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Deciphering crypto interconnections using a multi-analytical approach

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Abstract

Blockchain technology has primarily underpinned cryptocurrencies that are used either as speculative investment vehicles or for transaction facilitation. There has been a keen interest in understanding the dynamics of interconnectedness and conditional correlations among cryptocurrency prices. While most studies have primarily focused on Bitcoin or the top few cryptocurrencies, this study adopts a comprehensive, multi-analytical approach, incorporating other smaller cryptos that appeal to small and medium investors. Pearson correlational analysis explores the interconnectedness among cryptos and investigates co-movement in crypto prices through their returns, volatility, volume traded, and the CCi30 index returns. Principal Component Analysis (PCA) is used to identify highly correlated clusters, summarizing cross-sectional information based on covariance within the predictors. The predictive regression model of Granger Causality test is applied as a vector autoregression (VAR) forecasting method to examine Granger causality of price movements within the clusters identified. The findings from the correlational matrices of returns and volatilities show no difference in behaviours between larger and smaller cap ones, whereas correlations in trading volumes indicate high correlations in large market-caps. Smaller market-cap cryptos exhibit stronger correlations in volatilities than the larger market cap ones. Two highly correlated clusters emerged from the PCA analysis, with Binance Coin (BNB) and Ripple (XRP) exhibiting greater influence than Bitcoin (BTC) and Tether (USDT) *in the second cluster*. The findings will enable cryptocurrency users and investors to grasp price mechanisms better, offering valuable insights to improve their decision-making abilities.

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1. Introduction

Cryptocurrencies have been one of the most highly discussed areas in the global financial arena at present. Being the first of its kind, Bitcoin launched in January 2009 and has been on the market for on the market for fourteen years. When Satoshi Nakamoto created Bitcoin, his novel idea was to shift financial power from the hands of financial institutions to the people, providing an alternative to traditional banking. Cryptocurrencies are a part of the cryptographic assets, digital or virtual currencies that use cryptography for security and are difficult to duplicate. They operate on decentralized networks leveraging blockchain technology, ensuring transparency and immutability in conducting financial transactions. They have been popular as an exchange tool and investment vehicle (Baur, Hong, & Lee, 2018).

One of the major areas of concern has been the volatility in cryptocurrency prices[1]. The last decade has primarily witnessed upheavals in cryptocurrency prices. In 2013, Forbes named Bitcoin the year's best investment, and in the very next year, 2014, Bloomberg called it the year's worst investment. Figure 1 shows the price charts of three cryptocurrencies by market capitalization as of 20 September 2023. The price charts have displayed high price volatility since their inception. Markets experienced a meteoric rise in Bitcoin prices in November 2021, where its price rose to about $63,300, around more than 1200 percent in 9 months. A year later, it dropped drastically in November 2022 to around $16,700. This gives opportunities for exponential growth in wealth, simultaneously posing a very high risk for investors. As the crypto market is relatively new with complex financial instruments, factors affecting their prices are unclear, with investors having limited knowledge and trust as compared to other financial assets (Steinmetz, Von Meduna, Ante, & Fiedler, 2021).

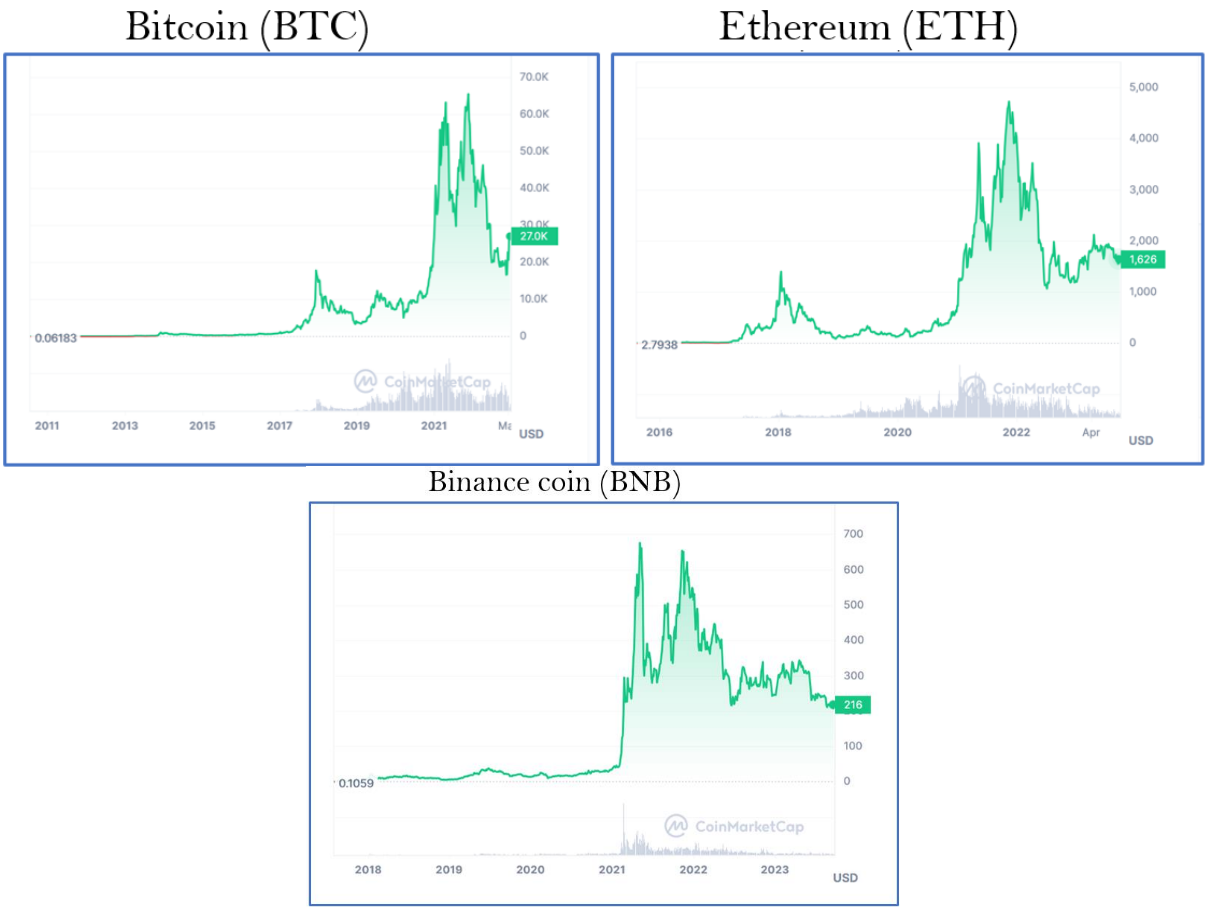

Figure 1. Prices charts of top 3 cryptocurrencies by market capitalization since their inception.

Source: CoinMarketCap.com, data as of 20 September 2023 since their respective inceptions.

Studies in cryptocurrencies have grown since 2017 (Jalal, Alon, & Paltrinieri, 2021), due to increased investment and markets exploding with different types of altcoins. Cryptocurrency research addressing business management and finance areas has been identified through bibliographic research by Corbet, Lucey, Urquhart, and Yarovaya (2019) and Manimuthu, Rejikumar, and Marwaha (2019), where they classified the studies as follow: (1) concerning bubbles in crypto prices; (2) efficiency of this asset; (3) diversification; (4) regulations and cybercrime issues. Coinciding with these areas of study, Jalal et al. (2021) classified them into four major areas that include (1) exploring factors that determine the returns of cryptocurrencies, (2) the efficiency of cryptocurrencies, (3) portfolio diversification and sheep flock or herding behaviour of investors, and (4) the regulation and governance aspects of cryptocurrencies.

This study investigates cryptocurrency price fluctuations and returns. It intends to delve deeper into this economic aspect concerning the pricing of cryptocurrencies that has majorly revolved around analysing the volatility of the crypto returns, among which the Bitcoin return and price volatility are the most studied (Aalborg, Molnár, & de Vries, 2019; Cheah & Fry, 2015; Estrada, 2017; Gbadebo, Adekunle, Adedokun, Lukman, & Akande, 2021). Some of the initial studies have focused on the price returns of Bitcoin and compared it to stock indices (Ciaian, Rajcaniova, & Kancs, 2016), while others have investigated the effect of oil prices on cryptocurrencies (Heikal, Saragih, Ilham, Khaddafi, & Rusydi, 2022; Yin, Nie, & Han, 2021). Some studies investigated the macroeconomic factors determining crypto price changes (Kyriazis, 2020; Sharma, Shahbaz,

[1] To read more about Bitcoin's price volatility visit https://investingnews.com/daily/tech-investing/blockchain-investing/bitcoin-price-history/.

Singh, Chopra, & Cifuentes-Faura, 2023; Syed, Ahmed, Kamal, Ullah, & Ramos-Requena, 2022; Teker, Teker, & Ozyesil, 2019). Many of these studies have focused on time periods before 2019, some have studied prices during the COVID pandemic (Assaf, Bhandari, Charif, & Demir, 2022; Mnif, Jarboui, & Mouakhar, 2020; Vidal-Tomás, 2021) and a few others have done a comparative study of prices during pre- and post-pandemic periods (El Montasser, Charfeddine, & Benhamed, 2022; Huang, Duan, & Mishra, 2021). The pandemic has fundamentally changed how we live, work, and view risk (Fullan, 2020; Hitt, Arregle, & Holmes Jr, 2021) along with the importance of technological advances (George, Lakhani, & Puranam, 2020). Hence, this study aims to capture the effects of these macro and behavioural changes on the investment of cryptocurrencies after the pandemic subsided, and the author sees the need for more studies exploring this area in recent times.

The literature related to pricing concerns can be broadly classified into two types: one that studies the correlation or spillover from other investment markets like equity indices, oil prices, commodity markets, and currencies, to name a few, that could help decipher the price changes of cryptocurrencies. The second category investigates the co-movement within the cryptocurrency types, considering that the nature of cryptocurrency differs from other markets, as Baur et al. (2018) emphasized that cryptocurrencies' risk and returns are unique, diverse, and uncorrelated with other assets. Existing studies have shown mixed results concerning the driving forces affecting cryptocurrencies' market value and volatility. This study addresses the second category of the literature, exploring the co-movements within the cryptos during the period after the pandemic subsided. Cryptocurrencies have experienced significant price volatility and herding biases in the past. Herding behaviour refers to the inclination of investors to base their decisions on the actions of similar investors rather than their own convictions (Bikhchandani & Sharma, 2000).

This behaviour can create speculative bubbles or trigger market crashes due to sustained deviations from the underlying fundamental asset values. Policy-makers are concerned as this could destabilize the markets and reflect the vulnerability of crypto markets. This study investigates the correlation in returns between the top twenty cryptocurrencies to explore the influence of one over the other and their spillover effects. It emerges from the premise that the cryptocurrency market is inefficient, and investors make decisions by assessing the movements in other cryptocurrencies (Corbet, Meegan, Larkin, Lucey, & Yarovaya, 2018; Fry & Cheah, 2016). Most existing studies focus on Bitcoin's influence on others or have studied the correlations among the top two or three major cryptocurrencies, mainly before 2019. Research concerning other cryptocurrencies is scarce as the market expands with diversity in newer digital assets. Hence, the author incorporates the top twenty currencies to explore their correlations, such as spillover effects and volatility similarities, to determine common factors driving prices in more recent periods.

The rest of this study is organized as follows: Section 2 describes the rise of cryptocurrencies and reviews the literature on the price fluctuations in the cryptocurrency markets. Section 3 discusses the research objectives and hypotheses formulated in the study. Section 4 describes the data and empirical methods applied using the multi-analytical approach of Pearson's correlation analysis for returns, volatilities, volume, and crypto index returns. PCA is used to identify clusters of correlated cryptos. The Granger causality test is applied to identify the existence of any predictor cryptos that cause price movements in other cryptos within the clusters. Section 5 highlights the empirical results and interpretations, and Section 6 summarizes the concluding points with implications for investor decisions and highlights the scope for future research.

2. Literature Review

2.1. Rise of the Cryptocurrencies

Since the emergence of the first cryptocurrency, Bitcoin, in January 2009, many new types of cryptocurrencies have entered the market, including stablecoins, non-fungible tokens, and dog memes, to name a few. Forbes reported the existence of approximately 22,932 cryptocurrencies, with a total market capitalization of $1.1 trillion as of March 2023 (Hicks, 2023). Many of them remain only for a short time and have become inactive. As of September 2023, there were 9,127 active cryptocurrencies registered on coinmarketcap.com[2], which indicates a significant increase in the last fourteen years. Only in April 2011, Namecoin, Litecoin, and Swiftcoin, to name a few, made their debuts after Bitcoin. In 2015, Ethereum entered the market and quickly rose to become the second-largest market capitalization. No central authority backs these cryptocurrencies, which allow for the purchase and sale of goods and services without the involvement of banks, a crucial component of traditional financial systems (Faturahman, Agarwal, & Lukita, 2021). The cryptocurrencies other than Bitcoin are known as 'Altcoins', which are of two types: one that uses Bitcoin's original open-source protocol with specific changes, such as Litecoin and Namecoin, and the others that have their own protocol and distributed ledgers, like Ethereum and Ripple. Table 1 shows the top 20 cryptocurrencies with their prices, market capitalization and price changes as of September 2023. These together form 90% of the total market cap and are used in the empirical analysis of the study. Bitcoin alone forms 54% of the top 20 and the second largest

[2] CoinMarketCap is the world's most-referenced price-tracking website for crypto assets in the rapidly growing cryptocurrency space. Its mission is to make crypto discoverable and efficient globally by empowering retail users with unbiased, high quality and accurate information for drawing their own informed conclusions. Founded in May 2013 CoinMarketCap has quickly grown to become the most trusted source by users, institutions, and media for comparing thousands of crypto assets and is commonly cited by CNBC, Bloomberg, and other major news outlets.

Ethereum, with a 20% share, showing that the top two contribute to almost 75% of the market cap in this group, as shown in Figure 2.

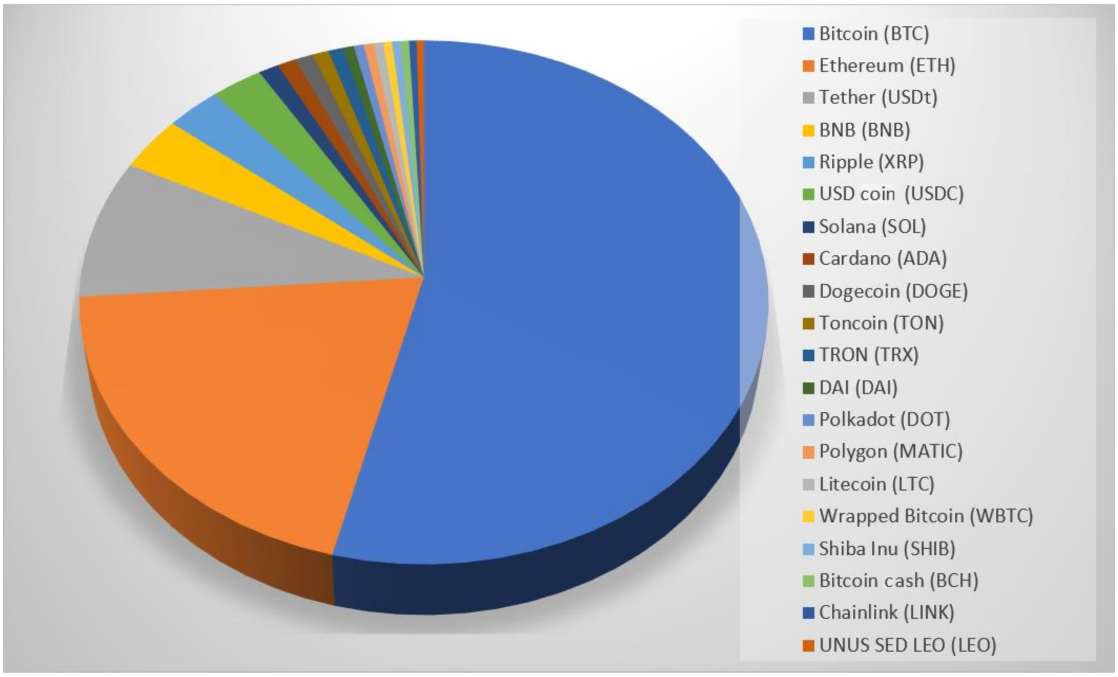

Figure 2. Market share of the top twenty cryptocurrencies.

Within the last decade, businesses and individuals have increasingly used cryptocurrencies for transactional purposes, thereby lowering transaction costs (Rejeb, Rejeb, & Keogh, 2021). Their use as an investment vehicle has been supported by some studies, where their correlation with traditional investments is very low and could improve portfolio performances (Andrianto & Diputra, 2017; Juškaitė & Gudelytė-Žilinskienė, 2022; Petukhina, Trimborn, Härdle, & Elendner, 2021). Additionally, they serve as a medium of exchange, frequently utilized for the controversial purchase of illicit items such as drugs. Proponents argue against control by banks and stock markets. In contrast, critics contend the lack of regulation provides an opportunity for criminals, terrorists, and rogue states (Dion-Schwarz, Manheim, & Johnston, 2019; Leuprecht, Jenkins, & Hamilton, 2022), apart from being subject to high price volatility. Other critics suggest that these assets stoke inequality, suffer from drastic market volatility, and consume vast amounts of electricity in production (Mohsin, 2021).

Table 1. Top 20 cryptocurrencies by market capitalization.

SN	Name	Market cap USD	Unit price USD	7 days %change
1	Bitcoin (BTC)	519,238,185,545	26641.00	0.05%
2	Ethereum (ETH)	191,771,109,082	1594.02	-2.16%
3	Tether (USDt)	83,180,311,888	0.99	-0.01%
4	Binance coin (BNB)	32,494,004,259	211.00	-0.95%
5	Ripple (XRP)	27,141,428,461	0.51	2.27%
6	USD coin (USDC)	25,766,173,828	0.99	-0.03%
7	Solana (SOL)	10,019,324,413	24.39	25.00%
8	Cardano (ADA)	9,389,750,595	0.27	9.14%
9	Dogecoin (DOGE)	8,969,291,768	0.06	3.90%
10	Toncoin (TON)	7,922,579,815	2.31	18.27%
11	TRON (TRX)	7,453,166,494	0.08	-0.12%
12	DAI (DAI)	5,345,053,843	0.99	-0.03%
13	Polkadot (DOT)	4,933,261,536	4.03	-1.44%
14	Polygon (MATIC)	4,868,558,533	0.52	-0.08%
15	Litecoin (LTC)	4,794,378,171	65.07	2.76%
16	Wrapped Bitcoin (WBTC)	4,341,028,022	26636.73	0.12%
17	Shiba Inu (SHIB)	4,282,739,463	0.0000073	-1.62%
18	Bitcoin cash (BCH)	4,081,821,246	209.00	-3.65%
19	Chainlink (LINK)	3,753,797,672	6.74	9.84%
20	UNUS SED LEO (LEO)	3,589,277,228	3.86	4.31%

2.2. Price Fluctuations and Volatility

Price fluctuations in cryptocurrencies have been the most studied area among others found in the literature related to cryptocurrencies. Among these, price fluctuations and volatility of Bitcoin have been more prominent. Cryptocurrencies like Bitcoin are not backed by any physical asset, and their value follows a fiat model whose prices are determined by demand and supply. The difference between them is that governments back fiat currencies, whereas cryptos are not, and as of date, they also lack mass acceptance not only as a substitute but also as a complement to fiat currencies (Hairudin, Sifat, Mohamad, & Yusof, 2022). The crypto-market has experienced high volatility since the last decade, and literature has investigated the reasons for this volatility. Among them, some have identified that they have no fundamental value and that their price fluctuates based on their popularity rather than demand and supply (Goczek & Skliarov, 2019). Others concluded that price bubbles are due to technological advances such as the innovation of blockchain technology (Meider, 2023). Some have suggested that cryptocurrencies are speculative investments rather than real currencies (Yermack, 2015). For Bitcoin, Moosa (2020) indicated that the limitation in supply could cause price spikes, and Bouri, Gupta, and Roubaud (2019) revealed that a lack of financial literacy among inexperienced investors would make them imitate others, causing price bubbles.

The hype influences such investors and does not show rational behaviors, which inflates the prices of cryptocurrencies in the short term (Bouri et al., 2019; Jalal et al., 2021). Forecasting volatility in crypto prices has also been one of the major areas of studies where traditional time series forecasting techniques were applied to study Bitcoin price fluctuations by Bergsli, Lind, Molnár, and Polasik (2022), and their findings suggested that among the GARCH models, EGARCH and APARCH models perform the best. They also compare these techniques with heterogeneous autoregressive (HAR) models and find that HAR models are better at forecasting short term fluctuations. More recently, machine learning and deep learning techniques in this area were applied, and Ammer and Aldhyani (2022) applied the long short-term memory (LSTM) algorithm, suggesting that time dependencies could be used effectively to predict prices.

The outcomes of relationships between crypto price changes have been ambiguous within the research literature. Numerous studies have concentrated on price bubbles in an attempt to understand the causes of price increases, particularly focusing on Bitcoin due to its popularity and high trading volume. Fry and Cheah (2016) used econophysics models to study bubbles and crashes in Bitcoin and Ripple prices, the two largest crypto markets. The maximum likelihood estimation methods revealed the existence of bubbles in both digital currencies and indicated a spillover from Ripple to Bitcoin, the second largest to the first. Corbet et al. (2018) analyzed similar relationships between 11 cryptocurrencies using the Supremum Augmented Dickey Fuller (ADF) test following a recursive approach to detect price bubbles and the CSSD[3] and CSAD[4] methods to detect herding behaviour. They concluded that herding is generally observed in most of them, which significantly decreases during price bubble periods, specifically in those cryptos with large market capitalizations. Whereas Vidal-Tomás, Ibáñez, and Farinós (2019) and Haykir and Yagli (2022) used the CSSD and CSAD methods that revealed herding was more dominant during the downward market trends, and Ballis and Drakos (2020) found that herding exists in both bull and bear markets. Some other studies, on the contrary, suggest that herding is common during normal periods and not during bull or bear markets (Susana, Kavisanmathi, & Sreejith, 2020).

Cagli (2019) investigated the co-movements of prices in Bitcoin and seven other altcoins. All seven exhibit co-explosive behaviours, showing how bubbles in one affect the others. He also conducted a study on pairs of some of these cryptocurrencies, which yielded similar results, with the exception of Nem, for the period from September 2015 to January 2018. Liew, Li, Budavári, and Sharma (2019) surveyed the correlations of price returns between the top 100 cryptocurrencies, which revealed a positive correlation between most of them. This correlation became more significant as the study's time frame grew. They also concluded that correlations between large market-cap cryptocurrencies were higher than those between small market-cap ones. It supports the author's selection of large market-cap cryptos described below in this study.

This study offers a perspective on the price relationships and interconnectedness among cryptocurrencies, exploring the top twenty cryptos according to market capitalization in the post-pandemic period. These twenty cryptos form almost 90% of the total market capitalization of the crypto market, which was at approx. USD 1.08 trillion as of 25 September 2023. Literature has provided studies majorly related to Bitcoin and some other top currencies like Litecoin and Ethereum. This study extends to other cryptos that have not yet been studied, like Solana, TRON, Cardano, and Chainlink. There is a scarcity of work considering other currencies, as Kyriazis (2020) emphasized, and this study aims to fill this gap. Secondly, it focuses on more recent times, the period after the pandemic, considering the changes in people's risk behaviours, technological advancements, government policies, and when markets and economies were returning to normal conditions. The sample data is from 1 January 2022 to 30 June 2023. With the technological dynamics rapidly transforming and markets emerging from pandemic influences, the author deems it pertinent to study the cryptocurrency price co-movements in more recent times as a more efficient prediction about the times ahead, using a multi-analytical approach.

The main focus of the statistical tests will be to conclude whether any co-movement in crypto prices exists through their returns, volatility, trading volume, and the crypto market index return, and to identify clusters

[3] Cross-sectional standard deviation (CSSD) suitable for linear relationships between market returns and CSSD of returns.
[4] Cross-sectional absolute deviation (CSAD) is where standard error is corrected for adjusting estimation for autocorrelation and heteroskedasticity.

that reveal high correlations. It will also ascertain the existence of any dominant cryptocurrency and whether it exerts any influence on other cryptocurrencies. Empirical methods are used to test the following hypotheses and research questions: (H1) Do cryptocurrencies exhibit interdependencies in their price movements? (H2) How are changes in volume associated with crypto returns? (H3) Does the crypto market index return reveal a high correlation to individual crypto prices? (H4) Are there cryptocurrency clusters that exhibit high correlations in their price movements, and what factors determine their interconnectedness? (H5) Which are the dominant cryptos, if any, that affect the prices of others?

3. Data and Research Methodology

3.1. Sample and Data

To investigate the interconnectedness of the price movements of cryptocurrencies, the author uses daily time series data from 1 January 2022 to 30 June 2023, forming a total of 546 observations for each of the twenty cryptocurrencies. The data source is CoinMarketCap (https://coinmarketcap.com), and it aggregates data from various cryptocurrency exchanges and is the most popular place for crypto prices. Moreover, they run data through data cleaning and verification algorithms to ensure data integrity and are more robust than data from a particular exchange. The data includes the closing price and the trading volume. A purposive sampling technique has been applied for data collection, where a sample of top twenty cryptos has been selected for the study, and the author has justified the same with the following reasons: (1) the top twenty cryptos together form almost 90% of the total cryptocurrency market capitalization value, as shown in Table 1, and these form an excellent representation of the crypto market size and influence in the overall market. (2) Many previous studies have focused on a very few cryptos, especially Bitcoin and a top few, and the author includes other cryptos like Tron, Dai, Shiba Inu, Polkadot, Chainlink, and Leo. The author expands the dataset to include twenty cryptocurrencies as many other smaller cryptos and stablecoins have gained interest among users and investors in recent times (Merkley, Pacelli, Piorkowski, & Williams, 2023). (3) Liew et al. (2019) highlighted that the correlation between large market-cap cryptocurrencies was higher than small market-cap ones, and the study will investigate this aspect further. The market returns for the cryptocurrencies are taken for the same period from the CCi30 index used by many studies (Haykir & Yagli, 2022; Liu & Serletis, 2019; Manahov, 2023) and Kendirli, Şenol, and Ergenoğlu (2022) when comparing cryptos with stock indices.

Figure 3 shows the price movement charts of nine out of the sample of twenty cryptocurrencies for the study period from 1 January 2022 to 30 June 2023. Here, we observe quite a few differences in their price movements during the same period. We observe that Tether rose sharply at the beginning of April 2023 while USD Coin fell sharply. Whereas in the beginning of July 2022 we see a sharp drop in prices of Bitcoin, Tron, Polygon, Wrapped Bitcoin, and Shiba Inu, but not so for Tether and USD Coin. In the last week of June 2023, we see Bitcoin, Tron and Leo rising, whereas Tether and Shiba Inu are in the fall. Hence, the charts at first observation indicate a positive correlation among some cryptos and a negative correlation among others. This warrants further empirical investigation to identify inter-relatedness among the cryptos and to explore some factors affecting prices.

Figure 3. Prices charts of some of the sample cryptocurrencies during the period 1 January 2022 to 30 June 2023.
Source: CoinMarketCap.com.

3.2. Variables of the Study

The daily price returns of each of the twenty cryptocurrencies *(i)* is calculated as:

$$R_{i,t} = ln(P_{i,t}) - ln(P_{i,t} - 1) \qquad (1)$$

Where Bitcoin ($i=1$), Ethereum ($i=2$), Tether ($i=3$), BNB ($i=4$), Ripple ($i=5$) and likewise for $i=1$ *to* 20 for the top twenty cryptocurrencies as in Table 1. And where $P_{i,t}$ is the daily closing price of cryptocurrency i on day t.

The daily change in volume for each of the twenty cryptocurrencies *(i)* is calculated as:

$$V_{i,t} = ln(V_{i,t}) - ln(V_{i,t} - 1) \qquad (2)$$

Where $i=1$ *to* 20 for the top twenty cryptocurrencies as in Table 1. And where $V_{i,t}$ is the daily volume of cryptocurrency i on day t.

The daily volatility of the cryptocurrencies is computed by using the square root of the daily variances of the returns calculated as:

$$\sigma_{i,t} = \sqrt{(R_{i,t} - \bar{R}_i)^2} \qquad (3)$$

Where $i=1$ *to* 20 for the top twenty cryptocurrencies as in Table 1. And where $R_{i,t}$ is the daily return of cryptocurrency i on day t, and $\bar{R}_i$ is the average return for the sample period for the i cryptocurrency.

The daily returns and volatility of the CCi30 index is also calculated as:

$$CCIR_{i,t} = ln(CCIP_{i,t}) - ln(CCIP_{i,t} - 1) \qquad (4)$$

$$CCI\sigma_{i,t} = \sqrt{(CCIR_{i,t} - CCI\bar{R}_i)^2} \qquad (5)$$

3.3. Empirical Methods

The study uses multiple analytical approaches to investigate the co-movements and interconnectedness among the samples of the top twenty crypto prices. This is a novel way of applying various techniques to investigate the research questions, which enhances the outcomes of the study. It begins by analyzing the correlations in price movements in order to examine which among the top twenty reveals the strongest connection. Previous research has typically focused on utilizing one or two variables to gauge price fluctuations. However, in this study, the author has chosen to integrate four variables previously examined in isolation, aiming to provide a more comprehensive analysis of their combined impact on price movements. These include (1) crypto returns ($R_{i,t}$) (2) their volatilities ($\sigma_{i,t}$) (3) their trading volumes ($V_{i,t}$) and (4) comparison with the crypto market index returns ($CCIR_{i,t}$), to examine the correlations based on multiple factors. This would also aide in suggesting whether a certain factor is more prominent for certain cryptos later in the interpretations. After identifying the correlations, ~~we~~ the author performs a PCA analysis to identify clusters of cryptos that exhibit strong price interconnectivity. Subsequently, the Granger Causality test is applied to the cryptocurrency clusters identified through PCA analysis to ascertain whether certain cryptos influence price movements within clusters, serving as indicators for investor decision-making.

Firstly, the statistical tests of Pearson correlational analysis are performed to examine the correlation coefficients between the twenty crypto returns and their volatilities, which are also extended to the CCi30 crypto market index returns, and then between their trading volume to identify co-movements from various perspectives and to evaluate the correlation dynamics from varied aspects. Previous studies have used this test to measure correlations between returns and volatility (Bouri, Lucey, & Roubaud, 2020; Corbet et al., 2018), and this study uses this technique, now applied to a broader sample of a larger number of cryptocurrencies. Moreover, it broadens the scope of analysis beyond pairwise comparisons, as demonstrated by Cagli (2019), who explored the interconnectedness among all the top twenty cryptocurrencies. Although the crypto market index was recently created in 2017, it has been identified as one of the best crypto indices and has been used by previous researchers[5] (Nie, 2020; Vidal-Tomás et al., 2019). The Pearson correlational analysis is also performed between the trading volumes of the twenty cryptocurrencies to examine whether factors driving buying decisions of cryptos are attributed to speculation, economic uncertainty, and herding behaviours by market players. The following equation is used for determining the Pearson correlation coefficient *(r)*:

$$r = \frac{n\sum xy - (\sum x)(\sum y)}{\sqrt{n(\sum x^2) - (\sum x)^2}\sqrt{n(\sum y^2) - (\sum y)^2}} \qquad (6)$$

Iterations are performed, and x and y pairs are replaced by $R_{i,t}$, $V_{i,t}$, $\sigma_{i,t}$ and $CCIR_{i,t}$ where $i = 1$ *to* 20 for the twenty cryptocurrencies for *n number of days*. *Secondly*, this study then proceeds to apply the novel Principal Component Analysis (PCA) approach to visually analyze the correlations among this sample set of twenty. This approach to examining clusters of similar cryptos has been very sparingly used in the literature, where Liew et al. (2019) used this technique for data from 2017, when the popularity of Bitcoin was gaining momentum. In recent times, more cryptocurrencies have been introduced since 2017, and with the increasing applicability of stablecoins for transactional purposes, this technique would help identify groups or clusters of cryptos whose price reveal co-movements. *Thirdly*, the empirical test of Granger Causality is performed based on highly correlated clusters to test whether any crypto with a cluster Granger causes price movements in others within the same cluster. As a cryptocurrency market has been described as mostly inefficient (Al-Yahyaee, Mensi, Ko, Yoon, & Kang, 2020; Vidal-Tomás et al., 2019), applying the Granger causality test is appropriate, which indicates that lags of one variable can be a good predictor of another variable, usually applicable to inefficient markets, to be exploited by speculative investors for gaining profitable outcomes (Corbet et al., 2019). Before proceeding with this test, the Augmented Dicker-Fully (ADF) test is performed to confirm the stationarity of the time series, where the null hypothesis was rejected with a p-value of less than 0.05 and the data was transformed to log returns for all crypto returns and the CCi30 index returns, and the first differencing technique used for the variable of daily change in volume. The bivariate model used is as follows:

$$Yt = \alpha 0 + \alpha 1Y_{t-1} + \alpha 2Y_{t-2} + \quad + \alpha mY_{t-m} + \varepsilon t \qquad (7)$$

$$Yt = \alpha 0 + \alpha 1Y_{t-1} + \alpha 2Y_{t-2} + \quad + \alpha mY_{t-m} + bpX_{t-p} + bqX_{t-q} + \varepsilon t \qquad (8)$$

Where $\alpha 0$, $\alpha 1$, $\alpha 2$ are model coefficients and *t-m* is the model lag. X and Y are the two variables in the model where the lagged values of X are tested against the Y values.

4. Empirical Results & Interpretations

4.1. Descriptive Statistics of Variables

The descriptive statistics for the returns, as shown in Table 2, reveal that from 1 January 2022 to 30 June 2023, the mean daily returns for only five of the twenty currencies were positive, whereas the others showed negative daily returns. Tether (USDT), USD Coin (USDC), Tron (TRX), Dai (DAI) & UNUS SED LEO (LEO) showed average positive returns only. The daily returns range from a minimum of -55% (SOL) to a maximum of +44% UNUS SED LEO (LEO). Comparing these to BTC, it had a minimum return of -17.4% and a maximum of +13.6%, suggesting a high variation in the top crypto and other smaller ones in the market. A high negative skewness for USDC (-6.384) and DAI (-4.952) suggests these two currencies had longer tails on the left, hence more instances of positive returns. All other distributions appear to be mostly symmetric and exhibit normal conditions. USDC and DAI also exhibit high kurtosis values, indicating the existence of outliers as shown in scatterplots in Figure 4 below when compared to BTC.

[5]. The CCi30 is a rules-based index designed to objectively measure the overall growth, daily and long-term movement of the blockchain sector. It does so by tracking the 30 largest cryptocurrencies by market capitalization, excluding stablecoins. It serves as a tool for passive investors to participate in this asset class, and as an industry benchmark for investment managers. The CCi30 has been designed with 5 main characteristics: 1. diversified; 2. replicable; 3. transparent; 4. provides in-depth coverage of the entire sector; 5. presents the best risk-adjusted performance profile possible. https://cci30.com/.

Table 2. Descriptive statistics of the sample top twenty cryptocurrency returns.

Statistic	**Returns BTC**	**Returns ETH**	**Returns USDT**	**Returns BNB**	**Returns XRP**	**Returns USDC**	**Returns SOL**	**Returns ADA**	**Returns DOGE**	**Returns TON**
Nbr. of observations	546	546	546	546	546	546	546	546	546	546
Minimum	-0.174	-0.192	-0.004	-0.205	-0.217	-0.028	-0.550	-0.204	-0.249	-0.188
Maximum	0.136	0.166	0.005	0.131	0.226	0.021	0.282	0.170	0.371	0.237
1st Quartile	-0.014	-0.019	0.000	-0.015	-0.021	0.000	-0.033	-0.025	-0.025	-0.022
Median	-0.001	-0.001	0.000	0.000	0.000	0.000	-0.004	-0.002	0.000	-0.001
3rd Quartile	0.014	0.019	0.000	0.015	0.018	0.000	0.028	0.020	0.020	0.017
Mean	-0.001	-0.001	0.000	-0.001	-0.001	0.000	-0.004	-0.003	-0.002	-0.002
Variance (n-1)	0.001	0.002	0.000	0.001	0.002	0.000	0.004	0.002	0.002	0.002
Standard deviation (n-1)	0.031	0.040	0.000	0.035	0.041	0.002	0.061	0.044	0.050	0.046
Skewness (Pearson)	-0.437	-0.442	0.808	-0.897	0.195	-6.384	-1.236	-0.225	0.432	0.340
Kurtosis (Pearson)	4.817	3.648	68.625	5.102	6.132	255.139	13.466	2.581	9.057	3.707
Statistic	Returns TRX	Returns DAI	Returns DOT	Returns MATIC	Returns LTC	Returns WBTC	Returns SHIB	Returns BCH	Returns LINK	Returns LEO
Nbr. of observations	546	546	546	546	546	546	546	546	546	546
Minimum	-0.180	-0.025	-0.238	-0.290	-0.189	-0.175	-0.288	-0.177	-0.216	-0.144
Maximum	0.176	0.019	0.182	0.325	0.244	0.135	0.318	0.305	0.148	0.441
1st Quartile	-0.013	0.000	-0.028	-0.029	-0.021	-0.013	0.000	-0.021	-0.027	-0.010
Median	0.002	0.000	-0.001	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
3rd Quartile	0.014	0.000	0.023	0.025	0.021	0.013	0.000	0.020	0.025	0.013
Mean	0.000	0.000	-0.003	-0.002	-0.001	-0.001	-0.003	-0.001	-0.002	0.000
Variance (n-1)	0.001	0.000	0.002	0.003	0.002	0.001	0.003	0.002	0.002	0.001
Standard deviation (n-1)	0.033	0.002	0.044	0.055	0.044	0.031	0.057	0.045	0.047	0.035
Skewness (Pearson)	-0.386	-4.952	-0.542	0.134	-0.089	-0.480	0.264	0.753	-0.600	4.025
Kurtosis (Pearson)	7.412	190.832	3.405	5.512	3.769	4.857	5.214	7.212	2.078	51.845

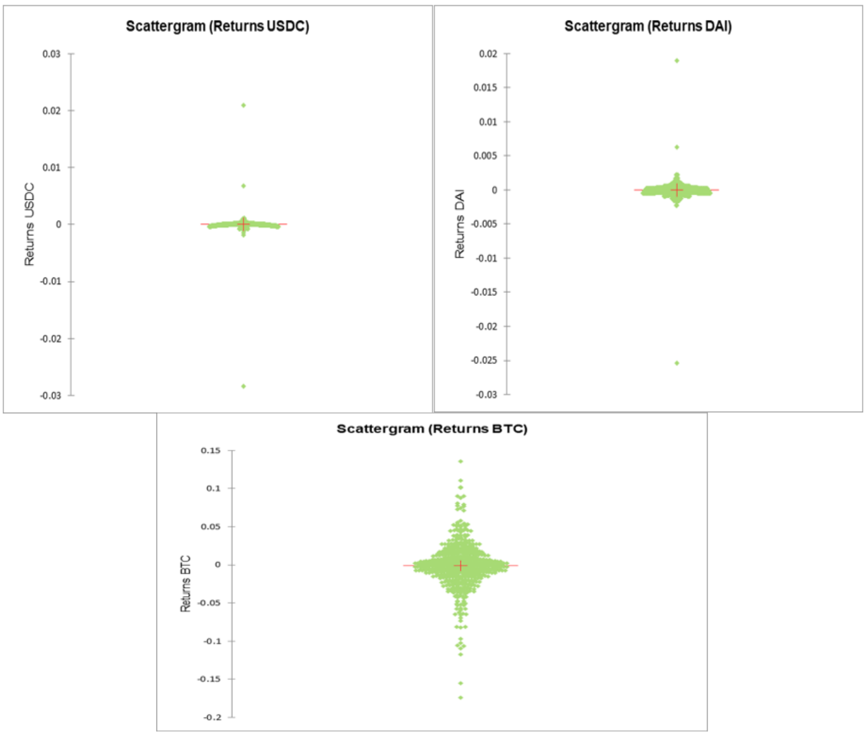

Figure 4. Scatterplots for returns on USDC, DAI and BTC.

The crypto market index CCi30 descriptive statistics in Table 3 give a standard deviation (0.037) higher than BTC, suggesting BTC to be less volatile than the overall market, whereas other smaller currencies like TON, DOGE, SHIB, and DOT appear to be more volatile.

Table 3. Descriptive statistics of returns on the cryptocurrency index CCi30.

Statistic	Crypto market returns
Nbr. of observations	546
Minimum	-0.187
Maximum	0.146
Median	0.001
Mean	-0.002
Variance (n-1)	0.001
Standard deviation (n-1)	0.037
Skewness (Pearson)	-0.791
Kurtosis (Pearson)	3.932

Table 4 shows the descriptive statistics of the daily change in volume for the twenty cryptocurrencies during the sample period. The minimum change was -3.44% (TON) and the maximum was 2.73% (TON). DOGE (0.47), SHIB (0.45), WBTC (0.46), and TON (0.45) were those that had a higher standard deviation of daily volume change as compared to others like USDT (0.275) and LEO (0.25). Since USDT and USDC are stablecoin categories pegged to the US dollar, we anticipate minimal variation in their trade volume due to their primary use in online transactions. DOGE, WBTC, SHIB, WBTC, and TON fall under the altcoin category and are mainly used for investments. As their founders come up with more transactional uses, their trading volume varies compared to other stablecoins. Furthermore, data reveals that the variation in the daily volume of the top three cryptos is much lesser than the smaller market cap cryptos.

Table 4. Descriptive statistics of daily change in volume of twenty cryptocurrencies.

Statistic	**Volume BTC**	**Volume ETH**	**Volume USDT**	**Volume BNB**	**Volume XRP**	**Volume USDC**	**Volume SOL**	**Volume ADA**	**Volume DOGE**	**Volume TON**
Nbr. of observations	546	546	546	546	546	546	546	546	546	546
Minimum	-1.099	-0.920	-0.814	-1.044	-1.104	-0.986	-1.165	-0.935	-1.420	-3.436
Maximum	1.025	1.012	0.819	1.222	1.517	1.254	1.576	1.137	2.473	2.729
Median	-0.010	0.007	-0.005	-0.033	-0.039	-0.004	-0.017	-0.013	-0.059	-0.025
Mean	-0.002	-0.001	-0.001	-0.002	-0.001	0.000	-0.002	-0.002	0.001	0.002
Variance (n-1)	0.101	0.106	0.075	0.091	0.162	0.096	0.161	0.133	0.225	0.200
Standard deviation (n-1)	0.317	0.326	0.275	0.302	0.402	0.309	0.402	0.365	0.474	0.448
Skewness (Pearson)	-0.110	0.009	0.073	0.434	0.417	0.137	0.302	0.418	0.608	0.005
Kurtosis (Pearson)	0.324	0.071	0.186	0.880	0.745	1.040	0.405	0.232	1.256	9.778
Statistic	Volume TRX	Volume DAI	Volume DOT	Volume MATIC	Volume LTC	Volume WBTC	Volume SHIB	Volume BCH	Volume LINK	Volume LEO
Nbr. of observations	546	546	546	546	546	546	546	546	546	546
Minimum	-1.020	-1.263	-0.977	-0.850	-1.010	-1.374	-1.294	-0.978	-1.359	-0.959
Maximum	1.436	2.083	1.252	1.133	2.144	1.660	2.403	1.968	1.742	1.966
Median	-0.020	-0.021	-0.018	-0.044	-0.018	-0.013	-0.070	-0.013	-0.012	-0.012
Mean	-0.004	-0.002	-0.003	-0.002	0.002	-0.002	-0.003	-0.003	-0.002	-0.002
Variance (n-1)	0.084	0.177	0.100	0.122	0.103	0.208	0.200	0.062	0.111	0.061
Standard deviation (n-1)	0.289	0.420	0.316	0.350	0.321	0.456	0.448	0.249	0.333	0.246
Skewness (Pearson)	0.418	0.381	0.259	0.473	0.892	0.086	1.106	1.522	0.384	0.809
Kurtosis (Pearson)	2.420	1.746	0.599	0.102	4.014	0.059	2.853	10.317	1.949	9.501

Figure 5 shows the average trading volume of the cryptos, revealing that the most highly traded still remain in the top three, with USDT (Tether) taking over BTC (Bitcoin) recently. As the skewness for all twenty is within -1,+1, the volume data exhibits normality conditions.

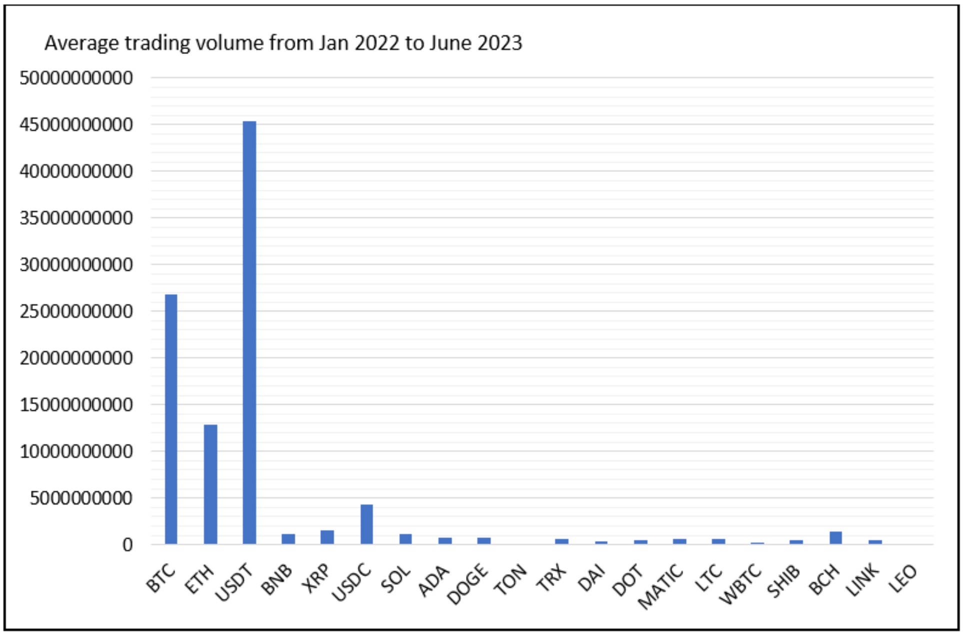

Figure 5. Average trading volume of 20 cryptos during 1 January 2022 to 30 June 2023.

4.2. Correlational Analysis

To investigate the interconnectedness among the top twenty cryptocurrencies and to find an answer to *H1, Do cryptocurrencies exhibit interdependencies in their price movements*? The Pearson correlation coefficient (Pearson *r*) is used to measure the strength and direction of the association between the variables of the daily change in returns ($R_{i,t}$) of the sample top twenty cryptocurrencies, their daily change in trading volume ($V_{i,t}$), their daily change in volatility ($\sigma_{i,t}$), and additionally the returns of each of the crypto currencies with the CCi30 ($CCIR_{i,t}$). It is the most suitable correlation measure as the study variables are continuous, and the empirical results of each of these analyses follow.

4.2.1. Correlation of Daily Returns of the Twenty Cryptocurrencies

Table 5 displays the correlations (Pearson r) for the 20 cryptocurrency price returns. Figure 6 shows the correlation matrix image that facilitates the visual interpretation of correlations. The empirical analysis reveals the following five interesting findings, which are as follows: Finding 1 Most of the values are in bold, where ρ is significantly different from 0, indicating that the empirical test determines a significant correlation between their populations, hence supporting various previous studies on herding behaviours, extreme correlation (Gkillas & Siriopoulos, 2018), and speculative investing in cryptocurrencies or crypto prices dominated by economic and other macro variables and investor decisions in cryptos that vastly differ from the way investment is made in other financial instruments. Finding 2 The results do not support previous studies that conclude correlation is more significant among large-cap cryptos than smaller market-cap ones (Liew et al., 2019). Here, the results find no significant difference in correlation patterns between large-cap and smaller-cap cryptos. Finding 3 A few negative correlations are observed in the sample, especially USDT (Tether), which reveals negative correlations with USDC and DAI, although not very strong. It is surprising to observe that cryptos having similar utility or features, in this case, stablecoins pegged to the US dollar, reveal negative correlations. It could indicate the functioning of demand-supply theory among competing stablecoins that can affect their prices. (Finding 4) Prices of USDT, USDC, DAI, LEO, TRX, TON, and SHIB are uncorrelated with mostly all other cryptos and, hence, are independent of price movements. USDT, USDC, and DAI are stablecoins pegged to the dollar, whereas LEO and others are utility tokens with limited use and, hence, not speculative. Cryptos pegged to the dollar or stablecoins do not show co-movement with BTC or other major altcoins. (Finding 5) Clusters of cryptos that exhibit the strongest positive correlations (correlation between 1 and 0.818) include (1) BTC, ETH, WBTC, (2) USDC, DAI, (3) DOT, ADA, and LINK. Clusters with a semi-strong correlation between 0.818 – 0.636, include (4) BNB, XRP, SOL, ADA, DOGE, DOT, MATIC, LTC, BCH, and LINK.

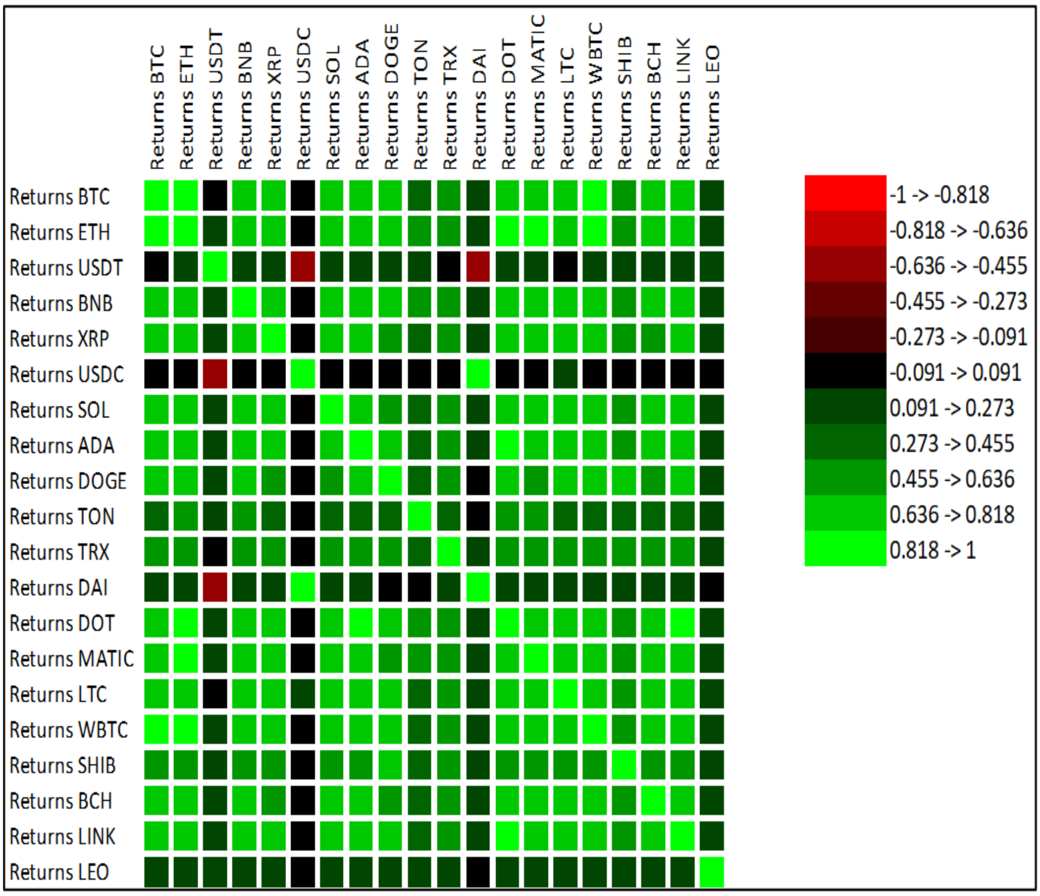

Figure 6. Image of correlation matrix of returns of the twenty cryptocurrencies.

Table 5. Correlation matrix (Pearson): Returns of the twenty cryptocurrencies.

Variables	Returns BTC	Returns ETH	Returns USDT	Returns BNB	Returns XRP	Returns USDC	Returns SOL	Returns ADA	Returns DOGE	Returns TON	Returns TRX	Returns DAI	Returns DOT	Returns MATIC	Returns LTC	Returns WBTC	Returns SHIB	Returns BCH	Returns LINK	Returns LEO
Returns BTC	1	0.890**	0.086**	0.802**	0.708	0.064	0.765**	0.773**	0.669	0.445	0.631	0.134	0.785**	0.763**	0.764**	0.998**	0.572	0.744	0.757**	0.222
Returns ETH	0.890**	1	0.118	0.816**	0.733	0.031	0.795**	0.791**	0.701	0.508	0.615	0.104	0.828**	0.828**	0.792**	0.894**	0.594	0.733	0.794**	0.214
Returns USDT	0.086	0.118	1	0.123	0.122	-0.497*	0.174	0.120	0.132	0.123	0.024	-0.478*	0.168	0.149	0.059	0.092	0.101	0.124	0.130	0.099
Returns BNB	0.802**	0.816**	0.123	1	0.699	0.048	0.765**	0.764**	0.672	0.481	0.614	0.119	0.811**	0.794**	0.746**	0.805**	0.616	0.674	0.753**	0.150
Returns XRP	0.708	0.733	0.122	0.699	1	0.018	0.688	0.732	0.618	0.383	0.575	0.092	0.726	0.730	0.689	0.710	0.585	0.622	0.705	0.206
Returns USDC	0.064	0.031	-0.497*	0.048	0.018	1	0.047	0.077	0.031	0.023	0.054	0.928	0.062	0.044	0.102	0.053	0.040	0.032	0.049	-0.017
Returns SOL	0.765**	0.795**	0.174	0.765**	0.688	0.047	1	0.761**	0.634	0.439	0.578	0.114	0.791**	0.768**	0.713	0.770**	0.552	0.660	0.737	0.171
Returns ADA	0.773**	0.791**	0.120	0.764**	0.732	0.077	0.761**	1	0.679	0.445	0.628	0.169	0.825	0.783**	0.763**	0.774**	0.628	0.682	0.790**	0.173
Returns DOGE	0.669	0.701	0.132	0.672	0.618	0.031	0.634	0.679	1	0.364	0.529	0.079	0.682	0.630	0.662	0.670	0.644	0.613	0.639	0.133
Returns TON	0.445	0.508	0.123	0.481	0.383	0.023	0.439	0.445	0.364	1	0.367	0.039	0.473	0.457	0.431	0.447	0.347	0.391	0.430	0.146
Returns TRX	0.631	0.615	0.024	0.614	0.575	0.054	0.578	0.628	0.529	0.367	1	0.117	0.627	0.586	0.571	0.632	0.546	0.537	0.544	0.156
Returns DAI	0.134	0.104	-0.478*	0.119	0.092	0.928**	0.114	0.169	0.079	0.039	0.117	1	0.151	0.130	0.167	0.121	0.095	0.098	0.138	0.014
Returns DOT	0.785**	0.828**	0.168	0.811	0.726	0.062	0.791**	0.825**	0.682	0.473	0.627	0.151	1	0.805	0.782**	0.790**	0.623	0.720	0.830**	0.159
Returns MATIC	0.763**	0.828**	0.149	0.794**	0.730	0.044	0.768**	0.783**	0.630	0.457	0.586	0.130	0.805**	1	0.739	0.767**	0.592	0.662	0.779**	0.138
Returns LTC	0.764**	0.792**	0.059	0.746**	0.689	0.102	0.713	0.763**	0.662	0.431	0.571	0.167	0.782**	0.739	1	0.765**	0.622	0.756**	0.758**	0.145
Returns WBTC	0.998**	0.894**	0.092	0.805**	0.710	0.053	0.770**	0.774**	0.670	0.447	0.632	0.121	0.790**	0.767**	0.765**	1	0.570	0.747**	0.760**	0.219
Returns SHIB	0.572	0.594	0.101	0.616	0.585	0.040	0.552	0.628	0.644	0.347	0.546	0.095	0.623	0.592	0.622	0.570	1	0.560	0.568	0.142
Returns BCH	0.744	0.733	0.124	0.674	0.622	0.032	0.660	0.682	0.613	0.391	0.537	0.098	0.720	0.662	0.756**	0.747**	0.560	1	0.707	0.158
Returns LINK	0.757**	0.794**	0.130	0.753**	0.705	0.049	0.737	0.790**	0.639	0.430	0.544	0.138	0.830**	0.779**	0.758**	0.760**	0.568	0.707	1	0.144
Returns LEO	0.222	0.214	0.099	0.150	0.206	-0.017*	0.171	0.173	0.133	0.146	0.156	0.014	0.159	0.138	0.145	0.219	0.142	0.158	0.144	1

Note: * The coefficients show a negative correlation in returns.
** Bold values show a significant correlation coefficient >0.75.

4.2.2. Correlation of Volatility of the Returns of the Twenty Cryptocurrencies

Table 6 shows the correlation coefficients of the volatility of the crypto price returns, and Figure 7 shows the image of the correlation matrix. (Finding 1) The volatilities of the cryptos reveal a lesser correlation than the returns in the test sample. (Finding 2) Here, the results reveal that cryptos with a smaller market cap exhibit stronger correlations in volatilities among themselves (the last five to seven in the sample) compared to correlations among the larger market cap ones (the first three to five in the sample). (Finding 3) USDT, USDC, DAI, and LEO are not correlated to other cryptos, hence independent of price co-movements with BTC and other altcoins, showing similar results to returns. (Finding 4) Clusters of cryptos showing high volatility correlations include (1) DAI and USDC (both stablecoins) with a strong positive correlation between 0.818 and 1, similar to the findings from the correlation matrix of returns. (2) BTC, ETH, and WBTC also have the strongest correlation in their volatilities between 0.818 and 1. The results of the volatility matrix confirm the findings of the return matrix.

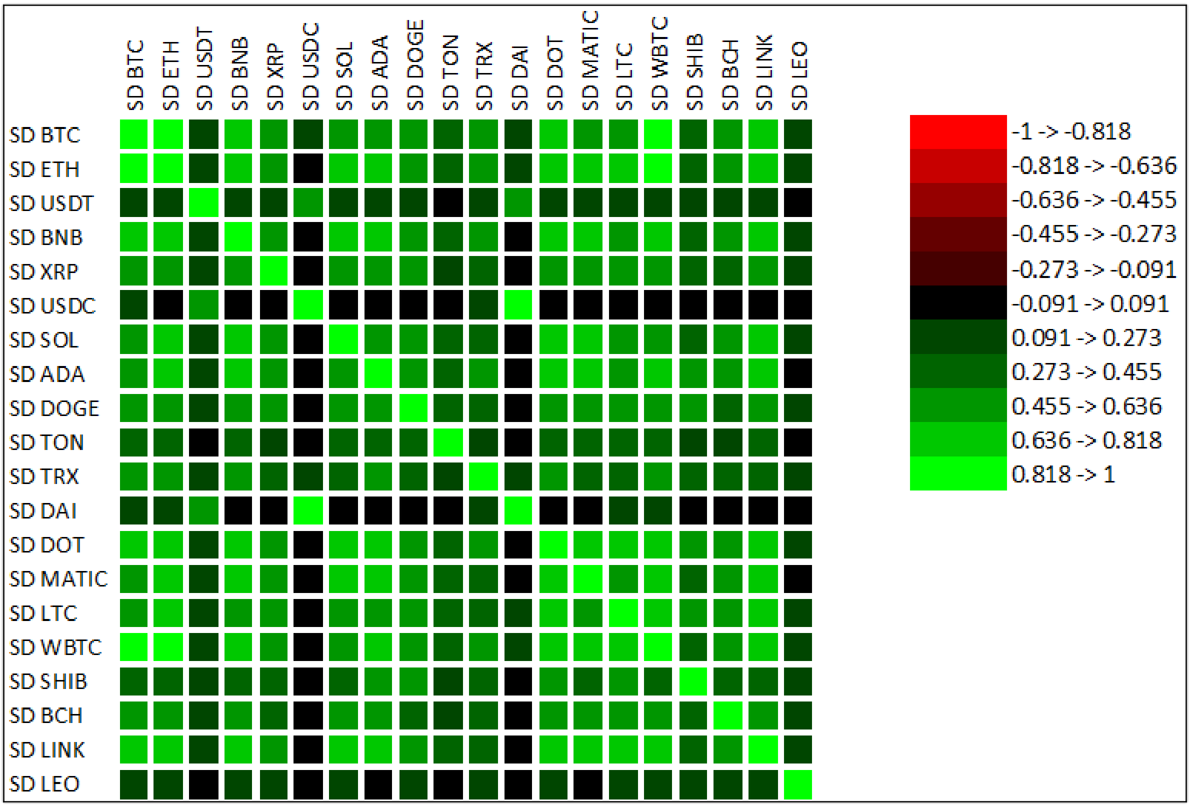

Figure 7. Image of correlation matrix of volatility of the twenty cryptocurrencies.

Table 6. Correlation matrix (Pearson): Volatility of the twenty cryptocurrencies.

Variables	SD BTC	SD ETH	SD USDT	SD BNB	SD XRP	SD USDC	SD SOL	SD ADA	SD DOGE	SD TON	SD TRX	SD DAI	SD DOT	SD MATIC	SD LTC	SD WBTC	SD SHIB	SD BCH	SD LINK	SD LEO
SD BTC	1	0.824**	0.175	0.688	0.556	0.093	0.608	0.634	0.510	0.294	0.503	0.130	0.644	0.629	0.634	0.997**	0.376	0.590	0.646	0.110
SD ETH	0.824**	1	0.158	0.706	0.593	0.071	0.655	0.662	0.564	0.367	0.459	0.108	0.693	0.731	0.666	0.831**	0.407	0.569	0.684	0.118
SD USDT	0.175	0.158	1	0.204	0.180	0.534	0.207	0.174	0.149	0.072	0.111	0.515	0.174	0.208	0.226	0.181	0.137	0.143	0.146	0.036
SD BNB	0.688	0.706	0.204	1	0.561	0.024	0.645	0.639	0.522	0.358	0.472	0.059	0.680	0.679	0.628	0.692	0.452	0.513	0.663	0.164
SD XRP	0.556	0.593	0.180	0.561	1	-0.004*	0.537	0.585	0.460	0.270	0.427	0.022	0.571	0.617	0.548	0.562	0.427	0.430	0.594	0.162
SD USDC	0.093	0.071	0.534	0.024	-0.004*	1	0.021	0.048	0.021	0.011	0.108	0.959	0.033	0.027	0.078	0.089	0.037	0.035	-0.002*	0.065
SD SOL	0.608	0.655	0.207	0.645	0.537	0.021	1	0.621	0.472	0.335	0.423	0.054	0.652	0.650	0.560	0.616	0.372	0.466	0.644	0.096
SD ADA	0.634	0.662	0.174	0.639	0.585	0.048	0.621	1	0.534	0.323	0.491	0.089	0.721	0.661	0.630	0.638	0.476	0.512	0.693	0.066
SD DOGE	0.510	0.564	0.149	0.522	0.460	0.021	0.472	0.534	1	0.307	0.352	0.051	0.525	0.494	0.531	0.511	0.502	0.429	0.541	0.111
SD TON	0.294	0.367	0.072	0.358	0.270	0.011	0.335	0.323	0.307	1	0.216	0.003	0.328	0.337	0.289	0.296	0.176	0.245	0.341	0.071
SD TRX	0.503	0.459	0.111	0.472	0.427	0.108	0.423	0.491	0.352	0.216	1	0.129	0.513	0.411	0.451	0.504	0.406	0.355	0.440	0.104
SD DAI	0.130	0.108	0.515	0.059	0.022	0.959**	0.054	0.089	0.051	0.003	0.129	1	0.086	0.086	0.108	0.127	0.064	0.070	0.043	0.042
SD DOT	0.644	0.693	0.174	0.680	0.571	0.033	0.652	0.721	0.525	0.328	0.513	0.086	1	0.690	0.661	0.649	0.478	0.572	0.744	0.101
SD MATIC	0.629	0.731	0.208	0.679	0.617	0.027	0.650	0.661	0.494	0.337	0.411	0.086	0.690	1	0.615	0.637	0.427	0.495	0.726	0.088
SD LTC	0.634	0.666	0.226	0.628	0.548	0.078	0.560	0.630	0.531	0.289	0.451	0.108	0.661	0.615	1	0.637	0.476	0.631	0.672	0.132
SD WBTC	0.997**	0.831**	0.181	0.692	0.562	0.089	0.616	0.638	0.511	0.296	0.504	0.127	0.649	0.637	0.637	1	0.375	0.594	0.652	0.109
SD SHIB	0.376	0.407	0.137	0.452	0.427	0.037	0.372	0.476	0.502	0.176	0.406	0.064	0.478	0.427	0.476	0.375	1	0.378	0.429	0.140
SD BCH	0.590	0.569	0.143	0.513	0.430	0.035	0.466	0.512	0.429	0.245	0.355	0.070	0.572	0.495	0.631	0.594	0.378	1	0.562	0.102
SD LINK	0.646	0.684	0.146	0.663	0.594	-0.002*	0.644	0.693	0.541	0.341	0.440	0.043	0.744	0.726	0.672	0.652	0.429	0.562	1	0.094
SD LEO	0.110	0.118	0.036	0.164	0.162	0.065	0.096	0.066	0.111	0.071	0.104	0.042	0.101	0.088	0.132	0.109	0.140	0.102	0.094	1

Note: * The coefficients show a negative correlation in returns.
** Bold values show a significant correlation coefficient >0.75.

4.2.3. Correlation of Daily Change in Trading Volume for the Twenty Cryptocurrencies

Table 7 shows the correlation coefficients of the trading volume of the cryptos, and Figure 8 shows the image of the correlation matrix that is visually appealing to interpret the findings. (Finding 1) All cryptocurrencies exhibit a positive correlation in trading volume, and none are negatively correlated, supporting the findings of the correlation of returns and confirming other studies that have found strong co-movements in cryptos. (Finding 2) The top three BTC, ETH, and USDT show a very strong correlation (between 1 and 0.818) in their daily trading volumes, indicating spillover of news from one to the other. This also reveals a stronger trading volume correlation among large-cap cryptos than smaller market-cap ones, thus contradicting the correlation within returns. These observations suggest that trading volume movements are not dependent on the type of crypto, as BTC and ETH are altcoins and USDT is a stablecoin, and investors' decisions are biased towards the movements of the large-cap cryptos. BTC and ETH are the two largest altcoins, and USDT is the largest among stablecoins. USDC, with a market-cap second to USDT in the stablecoin category, also has a high correlation with BTC, ETH, and USDT. (Finding 3) TON and LEO have no correlation in their trading volumes with any of the others in the group, this coincides with the findings of returns.

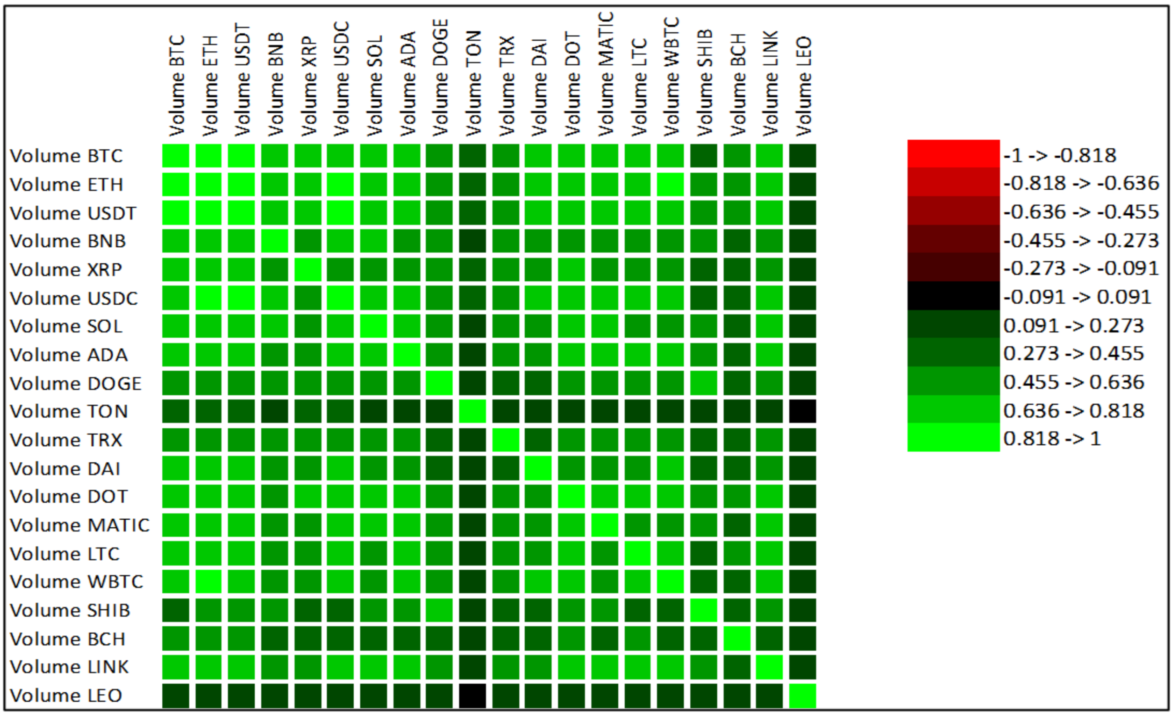

Figure 8. Image of correlation matrix of trading volume of the twenty cryptocurrencies.

Table 7. Correlation matrix (Pearson): Trading volume of the twenty cryptocurrencies.

Variables	BTC	ETH	USDC	BNB	XRP	USDC	SOL	ADA	DOGE	TON	TRX	DAI	DOT	MATIC	LTC	WBTC	SHIB	BCH	LINK	LEO
Volume BTC	1	0.900**	0.936**	0.674	0.656	0.813**	0.722	0.687	0.491	0.296	0.528	0.676	0.730	0.709	0.701	0.781**	0.449	0.461	0.702	0.217
Volume ETH	0.900**	1	0.939**	0.721	0.673	0.854**	0.734	0.744	0.525	0.336	0.561	0.715	0.765**	0.745**	0.737	0.830**	0.482	0.473	0.737	0.204
Volume USDT	0.936**	0.939**	1	0.755**	0.724	0.885**	0.786**	0.776**	0.588	0.312	0.596	0.738	0.812**	0.783**	0.762**	0.811**	0.548	0.503	0.775**	0.214
Volume BNB	0.674	0.721	0.755**	1	0.564	0.656	0.638	0.635	0.471	0.248	0.474	0.556	0.630	0.630	0.617	0.612	0.458	0.401	0.633	0.181
Volume XRP	0.656	0.673	0.724	0.564	1	0.630	0.585	0.622	0.505	0.284	0.474	0.533	0.656	0.610	0.587	0.563	0.424	0.386	0.597	0.191
Volume USDC	0.813**	0.854	0.885**	0.656	0.630	1	0.683	0.680	0.496	0.275	0.521	0.781**	0.708	0.672	0.682	0.751**	0.438	0.424	0.694	0.201
Volume SOL	0.722	0.734	0.786**	0.638	0.585	0.683	1	0.683	0.469	0.255	0.495	0.544	0.712	0.687	0.618	0.627	0.464	0.415	0.652	0.168
Volume ADA	0.687	0.744	0.776**	0.635	0.622	0.680	0.683	1	0.571	0.263	0.513	0.552	0.714	0.690	0.640	0.653	0.553	0.419	0.665	0.208
Volume DOGE	0.491	0.525	0.588	0.471	0.505	0.496	0.469	0.571	1	0.223	0.410	0.401	0.540	0.476	0.513	0.485	0.677	0.335	0.530	0.136
Volume TON	0.296	0.336	0.312	0.248	0.284	0.275	0.255	0.263	0.223	1	0.270	0.249	0.259	0.269	0.265	0.238	0.258	0.219	0.266	0.045
Volume TRX	0.528	0.561	0.596	0.474	0.474	0.521	0.495	0.513	0.410	0.270	1	0.431	0.511	0.491	0.498	0.487	0.339	0.326	0.461	0.180
Volume DAI	0.676	0.715	0.738	0.556	0.533	0.781**	0.544	0.552	0.401	0.249	0.431	1	0.625	0.556	0.552	0.662	0.360	0.344	0.569	0.172
Volume DOT	0.730	0.765**	0.812**	0.630	0.656	0.708	0.712	0.714	0.540	0.259	0.511	0.625	1	0.695	0.660	0.654	0.515	0.457	0.734	0.215
Volume MATIC	0.709	0.745**	0.783**	0.630	0.610	0.672	0.687	0.690	0.476	0.269	0.491	0.556	0.695	1	0.629	0.634	0.471	0.406	0.662	0.171
Volume LTC	0.701	0.737	0.762**	0.617	0.587	0.682	0.618	0.640	0.513	0.265	0.498	0.552	0.660	0.629	1	0.650	0.432	0.504	0.652	0.175
Volume WBTC	0.781**	0.830**	0.811**	0.612	0.563	0.751**	0.627	0.653	0.485	0.238	0.487	0.662	0.654	0.634	0.650	1	0.433	0.380	0.642	0.190
Volume SHIB	0.449	0.482	0.548	0.458	0.424	0.438	0.464	0.553	0.677	0.258	0.339	0.360	0.515	0.471	0.432	0.433	1	0.292	0.495	0.105
Volume BCH	0.461	0.473	0.503	0.401	0.386	0.424	0.415	0.419	0.335	0.219	0.326	0.344	0.457	0.406	0.504	0.380	0.292	1	0.436	0.182
Volume LINK	0.702	0.737	0.775**	0.633	0.597	0.694	0.652	0.665	0.530	0.266	0.461	0.569	0.734	0.662	0.652	0.642	0.495	0.436	1	0.167
Volume LEO	0.217	0.204	0.214	0.181	0.191	0.201	0.168	0.208	0.136	0.045	0.180	0.172	0.215	0.171	0.175	0.190	0.105	0.182	0.167	1

Note: ** Bold values show a significant correlation coefficient >0.75.

4.2.4. Correlation of Daily Market Returns and Returns of the Twenty Cryptocurrencies

Next, the study examines the correlation of the CCi30 crypto market returns with those of the top twenty cryptos. This index measures the movement of the top 30 cryptos (excluding stablecoins pegged to the dollar) to work as a benchmark for the industry available for investment decisions. Table 8 shows the correlation coefficients, and Figure 9 is the image of the correlation matrix. (Finding 1) Mostly all cryptocurrencies exhibit a very strong to strong positive correlation with market returns except for USDT, USDC, DAI, and LEO. This again confirms the results of the correlations with returns, volume, and volatility that cryptos having similar characteristics flock together, especially those that are pegged to the US dollar or stablecoins. (Finding 2) Clusters exhibiting high correlations with index returns are: (1) BTC, ETH, BNB, SOL, ADA, DOT, MATIC, LTC, WBTC, and LINK (2) XRP, TON, DOGE TRX, SHIB, and BCH are the other clusters with a semi-strong correlation.

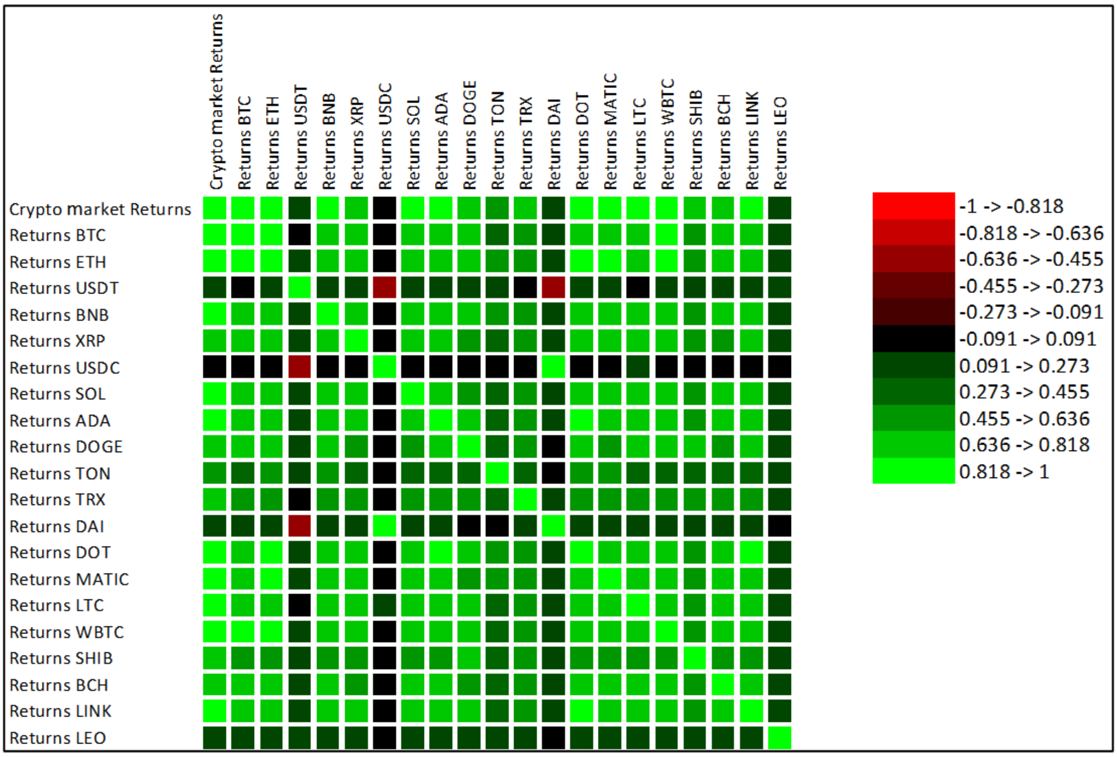

Figure 9. Image of correlation matrix of CCi30 returns with the twenty cryptocurrencies.

Table 8. Correlation matrix (Pearson): CCi30 returns with the twenty cryptocurrencies.

Variables	Crypto market returns	Variables	Crypto market returns
Crypto market returns	1	Crypto market returns	1
Returns BTC	0.923*	Returns TRX	0.688
Returns ETH	0.942*	Returns DAI	0.140
Returns USDT	0.148	Returns DOT	0.907*
Returns BNB	0.889	Returns MATIC	0.880
Returns XRP	0.815	Returns LTC	0.851
Returns USDC	0.056	Returns WBTC	0.924*
Returns SOL	0.862	Returns SHIB	0.689
Returns ADA	0.882	Returns BCH	0.796
Returns DOGE	0.766	Returns LINK	0.863
Returns TON	0.516	Returns LEO	0.215

Note: *Values with a very high correlation coefficient >0.9.

4.3. Principal Component Analysis (PCA)

To further explore the interconnectedness among the crypto price movements and identify highly correlated clusters of cryptos, the author utilizes the innovative approach of PCA analysis of the variables/observations. The advantage of visualizing cryptos in a two- or three-dimensional space is also beneficial in identifying atypical groups of cryptos that would be independent of others' price movements in the model. When there are many highly correlated variables, we also use PCA to narrow them down to the most desirable ones. This statistical exploratory approach to reducing the dimensionality enables narrowing down on the major variables having the highest correlation, which could then be applied in studies for future predictive research models. Firstly, the study uses multi-factor analysis with variables of returns, volatility, trading volume, and market returns that are described as $R_{i,t}$., $V_{i,t}$,.$\sigma_{i,t}$ *and* $CCIR_{i,t}$. The PCA analysis is used to reduce them to the most relevant factors that could be applied to the dataset to give efficient outcomes from the statistical analysis. The empirical results of the PCA analysis are as follows: Table 9 shows the summary statistics of four variables for the twenty cryptos, where the mean is around 0.6 and the standard deviation is around 0.2. Table 10 shows the correlation matrix of the four variables with a high correlation between crypto returns, volatility, and market returns.

Table 9. PCA: Summary statistics of four variables.

Variable	Observations	Mean	Std. deviation
Returns (F1)	20	0.629	0.288
Volume (F2)	20	0.656	0.200
Volatility (F3)	20	0.532	0.267
Market returns (F4)	20	0.688	0.299

Table 10. PCA: Correlation matrix (Pearson (n)).

Variables	Returns	Volume	Volatility	Market returns
Returns (F1)	1	0.238	0.964*	0.979*
Volume (F2)	0.238	1	0.440	0.183
Volatility (F3)	0.964*	0.440	1	0.907*
Market returns (F4)	0.979*	0.183	0.907*	1

Note: *Values with a very high correlation coefficient >0.9.

Table 11 shows the eigenvalues and eigenvectors of the variables. Figure 10 is the visual representation of the eigenvectors, explaining that studying either the correlations between crypto returns or their volatility or market returns can be a good representation of the datasets. Table 12 breaks up the importance of the variables for each of the cryptocurrencies, which interestingly reveals some similar behaviours among some groups, whereas for the majority of the cryptos, their returns carry the maximum importance. For USDT, USDC, and DAI, their trading volume influences the dataset positively more than other variables, indicating that these crypto prices fluctuate more with the demand and supply of their utility.

Table 11. PCA: Eigenvalues and eigenvectors.

Eigenvectors	F1	F2	F3	F4	Eigenvectors	F1	F2	F3	F4
Eigenvalue	3.023	0.921	0.055	0.001	Returns	0.565	-0.194	-0.097	0.796
Variability (%)	75.568	23.026	1.371	0.034	Volume	0.239	0.946	0.201	0.086
Cumulative %	75.568	98.595	99.966	100.000	Volatility	0.567	0.042	-0.672	-0.474
					Market returns	0.549	-0.256	0.706	-0.366

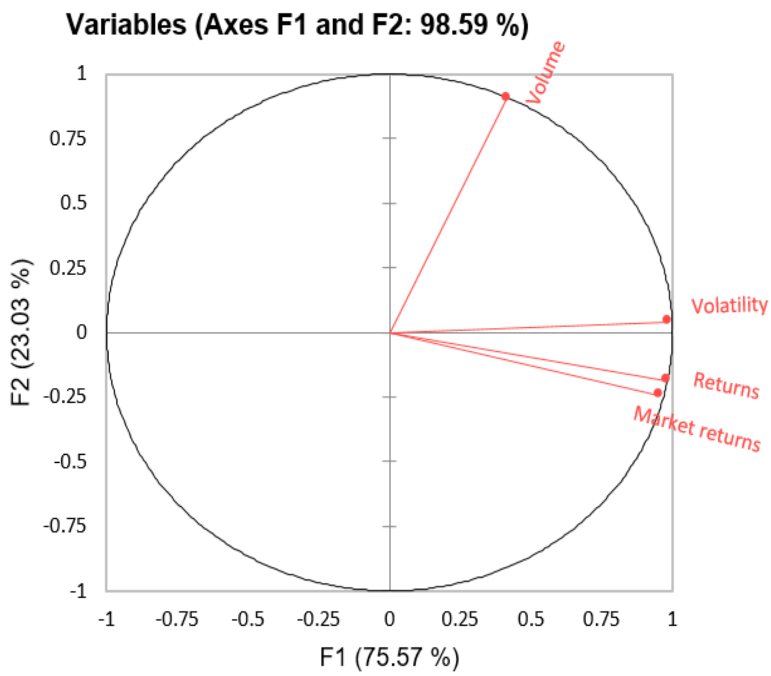

Figure 10. PCA: Eigenvectors.

Table 12. PCA: Crypto wise breakup of factor variables.

CRYPTO	F1	F2	F3	F4	CRYPTO	F1	F2	F3	F4
BTC	2.633**	1.278	-0.415	0.058	TRX	-0.215	-0.628	-0.056	0.004
ETH	1.939**	0.822	0.021	-0.003	DAI	-2.882	0.855*	-0.095	0.023
USDt	-2.543	2.148*	0.092	-0.091	DOT	1.063**	0.074	0.265	-0.001
BNB	1.091**	-0.186	0.043	-0.035	MATIC	0.909**	0.008	0.222	-0.013
XRP	0.450	-0.167	0.218	0.022	LTC	0.857**	-0.005	0.131	0.011
USDC	-3.093	1.635*	-0.037	0.058	WBTC	2.359**	0.216	-0.628	-0.039
SOL	0.848**	0.081	0.245	0.059	SHIB	-0.705	-0.993	0.213	0.031
ADA	0.917**	-0.108	0.187	-0.006	BCH	0.324**	-1.113	-0.130	0.001
DOGE	-0.023	-0.903	0.062	-0.016	LINK	0.893**	-0.004	0.132	-0.044
TON	-1.653	-1.507	-0.107	-0.033	LEO	-3.168	-1.502	-0.363	0.015

Note: * F2 (Trading volume) having the highest value.
** F1 (Crypto returns) having the highest value.

Below are the visual representations of the two-dimensional plots of the clusters of cryptos that exhibit high correlations, where Figure 11 plots the F1 and F2 combinations of crypto returns and volume. Figure 12 plots the F1 and F3 combinations of crypto returns and their volatility, and Figure 13 shows the F1 and F4 combinations of crypto returns and crypto market returns.

Firstly, we observe two distinct clusters in all three Figures 11,12, and 13, one of ETH, WBTC, XRP, SOL, BNB, ADA, DOT, MATIC, LTC, and BCH that show a high correlation, and the second distinct cluster is that of USDC, DAI, & LEO. Secondly, cryptos like TON, TRX, and SHIB reveal atypical behaviours. Figures 11 and 12 reveal an additional SHIB, DOGE, and TRX cluster. DOT, ADA, MATIC, XRP, and SOL appear to be the dominant clusters in all three models.

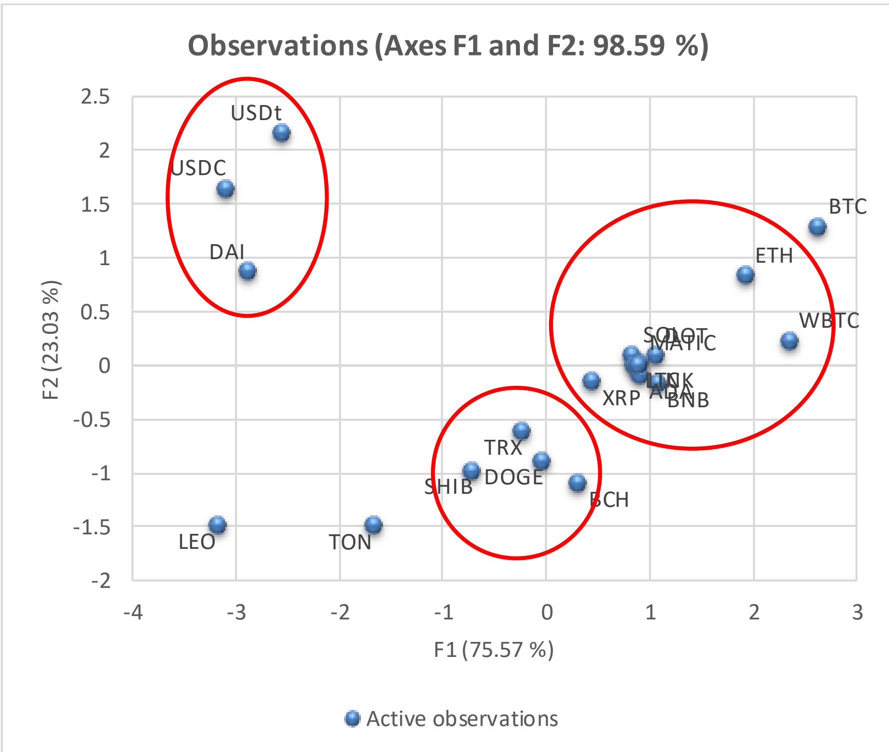

Figure 11. PCA: Two-dimensional biplot chart.

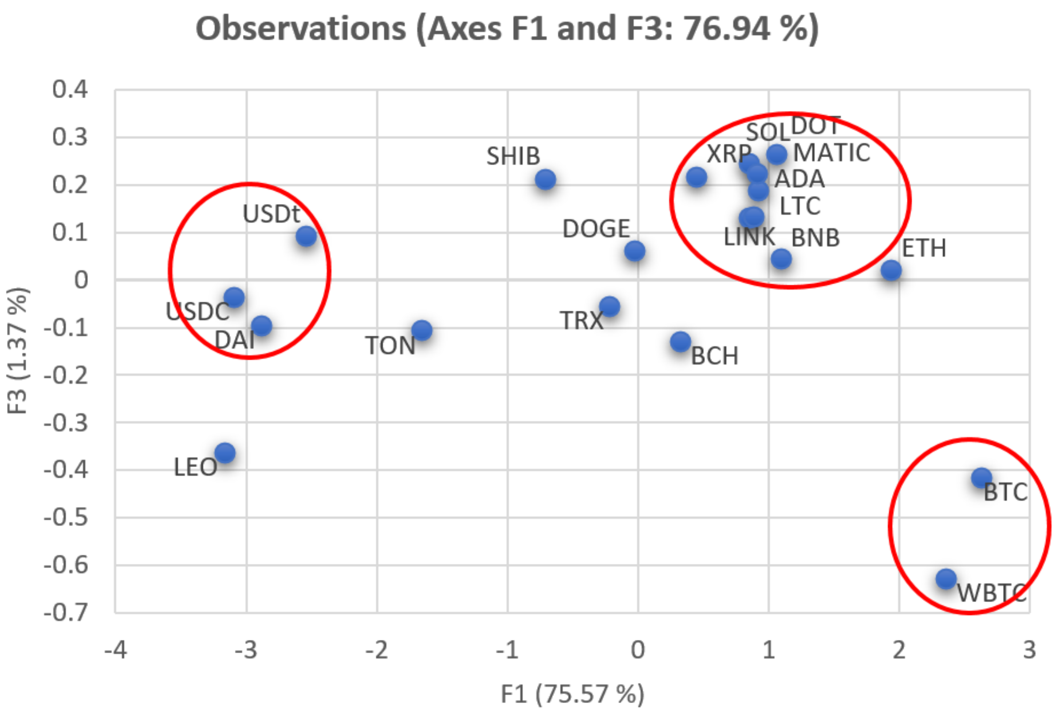

Figure 12. PCA: Two-dimensional biplot chart.

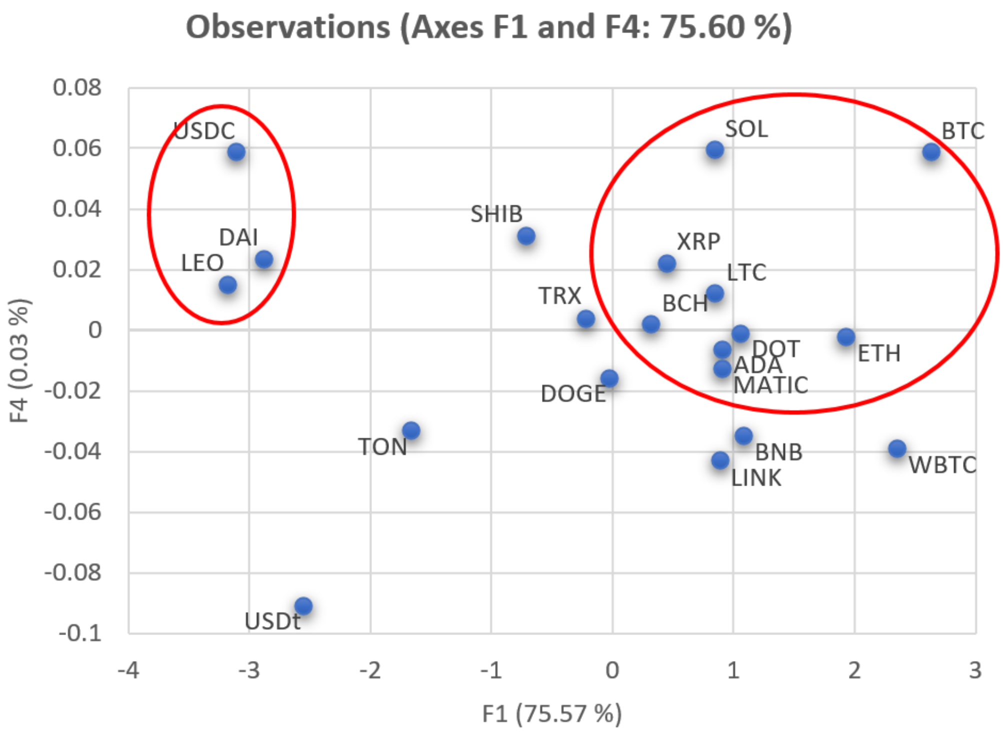

Figure 13. PCA: Two-dimensional biplot chart.

4.4. Granger Causality Test

The above PCA analysis has identified closely correlated groups of crypto currencies, revealing a significant level of interdependence in their price fluctuations. The study delves deeper into exploring the predominant influence of some cryptos within the clusters, showcasing their capacity to Granger cause price movements in others. Next, the empirical test of Granger Causality is performed, which is a vector autoregression (VAR) forecasting method to determine whether lags of one variable (returns of one crypto) are predictors of another variable (returns of another crypto) and to examine whether a causal relationship exists between them. Understand that Granger causality does not imply a direct cause-and-effect relationship. It is suitable for analysing such a relationship between cryptos considering the nature of the crypto market and industry being more speculative, following herd behaviours that differ from the fundamentals that underlie other financial assets

(Bouri et al., 2019; Cheah & Fry, 2015; Goczek & Skliarov, 2019; Jalal et al., 2021; Yermack, 2015). The test of Granger causality is applied to investigate the existence of any dominant cryptos within clusters that could be predictors for the others. The PCA eigenvalues determined cumulative 98.6% variance can be explained by F1 (crypto returns) and F2 (trading volume); hence, the Granger causality test is performed using the variables $R_{i,t}$ *and* $V_{i,t}$. Iterative tests were conducted within the two major clusters as below, by replacing the X values with $R_{i,t}$ returns for the large market cap cryptos of BTC, ETH, BNB, and XRP in Cluster 1 and USDT and USDC within Cluster 2 as predictor variables to investigate their influence within the cluster by examining the linkages between the pairs. Lags of 1 and 2 are used as m symmetric lags in the empirical model for all variables, given the short-term speculative nature of buying decisions in crypto markets, as suggested by previous studies such as Bouri et al. (2019) and Jalal et al. (2021).

Cluster 1: BTC, ETH, BNB, XRP, SOL, ADA, DOT, MATIC, LTC, WBTC, BCH.

Cluster 2: USDT, USDC, DAI, LEO.

Table 13 below shows the *p-values* resulting from the Granger causality test. The X values (crypto returns) have been iterated for each predictor variable in cluster 1 and Table 14 in cluster 2. Within cluster 1, the test findings reveal Binance Coin (BNB) and Ripple (XRP) to be more influential than the one with the largest market capital and most popular, Bitcoin. Both BNB and XRP have a causal relationship with Bitcoin (BTC), Ethereum (ETH), MATIC, and Wrapped Bitcoin (WBTC). BNB has a causal relationship with Litecoin (LTC) with a one-day lag, whereas XRP and Bitcoin Cash (BCH) reveal a causal relationship for the two-day lag outcomes. Within cluster 2, we find that Tether (USDT) influences all others in the group and reveals itself to be the most dominant crypto. Even USD Coin (USDC) reveals a causal relationship, with two out of the three in the group indicating good influence on the others. The results do not show a great difference in the outcomes between lags 1 and 2; however, comparatively more cryptos have lag 1 p-values less than 0.05, indicating the influence is more prominent in the shorter term.

Table 13. Granger causality test: Crypto returns cluster 1.

X value BTC			**X value ETH**		
	p-values Pr(>F)			**p-values Pr(>F)**	
CRYPTOS	**Lag 1**	**Lag 2**	**CRYPTOS**	**Lag 1**	**Lag 2**
ETH	0.844	0.731	BTC	0.984	0.998
BNB	0.239	0.164	BNB	0.120	0.056
XRP	0.740	0.878	XRP	0.535	0.502
SOL	0.675	0.518	SOL	0.327	0.017*
ADA	0.483	0.751	ADA	0.880	0.912
DOT	0.841	0.922	DOT	0.652	0.428
MATIC	0.258	0.200	MATIC	0.242	0.512
LTC	0.084	0.202	LTC	0.177	0.196
WBTC	0.002*	0.009*	WBTC	0.940	0.967
BCH	0.772	0.375	BCH	0.868	0.108
X value BNB			X value XRP		
	p-values Pr(>F)			p-values Pr(>F)	
CRYPTOS	Lag 1	Lag 2	CRYPTOS	Lag 1	Lag 2
BTC	0.020*	0.018*	BTC	0.018*	0.079
ETH	0.053	0.022*	ETH	0.030*	0.107
XRP	0.192	0.226	BNB	0.077	0.097
SOL	0.265	0.631	SOL	0.751	0.333
ADA	0.180	0.209	ADA	0.159	0.397
DOT	0.409	0.726	DOT	0.197	0.156
MATIC	0.001*	< 0.0001*	MATIC	0.014*	0.041*
LTC	0.022*	0.058	LTC	0.256	0.318
WBTC	0.027*	0.027*	WBTC	0.022*	0.095
BCH	0.223	0.450	BCH	0.107	0.025

Note: * p-values < 0.05 significance levels.

Table 14. Granger causality test: Crypto returns cluster 2.

X value USDT			**X value USDC**		
	p-values Pr(>F)			**p-values Pr(>F)**	
CRYPTOS	**Lag 1**	**Lag 2**	**CRYPTOS**	**Lag 1**	**Lag 2**
USDC	< 0.0001*	< 0.0001*	USDT	< 0.0001*	< 0.0001*
DAI	< 0.0001*	< 0.0001*	DAI	0.631	0.387
LEO	0.050*	0.149	LEO	0.0003*	0.002*

Note: * p-values < 0.05 significance levels.

To test the robustness of Granger causality, similar tests were repeated for the variable of trading volume (V_{it}) to examine the causal relationships in the change in volume that would determine the interconnectedness of price movements. Tables 15 and 16 show the *p-values* resulting from the Granger causality test, where the X values (trading volumes) have been iterated for each predictor variable in cluster 1 and cluster 2, respectively.

Table 15. Granger causality test: Crypto trading volumes cluster 1.

X value BTC			**X value ETH**		
	p-values Pr(>F)			**p-values Pr(>F)**	
CRYPTOS	**Lag 1**	**Lag 2**	**CRYPTOS**	**Lag 1**	**Lag 2**
ETH	0.085	0.184	BTC	0.387	0.816
BNB	0.039*	0.019*	BNB	0.356	0.268
XRP	0.064	0.053	XRP	0.518	0.293
SOL	0.877	0.809	SOL	0.149	0.408
ADA	0.050	0.004*	ADA	0.755	0.049
DOT	0.159	0.191	DOT	0.751	0.517
MATIC	0.048*	0.231	MATIC	0.368	0.866
LTC	0.003*	0.002*	LTC	0.080	0.024*
WBTC	0.037*	0.035*	WBTC	0.220	0.204
BCH	0.252	0.213	BCH	0.703	0.322
X value BNB			X value XRP		
	p-values Pr(>F)			p-values Pr(>F)	
CRYPTOS	Lag 1	Lag 2	CRYPTOS	Lag 1	Lag 2
BTC	0.830	0.824	BTC	0.907	0.603
ETH	0.397	0.718	ETH	0.550	0.466
XRP	0.272	0.505	BNB	0.233	0.114
SOL	0.937	0.743	SOL	0.803	0.890
ADA	0.882	0.744	ADA	0.639	0.797
DOT	0.184	0.160	DOT	0.521	0.423
MATIC	0.786	0.982	MATIC	0.531	0.623
LTC	0.386	0.412	LTC	0.067	0.113
WBTC	0.402	0.433	WBTC	0.430	0.391
BCH	0.939	0.994	BCH	0.632	0.602

Note: * p-values < 0.05 significance levels.

Table 16. Granger causality test: Crypto trading volumes cluster 2.

X value USDT			**X value USDC**		
	p-values Pr(>F)			**p-values Pr(>F)**	
CRYPTOS	**Lag 1**	**Lag 2**	**CRYPTOS**	**Lag 1**	**Lag 2**
USDC	0.016*	0.118	USDT	0.024*	0.187
DAI	0.048*	0.032*	DAI	0.137	0.036*
LEO	0.213	0.452	LEO	0.297	0.455

Note: * p-values < 0.05 significance levels.

The results of the Granger Causality tests between the trading volumes of cryptos in cluster 1 reveal that Bitcoin (BTC) is the major influencer, and Granger causes the change in trading volumes of BNB, MATIC, LTC and WBTC. This supports previous studies showing that investors in cryptocurrencies succumb to speculation rather than rational decisions based on gauging the movements of major market players and through social media, news, and other sources (Cagli, 2019; Cheah & Fry, 2015; Goczek & Skliarov, 2019). Similar behaviour is observed in cluster 2, where USDT affects the volume traded in USDC and DAI.

5. Discussion

In this section, the results from the empirical tests are summarized. Given that the combined market capitalization of cryptocurrencies is around $1.72 trillion, maintaining financial stability within the markets is crucial to ensuring the security and safety of investments. Understanding the dynamics between cryptocurrencies can empower investors to build diversified portfolios (Corbet et al., 2019). Although policymakers face difficulties regulating the decentralized cryptocurrency market, they can devise effective approaches, such as promoting initiatives to improve financial literacy regarding cryptocurrencies, to enhance outcomes. The author conducts this study to enhance understanding of price co-movements among crypto currencies, which are increasingly becoming a significant investment vehicle and a medium of exchange for economic transactions. The discussion of the findings from this multi-analytical study reveals answers to the research questions initiated earlier in the introduction.

(H_1) Do cryptocurrencies exhibit interdependencies in their price movements? The results of the Pearson *r* correlation matrices among the sample of twenty cryptos display a positive correlation in their returns, with no difference in behaviours between larger and smaller caps. These findings contradict the earlier studies that suggest price movements are stronger in larger market-cap cryptocurrencies. This can be observed as a change in investor behaviour in more recent times as compared to earlier studies where price data was taken from before the year 2019, as studied by Corbet et al. (2018) and Cagli (2019). This study also reveals that volatilities were positively correlated, but not as strongly as returns. Additionally, this study emphasizes that smaller market cap cryptos exhibit stronger correlations in volatilities among themselves than the larger market cap ones. Another finding indicates that stablecoins pegged to the dollar (USDT, USDC, and DAI) did not correlate highly with altcoins (BTC, BNB). Utility-based cryptos (LEO, TON, TRX, and SHIB) were majorly independent of any other cryptos for their returns and trading volumes. This research unveils variations in price fluctuations among various categories of cryptocurrencies, a level of specificity that contrasts with the discoveries of Liew et al. (2019), who observed that correlations among the top 100 cryptocurrencies were uniformly positive.

(H_2) How are changes in volume associated with crypto returns? The correlation matrices of the trading volumes showed higher correlations than those of the returns. The top three largest cryptos revealed high correlations (BTC, ETH, and USDT). The findings suggest that correlations in trading volume depend on the market cap size of cryptos and not on their functionality, supporting speculative investing and herding behaviours. Hence, when previous studies such as Cagli (2019) and Bouri et al. (2019) suggested that large cap cryptos have a stronger correlation, Cagli (2019) examined the return-volume relationship for Bitcoin and seven other altcoins, indicating bi-directional causality between trading volume and returns for Bitcoin. It suggests the advantages investors may gain from devising trading strategies based on trading volume. Bouri et al. (2019) proposed that trading volume Granger causes extreme negative and positive returns in the sample of seven cryptocurrencies examined.

(H_3) Does the crypto market index return reveal a high correlation to individual crypto prices? Mostly all cryptocurrencies from the sample of twenty exhibit very strong to strong positive correlations with the market returns, except for USDT, USDC, DAI, and LEO, indicating that altcoins were highly correlated but not stablecoins. The use of indices for stock markets has been common in conducting research related to price movements of stocks. The CCi30 index of cryptocurrencies has also been used by Kirsch (2021) to compare crypto indices to stock market indices. Previous studies are few that have employed the comparison of cryptocurrency indices with their individual returns, where Neslihanoglu (2021) used the CCi30 as a proxy for crypto market returns to compare with crypto price movements in pre-COVID during COVID times, justifying the use of the CCi30 as a predictor of crypto prices.

(H_4) Are there cryptocurrency clusters that exhibit high correlations in their price movements, and what factors determine their interconnectedness? The PCA analysis reveals majorly two highly correlated clusters, where one includes BTC, ETH, WBTC, XRP, SOL, BNB, ADA, DOT, MATIC, LTC, and BCH, and the other includes: USDT, USDC, DAI and LEO. The first cluster consists of large cap altcoins and some smaller cap cryptos, both altcoins and stablecoins. However, the second cluster includes stablecoins pegged to the US dollar. This study confirms the findings of Lorenzo and Arroyo (2022), who investigated associations among various clusters and suggested that clusters that exhibit similar characteristics could be determined. As investors gain a deeper understanding of the practical applications of cryptocurrencies, we notice a transition in their purchasing patterns, moving away from speculative behaviour towards a focus on utility-driven decisions. Very few studies have used the novel idea of clustering crypto-currencies using other techniques like wavelet coherence (Maiti, Vukovic, Krakovich, & Pandey, 2020).

(H_5) Which are the dominant cryptos, if any, that affect the prices of others? The study applies the Granger Causality test as the most appropriate test of causality pertinent to the cryptocurrencies. On returns and volumes, the study found some dominant cryptos that hold the power to influence others within their clusters. In cluster 1 for the variable of returns, both Binance (BNB) and Ripple (XRP) have a causal relationship with Bitcoin (BTC), Ethereum (ETH), MATIC, and Wrapped Bitcoin (WBTC). BNB has a causal relationship with Litecoin (LTC) with a one-day lag, whereas XRP and Bitcoin Cash (BCH) reveal a causal relationship for the two-day lag outcomes. For cluster 2 with the returns variable, Tether (USDT) was the most influential. Bitcoin (BTC) is the major influencer and Granger causing the change in BNB, MATIC, LTC, and WBTC trading volumes.

6. Conclusion

The results of this study aim to improve the understanding of interdependencies between a larger pool of cryptocurrencies that benefit seasoned and aspiring investors and users to make better-informed decisions. The observed correlation and causality in trading volumes as compared to those of returns and volatilities could primarily be attributed to public information as it becomes available. An investor could follow the influencer in the cluster and swap from one cryptocurrency to another to avoid losses or make a gain. The results of the clusters can be applied to other smaller cryptos with similar attributes and efficacies. The findings of the study partially support previous studies that indicate herding behaviours during unstable market or economic conditions. However, that forms just a small part of the findings of this study. The results presented herein are more comprehensive and provide numerous suggestions to those interested in cryptocurrency market transactions. The author thinks that the literature lacks studies including a broader range of cryptocurrencies, where most focus is on the price movements of large market-cap ones like Bitcoin and Ethereum. As markets mature and the knowledge and applicability of cryptos increase, studies encompassing other smaller cryptos will add value. It should be considered that the interconnectedness among cryptocurrencies can vary over time and may not be the same in the long term. The results of this study are based on the post-pandemic period between January 2022 and June 2023, and major shifts in socio-economic or technological changes could alter trends. However, sufficient care has been taken in selecting a larger group of cryptos within a reasonably appropriate period of time to draw conclusions about crypto interconnectedness.

The major limitation of the study is that the data examined is time dependent; however, this research used a sample post-covid, which is more applicable to recent times. However, as we progress into the future, certain changes in technological, financial, or even legal environments could impact the outcomes of this study. The study's sample comprises the top twenty cryptocurrencies, and as their acceptance and use grow in the future, it may expand to encompass a larger number of smaller cryptocurrencies. According to Coin Market Cap, currently there are around 23,000, and this study opens various avenues of future research that could incorporate larger sample sizes where statistical approaches could investigate a broader range of cryptos, as newer cryptocurrencies are continually being introduced. In conclusion, future studies could apply the results of this analysis to the canonical correlation analysis (CCA) to describe cross-covariance between clusters of comoving cryptos. The statistical exploratory approach, which reduces dimensionality, allows for the narrowing down of major variables with the highest correlation, a process that could inform future predictive research models.

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