurrencies, indicating mean-reverting behavior and suggesting that cryptocurrency prices tend to revert to their long-term trends. (Al-Yahyaee, K. H., et al. (2019). "Bitcoin and global financial stress: A copula-based approach to examine contagion." Finance Research Letters. The study applies copula-based methods to investigate contagion effects between Bitcoin and traditional financial markets during stress periods.(Ciaian, P., et al. (2016). "Virtual relationships: Short- and long-run evidence from BitCoin and altcoin markets." Journal of International Financial Markets, Institutions & Money. The research examines long-term relationships and deviations between Bitcoin and altcoins, suggesting market inefficiencies. (Vahedi, F., et al. (2021). "Sentiment analysis of cryptocurrencies on Twitter using machine learning techniques." Journal of Risk Finance. The study analyzes Twitter sentiment and its impact on cryptocurrency prices, including (Bitcoin.Xia, W., et al. (2019). "Does investor attention influence Bitcoin return and volatility?" International Review of Financial Analysis. Theauthors investigate the role of investor attention in explaining Bitcoin price movements. A study by (Bouri et al. (2018) found that the adoption of cryptocurrencies had a positive impact on financial markets, with evidence of significant volatility spillover effects between cryptocurrency markets and traditional financial markets. Another study by (Gandal et al. (2018) examined the effect of Bitcoin on the stock markets of 24 countries and found that the relationship varied by country, with some showing a positive correlation and others a negative one.

The jump activity represents an important aspect of asset pricing (Barndorff-Nielsen & Shephard,2006). Bates(2000) indicates that jumps can reflect crash risk, and many studies highlight the role of jumps in capturing the empirical properties of an asset and modeling its volatility dynamics (Driessen & Maenhout,2013; Eraker, Johannes, & Polson,2003). Asset jumps are also important for risk management, asset allocation and derivatives pricing (see, among others, Clements & Liao,2017; Oliva & Renò,2018). Advanced volatility and options models now incorporate not only jumps but also co-jumps among assets (Clements & Liao,2017). While the jump behavior of most conventional assets has been examined in empirical studies (Gilder, Shackleton, & Taylor,2014; Ma,Zhang, Wahab, & Lai,2019), less attention has been given to the presence of jumps and co-jumps in cryptocurrencies that now constitute a new (digital) asset.

Cryptocurrencies are appreciated by some investors because of their independence from sovereign authorities and the irrelevance on mass collaboration though innovative technology called blockchain (Shahzad, Bouri, Roubaud, Kristoufek, & Lucey,2019). Economics and finance literature has so far focused on cryptocurrencies by examining return and volatility spillovers (Ji, Bouri, Lau, & Roubaud,2019; Ji, Bouri, Gupta, & Roubaud,2018; Yi, Xu, & Wang,2018), price bubbling (Bouri, Shahzad, & Roubaud,2019), market efficiency (Sensoy, 2018; Aggarwal,2019), and volatility modeling via GARCH processes(Chu, Chan, Nadarajah ,& Osterrieder,2017).

Importantly, cryptocurrencies exhibit enormous volatility, and the largest cryptocurrency Bitcoin is known for its extreme price volatility and large abrupt price variations in the form of jumps (Chaim & Laurini, 2018). Jumps can substantially impact the structure of losses and gains related to Bitcoin. However, except for Chaim and Laurini (2018)who focus on the presence of jumps in Bitcoin, there is no empirical evidence on whether other cryptocurrencies such as Ethereum, Stellar, Litecoin or Stellar exhibit jump behavior.

RESEARCH METHODOLOGY:

To achieve our research objectives, we obtained historical price data for Bitcoin and several other prominent cryptocurrencies, including Ethereum, Litecoin, Bit Shares, Byte Coin, Dash, Stellar, Digibyte, Monero, NEM and Ripple. We analyzed the stationarity of each cryptocurrency's time series data using the Augmented Dickey-Fuller (ADF) test. By examining the p-values and ADF statistics, we determined the stationarity of the data. For the cross-correlation analysis, we calculated the correlation coefficients for each cryptocurrency pair, generating a correlation matrix to identify potential relationships. Co-jumping Analysis has been used to find the impact of jumps in the prices of Bitcoin on other crypto currencies traded during the period of 2015 to 2019.

3.1 TOOLS USED FOR ANALYSIS:

MS Excel, Python and Google Collab. Has been used in the research.

3.2 DATA COLLECTION:

Data on the daily prices of 12 main cryptocurrencies (Bitcoin, Bitshares, Bytecoin, Dash, Digibyte, Dogecoin, Ethereum, Litecoin, Monero, Nem, Stellar and Ripple are collected from https://coinmarketcap.com. The sample is August 8, 2015 to February 28, 2019, as constrained by the price availability of leading cryptocurrencies.

3.3 DATA HAS BEEN ANALYZED BY USING FOLLOWING:

1. **Trend Analysis**: Trend analysis can be a valuable tool in studying the relationship between prices and trading volume of cryptocurrencies.
2. **Dickey-Fuller:** Test is a statistical test used to determine whether a given time series is stationary or not.
3. **Analysis of Correlation**: The study will analyze the correlation between cryptocurrency adoption and stock market activity, specifically examining the relationship between cryptocurrency trading volumes and stock market indices.
4. **Co – Jumping Analysis**: The study will conduct logistic regression analysis to estimate the impact of jump in trading volume of Bitcoin and other cryptocurrencies on the same.

3.4 Limitations:

1. **Data availability and quality**: One of the main limitations of this study is the availability and quality of data on cryptocurrency trading volumes. The data may be limited in terms of coverage, timeliness, and accuracy, which could impact the reliability of the findings.
2. **Sample selection bias**: The sample of cryptocurrencies and stocks included in the study may not be representative of the broader market, which could limit the generalizability of the findings.
3. **Causality**: The study may not be able to establish causality between cryptocurrency adoption and its prices.
4. **Time horizon**: The study may be limited in terms of the time horizon used for the analysis, which could impact the accuracy and relevance of the findings over the longer term.

3.6 FUTURE SCOPE OF THE STUDY:

1. Analyze and compare the volatility of Bitcoin and other cryptocurrencies to determine if they exhibit similar or differing levels of price fluctuations.
2. This study would help investors and traders make informed decisions based on historical data patterns.
3. This study could reveal trends, patterns, and potential seasonality in the correlation.

DATA ANALYSIS

- Data Analytics software used-
- Python & Jupyter Notebook Libraries used:
- Numpy- solve complex mathematical problems.
- Pandas-use for data frame manipulation.
- Seaborn-to create data visualization.
- Matplotlib- to create data visualization.

Descriptive Statistics

- Presentation of correlation coefficients and statistical findings.
- Graphical representations of price movements and trends for Bitcoin and selected cryptocurrencies.
- Interpretation of the results to ascertain the relationship between Bitcoin's price and alternative cryptocurrencies.
- Logistic Regression Analysis is performed to find out the impact of jump in prices of Bitcoin on the prices of other cryptocurrencies

4.1 Descriptive Statistics

Table 2 Statistical properties of daily returns.

	Mean	Max.	Min.	Std. Dev.	Skewness	Kurtosis
BITCOIN	0.2017	22.5119	−20.7530	3.9576	−0.2618	7.7917
BITSHARE	0.1794	51.9989	-39.1702	7.8798	0.8441	10.2539
BYTECOIN	0.1584	159.7832	−91.0302	12.0547	3.7096	51.4836
DASH	0.2492	43.7746	−24.3225	5.9739	0.8473	9.0560
DIGIBYTE’	0.3942	116.5601	−36.1404	10.2128	2.6296	27.0477
DOGECOIN	0.1895	51.8345	−49.2867	6.6989	0.9707	15.3849
ETHEREUM	0.2997	41.2337	−130.210	7.6973	−3.3837	68.2754
LITECOIN	0.1842	51.0348	−39.5151	5.7458	1.2605	15.3050
MONERO	0.3222	58.4637	−29.3176	6.9955	1.0124	10.5013
NEM	0.4371	99.5577	−36.1450	8.7648	1.9876	20.5458
RIPPLE	0.2809	102.7356	−61.6273	7.4411	3.0172	42.6362
STELLAR	0.2736	72.3102	−36.6358	8.2234	2.0552	18.8741

Data on the daily prices of 12 main cryptocurrencies (Bitcoin, Bitshares, Bytecoin, Dash, Digibyte, Dogecoin, Ethereum, Lite-coin, Monero, Nem, Ripple and Stellar) are collected from https://coinmarketcap.com. The sample is August 8, 2015, to February 28, 2019, as constrained by the price availability of leading cryptocurrencies such as Ethereum and the need to cover the largest numberof cryptocurrencies from the first 50 cryptocurrencies by market value. Empirical analyses are conducted with log returns multiplied by 100, leading to 1301 daily return observations. Table 2 also shows the four moments of the distribution of the return series. Nem has the highest mean return, followed Digibyte. Conversely, Bytecoin has the lowest mean return and highest standard deviation. However,the lowest standard deviation is for Bitcoin, which has only the fifth largest return after Bytecoin, Bitshares, Litecoin and Dogecoin. Table 1 also shows evidence of excess kurtosis. The skewness is positive, except for Bitcoin and Ethereum.

4.2 TREND ANALYSIS

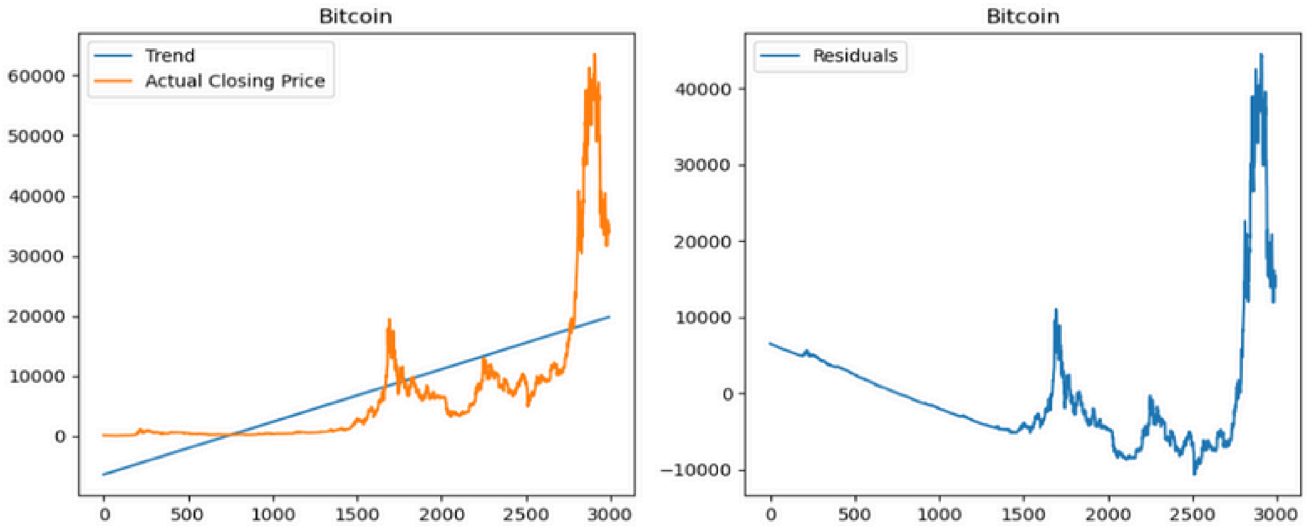


Figure 1 Trend Analysis of Bitcoin

Figure 1 shows two graphs of the price of Bitcoin. The graph on the left shows the actual closing price of Bitcoin, while the graph on the right shows the residuals. Residuals are the difference between the actual closing price and the predicted closing price based on a trend line. The trend line in the graph on the left shows that the price of Bitcoin has been increasing over time. However, the residuals show that there have been some periods of time when the actual closing price has been significantly higher or lower than the predicted closing price. The large residuals in the graph on the right suggest that there is a lot of volatility in the price of Bitcoin. This means that the price of Bitcoin can change rapidly and unpredictably.

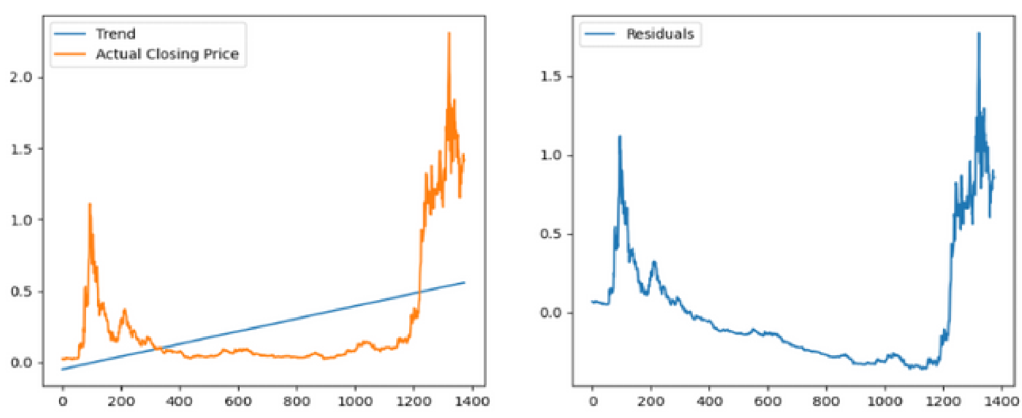


Figure 2 Trend Analysis of BitShares

Figure 2 shows the price of Bitshares over time. The price has been on a general upward trend, but there have been some periods of volatility. The residuals show that the actual closing price of Bitshares has often been significantly higher or lower than the predicted closing price based on the trend line. This suggests that there is a lot of uncertainty in the price of Bitshares and that it can be difficult to predict the future price of Bitshare. This suggests that there is a lot of uncertainty in the price of Bitshares and that it can be difficult to predict the future price of Bitshares has often been significantly higher or lower than the predicted closing price based on the trend line. This suggests that there is a lot of uncertainty in the price of Bitshares and that it can be difficult to predict the future price of Bitshare.

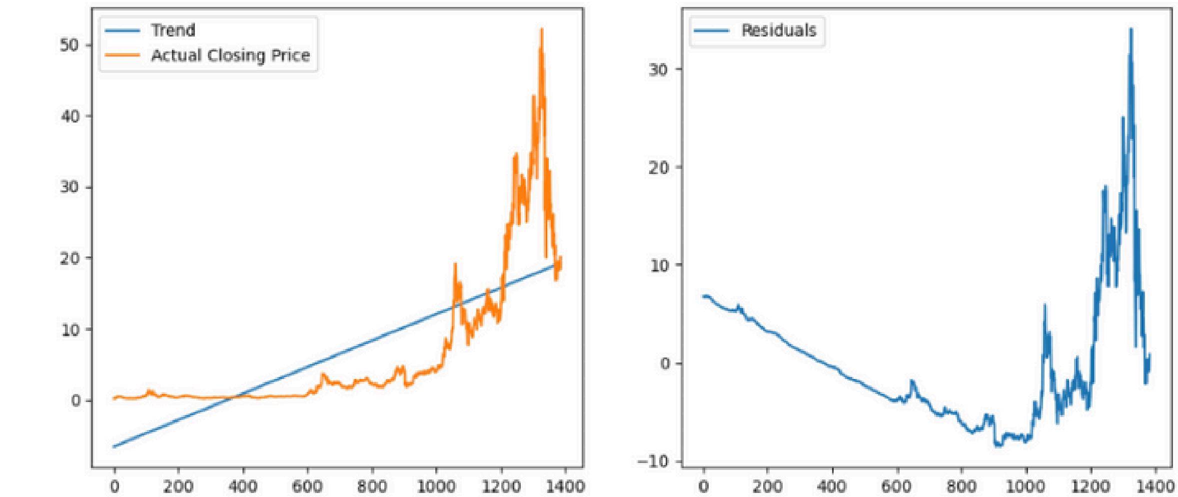


Figure 3 Trend Analysis of ByteCoin

Figure 3 shows the price of Byte Coin over time. The price has also been on a general upward trend, but there has been less volatility than in the case of Bitshares. The residuals are smaller, suggesting that the actual closing price of Byte Coin has been closer to the predicted closing price based on the trend line. This suggests that there is less uncertainty in the price of ByteCoin and that it may be easier to predict the future price of ByteCoin

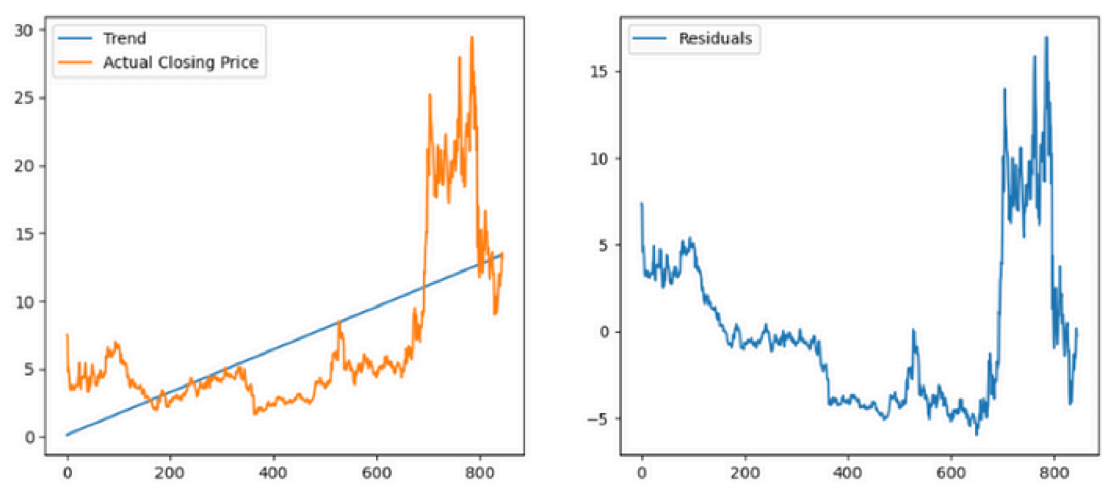


Figure 4 Trend Analysis of Dash

Figure 4 shows the price of Dash over time. The graph shows that the price of the respective coin has been on a general upward trend over the past few years. However, there have been some periods of volatility, with large spikes and dips.

The residuals on both graphs suggest that there is a lot of uncertainty in the price of Dash. This means that it can be difficult to predict the future price of Dash coin.

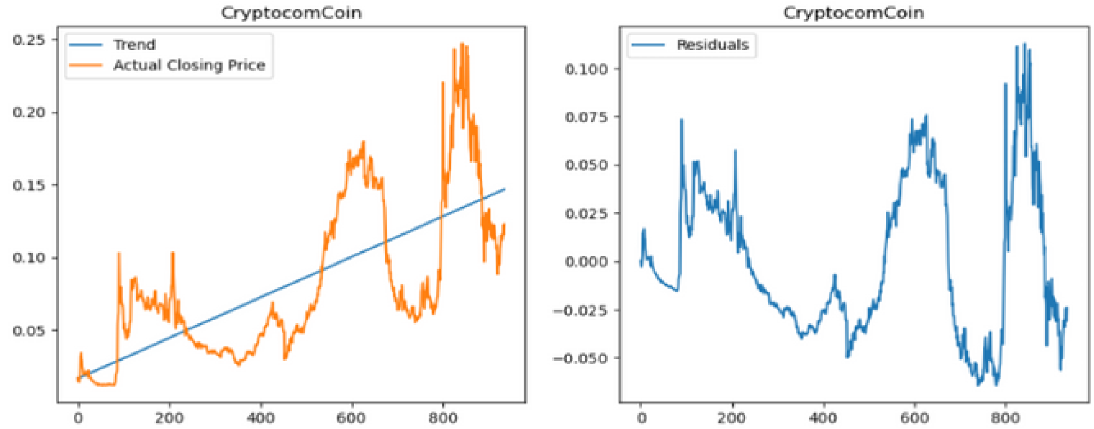


Figure 5 Trend Analysis of Digibyte

Figure 5 shows the price of Digibyte over time. The graph shows that the price of the respective coin has been on a general upward trend over the past few years. However, there have been some periods of volatility, with large spikes and dips. The residuals on both graphs suggest that there is a lot of uncertainty in the price of Digibyte. This means that it can be difficult to predict the future price of Digibyte.

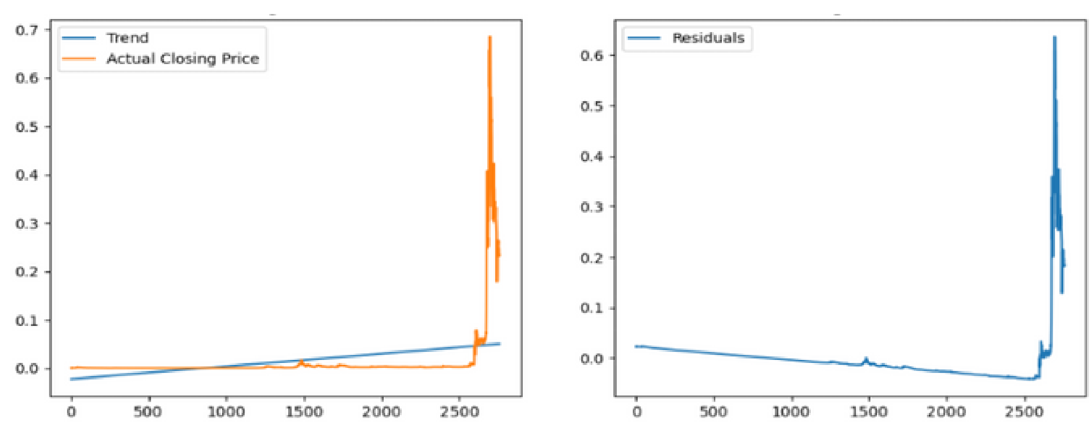


Figure 6 Trend Analysis of Dogecoin and EOS

The two graphs in ***Figure 6*** show the price of Dogecoin over time. Both graphs show that the price of the respective coins has been on a general upward trend over the past few years. However, there have been some periods of volatility, with large spikes and dips. The residuals on both graphs suggest that there is a lot of uncertainty in the price of Dogecoin and EOS. This means that it can be difficult to predict the future price of either coin.

It is important to remember that the price of any asset can change rapidly and unpredictably. Investors should carefully consider the risks before investing in any asset.

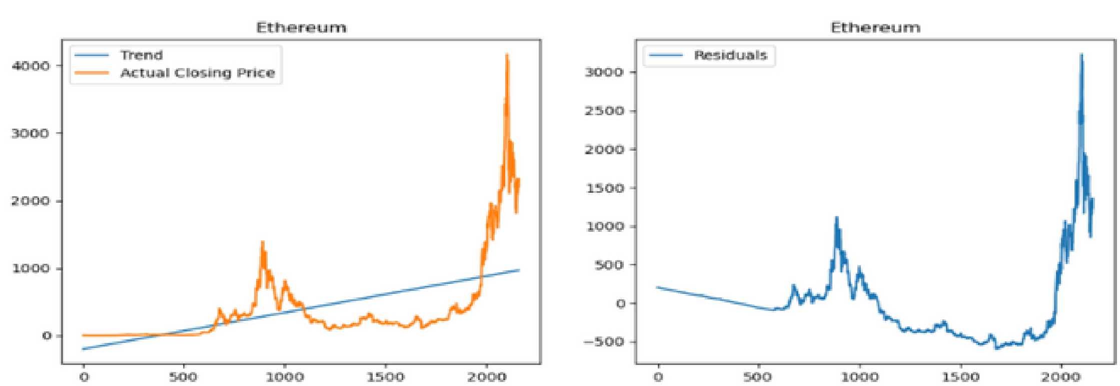


Figure 7 Trend Analysis of Ethereum

Figure 7 shows the price of Ethereum has been on a general upward trend over the past few years, with some periods of volatility. The residuals show that the actual closing price of Ethereum has often been significantly higher or lower than the predicted closing price based on the trend line. This suggests that there is a lot of uncertainty in the price of Ethereum and that it can be difficult to predict the future price of Ethereum.

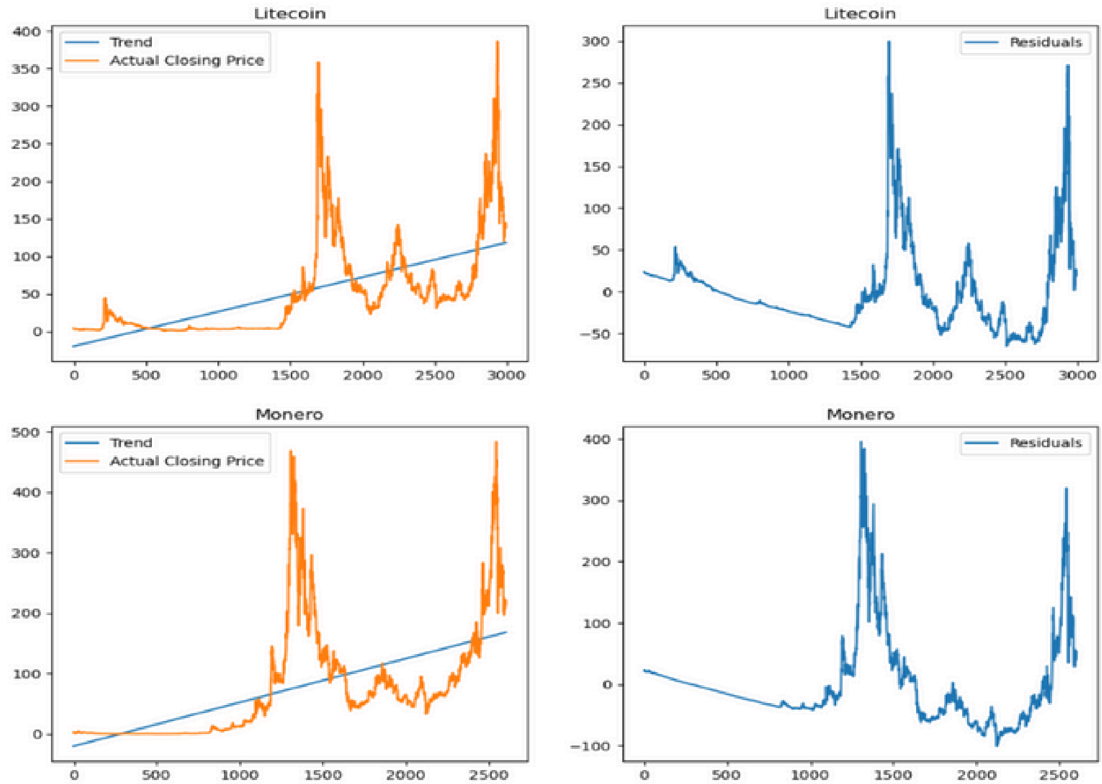


Figure 8 Trend Analysis of Litecoin and Monero

***Figure 8* depicts the following :-**

- **Litecoin**: The price of Litecoin has been on a general upward trend over the past few years, with some periods of volatility. The residuals show that the actual closing price of Litecoin has often been significantly higher or lower than the predicted closing price based on the trend line. This suggests that there is a lot of uncertainty in the price of Litecoin and that it can be difficult to predict the future price of Litecoin.

- **Monero**: The price of Monero has also been on a general upward trend over the past few years, but with more volatility than Litecoin. The residuals are larger for Monero, suggesting that the actual closing price of Monero has been further away from the predicted closing price based on the trend lines.This suggests that there is even more uncertainty in the price of Monero than in the price of Litecoin.

- The price of Litecoin has been more stable than the price of Monero. This could be due to a number of factors, such as the fact that Litecoin is a more established coin and that there is less speculation in the Litecoin market.

- The price of Monero has been more volatile than the price of Litecoin. This could be due to a number of factors, such as the fact that Monero is a newer coin and that there is more speculation in the Monero market.

Ultimately, the decision of whether to invest in Litecoin or Monero is a personal one. Investors should carefully consider their own risk tolerance and investment goals before making a decision.

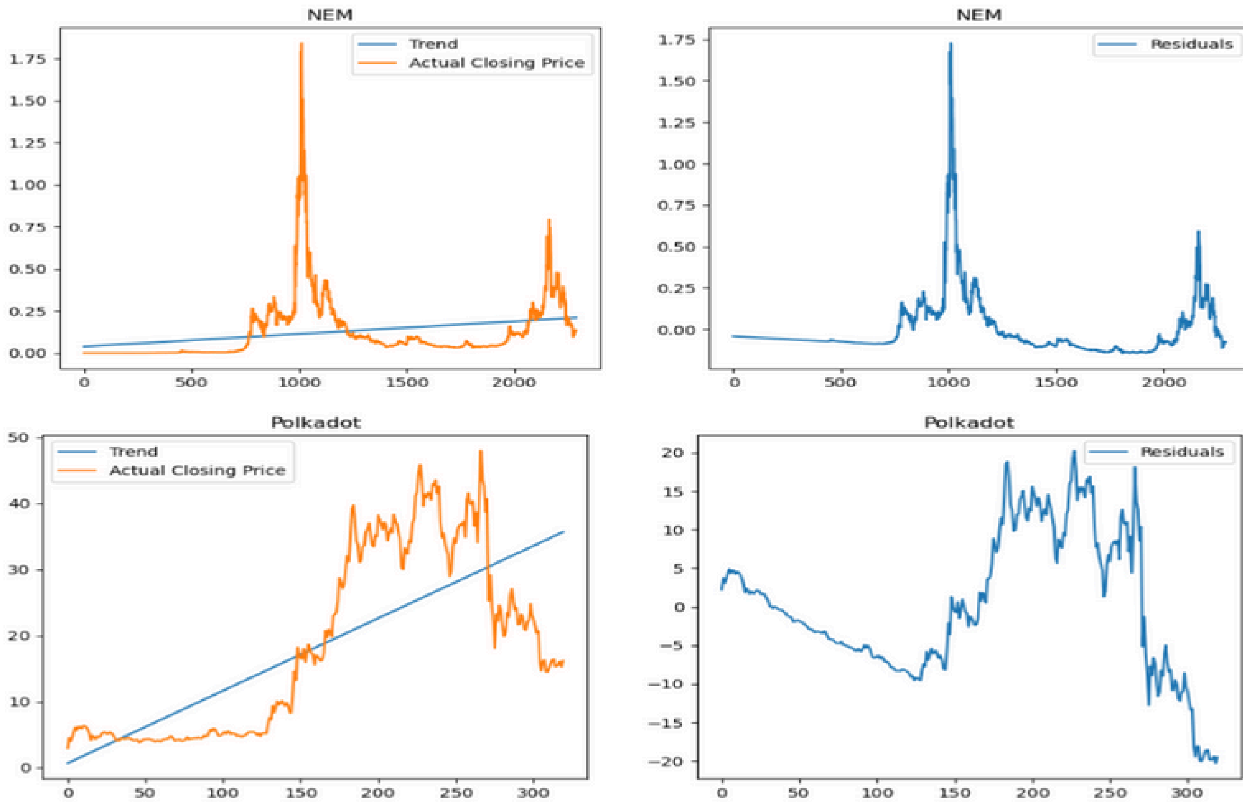


Figure 9 Trend Analysis of NEM and Ripple

FIGURE 9 DEPICTS THE FOLLOWING: -

- **NEM**: The price of NEM has been on a general upward trend over the past few years, with some periods of volatility. The residuals show that the actual closing price of NEM has often been significantly higher or lower than the predicted closing price based on the trend line. This suggests that there is a lot of uncertainty in the price of NEM and that it can be difficult to predict the future price of NEM.

- **Ripple**: The price of Ripple has also been on a general upward trend over the past few years, but with more volatility than NEM. The residuals are larger for Ripple, suggesting that the actual closing price of Ripple has been further away from the predicted closing price based on the trend line. This suggests that there is even more uncertainty in the price of Ripple than in the price of NEM.

- The price of NEM has been more stable than the price of Ripple. This could be due to a number of factors, such as the fact that NEMis a more established coin and that there is less speculation in the NEM market.
- The price of Ripple has been more volatile than the price of NEM. This could be due to a number of factors, such as the fact that Ripple is a newer coin and that there is more speculation in the Ripple market.

Ultimately, the decision of whether to invest in NEM or Ripple is a personal one. Investors should carefully consider their own risk tolerance and investment goals before making a decision.

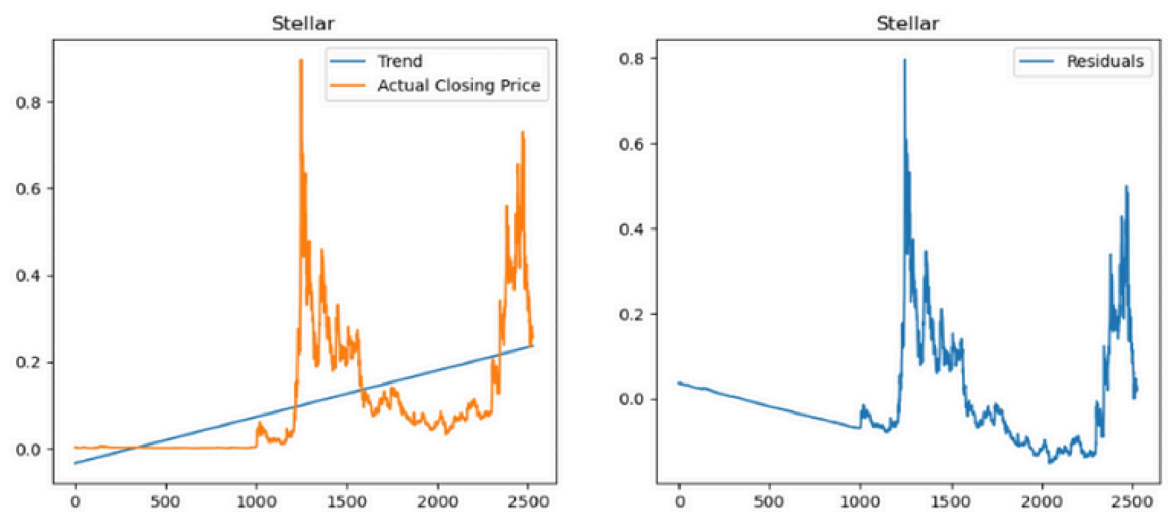


Figure 10 Trend Analysis of Stellar

Figure 10 shows that the price of Stellar has also been on a general upward trend over the past few years. The residuals are smaller for Stellar, suggesting that the actual closing price of Stellar has been closer to the predicted closing price based on the trend line. This suggests that there is slightly less uncertainty in the price of Stellar. This could be due to a few factors, such as the fact that Stellar is a more established coin and that there is less speculation in the Stellar market.

4.3 AUGMENTED DICKEY FULLER TEST

Table 3 Results of Augmented Dickey Fuller Test on Returns of Bitcoin and Other Cryptocurrencies

Crypto	N	Adf Statistics	P-value	CriticalValues		
				1%	5%	10%
Bitcoin	**2991 coins**	-8.91	0.01	-3.43	-2.86	-2.57
BitShares	**1374 coins**	-6.64	0.04	-3.43	-2.86	-2.57
ByteCoin	**1385 coins**	-7.71	0.03	-3.43	-2.86	-2.57
Dash	**845coins**	-9.20	0.05	-3.43	-2.86	-2.57
Digibyte	**935coins**	-35.26	0.00	-3.43	-2.86	-2.57
Dogecoin	**2760 coins**	-8.22	0.04	-3.43	-2.86	-2.57
Ethereum	**2160 coins**	-9.81	0.08	-3.43	-2.86	-2.57
Litecoin	**2991 coins**	-10.41	0.08	-3.43	-2.86	-2.57
Monero	**2602 coins**	-10.59	0.02	-3.43	-2.86	-2.57
NEM	**2288 coins**	-7.83	0.30	-3.43	-2.86	-2.57
Ripple	**320coins**	-5.56	0.05	-3.43	-2.86	-2.57
Stellar	**2527 coins**	-8.59	0.30	-3.43	-2.86	-2.57

The series of prices of Bitcoin and other 11 crypocurrencies are non-stationary time series as confirmed by the results of augmented Dickey-Fuller test. So, these non-stationary time series are transformed to stationary time series by estimating differentiated log of prices. Again the augmented Dickey-Fuller test is applied on differentiated log of price/d(log(Price)) to test the unit root. Table 3 indicates the results of augmented Dickey-Fuller test for differentiated log of returns of Bitcoin and other 11 cryptocurrencies.

The test results are interpreted as follows:

- ADF Statistic: This is the test statistic of the ADF test. The more negative this value, the stronger the evidence against the presence of a unit root and in favor of stationarity.
- P-value: This is the probability of observing the ADF statistic if the null hypothesis of non-stationarity is true . A small p- value (typically less than 0.05) indicates strong evidence against the null hypothesis and suggests that the data is stationary.
- Critical Values: These are the critical values at various significance levels (1%, 5%, and 10%). The ADF statistic should be more negative than these critical values for the data to be considered stationary.

Based on the test results, all the p-values are significantly small (close to 0), and the ADF statistics are more negative than the critical values at all significant levels. Therefore, we can conclude that all the time series data for cryptocurrencies are stationary.

With stationary data, the computed cross-correlation can provide meaningful insights into the relationships between different cryptocurrencies and their lagged effects on each other. The correlation matrix can be used to identify potential lead-lag relationships between cryptocurrencies and understand their co-movements in the market.

4.4 CORRELATION ANALYSIS

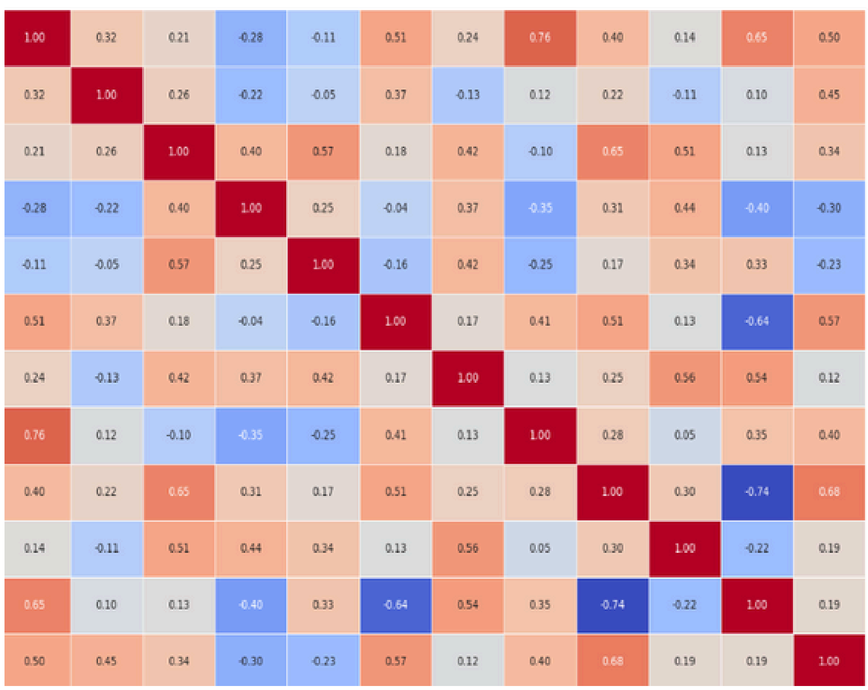


Figure 11 Correlation

Figure 11 appears to be a correlation matrix representing the correlation coefficients between various cryptocurrencies. Each cell in the matrix contains a correlation value along with a lag value in parentheses. The correlation coefficient indicates the strength and direction of the linear relationship between two cryptocurrencies.

Key observations from the correlation matrix:

The image shows a Kendall correlation matrix of 12 cryptocurrencies: Bitcoin, Bitshares, ByteCoin, Dash, Digibyte, Dogecoin, Ethereum, Litecoin, Monero, Nem, Ripple and Stellar. The Kendall correlation coefficient is a non - parametric distributions. The Kendall correlation matrix shows that all 12 cryptocurrencies are positively correlated with each other, but the degree of correlation varies. The strongest correlation is between Bitcoin and Ethereum, with a Kendall correlation coefficient of 0.76. This means that Bitcoin and Ethereum tend to move in the same direction, with Bitcoin having the greatest influence on Ethereum's movements.

- Bitshares and ByteCoin have a Kendall correlation coefficient of 0.65.
- Dash and Digibyte have a Kendall correlation coefficient of 0.57.
- Dogecoin and Monero have a Kendall correlation coefficient of 0.51.
- Litecoin and Ripple have a Kendall correlation coefficient of 0.54.
- NEM and Stellar have a Kendall correlation coefficient of 0.45.

4.4 Co-Jumping Analysis

To this purpose, we apply a logistic regression with the dependent variable being a dichotomous variable Y taking the value of 1 when there is a volatility jump and 0 otherwise.

log P(Y=1|X) = β0 + β iXi,t + εt …..Eq(1)
1−P(Y=1|X)

where, β0 and βi is the constant; Xi,t is a set of 11 dichotomous variables, where i = 1, 2. . ...11; each dichotomous variable indicates the presence of jump, as shown for the dependent variable, in each of the other remaining 11 return series. The distribution of the error term (εt) follows the logistic regression. We extend the analyses to assess whether the jumps detected in the return series of leading cryptocurrencies potentially concur with the occurrence of jumps in trading volume.This might give insight into whether the returns of cryptocurrencies and their corresponding trading volumes jump together. We therefore rerun the jump test of Laurent et al. (2016) on trading volume in each of the 12 cryptocurrencies shown in Table 4.

Trading volume data are collected from https://coinmarketcap.com. Figure 12 shows the plots of jumps in the trading volume, where there is evidence of co-jumping activity among the trading volume of cryptocurrencies. Importantly, we run the logistic regression and report the results for co-jumps in Table 5. The results are significant in all cases, except for Bitcoin, Dash and Stellar. They generally reveal that the occurrence of a jump in the trading volume of one cryptocurrency increases the likelihood of a jump in the volatility of the same cryptocurrency.

Table 4 Market capitalization of the 12 cryptocurrencies under study.

Ranking	Name	MarketCap
1st	Bitcoin	71,534,370,136
2nd	Ethereum	15,112,839,523
3rd	Stellar	13,341,320,084
4th	Litecoin	3,760,335,428
8th	Stellar	2,124,180,913
13th	Monero	932,105,239
15th	Dash	808,442,715
20th	Nem	456,094,403
27th	Dogecoin	246,750,908
37th	DigiByte	169,901,990
43rd	Bytecoin	150,407,572
46th	BitShares	139,972,815

Note: *The ranking is based on the rank of the 12 cryptocurrencies under study within the first largest 50 cryptocurrencies as in https://coinmarketcap.com.*

Figure 12. shows the plots of jumps in the trading volume, where there is evidence of co-jumping activity among the trading volume of cryptocurrencies. Importantly, we run the logistic regression and report the results for co-jumps in Table 5. The results are significant in all cases, except for Bitcoin, Dash and Ripple. They generally reveal that the occurrence of a jump in the trading volume of one cryptocurrency s increases the likelihood of a jump in the volatility of the same cryptocurrency. This finding nicely complements prior studies on the volatility-volume relationship in the cryptocurrency market (e.g., Bouri, Lauet al., 2019).For a robustness check, we apply the method of (Ma et al. (2019), and unreported result show quite similarvevidence of co-jumping between each cryptocurrency and its trading volume. Co-jumping is more frequent in Ethereum, Monero, Digibyte and Dogecoin, whereas it is almost nonexistent in Bitcoin and Dash (see Table 5). These results for cryptocurrencies can be compared to those in earlier studies on stock market indices (e.g., Jawadi, Louhichi, Cheffou, & Randrianarivony, 2016), confirming the importance of jumps in trading volume for the formation of jumps in cryptocurrencies. Such evidence adds to prior studies (e.g., Bouri, Lau et al., 2019) highlighting the role of jumps as an element characterizing the volatility of cryptocurrencies.

Table 5 Results of co-jumps between cryptocurrencies and their trading volumes

	BITCOIN	BITSHARES	BYTECOIN	DASH	DIGIBYTE	DOGECOIN	ETHEREUM	LITECOIN	MONERO	NEM	RIPPLE	STELLAR
BITCOIN	1.6689											
BITSHARES		4.2176***										
BYTECOIN			1.9951***									
DASH				1.7055***								
DIGIBYTE					4.8473***							
DOGECOIN						3.6415***						
ETHEREUM							3.0800***					
LITECOIN								3.5937***				
MONERO									4.2556***			
NEM										3.3361***		
RIPPLE											1.4008	
STELLAR											3.5322***	

Notes: *Estimated coefficient results are based on the logistic regression in Eq. (1), where the jumps in a cryptocurrency are regressed on jumps in its trading volume. ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively.*

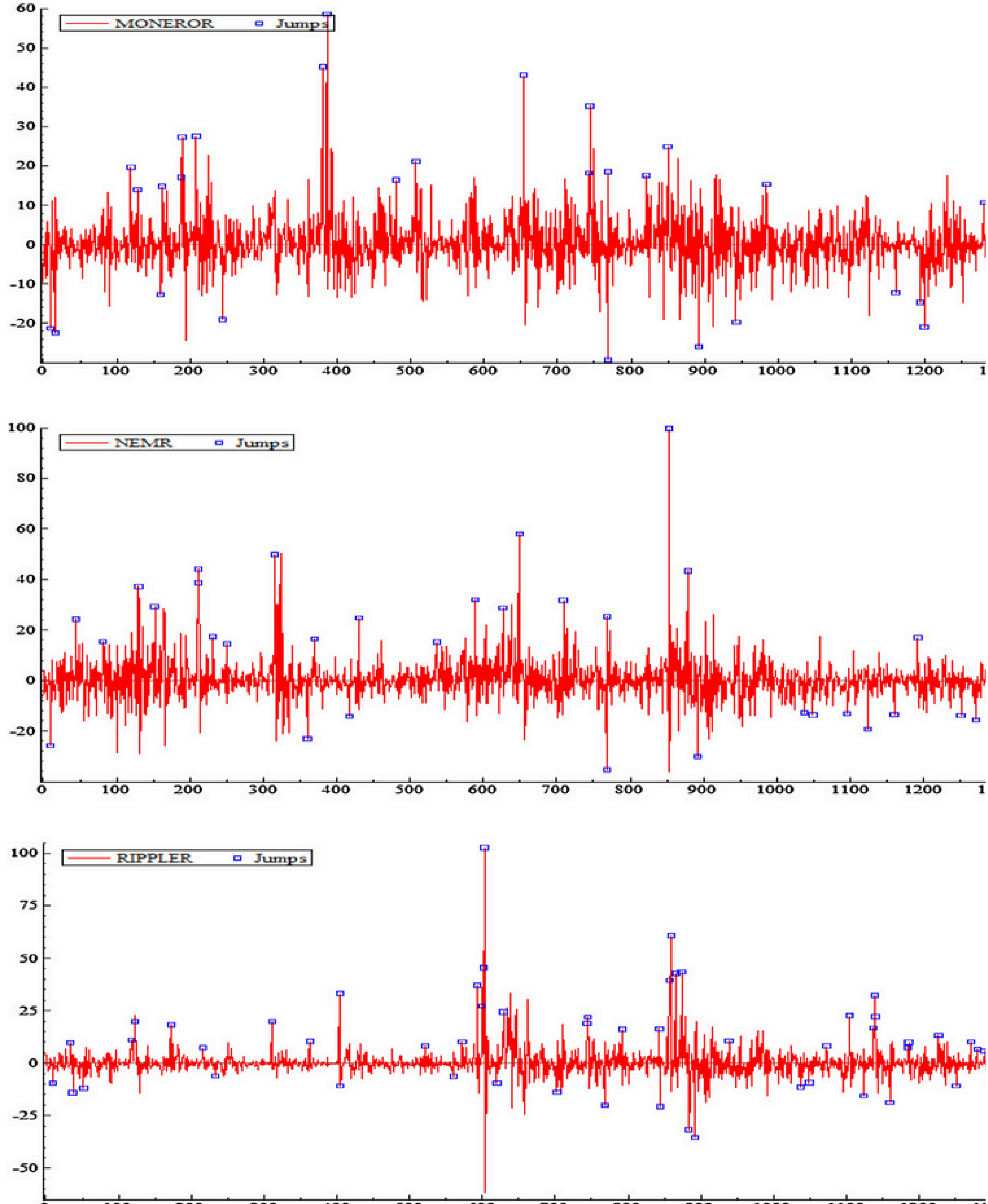


Figure . 12 PLOTS OF JUMPS ON THE TRADING VOLUME OF CRYPTOCURRENCIES UNDER STUDY.

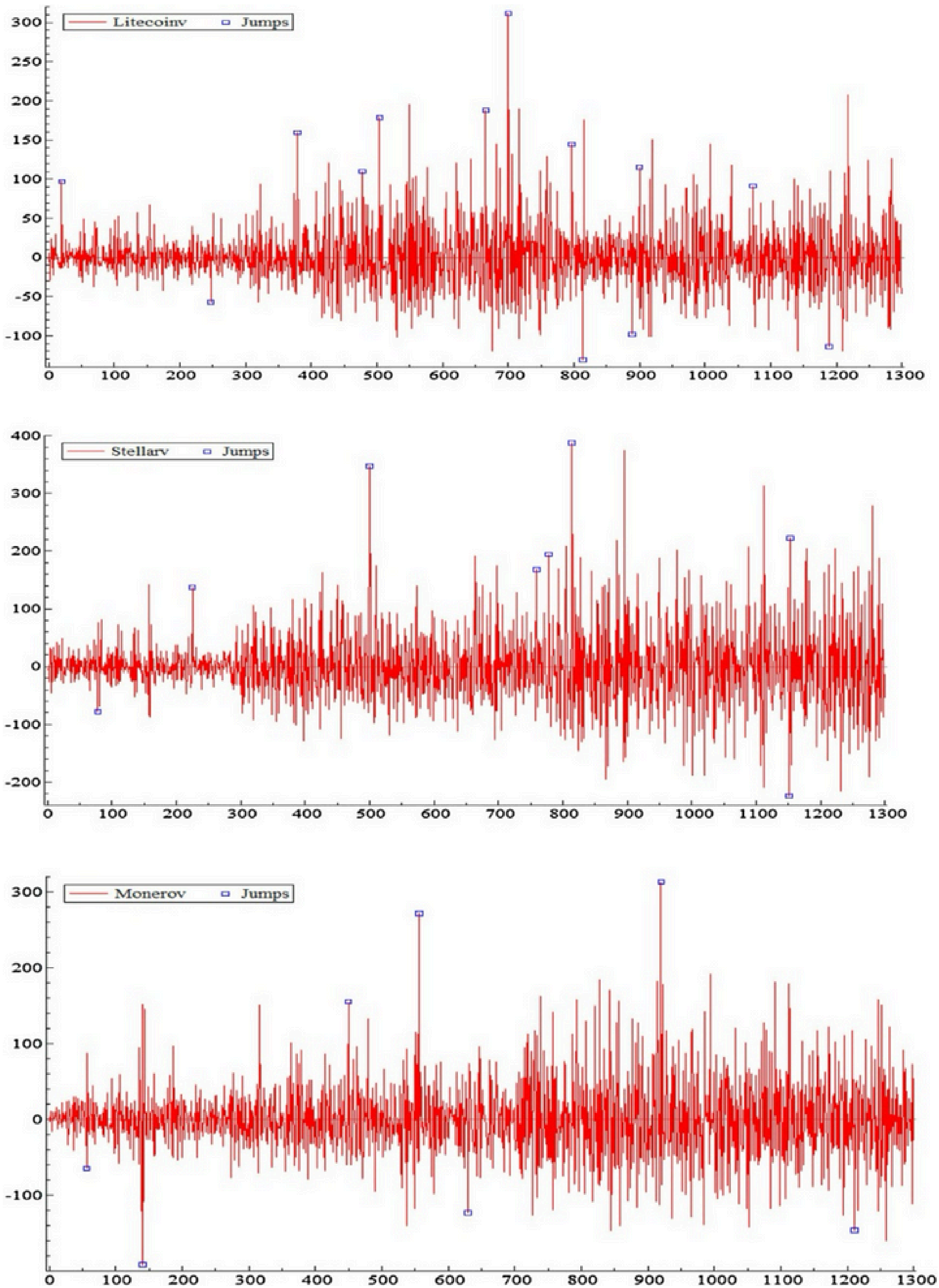
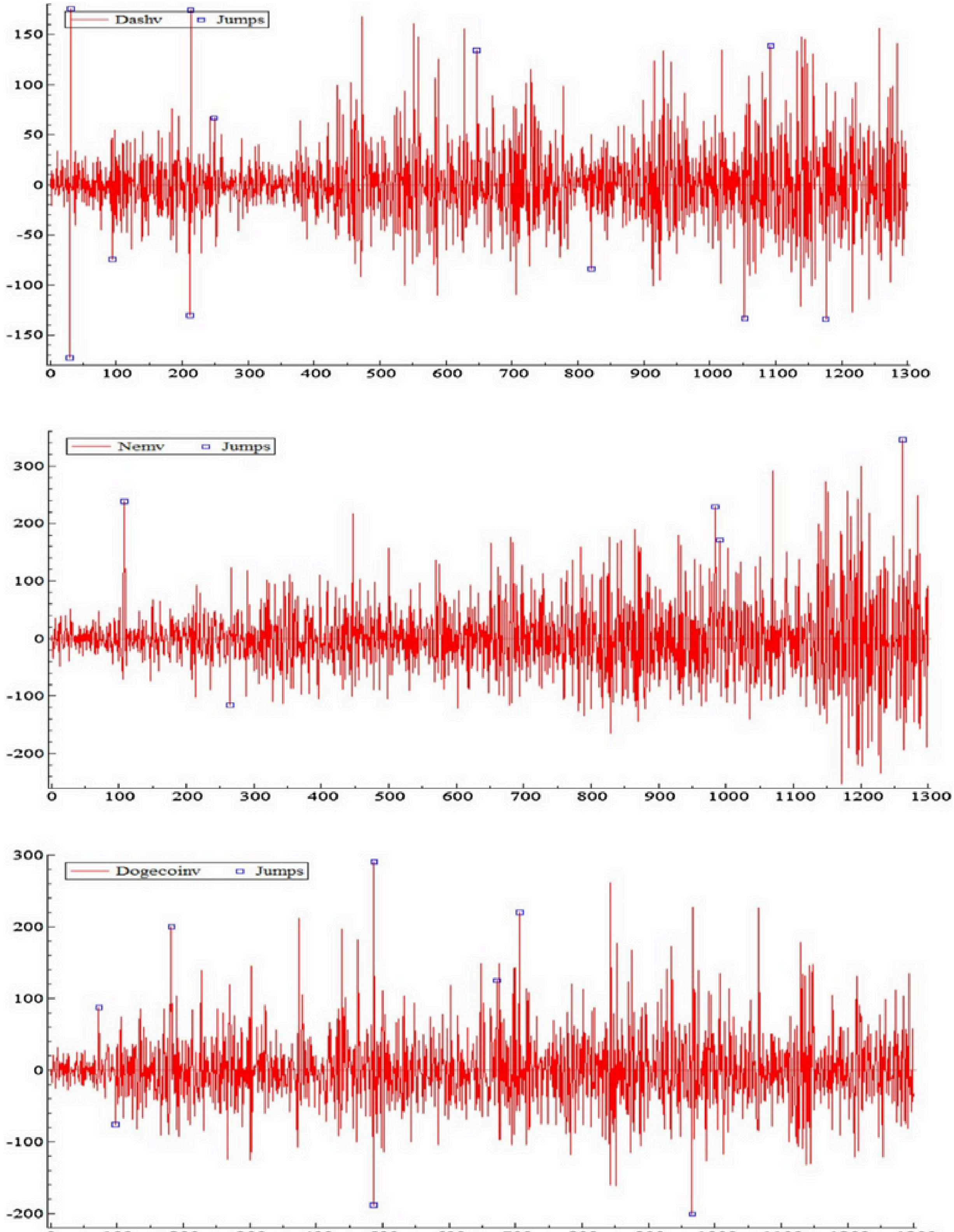


Figure 12 (Continued)



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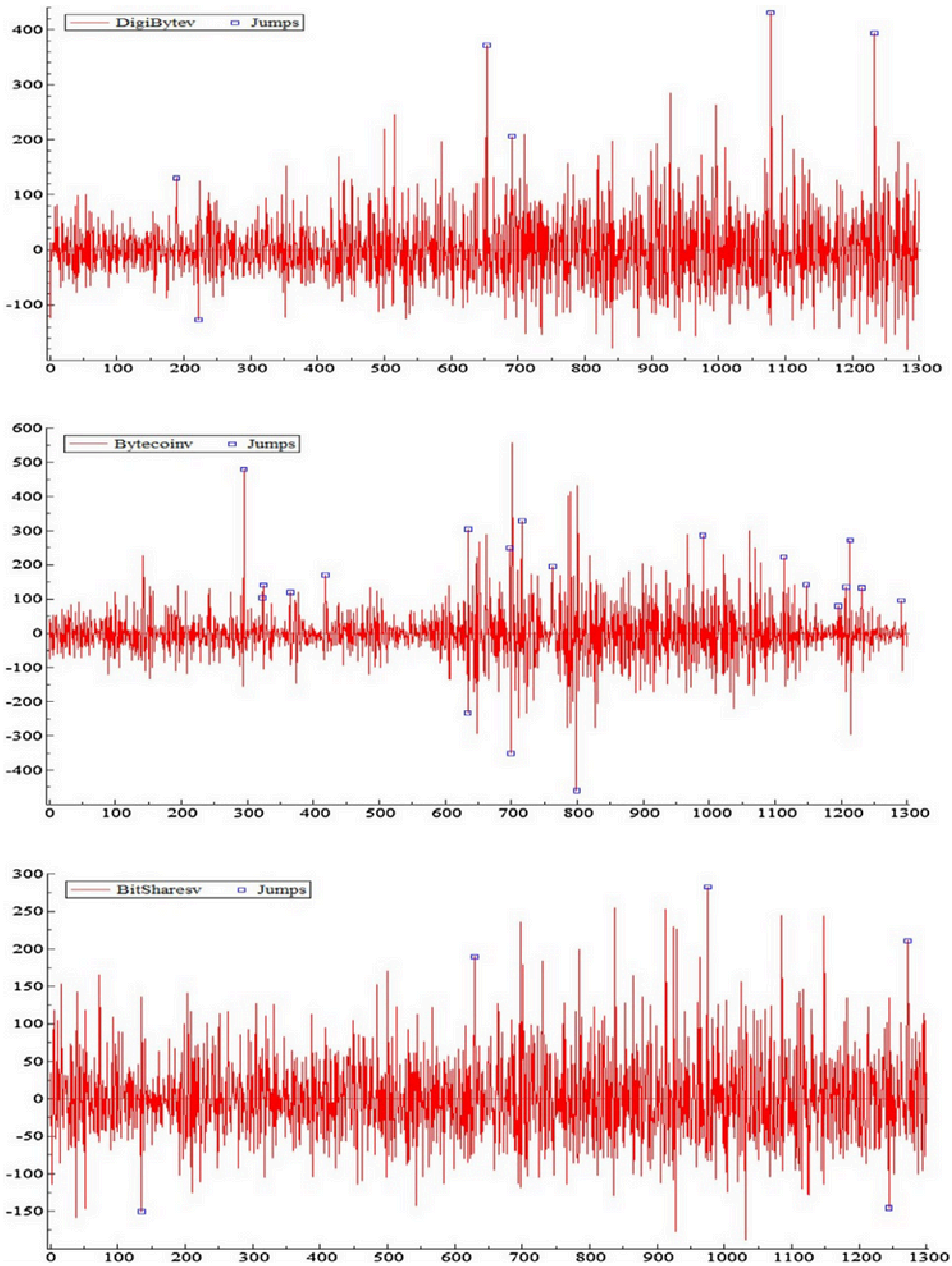

Figure 12 (Continued)

CONCLUSION

The comprehensive analysis conducted in this study sheds light on the intricate relationship between the prices and trading volumes of twelve major cryptocurrencies, namely Bitcoin, Bitshares, Bytecoin, Dash, Digibyte, Dogecoin, Ethereum, Litecoin, Monero, Nem, Ripple, and Stellar, over the period from August 8, 2015, to February 28, 2019. The research aims to provide valuable insights for investors navigating the dynamic landscape of the digital asset market.

- **Price Trends and Volatility**: The examination of price trends and residuals highlights significant variations in the behavior of different cryptocurrencies. While some coins like Bitcoin and Ethereum have displayed an overall upward trend, others like Bitshares and Digibyte have experienced periods of notable volatility. The presence of large residuals in the price graphs underscores the considerable volatility in the cryptocurrency market, suggesting rapid and unpredictable price changes.
- **Risk and Uncertainty:** The residuals analysis further emphasizes the substantial uncertainty inherent in the prices of most cryptocurrencies. This volatility can pose challenges for investors seeking to predict future price movements. It is crucial for investors to carefully consider their risk tolerance and investment goals before making decisions in this market.
- **Correlation Analysis:** The Kendall correlation coefficient reveals positive correlations among all twelve cryptocurrencies, but with varying degrees of strength. Bitcoin and Ethereum exhibit the strongest correlation, indicating that movements in Bitcoin's price tend to influence Ethereum's price significantly. Understanding these correlations can be instrumental for diversification strategies and managing portfolio risk.
- **Jumps in Trading Volume:** The study identifies evidence of co-jumping activity between trading volumes and returns of cryptocurrencies. This finding implies that spikes in trading volume can be associated with increased volatility, particularly in cryptocurrencies like Ethereum, Monero, Digibyte, and Dogecoin. Recognizing this relationship can provide investors with valuable insights for risk management.
- **Implications for Investors:** This research paper offers crucial insights for investors navigating the cryptocurrency market. It highlights the importance of understanding the unique characteristics and behaviors of individual cryptocurrencies. Investors should carefully assess their risk tolerance and investment objectives, taking into account the considerable volatility and uncertainty inherent in this asset class.

In conclusion, this study provides a comprehensive analysis of the relationship between prices and trading volumes of twelve major cryptocurrencies. The findings offer valuable insights for investors seeking to navigate the dynamic and rapidly evolving digital asset market. It is imperative for investors to approach the cryptocurrency market with caution, conduct thorough research, and implement sound risk management strategies. Ultimately, a well-informed and disciplined approach can help investors navigate the challenges and opportunities presented by this emerging asset class.

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