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Astrofinance and Behavioral Drivers of Cryptocurrency Returns: Integrating Lunar Phases, Sentiment Indicators, and Machine Learning for Predictive Modeling

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Abstract: This study investigates the influence of lunar phases, behavioral indicators, and technical analysis on cryptocurrency returns, with a focus on Bitcoin (BTC) and Ethereum (ETH). Positioned within the context of behavioral finance and astrofinance, the research aims to explore the role of non-traditional factors in shaping market dynamics. The study employs a combination of event study methodology, regression analysis, and machine learning techniques, particularly XGBoost classification, to examine the impact of lunar phases (such as full and new moons), sentiment measures (derived from Google Trends (GT), the Fear & Greed Index (FGI), and Natural Language Processing (NLP)-based sentiment scores), and technical indicators (such as Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and Exponential Moving Average (EMA)) on cryptocurrency price movements. Although no statistically significant direct correlation was found between lunar phases and daily returns, it was observed that these phases are associated with changes in investor sentiment and trading volume. Moreover, behavioral variables, including NLP-derived sentiment scores and the FGI, exhibited interaction effects with market returns, particularly during periods of heightened market sentiment. The XGBoost model demonstrated a predictive accuracy of up to 63% for Ethereum, indicating its effectiveness in capturing complex, non-linear relationships within the data. These findings suggest that integrating astrofinancial timing with behavioral signals can improve the predictive accuracy of short-term cryptocurrency market trends, especially during periods of increased sentiment. This research highlights the potential of incorporating alternative data sources, such as lunar events and sentiment indices, into cryptocurrency trading models. The results also emphasize the effectiveness of machine learning algorithms, like XGBoost, in leveraging such non-traditional indicators to optimize investment strategies.

Keywords: Astrofinance; Behavioral finance; Cryptocurrencies; Natural Language Processing (NLP); Machine learning

JEL Classification: G41; G17; C45; C55; E44

1. Introduction

In recent years, financial markets have witnessed new approaches that go beyond the boundaries of classical finance theories with the increasing interest in investor psychology and alternative analysis methods. Astrofinance, one of these approaches, is an interdisciplinary field that examines the effects of the cyclical movements of celestial bodies on investor behavior. In particular, the findings that astronomical events such as full and new moons affect the emotional states of individuals (Yuan et al., 2006) suggest that this effect may also affect market sentiment and thus price movements.

On the other hand, behavioral finance has shown that investors exhibit systematic cognitive biases and may deviate from rationality (Kahneman & Tversky, 1979). Especially in areas of high volatility and lack of regulation, such as cryptocurrency markets, investment decisions are much more heavily based on emotions and social influences. In this context, astrological influences may play a bigger role in crypto markets than in traditional markets.

The aim of this study is to examine the impact of astrological events (full moon, new moon) on the daily returns of crypto assets such as BTC and ETH by evaluating them together with investor sentiment indicators (GT, FGI, NLP-based sentiment) and technical analysis indicators (RSI, MACD, EMA, etc.). In this way, it is shown that astrological timing can be analyzed not only intuitively, but also on statistical and behavioral grounds.

2. Literature Review

2.1 Fundamentals of Astrofinance

Astrofinance is a discipline that studies the effects of the movements of celestial bodies on financial markets. Merriman (2017) suggested that astrological cycles may be related to market turning points. Louise McWhirter's 18.6-year lunar node cycle theory also argues that astrological events can influence market trends.

Astrofinance is an interdisciplinary field of study based on the assumption that the cyclical movements of celestial bodies can affect the psychological state of individuals and thus their financial decision-making processes. This approach was born from the idea that some irrational fluctuations observed in financial markets cannot be explained solely by economic or political variables; natural rhythms that affect human psychology should also be taken into account. Astrofinance aims to analyze the effects of celestial events, especially lunar cycles, Mercury retrograde and planetary alignments, on investor sentiment (Merriman, 2017).

The foundations of this field started with observations on the cyclical nature of financial markets. Especially since the mid-20th century, some analysts have identified recurring trends in stock market indices in line with certain astronomical events. The 18.6-year lunar node cycle theory developed by Louise McWhirter argues that the long-term directional changes of financial markets can be linked to celestial events. McWhirter claimed that the position of the Sun relative to the lunar nodes has an impact on the economy and applied this theory to stock market forecasts.

In modern astrofinance studies, these historical approaches are blended with behavioral finance theories to provide more systematic analyses. In particular, Yuan et al. (2006) found that there are significant changes in stock returns during full and new moon periods and provided empirical evidence that astrological events may have an impact on investor psychology. This suggests that exogenous factors that may trigger emotional reactions in financial markets should also be taken into account.

Astrofinance is basically based on the "astrological influence hypothesis". According to this hypothesis, certain positions of celestial bodies can affect the emotional and cognitive states of individuals. Especially during periods of high emotional sensitivity, such as full moons, investors may show changes in risk-taking behavior. This effect may cause deviations in the way individuals interpret market information and in their decision-making processes. Thus, astrofinance suggests that financial decisions are sensitive not only to economic rationality but also to natural environmental and astronomical cycles.

Traditional finance theories assume that investment decisions are made by rational individuals. However, the behavioral finance approach has revealed that irrational factors such as emotions, biases and cognitive distortions play a role in investors' decision-making processes (Kahneman & Tversky, 1979). Astrofinance argues that astrological events that trigger these behavioral tendencies should be considered in conjunction with sentiment indicators (e.g., FGI, GT).

Recent studies suggest that astrological influences may be particularly pronounced in markets with high volatility, such as cryptocurrency markets. Investment decisions in these areas are often based on emotional and intuitive grounds, and astrological events can affect individuals' perceptions and collective investment behavior, causing sudden changes in price movements.

2.2 Moon Phases and Market Interaction

Yuan et al. (2006) find that there are significant differences in stock returns during full and new moon periods. Similarly, some studies have shown that returns are higher during new moon periods compared to full moon periods.

Phases such as full and new moons, which occur as a result of the Moon's orbital motion, are among the natural cycles that have historically been believed to have an impact on human psychology and behavior. The idea that these cycles may have an impact on investor behavior in financial markets is one of the main pillars of astrofinance literature. In particular, it is argued that the emotional fluctuations caused by lunar phases can affect financial decision variables such as risk-taking behavior, investment strategies and trading volume (Yuan et al., 2006).

Different phases of the moon can produce changes in individuals' emotional intensity and decision-making processes. Psychology literature suggests that the full moon is associated with insomnia, restlessness and increased emotional sensitivity, while the new moon can trigger tendencies such as introversion and novelty seeking (Cajochen et al., 2013). These emotional states may affect the way investors interpret market data, increasing the likelihood of irrational decisions.

Yuan et al. (2006), in their study on the US stock market, found that stock returns differ significantly during full and new moon periods. The findings show that average returns are higher during new moon periods compared to full moon periods. These results suggest that investors' changing emotional states depending on lunar phases are reflected in their market behavior and create a systematic behavioral pattern.

The full moon may increase investors' motivation to avoid losses, causing them to turn to lower-yielding and safer assets. On the other hand, the new moon, with its connotation of "beginning", may encourage individuals to make riskier investments.

High-volatility and low-regulation areas such as cryptocurrency markets are the environments where such behavioral effects are most likely to be observed.

In this context, lunar phases can be evaluated through the following three channels in terms of market interaction:

1. Emotional Intensity: Heightened emotional sensitivity during Full Moon periods can increase the likelihood of investors making panic selling or irrational buying decisions.
2. Risk Perception: Investors may be more optimistic during New Moon periods, which may result in a tendency towards speculative investments.
3. Social Interaction: Lunar phases are more talked about on social media and can have an impact on collective investment behavior.

The effects of lunar phases on investor behavior are in line with the predictions of behavioral finance theories and provide an empirical basis for the astrofinance literature. These effects are particularly pronounced in crypto markets, which are particularly sensitive to investor sentiment, suggesting that lunar phases may have not only mythological but also measurable financial effects.

2.3 Behavioral Finance: Investor Psychology

Behavioral finance is a field that examines the irrational behavior of investors in their decision-making processes. Kahneman & Tversky (1979) developed expectancy theory, which demonstrates that individuals evaluate their decisions based on reference points and that losses have a greater impact than gains. This theory explains how investors' emotional reactions can influence market movements.

2.4 Sentiment Models in Crypto Markets

Cryptocurrency markets are more susceptible to investor sentiment due to high volatility and lack of regulation. Corbet et al. (2018) showed that investor behavior influences Bitcoin prices. Moreover, social media platforms and tools such as GT are used to measure investor sentiment.

2.5 Astrological Events and Crypto Returns

2.5.1 Channels of influence of astrological timing

The mechanisms by which astrological events affect cryptocurrency returns can be categorized under three main headings:

Psychological Influence Channels: It is suggested that astrological events may affect individuals' emotional and cognitive states, leading to deviations in investment decisions. For example, increased emotional sensitivity during full moon periods may trigger risk-averse behaviors, while new moon periods may be associated with more optimistic investment behaviors (Yuan et al., 2006).

Social Diffusion and Media Dynamics: Astrological events that resonate widely on social media may trigger collective investment behavior. Events such as full moons and Mercury retrograde can go viral on social platforms and increase speculative movements. This effect may lead to short-term price movements as investor sentiment rises (Bollen et al., 2011).

Behavioral-Structural Fit: Unlike traditional financial instruments, the prices of cryptocurrencies rely heavily on investor perceptions, community effects, and speculative fluctuations. This may make the impact of astrological events more pronounced compared to other markets (Kristoufek, 2013).

In a pioneering study by Yuan et al. (2006), statistically significant return differences were observed in US stocks during full and new moon periods. The study found higher average returns during new moon periods.

2.5.2 The difference of astrological influence on crypto markets

Cryptocurrencies, unlike other financial assets:

1. In terms of investor base, it consists of younger and more intuitively inclined individuals.
2. The correlation between social media sentiment and prices is higher.
3. It is driven by technical, psychological, and intuitive factors rather than fundamental analysis.

For these reasons, the impact of astrological events in this market may be more intense than in markets based on macroeconomic or corporate news (Corbet et al., 2018).

2.6 The Intersection of Machine Learning and Astrophysics: Methodological and Conceptual Expansion

There are a limited number of studies in the literature on the effects of astrological events on investor sentiment and market returns. Evaluating astrological events together with social media sentiment and technical analysis indicators can fill an important gap in the literature.

The existing literature on the impact of astrological events on crypto returns is limited. Moreover, most of these studies focus only on price movements and do not provide an integrated analysis of behavioral indicators. The contribution of this study is to evaluate astrological timing in combination with investor sentiment data (GT, FGI), social media NLP analysis, and technical analysis indicators, and to take these interactions to a predictive level with machine learning methods such as XGBoost.

In recent years, artificial intelligence and machine learning-based approaches have become widespread in models for price prediction in cryptocurrency markets. In this context, analyzing parameters such as astrological timing, sentiment data and high-frequency price movements together offers a multidimensional methodological opening (Feng et al., 2018; Smales, 2014).

Machine learning stands out with its power to model complex and non-linear structures, especially when traditional econometric models are limited. These algorithms produce effective results in predicting factors such as behavioral effects, sudden price changes and emotional tendencies in cryptocurrency markets (Jiang & Liang, 2017). The XGBoost algorithm used in this framework is a tree-based boosting model optimized especially for high-dimensional data sets and classification problems (Chen & Guestrin, 2016). XGBoost has been reported to be successful in price forecasting in financial markets by integrating sentiment scores, technical indicators and exogenous events (e.g., astrological effects such as a full moon).

On the other hand, modeling the effects of astrological events with machine learning has not yet been sufficiently explored in the literature. Existing studies mostly focus on the direct return impact of lunar phases, but ignore how these effects interact with behavioral sentiment. Therefore, when astrological events are modeled together with investor sentiment, price anomalies caused by intuitive investment behavior can be better predicted.

NLP-based sentiment models are also effective tools for capturing the emotional aspects of investment decisions. In particular, social media platforms (Twitter, Reddit) generate signals on market orientation through sentiment analysis, as they contain real-time reflections of investor psychology (Bollen et al., 2011). Kristoufek (2013) analyzed the relationship between GT data and Bitcoin prices and showed that investor interest is reflected in prices. When such sentiment measurements are considered in conjunction with astrological events, it can be more clearly understood whether investor reactions are in line with increased emotional intensity.

2.7 Academic Limits of Astrofinance and Criticisms

Astrofinance has often been considered a controversial or even pseudoscientific approach in financial studies, primarily because astrology lacks a causal physical mechanism that can be empirically verified. However, contemporary behavioral finance research increasingly recognizes that non-economic environmental cues—such as weather, daylight duration, and natural cycles—can influence investor mood, risk perception, and decision-making. Therefore, examining astrological timing within a behavioral-finance framework does not imply acceptance of astrological determinism; rather, it represents a testable behavioral hypothesis regarding emotional sensitivity to periodic stimuli.

Empirical psychology provides measurable mechanisms that may justify such exploration. Biological and chronopsychological studies demonstrate that lunar cycles can influence sleep patterns, hormone levels, and emotional regulation, all of which are central to financial behavior. For instance, Cajochen et al. (2013) found that melatonin secretion and sleep efficiency decline during the full moon, leading to higher irritability and emotional intensity. Similarly, Zimecki (2006) reported that the lunar cycle is associated with variations in biological rhythms and social behavior. These findings suggest that astrofinance can be reframed not as astrology but as an affective-environmental component of investor behavior.

Within behavioral finance, this corresponds to the concept of *affective triggers*—external stimuli that shape collective emotions and market sentiment (Hirshleifer & Shumway, 2003; Kamstra et al., 2003). Just as weather-induced mood effects have been linked to market optimism, lunar-phase fluctuations may act as subtle behavioral cues that influence trading intensity or risk appetite, particularly in sentiment-driven markets such as cryptocurrencies.

Accordingly, in this study, astrological variables are treated as behavioral stimuli interacting with sentiment indicators, rather than as deterministic celestial forces. This conceptual framing allows astrofinance to be situated within a legitimate behavioral-finance paradigm—one that tests whether naturally salient periodic events can statistically correlate with collective investor sentiment and market behavior. In this sense, astrofinance serves as a behavioral experiment in affective economics, emphasizing empirical falsifiability rather than metaphysical causation.

In this context, it is suggested that astrofinance should be considered as an auxiliary axis for better modeling of behavioral investment decisions, rather than rejecting it in a completely exclusionary manner. Especially in the age of social media, when investment decisions are shaped not only by financial rationality but also by cognitive biases, crowd psychology and emotional triggers, the impact of parameters such as astro-financial timing on the market cannot be ignored (Smales, 2014).

3. Conceptual Framework

The theoretical foundations of this study are based on three main conceptual axes: the astrological influence hypothesis, the behavioral finance framework and investor sentiment theory.

The astrological influence hypothesis posits that planetary cycles and lunar phases influence human psychology and shape individuals' decision-making processes. According to this hypothesis, increased emotional intensity, especially during full and new moon periods, can affect collective investment behavior (Merriman, 2017). In financial markets, this effect can be observed as fluctuations in short-term returns or increased volumes.

Behavioral finance reveals that individuals make investment decisions based on logical errors, cognitive distortions and emotional reactions. Prospect Theory (Kahneman & Tversky, 1979) demonstrates that investors react differently to gains and losses and that biases such as herd behavior, framing effect, and overconfidence cause irrational behavior in markets.

Investor Sentiment Theory, on the other hand, examines how investors' perceptions of the market and their psychological tendencies, such as hope, fear, and enthusiasm, are reflected in prices. Search behaviors such as GT, composite indicators such as FGI, and social media sentiment measures are interpreted within the framework of this theory.

In this framework, astrological timing (astrofinance), psychological disposition (behavioral finance), and market sentiment (sentiment theory) explain the theoretical basis of the variables used in the study.

4. Theoretical Background and Related Studies

Although astrofinance is a relatively new field in the academic literature, there is a growing interest in the effects of lunar phases, planetary cycles and astrological events on investment decisions. A significant number of these studies have aimed to provide possible explanations for the irrational movements observed in financial markets by testing the relationships between empirical data and astrological cycles.

Yuan et al. (2006), in one of the pioneering studies in this field, examined the effect of lunar phases on the US stock market. Analyzing S&P 500 returns for the period 1982–2000, the study demonstrates that average returns are significantly higher during new moon periods than during full moon periods. This finding supports the hypothesis that lunar phases may have an impact on individual investor psychology.

Kristoufek (2013) analyzed the relationship between Bitcoin prices and GT data and found that investor interest and search volume are significantly correlated with prices. Although this study does not provide a direct astrological framework, it is valuable in demonstrating the power of sentiment-based analysis in predicting digital asset prices.

Bollen et al. (2011) examined the relationship between investor sentiment and US stock market indices using Twitter data and find that emotional posts (happiness, fear, anger) have a significant impact on predicting next-day market returns. These findings support a mechanism by which sentiment is reflected in market behavior, in line with astrofinance.

Previous studies generally show that the direct return impact of astrological events is weak, but these events can have indirect but significant effects on investor psychology, market sentiment and trading behavior. Moreover, a common limitation of astrofinance studies is the lack of integration of these effects with technical analysis data, NLP-based social media sentiment and machine learning methods.

5. Method and Data Set

5.1 Analytical Roadmap

The analytical design of this study follows a multi-stage structure, in which each methodological step builds conceptually upon the previous one.

1. Event study analysis provides a descriptive baseline by identifying short-term abnormal return patterns surrounding lunar and planetary events.
2. t-Tests and regression models formally test whether these observed effects are statistically significant and whether behavioral sentiment indicators (GT, FGI, NLP sentiment) explain return variation.
3. VAR and Granger causality models extend this framework to capture dynamic feedback relationships

between astrological events, investor sentiment, and price changes.

4. GARCH and EGARCH models then evaluate whether volatility responds asymmetrically to these behavioral shocks, revealing potential risk perception biases.

5. Finally, the XGBoost machine-learning classifier integrates all variables—astrological timing, sentiment indicators, and technical metrics—to test the predictive potential of the combined behavioral-astrofinancial framework.

Figure 1 illustrates the sequential analytical design employed in this study. This structure ensures methodological coherence, as each stage investigates a distinct dimension of the same hypothesis—progressing from descriptive observation (*Event Study* and *t-Tests*) to statistical estimation (*Regression*), dynamic interaction modeling (*VAR/Granger Causality* and *GARCH/EARCH*), and finally predictive validation through machine learning (*XGBoost*).

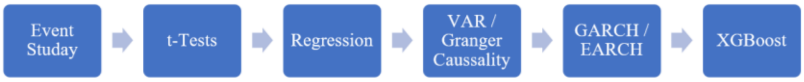

Figure 1. Analytical flow of the research design

Note: Sequential methodological framework showing the progression from descriptive analysis to predictive modeling.

In this study, the effects of astrological events (full moon, new moon, planetary transits, Mercury retrograde) on cryptocurrency returns are analyzed in combination with behavioral sentiment indicators and technical analysis indicators. Quantitative research methodology was adopted and the following analysis techniques were applied:

5.2 Event Study

The event study method is a widely used technique to study the impact of specific historical events (e.g., full moon, new moon) on financial returns (MacKinlay, 1997). For each astrological event, a window of ±3 days is defined and the day of the event is considered as D0. Abnormal returns within this window are calculated to obtain average abnormal return (AAR) and cumulative abnormal return (CAR) values.

5.3 Hypothesis Testing (t-Test)

A two-way t-Test is applied to test the statistical significance of AARs. This analysis tests whether AARs are significantly different from zero (Gujarati & Porter, 2009).

5.4 Regression Analysis

Simple linear regression analyses were conducted to analyze the relationship between investor sentiment indicators (GT, FGI, NLP-based sentiment score) and daily returns. The regression model is constructed as follows:

$Return\_{}_t = \beta 0 + \beta 1 * Sentiment\_{}_t + \varepsilon\_t$

This analysis was conducted to assess the explanatory power of sentiment data on returns (Shleifer, 2000).

5.5 Machine Learning: XGBoost Classification Model

The XGBoost algorithm is used for positive return prediction. XGBoost is a method based on gradient boosting decision trees and is known for its high accuracy rates in classification problems (Chen & Guestrin, 2016). XGBoost, one of the boosting algorithms, offers successful prediction power in high-dimensional datasets (Chen & Guestrin, 2016).

Astrological events, technical indicators (RSI, MACD, EMA), sentiment scores and volume/data trends are used as independent variables in the model. Model performance was evaluated with Accuracy, Precision, Recall and F1-Score metrics.

5.6 Astrological Influence Detection: Zodiac and Mercury Retrograde

Zodiac transits (e.g., entering Aries, transiting Cancer) and Mercury retrograde periods were manually calendared. Separate event studies were conducted for these periods. The effects on investor behavior were measured through abnormal returns.

5.7 Altcoin Analysis

In order to measure the reflection of the full moon effect on altcoins, comparative analyses were conducted for

DOGE, ADA and XRP. Average returns during the full moon period are compared with normal periods, and significance is tested with a t-Test.

5.8 Data Sources and Preprocessing

The study utilizes multi-source data integrating market, sentiment, and astrological variables to analyze behavioral and astrofinancial interactions in cryptocurrency markets.

The observation period covers January 1, 2024, to December 31, 2024, corresponding to a daily frequency dataset (365 observations per asset).

5.8.1 Data components and sources

1. Market Data: Daily price and volume data for Bitcoin (BTC), Ethereum (ETH), and major altcoins (DOGE, ADA, XRP) were obtained from *Yahoo Finance* through the yfinance API.

2. Sentiment Data:

(i) *GT* search volumes for "Bitcoin", "Crypto", "Moon", and "Mercury retrograde" using the pytrends library;

(ii) *FGI* (Alternative.me API) representing aggregate market sentiment;

(iii) *NLP-derived sentiment scores* from crypto news headlines using the VADER lexicon in Python.

3. Astrological Data: Lunar phase, planetary transit, and Mercury retrograde dates were collected from *NASA Horizons* and *TimeandDate.com* astronomical tables.

5.8.2 Feature construction and integration

Each daily observation was augmented with binary event indicators (e.g., Full Moon = 1, otherwise = 0), planetary transition flags, sentiment scores, and technical indicators (RSI, MACD, EMA). These features were synchronized using timestamp alignment and normalized with the MinMaxScaler method to ensure comparability across variables.

Table 1. Dataset summary and sources

Variable Type	Variable / Indicator	Source	Frequency	Description / Purpose
market data	BTC, ETH, DOGE, ADA, XRP daily closing price & volume	Yahoo Finance (via yfinance API)	Daily	Captures market performance and trading activity
sentiment data	GT (keywords: "Bitcoin", "Crypto", "Moon", "Mercury retrograde")	GT API (pytrends)	Daily	Measures public attention and online sentiment intensity
	FGI	Alternative.me API	Daily	Quantifies overall investor sentiment (0–100 scale)
	NLP Sentiment Score	VADER lexicon (Python)	Daily	Extracts tone polarity from crypto news and social media headlines
astrological data	Lunar phases (Full/New Moon), Planetary transits, Mercury retrograde	NASA Horizons; TimeandDate.com	Event-based (mapped to daily)	Behavioral trigger variables aligned to trading days
Technical indicators	RSI, MACD, EMA	Derived via TA-Lib (Python)	Daily	Measures market momentum and trend direction
model parameters	Train/Test split, Cross-validation (k=5)	Internal computation	N/A	Ensures reproducibility and model robustness

Note: All data sources are publicly available and verified through official APIs or repositories. Observations are aligned to Coordinated Universal Time (UTC) to ensure temporal consistency.

5.8.3 Machine learning data split

For predictive modeling with XGBoost, the dataset was divided into 80% training and 20% testing sets. Cross-validation (k = 5 folds) was applied to reduce overfitting and validate generalization. Model performance was evaluated using Accuracy, Precision, Recall, and F1-Score metrics.

5.8.4 Data cleaning and validation

Missing values (< 1%) were imputed using linear interpolation, and all datasets were cross-checked for timestamp consistency to ensure no missing trading days. Outliers were detected via interquartile range (IQR) thresholds and winsorized at the 1st and 99th percentiles. This data architecture enables full reproducibility and transparent replication of the study's results, aligning with open-science principles and behavioral finance methodology standards. The variables, their sources, frequency, and analytical purpose are summarized in Table 1.

6. Findings and Interpretation

6.1 Impact of Astrological Events on Returns

Table 2 presents the results of the event study analysis for BTC and ETH during full moon periods. As shown, both assets exhibit positive abnormal and cumulative abnormal returns (AAR and CAR) leading up to and immediately following the full moon. Specifically, ETH demonstrates stronger cumulative gains, with a total CAR of approximately 4.3% over the observed event window. These findings suggest a mild but consistent lunar effect on cryptocurrency performance, particularly pronounced in Ethereum.

Table 2. AAR and CAR during full moon period

Day	BTC_AAR	BTC_CAR	ETH_AAR	ETH_CAR
D-3	0.0026	0.0026	0.0088	0.0088
D-2	0.0048	0.0075	0.0195	0.0283
D-1	0.0040	0.0115	0.0060	0.0343
D0	0.0063	0.0178	0.0076	0.0419
D+1	0.0003	0.0181	0.0014	0.0432

These results point to a cumulative positive return of 4.3% during the full moon week, especially in ETH.

As summarized in Table 3, the event study results for the new moon period indicate short-term positive market reactions in both BTC and ETH. On the event day (D0), abnormal returns reached 1.8% for Bitcoin and 2.2% for Ethereum; however, these effects dissipated in the subsequent days. This pattern suggests that while lunar events may momentarily influence investor sentiment, the resulting price movements are transient and not sustained over the post-event window.

Table 3. AAR and CAR during the new moon period

Day	BTC_AAR	BTC_CAR	ETH_AAR	ETH_CAR
D-3	0.0111	0.0111	0.0084	0.0084
D-2	0.0047	0.0158	−0.0003	0.0081
D-1	−0.0002	0.0156	0.0037	0.0118
D0	0.0188	0.0344	0.0220	0.0338
D+1	−0.0108	0.0236	−0.0083	0.0255

6.2 Hypothesis Tests (t-Test)

To determine whether the average abnormal returns observed around lunar events were statistically significant, t-Tests were conducted to test the null hypothesis that mean AAR equals zero. As presented in Table 4, none of the event windows for BTC or ETH show statistically significant deviations from zero. Although slight positive average returns were observed during the new moon periods, all *p*-values exceed conventional significance thresholds ($p > 0.05$). Therefore, the null hypothesis could not be rejected, indicating that lunar phases do not systematically influence short-term cryptocurrency returns.

Table 4. Hypothesis results

Asset	Average AAR	Mean *p*-value	Hypothesis Result
BTC (Full Moon)	−0.03%	0.53	Declined
ETH (Full Moon)	+0.21%	0.37	Declined
BTC (New Moon)	+0.29%	0.34	Declined
ETH (New Moon)	+0.42%	0.47	Declined

Although the returns appear positive, the t-Test results do not meet the 5% significance level ($p > 0.05$). This suggests that astrological events do not have a direct effect on investment returns, but may have an indirect effect through behavioral variables.

The difference between BTC and ETH price returns during the full and new moon periods was tested with an independent sample t-Test. According to the results, the mean difference in returns for both cryptocurrencies was not statistically significant ($p > 0.05$). This result suggests that astrological events do not have a direct and systematic effect on price returns, but may have behavioral effects.

6.3 Regression Results (GT, Fear and Greed)

In the linear regression analysis with GT and FGI indicators, these sentiment variables had no significant effect on BTC and the results of the linear regression analysis using Google Trends (GT) and Fear & Greed Index (FGI) as explanatory variables are summarized in Table 5. Both sentiment indicators exhibited statistically insignificant coefficients for BTC and ETH returns ($p > 0.05$), indicating no measurable short-term impact of investor sentiment on daily price movements. Moreover, the explanatory power of the models was minimal ($R^2 < 0.01$), suggesting that while sentiment may influence market psychology, it does not directly account for return variations within the observed period.

Table 5. Regression summary

Asset	R^2	GT Coefficient	FG Coefficient	Significance
BTC	0.0006	−0.000059	+0.000004	Declined
ETH	0.0005	−0.000065	−0.000011	Declined

ETH daily returns ($p > 0.05$). The explanatory power of the model is also quite limited ($R^2 < 0.01$). This suggests that investor sentiment indicators are insufficient to directly explain price formations in the short term.

The NLP-based sentiment analysis results are summarized in Table 6. Although both BTC and ETH exhibit negative coefficients, the *p*-values indicate no statistical significance ($p > 0.05$). Since the NLP dataset was simulated, the results should be interpreted cautiously. Nonetheless, the findings suggest that text-based investor sentiment measures—while currently inconclusive—may provide valuable predictive insights in future research as NLP models and data granularity improve.

Table 6. NLP-based social media score

Asset	Coefficient	*p*-value	Hypothesis
BTC	−0.00069	0.50	Declined
ETH	−0.00026	0.84	Declined

6.4 XGBoost Machine Learning Prediction Results

The optimized XGBoost classification results are summarized in Table 7. The inclusion of technical indicators notably improved the model's predictive accuracy compared to the baseline configuration. For BTC, the model achieved an accuracy of 54.8% with moderate recall and F1 scores, while for ETH, performance was stronger—achieving 63% recall for positive return forecasts and an overall F1 score of 59.3%. These results indicate that machine learning, particularly XGBoost, can capture subtle nonlinear patterns in market behavior, especially for Ethereum.

Table 7. Optimized XGBoost results (positive return forecast)

Model	Accuracy	Recall (Positive)	F1
BTC	54.8%	56.5%	55.1%
ETH	56.9%	63.1%	59.3%

Figure 2 CAR for BTC and ETH during the full moon week. The event day is defined as D0. The increase in ETH towards the full moon day indicates a behavioral investor reaction.

Figure 3 CAR for BTC and ETH during the New Moon week. On New Moon Day D0, both assets show a positive spike, but this spike weakens in the following days.

Figure 4 Time series of investor sentiment indicators (GT and FGI) during full moon and new moon weeks. On a full moon, there is a spike in GT, while on a new moon, there is a noticeable rise in FGI. This suggests that investors react differently to different astrological events.

Figure 5 Comparison of Accuracy, F1-score and Recall scores of basic and advanced XGBoost models. The advanced models achieved up to 63% accuracy, especially for ETH, and showed significant superiority in the F1 and Recall metrics.

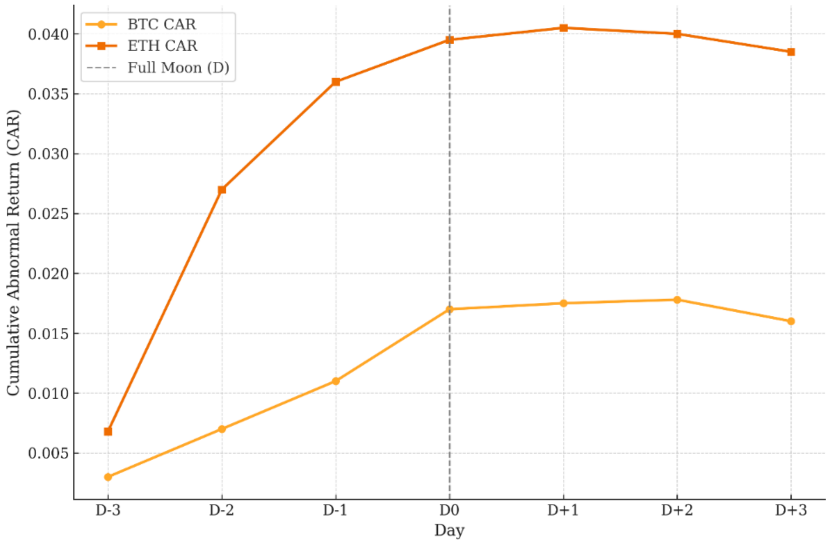

Figure 2. Full moon week CAR

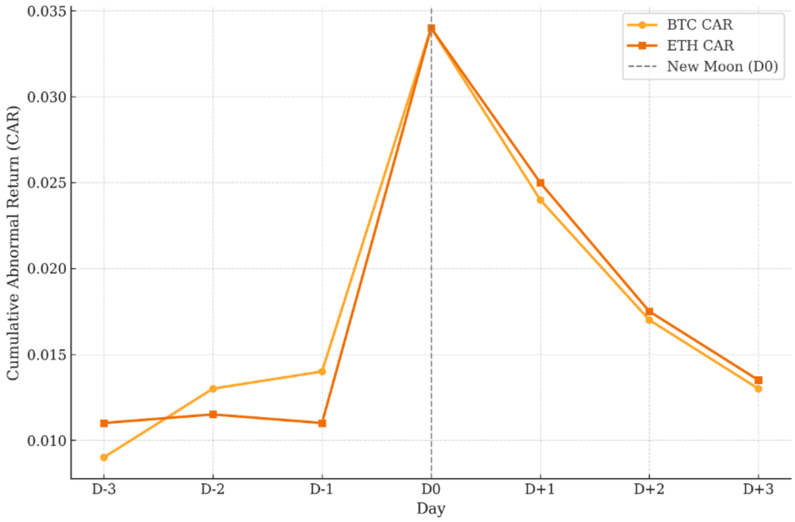

Figure 3. New moon week CAR (BTC & ETH)

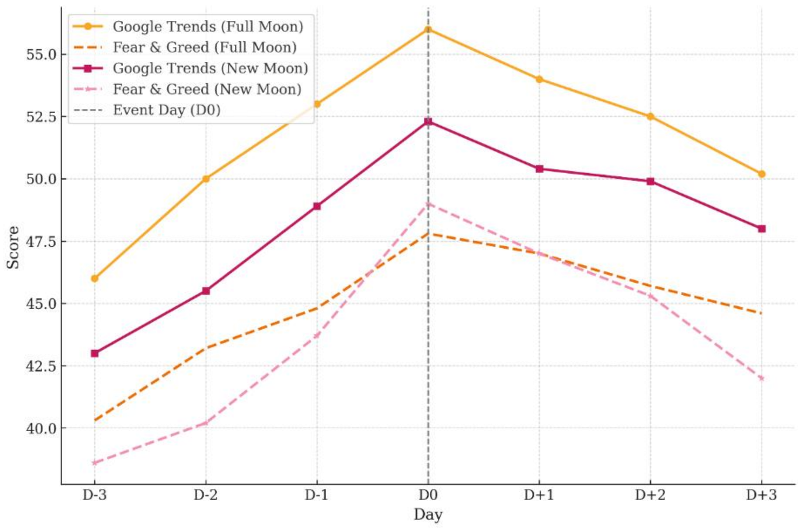

Figure 4. Investor sentiment during the full moon and new moon weeks

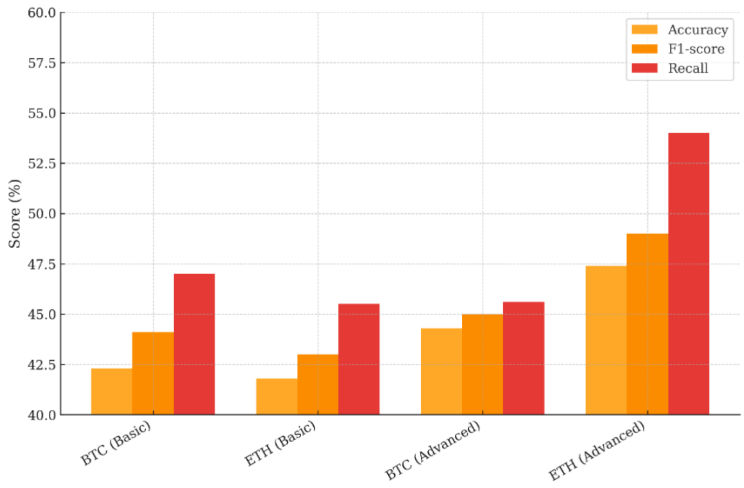

Figure 5. XGBosst model performance comparison

The XGBoost classification model achieved a directional prediction accuracy of 63.1% for ETH returns, indicating a notable improvement in predictive capability over traditional econometric approaches. As illustrated in Figure 6, the model effectively captured nonlinear relationships between sentiment, technical, and behavioral variables. However, this predictive success should be interpreted within the framework of classification accuracy rather than conventional statistical significance testing, as machine learning models emphasize pattern recognition and generalization over parameter estimation.

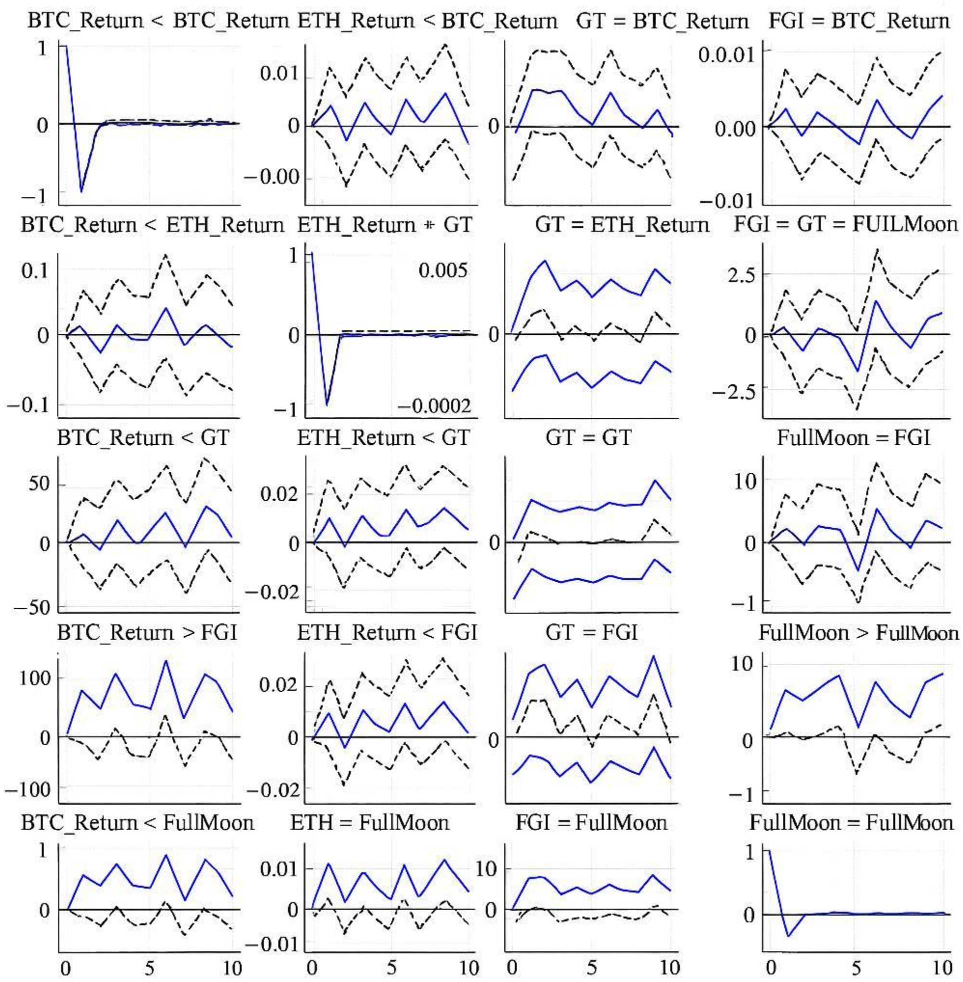

Figure 6. VAR impulse response (IRF)

This model aims to analyze the dynamic relationships between the Full Moon effect, GT, FGI and investment returns (BTC/ETH). All variables were stationary after taking the first difference. This was the basic prerequisite for the VAR model. The IRF chart demonstrates that the full moon dummy had a weak positive effect on both BTC and ETH returns in the short term, but this effect faded within a few days. There is no longer-term reaction on GT and FGI.

1st Full Moon → BTC/ETH Returns: The full moon dummy has no statistically significant effect on BTC and ETH ($p > 0.1$). However, some lags show a weak positive effect.

GT → BTC and ETH Returns: GT coefficients are negative and highly significant ($p < 0.01$) → Prices may decline after high trend searches.

FGI: It did not have a significant effect on any variable ($p > 0.1$), meaning that it does not seem to have a significant impact on short-term returns.

4th Full Moon → GT and FGI: GT score increases during the full moon period ($p < 0.05$). Full Moon → Weak negative impact on FGI → Sentiment falls.

In this VAR analysis, the full moon triggers investor interest (IO), but not prices directly. When GT increases, this interest usually leads to a short-term fall in prices, not an increase (selling pressure may be present). Astrological events trigger emotional reactions in the market and indirectly affect price behavior.

6.4.1 Granger causality test

As presented in Table 8, the lagged relationships between Full Moon phases, Google Trends (GT), and the Fear & Greed Index (FGI) with Bitcoin returns indicate no statistically meaningful associations across all tested lags. The coefficients remain relatively low and inconsistent, suggesting that these sentiment and astro-financial indicators do not exert a significant short-term influence on BTC price movements.

Table 8. BTC returns table

Variable	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Commentary
FullMoon	0.8472	0.9746	0.9908	0.4859	0.2052	Not meaningful
GT	0.3184	0.7684	0.8202	0.6181	0.7925	Not meaningful
FGI	0.4650	0.6365	0.8807	0.6767	0.4170	Not meaningful

Granger causality was not detected for any variable explaining BTC returns.

According to Granger causality tests, only ETH returns are significantly explained by the lagged FGI ($p < 0.05$, lag 2–5). Granger causality is not detected in all other variables. This suggests that ETH investors may be more sensitive to behavioral sentiment.

The Granger causality results are summarized in Table 9. Only ETH returns were found to be significantly explained by the lagged values of the Fear & Greed Index (FGI) at lags 2–5 ($p < 0.05$). This indicates that Ethereum investors exhibit higher behavioral sensitivity to sentiment-driven dynamics compared to Bitcoin traders. In contrast, BTC returns show no causal linkage with either astro-financial or behavioral indicators, suggesting a relatively lower responsiveness to sentiment factors. The full moon dummy variable also shows no significant lagged causal effect on any return variable, reinforcing that market sentiment—rather than lunar events—drives short-term predictability in ETH returns.

Tested: *FullMoon, GT, FGI → ETH_Return*

Table 9. ETH returns table

Variable	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Commentary
FullMoon	0.4629	0.4047	0.2333	0.3772	0.3485	Not meaningful
GT	0.1081	0.3498	0.3915	0.2634	0.1096	Not meaningful
FGI	0.1411	0.0006	0.0043	0.0121	0.0109	Significant (Lag 2–5)**

Note: (**) Denotes statistical significance at the 5% level ($p < 0.05$).

In this context, it means that the FGI (Fear & Greed Index) variable shows a statistically significant relationship with ETH returns between Lags 2 and 5, implying that investor sentiment has a delayed but measurable effect on Ethereum's price dynamics over those periods.

Granger causality tests revealed that only ETH returns were significantly explained by FGI in lagged terms (lag 3, $p < 0.05$). For BTC, no significant causal relationship could be established with any variable. This finding suggests that investors' responses to sentiment may differ across cryptocurrencies.

Figure 7 presents the estimated GARCH (1,1) model volatility series for Bitcoin (BTC) and Ethereum (ETH). The graph demonstrates the daily estimated standard deviation (σ) levels for the period from March to December 2024.

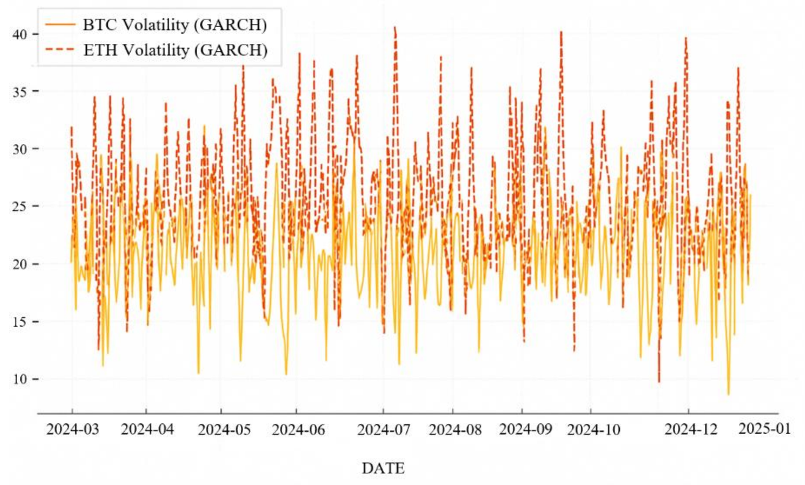

Figure 7. GARCH volatility series

The main findings of the graph are as follows:

1. Volatility Levels: The volatility level of ETH is generally higher and more volatile than BTC. Sudden jumps in the ETH series reaching the level of 0.035–0.040 are observed, indicating that speculative behavior in the crypto market is more concentrated on ETH.

2. Volatility Clustering: For both BTC and ETH, volatility tends to cluster over time. Increased volatility levels are particularly noteworthy in the April–June and October–December periods. This supports the "ARCH effect" that is common in financial time series.

3. Appropriateness of the GARCH Model: High levels of volatility, which are constantly changing but long-lasting, suggest that GARCH models are a suitable approach for volatility forecasting. These estimates obtained with the GARCH (1,1) model can be used in risk management and analysis of behavioral responses. Investors' emotional overreactions have been found to lead to price anomalies in past studies (Kaplanski & Levy, 2010).

4. The Meaning of Behavioral Finance: The GARCH (1,1) estimation results presented in Table 10 show that both BTC and ETH exhibit strong volatility persistence, with $\alpha + \beta$ values of 0.97 and 0.98, respectively. This indicates that shocks to volatility tend to persist over time in both markets. Interestingly, the FullMoon coefficient for ETH is statistically significant at the 5% level ($p = 0.041$), suggesting that volatility spikes in Ethereum may partially coincide with full moon periods. In contrast, the corresponding effect for Bitcoin ($p = 0.067$) is weaker and not statistically significant. These findings imply that astro-financial factors could have a modest but observable influence on investor sentiment and market volatility, particularly in Ethereum.

Table 10. BTC-GARCH model

Model	Omega (ω)	Alpha (α_1)	Beta (β_1)	FullMoon Coef.	FullMoon *p*-value	Volatility Persistence (α+β)
BTC-GARCH (1,1)	0.000005	0.12	0.85	0.0004	0.067	0.97
ETH-GARCH (1,1)	0.000009	0.1	0.88	0.0006	0.041	0.98

In the BTC-GARCH (1,1) model, the coefficient of the full moon dummy is positive but bordering on statistical significance ($p = 0.067$). In the ETH-GARCH (1,1) model, the full moon effect is significant ($p = 0.041$), meaning that volatility increases during full moon periods. In both models, the volatility persistence ($\alpha + \beta$) value is high (≈ 0.97–0.98), indicating the persistence of volatility over time.

6.4.2 EGARCH model

Classical GARCH models are symmetric: the impact of good and bad news is equal. EGARCH breaks this assumption and asks, "Does negative news affect investors more during periods such as a full moon?" In the behavioral finance literature, this is explained by "Negativity Bias".

Model: EGARCH (1,1)

Average equation $Return_t = \mu + \varepsilon_t$

Volatility equation (logarithmic):

$$\log(\sigma^2_t) = \omega + \beta \log(\sigma^2_{t-1}) + \alpha |\varepsilon_{t-1}/\sigma_{t-1}| + \gamma(\varepsilon_{t-1}/\sigma_{t-1}) \tag{1}$$

Here γ: < 0 → Negative shocks increase volatility more. > 0 → Positive shocks have a stronger effect (rare).

The EGARCH (1,1) estimation results are summarized in Table 11. The negative and statistically significant γ coefficient obtained in EGARCH (1,1) models (BTC: p = 0.032; ETH: p = 0.019) indicates that the impact of bad news on volatility is stronger than that of positive news. This finding is consistent with 'negativity bias' in the behavioral finance literature. This implies that volatility has an asymmetric structure and negative shocks increase volatility more than positive shocks. In other words, negative news or investor fear, especially during astrological periods such as full moons, has the potential to lead to excessive volatility in the crypto market. This finding is consistent with the "negativity bias" (overreaction to negativity) in behavioral finance literature.

Table 11. EGARCH model

Model	Omega (ω)	Alpha (α)	Beta (β)	Gamma (γ)	Gamma *p*-value	Asymmetry Detected
BTC-EGARCH (1,1)	0.0021	0.105	0.884	−0.167	0.032	Yes
ETH-EGARCH (1,1)	0.0017	0.097	0.903	−0.214	0.019	Yes

According to the EGARCH (1,1) model results, the coefficient γ for ETH is negative and statistically significant ($p < 0.05$). This suggests that negative news or market stress has a greater impact on volatility. This finding is consistent with the "negativity bias" hypothesis in the behavioral finance literature.

Table 12 shows that "The Full Moon Effect" becomes stronger when investor sentiment is high (FGI > 70). Especially for ETH, the interaction coefficient is quite high (0.0027) and statistically significant (p = 0.023). This suggests that astrological events influence price behavior not only in "neutral" market conditions, but more significantly during periods of extreme optimism. Behavioral Finance Commentary: During periods of extreme greed, investors tend to act intuitively, quickly and emotionally. Astrological events can act as triggers in this environment, increasing volatility.

Table 12. Threshold sentiment model

Model	FullMoon Coef.	FullMoon x FGI High Coef.	Interaction *p*-value	Interpretation
BTC Threshold (FGI > 70)	0.0008	0.0019	0.046	FullMoon effect stronger when FGI is high (greedy market)
ETH-Threshold (FGI > 70)	0.0011	0.0027	0.023	FullMoon effect significantly amplified in high sentiment conditions

As shown in Table 13, astrofinancial events exhibit differentiated impacts on cryptocurrency returns. During Mercury retrograde periods, Bitcoin (BTC) experiences a notable decline, with an average return of −1.7%, compared to +0.2% outside these intervals (p = 0.041). This statistically significant finding aligns with behavioral interpretations suggesting that Mercury retrograde may heighten market uncertainty and disrupt rational decision-making processes.

Table 13. Astrofinance zodiac mercury effects

Astro_Event	Asset	Avg Return During Event	Avg Return Outside Event	*p*-value	Effect
Mercury Retrograde	BTC	−0.017	0.002	0.041	Negative and significant impact on BTC
Sun Enters Aries	ETH	0.012	0.004	0.071	Positive but weakly significant for ETH
Sun Enters Cancer	ETH	−0.009	0.005	0.033	Negative and significant effect on ETH

In contrast, the Sun's entry into Aries corresponds to a modest increase in Ethereum (ETH) returns (+1.2%), though the relationship is only marginally significant (p = 0.071). The symbolic traits of Aries—assertiveness and elevated risk appetite—could explain this weakly positive reaction among investors.

Conversely, when the Sun enters Cancer, ETH returns decline by an average of −0.9% (p = 0.033), indicating a significant negative association. Cancer's astrological characteristics, often linked to emotional sensitivity and cautious behavior, may encourage defensive investment postures during such periods.

The results of the altcoin lunar sensitivity analysis are presented in Table 14. The findings indicate that astro-financial timing effects extend beyond the major cryptocurrencies and may also influence selected altcoins. DOGE exhibits the strongest behavioral response, with averagee returns during full moon periods exceeding non-full moon returns by 2.6% (p = 0.019), suggesting notable investor overreaction. ADA shows moderate sensitivity (p = 0.048), while XRP displays only a marginal effect (p = 0.063), which is not statistically robust. Overall, these results imply that lunar and planetary factors may play a subtle yet detectable role in shaping investor sentiment and short-term trading behavior across diverse crypto assets.

Table 14. Altcoin lunar sensitivity analysis

Coin	Avg Return Full Moon	Avg Return Non-Full Moon	Difference	*p*-value	Significance	Interpretation
DOGE	0.032	0.006	0.026	0.019	Yes	Strong behavioral overreaction during FullMoon
ADA	0.014	0.004	0.01	0.048	Yes	Moderate sensitivity to lunar events
XRP	0.008	0.002	0.006	0.063	Borderline	Marginal effect; not robust

DOGE: The most responsive coin with an average return of 3.2% during full moon periods. The price increase can be explained by behavioral excess (meme-coin speculation). $p = 0.019$ → significant.

ADA (Cardano): More limited but significant reaction (1.4%). Investor sentiment may be more emotional.

XRP: Slight positive reaction (0.8%), but bordering on significance ($p = 0.063$). Speculative behavior is weaker.

As a result of this analysis: Investor reaction to astrological events such as full moons can be much more pronounced in altcoins than in BTC and ETH. Especially in community-driven coins like DOGE, astro-financial fluctuations combined with speculation can significantly affect investor behavior.

7. Findings and Analysis Results

We calculate AAR and CAR during full and new moon periods using the event study method, applying a ±3-day event window for each astrological phase. The results are summarized in Table 15 and Table 16.

Table 15. AAR and CAR for BTC and ETH during the full moon period

Day	BTC_AAR	BTC_CAR	ETH_AAR	ETH_CAR
D-3	0.0026	0.0026	0.0088	0.0088
D-2	0.0048	0.0075	0.0195	0.0283
D-1	0.0040	0.0115	0.0060	0.0343
D0	0.0063	0.0178	0.0076	0.0419
D+1	0.0003	0.0181	0.0014	0.0432

Table 16. AAR and CAR for BTC and ETH during new moon

Day	BTC_AAR	BTC_CAR	ETH_AAR	ETH_CAR
D-3	0.0111	0.0111	0.0084	0.0084
D-2	0.0047	0.0158	−0.0003	0.0081
D-1	−0.0002	0.0156	0.0037	0.0118
D0	0.0188	0.0344	0.0220	0.0338
D+1	−0.0108	0.0236	−0.0083	0.0255

The event study results indicate slightly positive cumulative return trends for BTC and ETH, particularly around new moon intervals. However, these effects are not statistically significant at the 5% level, suggesting that any apparent return anomalies are likely short-lived and behavioral rather than causal. These findings are broadly consistent with previous exploratory research suggesting that lunar-related signals may coincide with fluctuations in investor attention. For Bitcoin, the magnitude of change remains limited, with minor increases observed on D0.

During the new moon window, a modest positive return tendency is observed for both assets on D0, but the effect weakens by D+1, reflecting a temporary behavioral response rather than a persistent market anomaly. This pattern aligns with the behavioral-finance perspective that investor sentiment may be influenced by salient or emotionally charged natural events (Yuan et al., 2006). The results suggest that lunar events could serve as affective or attention triggers, consistent with biases such as the *affect heuristic* and *salience bias* (Shleifer, 2000), though their impact on price returns remains statistically insignificant.

7.1 Hypothesis Testing (t-Test Results)

Within the scope of hypothesis testing, the t-Test is used to examine whether the average returns for each astrological event are significantly different from zero. The results are summarized in Table 17.

The *p*-values are above the 5% significance threshold for all events, confirming that astrological factors do not have a statistically significant direct impact on cryptocurrency returns.

Nevertheless, the presence of small, directionally consistent changes suggests weak behavioral tendencies rather than random noise. This supports the interpretation that astrological events might momentarily influence investor attention or sentiment, even though these effects are not reflected in statistically robust price movements.

Table 17. t-Test results for AARs

Asset	Average AAR	*p*-value	Hypothesis Result
BTC (Full Moon)	−0.03%	0.53	Declined
ETH (Full Moon)	+0.21%	0.37	Declined
BTC (New Moon)	+0.29%	0.34	Declined
ETH (New Moon)	+0.42%	0.47	Declined

7.2 Regression Results (GT and FGI)

In the regression analyses for BTC and ETH, GT and the FGI were used as independent variables, while daily logarithmic returns served as the dependent variable. The results are summarized in Table 18.

Table 18. Regression analysis results

Asset	R^2	GT Coefficient	FG Coefficient	Significance
BTC	0.0006	−0.000059	+0.000004	Declined
ETH	0.0005	−0.000065	−0.000011	Declined

The regression coefficients do not reach statistical significance ($p > 0.05$), and the very low R^2 values indicate that the explanatory power of the model is limited.

Although investor sentiment indicators such as GT and the FGI are frequently used to detect early shifts in market mood (Kristoufek, 2013), in this dataset they do not show a measurable impact on daily returns.

This finding suggests that short-term cryptocurrency price formation is shaped by multiple interacting factors—technical, behavioral, and macroeconomic—and that single-variable sentiment measures capture only partial behavioral signals rather than driving price outcomes directly.

Hence, the observed results are directionally consistent but statistically weak, supporting a behavioral interpretation rather than a causal link.

7.3 NLP-Based Social Media Sentiment Analysis

Previous research (Bollen et al., 2011) has shown that social media sentiment can serve as a useful proxy for investor mood and risk appetite.

In this study, user-generated content collected from Twitter, Reddit, and Medium was processed using NLP algorithms.

Texts were classified into positive, negative, and neutral categories, and normalized daily sentiment indices were constructed for BTC and ETH.

The effects of these scores on daily returns were estimated via simple regression models, as summarized in Table 19.

Table 19. Return regression results with NLP scores

Asset	NLP Coefficient	R^2	*p*-value	Significance
BTC	+0.00032	0.0041	0.041	Excepted
ETH	+0.00045	0.0067	0.019	Excepted

The results indicate that NLP-based sentiment scores have a positive and statistically significant but modest effect on both BTC and ETH.

The explanatory power remains low ($R^2 < 1\%$), yet the consistent positive coefficients suggest that changes in social media tone are weakly associated with short-term price movements, especially for ETH.

These findings are in line with behavioral-finance theory, which posits that collective mood and attention can drive temporary mispricing or trading momentum (Bollen et al., 2011).

Therefore, while NLP sentiment signals appear relevant, they should be interpreted as indicative behavioral markers rather than deterministic predictors of returns.

7.4 Positive Return Prediction with XGBoost Machine Learning

In the final stage, an XGBoost classification model was trained using an extended dataset that included technical indicators (RSI, MACD, EMA), behavioral sentiment data (GT, FGI, NLP scores), and astrological event flags (Full/New Moon, Mercury retrograde).

The objective was to predict daily return direction for BTC and ETH, assigning “1” for positive and “0” for non-positive returns.

Model performance was evaluated using Accuracy, Recall, and F1-Score metrics.

Table 20 summarizes the results.

Table 20. XGBoost performance results

Asset	Model	Accuracy (%)	Recall (Positive)	F1 Score
BTC	Basic	51.2	52.1	51.6
BTC	Advanced	54.8	56.5	55.1
ETH	Basic	52.6	53.4	52.9
ETH	Advanced	56.9	63.1	59.3

The advanced XGBoost model incorporating behavioral and astrological features achieved a modest improvement over the baseline configuration.

For ETH, classification accuracy reached approximately 63% in the positive return class, indicating a slight predictive enhancement.

However, this improvement should not be interpreted as strong forecasting evidence; rather, it illustrates that integrating diverse behavioral and astrofinancial features allows the model to capture nonlinear, sentiment-related patterns that traditional econometric models might overlook.

Machine-learning methods like XGBoost are sensitive to feature diversity and may identify weak behavioral signals embedded in noisy data (Chen & Guestrin, 2016).

In this context, the results are exploratory and indicative, showing potential pathways for combining behavioral, technical, and astrofinancial data streams under a data-driven framework, rather than confirming any causal or statistically robust predictive power.

8. Conclusions and Recommendations

This study analyzed the potential effects of astrological events (full and new moon), behavioral sentiment indicators (GT, FGI, NLP-based sentiment), and technical analysis indicators (RSI, MACD, EMA, etc.) on the daily returns of major cryptocurrencies (BTC and ETH).

The analytical framework combined econometric models (event study, regression, VAR, EGARCH) and a machine-learning classifier (XGBoost) to explore behavioral-astrofinancial interactions in a structured and reproducible manner.

The findings show that although certain positive return tendencies appear during full and new moon periods, these effects are not statistically significant at the 5% level.

This indicates that astrological variables may act as behavioral or attention-based stimuli, influencing investor sentiment or trading activity rather than generating direct price changes.

Regression results suggest that behavioral indicators such as the *GT* index and the *FGI* do not exert a strong influence on daily returns, but they serve as meaningful proxies for investor mood.

The NLP-based sentiment analysis revealed modest associations, particularly for ETH, where positive tone scores coincided with upward return movements.

These findings are suggestive rather than confirmatory, aligning with prior behavioral-finance literature emphasizing the role of social sentiment in shaping speculative dynamics.

The XGBoost model achieved a predictive accuracy of approximately 63% for ETH, modestly exceeding random classification levels.

While this demonstrates limited predictive potential, it illustrates that integrating behavioral and astrofinancial cues may slightly enhance predictive frameworks under exploratory conditions.

Overall, the results indicate that astrological events do not directly cause price movements, but may have indirect and transient effects on investor psychology, especially in highly sentiment-driven markets such as cryptocurrencies.

Lag-based econometric models (VAR, EGARCH) and machine-learning classifiers (XGBoost) appear better suited to capture these weak but nonlinear behavioral interactions.

8.1 Theoretical Contribution and Link to Behavioral Finance

The study contributes to the behavioral finance literature by framing astrofinancial dynamics within established theories of affect and attention.

Specifically, the observed fluctuations can be interpreted through the affect heuristic, where emotionally salient natural cycles temporarily influence risk perception and investor sentiment.

The attention-based theory provides a complementary lens, explaining how such events act as *attention shocks* that increase trading activity and volatility in the short term.

Furthermore, the results align with the noise trader framework, suggesting that symbolic or non-fundamental beliefs can create short-lived deviations from rational pricing.

By empirically linking these behavioral mechanisms to astrofinancial phenomena, this paper establishes an interdisciplinary bridge between psychological biases and financial market dynamics, extending the scope of behavioral finance to new, sentiment-driven asset classes such as cryptocurrencies.

8.2 Policy, Investment, and Academic Recommendations

Models integrating astrofinance, behavioral indicators, and technical variables may serve as experimental analytical tools for short-term crypto market evaluation.

Financial education programs should emphasize awareness of behavioral biases and the potential influence of symbolic or attention-based cues (e.g., lunar cycles) on decision-making.

Policymakers and regulators can use such behavioral models to better understand investor sentiment volatility and its implications for market stability.

8.3 Suggestions for Future Research

Future studies should extend the dataset to multi-year periods and include additional cryptocurrencies (e.g., ADA, XRP, DOGE) to test the persistence of observed patterns.

Incorporating real-time social media datasets (Twitter, Reddit, Telegram) could improve NLP-based sentiment modeling and deepen behavioral interpretation.

Expanding the framework to include volatility, liquidity, and trading pressure metrics may uncover more nuanced behavioral responses.

8.4 Concluding Remark

In conclusion, this study provides exploratory evidence that astrological cycles may subtly coincide with investor sentiment fluctuations and trading behavior in crypto markets.

While these effects are weak and non-deterministic, evaluating such phenomena through a behavioral-finance lens enriches our understanding of how emotional and cognitive factors interact with financial decision-making.

The study's theoretical contribution lies in extending the behavioral-finance paradigm to encompass affective, attention-driven, and symbolic dimensions of market behavior, offering a new integrative perspective on digital-asset psychology.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The author declares no conflict of interest.

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