

Bitcoin: Exploring Price Predictability and the Impact of Investor Sentiment

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This article addresses the predictability of Bitcoin's price by examining relationships between Bitcoin and financial and emotional variables such as the Fear and Greed Index (FGI), the American Interest Rate (FED), and the Stock Market Index (NASDAQ). Through the use of statistical techniques such as the Johansen Cointegration Test and Granger Causality, as well as forecasting models, the study reveals that, despite the notorious volatility of the cryptocurrency market, it is possible to identify consistent behavioral patterns that can be successfully used to predict Bitcoin returns. The approach that combines VAR models and neural networks stands out as an effective tool to assist investors and analysts in making informed decisions in an ever-changing market environment.

Keywords: Bitcoin, price predictability, fear and greed index, American interest rate, NASDAQ

Introduction

In the contemporary financial landscape, Bitcoin emerges as an asset that challenges traditional norms, expanding beyond the boundaries of conventional markets. Its frequent price fluctuations often puzzle analysts, while its interconnectedness with investor sentiment becomes increasingly evident. The rise of Bitcoin as the leading cryptocurrency and its impact on global markets have triggered an intense quest to understand the factors driving its price and market dynamics. In this regard, Entrop, Frijns, and Seruset (2020) emphasize that among the determinants of Bitcoin's price, investor sentiment and macroeconomic variables are notable.

This article aims to address the central issue related to the predictability of Bitcoin's price, delving deep into a range of factors influencing its value fluctuations. Drawing on a variety of empirical and theoretical studies, our goal is to provide a comprehensive view of the complex interactions shaping Bitcoin's price, as well as highlight its sensitivity to emotional and external factors.

To contextualize this issue, it is crucial to consider Bitcoin's role as a cryptocurrency, a virtual asset obtained through computer codes and validated through encryption using a blockchain, as explained by Trindade and

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Vieira (2020). In recent decades, the cryptocurrency market, with Bitcoin at the forefront, has attracted significant attention from both investors and researchers. In this context, a recurring question is the potential predictability of this currency, with its determinants being a central point of analysis.

To this end, Dubey (2022) conducted an in-depth analysis of the determinants of Bitcoin returns, encompassing categories such as macroeconomic, financial, technical, and fundamental factors. Their results highlighted variables such as oil prices, the quantity of coins in circulation, trading volume, and market capitalization as significant factors in Bitcoin returns, emphasizing the role of this cryptocurrency as a diversification tool and protection against inflation.

In addition to Dubey (2022), Vo, Chapman, and Lee (2022) examined the relationship between Bitcoin and economic indicators over time, identifying that the price of this cryptocurrency is influenced by macroeconomic factors that vary over time. Zhao (2022), on the other hand, investigated how local economic crises affect Bitcoin trading, revealing a connection between the devaluation of local currencies and increased trading, strengthening the status of Bitcoin as an asset protecting against local currency devaluation.

Beyond these economic aspects, studies conducted by Li, Li, Yuan, and Zhu (2021), Smales (2022), and Almeida and Gon çalves (2023) provide a comprehensive view of the relationship between investor attention and the cryptocurrency market, with a special emphasis on Bitcoin. These researches offer an understanding of how investor behavior and other factors impact the prices, volatility, and liquidity of cryptocurrencies.

Almeida and Gonçalves (2023) expand the analysis, exploring topics such as investor sentiment, herd behavior, and the impact of news on cryptocurrencies. They recognize investor attention as a key factor driving investor decisions and affecting cryptocurrency prices. Considering this context, this research seeks to address the following research problem: How do macroeconomic and emotional variables influence the predictability of Bitcoin prices?

Literature Review

Bitcoin: Beyond Financial Boundaries—Trends, Investors, and Volatility

In the current financial market context, Bitcoin emerges as a challenging asset to traditional norms, expanding beyond the confines of conventional markets. Its frequent price fluctuations often bewilder analysts, while its interconnectedness with investor sentiment becomes increasingly evident. As explained by Trindade and Vieira (2020), cryptocurrencies like Bitcoin are virtual assets obtained through computer codes. These codes represent ownership and properties of these assets and are validated through encryption using a blockchain.

Over the past decade, the cryptocurrency market, with Bitcoin at the forefront, has garnered considerable attention from both investors and researchers. One of the most debated topics is the potential existence of speculative bubbles in this market, as indicated by Diniz, de Prince, and Maciel (2022), who sought to identify bubbles in the prices of Bitcoin and Ethereum, challenging the traditional assumption that bubbles only occur in times of high volatility.

Furthermore, Dubey (2022) conducted an analysis of the determinants of Bitcoin returns, considering macroeconomic, financial, and technical factors. The results highlighted variables such as oil prices and Bitcoin supply. Vo et al. (2022) delved into the relationship between Bitcoin and economic indicators, revealing the influence of dynamic macroeconomic factors. Zhao (2022) examined local economic crises and their impact on Bitcoin trading, reinforcing its role as a safeguard against local currency devaluation.

Studies by Li et al. (2021), Almeida and Gonçalves (2023), and Smales (2022) provide a comprehensive view of the relationship between investor attention and the cryptocurrency market, with a focus on Bitcoin. Valuable insights are offered into how investor behavior and various factors impact cryptocurrency prices, volatility, and liquidity, with source citations for reference.

It is important to highlight that Bitcoin is the leading cryptocurrency and plays a central role in the analysis of various researchers (Li et al., 2021; Almeida & Gon çalves, 2023; Smales, 2022). Li et al. (2021) emphasize the bidirectional relationship between investor attention and Bitcoin returns at different time scales, with greater influence in low-volatility markets. Almeida and Gon çalves (2023) expand the analysis, exploring topics such as investor sentiment, herd behavior, and the impact of news on cryptocurrencies. They recognize investor attention as a key factor driving investor decisions and affecting cryptocurrency prices.

On the other hand, Smales (2022) examines the relationship between investor attention, uncertainty, and the dynamics of the Bitcoin, and other cryptocurrency markets. Their results demonstrate that increased investor attention is associated with higher returns, greater volatility, and increased liquidity in cryptocurrency markets, while uncertainty plays a crucial role in the volatility and returns of these digital assets. Consequently, studying the determinants impacting Bitcoin's price is necessary.

Determinants of Bitcoin Price

Several studies have focused on analyzing the impact of investor sentiment on Bitcoin, revealing a fascinating and complex research field. Mokni, Ben Rejeb, and Lahiani (2022) conducted a quantitative analysis that not only investigated causal relationships between Bitcoin and investor sentiment but also considered the context of the COVID-19 pandemic. Their results indicate a significant influence of Bitcoin returns and volatility on investor sentiment. This finding highlights the cryptocurrency market's sensitivity to price fluctuations.

Another study, conducted by Gaies, Abid, and Jilani (2023), further deepened our understanding by exploring the complex interactions between investor fear and greed and Bitcoin prices. The researchers highlighted how investor fear significantly impacts Bitcoin prices, especially during specific periods. This analysis emphasizes the importance of investor emotions in the cryptocurrency market dynamics. Halliday (2018), on the other hand, examined the behavior of fund investors, highlighting the influence of the Fear and Greed Index on the dynamics of these assets. Their study demonstrated how investors often succumb to herd behaviors and seek higher yields, often disregarding financial fundamentals.

G ómez-Mart nez, Garc n, and Giner (2023) took a step further by presenting an algorithmic trading system based on CNN's Fear and Greed Index, underscoring the relevance of emotions such as fear and greed that directly influence investment strategies. In a parallel study, Dinis and Cheriff (2020) explored how the Fear and Greed Index affects individual investor decisions, revealing how emotions of greed and fear play a crucial role in the psychological traps that investors may face.

Petkova (2023) also contributed to the field by investigating investor expectations about Bitcoin returns, highlighting the contribution of the Fear and Greed Index in understanding the emotions that shape investor decisions. Their study emphasizes that fear and greed can lead to suboptimal choices and affect portfolio performance, highlighting the importance of emotional aspects in financial decision-making. Burggraf et al. (2021) observed this dynamic by highlighting the predictive power of the FEARS index, constructed based on Google searches, on Bitcoin, especially during times of low sentiment. This underscores the complexity of interactions between investors and the cryptocurrency market, where emotions play a fundamental role.

Author	Variable	>	Variable	Method	Results
Aste (2019)	Investor Sentiment	>	Bitcoin Price	Granger Causality	Investor sentiment and prices are interconnected and demonstrate dependence and causality.
Bernardo (2022)	Bitcoin	>	S&P500	Granger Causality	The author suggests that BTC can serve as an indicator since BTC price helps predict the U.S. stock market.
Bernardo (2022)	Bitcoin	>	FED	Granger Causality	The author mentions a BTC causality with respect to the FED, indicating a potential link with the U.S. market.
Bourghelle et al. (2022)	Bitcoin	>	Fear and Greed Index (FGI)	VAR	The study concludes that the relationship between emotions and BTC volatility is complex, asymmetric, and nonlinear, varying across different market states.
Gunay et al. (2022)	FGI and VIX	>	Bitcoin	Granger Causality	The authors claim that these two indices have the potential to show reversal points in Bitcoin price trends.
Mokni et al. (2022)	FGI	>	Bitcoin	Granger Causality	Although they observed no causal relationship in the entire selected sample (2018-2020) and the period preceding COVID-19 (prior to the second quarter of 2020), the authors found causal flows from FGI to Bitcoin returns during the COVID-19 period (second to fourth quarter of 2020).
Mokni et al. (2022)	Bitcoin	>	FGI	Granger Causality	The authors observed causal flows in the entire sample and in sub- samples (before and during the COVID-19 pandemic).
Anamika et al. (2023)	S&P500	>	Bitcoin	MQO	The author concluded that the relationship between S&P500 and BTC is relevant, as it shows how sentiment and confidence in traditional financial markets can affect cryptocurrencies, especially Bitcoin.
Gaies et al. (2023)	FGI	>	Bitcoin	Granger Causality	The authors indicate that investor fear sentiment influences Bitcoin price, but it is not constant. The authors also concluded that external factors contribute to the price, such as economic and stock market events.
Helmi (2023)	S&P500	>	Bitcoin	VAR	According to the author, the S&P500 index is a candidate for explaining Bitcoin price variation along with other variables.

Theoretical and Empirical Evidence on Bitcoin Price Determinants

Compiled by the author (2023).

Table 1 presents a set of theoretical and empirical evidence highlighting the factors that shape Bitcoin's price. These variables include the Fear and Greed Index (FGI), Bitcoin Returns (BTC), the S&P500 index, and the U.S. Federal Reserve Interest Rate (FED). Authors have adopted various analytical approaches to explore the complex interactions between these variables and understand the underlying causal relationships.

Aste (2019) examined the relationship between Investor Sentiment on Social Media (such as Twitter) and Bitcoin's Price, using Granger Causality. His study emphasized a significant interdependence and causality between investor sentiment and cryptocurrency prices, highlighting the influence of social media on cryptocurrency market dynamics.

Bernardo (2022) provided insights, demonstrating that Bitcoin can serve as an indicator due to its causal relationship with the FED and, consequently, with the U.S. market represented by the S&P500. This research underscores Bitcoin's sensitivity to economic policies and conditions in traditional markets.

Bourghelle et al. (2022) adopted a Vector Autoregression (VAR) model to investigate the complex relationship between Bitcoin price volatility and the Fear and Greed Index (FGI). Their results pointed to the nonlinear and asymmetric role of investor emotions in Bitcoin volatility, highlighting that this relationship varies depending on market conditions.

Table 1

Meanwhile, Gunay et al. (2022) explored the relationship between FGI and the Volatility Index of the U.S. Stock Market (VIX) and their ability to predict trend reversals in the U.S. stock market. They identified these indices as significant indicators for anticipating changes in market trends.

Mokni et al. (2022) investigated the relationship between FGI and Bitcoin Returns (BTC) using Granger Causality. Although they did not find a causal relationship throughout the sample period, they observed causal flows during the COVID-19 period, indicating the influence of investor emotions during times of uncertainty.

Furthermore, Gaies et al. (2023) analyzed the influence of FGI on Bitcoin's price, highlighting that investor fear sentiment can impact Bitcoin, although this relationship is variable. They also emphasized the importance of external factors such as economic and stock market events in determining Bitcoin's price.

Helmi (2023) suggested that the S&P500 index plays a relevant role in explaining Bitcoin price variation, using a Vector Autoregression (VAR) model. This indicates an interconnection between the traditional stock market and the cryptocurrency market.

Finally, Anamika et al. (2023) investigated the relationship between the S&P500 index and Bitcoin through Simple Regression, demonstrating how sentiment and confidence in traditional financial markets can affect investor behavior regarding cryptocurrencies.

Collectively, these theoretical and empirical pieces of evidence reveal the complex network of interactions shaping Bitcoin's price and its relationship with traditional markets, emphasizing the importance of considering emotional and external factors when analyzing cryptocurrency dynamics. These findings provide valuable insights for investors, researchers, and market observers seeking to understand Bitcoin trends and behavior.

Methodology

In this section, we will elaborate on the methodology used to analyze the complex relationship between various determining factors and the price of Bitcoin, while also investigating the role of investor sentiment in this context. The aim is to provide a comprehensive overview of the research process, from data collection to the selection of statistical and machine learning models used to predict Bitcoin behavior.

Data Collection

The data used in this research cover the period from July 2022 to June 2023 and include information on the price of Bitcoin (BTC) in US dollars, the Fear and Greed Index (FGI), the US Federal Reserve Interest Rate (FED), the NASDAQ Stock Exchange Index, and other relevant indicators. A descriptive analysis of the data was conducted to understand the behavior and distribution of the variables used in the study.

Unit Root Test

The unit root test, to assess the stationarity of time series, was conducted using the Augmented Dickey-Fuller (ADF) test. Three variations of the test were applied: None (No Trend and No Intercept), Const (With Intercept), and Trend (With Trend and Intercept), as demonstrated in Equations (1)-(3), respectively.

$$\Delta Y_t = \delta Y_{t-1} + u_t \tag{1}$$

$$\Delta Y_t = \alpha + \delta Y_{t-1} + u_t \tag{2}$$

$$\Delta Y_t = \alpha + \beta t + \delta Y_{t-1} + u_t \tag{3}$$

where *Y* is the time series, Δ represents the first difference, δ is the lag coefficient, and u_t is the error term, α is the intercept, and *t* is the coefficient of time trend.

Johansen Cointegration Test

The Johansen cointegration test is employed to identify long-term relationships among variables. This is represented through the equations of the Vector Error Correction Model (VEC):

$$\Delta Y_t = \pi Y_{t-1} + \rho_1 \Delta Y_{t-1} + \dots + \rho_{p-1} \Delta Y_{t-p+1} + u_t$$
(4)

where π is the cointegration matrix, ρ_i is the matrices of coefficient of the first difference, p is the lag order, and u_i is the error vector.

Granger Causality Test

The Granger causality test is applied to identify cause-and-effect relationships among variables. Using the Vector Autoregressive (VAR) approach, the equation is given by:

$$\Delta Y_t = A_1 \Delta Y_{t-1} + \dots + A_p \Delta Y_{t-p} + u_t \tag{5}$$

where: ΔY_t is the vector of the first difference of time series, A_i is the autoregressive coefficiente matrices, and u_t is the error vector. The test explores whether past information from one time series improves the forecast of the other, indicating Granger causality.

VAR Modeling and Neural Networks

To predict Bitcoin price returns, we employed two different methods: VAR Modeling and Neural Networks. VAR Modeling is a statistical approach that considers linear relationships between variables, while Neural Networks are a machine learning technique capable of capturing complex non-linear relationships. In the case of Neural Networks, we experimented with various architectures, including different layers and numbers of neurons, to determine the optimal configuration. To further enhance our predictions, we combined the results of VAR Modeling and Neural Networks. In our research, the residuals from individual predictions were used to calculate the weight of each of these predictions (w_i):

$$w_{i} = \frac{\left(\sum_{i=1}^{t} e_{1}^{2}\right)^{-1}}{\sum_{j=1}^{n} \left(\sum_{i=1}^{t} e_{1}^{2}\right)^{-1}}$$
(6)

To assess the success of the predictions, as outlined by Ivaknenko, Ivakhnenko, and Müler (1993), we utilized Equation (7). Results equal to or less than 0.5 would be deemed adequate; those falling between 0.5 and 0.8 would be considered satisfactory; values greater than 1 would be regarded as incorrect information, rendering the models inefficient.

$$\delta_i^2 = \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \to \min.$$
 (7)

To compare the efficiency of the predictions, we employed the sample coefficient of determination R^2 (as shown in Equation (8)). Two other indicators were used: MSE (Mean Squared Error) and MAE (Mean Absolute Error), demonstrated in Equations (9) and (10).

$$R^{2} = 1 - \frac{\sum_{i}^{N} (\hat{y}_{i})^{2}}{\sum_{i}^{N} (y_{i} - \overline{y})^{2}}.$$
(8)

$$MSE = \sqrt{\frac{1}{N} \sum_{1}^{N} (y_{i} - \hat{y}_{i})^{2}}.$$
(9)

$$MAE = \frac{1}{N} \sum_{1}^{N} \left| \sqrt{y_{i}^{2}} - \sqrt{\hat{y}_{i}^{2}} \right|.$$
(10)

Additionally, we analyzed the Theil inequality coefficients, also referred to as U. The numerator is MSE, but the scale of the denominator is such that U exists in the range between 0 and 1, where U = 0 would indicate a perfect fit of the prediction to the observed value, and where U = 1, the model's prediction performance would be at its worst. The Theil inequality coefficient is shown in Equation (11).

$$U = \frac{\sqrt{\frac{1}{N} \sum_{i}^{N} (y_{i} - \hat{y}_{i})^{2}}}{\sqrt{\frac{1}{N} \sum_{i}^{N} (y_{i})^{2}} + \sqrt{\frac{1}{N} \sum_{i}^{N} (\hat{y}_{i})^{2}}}.$$
 (11)

In addition to the Theil inequality coefficient, we analyzed the U^M and U^S ratios (Trend Ratio and Variance Ratio) that allow us to decompose the error into its characteristic sources. According to Pindyck and Rubinfeld (1991), the Trend Ratio (U^M) examines potential systematic error by measuring how much the average values of the series deviate from each other. Regardless of the value of the Theil inequality coefficient (U), we expect U^M to be close to 0. A high U^M (above 0.1 or 0.2) would be concerning as it would indicate the presence of a systematic trend, necessitating a review of the models. In Equations (12) and (13), we demonstrate the Trend Ratio and Variance Trend, respectively.

$$U^{M} = \frac{\left(\bar{y}^{S} - \bar{y}^{A}\right)^{2}}{(1/T)\sum\left(\bar{y}^{S}_{t} - \bar{y}^{A}_{t}\right)^{2}}.$$
(12)

$$U^{s} = \frac{\left(\sigma_{s} - \sigma_{A}\right)^{2}}{\left(1/T\right)\sum\left(\bar{y}_{t}^{s} - \bar{y}_{t}^{A}\right)^{2}}.$$
(13)

The variance ratio (U^{S}), as mentioned by Pindick and Rubinfeld (1991), indicates the ability to replicate the degree of variability of the variable of interest. If U^{S} is high, it would mean that the actual series fluctuated significantly while the simulated series showed little fluctuation, or vice versa. This would also be concerning and could lead to a review of the models.

Results

In this section, we present the findings of this study, which focus on understanding the complex relationship between various determinants and the price of Bitcoin while also exploring the role of investor sentiment in this constantly evolving financial ecosystem. Our investigations aim to shed light on patterns, trends, and underlying relationships, revealing insights for investors, researchers, and market analysts, highlighting the importance of predictability amid the inherent volatility of Bitcoin and the cryptocurrency market. Below, Table 2 presents the descriptive statistics of the variables used in the research.

Table 2 provides a descriptive statistical analysis of five distinct variables, each offering a deeper understanding of their behavior and distribution. The Fear and Greed Index (FGI) exhibits a range from 16.00 to

68.00, with a mean of 39.27, indicating a tendency toward higher values. Furthermore, the positive skewness (0.16) suggests a mild inclination toward higher values, while the kurtosis (1.58) points to a distribution with a moderate concentration of data around the mean, without being excessively flat or elongated.

 Table 2

 Descriptive Statistics of Variables

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Variable	Minimum	Maximum	Mean	Skewness	Kurtosis	
Fear and greed index (FGI)	16.00	68.00	39.27	0.16	1.58	
Bitcoin (BTC) in US\$	15,787.28	30,271.13	22,503.56	0.13	1.94	
American interest rate (FED) in %	1.58	5.08	3.82	-0.63	2.05	
Stock market index (NASDAQ)	10,466.48	13,689.57	11,705.88	0.51	2.53	

Source: Own elaboration (2023).

In the case of Bitcoin price (in US dollars), prices range from 15,787.28 to 30,271.13, with a mean of 22,503.56. Positive skewness (0.13) indicates a slight tendency toward higher values, while kurtosis (1.94) suggests a distribution with heavier tails, meaning extreme events may occur more frequently.

American interest rates (FED), on the other hand, range from 1.58% to 5.08%, with a mean of 3.82%. Negative skewness (-0.63) points to a bias toward lower values, indicating that most observations are above the mean. Additionally, kurtosis (2.05) indicates heavy tails in the distribution, implying a higher probability of extreme events. Finally, the Stock Market Index (NASDAQ) ranges from 10,466.48 to 13,689.57, with a mean of 11,705.88. It exhibits a tendency toward higher values, as indicated by positive skewness (0.51), and heavy tails, as indicated by kurtosis (2.53). Following this, Table 3 presents the unit root test for the variables used in the research.

Table 3

Unit Root Test for Variables: Bitcoin (BTC), Fear and Greed Index (FGI), American Interest Rate (FED) in %, and Stock Market Index (NASDAQ), on a Weekly Basis From July 2022 to June 2023

Variable	Transformation	Trend	Const	None	
	Level data	-2.427	-1.628	-0.285	
Bitcoin	Return (Δ%)	-7.023***	-6.868***	-6.915***	
FOL	Level data	-2.938	-1.822	0.071	
FGI	Return (Δ%)	-9.242***	-9.023***	-8.602***	
FED	Level data	0.593	-4.721***	-0.151	
FED	Return (Δ%)	-3.202*	-3.714***	-4.294***	
NASDAO	Level data	-1.435	-0.608	0.788	
NASDAŲ	Return (Δ %)	-8.317***	-8.185***	-8.142***	

Notes. * 10% significance; ** 5% significance; *** 1% significance; Δ % indicates percentage change; Δ 1st Difference indicates the first difference. None: deterministic model without trend and intercept; Const: deterministic model with intercept; Trend: deterministic model with intercept and trend. Source: Own elaboration (2023).

Table 3 presents the results of a unit root test on Bitcoin (BTC) prices, Fear and Greed Index (FGI), U.S. Interest Rate (FED), and Stock Exchange Index (NASDAQ) based on weekly data from July 2022 to June 2023.

The unit root test is commonly used to check if time series data have unit roots, indicating the presence of trends and non-stationarity in the data. In other words, the null hypothesis (H_0) in unit root tests states that the series are non-stationary, meaning they have unit roots.

Looking at the results in the table, we notice that for all three versions of the test (None: deterministic model with no trend and no intercept; Const: deterministic model with intercept; Trend: deterministic model with intercept and trend), the null hypothesis (H_0) was not rejected in the level data, suggesting that these series may have unit roots when analyzed in their raw form.

However, when considering the data transformed into returns, the null hypothesis (H_0) was rejected with high statistical significance for these variables. This implies that, after transformation, the series became stationary, without unit roots, and may be more suitable for economic analysis and financial modeling.

In summary, rejecting the null hypothesis (H_0) in a unit root test means that the series are stationary and do not have unit roots, making them more suitable for statistical and economic analysis. The non-rejection of the null hypothesis suggests that the series may be non-stationary and have trends. This information is crucial for conducting the Cointegration and Granger Causality test, as described in Table 4 below.

Table 4

Johansen Cointegration Test Applied to Variables: Bitcoin Return (BTC), Fear and Greed Index Return (FGI), American Interest Rate Return (FED), and Nasdaq Return (NASDAQ), on a Weekly Basis From July 2022 to June 2023

	$\Delta\%$ of BTC Cointegrated with $\Delta\%$ of FGI			$\Delta\%$ of BTC Cointegrated with $\Delta\%$ of FED			$\Delta\%$ of BTC Cointegrated with $\Delta\%$ of NASDAQ		
H ₀	Trend	Const	None	Trend	Const	None	Trend	Const	None
	0.447	0.417	0.417	0.344	0.297	0.287	0.438	0.415	0.414
$r \leq 2$	***	***	***	***	***	***	***	***	***
< 1	0.418	0.311	0.282	0.434	0.366	0.325	0.396	0.387	0.387
$r \leq 1$	***	***	***	***	***	***	***	***	***
<i>n</i> < 0	0.460	0.440	0.440	0.422	0.392	0.387	0.460	0.444	0.443
$r \leq 0$	***	***	***	***	***	***	***	***	***

Notes. * 10% significance level; ** 5% significance level; *** 1% significance level; Δ %: Percentage Variation; Δ : First Difference; None: deterministic model without trend and intercept; Const: deterministic model with intercept; Trend: deterministic model with intercept and trend. Source: Own elaboration (2023).

Table 4 presents the results of the Johansen Cointegration test applied to the variables, including Bitcoin return (BTC), Fear and Greed Index return (FGI), Federal Reserve Return (FED), and Nasdaq return (NASDAQ), during the period from July 2022 to June 2023. This statistical analysis is important for understanding the long-term relationships between these variables and how they relate to the studies mentioned in their references.

The Johansen Cointegration test proposes in its null hypothesis (H_0) that there is no cointegration between the variables. In other words, this null hypothesis suggests that there is no long-term relationship between Bitcoin and the variables under analysis. The Johansen Cointegration test was conducted in three forms (None, Const, and Trend). The first test refers to the deterministic model without trend and without intercept. The second test (Const) refers to the deterministic model with intercept. Finally, the Trend test is the deterministic model with intercept and trend.

The analysis of the results in Table 4 shows that, for all model configurations (Trend, Const, and None) and at all levels of cointegration relationships ($r \le 3$, $r \le 2$, $r \le 1$, and $r \le 0$), the null hypothesis was rejected at a 99% confidence level. This indicates that the analyzed variables are cointegrated, meaning that, for the analyzed period, there is a statistically significant long-term relationship. These results are in line with Aste (2019), Bernardo (2022), Bourghelle et al. (2022), and Mokni et al. (2022).

PRICE PREDICTABILITY AND THE IMPACT OF INVESTOR SENTIMENT

Firstly, Aste's (2019) research identified the influence of investor sentiment on social media on Bitcoin's price. The results of this study found a significant interdependence between investor sentiment and cryptocurrency prices. The results in Table 4 corroborate this finding, indicating that Bitcoin's return is cointegrated with the Fear and Greed Index (FGI), which partially reflects investor sentiment.

Similarly, Bernardo (2022) highlighted Bitcoin's ability to serve as an indicator, with a significant causal relationship with the FED and the U.S. market represented by the S&P500. The results in Table 4 confirm this relationship, showing that Bitcoin's return is cointegrated with the Federal Reserve Return (FED), and therefore, its dynamics are linked to economic policies and conditions in traditional markets.

Furthermore, Bourghelle et al. (2022) examined the complex relationship between the Fear and Greed Index (FGI) and Bitcoin price volatility. The results of this study suggested that investor emotions play a nonlinear role in Bitcoin's volatility. The results in Table 4, which show cointegration between Bitcoin's return and FGI, support this finding and indicate that the relationship between investor emotions and Bitcoin is long-term. Similarly, the studies by Mokni et al. (2022) investigated the relationship between FGI and Bitcoin, especially in the context of the COVID-19 pandemic. The results in Table 4 show that Bitcoin's return is cointegrated with FGI, suggesting that investor emotions can influence Bitcoin during periods of uncertainty.

In summary, the results in Table 4 demonstrate cointegration between Bitcoin's return and the variables FGI, FED, and NASDAQ, validating the findings of previous studies related to the impact of investor sentiment, economic policies, and traditional markets on Bitcoin's behavior. This reinforces the idea that Bitcoin is not an isolated asset but is interconnected with a series of factors, making its analysis and forecasting a multidimensional and important challenge for both investors and researchers. Since cointegration between the variables has been confirmed, the Granger causality test was conducted, as shown in Table 5.

Table 5

June 202.	3					
	Bitcoin return	FGI return	Bitcoin return	FED return	Bitcoin return	NASDAQ return
Lag	~	~	~	~	~	~
	FGI return	Bitcoin return	FED return	Bitcoin return	NASDAQ return	Bitcoin return
1	0.666	0.002**	13.88***	0.060	0.810	0.002**
2	2.188	0.046**	7.725***	0.873	0.558	0.054**
3	2.327*	1.533	5.114***	0.710	0.676	0.180*
4	2.169*	1.180	4.188***	0.840	0.556	0.266
5	2.881**	0.557	3.316***	0.666	0.388	0.638
6	2.106*	0.474	1.052	0.831	0.303	0.577

Granger Causality Test Applied to the Variables: Bitcoin Return (BTC), Fear and Greed Index Return (FGI), American Interest Rate Return (FED), and Nasdaq Return (NASDAQ), on a Weekly Basis From July 2022 to June 2023

Notes. * 10% significance; ** 5% significance; *** 1% significance; Δ %: Percentage Change; Δ indicates the first difference; ~ indicates: does not Granger cause. Source: Own elaboration.

Table 5 presents the results of the Granger Causality Test applied to the variables: the percentage change in Bitcoin Price, the percentage change in the Nasdaq index, and the percentage change in the US interest rate (FED). This analysis was conducted on a weekly frequency over the period from July 2022 to June 2023. The Granger Causality Test is a statistical technique that seeks to determine whether a time series can be used to predict another time series, i.e., whether a cause-and-effect relationship exists between the variables. The results of the Granger

Causality Test indicate that the null hypothesis of non-causality was rejected for several combinations of variables and lags.

The null hypothesis that Bitcoin Return does not Granger cause FGI Return was rejected at lags 3, 4, 5, and 6. This suggests that Bitcoin Return has a significant causal effect on FGI Return at longer lags, indicating that variations in Bitcoin prices can influence investor sentiment represented by FGI. One possible reason for these time delays is the volatile nature of Bitcoin, as mentioned by Trindade and Vieira (2020) and Diniz, de Prince, and Maciel (2022). Significant changes in Bitcoin prices may take some time to be absorbed by the market and reflected in investor sentiment.

Mokni et al.'s (2022) analysis also highlights that during the COVID-19 pandemic, there was a greater impact of Bitcoin Return on FGI, which may explain the observed lags, as exceptional events can have long-term effects on investor sentiment.

On the other hand, the null hypothesis that FGI Return does not Granger cause Bitcoin Return was rejected at lags 1 and 2. This implies that FGI Return has a significant causal impact on Bitcoin behavior at shorter lags, indicating that investor emotions have an immediate effect on Bitcoin fluctuations. This can be attributed to investors' immediate reaction to changes in sentiment, as highlighted by Gaies et al. (2023). When FGI reflects extreme emotions such as fear or greed, investors may react quickly, leading to changes in Bitcoin behavior at short lags. Additionally, Li et al.'s (2021) analysis emphasizes the bidirectional relationship between investor sentiment and Bitcoin returns at different time scales, which may explain the observed causality at short lags.

Similarly, the null hypothesis that FED Return does not Granger cause Bitcoin Return was rejected at lags 1, 2, 3, 4, and 5. This suggests that economic policy decisions represented by FED Return have a significant causal influence on Bitcoin price variations, demonstrating a connection between the cryptocurrency market and US economic policies. This result can be explained by the speed at which economic policy decisions can affect financial markets, as mentioned by Bernardo (2022). When the FED announces changes in interest rates or its policies, investors may react promptly, leading to variations in Bitcoin prices at both short and long lags. Additionally, Zhao's (2022) analysis, which investigated how local economic crises affect Bitcoin trading, may be related to these lags, as significant economic events can have delayed effects on the cryptocurrency market.

Finally, the null hypothesis that NASDAQ Return does not Granger cause Bitcoin Return was rejected at lags 1 and 2. This indicates that variations in NASDAQ performance, a significant stock market index, have an immediate causal effect on Bitcoin price. This may be due to the interconnection between the traditional stock market and the cryptocurrency market, as suggested by Helmi (2023). Rapid changes in NASDAQ performance can lead investors to adjust their investment strategies, immediately affecting Bitcoin prices. Moreover, the influence of the stock market on Bitcoin, as mentioned by Burggraf et al. (2021), may also explain these lags, as the search for indicators like the FEARS index can lead to rapid changes in the cryptocurrency market.

These potential causes for the time delays in the causal relationships between variables align with the references cited in this work, highlighting the complexity of interactions in financial markets, where emotional factors, exceptional events, and economic policy decisions play crucial roles in the dynamics of cryptocurrencies, such as Bitcoin. Thus, after conducting the Granger Causality tests, the determinants of Bitcoin price returns (BTC) were selected as the return of the Fear and Greed Index (FGI) and the return of the NASDAQ Index, which will compose the VAR modeling.

However, before starting the modeling, it is necessary to determine how many lags will be included in the model. Therefore, to determine the best modeling approach, the following criteria were used: Akaike Information

Criterion (AIC), Bayesian Information Criterion (BIC), Hannan-Quinn Criterion (HQ), and Final Prediction Error Criterion (FPE), as shown in Table 6.

Table 6

Results of the AIC, BIC, HQ, and FPE Tests for Determining the Number of Lags for Bitcoin Forecasting Using the VAR Model on a Weekly Basis, From July 2022 to June 2023

	•	•		
Lags	AIC	BIC	HQ	FPE
1	-20.666	-20.375	-19.902	1.06E-09
2	-20.605	-20.312	-19.832	1.13E-09
3	-20.847	-20.552	-20.068	8.87E-10
4	-20.805	-20.509	-20.018	9.24E-10
5	-20.755	-20.457	-19.960	9.72E-10
6	-20.722	-20.423	-19.919	1.01E-09
7	-20.675	-20.374	-19.864	1.05E-09
8	-21.047	-19.053	-15.641	5.20E-09
9	-25.119	-22.875	-18.996	6.68E-10

Source: Own elaboration (2023).

Table 6 presents the results of AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion), HQ (Hannan-Quinn Criterion), and FPE (Final Prediction Error) tests to determine the appropriate number of lags in VAR (Vector Auto regression) modeling for predicting weekly Bitcoin returns. These tests are widely used in selecting statistical models, helping to identify the suitable complexity of the VAR model.

The analysis of the results reveals insights for choosing the most suitable model. The main idea behind these criteria is to select a model that minimizes these statistics, indicating a balance between data fit and model complexity.

Overall, the results suggest a preference for models with lags between 2 and 3, with lag 2 being favored according to BIC and HQ, and lag 3 being favored according to AIC and FPE. Considering the principle of parsimony, the choice of the number of lags should favor simpler models as long as they still adequately capture the temporal structure of the data. Therefore, modeling with 2 lags (lags at t-1 and t-2) was chosen.

Subsequently, the same information tests were performed for different neural network architectures. Each row of the table represents a specific neural network architecture, with information about the number of layers and neurons, as well as the calculated values for AIC, BIC, HQ, and FPE criteria, as observed in Table 7.

Table 7

Layer	Neurons	AIC	BIC	HQ	FPE	
5-3-3	8	-236.954	-231.887	-235.122	-234.966	
10-5-3	15	-236.876	-231.809	-235.043	-234.888	
15-5-3	20	-237.150	-232.083	-235.318	-235.162	
5-5-3	13	-203.396	-196.641	-200.954	-201.805	
10-10-5	25	-235.633	-228.878	-233.191	-234.042	
15-10-5	30	-234.326	-227.571	-231.884	-232.734	
5-5-5-3	18	-201.372	-192.928	-198.319	-200.386	
10-10-10-5	35	-201.571	-193.127	-198.518	-200.585	
15-15-10-5	45	-201.595	-193.151	-198.542	-200.610	

AIC, BIC, HQ, and FPE Test Results for Determining the Best Network Architecture in Weekly Datasets From July 2022 to June 2023

Source: Own elaboration (2023).

Table 7 presents results from different neural network architectures used to predict Bitcoin price returns, based on criteria such as AIC, BIC, HQ, and FPE. These criteria are tools that aid in selecting the most appropriate neural network architecture as they help balance data fit and model complexity.

Upon examining the values in the table, it becomes evident that simpler architectures tend to excel. Architectures 5-5-5-3 and 5-5-3 consistently exhibit the lowest values across all criteria, suggesting they are solid choices for Bitcoin return prediction. This aligns with the principle of parsimony, favoring simpler models when they offer comparable performance.

The simplest architecture, 5-5-3, is a leaner option and likely easier to train. However, its simplicity may also limit its ability to capture complex relationships in the data if they exist. Therefore, the architecture 5-5-5-3, slightly more complex with additional neuron layers, was chosen. This architecture represents a neural network with four layers: the first is the input layer with five neurons, followed by two intermediate layers with five neurons each, and finally, an output layer with three neurons.

To make predictions, the data series was split into two parts. The first part (containing 80% of the observations) will be used for training the neural network and the VAR model. The second part (comprising 20% of the observations) will be used for making predictions. After generating forecasts for t+1, a combination of these predictions was performed as shown in Equation 6. The prediction results are presented in Table 8.

Table 8

Combination

Treaterions for t+1 (on a weekly basis) for bicoin Trice Retarns From July 2022 to June 2025								
Method	R-squared	MSE	MAE	U	U^M	U^S	Ivakhnenko	
VAR	0.276	0.007	0.077	2.575	3.913	2.559	0.097	
Neural network	0.239	0.001	0.074	0.019	0.708	1.075	0.197	

Predictions for t+1 (on a Weekly Basis) for Bitcoin Price Returns From July 2022 to June 2023

0.009

Source: Own elaboration (2023).

0.352

0.000

Table 8 presents the results of predictions for Bitcoin price returns from July 2022 to June 2023 using three different methods: VAR, Neural Network, and a Combination of predictions from both methods. Analyzing these results reveals important insights into the performance of the models.

0.346

0.526

0.344

0.122

Initially, the *R*-squared (coefficient of determination) is used to measure the proportion of variability in the data explained by the model. In this case, the Combination of methods stands out, with the highest *R*-squared (0.352). This suggests that this model is the most effective in explaining the variation in Bitcoin returns compared to the other methods.

Furthermore, the Mean Squared Error (MSE) and Mean Absolute Error (MAE) are error metrics that indicate how close the predictions are to the actual values. Once again, the Combination of methods demonstrates superior performance, recording the lowest MSE (0.000) and the lowest MAE (0.009). This suggests that the predictions of this model are the most accurate compared to the other approaches.

The Theil U parameter, used to measure the accuracy of predictions relative to actual values, indicates that Neural Networks perform the best with a value of 0.019, while the Combination obtains a value of 0.346, standing out as the second-best option in this regard.

When considering Theil's (U^M) and Theil's (U^S) , which represent standardized and deviation measures of Theil's U, the Combination (VAR + Neural Networks) shows its best performance with a U^M of 0.526 and a U^S

of 0.344, reinforcing its superiority in terms of accuracy and consistency in predictions. In the last parameter, Ivakhnenko's criterion, Neural Networks achieve a value of 0.197, indicating excellent precision, as values between 0.2 and 0.5 represent this quality.

In summary, the comprehensive analysis consistently points to the Combination (VAR + Neural Networks) as the preferred choice for predicting Bitcoin price returns during the evaluated period. This combination performs the best in terms of *R*-squared, MSE, MAE, standardized and deviation Theil's U, and offers highly accurate results compared to VAR and Neural Networks used separately. Therefore, the Combination proves to be the most effective and reliable approach for this specific Bitcoin return prediction scenario.

Final Considerations

This article focused on analyzing the behavior of Bitcoin prices in relation to financial and emotional variables, with an emphasis on the predictability of these relationships. We explored statistical techniques and forecasting models to better understand the dynamics affecting this cryptocurrency asset.

Throughout the research, we conducted descriptive statistical analyses that highlighted the volatile nature of Bitcoin prices, reflecting its ability for rapid appreciation and depreciation. However, our investigation aimed to go beyond this volatility and seek underlying patterns that could be useful for prediction.

By analyzing the Fear and Greed Index (FGI), the American Interest Rate (FED), and the Stock Market Index (NASDAQ) in relation to Bitcoin, we identified complex relationships that impact predictability. Johansen cointegration tests provided a solid foundation by demonstrating that Bitcoin is cointegrated with these variables. This cointegration suggests that long-term relationships are at play, which is crucial for forecasting.

Granger causality tests revealed that Bitcoin and the variables under analysis influence each other in various ways. For example, Bitcoin was shown to cause FGI at longer lags, and FED exerted significant causal influence over Bitcoin. These findings are essential for understanding how external information and events affect Bitcoin and can be leveraged in price prediction.

Regarding prediction, the combination of VAR models and neural networks proved to be highly effective. By optimizing the number of lags and the neural network architecture, we achieved remarkable results in terms of predictability. The combination of methods resulted in the highest coefficient of determination (R), the lowest mean squared error (MSE), and the lowest mean absolute error (MAE), highlighting its ability to predict Bitcoin returns accurately.

This research emphasizes that, while the cryptocurrency market is notoriously volatile, it is not unpredictable. The identified relationships and developed models demonstrate that valuable insights can be gained to make informed decisions in the world of cryptocurrencies. However, it is crucial to note that the market is constantly evolving, and predictability must be closely monitored and adjusted as needed.

In summary, this study contributed to the understanding of the complex relationships involving Bitcoin, highlighting the predictability of these relationships through statistical and machine learning models. This emphasis on predictability can serve as a solid foundation for investors, analysts, and researchers seeking to make informed decisions and adapt to a constantly changing market. As the cryptocurrency market continues to evolve, further research can delve even deeper into these complex relationships and improve forecasting models to better meet the demands of this dynamic environment.

References

- Almeida, J., & Gon çalves, T. C. (2023). A systematic literature review of investor behavior in the cryptocurrency markets. *Journal* of Behavioral and Experimental Finance, 37, 100785.
- Anamika, Chakraborty, M., & Subramaniam, S. (2023). Does sentiment impact cryptocurrency? *Journal of Behavioral Finance*, 24(2), 202-218.
- Aste, T. (2019). Cryptocurrency market structure: Connecting emotions and economics. Digital Finance, 1(1-4), 5-21.
- Bakhtiar, T., Luo, X. J., & Adelopo, I. (2023). The impact of fundamental factors and sentiments on the valuation of cryptocurrencies. Blockchain: Research and Applications. (in press)
- Bernardo, M. Â. V. D. F. F. (2022). Compara ção do mercado de criptomoedas com os mercados de ativos tradicionais (Master's thesis, Universidade de Évora, 2022).
- Bourghelle, D., Bourghelle, C., & Ye, Y. (2022). Do fear and greed drive cryptocurrency prices? An analysis of bitcoin's behavior. *International Review of Financial Analysis*, 24, 101057.
- Bourghelle, D., Jawadi, F., & Rozin, P. (2022). Do collective emotions drive bitcoin volatility? A triple regime-switching vector approach. Journal of Economic Behavior & Organization, 196, 294-306.
- Burggraf, T., Huynh, T. L. D., Rudolf, M., & Wang, M. (2021). Do FEARS drive bitcoin? *Review of Behavioral Finance*, 13(3), 229-258.
- Dinis, A., & Cheriff, A. (2020). Do investors react to psychological barriers? An empirical study on bitcoin. SSRN Electronic Journal.
- Diniz, R., de Prince, D., & Maciel, L. (2022). Bubble detection in bitcoin and ethereum and its relationship with volatility regimes. *Journal of Economic Studies*, 50(3), 429-447.
- Dubey, P. (2022). Short-run and long-run determinants of bitcoin returns: Transnational evidence. *Review of Behavioral Finance*, 14(4), 533-544.
- Entrop, O., Frijns, B., & Seruset, M. (2020). The determinants of price discovery on bitcoin markets. *Journal of Futures Markets*, 40(5), 816-837.
- Gaies, B., Abid, F., & Jilani, F. (2023). Investigating the fear and greed investors' sentiment influence on bitcoin price: The COVID-19 crisis perspective. *Journal of Risk and Financial Management*, *16*(3), 122.
- Gaies, B., Nakhli, M. S., Sahut, J. M., & Schweizer, D. (2023). Interactions between investors' fear and greed sentiment and bitcoin prices. *The North American Journal of Economics and Finance*, 67, 101924.
- Gómez-Mart nez, E., Garc n, J. D., & Giner, B. G. (2023). Profitability of a fear and greed algorithmic trading system based on CNN sentiment index. *Finance Research Letters*, *41*, 101841.
- Gunay, S., Muhammed, S., & Nguyen, D. K. (2022). Identifying the role of investor sentiment proxies in NFT market: Comparison of google trend, fear-greed index and VIX. Fear-Greed Index and VIX.
- Gurdgiev, C., & O'Loughlin, D. (2020). Herding and anchoring in cryptocurrency markets: Investor reaction to fear and uncertainty. *Journal of Behavioral and Experimental Finance*, 25, 100271.
- Halliday, J. (2018). Herding behavior in closed-end country funds: US versus Japan. Managerial Finance, 44(5), 527-541.
- Helmi, M. H., Çatık, A. N., & Akdeniz, C. (2023). The impact of central bank digital currency news on the stock and cryptocurrency markets: Evidence from the TVP-VAR model. *Research in International Business and Finance*, 65, 101968.
- Ivakhnenko, A., Ivakhnenko, G., & Müller, J. (1993). Self-organization of optimum physical clustering of the data sample for weakened description and forecasting of fuzzy objects. *Pattern recognition and image analysis*, 3(4), 415-421.
- John, D. L., & Stantic, B. (2022). Forecasting cryptocurrency price fluctuations with granger causality analysis. In *Asian conference* on intelligent information and database systems. Singapore: Springer Nature Singapore.
- Kulcsar, L., & van Engelen, F. (2023). Twitter sentiment analysis on the cryptocurrency market. Retrieved from www.divaportal.org/smash/get/diva2:1762598/FULLTEXT01.pdf
- Li, R., Li, S. F., Yuan, D., & Zhu, H. M. (2021). Investor attention and cryptocurrency: Evidence from wavelet-based quantile Granger causality analysis. *Research in International Business and Finance*, 56, 101389.
- Mokni, K., Ben Rejeb, A., & Lahiani, A. (2022). Bitcoin and investor sentiment: A quantile causality analysis. *Finance Research Letters*, 41, 101839.
- Mokni, K., Bouteska, A., & Nakhli, M. S. (2022). Investor sentiment and bitcoin relationship: A quantile-based analysis. *The North American Journal of Economics and Finance*, 60, 101657.
- Petkova, B. (2023). Sentiment-induced mispricing: Evidence from bitcoin expectations. SSRN Electronic Journal.

Pindyck, R. S., & Rubinfeld, D. L. (1991). Econometric models and economic forecasting. New York: McGraw-Hill.

- Shahvari, N. (2022). The relation between gold price movement and bitcoin investment sentiment. International Journal of Management, Accounting & Economics, 9(9), 566-582.
- Smales, L. A. (2022). Investor attention in cryptocurrency markets. International Review of Financial Analysis, 79, 101972.
- Trindade, M. G. N., & Vieira, M. D. S. (2020). Criptoativos: conceito, classifica ção, regula ção jur flica no Brasil e pondera ções a partir do prisma da An álise Econ ômica do Direito. *RJLB-Revista Jur álica Luso-Brasileira*, *6*, 867.
- Vo, A., Chapman, T. A., & Lee, Y. (2022). Examining bitcoin and economic determinants: An evolutionary perspective. *Journal* of Computer Information Systems, 62(3), 572-586.

Zhao, J. (2022). Do economic crises cause trading in Bitcoin? Review of Behavioral Finance, 14(4), 465-490.