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A DANCE OF CRYPTOCURRENCIES: CAUSALITY, VOLATILITY SPILLOVER, AND CO-INTEGRATION OF BITCOIN AND ETHEREUM

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Abstract

This study examines Bitcoin and Ethereum's dynamic interactions and causal relationships. Our research uses many advanced statistical and econometric methods. These include Augmented Dickey-Fuller (ADF) tests for stationarity, GARCH models for volatility, VAR models for multivariate analysis, Granger causality tests for predictive relationships, and co-integration analysis for long-term associations. Our study found significant skewness and kurtosis in both cryptocurrencies' return distributions, highlighting the need for specialized statistical methods. Bitcoin and Ethereum returns have a strong positive correlation, indicating their interdependence. The analysis of volatility spillover underscores their interdependence. Bitcoin exhibits volatility clustering and Ethereum's volatility is influenced by past shocks. Granger causality tests show a one-way relationship between Bitcoin and Ethereum. Co-integration analysis shows that the two entities have lasting relationships despite their instability. The above findings find use in risk management, portfolio diversification, trading strategies, and policy decisions in the ever-changing cryptocurrency market. Despite limitations, this study lays the groundwork for future cryptocurrency research. Risk managers, investors, academics, and policymakers can use these insights to improve their cryptocurrency strategies and decisions.

Keywords: Bitcoin, Ethereum, Volatility Spillover, Co-integration, Correlation Coefficient, GARCH.

INTRODUCTION

In the span of the last 13 years, cryptocurrencies have undergone a significant transformation, transitioning from a specialized technological concept aimed at facilitating peer-to-peer transactions to a financial asset category that is actively traded by a global user base comprising millions of individuals (Bommer, Milevoj, & Rana, 2023). Bitcoin, which was introduced in 2009 by an anonymous developer using the pseudonym Satoshi Nakamoto (Nakamoto, 2008), continues to hold the position of the most significant cryptocurrency in terms of market capitalization. The value of Bitcoin experienced a substantial increase, starting at $1 in February 2011 and reaching its highest point at $69,000 in November 2021 (Auer R. , Cornelli, Doerr, Frost, & Gambacorta, 2023). At the time of writing this introduction, the price of Bitcoin was $29,808 in October 2023. The global ownership of cryptocurrencies experienced a significant increase, with an estimated figure of more than 220 million individuals possessing a cryptocurrency in June 2021, marking a substantial rise from the 5 million recorded in 2016 (Auer R. , Cornelli, Doerr, Frost, & Gambacorta, 2023). The market for cryptocurrencies is growing rapidly to be a significant component of the global financial system (Gajardo, Kristjanpoller, & Minutolo, 2018). It is now hailed as a new asset class altogether (Corbet, Meegan, Larkin, Lucey, & Yarovaya, 2018). The market value of digital coins has increased

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exponentially, increasing from about $17.7 billion at the beginning of 2017 to more than $700 billion in the first months of 2018. The total market capitalization, as per a CoinMarketCap report on Forbes.com in March 2023 has crossed 1.2 trillion dollars (Hicks, 2023).

Cryptocurrencies have emerged as a significant driver of economic transformation since its inception (Bulut, 2018). Bitcoin and the blockchain technology that underpins it possess the potential to revolutionize the conventional financial services sector. (Morkunas, Paschen, & Boon, 2019). Cryptocurrencies such as Bitcoin and Ethereum have witnessed an unparalleled surge in value since 2017, accompanied by significant volatility (Dangi, 2020). This phenomenon has garnered increasing attention in various domains, including public discourse, regulatory frameworks, and the portfolios of investors (Nemeczek & Weiss, 2023) (García-Corral, Cordero-García, de Pablo-Valenciano, & Uribe-Toril, 2022). Recent cryptocurrencies like Ethereum, Ripple, Binance, dogecoin, and new memecoins are slowly chipping away at Bitcoin's share of the market value (Gerard, 2017). This shows that investors are taking a break from Bitcoin and looking into other cryptocurrencies. These alternatives, which generally use some of Bitcoin's ideas and technologies (like blockchain technology), have gotten a lot of attention and given cryptocurrency investors a lot of chances to make the most of their investments. This isn't surprising, since each of these other cryptocurrencies did better than Bitcoin in 2017, with returns ranging from 500% (Litecoin) to 36,000% (Ripple) compared to Bitcoin's 130% price increase (Ji, Bouri, Lau, & Roubaud, 2019). Even though cryptocurrencies are volatile by nature, middle-class investors and fund managers both see them as a class of assets that can be invested in and make good returns (Ji, Bouri, Lau, & Roubaud, 2019). Even though people are becoming more interested in putting money into alternative cryptocurrencies, it's interesting that we still don't know much about how the leading cryptocurrencies that have a market value of more than 10 billion USD and have high liquidity in terms of their returns and volatility work together. In fact, the short history of the cryptocurrency market has shown that the leading cryptocurrencies are not all the same when it comes to returns, volatility, and market value. It makes sense to think that Litecoin, which started in 2011 as a "fork" of Bitcoin, and Bitcoin itself are related (Gerard, 2017).

In fact, Fabian Nemeczek and Daniel Weiss conducted an empirical analysis employing data sourced from a German personal finance management application, wherein users create connections between their bank accounts and investment portfolios (Nemeczek & Weiss, 2023). Students, self-employed people, and young, male people are more likely to invest in crypto assets, according to the findings. Risk-takers and impatient people are more likely to invest. Most cryptocurrency owners have little financial advisory experience. Due to their high financial literacy, many people view it as too time-consuming and low-quality, opting for independent decision-making. After examining their consumption patterns, cryptocurrency investors spend more on travel, electronics, and food delivery than on healthcare (Nemeczek & Weiss, 2023). Currently, the fluctuating nature of cryptocurrency prices hinders their widespread adoption as a viable medium of exchange. Furthermore, cryptocurrencies are not utilized as a unit of account due to their inherent volatility. This volatility renders it impractical to establish a consistent price in a particular cryptocurrency or to employ cryptocurrencies as a benchmark for assessing the value of real economic transactions (Auer R. , Cornelli, Doerr,

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Frost, & Gambacorta, 2023). Crypto investors, who consider research in cryptocurrencies excessively time-consuming (Nemeczek & Weiss, 2023) would benefit greatly from more research on how volatility, dynamic connections and integration work in cryptocurrency markets. This would help them come up with investment and trading strategies that use a mix of leading cryptocurrencies in their portfolios. So, the goal of this study is to look at how connected these two large cryptocurrencies are by analyzing the volatility spillover between them.

The rest of the paper is structured as follows…

The next section titled, 'Research objectives' will be followed by 'Literature Review' which will reveal the latest updates in the field. This will be followed by 'Data, Data Preparation and Data Visual Representation' which will discuss the data source and data characteristics. After that, in the section titled 'Methodology/ Process', we will explain the steps and tools employed to achieve the results. For sake of simplicity, we will first explain the tool/ metric employed, give its significance, discuss the results obtained and finish with the interpretation of those results. This will be followed by an "Overall Discussion" of all results, followed by "Conclusion", "References" and "Appendix".

Research Objectives

1. To assess and analyze the volatility patterns exhibited by the returns of Bitcoin and Ethereum for investigating the clustering behaviour and persistence of these patterns over time via employment of GARCH and EGARCH models.
2. To examine the Granger causality relationship between the returns of Bitcoin and Ethereum to ascertain whether the historical returns of one cryptocurrency can serve as a predictor for the future returns of the other, while also identifying the direction of causality.
3. To investigate the interconnectedness between Bitcoin and Ethereum through the utilization of the Volatility Spillover Index, Volatility Spillover Coefficients, and the covariance matrix to provide insights into the extent of shared volatility between the two cryptocurrencies.
4. To investigate the existence of a sustained association, correlation and co-integration between the returns of Bitcoin and Ethereum via the application of the Spearman's Rank Correlation Coefficient, Johansen Co-integration test, which will provide insights into potential shared underlying factors.

To evaluate the risk management implications associated with volatility patterns and spillover effects in Bitcoin and Ethereum for elucidating strategies that investors and traders can employ to enhance risk management in their cryptocurrency portfolios.

LITERATURE REVIEW

Throughout the historical shift from barter-based economies to the adoption of monetary systems, individuals have endeavored to develop frameworks that facilitate logical methods of value exchange. The Greek philosopher Aristotle formulated four criteria (viz. durability,

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portability, divisibility and possessing of intrinsic value) to determine the characteristics of "good money" in order to facilitate the comparability of goods and services (Wang M. , 2020). When applied to cryptocurrencies, we find that Aristotle's two-thousand-year-old definition does not completely apply here, as only portability and divisibility apply to cryptocurrencies. In any case, cryptocurrencies have existed since before 2009 and continue to impact the realm of finance. A cryptocurrency refers to a form of digital currency that is safeguarded through the use of cryptographic means. In retrospect, individuals have been actively seeking alternative payment solutions for several decades throughout the course of history. During the 1990s, the emergence of eCash, developed by DigiCash Inc, marked a significant milestone in the realm of digital currencies, bearing resemblance to contemporary cryptocurrencies. Nevertheless, it failed to withstand the burst of the 2000 Internet bubble (Martino, Wang, Bellavitis, & DaSilva, 2020). The potential of cryptocurrency lies in its ability to provide a novel form of currency that is constructed upon blockchain technology and substantiated through cryptographic evidence rather than reliance on trust. The problem of dependency on a third party when utilizing a non-cash payment method was effectively resolved. Thus, using blockchain protocols, it's now possible to use cryptocurrencies to remove dependence on third parties, reduce costs, save time and make secure anonymous transactions (Deepika & Kaur, 2017).

Coming to Blockchain; the underlying technology which allows cryptocurrencies to do what they do, according to Narayanan et al (Narayanan, Bonneau, Felten, Miller, & Goldfeder, 2016), blockchain can be defined as an ever-expanding collection of records known as blocks, which are interconnected and safeguarded through cryptographic techniques. Every block is comprised of several components, including a hash pointer, which serves as a reference to the previous block, a link to the previous block, a timestamp indicating when the block was created, and transaction data associated with the block. The blockchain is responsible for ensuring the authenticity of the coins associated with each cryptocurrency. Blockchains are inherently designed to possess resistance against any form of data modification. A distributed ledger, commonly referred to as blockchain, is a transparent and decentralized system that effectively and durably documents transactions between two entities (Iansiti & Lakhani, 2017). A decentralized network, known as a peer-to-peer network, is responsible for overseeing and managing the blockchain system. This network operates collectively following a set of rules and guidelines, referred to as a protocol, to verify and validate newly created blocks. The blockchain, in turn, serves as a distributed ledger, enabling secure and transparent record-keeping (Chougule & Tulpule, 2021). Raval (year) highlights the inherent security of blockchains, emphasizing their status as a distributed computing framework characterized by a robust Byzantine fault tolerance mechanism. Furthermore, Raval underscores the successful attainment of decentralized consensus through the implementation of blockchain technology (Raval, 2016). Bitcoin (BTC) introduced by Satoshi Nakamoto (Nakamoto, 2008) represents the pioneering decentralized cryptocurrency, which was introduced in the year 2009 as open-source software (Sagona-Stophel, 2016). They described Bitcoin as a form of digital currency that operates in a decentralized manner, allowing users to engage in direct transactions on the peer-to-peer bitcoin network. This currency system does not rely on a central bank or an

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administrator, thereby eliminating the need for intermediaries. The verification of transactions is conducted by network nodes utilizing cryptographic techniques, and subsequently documented in a publicly accessible distributed ledger known as a blockchain. Bitcoins are generated through a process called mining, wherein individuals are rewarded for their computational efforts. These digital assets have the capability to be exchanged for various currencies, goods, and services (Velde, 2013). At present, it stands as the most widely adopted cryptocurrency (Auer R. , Cornelli, Doerr, Frost, & Gambacorta, 2023).

Ethereum (ETH) is classified as an Altcoin, a term used to encompass various alternative cryptocurrencies that exist alongside Bitcoin, denoting digital assets of different types (Yang, 2018). Additionally, it is a decentralized and open source blockchain that incorporates the capabilities of Smart Contract functionality, alongside its inherent native cryptocurrency. According to Bloomberg.com, Ethereum is widely recognized as the second-largest cryptocurrency in terms of market capitalization and market prices denominated in USD, following Bitcoin. The concept of Ethereum was introduced in 2013 by a programmer named Vitalik Buterin (Buterin, 2014). In 2014, the development of Ethereum was funded through a crowdfunding campaign. Subsequently, on July 30, 2015, the Ethereum network was launched, having pre-mined approximately 72 million coins (Tapscott & Tapscott, 2016). Since its inception, Ethereum has garnered significant attention in the realm of digital assets, achieving a record peak of $4,636.7 in November 2021. This growth is evidenced by its value surging from $11.41 in March 2016 to $1,814 in May 2022, as reported by Quandl.com. Cryptocurrency volatility is a major concern for all stakeholders. The occurrence of frequent fluctuations in cryptocurrency prices is a commonly observed phenomenon, which often perplexes individuals seeking to understand its underlying causes. The volatility of cryptocurrency prices is influenced by a multitude of factors. The Volatility Index, also referred to as the CBOE Volatility Index, is employed for the computation of volatility in trading assets within traditional markets. Given the nascent nature of cryptocurrencies, a definitive characterization of their volatility remains elusive (Khan & Hakami, 2022).

Li, X., Gan, K., & Zhou, Q. explain that a body of literature exists that examines cryptocurrencies, with a primary emphasis on the efficiency of the market, price dynamics, return distribution, and portfolio analysis (Li, Gan, & Zhou, 2023). In recent years, there has been an increasing focus on the interdependency structure and spillover effect of cryptocurrencies. This phenomenon can be categorized into two distinct branches. The initial branch of study focuses on examining the relationships and dynamics between cryptocurrencies and various other financial assets. In 2 studies conducted by Dyhrberg in 2016, it was determined that Bitcoin exhibits a hedging capacity comparable to that of gold as well as the US dollar (Dyhrberg, Hedging capabilities of bitcoin. Is it the virtual gold? , 2016) and (Dyhrberg, 2016). According to the study conducted by Chan et al., it was observed that Bitcoin demonstrates a significant ability to serve as an effective and robust hedge for major global stock indices (Chan, Le, & Wu, 2019). Similarly, Guesmi et al. discovered that short positions in the Bitcoin market can effectively mitigate investment risk across various financial assets (Guesmi, Saadi, Abid, & Ftiti, 2019). Nevertheless, the research conducted by Bouri et al. reveals that Bitcoin exhibits limited effectiveness as a hedging instrument (Bouri, Molnár,

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Azzi, Roubaud, & Hagfors, 2017). According to the findings of Selmi et al., it has been observed that both Bitcoin and gold possess the potential to function as safe havens during periods of significant volatility in oil prices (Selmi, Mensi, Hammoudeh, & Bouoiyour, 2018). In a similar vein, the research conducted by Urquhart and Zhang reveals that Bitcoin serves as a secure investment option during times of heightened volatility in foreign exchange markets (Urquhart & Zhang, 2019). According to the findings of Ji et al., Bitcoin exhibits a high degree of isolation from other financial assets (Ji, Bouri, Gupta, & Roubaud, 2018). According to the study conducted by Wang et al., it was determined that USD-pegged stablecoins exhibit superior risk diversification properties in comparison to gold-pegged stablecoins within the realm of traditional cryptocurrencies (Wang, Ma, & Wu, 2020).

The second branch of study focuses on analyzing the interconnectedness among various cryptocurrencies. Yi et al. use the VAR model to investigate volatility connectedness among 8 cryptocurrencies and construct a volatility connectedness network with 52 cryptocurrencies (Yi, Xu, & Wang, 2018). In their study, Ji et al. investigate the phenomenon of asymmetric return and volatility connectedness among a selection of six cryptocurrencies. This investigation is conducted through the utilization of the Vector Autoregressive (VAR) model (Ji, Bouri, Lau, & Roubaud, 2019). In their study, Antonakakis et al. employ a VAR model that incorporates time-varying parametric factors (referred to as TVP-FAVAR) to investigate the interconnectedness of returns among nine cryptocurrencies. Additionally, they construct a market factor using data from 45 cryptocurrencies (Antonakakis, Chatziantoniou, & Gabauer, 2019). In their study, Moratis utilizes the Bayesian Vector Autoregression (VAR) model to examine the spillover effects exhibited by the 30 most prominent cryptocurrencies (Moratis, 2021). The VAR model is employed by Aslanidis et al. in their investigation of the interdependence of returns and volatility spillovers within a set of 17 cryptocurrencies (Aslanidis, Bariviera, & Perez-Laborda, 2021). In their study, Kumar et al. utilize the Vector Autoregressive (VAR) model to examine the interdependencies in terms of both time and frequency between the returns and volatilities of a set of ten cryptocurrencies (Kumar, Iqbal, Mitra, Kristoufek, & Bouri, 2022). Moreover, the studies conducted by Koutmos (Koutmos, 2018) and Moratis (Moratis, 2021) reveal that Bitcoin plays a prominent role in generating spillover effects within the selected cryptocurrencies. In a study conducted by Katsiampa et al., it was discovered that there are reciprocal shock transmission effects observed between Bitcoin and Ethereum (Katsiampa, Corbet, & Lucey, 2019). Similarly, Xu et al. determined that Bitcoin and Ethereum serve as the primary recipients and emitters of systemic risk, respectively (Xu, Zhang, & Zhang, 2021). Slowly but gradually, the emphasis is increasing on examining the spillover effect amongst cryptocurrencies and other traditional or mainstream financial assets using either the VAR model (Corbet, Meegan, Larkin, Lucey, & Yarovaya, 2018) or its variations (Wang, Tang, Xie, & Chen, 2019) (Ghorbel & Jeribi, 2021) The crypto type of asset is a recently emerged and rapidly expanding category of assets. According to a recent report published by J.P. Morgan, it has been suggested that the price of Bitcoin has the potential to increase to a value exceeding $146,000 in the long run (Godbole, 2021). Furthermore, it is noteworthy that several merchants have begun to embrace the acceptance of cryptocurrency as a form of payment, exemplified by prominent entities such as Tesla and PayPal. There is a

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noticeable increase in scholarly literature examining the factors that determine cryptocurrency prices, as demonstrated by the works of Bhambhwani, Delikouras, and Korniotis (Bhambhwani, Delikouras, & Korniotis, 2019). Additionally, some research has been conducted on portfolio choice in relation to cryptocurrencies, as exemplified by the work of Bonaparte (Bonaparte, Time horizon and cryptocurrency ownership: Is crypto not speculative?., 2022). However, there remains a dearth of attention given to the creation of novel cryptocurrency indicators that can assist researchers and the business community in making informed decisions pertaining to cryptocurrencies (Bonaparte, 2023). As we saw, most of the research focuses only on just one or few indicators of volatility and interconnectedness. Also, concentrated attention on just Bitcoin and Ethereum, 2 of the most popular and most traded cryptocurrencies in the world, and how they perform the dance of volatility interconnectedness is not explored at a high degree. This study hopes to remedy this research gap by employing an extensive battery of tests to investigate the Causality, Volatility Spillover, and Co-integration between Bitcoin and Ethereum exclusively.

DATA, DATA PREPARATION & DATA VISUAL REPRESENTATION

The 2 large cryptocurrencies chosen for this study are Bitcoin and Ethereum. Bitcoin and Ethereum are among the most notable and extensively exchanged digital currencies within the marketplace. Cryptocurrency ecosystem participants play crucial roles and exert a considerable influence on the market dynamics at large (Adhami, Giudici, & Martinazzi, 2018) (Afilipoaie & Shortis, 2015). Consequently, an examination of the volatility spillover phenomenon between Bitcoin and Ethereum can yield significant findings regarding the interrelationships and transmission of effects within the cryptocurrency domain. Coinmarketcap.com supplies the daily closing prices of Bitcoin, Ethereum, Ripple, Tether, Litecoin, and Stellar, which previous researchers (Poongodi, Vijayakumar, & Chilamkurti, 2020), (Basilico & Johnsen, 2019), (Singh & Mittal, 2022) have found reliable. The daily price data for the 2 selected cryptocurrencies, Bitcoin and Ethereum, was taken from these sources. The temporal scope under consideration spans from January 1st, 2015, to December 31st, 2022. The process of data cleaning will be implemented through the utilization of Python code to address any potential issues such as data being absent, outliers, or errors. The utilization of Jupyter Notebook within the Anaconda Platform has been chosen for the aforementioned purpose. The downloaded data was saved in 2 separate .csv files (short for Comma Separated Values) named bitcoin_hist_data.csv & Ethereum_hist_data.csv which was then uploaded onto Jupyter Notebook. Both the files contained the following columns.

1. Date- date on which the row data was recorded.
2. Price- closing price of Bitcoin/ Ethereum.
3. Open- opening price of Bitcoin/ Ethereum
4. High- highest price of Bitcoin/ Ethereum for that date.
5. Low- lowest price of Bitcoin/ Ethereum for that date.
6. Vol.- Volume for Bitcoin/ Ethereum

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7. Change%- Percentage change in price for that date

There were 2921 entries/ rows for Bitcoin data and 2487 entries/ rows for Ethereum data. The difference is because Ethereum was launched officially on July 30, 2015, and regular data collection was available from March 10, 2016. The 2 files were then combined into a single dataframe for ease of operations. For this "inner join" operation was employed using date as index. So, we were left with 2487 rows as additional dates (from bitcoin data) before March 10, 2016, were ignored. So, now our dataframe had 2487 rows and 13 columns (date column was common).

This new dataframe was checked for missing data. None were found and thus the next step of calculation of daily returns for Bitcoin and Ethereum using their closing prices was undertaken. The method utilized for this was the ".pct_change" method in python. The technique computes the percentage variation between the present and antecedent elements in either a Series or DataFrame. Daily returns in cryptocurrency data refer to the percentage variation in the price of the digital currency between two consecutive days. The computation is executed through the division of the disparity between the present day's value and the value of the day prior by the value of the day prior.

Mathematical expression.

$$\text{Daily Return} = (\text{Price}_t - \text{Price}_{t-1}) / \text{Price}_{t-1}$$

where:

The variable Price_t represents the value of the asset in question at a specific point in time, namely the present day denoted as "t".

The variable Price_{t-1} represents the value of the asset at the time t-1, which corresponds to the preceding day.

Using the above, 2 new columns titled 'Bitcoin_Returns' & 'Ethereum_Returns' were calculated and added to the dataframe. These columns were populated for each date. Now the data is ready for further processing.

Consider some basic statistics of the data:

	Bitcoin_Close	Ethereum_Close	Bitcoin_Returns	Ethereum_Returns	Bitcoin_Realized_Volatility	Ethereum_Realized_Volatility
count	2459.000000	2459.000000	2459.000000	2459.000000	2459.000000	2459.000000
mean	15554.339772	870.708849	-0.000693	-0.000306	0.138430	0.196249
std	16739.609282	1132.082186	0.041016	0.057431	0.077091	0.100402
min	408.200000	6.700000	-0.203559	-0.227868	0.016642	0.047585
25%	3880.600000	144.995000	-0.018478	-0.028109	0.089225	0.135382
50%	8754.700000	295.810000	-0.001918	-0.000846	0.128507	0.175813
75%	20528.700000	1296.215000	0.014368	0.023199	0.169777	0.234631
max	67527.900000	4808.380000	0.644240	0.803336	0.711478	0.883589

It is clear that the mean returns for bitcoin and Ethereum are both negative, but they are more so for Bitcoin as compared to Ethereum. Also, Mean realized volatility of Ethereum is more

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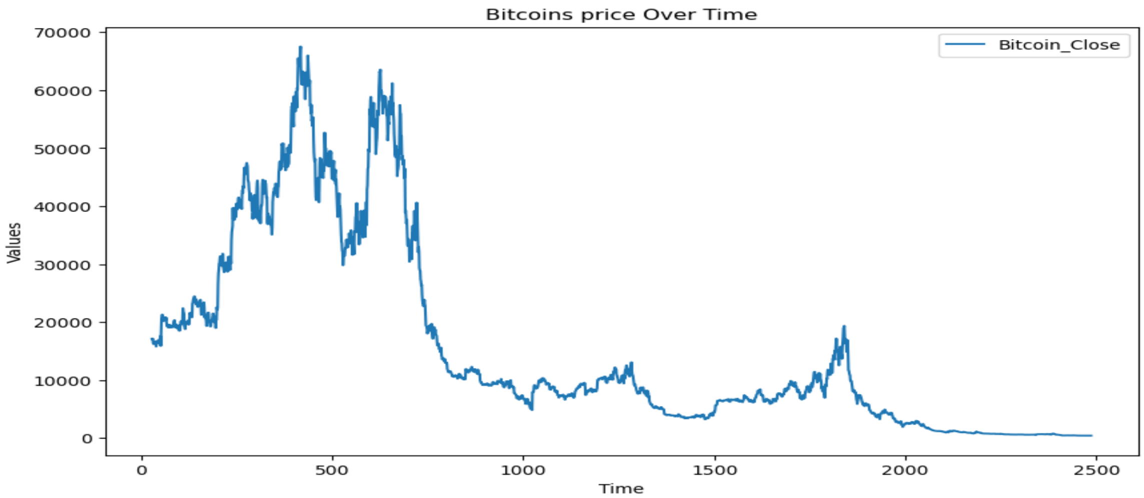
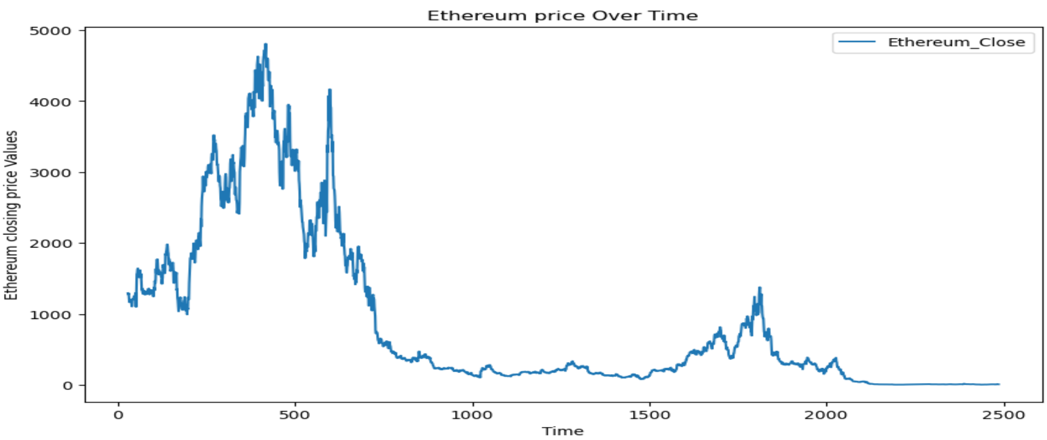
than that of Bitcoin, painting a picture that bitcoin is generally more stable than Ethereum. The minimum and maximum values also present a similar picture.

Let's take a look at the visual representation of data:





Comparison of closing prices of both cryptocurrencies over time:

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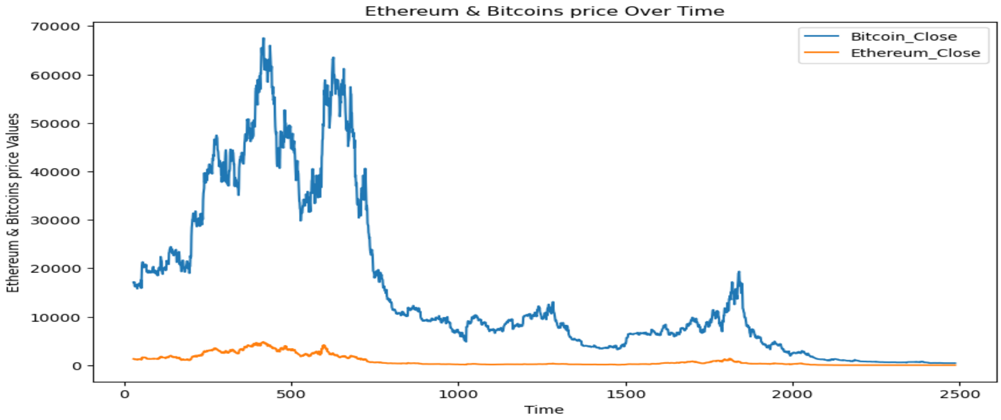
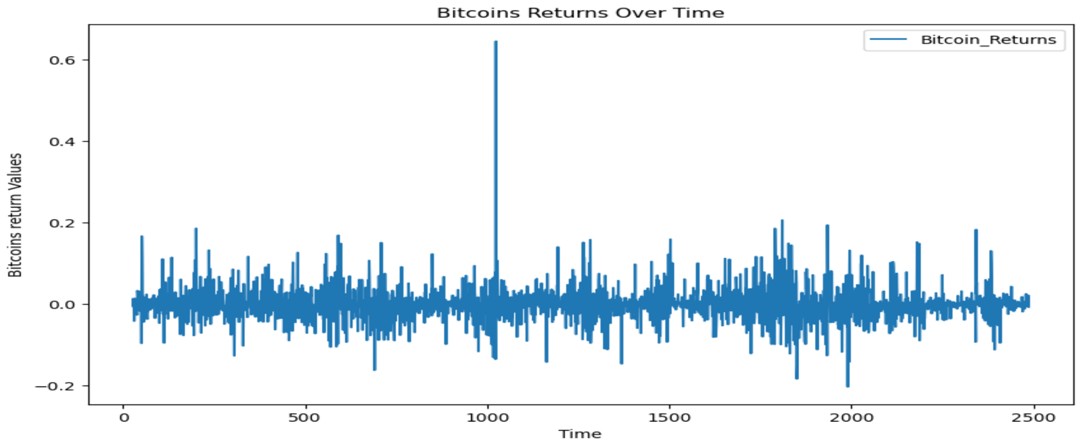
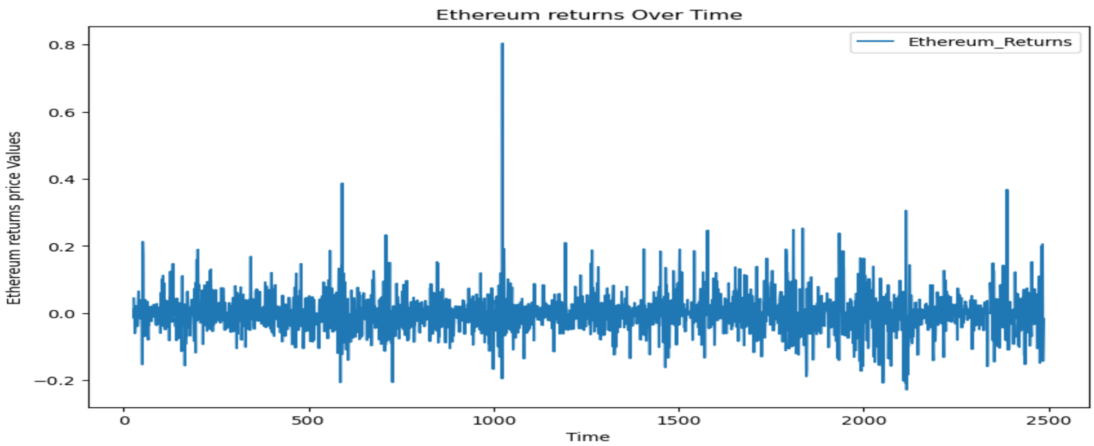


Bitcoin Returns:



Ethereum Returns:



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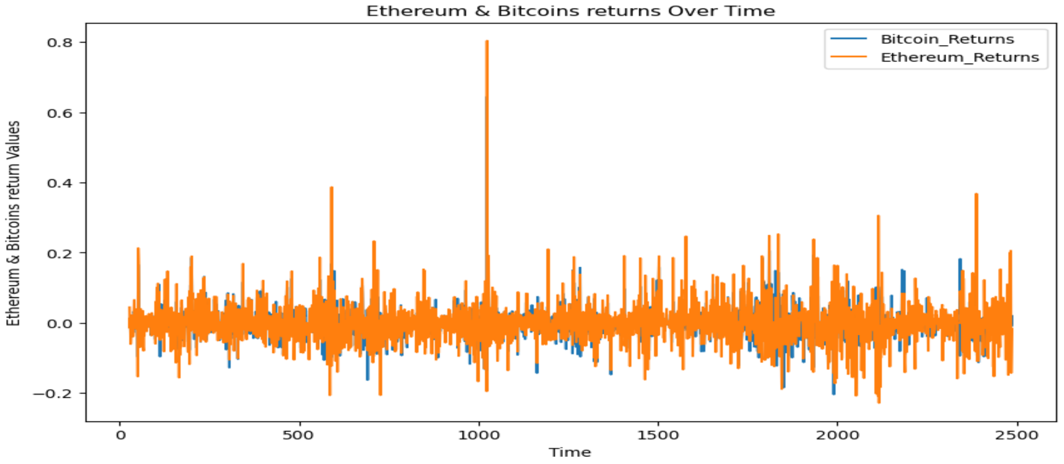
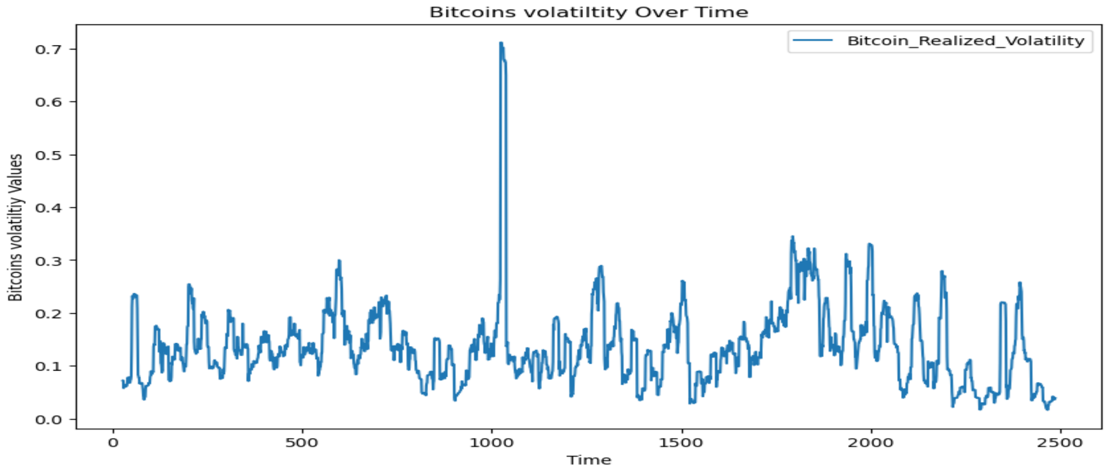
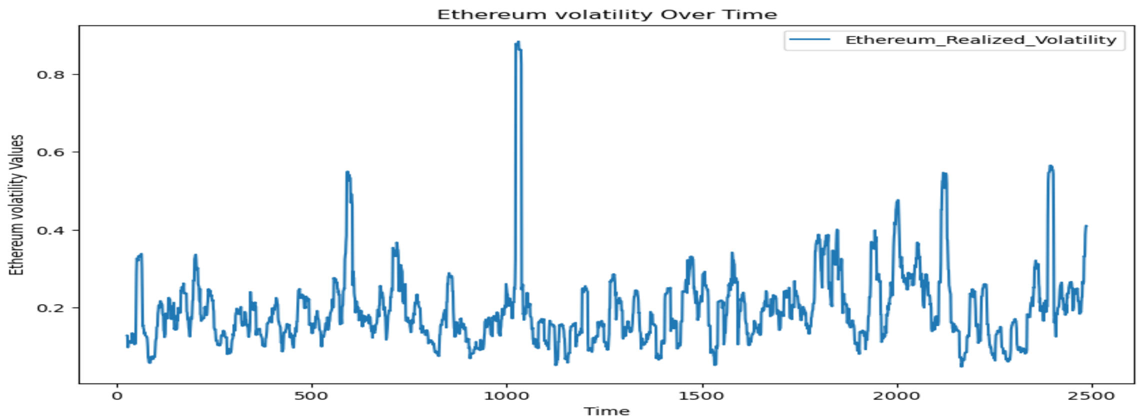
Returns of both currencies over time:



Bitcoin Volatility:



Ethereum Volatility:



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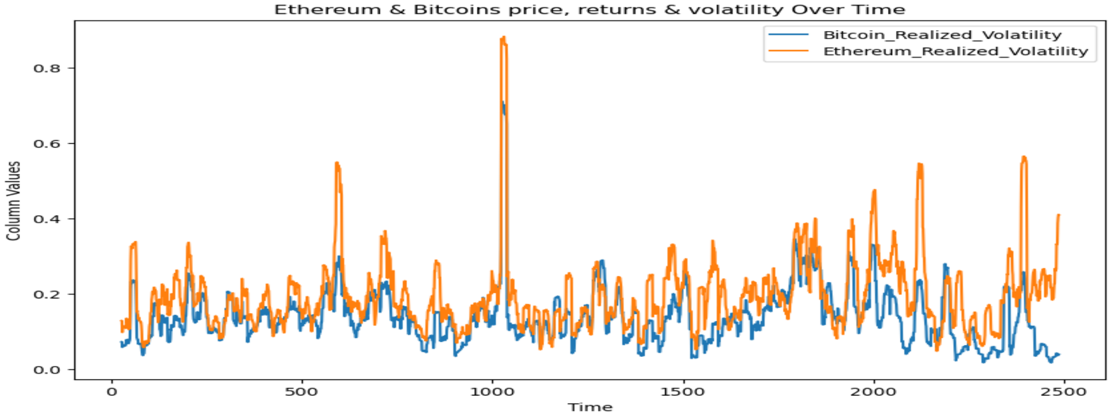
Bitcoin and Ethereum Volatility:



METHODOLOGY/ PROCESS:

After processing was done, then, the data was checked for stationarity.

The requirement to assess stationarity arises from multiple considerations:

1. The concept of stationarity holds significant importance in various statistical techniques and time series models as it serves as a fundamental assumption. Autoregressive Integrated Moving Average (ARIMA) models necessitate the data to be stationary to ensure precise forecasting and parameter estimation (Metes, 2005).
2. Non-stationary time series frequently display trends and seasonality, which may introduce analytical biases. Through the identification and elimination of such trends, it is possible to direct attention towards the fundamental stationary constituents, thereby enhancing the quality of discernment and prognostication (Sjö, 2008).
3. The notion of mean reversion serves as the foundation for numerous economic and financial theories, positing that a given series has a tendency to return to its average value over a period of time. The condition of stationarity is a necessary requirement for the phenomenon of mean reversion, thereby underscoring the significance of conducting stationarity tests on financial and economic data (Sjö, 2008).

For this purpose, the ADF test was used. Time series stationarity is tested using the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979), a popular statistical test. In time series analysis, stationarity implies that statistical characteristics like mean, variance, and autocovariance remain constant. The Augmented Dickey-Fuller (ADF) test determines time series stationarity. The test is designed to cater to the requirement of testing for stationarity by assessing the presence of a unit root in the given time series (Dickey & Fuller, 1979). The presence of a unit root in a series implies the existence of a stochastic trend, which in turn leads to the absence of stationarity. The ADF test is utilized to ascertain whether the process of differencing the series, with the aim of eliminating the trend, can render it stationary.

In this case, the hypotheses are as follows.

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$H0_{Bitcoin}$- Stationarity is absent in the Bitcoin Returns time series data.

$H1_{Bitcoin}$ - Stationarity is present in the Bitcoin Returns time series data.

$H0_{Ethereum}$- Stationarity is absent in the Ethereum Returns time series data.

$H1_{Ethereum}$- Stationarity is present in the Ethereum Returns time series data.

The results of the ADF test for our dataframe are as follows.

```
ADF test for Bitcoin Returns:
ADF Statistic: -34.55821780098068
p-value: 0.0
ADF test for Ethereum Returns:
ADF Statistic: -34.39558533034795
p-value: 0.0
```

The interpretation for the above results is as follows.

This study's ADF tests show Bitcoin Returns' stationarity. H1Bitcoin's stationarity alternative hypothesis is supported by the large negative ADF statistic of -34.55821780098068. A negative value contradicts the non-stationarity null hypothesis (H0Bitcoin), suggesting Bitcoin Returns are stationary. This conclusion is supported by 0.0 p-value. A negative ADF statistic is unlikely under non-stationarity due to the low p-value. This confirms dataset stationarity. That Bitcoin Returns is stable and predictable over time is important for time series analysis. This supports accurate statistical modeling and interpretations. The Augmented Dickey-Fuller (ADF) test used in this study suggests Ethereum Returns are stationary. Bitcoin Returns matches the negative ADF statistic of -34.39558533034795. This supports Ethereum's return series' stationarity (H1Ethereum replaces H0Ethereum). ADF size disproves non-stationarity. This strongly suggests Ethereum returns are stable. ADF's 0.0 p-value indicates statistical significance. The assumption of non-stationarity makes a negative ADF statistic unlikely.

Then the data was tested for normality using the Jarque- Bera test (Jarque & Bera, 1980). The Jarque-Bera test is a statistical tool utilized to evaluate the conformity of a given sample to a normal distribution. The analysis assesses the degree of asymmetry and peakedness of the dataset to determine deviations from the normal distribution. The JB test holds importance due to its capacity to furnish a rigorous statistical gauge of deviations from the normal distribution. The assessment derives a test statistic by utilizing measures of skewness and kurtosis, which is subsequently juxtaposed with a chi-squared distribution featuring two degrees of freedom. The attainment of a noteworthy p-value from the test implies proof against the null hypothesis of normality, thereby indicating that the data is improbable to conform to a normal distribution (Rana, Eshita, & Al Mamun, 2021).

In this case, The Hypotheses are as follows.

$H0_{Bitcoin}$- Normality is present in the Bitcoin Returns time series data.

$H1_{Bitcoin}$ - Normality is absent in the Bitcoin Returns time series data.

$H0_{Ethereum}$- Normality is present in the Ethereum Returns time series data.

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$H1_{Ethereum}$- Normality is absent in the Ethereum Returns time series data.

The results of the Jarque-Bera test for our dataframe are as follows.

```
Jarque-Bera test for Bitcoin Returns:
JB Statistic: 80028.33520007596
p-value: 0.0
Jarque-Bera test for Ethereum Returns:
JB Statistic: 39567.637526470135
p-value: 0.0
```

The interpretation of the above results is as follows:

1. Jarque-Bera test for Bitcoin Returns
   a. The JB statistic for Bitcoin returns is 80028.33520007596. Data deviates from a normal distribution as measured by the JB statistic. A large JB statistic indicates a significant deviation from the normal distribution.
   b. Jarque-Bera test significance is 0.0. If the data follows a normal distribution, the p-value indicates the likelihood of seeing the JB statistic. In this case, the p-value is extremely low, indicating that a JB statistic of such magnitude is unlikely under the normality assumption.
   c. We reject the null hypothesis ($H0_{Bitcoin}$) of normality for Bitcoin Returns in favor of alternative hypotheses ($H1_{Bitcoin}$).
2. Jarque-Bera test for Ethereum Returns
   a. Ethereum Returns' JB statistic: 39567.637526470135. Similar to Bitcoin returns, the JB statistic is large, indicating a significant deviation from the normal distribution.
   b. The Jarque-Bera test showed a p-value of 0.0 for Ethereum Returns. The extremely small p-value of the JB statistic indicates that such a statistic is unlikely under normality.
   c. We can reject the null hypothesis ($H0_{Ethereum}$) of normality for Ethereum Returns in favor of alternative hypotheses ($H1_{Ethereum}$).

In conclusion, the Jarque-Bera test shows that Bitcoin and Ethereum returns are not normally distributed. Asset returns may have skewness or kurtosis compared to a normal distribution. Normality-assuming statistical methods must account for deviation. Alternative modeling or conversions must be investigated for non-normal data. Skewness and kurtosis will be examined.

Consider the information about the skewness and kurtosis of the data.

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```
Skewness:
 Bitcoin_Close                      1.317055
Ethereum_Close                     1.559046
Bitcoin_Returns                    1.924417
Ethereum_Returns                   1.629439
Bitcoin_Realized_Volatility        2.536171
Ethereum_Realized_Volatility       2.631018
dtype: float64
```

```
Kurtosis:
 Bitcoin_Close                      0.542940
Ethereum_Close                     1.392322
Bitcoin_Returns                   27.329413
Ethereum_Returns                  19.146753
Bitcoin_Realized_Volatility       14.595053
Ethereum_Realized_Volatility      12.447430
dtype: float64
```

Skewness and kurtosis are statistical parameters that offer valuable insights into the configuration and dispersion of a given dataset (Groeneveld & Meeden, 1984).

Skewness is a statistical measure used to quantify the degree of asymmetry present in each distribution. A positive value of skewness denotes a distribution with an extended right tail, whereas a negative value of skewness denotes a longer left tail.

Drawing from the provided skewness values:

- The skewness value of Bitcoin_Close is 1.317055, which suggests that the distribution is moderately skewed towards the right.
- The Ethereum_Close variable exhibits a skewness value of 1.559046, which suggests a distribution that is moderately skewed to the right.
- The skewness of Bitcoin_Returns is 1.924417, indicating a significant right-skewness.
- The variable Ethereum_Returns exhibits a skewness value of 1.629439, which suggests that its distribution is moderately skewed to the right.
- The skewness of Bitcoin_Realized_Volatility is 2.536171, which suggests a distribution that is notably skewed to the right.
- The skewness of Ethereum_Realized_Volatility is 2.631018, which suggests a distribution that is notably skewed to the right.

Bitcoin and Ethereum variables always have right-skewness. Moderate skewness in Bitcoin and Ethereum's closing price distributions suggests longer right tails and occasional high prices. Right-skewness suggests both cryptocurrencies favor outliers or extreme positive returns. This information is important for risk assessments and investment decisions because it shows large gains and high fluctuations in asset values. Also, Bitcoin and Ethereum volatility distributions are skewed. Extremely high positive volatility outliers show that digital currencies are dynamic. Understanding market dynamics requires understanding these variables' skewness. Policymakers and investors need this knowledge to navigate cryptocurrency.

Kurtosis is a statistical measure that quantifies the degree of concentration of data in the tails of a distribution. A greater kurtosis value signifies a greater degree of concentration of data in the tails and a possible increase in the heaviness of the tails in comparison to a normal distribution.

Drawing from the provided kurtosis values:

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- The kurtosis value of Bitcoin_Close is 0.542940, indicating a distribution that is relatively light-tailed.
- The kurtosis value of Ethereum_Close is 1.392322, suggesting a distribution with a slightly heavier tail.
- The kurtosis value of Bitcoin_Returns is 27.329413, which suggests a distribution with heavy tails and the existence of outliers.
- The kurtosis value of Ethereum_Returns is 19.146753, which suggests that the distribution of returns is characterized by heavy tails and the possible existence of outliers.
- The kurtosis value of 14.595053 for Bitcoin_Realized_Volatility suggests that the distribution is moderately heavy-tailed.
- The Ethereum_Realized_Volatility exhibits a kurtosis value of 12.447430, which suggests a distribution that is moderately heavy-tailed.

Kurtosis shows cryptocurrency market dynamics variables. Bitcoin closing prices have kurtosis of 0.542940, indicating low tail heaviness and few extreme values. The kurtosis of Ethereum closing prices is 1.392322, indicating a heavier tails distribution. This suggests a slightly higher extreme price event probability. However, Bitcoin and Ethereum's investment performance is most intriguing. Outliers and tail clustering are indicated by kurtosis values of 27.329413 and 19.146753. This suggests that cryptocurrency returns may vary greatly, requiring risk management. Investors should also note Bitcoin and Ethereum's moderately heavy-tailed volatilities. Kurtosis is 14.595053 and 12.447430 for these distributions. Market participants must prepare for sudden and significant changes. The cryptocurrency market is volatile, requiring thorough risk assessment and flexible investment strategies.

Next comes the test of heteroskedasticity. We used Ljung-Box Q test (Verbeek, 2017) to test for Autocorrelation and corroborated the same with the ARCH-LM test (Engle, 1982).

The Ljung-Box Q test is used to determine whether autocorrelation is present in a time series. The correlation between a variable and its lagged values is known as autocorrelation. The test determines whether a model still contains any significant residual autocorrelation after taking into account the anticipated randomness. The test assists in determining whether the observed autocorrelation is statistically significant by examining the Q-statistic and related p-values. Commonly, time series models are checked for accuracy using the Ljung-Box Q test, which also looks for any missed patterns or serial dependencies (Verbeek, 2017)s.

The ARCH-LM test, on the other hand, focuses on identifying conditional heteroskedasticity in a time series, specifically the presence of ARCH effects. The volatility clustering, or ARCH effect, is the tendency for large or small returns to be followed by similarly sized returns. The ARCH-LM test determines whether a model's squared residuals show meaningful autocorrelation. To ascertain whether the ARCH effects are statistically significant, it measures the test statistic and associated p-value. The test helps capture and model time-varying volatility, which is essential for risk management and asset pricing in financial analysis (Engle, 1982).

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In time series analysis, both tests have significant functions. The Ljung-Box Q test aids in locating any residual autocorrelation that might point to poor modelling or misspecification. It ensures that the model accurately depicts the data's underlying temporal structure. The ARCH-LM test, on the other hand, offers information about the presence of conditional heteroskedasticity, which is crucial for modelling volatility and risk estimation. It helps increase the precision of volatility models and deepen our understanding of the dynamics of financial markets by identifying ARCH effects. They make it possible for analysts and researchers to evaluate the presence of conditional heteroskedasticity and autocorrelation, respectively. By performing these tests, one can enhance risk management tactics, model specifications, and gain a deeper understanding of the characteristics of financial and economic data.

Our received Ljung-Box Q-test statistics are as follows:

```
Ljung-Box Q-test for Bitcoin Returns
Q-statistics:
[5.16780293]
p-values:
[0.0230093]
```

```
Ljung-Box Q-test for Ethereum Returns
Q-statistics:
[5.57003087]
p-values:
[0.01827044]
```

Interpretation of Ljung-Box Q-test results:

The Ljung-Box Q-test detects autocorrelation in time series residuals. The test assumes no residual autocorrelation. We reject the null hypothesis and find residual autocorrelation if the p-value is less than a significance level (e.g., 0.05).

Bitcoin return Q-statistics are 5.16780293 and 0.0230093. Bitcoin returns show autocorrelation since the p-value is below the significance level. This suggests that residuals are dependent or serially correlated, indicating that past Bitcoin returns can predict future values.

Q-statistic 5.57003087, p-value 0.01827044, Ethereum returns. Like Bitcoin returns, Ethereum returns show autocorrelation with a p-value below the significance level. This suggests that past Ethereum returns can predict future values.

The Ljung-Box Q-test shows autocorrelation in Bitcoin and Ethereum returns. This suggests that these cryptocurrencies' returns are not completely independent and have a pattern.

Our received ARCH-LM statistics are as follows:

```
ARCH-LM Test for Bitcoin Returns
Test Statistic- Bitcoin: 7.4748443240324285
Bitcoin p-value: 0.006256697499515185
```

```
ARCH-LM Test for Ethereum Returns
Test Statistic- Ethereum: 21.932217130441906
Ethereum p-value: 2.824520524266802e-06
```

Interpretation of the ARCH-LM test results:

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The ARCH-LM test shows heteroskedasticity in Bitcoin returns. The test statistic of 7.4748 and p-value of 0.0063 indicate that Bitcoin returns are significantly volatile. Bitcoin returns are heteroskedastic. The test result suggests that Bitcoin volatility is clustered. This means that Bitcoin price changes are not uniform and exhibit volatility clustering, where periods of high volatility are followed by periods of high volatility and vice versa. Bitcoin return heteroskedasticity can affect risk management, portfolio allocation, and trading strategies. It implies that Bitcoin risk fluctuates, so investors and traders must take volatility into account when making decisions. It may also indicate market dynamics that affect Bitcoin return volatility. The ARCH-LM test shows heteroskedasticity in Bitcoin returns, emphasizing the importance of volatility patterns and risk management. Ethereum returns show heteroskedasticity according to ARCH-LM. Ethereum has a test statistic of 21.9322 and a very small p-value of 2.8245e-06. This suggests Ethereum returns are highly volatile. Heteroskedasticity in Ethereum returns means returns vary over time. The test shows that Ethereum return volatility clusters. Ethereum's high volatility tends to be followed by other high volatility and vice versa. Heteroskedasticity affects Ethereum trading, risk management, and portfolio allocation. It emphasizes the importance of considering volatility when investing. It also implies that market dynamics affect Ethereum return volatility.

The ARCH-LM test for Ethereum returns shows heteroskedasticity, emphasizing the need to understand and manage Ethereum market volatility. Although, we must add that the heteroskedasticity is more strongly visible in Ethereum as compared to Bitcoin. It could be because Bitcoin, as a cryptocurrency, is more matured as compared to Ethereum. The volatility profile of cryptocurrencies does keep changing over time. In any case, this is grounds for further research as it is beyond the scope of this paper.After determining the stationarity, normality and heteroskedasticity, we will now employ 2 GARCH family models onto our data. The 2 GARCH family models are:

1) GARCH
2) E-GARCH

As usual, we will first begin with the purpose and significance of each model, followed by the results and their interpretation.

1) GARCH

Purpose and significance:

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model (Bollerslev, 1986) is a popular econometric model that accounts for heteroskedasticity, or time series data volatility. GARCH models model volatility dynamics over time, unlike linear regression models. It helps assess volatility clustering, leverage effects, and shock persistence in financial and economic data. The GARCH model quantifies risk and future observation uncertainty by modeling data conditional variance. Finance, economics, and risk management use it. This is used in portfolio optimization, option pricing, risk assessment, volatility forecasting, and value-at-risk calculations. Students and professionals can better assess risk and return by using the

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GARCH model in financial and economic analysis. Overall, the GARCH model improves risk management, decision-making, and financial analysis by understanding and formulating data volatility over time. The subject's widespread use and varied applications show its importance in academia and industry.

GARCH (1,1) model results:

Results for GARCH (1,1) model implemented on Bitcoin data.

Volatility Model

	coef	std err	t	P>|t|	95.0% Conf. Int.
omega	1.6653e-04	1.746e-04	0.954	0.340	[-1.758e-04,5.088e-04]
alpha[1]	0.2000	5.123e-02	3.904	9.471e-05	[9.959e-02, 0.300]
beta[1]	0.7000	0.157	4.464	8.026e-06	[0.393, 1.007]

Covariance estimator: robust

Interpretation:

The Bitcoin dataset GARCH model analysis reveals estimated coefficients and statistical significance. This analysis interprets the results and discusses Bitcoin's volatility dynamics.

1. The coefficient for omega (ω) is estimated at 1.6653e-04. The baseline or long-term average volatility of Bitcoin returns may not affect volatility dynamics, as the coefficient's p-value (0.340) is insignificant. Thus, Bitcoin volatility patterns are not explained by the constant term variable omega.
2. The estimated alpha (α) coefficient is 0.2000. Estimated coefficient p-value (9.471e-05) is statistically significant due to its small magnitude. The squared residuals from previous periods, which represent prior disturbances, affect Bitcoin's volatility. The positive alpha coefficient suggests that Bitcoin return volatility clusters, with high volatility periods followed by high volatility periods.
3. The beta (β) coefficient is estimated at 0.7000, with a p-value of 8.026e-06 indicating statistical significance. The above suggests that Bitcoin's lagged conditional variance, which measures its past instability, affects its current volatility. A positively oriented beta coefficient indicates leverage effect, where high volatility is followed by high volatility and vice versa.

Results for GARCH (1,1) model implemented on Ethereum data.

Volatility Model

	coef	std err	t	P>|t|	95.0% Conf. Int.
omega	3.2958e-04	1.195e-04	2.757	5.835e-03	[9.527e-05,5.639e-04]
alpha[1]	0.2388	6.820e-02	3.502	4.617e-04	[0.105, 0.373]
beta[1]	0.6845	7.755e-02	8.827	1.076e-18	[0.533, 0.837]

Covariance estimator: robust

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Interpretation:

The findings of the GARCH model analysis on Ethereum data offer valuable insights into the estimated coefficients and their statistical significance.

1. The coefficient for omega (ω) is estimated to be 3.2958e-04. At 5% significance, the analysis's p-value (0.005835) is significant. The baseline or long-term average volatility of Ethereum returns appears to affect volatility dynamics. Ethereum returns' baseline volatility affects its volatility dynamics, as shown by a positive omega coefficient.
2. The estimated alpha (α) coefficient is 0.2388. The statistical test p-value is 4.617e-04, indicating statistical significance. The squared residuals from previous periods, which represent past shocks, appear to influence Ethereum volatility. Ethereum's volatility clusters, with consecutive periods of high volatility, according to its positive alpha coefficient.
3. The beta coefficient is estimated at 0.6845, with a p-value of 1.076e-18 indicating statistical significance. The above suggests that Ethereum's lagged conditional variance, which measures its volatility in the past, affects its current volatility. A positive beta coefficient indicates a leverage effect, where periods of high volatility are followed by similarly high volatility.
4. The GARCH model analysis of Ethereum aligns with current knowledge of its volatility dynamics. The nonzero omega coefficient indicates a baseline volatility level, which matches Ethereum's cryptocurrency and blockchain platform volatility. Ethereum's alpha coefficient suggests clustering, a common feature of highly volatile assets like cryptocurrencies. The large beta coefficient confirms a leverage effect, where previous volatility affects subsequent volatility.

2) EGARCH

Purpose and significance:

Asymmetry is added to volatility dynamics in the EGARCH model, a GARCH variant. Asymmetric volatility response to shocks in financial time series data is modeled in this study. The EGARCH model addresses volatility clustering and leverage effects in financial markets (Sen & Sarkar, 1981). When high volatility is followed by low volatility, volatility clustering occurs. Leverage effects affect volatility's response to up and down shocks. The EGARCH model simplifies leverage effects' magnitude and significance by directly interpreting coefficients in terms of conditional volatility's logarithmic transformation. By capturing how positive and negative shocks affect future volatility, the EGARCH model accurately depicts financial time series dynamics. The EGARCH model captures volatility's asymmetry, which is crucial for risk management and option pricing. The essential financial risk management computations Value-at-Risk (VaR) and Expected Shortfall (ES) are improved by this method. The EGARCH model addresses option price volatility skew or smile. Markets expect volatility asymmetry. Last, the EGARCH model models asymmetric volatility dynamics, including leverage and volatility clustering. Risk management and option pricing applications benefit

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from this more complete and accurate financial time series data representation. Asymmetry in the EGARCH model improves volatility prediction, financial market risk assessment, and decision-making.

EGARCH (1,1) model results:

Results for EGARCH (1,1) model implemented on Bitcoin data

```
                           Volatility Model
=========================================================================
                 coef    std err          t      P>|t|  95.0% Conf. Int.
-------------------------------------------------------------------------
omega         -0.3751  9.180e-02     -4.086  4.388e-05 [ -0.555, -0.195]
alpha[1]       0.3645  6.331e-02      5.758  8.501e-09 [  0.240,  0.489]
beta[1]        0.9380  1.443e-02     64.978      0.000 [  0.910,  0.966]
=========================================================================

Covariance estimator: robust
```

Interpretation:

- The utilization of the EGARCH (Exponential Generalized Autoregressive Conditional Heteroskedasticity) model on Bitcoin data has yielded significant findings regarding the volatility dynamics of Bitcoin.
- The coefficient "omega" (-0.3751) represents the EGARCH model's intercept term. The statement implies a consistent element in the conditional variance equation. In this case, the negative value indicates statistically significant Bitcoin return volatility.
- Historical squared residuals, which represent volatility shocks, affect the present conditional variance through the parameter "alpha [1]" at 0.3645. A statistically significant positive value indicates that positive volatility shocks affect future volatility, clustering volatility. This is consistent with Bitcoin returns, which often show periods of high volatility followed by further high volatility.
- The coefficient "beta [1]" with a value of 0.9380 represents the previous conditional variance's effect on the present variance. The statement quantifies volatility's persistence and responsiveness to its historical values. The high and statistically significant value suggests volatility clustering because previous volatility levels positively affect current volatility.

Results for EGARCH (1,1) model implemented on Ethereum data.

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Volatility Model

	coef	std err	t	P>|t|	95.0% Conf. Int.
omega	-0.6110	0.152	-4.028	5.617e-05	[-0.908, -0.314]
alpha[1]	0.3935	7.097e-02	5.544	2.953e-08	[0.254, 0.533]
beta[1]	0.8911	2.633e-02	33.841	4.841e-251	[0.839, 0.943]

Covariance estimator: robust

Interpretation:

- The utilization of the EGARCH (Exponential Generalized Autoregressive Conditional Heteroskedasticity) model on Ethereum data has yielded outcomes that offer valuable perspectives on the volatility dynamics of Ethereum.
- The coefficient "omega" (-0.6110) represents the EGARCH model's intercept term. The statement implies a consistent conditional variance equation element. In this case, a negative value indicates statistically significant Ethereum return volatility.
- The parameter "alpha [1]" (0.3935) measures how previous squared residuals, which represent unexpected volatility changes, affect the current conditional variance. A statistically significant positive value indicates that positive volatility shocks persist in affecting future volatility, producing volatility clustering. This matches Ethereum returns, which show periods of high volatility followed by periods of rising volatility.
- The previous conditional variance influences the present conditional variance through the coefficient "beta [1]" at 0.8911. The statement indicates long-term volatility and its reactivity to past values. The high and statistically significant value suggests volatility clustering due to a strong positive relationship between past and present volatility.

After studying Bitcoin and Ethereum volatility dynamics with GARCH & EGARCH, we analyze volatility spillover. To do this, a VAR model was built. The Vector Autoregression (VAR) model (Zivot & Wang, 2006) enables the evaluation of the dynamic interdependence between the returns of Bitcoin and Ethereum. Coefficient estimation and significance analysis can determine if volatility shocks in one cryptocurrency affect another's volatility. This analysis helps understand Bitcoin-Ethereum volatility spillovers' magnitude and direction. It reveals their volatility dynamics' interrelationships and plausible interdependencies.

Results of the Vector Autoregression Model:

No. of Equations:	2.00000	BIC:	-12.7406
Nobs:	2458.00	HQIC:	-12.7496
Log likelihood:	8706.13	FPE:	2.88846e-06
AIC:	-12.7548	Det(Omega_mle):	2.88142e-06

Correlation matrix of residuals

	Bitcoin_Returns	Ethereum_Returns
Bitcoin_Returns	1.000000	0.690632
Ethereum_Returns	0.690632	1.000000

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Results for equation Bitcoin_Returns

	coefficient	std. error	t-stat	prob
const	-0.000727	0.000827	-0.879	0.380
L1.Bitcoin_Returns	-0.037654	0.027893	-1.350	0.177
L1.Ethereum_Returns	-0.008106	0.019921	-0.407	0.684

Results for equation Ethereum_Returns

	coefficient	std. error	t-stat	prob
const	-0.000412	0.001155	-0.357	0.721
L1.Bitcoin_Returns	-0.136395	0.038954	-3.501	0.000
L1.Ethereum_Returns	0.020323	0.027820	0.731	0.465

Interpretation of the results:

- The utilization of the VAR model for the purpose of analyzing volatility spillover between Bitcoin and Ethereum has yielded outcomes that offer valuable perspectives on the interconnection between the two digital currencies.
- The present study finds no statistically significant impact of the lagged values of Bitcoin and Ethereum returns on current Bitcoin returns with regard to Bitcoin returns. The regression analysis indicates a marginal adverse impact on Bitcoin returns from lagged Ethereum returns, albeit lacking statistical significance. This suggests that the present returns of Bitcoin are not significantly impacted by the past returns of Ethereum.
- Conversely, with regards to Ethereum yields, the delayed Bitcoin yields exhibit a noteworthy adverse influence, implying a transfer of volatility from Bitcoin to Ethereum. An increase of one unit in the lagged Bitcoin returns results in a reduction of present Ethereum returns. The findings indicate that the volatility of Bitcoin exerts a significant impact on the volatility of Ethereum, and fluctuations in the prices of Bitcoin may plausibly affect the prices of Ethereum.
- The correlation matrix of the residuals reveals a positive correlation between the unexplained variations, or residuals, of the returns of Bitcoin and Ethereum. The aforementioned statement implies the presence of a certain level of co-movement or shared volatility factors between the two aforementioned cryptocurrencies.

Next, Variance Decomposition Analysis was performed using the Impulse Response Function (IRF) on the VAR model results (Iorngurum & Nwaobi, 2021). The Impulse Response Function (IRF) quantifies the impact of exogenous perturbations or unexpected changes in one variable on the response of other variables in the model over a specified period. The volatility spillover effects between Bitcoin and Ethereum can be analyzed by plotting the Impulse Response Function (IRF), which provides valuable insights. The plot shows how each variable affects the predicted volatility of the others. The provided information shows how much each variable's volatility is accounted for by its own innovations compared to the other variables in the model. The above data helps analyze volatility spillover by determining how much Bitcoin or Ethereum perturbations affect the alternative cryptocurrency. The above statement sheds light on the two assets' interdependence and volatility transmission. Plot analysis can reveal the

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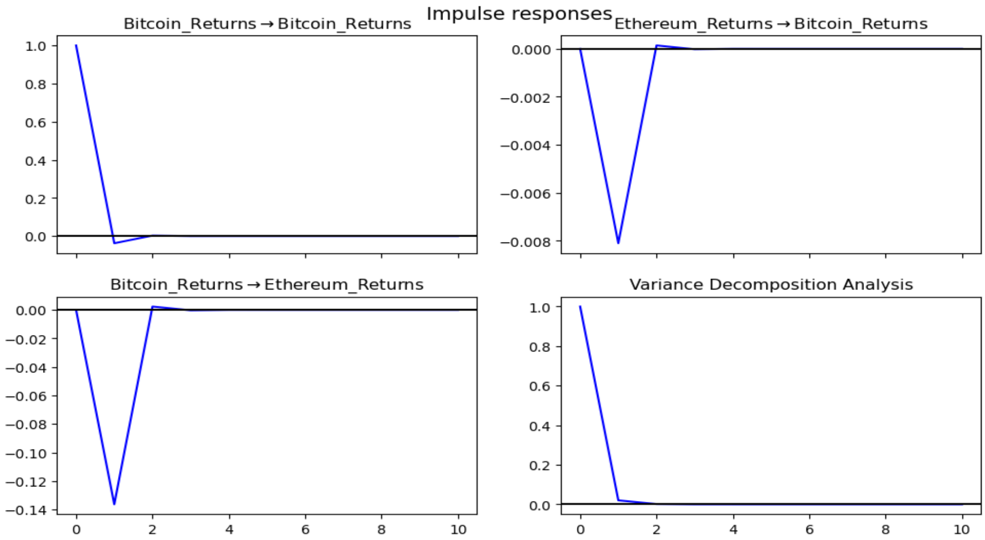
dynamic response of variables to external stimuli and identify periods when one variable's volatility affects another. This study helps understand Bitcoin and Ethereum volatility spillover mechanisms, guiding investment, risk management, and portfolio diversification strategies.

Results:



Our previous analysis matches these results. IRA followed Variance Decomposition. Impulse Response Analysis reveals dynamic interrelationships and temporal disturbances for volatility spillover analysis. A shock in one variable can affect other variables' future values, revealing volatility spillover effects. It measures shock-induced variable reactions and their duration. Variable volatility spillover effects can be measured in magnitude and duration.

Dynamically understanding volatility spillovers makes it useful. The statement discusses shock propagation and system variable volatility. Impulse responses show which variables are most affected by exogenous disturbances and track volatility spillovers.

It also evaluates volatility spillover policy and risk management. Shock simulations and analysis help policymakers and market participants manage volatility spillover. It measures variable dynamics and transmission mechanisms to understand financial market volatility's interdependencies and contagion effects.

IRA results:

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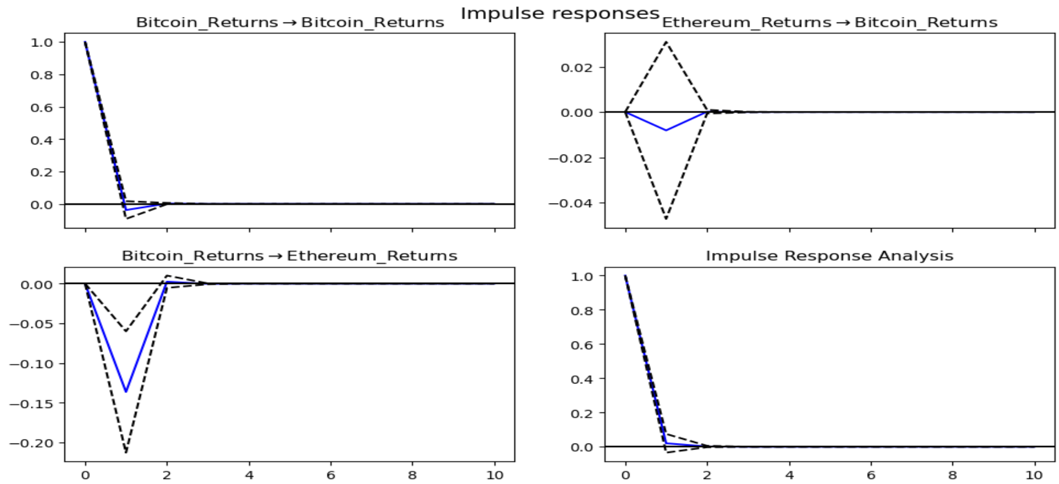

This was followed by Granger Causality Test to check if there is a statistically significant causality relationship between Bitcoin and Ethereum. It determines whether one time series variable predicts or causes another. This method evaluates causal relationships in time series. The test determines how well past values of a variable predict future values of another (Konya, 2004). It shows variable sequences and causal relationships, making it important. Through statistical analysis of test results, researchers can determine significance and whether a variable can predict another, proving a causal relationship. The above examination is widely used in economics, finance, social sciences, and engineering to examine causal relationships. It has many uses. This approach helps researchers analyze relationship direction and strength, evaluate predictive models, validate economic theories, and guide decision-making. Granger Causality analysis in finance can assess the predictive power of past asset returns on future asset returns. Portfolio allocation and risk management strategies can benefit from this.

Granger Causality Test results:

Test statistic	Critical value	p-value	df	Test statistic	Critical value	p-value	df
12.26	3.843	0.000	(1, 4910)	0.1656	3.843	0.684	(1, 4910)

Granger causality F-test. H_0: Bitcoin_Returns does not Granger-cause Ethereum_Returns. Conclusion: reject H_0 at 5% significance level.

Granger causality F-test. H_0: Ethereum_Returns does not Granger-cause Bitcoin_Returns. Conclusion: fail to reject H_0 at 5% significance level.

Granger Causality Test Results Interpretation:

Granger Causality tests show whether Bitcoin Returns and Ethereum Returns are causally

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related.

The null hypothesis (H0) in the hypothesis test for Granger causality between Bitcoin Returns and Ethereum Returns states that there is no causal relationship. At 5% significance, the null hypothesis is rejected because the test statistic of 12.26 exceeds the critical value of 3.843. According to the Granger causality test, Bitcoin returns affect Ethereum returns. Historical Bitcoin Returns may predict Ethereum Returns.

Ethereum Returns and Bitcoin Returns have different Granger causality results. Ethereum Returns do not cause Bitcoin Returns, according to H0. The test statistic falls below the 3.843 critical value at 5% significance. Null hypothesis cannot be rejected, suggesting there is insufficient evidence to claim Ethereum Returns Granger-causes Bitcoin Returns. In other words, past Ethereum Returns values seem to have little impact on future Bitcoin Returns.

Bitcoin Returns affect Ethereum Returns, but Ethereum Returns do not affect Bitcoin Returns. Granger causality refers to statistical predictability and information content, not a causal mechanism. Next, we perform the Johansen Co-integration test (Johansen, 1988) on our data. The Johansen Co-integration test is essential for volatility spillover analysis because it assesses the long-term relationship between time series variables, especially volatility dynamics. Volatility spillover occurs when sudden and significant volatility fluctuations spread to another variable (Konya, 2004).

Johansen Co-integration tests the equilibrium of variables over time. This test determines if multiple variables move together in volatility in volatility spillover analysis. If the test is positive, the variables are co-integrated over time, meaning disturbances in one may affect others' volatility. This suggests volatility spillover effects, where one asset's volatility affects another's. Testing for co-integration reveals volatility interdependencies and transmission mechanisms across variables. This data is essential for portfolio management, risk assessment, and financial market hedging.

Johansen Co-integration test results:

```
Eigenvalues:
[0.01128209 0.00223186]
```

```
Critical Values:
[[13.4294 15.4943 19.9349]
 [ 2.7055  3.8415  6.6349]]
```

Johansen Co-integration test results Interpretation:

Test results showed eigenvalues [0.01128209, 0.00223186]. The eigenvalues reveal the system's co-integrating vector count. Dual eigenvalues indicate two co-integrating relationships between variables. Critical values come from the matrix [[13.4294, 15.4943, 19.9349], [2.7055, 3.8415, 6.6349]]. Critical values are essential for assessing test results' statistical significance. By comparing eigenvalues and critical values, co-integration can be confirmed and its significance assessed. Analysis of volatility spillover variables revealed two co-integrating relationships. In long-term balance, perturbations in one variable may affect the instability of others. The statement implies volatility spillover, where one variable's volatility

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affects others. The Johansen Co-integration test is essential for volatility spillover dynamics analysis and risk management strategy development. Volatility interdependencies and transmission mechanisms teach portfolio diversification, hedging, and risk assessment.

Volatility Spillover Calculation:

This was followed by an attempt to quantify the volatility spillover using the volatility spillover index and volatility spillover coefficient.

Volatility Spillover Index:

The Volatility Spillover Index measures volatility transmission between two variables. The above statement measures volatility transmission between variables. Zero means no volatility spillover or transmission, and 1 means full volatility spillover or transmission.

Formula:

$$\text{Volatility Spillover Index}=\frac{(Sum\ of\ squared\ residuals\ of\ dependent\ variable)}{(sum\ of\ squared\ residuals\ of\ total\ model)}$$

Volatility Spillover Coefficient:

The Volatility Spillover Coefficient measures how much one variable affects another, indicating its strength. The proportion of volatility shocks caused by previous values of another variable that affect one variable is measured above. Volatility Spillover Coefficient ranges from 0 to positive infinity. Zero indicates no spillover effect, while higher values indicate a stronger spillover effect from X to Y.

Formula:

$$\text{Volatility Spillover Coefficient}=\frac{Covariance(X_{t-1},Y_t)}{Variance(X_{t-1})}$$

Here, $Covariance(X_{t-1}, Y_t)$ denotes the covariation existing between the past observation of variable X (X_{t-1}) and the present observation of variable Y (Y_t).

Results:

```
Volatility Spillover Index: 0.9644865109787503
Volatility Spillover Coefficients: 0.6906321663039696
```

Interpretation:

The findings of the analysis on volatility spillover reveal a Volatility Spillover Index of 0.9644865109787503 and Volatility Spillover Coefficients of 0.6906321663039696.

The Volatility Spillover Index measures volatility transmission or spillover between variables. This index value of 0.9644865109787503 indicates significant volatility spillover, meaning changes in one variable affect the volatility of the other. They indicate volatility spillover intensity. The coefficient value of 0.6906321663039696 indicates moderate spillover, meaning changes in one variable significantly affect the volatility of the other.

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When using volatility spillover analysis, the results indicate a significant volatility transfer between variables. The proposition states that each variable's oscillations significantly affect the other's volatility. The data is crucial for risk mitigation, portfolio optimization, and financial market interdependence and transmission.

Pearson's Correlation Coefficient:

We then applied Pearson's Correlation Coefficient to our data. When studying volatility spillover, the correlation coefficient is useful. It measures linear relationships between variables, like asset volatility. The interdependence of volatilities can be determined by measuring their magnitude and direction. A robust positive correlation suggests volatility spillover, where changes in one asset's volatility are often accompanied by similar changes in the other. However, a low or negative correlation reduces volatility spillover, suggesting the two assets may have different volatility patterns.

Results:

```
Correlation coefficient: 0.7494149928807461
```

Interpretation:

Bitcoin and Ethereum volatilities are positively correlated with a correlation coefficient of 0.7494. The observation suggests a strong volatility spillover between the two assets. Bitcoin volatility is likely to increase Ethereum volatility, and vice versa. Bitcoin and Ethereum's volatility dynamics are correlated, suggesting interdependence and interconnectedness. The statement implies that asset volatility affects other asset volatility. This must be considered when analyzing volatility spillover and developing Bitcoin and Ethereum risk management strategies.

Spearman's Rank-Order Correlation Coefficient:

Pearson's Correlation Coefficient is a reliable statistical analysis of two variables. When researching cryptocurrencies like Bitcoin and Ethereum, this method's assumptions of linearity, normality, and non-consideration of time dependency do not apply to our data, which is not linearly related, has a normal distribution, and is time dependent. Even if we find a strong correlation, misinterpretation is likely. We must run Spearman's Rank-Order Correlation Coefficient to fix this.The Spearman correlation of ranks is one of the most famous nonparametric procedures (Zar, 1972). The rank correlation coefficient, r, is usually expressed as

$$r_s = 1 - 6\sum\frac{d^2}{(n^3-n)} \quad \text{(Zar, 1972)} \qquad (1.1)$$

In this context, "n" represents the quantity of measurements conducted for each of the two variables involved in the correlation analysis. $\sum d^2 = \sum_{i=1}^{n} d_i^2$ and d_i is the ranked difference which refers to the disparity in rankings between the i^{th} measurements of the two variates (Zar, 1972). The measure being referred to is a non-parametric method used to evaluate the magnitude and direction of monotonic associations between two variables. The method does

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not make assumptions about linearity and exhibits resilience to outliers. Considering the departure from normality in the returns of cryptocurrencies, the utilization of Spearman's rank-order correlation may offer an alternative viewpoint (Gauthier, 2001).

Spearman's Rank-Order Correlation Coefficient Results for Bitcoin and Ethereum Returns data

```
Spearman's Rank-Order Correlation Coefficient (ρ): 0.6667368307062667
P-Value: 4.90219305e-316
```

```
The correlation is statistically significant.
```

Interpretation of Spearman's Rank-Order Correlation Coefficient Results for Bitcoin and Ethereum Returns Data

The ρ (Rho) value of 0.667 suggests a strong positive correlation between Bitcoin and Ethereum returns. The returns of Bitcoin and Ethereum are positively correlated, meaning that when one cryptocurrency rises, the other rises too. The positive coefficient indicates a positive relationship between the returns of one cryptocurrency and the other, suggesting that an increase in one usually increases the other. This discovery is significant and suggests a positive return correlation between the two assets. A very small p-value (4.90219305e-316) indicates that the correlation is statistically significant. This implies that the correlation is unlikely to be random. However, it provides strong evidence that Bitcoin and Ethereum returns are correlated. Investors, traders, and portfolio managers must understand the strong correlation between Bitcoin and Ethereum returns. This suggests that fluctuations in one cryptocurrency's returns may predict the trajectory of another. This information is useful for Bitcoin and Ethereum portfolio diversification and risk management. The study shows that Bitcoin and Ethereum returns are highly correlated, indicating significant co-movement. This supports the overall focus of our study and shows how these assets' price fluctuations are interconnected.

Spearman's Rank-Order Correlation Coefficient Results for Bitcoin and Ethereum Returns data

```
Spearman's Rank-Order Correlation Coefficient (ρ): 0.6256411992747748
P-Value: 2.743471764290006e-267
```

```
The correlation is statistically significant.
```

Interpretation of Spearman's Rank-Order Correlation Coefficient Results for Bitcoin and Ethereum Realized Volatility Data

The ρ (Rho) coefficient of 0.626 suggests a strong positive correlation between Bitcoin and Ethereum volatility.

Simply put, when Bitcoin volatility rises, Ethereum volatility rises, and vice versa. A positive coefficient indicates that the second cryptocurrency will move in the same direction as the first when its realized volatility rises. This discovery is significant and suggests similar volatility

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patterns for these two assets. The extreme low p-value (2.743471764290006e-267) suggests that the correlation is highly significant. This implies that the correlation is unlikely to be random. However, this study provides strong evidence that Bitcoin and Ethereum volatilities are correlated. Understanding the strong correlation between Bitcoin and Ethereum volatilities is essential for risk management and trading strategy development. This suggests that increasing volatility in one cryptocurrency often increases volatility in the other. Traders and investors must consider this relationship when choosing these assets. The study confirms that Bitcoin and Ethereum co-move when considering their volatility. This observation supports your study's central finding that these assets are linked by volatility as well as returns. These findings add significant value to the findings of the Pearson's Correlation Coefficient. We will consider the Spearman's Rank Correlation Coefficient for further analysis pertaining to our study.

GARCH (1,1) parameter and conditional volatility analysis:

Further we attempted to gain access to the estimated parameters and conditional volatilities of the Bivariate GARCH (1,1) model fitted onto the Bitcoin and Ethereum data. These are essential for comprehending the volatility dynamics of these two digital currencies.

Results:

```
Estimated Parameters:
 mu           0.140824
omega        0.000177
alpha[1]     0.200000
beta[1]      0.779999
Name: params, dtype: float64
```

```
Conditional Volatilities:
 [0.09501099 0.09028828 0.08646266 ... 0.17497118 0.19426945 0.21019692]
```

Interpretation:

The GARCH (1,1) model's estimated parameters offer insights into the volatility dynamics of the two cryptocurrencies as follows:

- According to the analysis, the calculated value for the constant mean (mu) is 0.140824. This denotes the anticipated level of volatility for Bitcoin and Ethereum over an extended period of time.
- According to the analysis, the calculated value for the constant term (omega) is 0.000177. The intercept term in the GARCH model captures the volatility level that is averaged over a long period of time. A diminutive numerical output implies that the model anticipates a comparably subdued level of volatility in the absence of recent exogenous perturbations.
- The coefficient alpha [1] was estimated to be 0.200000. The aforementioned parameter is designed to measure the influence of previously computed squared residuals (ARCH term) on the current conditional volatility. A coefficient of 0.2 signifies that the present volatility calculation incorporates 20% of the squared residuals' historical impact.

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- The point estimate for the coefficient beta [1] is 0.779999. The aforementioned parameter is designed to measure the influence of previous conditional volatility, specifically in relation to the GARCH term, on the present level of volatility. The numerical value of 0.779999 denotes that the present calculation of volatility retains 77.9999% of the impact of past conditional volatility.
- The conditional volatilities denote the assessed volatility estimates for individual cryptocurrencies across varying temporal intervals. The aforementioned values, which are [0.09501099, 0.09028828, 0.08646266, ..., 0.17497118, 0.19426945, 0.21019692], serve as indicators of the dynamic nature of volatility over time. Each of these values corresponds to a particular time period and represents an estimation of volatility. The aforementioned estimates are derived through the utilization of historical data and the estimated parameters of the GARCH (1,1) model.

GARCH (1,1) parameter and conditional volatility analysis:

Next, the covariance between Bitcoin and Ethereum's conditional volatilities is calculated and assessed. Additionally, the covariance matrix is standardized for volatility spillover analysis. The goal is to use volatility spillover analysis to determine the correlation between Bitcoin and Ethereum's conditional volatilities. By computing and standardizing the covariance matrix, the code helps analyze how volatility shocks or changes in one cryptocurrency affect another. Quantitative methods allow analysis of Bitcoin-Ethereum volatility spillover. This analysis is crucial to understanding cryptocurrency market interdependence and risk dynamics.

Results:

```
Covariance Test:
 [[1.00040683 1.00040683]
 [1.00040683 1.00040683]]
```

Interpretation:

The matrix of covariance shows Bitcoin and Ethereum volatilities under conditional conditions. Each matrix element represents two variables' covariance. Both the top-left and top-right elements represent the covariance between Bitcoin's volatility and its own and Ethereum's volatility, respectively. The bottom-left and bottom-right elements represent Ethereum's volatility covariance with Bitcoin and its own volatility, respectively. Volatility spillover analysis suggests that the covariance matrix is essential for understanding the two cryptocurrencies' relationship. The covariance values indicate how cooperative two variables' volatility patterns are. The covariance values of 1.00040683 show a strong positive linear association and significant co-movement between Bitcoin and Ethereum volatilities.

The covariance values.

- The variance of each cryptocurrency's volatility is represented by the diagonal entries located at the top-left and bottom-right positions. A value in proximity to 1 denotes a comparatively elevated level of volatility for both Bitcoin and Ethereum.

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- The elements located outside the main diagonal of the matrix, specifically those in the upper-right and lower-left quadrants, denote the degree of covariance that exists between the volatility of Bitcoin and Ethereum. The numerical value of 1.00040683 indicates a robust positive covariance, implying that fluctuations in volatility within one cryptocurrency are typically accompanied by corresponding fluctuations in the volatility of the other cryptocurrency.

The volatility spillover analysis shows a strong correlation and interconnectedness between Bitcoin and Ethereum volatility trends. Volatility spillover effects occur when one cryptocurrency's volatility shocks another. The discovery helps explain Bitcoin-Ethereum interdependence and risk dynamics. It implies that one cryptocurrency's volatility may affect the other's volatility and risk exposure.

Index measure for the relative contribution of each cryptocurrency's shocks to the total volatility:

Using a VAR model, we tried to calculate the volatility spillover index between the 2 cryptocurrencies. The objective of this code is to furnish a numerical gauge of volatility spillover, thereby enabling an evaluation of the extent to which alterations in volatility in a particular cryptocurrency affect the volatility of the other.

Result:

```
[[0.20480518 0.19773476]
 [0.19773476 0.39972531]]
```

Interpretation:

This matrix offers insights into the extent to which volatility spillover occurs between different cryptocurrencies, as viewed through the lens of volatility spillover analysis.

- The numerical entry situated at the upper-leftmost position, specifically 0.20480518, denotes the ratio of the transmission of volatility from Bitcoin to Bitcoin itself. The aforementioned statement suggests that approximately 20.48% of Bitcoin's volatility can be attributed to its internal shocks or the volatility experienced in previous periods.
- The proportion of volatility spillover from Ethereum to Ethereum itself is represented by the value located in the bottom-right position, which is 0.39972531. The aforementioned statement suggests that Ethereum's internal shocks or previous volatility account for roughly 39.97% of its overall volatility.
- The numerical value located in the upper-right quadrant, specifically 0.19773476, denotes the ratio of the transmission of volatility from Bitcoin to Ethereum. This suggests that approximately 19.77% of Ethereum's volatility can be attributed to the impact of shocks or fluctuations in Bitcoin.
- The numerical value located in the lower-left quadrant, specifically 0.19773476, denotes the ratio of the transfer of volatility from Ethereum to Bitcoin. This implies that

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approximately 19.77% of the volatility exhibited by Bitcoin can be ascribed to perturbations or fluctuations in Ethereum.

The spillover index values offer valuable insights into the respective impacts of the shocks or volatility of individual cryptocurrencies on the overall volatility of Bitcoin and Ethereum. The data suggests a noteworthy level of interdependence between Bitcoin and Ethereum, with both digital currencies exerting a substantial influence on each other's volatility.

OVERALL DISCUSSION

The Augmented Dickey-Fuller (ADF) test confirms Bitcoin and Ethereum return stationarity, which is crucial. Stationarity is crucial in time series analysis because it ensures statistical properties like mean and variance remain constant over time. Stability is crucial in modeling and forecasting, especially in finance, where precise predictions are crucial. Both cryptocurrencies show stationarity, suggesting that historical data patterns may predict future movements, which is significant for investors and analysts. Stationarity ensures data statistical properties remain stable over time, making predictive analytics reliable. Stability is crucial in financial modeling because accurate predictions aid decision-making. The JB test for Bitcoin and Ethereum returns rejects the null hypothesis, indicating a deviation from normal distribution. JB statistics and low p-values show that returns deviate from normality. Financial modeling typically assumes normality. However, these findings suggest caution. Extreme events, which are important in finance, are more likely to occur when deviation from normality is assumed. Risk management strategies should be adjusted to anticipate and respond to unexpected market fluctuations to address atypical situations. The lack of normality in cryptocurrencies makes applying conventional financial models difficult. Researchers need advanced statistical methods to handle non-normal data distributions. Skewness and kurtosis reveal return distribution shape. An elongated right tail with a positive skewness value indicates higher risk and potential positive returns. Heavy tails, which indicate more extreme events, are indicated by kurtosis values that significantly exceed 3. The cryptocurrency market is known for its volatility, which explains its heavy tail. Investors must consider these factors when planning risk management. Skewness and kurtosis reveal return distribution asymmetry and tail risk. Understanding these characteristics is essential for risk assessment and mitigation in the dynamic world of cryptocurrencies.

The Ljung-Box Q Test and ARCH LM Test show autocorrelation and heteroskedasticity in Bitcoin and Ethereum returns. The Ljung-Box Q test shows residual autocorrelation, indicating return patterns. The historical performance of both cryptocurrencies suggests that past returns may predict future values, implying predictability. However, the level of predictability may be uncertain, requiring advanced modeling methods to effectively exploit this data. Understanding autocorrelations can help investors develop trading algorithms and make better decisions. However, heteroskedasticity in Bitcoin and Ethereum returns indicates that volatility is not uniform. Clusters of high volatility are followed by periods of similar volatility. This clustering phenomenon must be acknowledged for risk management to work. Investors must be aware that market conditions can change quickly, requiring dynamic strategies to adapt.

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Autocorrelation analysis unveils the enduring nature of trends in cryptocurrency prices, thereby offering valuable insights for traders. Nevertheless, it is important to note that a trading strategy based solely on historical data may not effectively account for abrupt market fluctuations. Thus, it is crucial to adopt a well-rounded approach that incorporates various factors in order to mitigate potential risks and maximize trading outcomes. The presence of heteroskedasticity highlights the significance of implementing dynamic risk management strategies. The ability to adjust strategies in response to the clustering of volatility is a valuable skill for finance professionals operating in a dynamic and evolving cryptocurrency market.

The GARCH and EGARCH models illuminate these cryptocurrencies' volatility dynamics. GARCH coefficients reveal much. Positive alpha coefficients indicate consistent volatility. Periods of high volatility tend to be followed by periods of comparable volatility, supporting clustering. Beta coefficients above 0 indicate the leverage effect, where high volatility is followed by high volatility. These findings support the market's inherent tendency to repeat high-activity periods. Due to their focus on volatility patterns, GARCH models are essential for cryptocurrency analysis. The ability to capture clustering and leverage effects helps traders make informed trading decisions and understand market behavior. EGARCH models are comprehensive and nuanced. Both scenarios have negative intercepts, indicating inherent volatility even without external disturbances. Positive alpha coefficients indicate that past volatility shocks affect future volatility asymmetrically. Positive beta coefficients indicate that high volatility lasts. The above findings show that cryptocurrency markets have irregular, asymmetric, and persistent volatility. The Vector Autoregressive (VAR) model shows unidirectional volatility spillover effects from Bitcoin to Ethereum. The VAR model shows a one-way causality from Bitcoin to Ethereum, highlighting Bitcoin's market dominance. However, Ethereum's lack of impact on Bitcoin's returns suggests Bitcoin's autonomy. Portfolio diversification and risk management require understanding these directional influences. The VAR (Vector Autoregression) model shows how major cryptocurrencies interact. Investors should diversify their portfolios to reduce spillover risks and manage cryptocurrency market volatility. Granger causality tests support the one-way influence relationship between Bitcoin and Ethereum returns. Granger causality analysis provides nuanced understanding. The impact of Bitcoin on Ethereum suggests a correlation between Bitcoin's historical returns and Ethereum's predictive ability. The predictive association shows how popular cryptocurrencies are linked. However, Ethereum's lack of influence on Bitcoin shows market behavior, highlighting these cryptocurrencies' unique dynamics. Granger causality analysis illuminates cryptocurrency temporal associations, improving our understanding of market leadership dynamics. Understanding these dynamics is essential for cryptocurrency market strategy.

The existence of two eigenvalues in the Johansen co-integration test indicates the presence of two co-integrating relationships between Bitcoin and Ethereum. The identification of co-integrating vectors between Bitcoin and Ethereum implies the existence of enduring associations between the two cryptocurrencies. Although the specific details of these relationships are not provided, their presence suggests a potential interconnectedness that may be influenced by market-wide factors that affect both cryptocurrencies in a similar manner. This observation indicates that there are shared long-term trends between these two

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cryptocurrencies. A comprehensive grasp of co-integration is imperative in the context of portfolio diversification and risk management. The high correlation coefficient between Bitcoin and Ethereum volatilities suggests a strong positive correlation. This implies that one cryptocurrency's volatility usually reflects the other's. Both Bitcoin and Ethereum Returns and Realized Volatility data show a statistically significant positive correlation. The correlation between these digital assets is crucial to understanding their interconnectedness and influence. A strong correlation suggests Bitcoin and Ethereum prices, returns, and volatilities move together. Diversification across asset classes reduces risks associated with correlated assets, making it essential for cryptocurrency investment management.The covariance matrix shows a strong positive linear and statistically significant correlation between Bitcoin and Ethereum volatilities. The covariance matrix shows intensity and direction of co-movement. A strong positive linear relationship has a covariance value around 1. Our high covariance suggests that one cryptocurrency's volatility shocks affect the other. Bitcoin and Ethereum's risk spillover and interdependence are shown here. This suggests that their volatility patterns are highly interconnected. The covariance values reveal Bitcoin and Ethereum co-movements. These common trends must be understood by investors to build a well-rounded and diversified portfolio.

Bitcoin and Ethereum volatility spillover index. The results indicate that one cryptocurrency's volatility affects another's and that both have a significant reciprocal effect. The high spillover indices show how interconnected major cryptocurrencies are. Our Volatility Spillover Index shows Bitcoin and Ethereum volatility moving together. Spillover coefficients measure how much one cryptocurrency shocks affect another's volatility. This context's coefficients quantify variable interdependence, aiding risk assessment and portfolio management. Investors should be aware of this interdependence and adapt their strategies to market dynamics. Large spillover indices show how interdependent major cryptocurrencies are. Investors must monitor this interdependence and adapt their strategies to market dynamics. Individual cryptocurrency shocks affect market volatility as shown by the spillover index. Bitcoin and Ethereum have high self-spillover, indicating internal issues cause their volatility. Significant volatility influences suggest they are risk-connected.

Importantly,

a. The aforementioned statement suggests that approximately 20.48% of Bitcoin's volatility can be attributed to its internal shocks or the volatility experienced in previous periods.

b. The aforementioned statement suggests that Ethereum's internal shocks or previous volatility account for roughly 39.97% of its overall volatility.

c. Approximately 19.77% of Ethereum's volatility can be attributed to the impact of shocks or fluctuations in Bitcoin.

d. Approximately 19.77% of the volatility exhibited by Bitcoin can be ascribed to perturbations or fluctuations in Ethereum.

These insights possess significant value not only for individuals in academia but also for

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investors, traders, and policymakers alike. Comprehending the intricate nuances of these relationships is imperative within the dynamic and interconnected realm of cryptocurrencies. The utilization of this approach facilitates the development of resilient investment strategies, efficient risk mitigation, and well-informed decision-making, consequently augmenting the overall stability and resilience of the cryptocurrency market.

CONCLUSION

Bitcoin and Ethereum are prominent partners in the complex dance of cryptocurrencies, each making individual movements while synchronizing in a coordinated rhythm. Our thorough analysis sought to elucidate the subtleties of this crypto tango by illuminating their causal connections, volatility trends, and common dynamics. We have gained important insights through thorough statistical testing and analysis, revealing the key findings listed below:

1. Volatility Patterns and Causality

This study used GARCH and EGARCH models to analyze Bitcoin and Ethereum volatility. These crypto assets' intrinsic characteristics were revealed by captivating clustering patterns and enduring volatility. Our Granger causality analysis showed a one-way causal relationship between Bitcoin and Ethereum. We found that past Bitcoin returns significantly affect Ethereum returns, but not otherwise. This discovery improves our understanding of their relationship and affects predictive models and trading tactics. The identification of this causal relationship can help investors and traders make informed decisions. By using historical Bitcoin returns to predict Ethereum performance, traders can improve their investment strategies.

2. Interdependence and Spillover effects

This study examined Bitcoin and Ethereum volatility using GARCH and EGARCH models. Charming clustering patterns and persistent volatility revealed these crypto assets' intrinsic qualities. Bitcoin and Ethereum had a one-way Granger causality relationship. Past Bitcoin returns significantly affect Ethereum returns, but not otherwise. This discovery enhances our understanding of their relationship and impacts predictive models and trading strategies. Understanding this causal relationship can help investors and traders make decisions. Trading strategies can be improved by using historical Bitcoin returns to predict Ethereum performance.

3. Long-term Co-integration and Diversification Opportunities

The Johansen test co-integration findings were insightful. Despite short-term volatility, co-integrating vectors indicate a long-term relationship between Bitcoin and Ethereum. This discovery helps us understand their common factors and implement strategic diversification. Diversifying portfolios with these cryptocurrencies can help investors manage risks and improve stability due to their co-integration. Investors can diversify long-term with co-integration. Bitcoin and Ethereum can boost risk-adjusted returns and reduce price volatility for investors.

4. Implications for Risk Management and Future Research

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The findings have wide-ranging implications. Understanding Bitcoin-Ethereum causal relationships, volatility spillovers, and co-integration dynamics is essential for risk management. These insights allow investors to use advanced strategies to reduce risks and optimize their portfolios. Our study also encourages academics and professionals to study cryptocurrencies further. Predictive modeling, behavioral analysis, and digital resources can enable more complex research. This study's findings can inform future research and policymaking. Predictive modelling and behavioral analysis of Bitcoin and Ethereum can reveal their dynamics. Our research shows the Bitcoin-Ethereum correlation's complexity and has implications for investors, policymakers, and scholars. By analyzing the relationships between cryptocurrency digital entities, our research advances the industry. This investigation will provide direction for future projects and deepen understanding of digital economics as people navigate the ever-changing cryptocurrency domain.

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