ANALYZING LAGGED CAUSALITY OF MULTIPLE MARKET FACTORS ON BITCOIN PRICE: AN INTERDISCIPLINARY APPROACH

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ABSTRACT

The cryptocurrency market, particularly Bitcoin, is characterized by high volatility influenced by various factors including public sentiment on social media, trading volume, and psychological market indicators such as the Fear and Greed Index (FGI). This study analyzes the lagged relationships and directional causality between Platform X sentiment, Bitcoin trading volume, the FGI, and Bitcoin price movements through an interdisciplinary approach that integrates Natural Language Processing and econometric modeling. The novelty of this research lies in its comprehensive multivariate framework that simultaneously examines bidirectional causality among four key market variables using optimal lag selection (10 periods) and the Toda-Yamamoto procedure, addressing critical gaps in temporal dynamics that previous studies overlooked. Sentiment data from Platform X was extracted using FinBERT, a model optimized for financial text analysis, and Vector Autoregression together with Granger Causality Tests were implemented to identify temporal lag patterns and causal relationships over the period from March 2022 to March 2023. The results indicate that Bitcoin price exerts a significant influence on Platform X sentiment, Bitcoin trading volume, and the FGI, with trading volume being the only variable that also exhibits a reverse influence on Bitcoin price. These findings suggest that price movements play a dominant role in shaping sentiment, trading activity, and market psychology, while trading volume maintains a feedback loop with price. This study provides both practical and theoretical contributions by offering a comprehensive framework for understanding the dynamics of the cryptocurrency market and the interactions among social media sentiment, trading behavior, and investor psychology in relation to Bitcoin price movements.

Keywords: *Machine Learning, Sentiment Analysis, FinBERT, Cryptocurrency, Granger Causality*

1. INTRODUCTION

Over the past decade, cryptocurrencies have reshaped global finance by introducing decentralized and transparent transactions independent of central authorities [1]. Bitcoin, as the first cryptocurrency, has created an alternative financial ecosystem with a market capitalization reaching trillions of dollars [2]. Yet, the market remains highly volatile, with price movements often driven not just by technical or regulatory factors, but also by public sentiment—especially on social media. For example, a single tweet from Elon Musk in 2021 caused Dogecoin's price to surge over 40% within hours [3], illustrating how online discourse can sway market behaviour. While such effects are well documented for altcoins, the extent to which social sentiment affects Bitcoin remains underexplored.

Platform X (formerly Twitter) serves as a major hub for cryptocurrency discussions, where millions of users exchange insights and opinions daily [4]. Studies like Ante (2021) show that tweets from influential figures can move markets, while others, such as van Engelen and Kulcsár (2023), argue that price changes can also shape sentiment. This raises a central question: Does sentiment drive Bitcoin's price, or do price shifts influence public mood? [5], [6].

Alongside sentiment, trading volume is a crucial indicator of market activity and liquidity. Research shows that extreme price movements often align with volume spikes, and responses to news can be asymmetric [7]. For example, on March 13, 2020, also known as Black Friday in the crypto market, Bitcoin trading volume surged to 75 billion US dollars, followed by a price drop of approximately 40 percent [2]. In addition to trading activity, investor behaviour is also shaped by broader psychological factors, which are captured by the Fear and Greed Index [8]. The index combines multiple indicators such as volatility, momentum, volume, Bitcoin dominance, and social media trends into a single score that reflects the overall market mood [9]. On June 18, 2022, the index showed extreme fear, after which Bitcoin's price increased by around 35 percent. These examples highlight the importance of both trading volume and the Fear and Greed Index in influencing price dynamics, supporting their inclusion as key variables in this study [9], [10].

Analyzing these relationships poses methodological challenges. Social media data is unstructured and subjective, making it difficult for traditional techniques to extract meaningful insights [11]. Many studies identify correlations between tweet volume and price but often neglect lag effects or temporal causality [12], [13]. Likewise, studies on volume and FGI often analyse these factors in isolation [8].

To overcome these limitations, this study adopts an interdisciplinary approach that integrates natural language processing and econometric modelling to examine the dynamic relationships among Bitcoin price, social media sentiment, trading activity, and investor psychology. Specifically, FinBERT, a financial-domain NLP model, is employed to extract sentiment from English-language tweets containing the keywords "BTC" and "Bitcoin" on Platform X. Econometric analysis is conducted using Vector Autoregression (VAR) and Granger causality testing based on the Toda–Yamamoto procedure to rigorously assess lagged and directional relationships among four key variables: Bitcoin price, Platform X sentiment, Bitcoin trading volume, and the Fear and Greed Index (FGI). The analysis focuses on daily data from March 2022 to March 2023, a post-pandemic period characterized by distinct volatility patterns and evolving investor behavior, with lag structures extending up to ten periods to capture delayed market responses.

The scope of this study is deliberately bound. The analysis is restricted to Bitcoin, as the dynamics of alternative cryptocurrencies may differ substantially due to variations in market capitalization, liquidity, and community structures. Sentiment data is sourced exclusively from Platform X and does not incorporate discussions from other influential platforms. The study employs daily frequency data and does not examine high-frequency intraday trading patterns to avoid excessive noise that may obscure underlying causal relationships. Furthermore, external factors, including regulatory announcements, macroeconomic indicators, institutional adoption trends, market manipulation, whale trading behavior, and technical indicators beyond trading volume, are excluded from the analytical framework, and long-term structural breaks or regime changes outside the designated study period are not examined.

This research operates under several key assumptions and is subject to inherent limitations. It assumes that sentiment expressed on Platform X reasonably represents broader market sentiment and that the Fear and Greed Index effectively capture investor psychology through its composite methodology. It further assumes relative stability in the relationships among the examined variables during the study period and that FinBERT adequately captures the nuances of financial sentiment in cryptocurrency-related discourse. Nevertheless, the one-year temporal scope may not fully capture long-term market cycles, the restriction to English-language content may underrepresent sentiment from non-English-speaking markets, and residual automated or bot-generated content may introduce noise despite filtering efforts. Finally, while Granger causality provides evidence of predictive relationships and temporal precedence, it does not imply true causal mechanisms, and the results should be interpreted accordingly.

2. LITERATURE REVIEW

2.1 Natural Language Processing for Financial Sentiment

Natural Language Processing (NLP) has become an essential tool in financial analytics, particularly for extracting sentiment from unstructured text sources such as news articles, analyst reports, and social media. Traditional rule-based and statistical approaches, such as n-grams and TF-IDF, have evolved with the adoption of machine learning and deep learning techniques [14]. These conventional methods, while interpretable, often struggle with semantic nuances and domain-specific vocabulary [13].

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Recent advancements, including transformer-based models like BERT and FinBERT, have significantly improved sentiment classification by capturing contextual meaning specific to financial language [15]. FinBERT, in particular, has demonstrated superior performance in disambiguating financial terms that may carry different meanings in general versus financial contexts (e.g., "bullish", "volatile"). These models are widely used to assess market mood, investor confidence, and risk perception in real time, with applications in investment decision-making and regulatory monitoring [16].

2.2 Cryptocurrencies Market Behavior Indicators

Cryptocurrencies, exemplified by Bitcoin, represent a decentralized digital financial system secured by cryptographic protocols and enabled by blockchain technology [1]. Unlike traditional assets, cryptocurrencies lack centralized regulation and are traded continuously across global markets, leading to heightened sensitivity to news and sentiment [17]. Their market behaviour is strongly influenced by sentiment dynamics, making them highly reactive to external narratives, including tweets, public statements, and macroeconomic rumours [18].

One widely observed metric is the Fear and Greed Index (FGI), which reflects the overall sentiment of the cryptocurrency market by combining indicators such as price momentum, social media trends, volatility, and trading volume [9]. Research indicates that periods of extreme fear or greed often come before synchronized price shifts across different crypto assets, suggesting the presence of herd behaviour among investors [19]. This pattern tends to be more visible in retail-dominated environments like the crypto market, where investor sentiment plays a key role in driving both rallies and downturns [20].

Meanwhile, social media platforms like Platform X have become critical data sources for sentiment extraction, reflecting real-time market expectations and public opinion [18]. The sheer volume and velocity of posts create a rich dataset for tracking investor mood. Moreover, hashtags, emojis, and slang have been shown to correlate with market events, prompting researchers to incorporate linguistic pre-processing and domain-specific normalization for more accurate sentiment interpretation. Additional indicators such as on-chain activity (e.g., wallet transfers, mining hash rates) and Google Trends have also been used to gauge market interest and behaviour, further enriching the behavioural analysis of crypto markets [21].

2.3 Econometric Modeling in Financial Analysis

Econometric models are essential tools for examining complex interactions between investor sentiment, trading behaviour, and cryptocurrency prices. The dynamic nature of cryptocurrency markets requires analytical frameworks that can capture multidirectional relationships and temporal dependencies among variables [22].

Among these analytical frameworks, the Vector Autoregression (VAR) model is widely used for analyzing multivariate time series in financial research, particularly for studying how variables such as Bitcoin price, social media sentiment, Fear and Greed Index (FGI), and trading volume influence each other over time [6]. Unlike univariate models, VAR model captures bidirectional relationships among multiple time series simultaneously, making it suitable for cryptocurrency market analysis where variables exhibit complex interdependencies, assuming each variable is influenced by its own lagged values and the lagged values of all other variables in the model [23]. This approach does not require prior assumptions about causality direction, allowing data to reveal underlying relationships. A critical component is determining optimal lag length using information criteria such as AIC, BIC, FPE, and HQIC, which balance model fit against complexity to capture essential temporal dependencies without introducing noise [24].

Granger Causality tests are employed within the VAR framework to assess whether sentiment indicators possess predictive power for cryptocurrency price movements [25]. This statistical concept evaluates whether past values of one variable contain useful information for forecasting another variable, indicating predictive precedence rather than actual causation [22]. Traditional Granger Causality tests face limitations when applied to financial time series that exhibit non-stationarity, unit roots, and structural breaks, leading to spurious correlations particularly in volatile cryptocurrency markets. To address these issues, researchers adopt the Toda-Yamamoto procedure, which provides robust causal inference in non-stationary environments [26]. The Toda-Yamamoto approach extends classical Granger Causality by estimating an augmented VAR model in levels, regardless of integration order or cointegration properties. This methodology eliminates pre-testing requirements, preserves long-

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run information, and provides valid test statistics even when variables are integrated or cointegrated [22], [26].

2.4 Related Works

Recent studies have increasingly focused on the predictive value of social media sentiment in cryptocurrency price dynamics, reflecting the broader shift toward behavioral and data-driven market analysis. Arslan (2024) introduced a hybrid EMD–LSTM framework that integrates empirical mode decomposition with deep learning to capture nonlinear patterns in Bitcoin prices, showing that sentiment-informed models outperform baseline approaches during periods of heightened volatility [27]. Japar et al. (2022) employed lexicon-based sentiment analysis combined with Granger causality to compare sentiment–price interactions before and after the COVID-19 shock, revealing that collective mood exerts stronger influence during macroeconomic uncertainty [28]. Complementing these findings, Yin et al. (2020) demonstrated that tweets containing financial or technical terminology are significantly more informative for price direction than general emotional expressions, highlighting the importance of domain-specific linguistic cues [18].

Despite these contributions, the existing literature still exhibits several methodological blind spots. Many studies treat sentiment as an exogenous predictor and overlook its bidirectional feedback loop with price movements. This assumption oversimplifies crypto market behavior, where investor mood simultaneously reacts to and shapes market outcomes. In addition, optimal lag selection is frequently neglected, resulting in temporal misalignment that can distort causal inference and understate the real impact of sentiment shocks. Van Engelen and Kulcsár (2023) provided evidence that short-term causality runs predominantly from Bitcoin returns to sentiment rather than the reverse, reinforcing the need for models that can capture more intricate, time-varying lag structures [6].

These limitations point to a broader gap in the literature: current models often fail to integrate the reflexive, fast-changing nature of crypto sentiment, and they rarely incorporate cross-platform heterogeneity, where user behavior, linguistic style, and information velocity differ substantially across channels [29]. Consequently, there remains a need for more comprehensive, temporally sensitive frameworks that reflect the dynamic interplay between sentiment and market behavior.

2.5 Research Gap and Problem Statement

Despite substantial progress in cryptocurrency sentiment and market behavior research, several critical gaps remain. First, much of the existing literature examines sentiment and price relationships in isolation, neglecting the joint roles of trading volume and market psychology. This narrow focus limits understanding of cryptocurrency markets as complex systems in which price, sentiment, volume, and psychological indicators interact dynamically within a multivariate setting.

Second, optimal lag selection is frequently overlooked or inadequately justified in cryptocurrency time series studies. Many analyses rely on arbitrary or pre-defined short lag structures, potentially distorting causal inference in markets where information diffusion and behavioral responses may unfold over longer horizons than in traditional financial markets. Third, bidirectional causality is often assumed rather than rigorously tested using econometric methods that account for non-stationarity. The application of standard Granger causality tests without addressing unit roots and integration properties raises concerns regarding spurious findings and weakened inference.

Based on these gaps, this study addresses the following problem: how lagged temporal dynamics and directional causality operate among Bitcoin price, Platform X sentiment, trading volume, and the Fear and Greed Index when examined simultaneously within a robust multivariate econometric framework that incorporates optimal lag selection and accommodates non-stationarity.

Accordingly, the research is guided by four questions:

RQ1: What is the optimal lag structure for modeling the dynamic relationships among Bitcoin price, Platform X sentiment, trading volume, and the Fear and Greed Index?

RQ2: Does Platform X sentiment exert causal influence on Bitcoin price after controlling for trading volume and market psychology, or does causality predominantly run from price to sentiment?

RQ3: What is the direction of causality between Bitcoin trading volume and price, and does a bidirectional relationship exist across different lag structures?

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RQ4: Does the Fear and Greed Index demonstrate predictive power for Bitcoin price movements, or does it primarily reflect contemporaneous or lagging market conditions?

3. METHODOLOGY

3.1 Research Framework

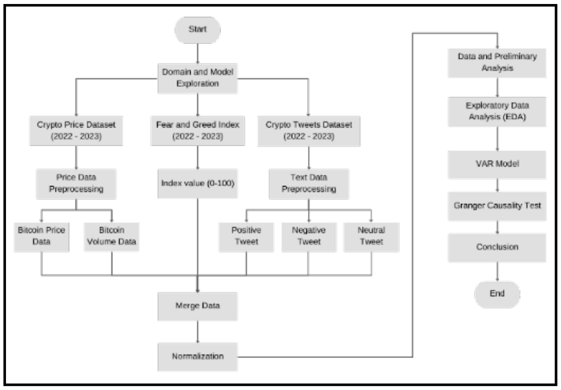

Figure 1: Proposed Framework Model

This study aims to examine the relationship between Bitcoin prices, public sentiment on Platform X, Bitcoin trading volume, and the Fear and Greed Index (FGI). The research framework, illustrated in Figure 1, is structured to explore potential causal links among the four variables. To gain a comprehensive understanding of their interconnections, this study employs a multi-stage analytical approach. The analysis begins with Exploratory Data Analysis (EDA), which includes correlation heatmap analysis and parallel coordinates plot analysis. This is followed by the application of the VAR model and the Granger Causality test. The analysis is conducted using data spanning from March 2022 to March 2023.

3.2 Data Collection and Preprocessing

In this study, ta total of four datasets are required, Bitcoin prices, Platform X's tweet, Bitcoin trading volume, and FGI Index on a range of analysis period. Bitcoin price data was collected from Kaggle, sourced from Coingecko, one of the largest cryptocurrency data aggregators in the world and was retrieved via API connection. After collection, relevant columns were selected, and column names were standardized. The variables used are as outlined in Table 1.

Table 1: Bitcoin Price Dataset Variables

Variable Name	Description	Data Type
datetime	Date and time of the price data	Datetime
price	BTC closing price at the given time	Float64

Next, tweet data was collected from Kaggle, originally sourced from Platform X using the Tweepy API. The dataset includes tweets containing the keywords "BTC" and "Bitcoin" from the analysis period. Several preprocessing steps were carried out, including:

- Only original tweets were collected, excluding retweets and quoted tweets by other users.
- All duplicate tweets were removed to eliminate redundancy.
- Tweets containing marketing words, like; "giveaway", "airdrop", "link in bio" were filtered out to minimize noise and ensure the relevance of the data.

To improve the accuracy of sentiment analysis, two main stages were conducted:

- Text Normalization: The T5 model was used to convert informal text into a more formal structure.
- Sentiment Analysis: Tweets were analyzed using FinBERT, a BERT-based model specifically trained for the financial domain. Each tweet produced a compound score, a numerical value representing the overall sentiment intensity ranging from -1 (highly negative) to +1 (highly positive).

Based on the compound score, sentiments were categorized into three categories:

- Positive if the compound score is greater than 0.05
- Neutral if the compound score falls between -0.05 and 0.05
- Negative if the compound score is less than -0.05

The final variables used are summarized in Table 2.

Table 2: Tweet Dataset Variables

Variable Name	Description	Data Type
datetime	Date and time when the tweet was posted	Datetime
compound	Overall sentiment score (range -1 to +1)	Int64
sentiment	Sentiment label: Positive, Negative, or Neutral	Float64

The next variable is the Bitcoin trading volume, which was obtained from the same source as the price data, covering the same period. This dataset consists of only two main columns, as summarized in Table 3.

Table 3: Bitcoin Trading Volume Dataset Variables

Variable Name	Description	Data Type
datetime	Date and time of the volume data	Datetime
volume	Amount of BTC trading volume during that period	Float64

The next variable is the Fear and Greed Index (FGI), which was collected from Alternative.me. The dataset contains daily index values during the same period. This index reflects the level of investor fear or greed on a scale from 0 to 100. The variables used are presented in Table 4.

Table 4: Fear and Greed Index (FGI) Dataset Variables

Variable Name	Description	Data Type
datetime	Date of index measurement	Datetime
value	Fear and Greed Index value (0–100)	Int64

3.3 Vector Autoregression (VAR) Model

The Vector Autoregression (VAR) model is utilized in this study to analyse the dynamic interdependencies between cryptocurrency price returns and sentiment scores. Selecting the appropriate lag length is critical to the effectiveness of Granger Causality analysis [28]. This study employs information criteria such as the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Final Prediction Error (FPE), and Hannan-Quinn Information Criterion (HQIC) to determine the optimal lag [30]. These criteria balance the model's fit and complexity, with AIC and FPE focusing on minimizing error variance, while BIC and HQIC penalize complexity more heavily to avoid overfitting [6], [30]. Identifying the best lag ensures the model captures essential temporal dependencies without introducing unnecessary noise [6], [28]. This careful lag selection enhances the model's ability to analyse the intricate dynamics of cryptocurrency prices and sentiment [30], [31].

3.4 Granger Causality

In this study, this original Granger Causality test proposed by Granger (1969) is not suitable, as it can lead to spurious correlations, rendering the results invalid [6], [32]. To address this issue, alternative approaches like the Toda and Yamamoto (1995) method are used [6]. The Toda and Yamamoto approach extends the classical Granger causality framework by estimating an augmented VAR (Vector Autoregression) model in levels, regardless of the stationarity or integration order of the variables [22]. The test involves determining the maximum order of integration ($d$max) among the variables using stationarity tests like the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. Then, a VAR model is estimated with the lag length equal to the optimal lag (l) plus $d$max [28].

$$X_t = \theta_0 + \sum_{(i=1)}^{(l+dmax)} \theta_i Y_{(t-i)} + \sum_{(i=1)}^{(l+dmax)} \delta_i X_{(t-i)} + \varepsilon_t, (1)$$

$$Y_t = \beta_0 + \sum_{(i=1)}^{(l+dmax)} \beta_i X_{(t-i)} + \sum_{(i=1)}^{(l+dmax)} \gamma_i Y_{(t-i)} + \eta_t, (2)$$

By incorporating the Toda and Yamamoto method, this study ensures that the Granger causality analysis is robust to issues of non-stationarity and spurious correlations, providing reliable insights into the potential causal relationships between sentiment and cryptocurrency price movements [22], [25].

4. RESULT

4.1 Data Analysis

After preprocessing the data, this study then analyzes the data through several steps to address the hypotheses. Six hypotheses were formulated to investigate the bidirectional causality between Bitcoin price (Price), Bitcoin trading volume (Volume), Platform X sentiment (Sentiment), and the Fear and Greed Index (FGI). Each hypothesis tests whether changes in one variable significantly cause changes in another across various time lags. The relationships tested include H1: Price → Sentiment, H2: Price → Volume, H3: Price → FGI, H4: Sentiment → Price, H5: Volume → Price, H6: FGI → Price.

The analysis begins with Exploratory Data Analysis (EDA), which includes correlation heatmap analysis and parallel coordinates plot analysis to visualize trends, correlations, and preliminary patterns in the data. Granger Causality

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tests were then applied to uncover potential causal relationships. For each hypothesis, multiple lags were tested to identify significant causality, with results evaluated based on p-values and adjusted R^2 values. “Significant” results indicate the presence of predictive power, while “Not Significant” results suggest independence between the variables.

4.1.1 Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) is a crucial first step in any data-driven research, providing a foundational understanding of the dataset's structure, trends, and potential anomalies [33]. Visualizing the relationships between Bitcoin price, trading volume, sentiment, and the Fear and Greed Index (FGI) allows for the identification of key patterns, correlations, and possible irregularities [10]. The EDA process in this study involves the use of correlation heatmaps and parallel coordinates plots to examine how these variables interact with one another. This stage helps uncover hidden dependencies or unusual patterns, such as sentiment shifts or sudden changes in market behaviour, which could influence the results of later econometric tests. By establishing this foundation, the study ensures that subsequent analyses, including Vector Autoregression (VAR) and Granger Causality tests, are based on a clear and well-informed understanding of the data [33], [34].

4.1.1.1 Correlation Heatmap Analysis

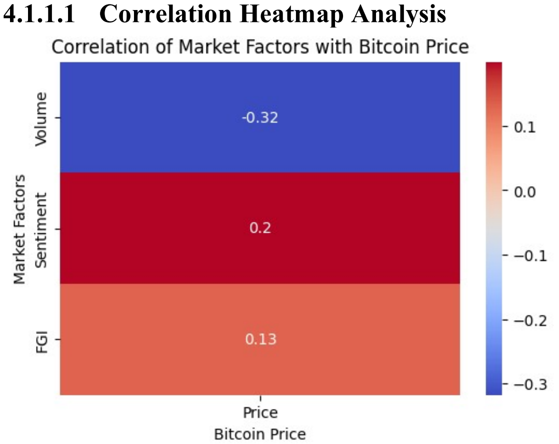

Figure 2: Correlation Heatmap Analysis

The correlation heatmap shown in Figure 2 provides a snapshot of the contemporaneous linear relationships between Bitcoin price (Price), Bitcoin trading volume (Volume), platform X sentiment (Sentiment), and the Fear and Greed Index (FGI). Bitcoin price shows a weak positive correlation with platform X sentiment (0.20) and FGI (0.13), suggesting that higher sentiment scores and a more optimistic market climate tend to coincide with slightly higher Bitcoin prices. In contrast, Bitcoin price exhibits a moderate negative correlation with Bitcoin trading volume (-0.32), indicating that periods of higher trading activity often occur when prices are declining. These relationships offer preliminary insights into how market psychology and trading activity align with price movements. However, this heatmap only reflects static correlations at the same time point and does not capture potential lagged effects or causal dynamics between the variables, making further time-series modelling essential to uncover the temporal interplay among them.

4.1.1.2 Parallel Coordinates Plot Analysis

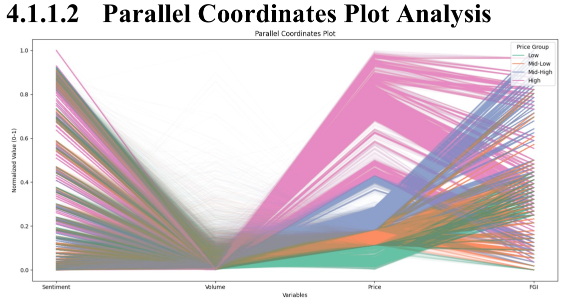

Figure 3: Parallel Coordinates Plot Analysis

In this parallel coordinates plot shows in Figure 3, Bitcoin price is divided into four categories—Low, Mid-Low, Mid-High, and High—representing different ranges of normalized price levels within the dataset. These categories group observations by relative market position, with "Low" indicating the lowest Bitcoin prices and "High" representing the highest. The plot shows how Platform X sentiment, Bitcoin trading volume, and the Fear and Greed Index (FGI) vary across these price groups. Higher price groups (pink and purple lines) generally correspond with higher sentiment scores and elevated FGI values, indicating greater market optimism and confidence during price peaks. Lower price groups (green and orange lines), on the other hand, align with lower sentiment and FGI values, reflecting more fearful or pessimistic market conditions. Trading volume appears more scattered across all groups, suggesting that its relationship with Bitcoin price is more complex and not strictly tied to price level. This visualization underscores how sentiment and investor psychology shift predictably with price, while trading activity shows a more nuanced interplay.

The combined insights from the heatmap and parallel coordinates plot reveal a consistent association between Bitcoin price, Platform X sentiment, the Fear and Greed Index, and Bitcoin trading volume. Higher price levels generally align

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with stronger sentiment, elevated FGI values, and notable shifts in trading activity, indicating that market perception and investor psychology move in tandem with price fluctuations. While these patterns highlight important co-movements, they remain descriptive in nature and cannot establish whether these variables drive Bitcoin price or respond to it. To address this limitation and assess the temporal and directional nature of these relationships, the analysis proceeds with lag-based econometric techniques, specifically Vector Autoregression (VAR) and Granger Causality tests.

4.2 Vector Autoregression (VAR) Model

Table 5: Vector Autoregression Lag Result

Lag	AIC	BIC	FPE	HQIC
0	-1.547	-1.547	0.2129	-1.547
1	-20.68	-20.68	1.042e-09	-20.68
2	-20.74	-20.74	9.868e-10	-20.74
3	-20.76	-20.76	9.608e-10	-20.76
4	-20.78	-20.78	9.468e-10	-20.78
5	-20.79	-20.78	9.386e-10	-20.79
6	-20.79	-20.79	9.331e-10	-20.79
7	-20.80	-20.79	9.297e-10	-20.80
8	-20.80	-20.80	9.270e-10	-20.80
9	-20.80	-20.80	9.244e-10	-20.80
10*	-20.80*	-20.80*	9.224e-10*	-20.80*

The results of the Vector Autoregression (VAR) lag order selection from Table 5, show that AIC, BIC, FPE, and HQIC consistently identify lag 10 as the optimal specification. This indicates that the temporal dynamics linking Bitcoin price, Platform X sentiment, the Fear and Greed Index (FGI), and Bitcoin trading volume are best captured when incorporating interactions over the past ten periods. Using this lag structure in the subsequent Granger causality analysis allows for a comprehensive examination of both short-term fluctuations and longer-term dependencies, ensuring robust evaluation of the directional and lagged relationships among the variables.

4.3 Granger Causality Test

Table 6: Granger Causality Test Result

Relation	Lag	p-Values	R2	Result
(H1) Price ↓ Sentiment	1	0.679293	-4.850574	Not Significant
	2	0.041460	0.685837	Significant
	3	0.053128	0.609343	Not Significant
	4	0.032416	0.620063	Significant
	5	0.039308	0.572257	Significant
	6	0.049348	0.524860	Significant
	7	0.079810	0.448762	Not Significant
	8	0.087395	0.419909	Not Significant
(H2) Price ↓ Volume	1	4.380870e-02	0.753934	Significant
	2	2.662498e-04	0.878512	Significant
	3	1.322488e-06	0.900296	Significant
	4	1.750001e-07	0.892075	Significant
	5	3.745254e-09	0.895594	Significant
	6	2.359465e-08	0.870962	Significant
	7	8.558369e-13	0.901656	Significant
	8	4.367630e-13	0.893717	Significant
(H3) Price ↓ FGI	1	0.004906	0.873638	Significant
	2	0.000010	0.912893	Significant
	3	0.000026	0.874590	Significant
	4	0.000076	0.834117	Significant
	5	0.000122	0.802370	Significant
	6	0.000031	0.803701	Significant
	7	0.000061	0.774429	Significant
	8	0.000138	0.742328	Significant
(H4) Sentiment ↓ Price	1	0.884826	-46.657890	Not Significant
	2	0.942032	-15.745929	Not Significant
	3	0.989690	-24.585510	Not Significant
	4	0.941314	-4.138382	Not Significant
	5	0.910014	-2.275819	Not Significant
	6	0.955023	-2.832477	Not Significant
	7	0.970303	-2.899246	Not Significant
	8	0.984555	-3.262131	Not Significant
(H5) Volume ↓ Price	1	8.679800e-08	0.965095	Significant
	2	4.759095e-08	0.940693	Significant
	3	2.922039e-09	0.929662	Significant
	4	1.013188e-08	0.907077	Significant
	5	1.692175e-08	0.888078	Significant
	6	1.247353e-08	0.874701	Significant
	7	3.174234e-08	0.854947	Significant
	8	9.224418e-08	0.833884	Significant
(H6) FGI ↓ Price	1	0.618840	-3.040364	Not Significant
	2	0.700331	-1.807370	Not Significant
	3	0.486543	-0.230343	Not Significant
	4	0.660804	-0.659661	Not Significant

	5	0.774223	-0.987975	Not Significant
	6	0.803398	-0.971525	Not Significant
	7	0.867682	-1.199902	Not Significant
	8	0.836343	-0.893764	Not Significant

The Granger causality analysis shows in Table 6, identifies clear asymmetries in the directional relationships between Bitcoin price and the other market factors. Bitcoin price exerts a significant causal influence on both Bitcoin trading volume and the Fear and Greed Index across all lag periods tested, and on Platform X sentiment at several mid-range lags. In contrast, neither Platform X sentiment nor the Fear and Greed Index demonstrate significant causal effects on Bitcoin price at any lag, while Bitcoin trading volume shows a consistently strong bidirectional relationship with Bitcoin price across all lags. These results indicate that price movements are a primary driver of market sentiment, investor psychology, and trading activity in the Bitcoin ecosystem, with trading volume being the only factor to display reciprocal influence on price.

4.4 Comparative Analysis and Critical Discussion

To contextualize the findings of this study within the broader literature and critically evaluate their significance, this section presents a structured comparative analysis with recent related works, organized according to the Plus-Minus-Interesting (PMI) framework. Table 7 summarizes methodological differences and key outcomes across studies.

Table 7: Comparative Analysis with Previous Studies

Study	Methodology	Variables Examined	Lag Structure	Key Findings
Arslan (2024) [27]	EMD–LSTM	Sentiment, Price	-	Incorporating sentiment enhances Bitcoin price prediction, particularly during periods of high volatility.
Japar et al. (2022) [28]	Lexicon-Based Sentiment + Granger Causality	Sentiment, Price	Pre-defined lags	The influence of sentiment on price strengthened in the post-COVID period.
van Engelen & Kulcsár (2023) [6]	VAR + Granger Causality	Sentiment, Returns	Short-term lags only	Causality predominantly runs from returns to sentiment rather than the reverse.
Yin et al. (2020) [18]	LSTM	Sentiment, Price	-	Financial-domain terminology provides more predictive information than general emotional indicators.
This Study	FinBERT + VAR + Toda–Yamamoto	Sentiment, Trading Volume, FGI, Price	Optimal lag selection (up to 10 periods)	Price significantly drives sentiment, while trading volume exhibits bidirectional causality with price.

4.4.1 Strengths and Confirmatory Findings

This study demonstrates several key strengths relative to prior research on cryptocurrency sentiment and price dynamics. Most importantly, the findings provide strong empirical confirmation of van Engelen and Kulcsár (2023), showing that causality predominantly runs from Bitcoin price to social media sentiment rather than in the opposite direction. This result is reinforced within a broader multivariate framework that incorporates trading volume and the Fear and Greed Index, thereby extending earlier studies that examined sentiment in isolation. The consistency of this directional relationship across different variable sets and econometric specifications strengthens confidence in this characterization of Bitcoin market behavior.

A second major contribution lies in the systematic determination of the optimal lag structure. Unlike previous studies that relied on arbitrary or pre-defined short lags, this study identifies an optimal lag length of ten periods using multiple information criteria. This finding suggests that interactions among Bitcoin price, sentiment, and trading activity unfold over longer horizons than previously assumed, with important implications for both theoretical modeling and forecasting. Additionally, the identification of bidirectional causality between trading volume and price highlights the critical role of market activity in price formation, a dynamic that sentiment focused studies have largely overlooked.

Finally, the use of FinBERT represents a methodological advancement over generic lexicon based or general-purpose language models. By leveraging a financial domain specific model, this study improves the accuracy of sentiment measurement and reduces semantic ambiguity in cryptocurrency related discourse, thereby enhancing the reliability of the sentiment variable used in the econometric analysis.

4.4.2 Limitations and Contradictory Evidence

Despite these strengths, several limitations must be acknowledged. The results contradict claims by Arslan (2024) that sentiment enhanced models provide superior predictive power for Bitcoin prices, particularly during volatile periods. The absence of sentiment to price causality in this study suggests that such predictive gains may reflect overfitting or contemporaneous correlations rather than genuine causal relationships, underscoring the distinction between machine learning prediction accuracy and econometric causality.

The one-year study period limits the ability to generalize findings across different market regimes, such as extreme bull or prolonged bear markets. In addition, the exclusive reliance on Platform X as a sentiment source excludes other influential communities that may exhibit different dynamics. The omission of major crisis events outside the study window further constrains the applicability of the results to periods of extraordinary market stress.

4.4.3 Novel and Unexpected Observations

Several unexpected patterns emerge from the analysis. Most notably, the Fear and Greed Index shows no causal influence on Bitcoin price at any lag, despite its widespread use as a market sentiment indicator. This suggests that the index functions primarily as a descriptive or reactive measure rather than a forward-looking predictor. In contrast, trading volume is the only variable exhibiting a stable bidirectional relationship with price, indicating that actual trading behavior plays a more active role in price formation than sentiment or aggregated psychological indicators.

The temporal response of social media sentiment to price changes is also informative. Sentiment reacts at intermediate lags rather than immediately, implying a cognitive and social processing period before opinions are formed and expressed online. Moreover, the Fear and Greed Index responds to price movements more rapidly and consistently than social media sentiment, reflecting its mechanically constructed nature. Together, these findings highlight that different behavioral measures operate on distinct time scales, offering important insights for future research on market behavior and sentiment driven dynamics.

5. CONCLUSIONS

This study investigates the lagged and directional relationships among Bitcoin price, trading volume, Platform X sentiment, and the Fear and Greed Index by integrating FinBERT-based sentiment analysis with VAR modelling and Granger causality tests. The results demonstrate that Bitcoin price exerts a dominant causal influence on trading volume, market psychology, and social media sentiment, indicating that sentiment and psychological indicators are largely reactive rather than predictive. Trading volume emerges as the only variable exhibiting a robust bidirectional relationship with price, underscoring its central role in price formation and liquidity dynamics. In contrast, neither Platform X sentiment nor the Fear and Greed Index shows significant causal influence on Bitcoin price across tested lags, reinforcing the interpretation that these indicators primarily reflect prevailing market conditions rather than drive price movements.

These findings contribute methodologically, theoretically, and practically to the cryptocurrency literature. Methodologically, the study introduces a robust multivariate framework using an empirically determined 10-period optimal lag structure combined with the Toda–Yamamoto procedure, addressing persistent weaknesses in lag selection and non-stationarity handling in prior research. Theoretically, the results challenge dominant behavioral finance narratives by positioning price, rather than sentiment, as the primary driver of market psychology, while empirically highlighting trading volume as the key feedback mechanism in Bitcoin markets. Practically, the findings imply that sentiment-based trading strategies offer limited predictive value, whereas volume-price dynamics provide more actionable signals for investors, analysts, and policymakers. In the current market environment characterized by rising institutional participation and ETF-driven liquidity, these dynamics are likely to be even more pronounced. Future research should extend this framework across platforms, languages, market regimes, and additional macroeconomic and on-chain variables, while repositioning sentiment as a confirming or risk indicator rather than a primary forecasting tool.

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