HOW DOES THE BITCOIN SENTIMENT INDEX OF FEAR & GREED AFFECT BITCOIN RETURNS?

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Abstract

The efficient market hypothesis encounters scrutiny from behavioral finance insights, highlighting the pronounced influence of investor emotions on market dynamics, a phenomenon especially evident in the tumultuous cryptocurrency markets. This investigation utilizes the autoregressive distributed lag (ARDL) model and the error correction model (ECM) to examine the impact of the Bitcoin Sentiment Index (BSI), also known as the Crypto Fear & Greed Index (CFGI), on Bitcoin returns, leveraging monthly data spanning from 2016 to 2021. The ARDL analysis identifies a positive and statistically significant correlation between BSI and Bitcoin returns, indicating that strong sentiment may beneficially affect Bitcoin's long-term returns. Concurrently, the ECM analysis reveals that fluctuations in the BSI positively influence the changes in Bitcoin returns in the short term. The error correction term demonstrates a significantly negative value, signifying an expedient adjustment toward long-term equilibrium following transient disturbances. These findings remain robust upon the integration of additional macroeconomic control variables. Unlike prior studies centered on singular sentiment indicators or limited temporal analyses, this research employs an extensive sentiment measure over an extended duration. The integrated application of ARDL and ECM methodologies facilitates a thorough and rigorous examination of short-term fluctuations alongside long-term equilibrium dynamics.

Keywords: Behavioural Finance, Bitcoin Sentiments, Bitcoin Returns, Cryptocurrency Market, Autoregressive Distributed Lag Model, Error Correction Model

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1. INTRODUCTION

In January 2009, Satoshi Nakamoto mined the genesis block of Bitcoin, ushering in the era of cryptocurrencies. Within 15 years, Bitcoin's valuation transitioned from an initial US$0.004 per Bitcoin (BTC), to an unprecedented zenith of US$71,333 by March 31, 2024, delineating an exponential trajectory in growth and amassing a market capitalization of approximately US$1,400 billion (Yahoo, n.d.). Concurrently, data from Bitcoin Visuals (n.d.) illustrates an escalation in trading volume, ascending from US$20.5 million on December 31, 2013, to a staggering US$100.7 billion by March 6, 2024, evidencing Bitcoin's expanding dominance within global financial markets.

Bitcoin's extraordinary rise is characterized by its significant volatility, setting it apart from conventional currencies. This feature, however, attracts investors with a penchant for risk (Urquhart, 2018). Unlike traditional fiat currencies like the US dollar (USD), euro (EUR), and pound (GBP), Bitcoin operates on a decentralized model, ensuring that no single government entity controls its valuation, issuance, or transactions. As articulated by Gaies et al. (2021), the value of Bitcoin is derived from a collective agreement and is anchored in the trust of its holders, rendering it highly sensitive to the sentiments of its investors and owners. Musk's influence on Bitcoin's valuation through Twitter is a prime example of this. On March 24, 2021, Musk's announcement Tesla could be acquired using Bitcoin led to a surge in its price from US$52,774 to US$63,503 per BTC, marking a 20.3% increase (Crawley, 2021). Conversely, on May 13, 2021, Musk retracted this option, citing environmental concerns, this caused the price of Bitcoin to fall by 30.4% from US$49,716 to US$34,616 per BTC (Mccrank, 2021). Musk's pronounced influence on Bitcoin's market value through Twitter has ignited an extensive scholarly debate, with a consensus forming around the notion that Musk has swayed Bitcoin's pricing by significantly impacting investor sentiment.

The influence of emotion on financial markets is a cornerstone of behavioral finance. Before the emergence of Bitcoin, thorough investigations into stock sentiment demonstrated that both positive and negative emotions and attention shape investment choices, subsequently affecting the valuation and liquidity of securities (Kurov, 2010; Chue et al., 2019; Kumar & Lee, 2006; Kaniel et al., 2008; Xu et al., 2024; Zhao & Zhang, 2024). Kaplanski and Levy (2010) argued that this impact was pronounced in volatile sectors and among smaller, high-risk stocks. Subsequently, the advent of Bitcoin prompted scholars to examine the nexus between social media platforms like Twitter, Google searches, news, and Bitcoin returns (Bouri & Gupta, 2021; Bukovina & Marticek, 2016; Kaminski, 2014; Yu & Zhang, 2023). Diaconașu et al. (2022) discerned that both positive and negative surprises precipitate a surge in trading volume. Aysan et al. (2023) delved into the significance of Bitcoin sentiment for investors before and amidst the COVID-19 pandemic, underscoring the pivotal influence of investor sentiment on cryptocurrency valuations. Such research highlights the acute sensitivity of Bitcoin market valuations to sentiment, accentuated by its decentralized essence, which potentially renders its prices more prone to sentiment-induced variances. AlNemer et al. (2021) and Bogdan et al. (2023) emphasized the sway of investor sentiment over cryptocurrency valuations and market phenomena such as herd behavior, particularly across different liquidity contexts. These insights suggest that sentiment affects cryptocurrency returns directly and influences market dynamics via liquidity and trading patterns. Notwithstanding, existing studies establishing a positive correlation between social attention and Bitcoin returns are limited in two aspects: firstly, they predominantly utilize single-source sentiment measures, either from social media or singular search volume metrics; secondly, they cover an average duration of merely three years. Accordingly, this study introduces the Bitcoin Sentiment Index (BSI), also known as the Crypto Fear & Greed Index (CFGI), an encompassing metric aggregating sentiment from diverse sources.

Using monthly data from January 2016 to June 2021, this study scrutinizes the impact of Bitcoin sentiment on its returns. The autoregressive distributed lag (ARDL) model is used to estimate long-term effects, while the error correction model (ECM) is used to analyse short-term effects. The results show that the long- and short-term effects of Bitcoin sentiment on Bitcoin returns are significantly positive. The error correction term is particularly negative, indicating a rapid process of recalibration back to the long-term equilibrium after short-term deviations. It is hypothesized that heightened optimism and increasing greed catalyse an influx of capital into the market, thereby elevating Bitcoin prices and returns. Conversely, a shift towards pessimism and fear prompts a more cautious investment approach, leading to reduced investments, lower prices, and diminished returns for Bitcoin. In addition, the inclusion of one control variable, the Broad US Dollar Index (BDI), and the substitution of Economic Policy Uncertainty (EPU) Index for the US with Global Economic Policy Uncertainty (GEPU) confirm the robustness of the results.

This study makes significant contributions to the behavior finance literature, especially regarding cryptocurrency markets, through its detailed exploration of the relationship between Bitcoin sentiment and its returns. The discovery of a notable positive correlation between Bitcoin sentiment and returns, across both long and short terms, highlights the critical influence of investor sentiment on Bitcoin's market dynamics. The result of the ECM model accentuates the market's adeptness in adjusting back to a state of equilibrium after disruptions. Moreover, the study sheds light on how variations in collective investor sentiment, oscillating between optimism and pessimism, directly impact the flow of market capital, pricing, and returns, thereby providing a concrete application of behavioral finance principles within cryptocurrency. Furthermore, the investigation furnishes investors with essential evidence suggesting the BSI functions as a reliable measure of Bitcoin sentiment and a predictor of Bitcoin returns, enabling them to formulate an optimal investment strategy.

The subsequent sections are organized in the following manner. Section 2 scrutinizes pertinent literature and formulates the hypotheses. Section 3 delineates the data and the research methodology. Section 4 unveils the findings. Section 5 discusses the results. Finally, Section 6 offers the conclusion.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1. Investor sentiments

The efficient-market hypothesis (EMH) has historically constituted the foundational framework for comprehending financial markets (Fama, 1970). Two pivotal assumptions underpin it. First, it posits that prices instantaneously integrate all available information. Secondly, it assumes the rationality of all market participants. Given these premises, financial asset prices are expected to manifest stratified: escalating upon receipt of favorable news, declining in response to adverse developments, and remaining static without novel stimuli. Nevertheless, the emergence of behavioral finance has opened a new chapter in the analysis of financial markets, challenging the long-standing principles of the EMH. The observed market behaviors often deviate from these theoretical forecasts. Beyond simple reactions to news, price fluctuations also reveal oscillations suggestive of underlying factors beyond new information, thus eluding complete elucidation by the EMH paradigm.

Tracing the genesis of behavioral finance, Selden (1912) was one of the first to argue that the psychology of market participants significantly influences stock prices. This groundbreaking insight facilitated extensive research into investor behavior's psychological and emotional determinants. The seminal works of Tversky and Kahneman (1974, 1981) introduced the concept of cognitive biases to illustrate systematic biases in judgment that influence financial decision making. Thaler (1980) and Shiller (1981) further enriched this discourse by illuminating the irrational behaviors contributing to pricing anomalies within financial markets. The nexus between emotions and market phenomena has attracted heightened scrutiny in the modern context. Hirshleifer and Shumway (2003) identified a positive association between sentiment and stock market returns, whereas Kaplanski and Levy (2010) explored how fear can precipitate market volatility, especially in high-risk sectors. These explorations bear acute relevance within cryptocurrency markets, characterized by their heightened volatility and the significant role of sentiment in dictating price trajectories.

2.2. Bitcoin returns

The academic discourse surrounding Bitcoin's essence reveals disparate perspectives. Cheung et al. (2015) posit that Bitcoin represents an innovative form of currency, offering advantages such as accelerated international transactions, low processing fees, non-reversible transactions, and user anonymity. Conversely, Yermack (2015) contends that Bitcoin's pronounced volatility undermines its utility as a traditional currency, categorizing it as a speculative asset. Similarly, Dyhrberg (2016) contends that Bitcoin's valuation, independent of governmental control and sensitive to demand fluctuations, is akin to gold, occupying a liminal space between currency and investment asset. Expanding upon this analysis, Ciaian et al. (2016) highlight the negative correlation between the US dollar's strength and Bitcoin returns, underscoring the unique valuation mechanisms characteristic of cryptocurrencies.

Bitcoin returns are affected by various macroeconomic variables. The correlation between Bitcoin performance and the Federal Reserve Bank's Financial Stress Index (FSI) during economic recessions has been documented. Jareño et al. (2020) observed a negative relationship between the change in FSI and Bitcoin returns. Sevillano and Jareño (2018) found Bitcoin's high returns linked to economic downturns. Beyond the FSI, numerous studies have identified other macroeconomic factors. The Volatility Index (VIX), a measure of market volatility derived from the S&P 500 Index reported by the Chicago Board Options Exchange (CBOE), negatively affects Bitcoin returns, with Al-Yahyaee et al. (2019) and Koutmos (2020) identifying the volatility index as a critical predictor of Bitcoin's performance. Bouri et al. (2017) explored Japan's EPU, while Aalborg et al. (2019) investigated China's EPU. Demir et al. (2018) analysed EPUs across various nations, revealing a positive association between Bitcoin returns and EPUs, especially the US EPU. Jareño et al. (2020) found that the US nominal interest rate adversely impacts Bitcoin returns during economic expansion phases. Corbet et al. (2020) highlighted the responsiveness of cryptocurrency to announcements from the federal Open Market Committee (FOMC), establishing it as an effective predictor of Bitcoin volatility.

2.3. Investor sentiments and Bitcoin returns

Subsequent inquiries have scrutinized the relevance of sentiment analyses in stock markets for their application within the cryptocurrency sphere. Baker and Wurgler (2006; 2007) pinpointed specific stock attributes, including minimal capitalization, nascent stages, profitability deficits, elevated volatility, and dividend nonexistence, as factors rendering them exceptionally susceptible to investor sentiment. They conjectured that cryptocurrencies may demonstrate comparable sensitivities to sentiment shifts due to their ambiguous valuation and constrained opportunities for arbitrage. Conversely, Hayes (2017) offered a contrarian perspective, contending that cryptocurrencies diverge from conventional stock or asset valuation models, as their value is primarily influenced by regulatory algorithms rather than market sentiment.

Although emotions and sentiments appear predominantly qualitative, technological advancements now enable their quantitative analysis. Various studies have probed psychological predispositions within cryptocurrency markets, including Bitcoin, uncovering a pronounced correlation between public sentiment and Bitcoin's foundational aspects, such as returns, trading volumes, and volatility. Kristoufek (2013) employed two indicators of investor sentiment: 1) the quantity of Bitcoin searches on Google, and 2) the rate of visits to Bitcoin-related Wikipedia pages, to establish a bidirectional causal link between Bitcoin returns and these indicators. Investigating the responsiveness of Bitcoin to market sentiment, Feng et al. (2018) argued that positive (negative) news precedes future rise (fall) in Bitcoin prices, with this effect occurring nearly two days before the announcement. Bukovina and Marticek (2016) used the sentiment index (http://sentdex.com/) to verify that Bitcoin sentiment has little effect on price movements. They further advocated for Google searches as a superior measure of Bitcoin sentiment. Kaminski (2014) empirically confirmed his theory, which mentions that emotional tweets positively correlate with Bitcoin trading volume. AlNemer et al. (2021) and Bogdan et al. (2023) emphasized the importance of investor sentiment by demonstrating its ability to predict cryptocurrency prices and their impact on market phenomena such as herd behavior, especially in different liquidity scenarios. These insights indicate that sentiment directly influences cryptocurrency returns and adjusts market mechanisms through liquidity and trading activities.

In response to these advancements, this study presents the BSI as an exhaustive sentiment gauge that amalgamates volatility, market volume, social media interactions, survey insights, market dominance, and trend scrutiny. We aim to evaluate the BSI's predictive capacity concerning Bitcoin returns over short and extended temporal spans, culminating in the proposition of the ensuing hypotheses:

H1: The BSI positively influences Bitcoin returns in the long term.

H2: The BSI positively influences Bitcoin returns in the short term.

3. RESEARCH METHODOLOGY

3.1. Data sample

To investigate the effect of Bitcoin sentiment on Bitcoin returns, we aggregate monthly data on Bitcoin price in US dollars, VIX[1], and FSI[2] spanning January 2016 to June 2021, extracted from the Bloomberg terminal. The closing price of Bitcoin on the first day of each month is then transformed into the first difference of its logarithms to compute Bitcoin returns. The monthly EPU for the United States is sourced from the EPU index, which is available online[3]. The US nominal interest rate (IR) is obtained from the International Monetary Fund's (IMF) database of international financial statistics[4].

This study employs the BSI[5], alternatively referred to as the CFGI, to quantify investors' emotions and sentiments derived from diverse sources. The BSI indicates Bitcoin sentiment, integrating five principal components: volatility, market volume, social media, dominance, and trends. As Kaabia et al. (2020) highlighted, the BSI effectively captures diverse emotional dimensions relevant to behavioral finance. The BSI is quantified on a scale from 0 to 100, where 0 indicates extreme fear, and 100 represents maximum greed, mirroring Bitcoin investors' psychological state. This range offers insights into the collective mood of pain or joy among Bitcoin investors. Given the pronounced volatility of Bitcoin, the BSI is regarded as a crucial technical tool that aids investors in identifying optimal moments for executing trades to maximize profitability.

3.2. Methodology

This study employs the ARDL model to analyse the short-term and long-term impacts of BSI, EPU, IR, VIX, and FSI on Bitcoin returns. The ARDL bounds testing approach was pioneered by Pesaran and Shin (1998) and further developed by Pesaran et al. (2001). We choose the ARDL model for three main advantages over other cointegration methodologies: 1) the ARDL model facilitates the examination of long-term relationships among variables irrespective of their integration orders; 2) it enables the estimation of both long-run coefficients and short-run dynamics; 3) ARDL yields reliable estimates even with small sample sizes. The specified ARDL model is delineated as follows:

$$\begin{aligned} BTC_t = \alpha &+ \sum_{i=1}^{p_1} \lambda_{1i} BTC_{t-i} + \sum_{i=0}^{p_2} \lambda_{2i} BSI_{t-i} \\ &+ \sum_{i=0}^{p_3} \lambda_{3i} EPU_{t-i} + \sum_{i=0}^{p_4} \lambda_{4i} IR_{t-i} \\ &+ \sum_{i=0}^{p_5} \lambda_{5i} VIX_{t-i} + \sum_{i=0}^{p_6} \lambda_{6i} FSI_{t-i} \\ &+ \varepsilon_t \end{aligned} \tag{1}$$

where, *BTC* denotes Bitcoin returns, *BSI* signifies the Bitcoin Sentiment Index, *EPU* represents the economic policy uncertainty, *IR* corresponds to the interest rate, *VIX* is the volatility index, and *FSI* is the financial stress index, α serves as the intercept, and ε is designated as the noise error term; λ reflects the short-term and long-term relationships between variables; p is assigned to denote the lag period for the variables. This study employs

[1] The VIX, known as the Chicago Board Options Exchange Volatility Index, measures expectations of stock market volatility over the forthcoming 30 days, derived from S&P 500 Index options. A high VIX indicates that traders expect significant price fluctuations, suggesting uncertainty in the market. Conversely, a low VIX suggests an expectation of less volatility, indicating a more stable market environment.

[2] The Financial Stress Index (FSI), developed by the Federal Reserve Bank of St. Louis, quantifies market financial stress through an aggregate of 18 weekly data series, encompassing seven interest rate series, six yield spreads, and five additional indicators. Initiated in late 1993, the index's mean is calibrated at zero, serving as a benchmark for normal financial market conditions. Indices below zero indicate below-average financial market stress, whereas values above zero suggest above-average financial market stress.

[3] The Economic Policy Uncertainty (EPU) Index serves as a quantitative metric assessing the degree of uncertainty associated with economic policies within a specific country or on a global scale, illustrating the extent of uncertainty among policymakers, businesses, and investors regarding forthcoming policy changes and their potential impact on the economic landscape. Retrieved on July 1, 2021, from https://www.policyuncertainty.com

[4] Retrieved on July 1, 2021, from https://data.imf.org/regular.aspx?key=63087881

[5] The Bitcoin Sentiment Index (BSI) assesses the prevailing sentiment within the Bitcoin market, consolidating this analysis into a straightforward gauge ranging from 0 to 100. A score of zero signifies "extreme fear," while a score of 100 denotes "extreme greed." It integrates several variables to measure the market's sentiment towards Bitcoin: 1) volatility (25%), quantifying the coin's volatility and maximum drawdowns; 2) market momentum/volume (25%), evaluating current trading volumes and market momentum; 3) social media (15%), monitoring engagement with Bitcoin-related hashtags on Twitter; 4) surveys (15%, currently paused), surveying investor sentiment; 5) dominance (10%), indicating Bitcoin's market capitalization proportion against the entire cryptocurrency market, where an increase in dominance suggests a preference for Bitcoin as a safe haven; and 6) trends (10%), analysing data from Google trends on Bitcoin-centric searches. This index furnishes a detailed perspective on market sentiment, merging conventional financial metrics with contemporary media indicators to elucidate the cryptocurrency market's intricacies. Data were obtained on July 1, 2021, from https://alternative.me/crypto/fear-and-greed-index.

the Schwarz criterion (SC) to identify each variable's optimal lag length.

The bounds F-test is employed to examine the long-term cointegration among the variables. The null hypothesis posits no cointegration, denoted as H_0: $\lambda = 0$, whereas the alternative hypothesis, $H1: \lambda \neq 0$, suggests cointegration. Should the calculated F-statistic fall below the lower bound, the null hypothesis (H_0) of the absence of cointegration is upheld. Conversely, an F-statistic exceeding the upper bound leads to rejecting the null hypothesis, indicating a long-term cointegration relationship between the variables. The results are ambiguous if the F-statistic is situated between the lower and upper bounds.

Once cointegration is established, we can reparameterize the ARDL model into an ECM. This is done to incorporate the mechanism that adjusts deviations from the long-term equilibrium in the short-run dynamics. The ECM can be written as:

$$\Delta BTC_t = \sum_{i=1}^{p_1} \beta_{1i}\, \Delta BTC_{t-i} + \sum_{i=0}^{p_2} \beta_{2i}\, \Delta BSI_{t-i} + \sum_{i=0}^{p_3} \beta_{3i}\, \Delta EPU_{t-i} + \sum_{i=0}^{p_4} \beta_{4i}\, \Delta IR_{t-i} + \sum_{i=0}^{p_5} \beta_{5i}\, \Delta VIX_{t-i} + \sum_{i=0}^{p_6} \beta_{6i}\, \Delta FSI_{t-i} + \varphi EC_{t-1} + \eta_t \quad (2)$$

where, Δ represents the first difference of the variables, EC_{t-1} denotes the error correction term derived from the long-term relationship, i.e., the residual from the cointegration equation presented in Eq. (1) from the preceding period. The coefficient φ indicates the speed of adjustment toward the model's long-run equilibrium following a short-run shock. A negative and statistically significant value of φ suggests that any short-term deviations are realigned with the long-run equilibrium.

4. RESEARCH RESULTS

4.1. Main results

This study investigates the influence of BSI on Bitcoin returns, accounting for four key determinants identified in the literature: *EPU*, *IR*, *VIX*, and *FSI*. Descriptive statistics for sentiment and financial indices related to Bitcoin are presented in Table 1.

Table 1. Descriptive statistics

Variable	*Obs.*	*Mean*	*Std. dev.*	*Min*	*Max*	*Median*	*Kurtosis*	*Skewness*
BTC	66	0.07	0.22	-0.45	0.53	0.06	-0.23	-0.11
BSI	66	50.15	23.12	13.00	92.00	45.50	-0.23	0.37
EPU	66	251.60	8.18	237.30	271.00	124.94	2.20	1.59
IR	66	1.10	0.90	0.04	2.92	1.09	-1.27	0.41
VIX	66	18.13	8.08	9.51	53.54	15.70	5.23	2.04
FSI	66	-0.23	0.81	-0.97	5.07	-0.33	28.18	4.64
BDI	66	114.18	3.35	107.65	123.60	114.38	0.83	0.57
GEPU	66	224.41	69.65	123.76	430.02	219.50	-0.08	0.68

Note: The table displays descriptive statistics for monthly datasets from January 2016 to June 2021.

The average Bitcoin return is 0.07, with a standard deviation of 0.22, underscoring the volatile nature of Bitcoin returns. The *BSI* averages 50.15, ranging from a minimum of 13 to a maximum of 92, reflecting periods of extreme fear and greed within the cryptocurrency market. The average *EPU* is 251.60, and the average interest rate (*IR*) is 1.10%. The *VIX* averages 18.13, with values spanning from 9.51 to 53.54. The average *FSI* is -0.23, with a standard deviation of 0.81.

We first assess the stationarity of the variables using the augmented Dickey-Fuller (ADF) test, with results presented in Table 2. The null hypothesis of nonstationary is rejected for *BTC*, *EPU*, *VIX*, *FSI*, *BDI*, and *GEPU*, indicating that these series are integrated of order zero and are already stationary. Conversely, *BSI* and *IR* achieve stationarity upon first differencing, signifying integration of order one. No variable is integrated of order two. Given that the ARDL model can be applied regardless of whether the variables are integrated of orders zero or one, we confirm that the prerequisites for utilizing the ARDL framework are met.

Table 2. Stationarity tests

Variable	*Level*	*First difference*	*Order of integration*
BTC	-6.79***	-12.9***	I(0)
BSI	-2.44	-7.55***	I(1)
EPU	-3.64**	-10.75***	I(0)
IR	-0.85	-6.10***	I(1)
VIX	-3.80**	-8.01***	I(0)
FSI	-4.33***	-8.96***	I(0)
BDI	-4.91***	-5.58***	I(0)
GEPU	-3.94**	-3.02	I(0)

*Note: This table presents the results of stationarity tests conducted using the ADF test. I(0) indicates integration of order zero, signifying that the time series is stationary. I(1) indicates integration of order one, suggesting that the time series requires differencing once to achieve stationarity. *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively.*

Table 3 presents the bounds F-test results for cointegration between Bitcoin returns and *BSI*, *EPU*, *IR*, *VIX*, and *FSI*. The findings indicate that the F-statistic exceeds the 99% upper bound, allowing for the rejection of the null hypothesis of no cointegration at the 1% significance level. This suggests a long-term cointegration relationship between Bitcoin returns and the variables above. Once a cointegration relationship is established, the ECM is employed. The ECM includes an error correction term for short-term adjustments toward long-term equilibrium.

Table 3. Bounds test for cointegration

F-statistics	*99% upper bound*	*1% lower bound*	*Conclusion*
8.40	4.43	3.15	Cointegration

Note: This table reports the bounds test results for cointegration in the ARDL model. If the computed F-statistic surpasses the upper bound of the critical values, the null hypothesis of no cointegration is rejected, indicating a cointegration relationship.

Table 4 presents the long-run coefficient estimates from the ARDL model, illustrating the influence of various predictors on Bitcoin returns. This table provides coefficients for each variable and their respective t-statistics, shedding light on the significance and direction of their relationships with Bitcoin returns. The first and second lags of Bitcoin returns exhibit a significant negative relationship with current Bitcoin returns. This indicates that past Bitcoin returns reduce future returns, suggesting a mean reversion phenomenon.

Table 4. ARDL model results

Variable	*Coefficient*	*t-statistics*
BTC_{t-1}	-0.7182***	-6.896
BTC_{t-2}	-0.4349***	-5.103
BSI_t	0.0064***	11.572
BSI_{t-1}	-0.00002	-0.032
EPU_t	-0.0002	-0.770
EPU_{t-1}	-0.0002	-0.813
IR_t	-0.0338	-0.955
IR_{t-1}	-0.0450	-1.257
VIX_t	-0.0027*	-1.694
VIX_{t-1}	-0.0073***	-3.436
FSI_t	0.0440***	2.701
FSI_{t-1}	0.0397**	2.458
Constant	-0.0001	-0.014
Observations	66	
Adjusted R^2	0.7896	

*Note: This table presents the results of the ARDL model. The dependent variable is the Bitcoin return at time t, labeled BTC_t. The key independent variable is BSI_t. *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively.*

The *BSI* exerts a positive and significant influence on Bitcoin returns, indicating that an increase in greedy (fear) sentiment positively (negatively) impacts Bitcoin returns. A plausible explanation is that rising investor sentiment in the Bitcoin market leads to increased optimism, causing investors to anticipate future price rises and purchase Bitcoin, thus boosting Bitcoin returns. The coefficients for *EPU* and *IR* are insignificant, indicating that policy uncertainty and interest rates do not drive Bitcoin returns. The significant negative coefficient on the *VIX* terms highlights the negative effect of market volatility on current Bitcoin returns, underscoring Bitcoin's sensitivity to options market turbulence. The *FSI* and its lagged term exhibit a positive relationship with Bitcoin returns, showing statistical significance. This suggests that higher levels of financial stress correspond with increased Bitcoin returns, potentially reflecting Bitcoin's role as a safe haven during turbulent times. The model reports an adjusted R-squared value of 0.7896, demonstrating robust explanatory power. This substantial figure indicates that the variables included in the ARDL model account for a significant portion of the variation in Bitcoin returns, providing a comprehensive analysis of the factors influencing Bitcoin returns over the long term.

Table 5 presents the results from the ECM, focusing on the short-term impacts of changes in *BSI*, *EPU*, *IR*, *VIX*, and *FSI* on the changes in Bitcoin returns. Δ denotes the change from one period to the next, offering insights into how fluctuations in these indicators influence the change in Bitcoin returns in the short term. ΔBTC_{t-1} exhibits a significant positive coefficient, indicating that past changes in Bitcoin returns significantly impact current return fluctuations. ΔBSI_t also shows a significant positive effect on Bitcoin returns, suggesting that recent shifts in market sentiment directly affect Bitcoin's performance in the short run. ΔEPU_t and ΔIR_t display insignificant negative coefficients, pointing to a minimal impact of economic uncertainty and interest rate fluctuations on Bitcoin returns in the immediate term. ΔVIX_t significant negative coefficient underscores the short-term inverse relationship between market volatility and Bitcoin returns, supporting the notion that increased uncertainty in financial markets can dampen Bitcoin's short-term growth. ΔFSI_t exhibits a significant positive relationship with Bitcoin returns, indicating that short-term increases in financial stress may lead to higher Bitcoin returns, possibly reflecting its perceived role as a safe haven during turbulent times. The EC_{t-1} coefficient is significantly negative, emphasizing the model's effectiveness in adjusting from short-term shocks to long-term equilibrium, with a rapid reversion to the equilibrium following any short-term deviations. With an adjusted R-squared value of 0.9345, the model demonstrates a high degree of explanatory power concerning the short-term fluctuations in Bitcoin returns based on the specified predictors. This section meticulously quantifies the immediate effects of economic indicators and market sentiment on Bitcoin, providing a detailed understanding of its short-term financial dynamics.

Table 5. ECM results

Variable	*Coefficient*	*t-statistics*
ΔBTC_{t-1}	0.4349***	5.803
ΔBSI_t	0.0064***	16.905
ΔEPU_t	-0.0002	-1.465
ΔIR_t	-0.0338	-1.470
ΔVIX_t	-0.0027***	-2.773
ΔFSI_t	0.0440***	4.620
EC_{t-1}	-2.1531***	-14.882
Observations	66	
Adjusted R^2	0.9345	

*Note: This table presents the results of the ECM. Δ represents the first difference of the variables. The dependent variable is the change in Bitcoin returns, labeled ΔBTC_t. The key independent variable is ΔBSI_t. *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively.*

4.2. Additional control variables

In the previous section, we utilized *EPU*, *IR*, *VIX*, and *FSI* as control variables to ascertain the significant impact of *BSI* on Bitcoin returns in both the long and short term. To enhance the robustness of the findings, we incorporate two additional control variables, *BDI*[6] and *GEPU*[7]. Recent research by Diniz-Maganini et al. (2021) illustrates an intersubstitution relationship between Bitcoin and the US dollar. They suggest that Bitcoin is emerging as a safe haven relative to the US dollar during specific periods such as the COVID-19 pandemic. Consequently, this study also considers the BDI, which encompasses a broader array of currencies weighted according to international trade volumes. Moreover, while the United States remains a central hub for cryptocurrency exchanges, Bitcoin's inherently global nature mandates a broader geographical focus. Thus, this section substitutes the US-specific EPU with the GEPU to reflect Bitcoin's international trading scope. The updated ARDL model and ECM are specified below:

$$BTC_t = \alpha + \sum_{i=1}^{p_1} \lambda_{1i}\, BTC_{t-i} + \sum_{i=0}^{p_2} \lambda_{2i}\, BSI_{t-i} + \sum_{i=0}^{p_3} \lambda_{3i}\, GEPU_{t-i} + \sum_{i=0}^{p_4} \lambda_{4i}\, IR_{t-i} + \sum_{i=0}^{p_5} \lambda_{5i}\, VIX_{t-i} + \sum_{i=0}^{p_6} \lambda_{6i}\, FSI_{t-i} + \sum_{i=0}^{p_7} \lambda_{7i}\, BDI_{t-i} + \varepsilon_t \quad (3)$$

$$\Delta BTC_t = \sum_{i=1}^{p_1} \beta_{1i}\, \Delta BTC_{t-i} + \sum_{i=0}^{p_2} \beta_{2i}\, \Delta BSI_{t-i} + \sum_{i=0}^{p_3} \beta_{3i}\, \Delta GEPU_{t-i} + \sum_{i=0}^{p_4} \beta_{4i}\, \Delta IR_{t-i} + \sum_{i=0}^{p_5} \beta_{5i}\, \Delta VIX_{t-i} + \sum_{i=0}^{p_6} \beta_{6i}\, \Delta FSI_{t-i} + \sum_{i=0}^{p_7} \beta_{7i}\, \Delta BDI_{t-i} + \varphi EC_{t-1} + \eta_t \quad (4)$$

where, *BDI* represents the broad dollar index, and *GEPU* denotes Global Economic Policy Uncertainty. Other variables are defined similarly to Eq. (1) and (2).

Table 6 presents the long-run coefficient estimates from the ARDL model with an additional control variable. The model analyzes the effects of lagged Bitcoin returns, demonstrating a significant negative relationship for the first and second lags. This indicates that past Bitcoin returns diminish future returns, highlighting the significance of historical performance in forecasting long-term outcomes. The *BSI* and its lagged term exhibit a significant and intricate relationship with Bitcoin returns. The positive coefficient for *BSI* reveals a strong positive influence of current sentiment on Bitcoin returns, whereas the negative coefficient for the lagged *BSI* indicates a corrective effect over time. This underscores the complex role sentiment plays in shaping Bitcoin's market value.

Table 6. ARDL model results with additional control variables

Variable	*Coefficient*	*t-statistics*
BTC_{t-1}	-0.4552***	-4.221
BTC_{t-2}	-0.2311**	-2.484
BSI_t	0.0147***	13.339
BSI_{t-1}	-0.0047***	-3.024
$GEPU_t$	0.0002	0.642
$GEPU_{t-1}$	-0.0008**	-2.051
IR_t	-0.1583**	-2.139
IR_{t-1}	-0.0636	-0.706
IR_{t-2}	0.2222***	2.763
VIX_t	0.0040	1.127
VIX_{t-1}	-0.0139***	-3.148
VIX_{t-2}	0.0085*	1.990
FSI_t	-0.0117	2.701
FSI_{t-1}	0.0322	0.837
FSI_{t-2}	-0.0493	-1.424
FSI_{t-3}	0.0627**	2.667
BDI_t	0.0014	0.098
BDI_{t-1}	0.0113	0.867
BDI_{t-2}	0.2350*	1.768
BDI_{t-3}	-0.0233*	-1.785
Constant	-0.2264**	-2.678
Observations	66	
Adjusted R^2	0.8150	

*Note: This table presents the results of the ARDL model after incorporating BDI and substituting EPU with GEPU. The dependent variable is the Bitcoin return at time t, labeled BTC_t. The key independent variable is BSI_t. *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively.*

Unlike *EPU*, the lagged *GEPU* exhibits a small but significant negative impact, reflecting the delayed effects of global uncertainties on Bitcoin. Interest rates and their lagged terms display a complex impact on Bitcoin returns. The significant negative effect of current interest rates and the significant positive effect of the second lag show the varying influences of monetary policy over different periods. Consistent with previous results, the lagged *VIX* significantly negatively impacts Bitcoin returns. Similarly, the three-period lagged *FSI* significantly positively impacts Bitcoin returns. The lagged *BDI* terms have contrasting effects on Bitcoin returns, illustrating the intricate dynamics between the US dollar and Bitcoin returns. With an adjusted R-squared value of 0.8150, the model achieves a high degree of explanatory power, indicating that these factors can account for a substantial portion of the variation in Bitcoin returns. Overall, the results in Table 6 align with those in Table 4.

Table 7 presents the short-run coefficient estimates from the ECM, now including additional control variable *BDI* and replacing *EPU* with *GEPU*. The significant positive coefficient on ΔBTC_{t-1} indicates that past short-term increases in Bitcoin return positively affect its immediate future returns, emphasizing the short-term momentum effect in Bitcoin's price dynamics. ΔBSI_t exhibits a significant positive impact on the change in Bitcoin returns, underscoring the effect of immediate shifts in market sentiment on Bitcoin's performance.

[6] The Broad US Dollar Index quantifies the value of the US dollar relative to a basket of foreign currencies, encompassing a wider array of major trading partners' currencies compared to the commonly cited US Dollar Index. This broad index offers insights into the international valuation of the USD, impacting trade, investment, and inflation dynamics.
[7] The GEPU Index consolidates the national-level economic policy uncertainty indices from major economies, providing a comprehensive gauge of Global Economic Policy Uncertainty. This index captures the extent of uncertain economic policies worldwide, influencing investment, hiring, and growth decisions internationally.

Table 7. ECM results with additional control variables

Variable	*Coefficient*	*t-statistics*
ΔBTC_{t-1}	0.2311***	2.753
ΔBSI_t	0.0147***	16.744
$\Delta GEPU_t$	0.0002	0.806
ΔIR_t	-0.1583***	-2.722
ΔIR_{t-1}	-0.2222***	-3.695
ΔVIX_t	0.0040	1.283
ΔVIX_{t-1}	-0.0085**	-2.357
ΔFSI_t	-0.0117	-0.367
ΔFSI_{t-1}	-0.0134	-0.445
ΔFSI_{t-2}	-0.0627***	-3.191
ΔBDI_t	0.0014	0.145
ΔBDI_{t-1}	-0.0002	-0.025
ΔBDI_{t-2}	0.0233**	2.467
EC_{t-1}	-1.6864***	-10.910
Observations	66	
Adjusted R^2	0.9029	

*Note: This table presents the results of the ECM after incorporating BDI and substituting EPU with GEPU. Δ represents the first difference of the variables. The dependent variable is the change in Bitcoin returns, labeled ΔBTC_t. The key independent variable is ΔBSI_t. *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively.*

The significant negative coefficient on ΔIR_t suggests that increases in interest rates have a suppressive effect on Bitcoin returns in the short term. ΔVIX_{t-1} demonstrates a significant negative relationship with the change in Bitcoin returns, suggesting that increases in market volatility from the previous period lead to decreases in Bitcoin returns. Contrary to previous findings, ΔFSI_{t-2} displays a significant negative impact, indicating that financial stress adversely influences Bitcoin returns, with this effect manifesting after a delay. ΔBDI_{t-2} exhibits a significant positive impact, suggesting that a strengthened US dollar in the past enhances Bitcoin returns after a delay. The significant negative coefficient for EC_{t-1} confirms the model's efficacy in capturing the speed at which Bitcoin returns adjust to their long-run equilibrium following a short-run shock. The adjusted R-squared value of 0.9029 indicates that the model accounts for a substantial portion of the variance in Bitcoin returns based on these short-term dynamics. Overall, the results in Table 7 align with those in Table 5.

5. DISCUSSION OF THE RESULTS

The findings presented in Table 4 from the ARDL model estimation underscore the pivotal role of the BSI in influencing Bitcoin returns, corroborating *H1*. These results are consistent with behavioral finance theories, which propose that investor sentiment, whether optimistic or pessimistic, drives corresponding fluctuations in asset prices as investors act based on their expectations of future price movements. An increase in greedy or fearful sentiment leads to respective increases or decreases in Bitcoin returns, echoing the extensive literature on the influence of sentiment in financial markets. For example, Feng et al. (2018) support the hypothesis that news sentiment, positive or negative, can forecast future price movements in cryptocurrencies, reinforcing the notion that investor mood substantially impacts market dynamics. These findings also agree with Kristoufek (2013), who identified a bidirectional causal relationship between Bitcoin returns and investor sentiment measures, proxied by the volume of Bitcoin searches on Google and the frequency of visits to Bitcoin-related Wikipedia pages. Our results indicate that beyond conventional market indicators, sentiment indices such as the BSI offer critical insights into the behavioral drivers of market fluctuations, capturing broader market responses to news and events.

The negative correlation between the VIX and Bitcoin returns, as depicted in Table 4, suggests that increased market volatility results in lower Bitcoin returns. This pattern likely reflects investors' propensity to reallocate funds from Bitcoin to more traditional hedging options during periods of uncertainty. Conversely, investors may seek to diversify their risk exposure during low volatility, including investments in assets like Bitcoin, perceived as more speculative or high-risk. This observation is corroborated by findings from Al-Yahyaee et al. (2019), which also report the adverse impact of the VIX on Bitcoin returns. It suggests that traditional market uncertainties can extend their influence on cryptocurrency markets. Koutmos (2020) further asserts that a significant array of market risk factors, including the VIX, indicate negative Bitcoin returns, highlighting Bitcoin's susceptibility to broader financial market conditions. The consistency of these findings with prior research indicates the complex dynamics governing investor decisions in cryptocurrency markets, where traditional market indicators such as the VIX play a crucial role in shaping investment flows and returns.

Table 4 demonstrates the FSI's significant and positive effect on Bitcoin returns. These results are at odds with those of Pagano and Sedunov (2020), who identified a statistically significant negative relationship between Bitcoin returns and a set of variables, including the FSI. Similarly, the findings contrast with Jareño et al. (2020), where Bitcoin returns exhibit a negative and statistically significant sensitivity to changes in the FSI. However, at the 0.6 quantile, changes in the FSI have a positive and statistically significant impact on Bitcoin returns. According to Sevillano and Jareño (2018), low quantiles typically correspond with periods of economic crisis; thus, based on these results, Bitcoin may be considered a safe-haven assets during high financial stress periods. In such scenarios, we anticipate higher Bitcoin returns. As Isah et al. (2019) suggested, quantitative easing tends to channel money into the cryptocurrency market, thereby elevating Bitcoin prices. Bitcoin offers a diversification benefit as its price movements are not always correlated with those of other asset classes. During financial stress, when correlations between traditional asset classes might increase (all moving in the same direction, generally downwards), Bitcoin may behave independently. This perceived non-correlation renders it attractive as a portfolio diversifier during times of stress.

The short-term effects documented in Table 5 of the ECM analysis illustrate a compelling dynamic between the change in BSI and Bitcoin returns, underscoring the profound impact of market sentiment on cryptocurrency performance. The findings corroborate the long-term effects seen in Table 4 and support *H2*. As investor sentiment shifts from fear to greed, Bitcoin returns increase in the short term. The model's indication of a positive impact from the BSI suggests that extreme market sentiments, whether overly pessimistic (fearful) or overly optimistic (greedy), signal impending market corrections. This phenomenon echoes Warren Buffett's adage about being "*fearful when others are greedy and to be greedy only when others are fearful*", embodying the contrarian investment strategy that capitalizes on extremes in market sentiment.

Additionally, confirming the VIX's detrimental effect on Bitcoin returns in the short term corroborates the findings of Al-Yahyaee et al. (2019), emphasizing the enduring importance of conventional market volatility indicators in predicting cryptocurrency performance. The VIX, often called the "fear gauge" of the stock market, exerts a similar influence on Bitcoin: heightened market anxiety leads to reduced investment in Bitcoin and vice versa. This connection underscores the similarities and differences between the cryptocurrency sector and traditional financial markets, demonstrating that the same fundamental principles of market psychology and investor behavior sway both. These insights are particularly enlightening, as they provide a detailed understanding of the factors influencing short-term Bitcoin returns. By emphasizing the impact of both the BSI and the VIX, the analysis highlights the pivotal role of sentiment and market volatility in the cryptocurrency market's short-term fluctuations. It also suggests that cryptocurrency markets are susceptible to psychological influences and external shocks akin to traditional markets, thereby enriching the discussion on the application of behavioral finance theories in cryptocurrency research.

6. CONCLUSION

This study examines the nuanced impact of market sentiment, BSI, on Bitcoin returns, employing monthly datasets from January 2016 to June 2021. The BSI is a comprehensive indicator of the market mood, reflecting a spectrum of market sentiments, including volatility, social media buzz, survey results, trading volumes, market dominance, and trending searches. The ARDL analysis discloses a compelling positive correlation between the BSI and Bitcoin returns over the long term. This relationship highlights a critical market dynamic: capital inflows escalate as optimism and greed intensify, propelling Bitcoin's value upward. Conversely, increasing pessimism and fear trigger a retreat in investment, adversely impacting Bitcoin's market performance. The ECM findings further delineate the immediate, significant positive impact of sentiment changes on the change in Bitcoin returns, emphasizing the market's sensitivity to sentiment fluctuations. Despite short-term volatility, these sentiment-driven oscillations do not detract from the established long-term trend, confirming the robustness of our findings. Lastly, our ARDL and ECM results remain robust after integrating an additional control variable, BDI, and replacing the EPU with the GEPU.

The implication of this paper is to apply behavioral finance theories to the domain of cryptocurrency and investigate the impact of emotions on Bitcoin returns. It mirrors patterns observed in the equity market, where optimism can drive cycles of investment and withdrawal based on collective sentiment. The volatile trajectory of Bitcoin's value, particularly its substantial rise and subsequent correction in 2020, exemplifies the market's sentiment-driven dynamics. Our analysis indicates that the BSI can positively affect Bitcoin returns but also tends to signal changes in Bitcoin's direction one month in advance. This predictability enables the BSI to assist investors in determining the direction of Bitcoin prices and returns, facilitating the selection of appropriate investment strategies. Overall, this study's findings advocate for a more profound engagement with behavioral finance principles to effectively navigate the evolving landscape of cryptocurrency investments.

The present study still has certain limitations. Firstly, our analysis is based on monthly data from January 2016 to June 2021, a broad period that may not adequately capture the cryptocurrency market's rapid changes and volatile nature during the COVID-19 pandemic. As the market evolves, future research could benefit from incorporating more recent data. Secondly, our study predominantly focuses on the BSI as a proxy for Bitcoin market sentiment. Although the BSI is a robust indicator, incorporating diverse factors such as volatility, market momentum, social media, and trends, it represents sentiment for Bitcoin. The burgeoning field of cryptocurrencies encompasses a wide array of altcoins with distinct market behaviors and investor sentiments. Further research examining the sentiment measures of these other cryptocurrencies could provide a more nuanced understanding of the broader cryptocurrency market. Thirdly, despite being effective in capturing short- and long-term relationships, the ARDL and ECM methods used in our analysis may not fully account for all nonlinear dynamics and complex interactions within the Bitcoin market. Future research might employ machine learning methods or alternative econometric models to understand these intricate interactions fully. Lastly, unanticipated global events, legislative changes, or technological advancements may impact the external validity of our findings. These factors could significantly influence market sentiment and cryptocurrency returns. These elements underscore the necessity for additional control variables to act as determinants of Bitcoin returns. Acknowledging these limitations, our study contributes to the burgeoning field of behavioral finance within the context of cryptocurrencies and lays the groundwork for future research. As the cryptocurrency market matures, further investigations are imperative to decipher the evolving dynamics of investor sentiment and its implications for market performance.

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