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Spillover effect between cryptocurrency and stock markets: diversifying and hedging properties of Bitcoin

Bachelor's thesis

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and all works, important standpoints and data by other authors
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has not been previously presented for grading.

The document length is 8465 words from the introduction to the end of the conclusion.

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ABSTRACT

This paper undertakes a comprehensive study on the spillover effect between cryptocurrency and stock markets, specifically focusing on the diversifying and hedging properties of Bitcoin. The research addresses whether shocks in digital currencies such as Bitcoin and Ethereum impact stock market returns and vice versa. It also investigates the existence of cointegrating vectors between these two markets and whether Bitcoin acts as a diversifier or hedger asset against US stock indices: S&P 500 and NASDAQ. The author employs a robust methodology, utilizing the Vector Autoregression (VAR) model and Granger Causality tests to explore the predictive power of crypto assets and stock indices. The analysis includes the Johansen test and Vector Error Correction Model (VECM) to identify market equilibrium and observe the price dynamics of assets. The author's findings suggest that cryptocurrencies can predict returns of stock indices and vice versa, indicating the presence of spillover effects between the two markets. However, causality ceased starting in 2018, suggesting the development of independence of Bitcoin and Ethereum, which hints at the diversifying properties of digital assets. The study reveals an existing equilibrium between the two markets, with Bitcoin demonstrating rapid adjustments to developments and shocks of stock indices, while S&P and NASDAQ show slower adjustment processes. The results highlight the dual role of Bitcoin as a speculative asset and hedger.

Keywords: Bitcoin, Ethereum, US stock returns, hedger, diversifier, Granger Causality

INTRODUCTION

The significant rise of digital currencies caused transformative changes in the financial landscape, introducing new dynamics to traditional financial markets. Widespread research on cryptocurrency integration as a hedging and diversifying asset sparked interest in analyzing its relation to conventional financial markets. This thesis explores the dynamic interplay between cryptocurrency and stock markets, a recurring theme that has drawn significant attention due to developments in financial systems caused by digital currencies. This research explores the interplay between two markets, focusing on the influence of Bitcoin Ethereum movements on the S&P 500 and NASDAQ stock indices, which is crucial for theoretical and practical finance applications.

Studies on the relationship between digital currencies, macroeconomic variables, and traditional financial markets yielded differing results. They raised further questions regarding the effect of price movements. This paper constructs an empirical analysis using different indices to measure the relationship between cryptocurrencies and stock indices' closing prices. To construct an empirical investigation of regression analysis, the indices chosen to highlight the relation of prices of two markets, as well as differing reactions to fluctuations in the market that may suggest diversifying or hedging properties of digital currencies, are used. Bitcoin and Etherium closing prices were derived from CoinGecko, including trading volumes and market cap. S&P 500 and NASDAQ closing prices were derived from Yahoo Finance, including all the dates and trading volumes. The data timeline spans from 2013 to 2024 to capture the full market dynamics and significant rise of cryptocurrency prices, including all of the major events that affected the movement of two markets, such as COVID-19, the Russia-Ukraine war, policy changes, etc. The study utilized cointegration analysis to determine whether long-term equilibrium relationships exist between cryptocurrency prices and stock market indices, suggesting a coherent movement despite short-term volatilities. Further application of the Vector Error Correction Model (VECM) explores this relationship by analyzing the speed of corrections after long-term deviations, depicting the dynamic interplay between two markets. Varying adjustments to deviations can assist in indicating whether cryptocurrencies can act as hedging assets or diversifiers during short-term shocks in the market. Further, we utilized the VAR model consisting of digital currencies, stock market indices, and macroeconomic variables: CBOE volatility index (VIX), the 10-year breakeven inflation rate, Federal Funds Effective Rate (DFF, interest rate), and Real Gross Domestic Product. The VAR model allows for implementing Granger Causality tests, which provide insights into the interactions and predictive relationships between two markets based on the defined lag order. In other words, past values of one variable can predict future values of the other. It's important to mention that some macroeconomic variables caused multicollinearity during the analysis and, hence, had to be removed. Furthermore, residuals of VAR models failed the heteroscedasticity and normality tests, which are not as significant in the case of Granger Causality but may affect the accuracy. The decision of analysis to conduct resulted in the next research questions and hypotheses.

Research questions:

- Research question 1: Is there an equilibrium between stock and cryptocurrency markets?
- Research question 2: Can cryptocurrencies act as effective financial hedges or diversifiers against stock indices?
- Research question 3: Are the prices of cryptocurrency and stock markets related, is there a predictive power?

Hypotheses:

- Hypothesis 1: There is an equilibrium between cryptocurrency and stock markets
- Hypothesis 2: Cryptocurrencies adjust differently to deviations from equilibrium compared to stock indices
- Hypothesis 3: No Granger Causality between stock and cryptocurrency markets

1. LITERATURE AND THEORETICAL REVIEW

1.1 Theoretical link between cryptocurrency and stock markets

Although the cryptocurrency market may be considered new, being first proposed by Nakamoto (2008), it has experienced significant development over the last fifteen years, reaching a record trading volume of $9 trillion in March 2024 (Medium, 2024). It has garnered the attention of researchers and econometric experts alike to study the relationship between digital currencies and stock indices. The relationship between cryptocurrencies and stock market indices is widely researched in the current decade with the emerging force of blockchain technology to dive into the prospects of portfolio diversification through cryptocurrency and possible hedging abilities. Research on the relationship between cryptocurrencies and stock markets has yielded mixed results.

Studies by Thaker and Mahd (2021) used statistical metrics such as Granger causality and VECM to identify Bitcoin`s (BTC) long-run and short-run associations within Asian markets, which deduces that in the long-run BTC and JPN stock index shared strong co-movement. In contrast, other Asian stock indices had medium to low co-movement. That study was heavily inspired by the research of Baur et al. (2018), which employed GARCH volatility analysis to identify the relationship between Bitcoin, gold and the US dollar, yielding the conclusion that Bitcoin has distinct return values, volatility and correlation characteristics placing it in between gold and US dollar.

Jaroenwiriyakul (2020) found a dynamic linkage between cryptocurrencies and stock markets in ASEAN-5, except for Malaysia. Shi (2023) emphasized the significant impact of cryptocurrency on the financial market, particularly in the banking industry, and the need for policymakers and investors to understand its potential impact. The study by Jiang et al. (2021) highlighted the significant positive dependence between cryptocurrencies and stock markets, suggesting a diversifying role for cryptocurrencies. However, Ahmed (2022) cautioned that investment decisions regarding cryptocurrencies should be taken cautiously due to their extreme volatility and high degree of persistence. Tiwari et al. (2019) investigated the time-varying correlation between stock and cryptocurrency markets, with results suggesting a low correlation indicating the hedging capabilities of cryptocurrencies against the S&P 500, indicating the importance of digital assets in portfolio management.

1.2 Hedging and diversifying properties of Bitcoin

The definitions of diversifier and hedge are clearly defined by Baur and Lucey (2010), allowing further analysis of the assets. The definition of a hedger is that assets tend to move inversely in relation to other assets or the broader market, protecting against losses and reducing risk. The definition of diversifier suggests low or non-existing correlation within a portfolio, assisting in spreading risk across different investments and minimizing the effects of volatility.

Study by Garcia-Jorcano (2020) analyzed the properties of BTC as a diversifier and hedge asset in combination with international market stock indices: S&P500 (US), STOXX50 (EU), NIKKEI (JPN), CSI300 (Shanghai) and HSI (Hong Kong). Utilizing copula models suggested that during stable market conditions, the hedging properties of Bitcoin evolve against the stock price movements of every stock market index researched. Likewise, during unstable periods, cryptocurrency might serve as a diversifier asset. Utilizing time-varying copula analysis, they found that Bitcoin might fail as a hedger under stable market conditions. A study by Stensas et al. (2019) employed the GARCH Dynamic Conditional Correlation (DCC) model to elaborate on the hedging and diversifying properties of Bitcoin among seven developed and six developing countries, five regional indices and 10 commodity series. Results show that in most developing countries, for example, Brazil, Russia, India and South Korea, Bitcoin indicates hedging properties. However, in developed countries such as the US, UK, Germany, and France, Bitcoin acted as a diversifier. Additionally, results yield that digital currency only serves as a safe haven within some markets.

Chan et al. (2019) examine whether Bitcoin can hedge and diversify risk against the Euro STOXX, Nikkei, Shanghai A-Share, S&P 500, and the TSX Index. Utilizing GARCH and constant conditional correlation models, they found that Bitcoin is an effective hedge for all these indices with monthly data frequency. However, daily and weekly frequency results did not yield the hedging capability of Bitcoin. Further frequency dependence model tests reveal that

Bitcoin returns are strong hedgings against S&P 500 and Euro indices over medium data frequency, indicating the long-run hedging capabilities of Bitcoin.

1.3 Review of empirical studies

The empirical investigation of cryptocurrency price movements and their repercussions on traditional financial markets has garnered increasing attention from researchers and practitioners in recent years. As cryptocurrencies have become a prominent feature of the global financial landscape, understanding the dynamics of their interconnectedness with conventional asset classes such as stocks has become imperative. In this section, we delve into existing empirical studies that have shed light on the effects of cryptocurrency events on stock market performance and vice versa, employing various methodologies to analyze these relationships.

Granger Causality test utilization in the context of the relationship between cryptocurrency and stock market indices is prevalent in various research. It will serve as a basis for analyzing the interconnectedness between the two markets. Research of asymmetric contagion effect between the two markets employed the nonlinear Granger Causality test and ARMA-GARCH to define co-movement. Findings suggest strong co-movement dependencies during the decline between cryptocurrency and stock indices, with lower tail dependence coefficients higher than 0.2. In contrast, upper tail findings suggest a minimal co-movement during the market's rise period. Dividing the results of the Granger causality test by stages (months) yielded varying p-values that determine the strength of causality, implying evident unidirectional Granger causality during short-run periods. However, there is evidence of no nonlinear Granger causality during particular periods (Wang et al., 2022). Yielded results of the study suggest that the increased attention towards cryptocurrency and capital flooding towards the market will build a greater connectedness between cryptocurrency and stock markets. Proposed potentiality was further confirmed by Bouri et al.(2022), implicating co-movement analysis in 2019 and onwards, the interconnectedness emerged, intensifying during the COVID-19 outbreak, proposing solutions for investment decisions when considering US stocks (S&P 500) and cryptocurrency (BTC) and policy formulation to remain market stability.

Co-integration analysis will be utilized to establish the correlation between time-series variables to define the existence of equilibrium, which is heavily employed in studies of cryptocurrency markets and its connection towards stock market indices. Ahmed et al. (2022) examined fractional integration to analyze the stochastic properties and fractional cointegration. Studies conclude that there is a disconnection between the prices of the two markets. However, utilization of conditional volatility instead of prices yielded results that confirm the cointegration between cryptocurrencies and rising stock market indices, which implies long-run interconnectedness in volatility movement between the two markets. However, a study by Jeribi (2021), which analyzed the cointegrating vectors between cryptocurrency and stock indices of BRICS countries through the Johansen test, concluded that at least one cointegrating vector exists between two markets. Differences in yielded results suggest that cointegration between cryptocurrencies and stock indices differ based on the chosen indices.

A range of studies have utilized the Vector Error Correction Model (VECM) to explore various assets' hedging and diversifying capabilities. The study by Jahja (2018) determined that the VECM model effectively identifies the optimal hedge ratio and hedging effectiveness in the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) Futures. A study by Li (2008) used a threshold VECM to enhance the hedging effectiveness and design a hedge ratio with less risk between spots and futures of emerging markets (BSI) as well as developed markets (S&P 500). The study by Kharbanda (2020) compared three models - ordinary least square (OLS), vector error correction model and dynamic conditional correlation multivariate GARCH (DCC-MGARCH) to identify model performance to evaluate the hedge effectiveness of assets. The results concluded that VECM performance is inferior to the DCC-MGARCH model, which should be taken into account when identifying hedge ratio. Lee et al. (2022) utilized the vector error correction model and Granger Causality analysis of the dynamic between bitcoin prices and various indexes representing the US economy, including the US treasury`s 10-year yield, US consumer price index (US CPI), gold price and dollar index (DXY) set as a basis for the methodology. Implementing the Johansen test to reveal the presence of cointegration serves as a decider for further model implementation. Additional utilization of the Portmanteau test (PT) for serial correlation is imperative to move to the Granger Causality test. The test results revealed that US CPI and DXY granger cause the Bitcoin price, while vice versa, only DXY granger causes Bitcoin.

2. DATA AND METHODOLOGY

This chapter contains an overview of the data used in the analysis and a justification for its inclusion. Further explanation of vector autoregression, cointegration analysis, vector error correction model, Granger Causality test, and justification of chosen models and tests. Rstudio was selected as a primary analytical tool due to its robustness in statistical test implications and ability to plot graphs in its environment. An integrated development environment (IDE) in Rstudio ensures robust implementation of statistical tests and the ability to import datasets (CSV, xl) and manage the dataset.

2.1 Data and descriptive statistics

Accumulating information about cryptocurrency price fluctuations and similarities with stock markets, suitable currencies have been chosen for research. As of now Bitcoin (BTC) and Ethereum (ETH) are considered as main cryptocurrencies with the highest valuation in the market and have been accepted by multiple banks worldwide. Bitcoin is a decentralized store of value, a digital currency mainly for transactions stored in digital wallets. Ethereum on the other hand, is a decentralized smart application stored in memory. Furthermore, there is a distinct variety in volatility between the two cryptocurrencies, with Bitcoin leaning to the volatile side and Ethereum being one of the lowest in volatility, serving as a reason for choosing these two currencies (Anwar & Anayat, 2020). Data for closing prices of digital currencies was accumulated from CoinGecko.

Stock market indices are diverse, involving a multitude of industries and sectors; therefore, the selection of the S&P 500 index is reasoned due to its broad representation of the US economy, which includes conglomerates and dominating industries, including technology, healthcare, finance etc, that amounts to 500 listed stocks. The second choice is the NASDAQ composite index, which primarily focuses on technology and growth-oriented companies listed on the stock exchange. The stock indice includes major technology companies like Apple, Microsoft, Amazon, and Alphabet (Google). Widespread use of the further provided variables: VIX, which stands for volatility index, Interest rate (DFF), Real Gross Domestic Product, and 10-year Breakeven inflation rate in econometrics allows the choice of variables since the stock indices of the analysis represent the US economy.

The dataset timespan is a four-year period from April 29, 2013, to April 11, 2024, containing closing prices of four market indices capturing a variety of market conditions, including the economic recession caused by the COVID-19 pandemic and subsequent periods of recovery. The timeline was chosen due to the significant rise in Bitcoin closing prices during that period. Cryptocurrency prices with market cap and trading volumes were obtained from CoinGecko, the most-referenced price tracking source that provides data on prices, trading volumes and market capitalization.Similarly, data on S&P500 and NASDAQ stock indices were gathered from Yahoo Finance.

Given the volatility of cryptocurrencies and the fact that the stock market is not open on weekends or public holidays, emphasis was placed on the completeness and consistency of the data. Values for VIX were subsequently gathered from Yahoo Finance. Other variables, such as 10-year breakeven inflation, interest rates, and real GDP, were gathered from Federal Reserve Economics Data (FRED). Dates with missing values (NaN) were removed since they represent a small fraction of the dataset to ensure the consistency of the data and further ability to analyze the data. Implementation of Interpolation methods and MARSS multivariate approaches were in order, but these methods were mitigated due to the creation of unnecessary bias. Cryptocurrency data integrity checks were done to ensure the uniformity of the data and rows with NaN values of stock indices were fully removed. As data was imported to R, the author ran code for descriptive statistics summary (Table 1). Time series graphs were constructed to observe the overall movement patterns of variables created with package ggplot2 (Figure 1). To conduct further analysis, differentiated variable graphs were constructed to move on to the vector autoregression model (Figure 2). This step was for robust visualization and representation of variables to clearly define price movements. The code for the process is represented in Appendix 1.

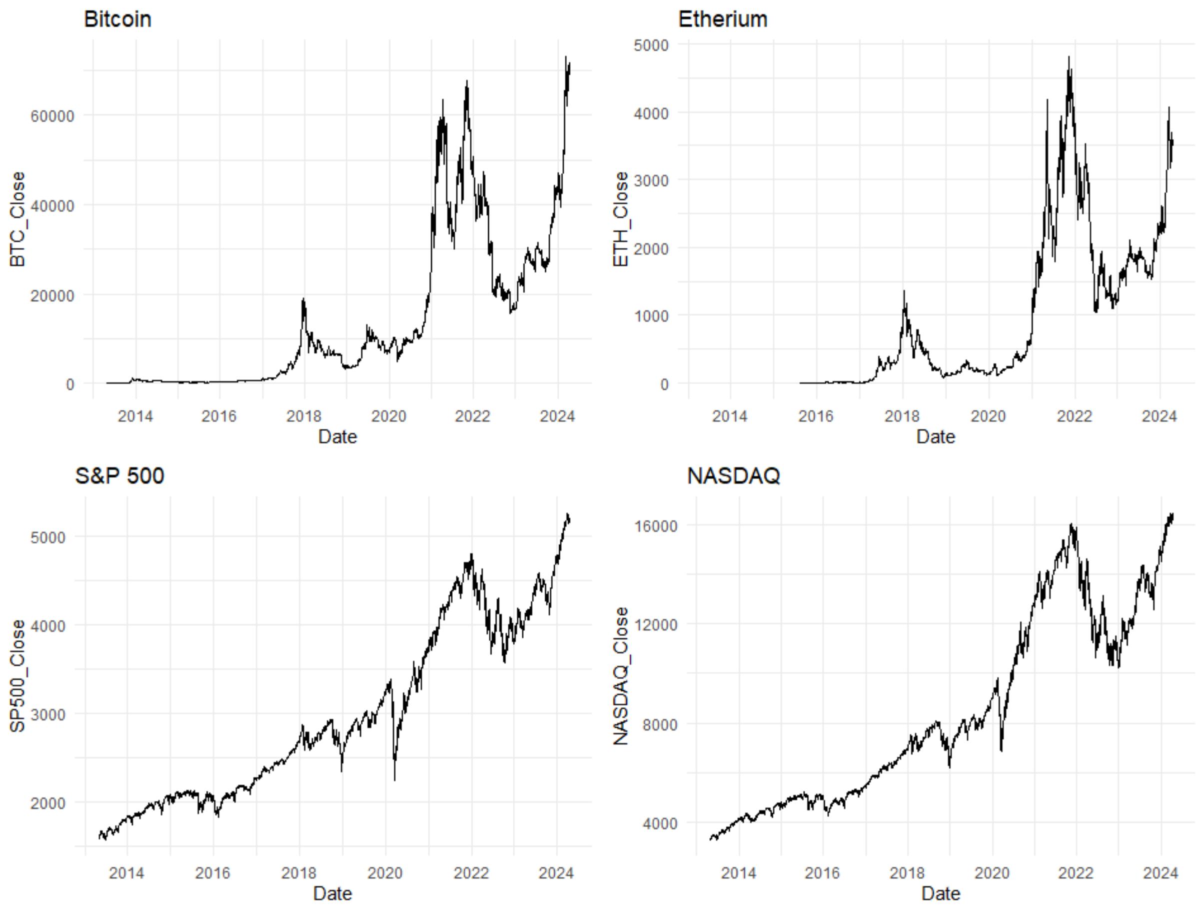

Figure 1. Time-series data for 2013-2024

Source: authors calculations

The graph for time-series data of Bitcoin closing prices shows a highly volatile trajectory with significant rises and falls. Starting at a low level in 2013, the digital currency experienced a series of dramatic increases and further sharp declines, gaining traction in 2017 and subsequently experiencing price downfall and stable correction before and during COVID-19 events between 2018 and 2021. Similar movements are notable in Ethereum time-series data, pointing out the connectivity of digital asset price movements. A significant rise for both cryptocurrencies is observed from 2021, pointing out the rising interest from major companies, financial institutions, and investment funds that started to view digital currencies as legitimate assets after the COVID breakout, referring to crypto as "digital gold" and hedging against inflation. Similarly, Ethereum experienced growth due to developments of decentralized finance (DeFi) and non-fungible tokens (NFT) ecosystems. The S&P 500 graph exhibits a generally upward trend through the timespan, notable for steady gains and downturns. The significant dips observed around 2018 and 2020 can be associated with market corrections and the economic impacts of the COVID-19 pandemic. Further steady recovery post-2020 marks the resilience of the equity markets. The NASDAQ graphs represent a more pronounced upward trend compared to the S&P 500, including similar dips in prices and sharp increases after 2020, marking the importance of the tech sector during the pandemic and its developments.

Table 1. Descriptive statistics of digital currencies and stock indices prices, VIX, interest and inflation rates and real GDP.

Variable	n	mean	sd	median	min	max	skew	kurtosis	se
BTC_Close	2756	13829.91	17136.05	6870.16	76.39	73097.77	1.36	0.88	326.42
ETH_Close	2184	991.14	1139.79	367.22	0.43	4815	1.18	0.47	24.39
SP500_Close	2756	2976.25	974.93	2760	1573.09	5254.35	0.48	-1.08	18.57
NASDAQ_Close	2756	8448.27	3783.95	7488.19	3299.13	16442.2	0.49	-1.14	72.08
VIX	2756	17.79	7.09	15.76	9.14	82.69	2.73	13.88	0.14
Interest_Rate	2756	1.3	1.64	0.4	0.04	5.33	1.39	0.77	0.03
Real_GDP	2756	20169.19	1429.82	20276.15	17709.67	22679.26	0.09	-1.13	27.24
TY_Breakeven_Inflation	2756	1.99	0.36	2.04	0.5	3.02	-0.23	0.03	0.01

Source: author`s calculations

Descriptive statistics are calculated through the “psych” package and “describe” function in R. Bitcoin, and Ethereum show similar skewness of 1.36 and 1.18, respectively, which indicates right-skewed distribution. The majority of Bitcoin and Ethereum price data points are clustered at the lower end of the scale with occasional extreme values on the higher end, marking the rapid increase of digital currency prices. Regarding S&P 500 and NASDAQ prices, the skewnesses are 0.48 and 0.49, respectively, suggesting a more symmetric distribution than cryptocurrencies and reflecting the general upward trend of the stock indices with slight right skewness. VIX exhibits significant right skewness (2.73), indicating that most values are clustered on the left with a long tail on the right. The breakeven inflation rate is negatively skewed (-0.23) with distribution to the right. Kurtosis values for Bitcoin and Ethereum are platykurtic relative to the normal distribution, suggesting fewer extreme outliers despite the volatility. The S&P 500 and NASDAQ have negative kurtosis values, which are significantly platykurtic, indicating fewer and less severe outliers. Regarding the variability, Bitcoin notably has the highest standard deviation of 17136.05 and the second highest represented by NASDAQ due to its tech-heavy composition.

Adhering to the requirements of a VAR model is necessary to create it. Differentiated data was compiled to meet the criteria. After differentiated data had been added to the dataset, further graph representation of the new variables was used to visualize changes and give a more in-depth understanding of changes in the returns.

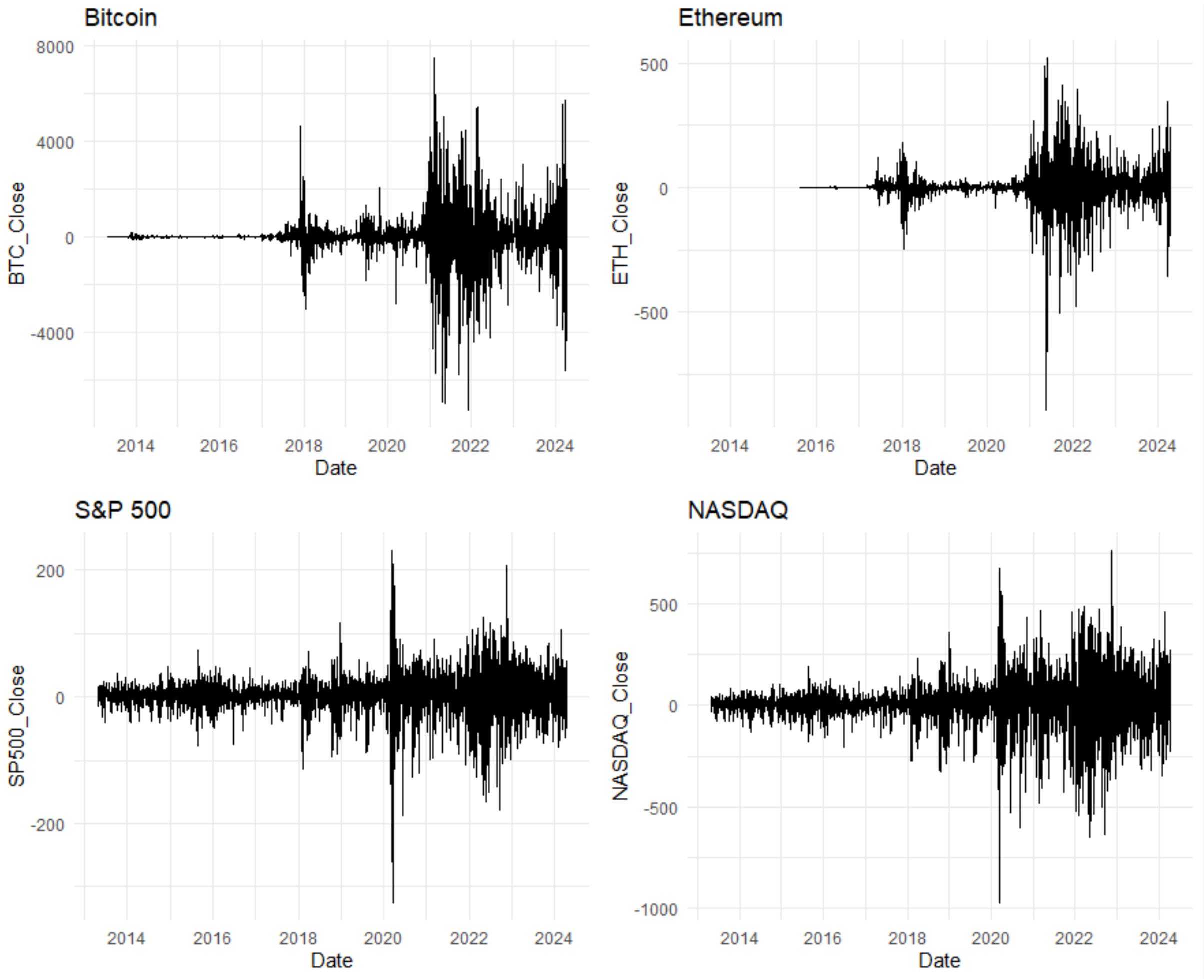

Figure 2. Differentiated Time Series data for 2013-2024

Source: author`s calculations

Both cryptocurrencies exhibit significant volatility throughout the dataset, with notable spikes during 2020 and 2021, reflecting major market events such as the COVID-19 pandemic and subsequent recovery phases. The S&P 500 stock index price movement shows more contained fluctuations than digital currencies, experiencing similar spikes during the pandemic. The NASDAQ prices display the same steady fluctuations as the S&P 500, with slightly higher volatility reflecting a tech-heavy composition.

2.2 Methodology

2.2.1 Vector Autoregression Model

To derive cointegrating values and further apply the Vector Autoregression model, Vector Autoregression (VAR) model was utilized, which is widely used in the existing studies regarding the relationship between cryptocurrencies and stock markets as studies by Zeng (2024), Yilmazer et al. (2021), Wang (2022) and Lee (2022). Lee et al. (2022) implemented the VAR model to run a cointegration analysis that suits the scope of this analysis. The VAR model does not require an indication of endogenous or exogenous variables, where lagged values are determined by the Akaike Information Criterion. The author employed a Vector Autoregression (VAR) model, which incorporates multiple interdependent time-series variables. This model is estimated using ordinary least squares (OLS) regression. The equation for the model, as formulated by Sims (1980), is represented in Equation 1.

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + A_p Y_{t-p} + u_t \tag{1}$$

Y_t = vector containing crypto prices and stock index values at time t

A_i = coefficient matrix of lagged relationships, from lag 1 to lag p relationship

p = lag order, time value (based on AIC & BIC)

u = errors in variables

The process of VAR model creation started by loading the dataset from a specified path, which contains comprehensive financial data crucial for our analysis. We then selected a subset of financial indicators, including Bitcoin closing prices, the Volatility Index (VIX), S&P 500 closing values, interest rates, and 10-year break-even inflation. The division of VAR models into pairs of cryptocurrency and stock indices was necessary to evade multicollinearity, which was proven by implementing a correlation matrix. The remaining variables are known to impact financial markets significantly and were chosen for in-depth analysis. The next step involved cleaning and transforming the data. We converted factors and characters to numeric values, ensuring the dataset was suitable for statistical testing. Non-available values were omitted to maintain data integrity. Application of Augmented Dickey-Fuller (ADF) tests by Dickey and Fuller (1981) to each variable to test for stationarity—a critical property in time series analysis that affects the validity of any inferential statistics applied to the data, as seen in Appendix 2. For variables identified as non-stationary, we induced stationarity by differencing, which involves subtracting the previous time point's observation from the current observation. The next step is a Vector Autoregression (VAR) model, selecting optimal lag lengths based on criteria such as the Akaike Information Criterion to effectively capture the dynamics and interdependencies between the multiple time series. The Akaike Information Criterion (AIC), developed by Hirotuge Akaike in the 1970s, is a model necessary for time-series variables to determine the appropriate lag order for the Granger Causality test.

AIC formula is expressed in Equation 2:

$$AIC = 2k - 2\,ln\,(L) \tag{2}$$

k = number of parameters in the dataset

L = the maximized value of the likelihood function of the model

AIC borders the complexity of the model to prevent overfitting, promoting models that achieve a good fit with fewer parameters (Burnham & Anderson, 2004). In the Granger Causality test context, the model determines the appropriate number of lags. A lag is a delayed value in a time series. For example, analyzing the closing prices of Bitcoin 1 lag is the previous day's closing price, examining if the past value of the time series predicts the current values. In financial markets, there is a notion of immediate responses to new information. Efficient Market Hypothesis (EMH) and market reaction times were the main principles that decided the appropriate lag order, where the speed at which markets utilize new information varies. Comparing the models, the lowest value of AIC is preferable, providing the best fitting lag order.

2.2.2 Johansen test

The Johansen test, which determines whether the time series of variables are cointegrated, was set as the first step for the analysis. Soren Johansen developed the statistical method to assess the cointegration of non-stationary time series data (Johansen, 1988).

The revelation of cointegration between variables is paramount to deriving the model on which this study will be based. At Least one cointegration validates the eligibility for implementation of VECM. Hypotheses testing compares critical values at the 10%, 5%, and 1% significance levels with test statistics computed for each hypothesized number of cointegrating vectors, r. If the null hypothesis stating the existence of r cointegrating vectors is rejected, then the test statistic exceeds the critical value at a given significance level. This implies that there are more than r cointegrating relationships. The analysis is implemented by loading the “urca” package in R and the function “ca.jo” which calculates the eigenvalues of VAR model variables. The analysis result will further allow the calculation of the Vector Error Correction Model. Due to the persisting issue of existing serial correlation in Ethereum VAR models as seen in Appendix 2, the decision was to exclude Ethereum from the Johansen test and VECM analysis. This test aimed to confirm Hypothesis 1: There is an equilibrium between cryptocurrency and stock markets

2.2.3 Vector Error Correction Model

The Vector Error Correction Model (VECM) created by Engle and Granger (1987) further explains the dynamic relationship of cointegrated variables, creating a matrix of set variables with residual values. It`s paramount that the variables maintain non-stationarity when implementing VECM. Augmented Dickey-Fuller test (ADF) is performed to reveal the variables I (1), or, in other words, non-stationary, or I (0). Defining the non-stationary and stationary variables further allows us to decide on the variables to be implemented in VECM. The Akaike information criterion (AIC) test is used to select the optimal lag. VECM is validated by the significance of the model coefficient and the characteristics of residual tests. Further expanding on the residuals analysis test for heteroscedasticity, autocorrelation of residuals and normality checks are performed. Moreover, including the fact that VECM is applied for non-stationary variables, it allows for results of long-run and short-run relationships between variables. The model allows for an understanding of price dynamics in the equilibrium between cryptocurrencies and stock markets, indicating the response time of one variable to another, further elaborating on the spillover effect. Differences in reactions of cryptocurrencies to stock market indices shocks may indicate diversifying or hedging properties of the asset, further confirming studies by Stensas et al. (2019). The VECM test is aimed to confirm Hypothesis 2: Cryptocurrencies adjust differently to deviations from equilibrium compared to stock indices. The formula for the VECM matrix is expressed in Equation 3:

$$\Delta y_t = \alpha\beta'(y_{t-1} - \mu) + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \epsilon_t \tag{3}$$

where

Δy_t - the first difference of the vector of endogenous variables

α - adjustment coefficients, measure the speed at which the previous period's deviations from a long-term equilibrium are corrected or adjusted in the current period

β' - transpose of the matrix which contains cointegration vectors

(y_{t-1}- μ) - error correction term, where y is lagged level of variables and μ is a vector of intercepts.

$\sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i}$ - summation term of short-term dynamics, each matrix Γ_i contains coefficients of lagged differences of variables to current change Δy_{t-i}

ϵ_t - error term or white noise

2.2.4 The Granger Causality Test

The Granger Causality Test is a statistical method to investigate the causal relationship between two variables over the event window. Created and first used by Clive W.J. Granger, it investigated causal relations through econometric models and cross-spectral methods in 1969. Granger`s innovative method challenged traditional approaches to causality, yielding the result of causality being inferred from one variable predicting changes in the second variable. Hence, it gained widespread recognition and became one of the foundational methods of econometric analysis, widely used in finance and economics. The test is considered versatile and can be applied to a wide range of variables, including more modern markets like cryptocurrency. The analysis provides causal inference, assisting in finding hidden relationships, and further informs decisions in the fields of economics and neuroscience, although they latter been subject to doubtful causality tests and found discrepancies with the objectives of neuroscience investigations (Stokes & Purdon, 2017) Set up for Granger Causality test required formulation of Hypothesis 3: No Granger Causality between stock and cryptocurrency markets.

The next step is to run multiple VAR models with different lag orders and compare the information through the Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). The lowest values of AIC and BIC will be the needed variables, allowing us to perform the Granger Causality test using the “var” package and “causality” function. The Granger Causality test from crypto to stocks formula is expressed in Equation 4:

$$Stocks_t = \alpha + \sum_{i=1}^{p} (\beta_{1i} Crypto_{t-i} + \beta_{2i} Stocks_{t-i}) + \nu_t \tag{4}$$

where

$Stocks_t$ - the value of stock variable at time t

$Crypto_{t-1}$ - the value of crypto variable at time t-i, for i lags

α - the intercept term

$\beta_{1i}\beta_{2i}$ - coefficients for i lags

ν_t - error term or white noise

The F-test measures whether the past values of one variable provide statistically significant information about the values of another variable; if the F value is greater than the critical value, reject the null hypothesis, confirming the Granger Causality between cryptocurrency market prices and stock market indices. The F-test statistic is calculated by comparing the fit of two models: The restricted model (H0), which excludes the predictor variable, and the unrestricted model (H1), which includes the predictor variable. If the calculated F-statistic is greater than the critical value of F-distribution at a 0.05 significance level, we can conclude that there is a Granger causality between variables. The formula for F-test is expressed in Equation 5:

$$F = \frac{(SSR_{H0} - SSR_{H1})/q}{SSR_{H1}/(n-k)} \tag{5}$$

Where

SSR_{H0}, SSR_{H1} - the sum of squared residuals from restricted and unrestricted models

q - number of parameters set to 0

n - total number of observations

k - total number of parameters estimated in the unrestricted model

3. EMPIRICAL ANALYSIS

3.1 Preparing the data for analysis

To study the dynamic relationship between variable implementations of the ADF test is paramount to fit the requirement for VECM of non-stationary variables. The results of ADF tests are located in Appendix 2. Necessary packages to perform further tests were implemented into the code ("tseries, forecast, urca, lmtest, zoo, vars, stats"). Results revealed that BTC, ETH, S&P500, NASDAQ closing prices, interest rates, and inflation rates proved to be non-stationary, with p values exceeding the standard cap of 0.05. To mitigate multicollinearity between variables, separate VECM models were created for each cryptocurrency and stock indices pair. For consistency in the analysis review, the implementation of cointegration analysis and VECM creation is explained with a pair of Bitcoin and S&P 500 (BTC_Close, SP500_Close). Prior, we defined the variables that proved to be non-stationary and were implemented in the model (Interest_Rate, TY_Breakeven_Inflation). Other variables caused multicollinearity, subsequently failing the serial tests, hence removing those variables from the model. Non-stationary variables were transformed into a matrix in order to perform the Akaike Information Criterion (AIC) to determine the optimal lag for the model. AIC returned an optimal lag of 10, which can be interpreted as 10 days of lagged values to subsequently fit the value into the VAR model. VAR model creation with type "trend" to account for the trend factor of cryptocurrency prices and stock indices. This step is performed to implement the serial test.

The Breusch-Godfrey LM test (BG) is well-suited for performing autocorrelation checks in the context of models where independent variables are not strictly exogenous, which is the case in my analysis of time series data. Due to the ability of the variables (BTC, S&P 500) of past values to influence future trends in the dataset, the BG test allows for the robustness of the analysis. It can adhere to the higher-order correlation. The BG test resulted in a p-value of 0.09785 with degrees of freedom of 125, exceeding the cap of 0.05 and rejecting the null hypothesis of the series being autocorrelated, which can be seen in Appendix 2.

3.2 Johansen test

The eigenvalues from the cointegration test present an insight into whether cointegrating relationships exist between variables and to what degree. In this case, higher eigenvalues indicate greater evidence for cointegration. All the positive eigenvalues are correct in the sense that they represent long-run equilibrium relationships between the respective variables. For instance, the sequence of eigenvalues from the cointegration test is as follows: {0.02447, 0.01541, 0.00825, 0.00406, 0.00196}.

Hypotheses testing compares critical values at the 10%, 5%, and 1% significance levels with test statistics computed for each hypothesized number of cointegrating vectors, r. If the null hypothesis stating the existence of r cointegrating vectors is rejected, then the test statistic exceeds the critical value at a given significance level. This implies that there are more than r cointegrating relationships. For instance, at = Null Hypothesis: r = 0, the test statistic is 68.03, well above the critical values at all of the levels of significance given, indicating very strongly at least one cointegrating relationship. Based on the test statistics exceeding their respective critical values, particularly for = 0 r=0 and ≤1, the null hypothesis of no cointegration is firmly rejected, even with r ≤ 1. This indicates that at least one cointegrating relationship would exist between the financial and economic variables considered. The results seem to infer that the chosen financial and economic variables are related in the long run and impact one another over time.

Table 2. Johansen test results

Model Relation	Test Statistic	10% Critical Value	5% Critical Value	1% Critical Value	Eigenvalue
$r = 0$	68.03	34.75	37.52	42.36	0.02447
$r \leq 1$	42.64	29.12	31.46	36.65	0.01541
$r \leq 2$	22.76	23.11	25.54	30.34	0.00825
$r \leq 3$	11.18	16.85	18.96	23.65	0.00406
$r \leq 4$	5.39	10.49	12.25	16.26	0.00196

Source: author's calculations

3.3 Vector Error Correction Model (VECM)

3.3.1 Long-term equilibrium relationships

Two main cointegrating vectors suggest stable long-term relationships in the data set. Interestingly, the second vector, focused on NASDAQ, does not include the Bitcoin variable, which is particularly relevant because it should be the focus of the analysis. In the first cointegrating vector, Bitcoin is normalized as well and is shown to have significant relationships with the S&P 500, Interest Rate, and Treasury Breakeven Inflation. The 1-unit error correction from the cointegrating relation reveals a negative association: an increase of 1 unit in Bitcoin is associated with a Bitcoin decrease in 11.235449 units versus a decrease of 49.65537 units with an increase in interest rates, and 45681.4949 decreases with an increase of 1 unit in inflation rates. The negative coefficient for interest and inflation rates highlights that deviations from the long-run relationship in Bitcoin prices are corrected through changes in interest and inflation rates. The second cointegrating vector, focused on NASDAQ, again does not directly involve Bitcoin, meaning there is no linear relationship in that specific long-run equilibrium setting. A 1 unit increase in NASDAQ would shift the S&P 500 in the opposite direction by 4.206678 units, the interest rate by 372.57622 units, and breakeven inflation by 501.4422 units; these two vectors also offer an intriguing comparison in terms of how Bitcoin influences versus effects on NASDAQ.

Table 3. Long-term equilibrium relationships indicated by VECM

Variable	Cointegrating Vector 1 (r1)	Cointegrating Vector 2 (r2)
BTC_Close	1.00E+00	-1.73E-18
NASDAQ_Close	0	1
SP500_Close	-11.235449	-4.206678
Interest_Rate	49.65537	372.57622
TY_Breakeven_Infl	-45681.4949	501.4422

Source: author's calculations

3.3.2 Short-term adjustment dynamics

The role of ECTs is to provide information on how lagged differences of variables interact with each other and with ECTs, which equips us with information about the short-term movement patterns of crypto assets and stock indices. The more negative and the smaller the ECTs, the shorter and the quicker the adjustment process converges to the long-run equilibrium. The results stimulate the creation of ECTs, which depict that Bitcoin returns have a statistically significant second ECT2 of 0.1602 (0.0427), or 16.02%, a correction of deviations from equilibrium. In contrast, the ECTs of NASDAQ and S&P 500 stock indices have smaller ECTs – 0.0207 (0.0060) and 0.0001 (4.6e-05), respectively. This suggests that BTC is reacting 8 times more intensely to market disruptions than the stock, reinforcing Bitcoin's position as a hedger. Lagged coefficients illustrate the significance of what has happened in the market before and what happens next. Thus, coefficients in the equation for Bitcoin, like NASDAQ_Close -1 and SP500_Close -1, show that the previous day's movements of the stock indices are significantly influencing Bitcoin prices: 3.3578 (0.3882) and -5.2342 (1.4631)***, respectively.

Table 4. Short-term adjustment values indicated by VECM

Coefficient / Variable	BTC_Close	NASDAQ_Close	SP500_Close	Interest_Rate	Breakeven_Inflation
ECT1	0.0002 (0.0012)	0.0005 (0.0002)**	0.0001 (4.6e-05)**	-3.8e-07 (6.0e-08)***	1.5e-07 (4.1e-08)***
ECT2	0.1602 (0.0427)***	0.0207 (0.0060)***	0.0065 (0.0016)***	-5.4e-06 (2.1e-06)*	1.1e-06 (1.5e-06)
Intercept	455.4525 (181.9221)*	111.8756 (25.5697)***	31.5745 (6.8866)***	-0.0542 (0.0090)***	0.0197 (0.0062)**
BTC_Close -1	-0.0382 (0.0192)*	0.0013 (0.0027)	0.0005 (0.0007)	8.9e-07 (9.5e-07)	9.3e-07 (6.5e-07)
NASDAQ_Close -1	3.3578 (0.3882)***	0.1328 (0.0546)*	0.0386 (0.0147)**	6.7e-05 (1.9e-05)***	-8.6e-06 (1.3e-05)
SP500_Close -1	-5.2342 (1.4631)***	-0.8383 (0.2056)***	-0.2243 (0.0554)***	-0.0003 (7.2e-05)***	7.5e-05 (5.0e-05)
Interest_Rate -1	-177.2903 (385.5266)	2.6997 (54.1869)	-7.5142 (14.5940)	-0.0653 (0.0191)***	0.0172 (0.0131)
Breakeven_Inflation -1	137.5129 (589.9132)	49.8174 (82.9140)	2.5634 (22.3310)	0.0713 (0.0292)*	0.0650 (0.0201)**
BTC_Close -2	0.0321 (0.0185).	-0.0022 (0.0026)	-0.0003 (0.0007)	-1.1e-06 (9.1e-07)	1.1e-06 (6.3e-07).
NASDAQ_Close -2	-0.0977 (0.3944)	-0.0824 (0.0554)	-0.0215 (0.0149)	-3.3e-06 (2.0e-05)	-1.3e-05 (1.3e-05)
SP500_Close -2	0.8311 (1.4747)	0.3273 (0.2073)	0.0876 (0.0558)	4.5e-05 (7.3e-05)	3.1e-05 (5.0e-05)
Interest_Rate -2	-553.3913 (384.7076)	54.8010 (54.0718)	23.4206 (14.5630)	-0.0244 (0.0190)	0.0099 (0.0131)
Breakeven_Inflation -2	194.6117 (588.2554)	232.9612 (82.6810)**	80.4017 (22.2683)***	-0.0385 (0.0291)	-0.0328 (0.0200)

Source: author's calculations

Also, the most negative and positive is BTC_Close -2, with a coefficient of 0.0321 (0.0185), which shows that Bitcoin is reacting significantly to market disruptions. The same coefficients for NASDAQ and S&P 500 have more neutral changes due to shocks, as reflected in their more stable adjustment coefficients. This transaction shows us that Bitcoin influences the stock, and thus, the asset is a diversifier within the portfolio. Concerning the economic indicators, Bitcoin Equation has a coefficient of Interest_Rate -1; -177.2903 (385.5266), which suggests any rise in interest rates would result in a decrease in Bitcoin prices, although the effect is not quite pronounced, meaning it is not the only factor driving performance. The 10-year Breakeven Inflation Rate with a coefficient of 137.5129 (589.9132) suggests that increasing inflationary expectations influence asset pricing; however, the effect has less direct implications on their values.

3.4 Granger Causality test results

To preserve all of the variables that could predict the prices of cryptocurrencies and stock indices, the decision was to retaliate to the VAR model, which does not limit the variables to non-stationary values. The Breusch-Godfrey LM test returned a p-value of 0.1575, rejecting the Null hypothesis of serial correlation between variables. CUSUM stability test of the residuals returned a graph confirming the stability of the model, where values do not exceed the caps shown in Appendix 4. Although the VAR model failed the normality tests, it's not a strict requirement for further Granger Causality test since it relies on the predictability aspect, irrespective of the distribution of residuals. However, analysis was done to analyze the predictive relationship between cryptocurrencies (Bitcoin, Ethereum) and stock indices (S&P500, NASDAQ) and remaining variables (VIX, Interest Rate, 10Y Breakeven Inflation, determining if the movements in stock prices can forecast movements in the cryptocurrency market and vice versa. Using Rstudio as a primary platform for analysis, the first step was to load the necessary libraries that contain the statistical functions. The “lmtest” package that contains the“causality” function is crucial for processing the Granger Causality test, involving the “zoo” package that is needed for managing time series data. Loading in the prepared dataset of daily closing prices of Bitcoin, Ethereum, SP500, NASDAQ and economic variables from April 29, 2013 to April 11, 2024. When conducting the “causality” function in Rstudio, the results firstly provide the F-test value, degrees of freedom (df), p-value that confirms or denies Granger causation, secondly Chi-squared value, degrees of freedom, p-value that confirms or denies instantaneous causality between variables. If the p-value is less than the standard cut-off of 5%, the author can reject the null hypothesis, confirming the granger cause between the two indices.

3.4.1 Bitcoin and stock indices, including economic indicators

First, to understand the economic relationship between variables, the Granger causality on the VAR model, including BTC, SP500 and the dataset bundle of economic variables: VIX, Interest rate, and 10YB inflation rate, is performed. According to the analysis in all cases, BTC Granger causes S&P 500 and NASDAQ stock indices, including economic variables. A test in the opposite direction reveals an even stronger coefficient of causality, where p values are near 0 value, extremely lower than the standard cap of 0.05.

Table 5: Granger Causality Test Results: BTC causing stock indices, VIX, Interest rate, Inflation

BTC → SP500		SP500 → BTC		BTC → NASDAQ		NASDAQ → BTC	
F-Value	p-Value	F-Value	p-Value	F-Value	p-Value	F-Value	p-Value
1.6195	0.007968	3.9958	4.441e-16	1.9164	0.000443	5.1894	less 2.2e-16

Source: author's calculations

It is worth noting the Chi-squared test for instantaneous causality of SP500 and NASDAQ causing BTC has a p-value of $< 2.2e-16$, which affirms the simultaneous movements or shocks that affect both series at the same time, including the bundle. Instantaneous causality p values of BTC causing SP500 and NASDAQ (including economic variables) are 0.003247 and 0.01732, respectively, which further confirms similar movements during shock events and provides the revelation of BTC and SP500 having a combined stronger reaction in comparison to BTC and NASDAQ. The analysis results contradict the previous results of Malladi et al. (2019), which employed the Vector Autoregression model and Granger causality tests to determine linkages between the SP500, gold, and Bitcoin prices and their respective returns and volatilities. Their analysis concluded that the Bitcoin returns do not granger cause of S&P 500 returns.

Table 6: Granger Causality Test Results: Bitcoin and stock indices excluding other variables

BTC → SP500		SP500 → BTC		BTC → NASDAQ		NASDAQ → BTC	
F-Value	p-Value	F-Value	p-Value	F-Value	p-Value	F-Value	p-Value
2.8911	0.001315	17.278	less 2.2e-16	2.502	0.00746	26.952	less 2.2e-16

Source: author's calculations

Thus, in addition to the detailed analysis provided by the first VAR model with BTC, S&P 500, and various economic indicators, one can better understand the dynamics between cryptocurrencies and stock indices, excluding the latter group of variables influencing BTC and S&P. A strong effect from S&P 500 closing prices on BTC differenced closing prices was found, with an F-test value of 26.952 and an extremely significant p-value of less than 2.2e-16, indicating that the S&P 500 significantly predicts Bitcoin's movements. As the analysis does not entail instantaneous causality, the model format assures that the S&P cannot directly cause BTC without simultaneous causality. However, the reverse causality model reveals that Bitcoin significantly predicts the movements of the S&P 500. The F-test value is 2.8911 with a p-value of 0.001315, which is again significantly below the 1% level and indicates that the past values of Bitcoin can be used to predict the future values of the S&P 500. Similarly, the Bitcoin granger causes NASDAQ at a p-value of 0.00746 and even stronger causation in the opposite direction. Nevertheless, the Breusch-Godfrey LM test for Bitcoin and NASDAQ relationship showed serial correlation, thus diminishing the accuracy of the results, which is not the case with the Bitcoin and S&P model with BG serial test p-value of 0.09963. This indicates serial correlation in the VAR model based on residuals, suggesting that the model may not entirely capture the dynamics between these two variables.

The next VAR model is created to observe the causality of singular pairings of variables and represent the effects of each economic variable in the dataset bundle.

Table 7: Granger Causality Test Results for BTC and a single Variable.

	BTC → Variable		Variable → BTC	
Variable	F-Value	p-Value	F-Value	p-Value
VIX	2.0576	0.02444	9.6471	4.441e-16
Interest Rate	1.6666	0.1012	0.9105	0.5064
10YB Inflation	1.6569	0.08478	1.6266	0.09259

Source: author's calculations

The results of the analysis contradict previous results in Lee et al. (2022), revealing granger causality between Bitcoin and VIX at a 2% significance level and an even lower level in the opposite direction. Interpretation of the contradiction may lie in the difference of the VAR and VECM models implemented for the Granger analysis. However, the difference in the results evokes questions about the validity of the choice of the models for the Granger Causality test in the context of cryptocurrencies and the economic variables. The remaining variables do not granger cause in both directions. since interest rate and inflation take up a broader spectre of the US economy

3.4.2 Etherium and stock indices

The exploration of Granger causality between Ethereum and major stock indices has revealed results that shed light on the financial interplay between these assets. Table 4, featuring the Granger Causality Test Results for ETH and Major Indices, provides a landscape of this dynamic interaction. It's worth noting that the inclusion of additional economic variables in the Ethereum analysis previously led to serial correlation. To avoid this complication, the current VAR model was simplified to include only Ethereum and the stock indices.

Table 8: Granger Causality Test Results for ETH and Major Indices

ETH → SP500		SP500 → ETH		ETH → NASDAQ		NASDAQ → ETH	
F-Value	p-Value	F-Value	p-Value	F-Value	p-Value	F-Value	p-Value
1.7885	0.05729	17.852	2.2e-16	2.1429	0.0185	23.095	2.2e-16

Source: author’s calculations

Ethereum does not Granger-cause the S&P 500, evidenced by an F-value of 1.7885 and a p-value of 0.05729. In other words, Ethereum’s historical prices do not significantly predict the S&P 500’s future movements. However, the opposite relationship – the S&P 500 unidirectionally causes Ethereum, confirmed by an F-value of 17.852 and a p-value of 2.2e-16, proving strong evidence. The relationship between Ethereum and NASDAQ is fully mutual, or bidirectional: this is evidenced by an F-value of 2.1429 and a p-value of 0.01854; the NASDAQ’s impact on Ethereum is even more powerful – evidenced by an F-value of 23.095 and a p-value of 2.2e-16. We conclude that the two datasets have a strong mutual predictive power. These results demonstrate the complex nature of cryptocurrency and the relationship between major stock indices that stakeholders and policymakers must understand. While Ethereum has no significant predictive influence on the S&P 500, the index possesses strong predictive input on Ethereum's performance on the market. Hence, the S&P 500 has more power to influence the cryptocurrency sector, while NASDAQ is more of a solo player.

3.5 Discussion

The research findings provide comprehensive revelations into the dynamic interplay between digital currencies and stock market indices, including macroeconomic variables. The Johansen cointegration test yielded at least one confirmed cointegrating relationship between Bitcoin and the S&P 500, and results indicate that despite the volatility factor, the relationship aligns in the long-term equilibrium. Further, VECM integration elaborates on this relationship, depicting certain mechanisms through which deviations are adjusted in the long run. The VECM indicates significant long-term equilibrium relationships among the variables, including Bitcoin, S&P 500, interest rates, and a 10-year Treasury Breakeven Inflation. The model confirmed that deviations from equilibrium are being adjusted over time. Notably, the Error Correction Terms (ECTs) indicate a relatively high speed of adjustment of Bitcoin prices to the equilibrium, reflecting how the asset responds to shocks of the other variables. These findings contrast with the slower adjustments of the S&P 500 and NASDAQ to the shocks, indicating the vast difference between the two markets, which may be connected to its more extensive and more diverse asset base, reflecting the inherent stability of the traditional financial markets. Findings reveal Bitcoin's double role in investment portfolios as a speculative asset or hedger and spillover effect between markets. However, it does not fully capture the hedging and diversifying properties of Bitcoin, suggesting a further need to quantify the hedge ratio relative to stock indices and hedge effectiveness to evaluate the reduction in portfolio variance. Adhering to the study by Kharbanda (2020) utilize dynamic conditional correlation multivariate GARCH (DCC-MGARCH) to observe dynamic relationships to further elaborate on hedging properties. Findings also reveal the counter-reaction of Bitcoin to the rise of inflation rates and interest rates. With the increase of the macroeconomic variable values, digital currency prices decrease. In the end, the results of the VECM analysis confirm the hedging capabilities of Bitcoin against major US stock indices. Different adjustment speeds in the VECM model results have significant implications for investment strategies, the development of economic policies, and the understanding of market efficiency and asset price dynamics.

The Granger Causality test provides evidence of bidirectional causality between cryptocurrency and stock markets, particularly Bitcoin's differentiated closing prices. Evidence confirms the mutual influence, and Bitcoin can predict the future values of the S&P 500 and NASDAQ and the remaining economic indicators. Vice versa, causation proved significantly stronger, implying the strong influence of stock market indices and macroeconomic variables on the cryptocurrency markets. However, findings also suggest a marginally significant influence of Ethereum prices on the stock markets, just passing the standard cap of 5% significance. Results suggest further elaboration on the causal relationship between Ethereum and stock market indices and the need for more variables affecting the dynamics of digital currency prices.

In Appendix 3, the author conducted further Granger Causality tests for Bitcoin and stock indices, where the starting date was subsetted to 2014, signifying the declining predictive power of Bitcoin over stock indices. Starting from 2018, Bitcoin did not granger cause the S&P 500, reaching over cap of 0.05, while for NASDAQ, granger causation of Bitcoin ceased in 2019. Findings signify the development of the digital asset, revealing segmentation between cryptocurrency and stock markets. The reasoning could be an increase in investor base size for digital currencies creating independent movement, the effect of the COVID-19 pandemic, where a substantial amount of investors considered Bitcoin a safe haven, and regulatory changes regarding blockchain. Granger Causality for Ethereum was not included due to persistent failures of serial correlation tests. These findings require further research, investigating the causality in seasonal or monthly timelines and observing the causality properties of crypto assets during global events in recent years to elaborate the spillover effect further.

CONCLUSION

The paper aimed to investigate the spillover effect between cryptocurrency and stock markets, researching diversifying and hedging properties of Bitcoin against US stock indices. The study has shown complex interdependencies between cryptocurrencies and traditional stock markets, answering each research question. Empirical evidence that shows cointegration with dynamics described by the VECM lends credibility to the stance that cryptocurrencies, in all their volatility, have long-term equilibria with the traditional financial markets, confirming the first hypothesis and research question.

Insights into VECM's error correction mechanisms offer insight into how quickly deviations in different markets are responded to, a move crucial in investors' management of asset price movements. Yielded results from the analysis confirm the setup hypothesis where Bitcoin exhibits rapid adjustment to the deviation of stock indices compared to the slow adjustment speed of S&P 500 and NASDAQ, which allows the author to confirm existing properties of Bitcoin in investment portfolios, either as diversifier or hedger against the movement of US stock indices, although requiring further calculations by conducting additional analysis to confirm the results. The author did not find a conclusive answer to the second research question. Findings from the Granger Causality test confirm the spillover effect between cryptocurrency and stock markets, denying the hypothesis of no Granger causality between markets investigating the predictive power of both asset types, where the stock market exhibits strong causation of Bitcoin and Ethereum price movements. In contrast, digital assets exhibit a smaller causation effect ceasing from 2018 and beyond. However, the predictive power of cryptocurrencies throughout the whole timeline of the dataset concerning stock indices reflects that they hold market information that can be used in investment and policy decisions. The results reveal a conclusive answer to the third research question and deny the hypothesis of no Granger causality. Moreover, it's worth noting the failure of normality and heteroscedasticity may diminish the accuracy of the results, meaning there is a need for further investigation of variables that may affect the predictive properties of cryptocurrencies and examining other variations of the VAR model. The results of the study may be implemented in the portfolio distribution of assets, serving as a decisive factor of cryptocurrency inclusion and contributing to widespread research on cryptocurrency and stock market relationships and hedging capabilities of Bitcoin.

This study elaborates on the dynamic interplay between the markets; however, rising developments in digital currency markets and differing results of studies imply a further need to investigate this complex relationship, opening up new ways to find valuable insights. Failure of heteroscedasticity and normality tests of residuals of VAR models suggests the need to integrate other macroeconomic variables that may affect the cryptocurrency and stock market movements to derive accurate results. The analysis demands subsequent investigation of the spillover effect and hedging capabilities in segmented timelines and during certain events that may have affected both markets to fully elaborate the relationship between digital assets and US stock indices.

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APPENDICES

Appendix 1. Link to author's code in R

Descriptive Statistics and graphs

VECM and Johansen test

VAR and Granger Causality test

Appendix 2. Results of ADF and BG tests

Table 1. ADF results of each variable, values lower than 0.05 indicate stationarity

ADF test	
Variable	**ADF p-value**
Bitcoin (BTC)	0.7885
S&P 500	0.3494
NASDAQ	0.4981
Interest Rate	0.99
10-Year Breakeven Inflation	0.2819
VIX (Volatility Index)	0.01
Real GDP	0.0148
Ethereum (ETH)	0.5818

Source: author's calculations

Table 2. Breusch-Godfrey LM test of VCEM model containing Bitcoin, S&P 500, NASDAQ, Interests rate, 10-Year Breakeven inflation

Test Description	Chi-squared	Degrees of Freedom	p-value
Breusch-Godfrey LM Test	145.86	125	0.09785

Source: author's calculations

Table 3. Breusch-Godfrey LM test of VAR model containing Bitcoin, S&P 500, VIX, Interest rate, 10-Year Breakeven inflation

Test Description	Chi-squared	Degrees of Freedom	p-value
Breusch-Godfrey LM Test	140.85	125	0.1575

Source: author’s calculations

Table 4. Breusch-Godfrey LM test of VAR model containing: Bitcoin and S&P 500

Test Description	Chi-squared	Degrees of Freedom	p-value
Breusch-Godfrey LM Test	28.429	20	0.09963

Source: author’s calculations

Table 5. Breusch-Godfrey LM test of VAR model containing Bitcoin and NASDAQ

Test Description	Chi-squared	Degrees of Freedom	p-value
Breusch-Godfrey LM	36.468	20	0.01354

Source: author’s calculations

Table 6. Breusch-Godfrey LM test of VAR model containing: Ethereum and S&P 500

Test Description	Chi-squared	Degrees of Freedom	p-value
Breusch-Godfrey LM Test	29.093	20	0.08594

Source: author’s calculations

Table 7. Breusch-Godfrey LM test of VAR model containing Ethereum and NASDAQ

Test Description	Chi-squared	Degrees of Freedom	p-value
Breusch-Godfrey LM Test	30.795	20	0.05796

Source: author’s calculations

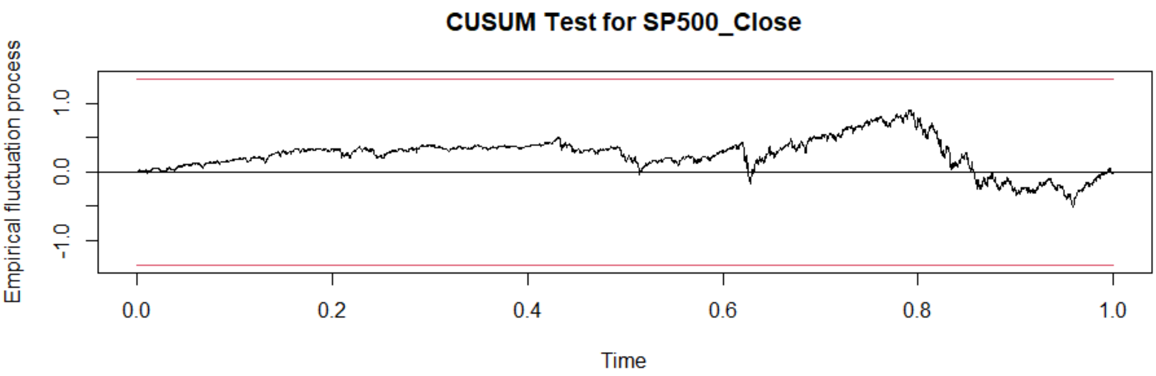
Appendix 3. Granger Causality tests after 2013

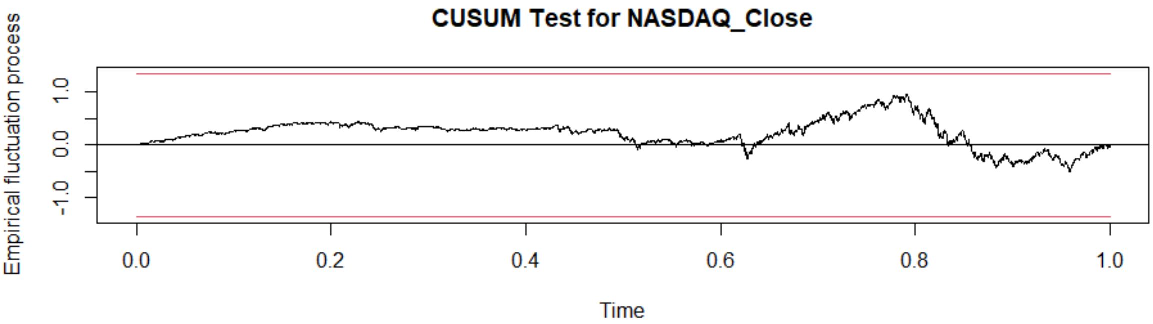
Table 1. Granger Causality tests of Bitcoin and stock indices from 2014 to 2024 with a segmented timeline, subsequently subsetting the starting date to next year

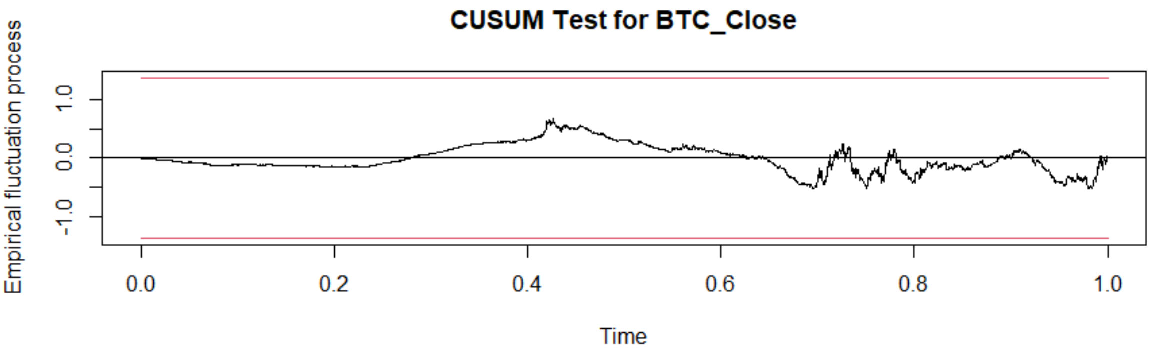
Year	Bitcoin and SP500				Bitcoin and NASDAQ			
	Cause Bitcoin		Cause SP500		Cause Bitcoin		Cause NASDAQ	
	F-test value	p-value	F-test value	p-value	F-test value	p-value	F-test value	p-value
2014	2.6184	0.00356	16.715	< 2.2e-16	3.2666	0.0003194	23.683	< 2.2e-16
2015	2.4126	0.007382	15.368	< 2.2e-16	2.9746	0.0009678	21.591	< 2.2e-16
2016	2.2439	0.0132	14.223	< 2.2e-16	2.7155	0.002519	19.606	< 2.2e-16
2017	2.0337	0.02653	12.768	< 2.2e-16	2.4219	0.007175	17.427	< 2.2e-16
2018	1.5447	0.1264	12.782	< 2.2e-16	2.1554	0.01783	15.816	< 2.2e-16
2019	1.5414	0.1276	11.374	< 2.2e-16	1.6481	0.09627	15.487	< 2.2e-16
2020	1.2854	0.2395	9.9916	3.78E-15	1.3819	0.1906	13.408	< 2.2e-16
2021	0.061785	0.8037	85.949	< 2.2e-16	0.020321	0.8867	103.94	< 2.2e-16
2022	2.2092	0.03998	14.676	4.44E-16	2.45	0.02336	18.069	< 2.2e-16

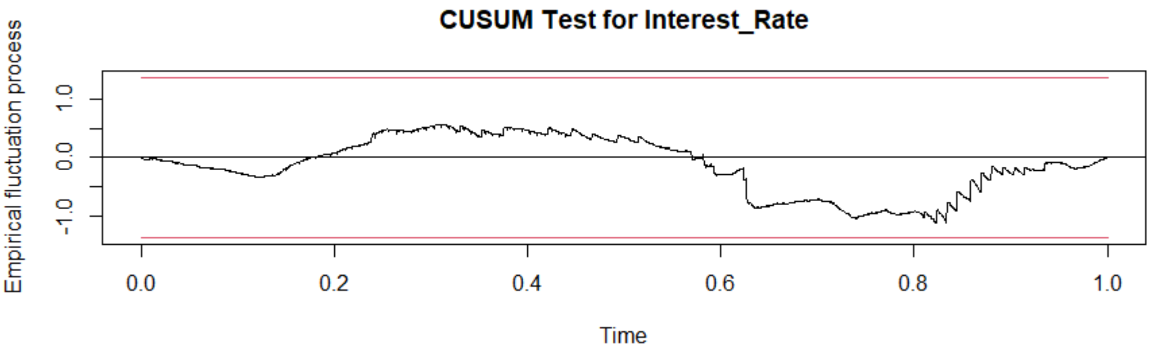
Source: author’s calculations

Appendix 4. Results of OLS-based CUSUM test









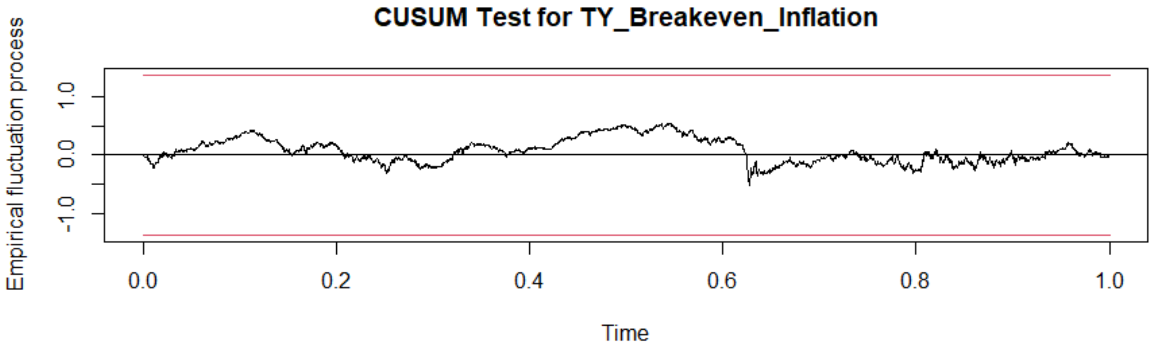


Figure 1. OLS-CUSUM test of the VAR model variables residuals for 2013-2024.

Source: author’s calculations

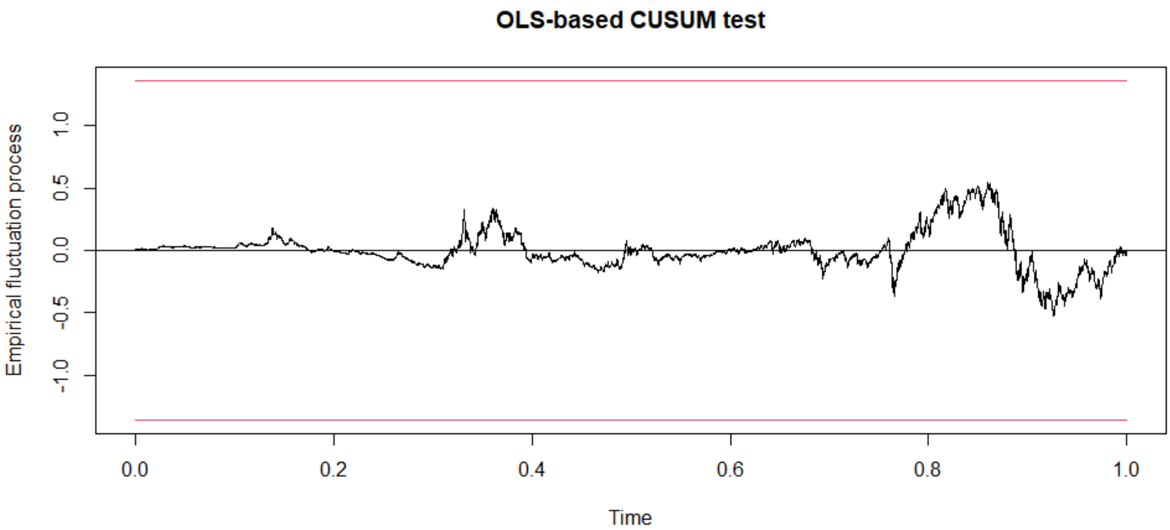


Figure 2. OLS-CUSUM test for VAR model including all variables for 2013-2024.

Source: author’s calculations

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