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BITCOIN SENTIMENT INDEX AND STOCK MARKET RETURNS

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Abstract

Predictions regarding returns and price movements in financial markets can be made using online search engines, which track the sentiments of individual investors. This study aims to analyse how the sentiments of Bitcoin investors impact changes in the American stock market returns. The Bitcoin sentiment index was created to benchmark the sentiments of Bitcoin investors from 2013 to 2018. This index is built by analysing terms from leading business magazines and online journals. Such an index measures potential investors' sentiments about Bitcoin and how those sentiments impact S&P returns. We use the ordinary least squares method to analyse this. It was found that BSI has a negative impact on S&P returns. Furthermore, the Vector Autoregressive (VAR) model is used to determine the relationship between these economic time series. VAR results indicated a significant positive impact of S&P returns on BSI, while BSI could not predict S&P returns. Consequently, it can be concluded that S&P returns cause changes in BSI. Recognising that Bitcoin sentiment can offer valuable insights and guidance for retail investors during market downturns, much like the S&P 500. By tracking changes in the S&P 500, analysts can anticipate shifts in cryptocurrency market sentiment and take preventative measures when needed. Understanding this relationship is crucial for assessing systemic risks, as volatility in traditional markets can impact the crypto space.

Keywords: Bitcoin investor, Bitcoin sentiments index, Google trend, S&P returns, vector autoregressive, volatility index.
JEL Classification: C22, E22, E44, E71, G40, N2.

I. Introduction

The science of psychology is the most fertile neighbouring science for Economics and Finance in recent decades. To understand how markets function, it is essential to comprehend the sentiments of investors.[1] According to Richard H. Thaler (2005), the

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[1] According to broader definition investors' sentiment can be said as a belief about investment risk and cash flows which cannot be acceptable by the available information (Baker & Wurgler, 2007).

actual behaviour of investors can be obtained through a real-time data set. Applied economics applies principles, models, and methods of psychology to understand the potential and social interactions of humans and to examine the effects of these interactions on economic behaviour. Behavioural finance focuses on social sentiments in financial decision-making. The basic requirement for sentiments is Attention. Noise traders[2] may increase the investors' attention, which is why behavioural biases create stronger sentiments (Da et al., 2011). Theories of attention allocation observe investors' behaviour and provide an understanding of their private information. These theories and models explain how attention affects asset holdings and vice versa (Mondria et al., 2010). Moreover, when researchers attempt to test theories of attention, they face the challenge of lacking a direct measure of investor attention.

Investor sentiment is not straightforward to measure. Therefore, researchers have always used proxies for analysis. Several indirect proxies have been examined by various researchers, including extreme returns, trading volume, news headlines, advertising expenses, and price limits (Barber & Odean, 2008; Chemmanur & Yan, 2019; Ding & Hou, 2015; Mao et al., 2011). Direct methods such as survey-based sentiment indices, term-based sentiment indices, and social media queries and comments are utilised to assess investor sentiments (Dalika & Seetharam, 2015; Klemola, 2020; Shen et al., 2019). These proxies suggest that extreme stock returns tend to attract the attention of investors, leading to increased media coverage of the stock's name. Retail investors are more likely to turn to Google for financial information about the stock market than institutional investors, who typically utilise more advanced services, such as Bloomberg terminals. It can be assumed that the trading of retail investors causes fluctuations in stock market prices and returns.

Financial theories suggest that investment in capital assets relies on fundamental and technical analysis. According to traditional finance theories, there is no room for investor sentiment (Habibah et al., 2017). However, the patterns of investors' sentiments are generated before these classical analysis trends are transmitted into capital markets (Klemola et al., 2016a). Through perception, investors' evaluation, and emotional elements, decisions are taken in behavioural finance (Suciu, 2015). Therefore, an asset value deviation from its economic fundamentals can be measured through investors' sentiments. According to Saura et al. (2019), sentiment analysis is one of the methodologies used to explore the feelings of the sample, and such feelings come from the digital environment (online platforms and social networks). One alternative method for measuring investors' sentiments is to derive it from market data (Klemola et al., 2016a).

Researchers have long viewed surveys as less authentic sources for understanding sentiments, due to biases stemming from the gap between how individuals feel and how they respond (Baker & Wurgler, 2006, 2007; Suciu, 2015). Recently, various

[2] Individual investors who make buy and sell decisions in financial markets based on non-informational factors, such as emotions.

methods have been used to explore and measure public sentiment from large-scale online data. As a result, no single data source is likely to capture the mood-related signals of investors with the best predictive power (Mao et al., 2011). It appears that the Google Search Volume Index is crucial for capturing the attention of retail investors.

Investors can diversify their investments across various avenues, including the stock market, real estate, and foreign currencies. There has been a sudden increase in academic studies examining new financial assets since digital currency has received extraordinary attention from the market (Eross et al., 2019). Digital currency can be considered a form of electronic value storage (Dwyer, 2015). No doubt there are several other cryptocurrencies (digital currencies) in the market, but no one has challenged the dominance of Bitcoin[3] (Kristoufek, 2015). Among all these digital currencies, Bitcoin has captured its dominance since 2009. Initially, Bitcoin was introduced as a currency for cash payments; however, as it relies on mass collaboration, it is worth considering as a unique digital asset (Urquhart & Zhang, 2018). Due to its many attractive characteristics, Bitcoin is not considered a safe haven for investment. With the rising attention shown by investors, Bitcoin prices are increasing daily (Kristoufek, 2015).

Bitcoin's role as an investment emerged during a delicate period in the global financial system, particularly during the 2010-13 European debt crisis (Shahzad et al., 2019). There is no central authority that regulates Bitcoin, which is why Bitcoin is volatile. The vast production of bitcoin and the lack of regulation have increased the black-market activities through bitcoin. According to the Buy Bitcoin website, 70 per cent of the bitcoins are produced in China, which occupies the largest share of the global transaction market (Li et al., 2019).

The nature of Bitcoin has motivated researchers to investigate Bitcoin as an investment and speculative commodity. Bitcoins are 26 times more volatile than the S&P 500 index, and the volatility associated with bitcoin is primarily due to the main determinants, i.e., buyers and sellers (Baek & Elbeck, 2015). Bitcoin exhibits significant price volatility, as its fluctuations are seven times greater than those of gold, eight times greater than the American stock market, and 18 times greater than the US dollar currency (Li et al., 2018). Figures 1 to 5 represent the trends of the indices plot. Each plot value is represented in US dollars.

Risky investment assets, such as stocks, can be better measured through investors' sentiments, which may provide a more accurate explanation of price changes (Eom et al., 2019). User thinking is expressed on digital platforms and in various online environments. Such an experience is referred to as user-generated content (Saura et al., 2019). User-generated content is used to measure users' sentiments. In this way, the researcher becomes able to analyse users' motivation.seminar one rectified version. Baker & Wurgler (2006) explored investors' sentiments that may explain expected stock returns in that context; they formed an investor index. Likewise, recent studies

[3] Bitcoin is a digital currency introduced in 2009 by a group named Satoshi Nakamoto.

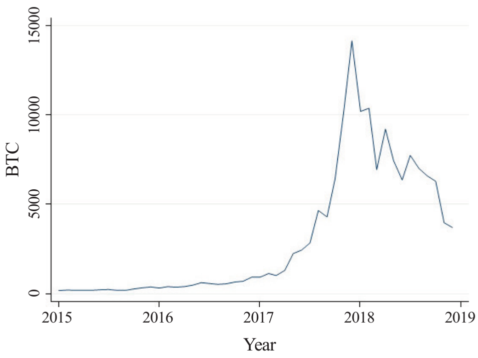

FIGURE 1

Bitcoin Price in US dollars

FIGURE 2

S&P500 prices

FIGURE 3

Russel 2000 Prices

FIGURE 4

Dow Jones Index prices

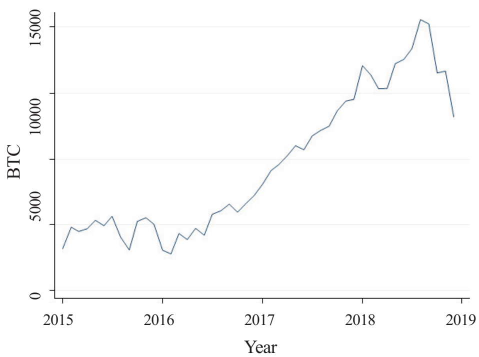

FIGURE 5

Nasdaq Price in US dollars

Note: Figure 1-5 represents a time series graph of Bitcoin price, S&P index price, Russel 2000, DJI, and Nasdaq prices in US dollars to represent fluctuating trends among them.
Sources: https://finance.yahoo.com/

(Da et al., 2015; Fang et al., 2019; Habibah et al., 2017; Klemola et al., 2016a) empirically demonstrate the usefulness of the Google search volume index as a measure of investor sentiment in stock markets.

Investors often use Google search engines to gather information about their investment options. The frequency of searching keywords reflects the level of investor interest and sentiment, which can change over time. The number of searches conducted by investors at any given moment can be found in Google Trends (Eom et al., 2019).

Considering the previous discussion, the research question to be addressed is 'How are Bitcoin Sentiments correlated with stock market returns? Moreover, this study aims to analyse and quantify the sentiment impact of Bitcoin investors on stock market returns. A sentiment index has been developed to assess investors' sentiments. The researcher has attempted to predict the impact of Bitcoin sentiment on stock market returns using a developed index. This study aims to examine the impact of Bitcoin-related sentiments on stock exchange returns by utilising a specially designed index of Bitcoin-related terms. The research aims to explore the relationship between the public's perceptions and attitudes towards Bitcoin and the fluctuations in stock market performance. By examining various indicators of Bitcoin sentiment, the study will shed light on how these factors potentially impact investor behaviour and overall market dynamics.

The study begins with an introductory section, a theoretical framework, and a comprehensive review of relevant literature highlighting significant research on how investor sentiment, as measured by the Bitcoin Sentiment Index, influences S&P returns. The literature review is presented in Section II, along with a definition of the theoretical framework. Furthermore, the Data and methodology are described in Section III, including the data set sources and methodology. This section details the construction process of the Bitcoin Sentiment Index and its associated model used in this study. The empirical findings are presented in Section IV, including descriptive statistics, model estimations, and their evaluations. The discussion and findings are based on previous literature. Furthermore, the theoretical and practical implications of the results are discussed in Section V, which can influence strategic decisions and the formulation of policies. A conclusion and recommendations are presented in Section VI.

II. Literature Review and Theoretical Framework

Behavioural finance develops as a critique of classical finance, which relies on the Efficient Market Hypothesis (EMH), Modern Portfolio Theory (MPT), and expected utility theory. Behavioural finance incorporates principles from cognitive psychology to clarify systematic biases and heuristics that influence investor behaviour. Moreover, it incorporates psychological realism into economic models to better understand how emotions, biases, and cognitive limitations influence financial decisions and market outcomes. The basics do not fully explain how investor feelings can cause future prices to change unexpectedly. Therefore, there needs to be an investigation into the sentiment of potential Bitcoin investors and how that sentiment-based behaviour could affect stock market returns.

1. Sentiment Index and Stock Markets

A growing body of literature examines the impact of sentiments on stock prices. In academic literature, investors' sentiments are occasionally studied, producing mixed results. (Klemola et al., 2016a). According to Eom et al. (2019), the occurrence of searches by keyword may indicate the potency of investors' interest, and this strength changes over time. Google, the world's largest search engine, has provided a way for users to access the Search Volume Index (SVI) through Google Trends (Da et al., 2011, 2015; Rajput et al., 2020). In a similar study, Baker and Wurgler (2006) developed an investor behaviour index to analyse the volatility of stock market returns. This index effectively explained the expected returns on stocks. However, our research is aiming for a more integrated approach, comparing sentiment analysis through a constructed index with the stock index to enhance the reliability of findings in this ongoing debate.

Investor sentiment may be overly speculative and may not accurately reflect future growth prospects. The stock markets of China and Brazil were investigated for the impact of the fear index (VIX) on emerging market volatility (Badshah et al., 2018). Utilising mixed quantile regression and Granger causality, they identified a robust positive correlation between the variables. They took a built-in index for comparison. In contrast, (Smales, 2014), using textual software, identified a substantial negative correlation between news-driven attitudes and the volatility index of stock market returns.

Several studies have analysed the impact of investors' attention on future market returns and found sufficient evidence that sentiments can explain stock market returns (Klemola et al., 2016a; Vozlyublennaia, 2014; Zhou, 2017). Based on the Google search volume index, Da et al. (2015) constructed the 'Fears' index to see the impact of negative sentiments on stock returns and volatility. This index showed that high-frequency sentiments can generate excess volatility. However, Habibah et al., (2017) constructed and compared the Google Search Volume Index (GSVI) with the Volatility Index[4] (VIX) and found that VIX explained a more robust predictability of returns than GSVI. Likewise, in China, to explore the volatility of China's stock markets, the Baidu sentiment index was constructed, which proved to be a better-performing model during high-volatility periods than during low-volatility periods, and it can predict market trends (Fang et al., 2019). On the other hand, Habibah et al., (2017) explored the dynamic analysis of the relationship between investor sentiment and the Chinese stock market. The study found that Investor sentiment is not always useful, as sentiment data do not always lead to stock prices. In contrast, this investigation exclusively concentrates on the United States as the sample country.

[4] Fear gauge by the Chicago board of exchange (CBOE).

Chau et al., (2016) explored investors' sentiments through two indices and the EGARCH model found that sentiment-driven buying and selling of stocks have a significant impact on stock market volatility. They examined bearish and bullish market returns to investigate the trading behaviour and role of sentiment. In recent times, market and sentiment-driven investors have been focused. In the field of finance, recent research has recognised two sides of persistent regularities: one is underreaction and the other is overreaction. Former evidence suggests that over the course of one to twelve months, security prices react negatively to news; therefore, news gradually influences stock prices (Jegadeesh & Thaler, 2006). They found a significant negative relationship between them. Similarly, in the Japanese stock market and the Chinese stock market, Google search intensity was explored, and the findings indicated that high search activity leads to high trading in the stock market, but it does not lead to an increase in stock price (Guo et al., 2017; Takeda & Wakao, 2014).

2. Sentiment Index and Crypto Markets

Similar to the stock market, the Bitcoin market is also influenced by trend chasers, short-term investors, noise traders, and speculators. Bitcoin prices are determined by the anticipated profits of holding the currency and selling it later. The price of Bitcoin is driven by investors' confidence in its future growth (Kristoufek, 2013). However, standard economic and financial theories cannot explain such soaring behaviour of Bitcoin. Here, we aim to provide literature that relates to the search queries regarding the price of Bitcoin. These search queries are analysed based on Google Trends as a proxy for investors' interest and attention to determine the impact of digital Currency Bitcoin on the S&P 500 index.

Kristoufek (2013); Shen et al. (2019) examined the sentiments as a driver of bitcoin volatility and found that investors' sentiment has the potential to yield positive returns on investment. Kristoufek (2013) quantified the relationship between price and search queries. By using Google Trends and specific keywords, he discovered a significant relationship between Bitcoin and Google searches. Additionally, the popular social media platform Twitter has been shown to have a positive impact on Bitcoin trading the following day (Shen et al., 2019)].

Similarly, Nasir et al. (2019) evaluated the predictability of bitcoin volume and returns through the Google search index. The findings suggested that Google searches yield positive returns, which last for approximately one week. On the other hand, Chen & Hafner (2019) and Ghiasvand (2018) analyzed speculations in cryptocurrency using sentiment indices from Reddit, Google Trend Index, and CRIX Index. Results indicate that sentiment indices provided conflicting results and did not show independence towards volatility, returns, and exchange volume.

According to Bleher & Dimpfl (2019), Cretarola & Patacca (2017), Gurdgiev & Loughlin (2019), and Karalevicius et al. (2018), the analysis of cryptocurrency price movement through changes in the Google search volume index yielded positive and significant results. On the other hand, Ibrahimov et al. (2019) investigated cryptocurrency investors in Pakistan and their behavioural unfairness in cryptocurrency investment decisions. They concluded that investors fall victim to biases due to the appeal of profits and the complexities involved in determining the prices of Bitcoin and other digital currencies. In a similar vein, Caporale & Plastun (2018) identified instances of price overreactions in the digital currency markets and found that these markets do not provide profitable opportunities.

III. Data and Methodology

The construction of a search term index is the primary objective of this study, which aims to reveal sentiments about potential bitcoin investors. The term 'index construction' begins with the search for bitcoin-related terms in top financial and economic newspapers, magazines, and social blogs (Bleher & Dimpfl, 2019; Ghiasvand, 2018).

1. Construction of Bitcoin Sentiment Index

Initially, we compiled a list of Bitcoin-related terms by extracting them from leading finance news sources and online magazines, resulting in nearly 650 unique words after eliminating duplicates. These terms were subsequently analysed using Google Trends, which provided daily data from 2013 to 2018, specifically for the USA. However, not all terms were available on Google Trends during the specified period. As a result, we only downloaded data for the terms that were accessible. This process enabled us to refine our list to a final total of 236 terms (Da et al., 2015; Habibah et al., 2017; Klemola et al., 2016b; Shaikh & Padhi, 2015).

These terms were then checked into the Google search engine and listed its top ten searches, which combined to make an exhaustive list of '2360' terms that further became '1450' after the removal of duplicates. Again, with the help of Google, in trends, the data for '1450' terms were collected, and '390' words/list came up in the final shape.

The search volume index terms list was downloaded for each of these 390 terms over a sample period from 2013 to 2018 from Google Trends. Google Trends allows users to restrict Search Volume Index (SVI) results to different specific countries. This study has focused on the stock market returns of the United States of America (USA); therefore, the search volume index results are restricted to the USA for the period from January 1, 2013, to December 31, 2018. Hence, it can be said that this sentiment index only predicts the sentiments of investors in the United States of America. The last step involves allowing the data to identify the most crucial search terms for returns. In other words, the final Bitcoin Search Term (BST) index was derived through a regression analysis.

The regression process includes the moving median of S&P log returns (SPR) as the dependent variable and 392 bitcoin search terms as independent variables. The moving median of search terms is used to mitigate the seasonality effect (Bijl et al., 2015; Da et al., 2011). The model for each search term regression is in Equation (1):

$$(\Delta BST_t) = lnBSTt - lnMedianBST_{t\text{-}7} \tag{1}$$

In Equation (1) Δ, the BST list is constructed by taking the moving median difference of the Bitcoin Sentiments Terms list. The reason behind the seventh lag is that investors continue to pay more attention to stocks after a week of extreme returns. The seventh lag is employed to capture weekly seasonality or impacts in stock market data, as the market functions on a weekly timetable, and price or volume patterns frequently recur on that temporal scale.

The regression model with the seventh lag can enhance predicted performance by incorporating periodic behaviour. It enables the model to account for both the recent past and the recurring weekly trend. Now, the list of 390 words is regressed (one by one) with the list of log-returns of Bitcoin to determine their t-statistic values. Equation (2) is as follows:

$$BSI_t = \frac{\sum_{i=1}^{n} \Delta BST_{it}}{n} \tag{2}$$

Now, based on these t-values (positive and negative), the top 30 terms for each side are selected. From this list of 60 terms, 8 Index models are selected, and 15, 20, 25, and 30 negative and positive terms are generated (Da et al., 2015; Klemola et al., 2016a). A list of these terms is shown in Table 1.

These eight indices are further regressed with S&P returns to determine the most appropriate index based on t-statistics, R2 and standard error (Nakagawa & Schielzeth, 2013). Out of these eight models, one index model has been finalised, namely the BSI (Bitcoin Sentiments Index), the main index of this paper, which serves as an independent variable in this study. For the final selection of the Bitcoin Sentiment Index, the model presented in Equation (3) is used.

$$SPR_t = \alpha_{i0} + \beta_i\, BSI_{(NM30)} + \delta_i SPV_t + \theta_i VIX_t + e_t \tag{3}$$

Where $\beta_i\, BSI_{(NM30)}$ is the optimal index in the model, all other indices are also regressed in the same manner as S&P 500 returns. S&P volume (SPV) and the Volatility Index (VIX) are taken as control variables. The robust check of optimal model selection is given in Table 2.

2. *Methodology*

From the terms list, it can be inferred that BSI hurts returns, as evidenced by the negative list of terms, which suggests a pessimistic nature. Bitcoin investors create

TABLE 1

ΔBST terms

Sr. No.	Panel A Search Terms with Positive T-stat value		Panel B Search Terms with Negative T-stat value	
	Search Term	t-statistics	Search Term	t-statistics
1	Bitcoin exchanges by volume	4.94	Bitcoin regulation	-2.13
2	Bitcoin news sites	4.72	Currency Bitcoin converter	-2.10
3	Bitcoin miners for sale	3.72	Financing terrorism	-2.09
4	Bitcoin mining	3.72	Bitcoin in the future	-1.94
5	Level of Bitcoin	3.55	Make a Bitcoin wallet	-1.91
6	Bitcoin Building	3.46	Barclays credit card	-1.80
7	Bitcoin exchanges list	3.44	Bitcoin Games online	-1.76
8	Bitcoin heist	3.21	Currency Bitcoin USD	-1.66
9	Value of Bitcoin over time	3.02	Digital Identity	-1.64
10	Bitcoin Safety	3.00	About Bitcoin	-1.57
11	Blockchain wallet download	3.00	Bitcoin speculation	-1.55
12	Bitcoin Push	2.89	Reddit Bitcoin wallet	-1.54
13	Bitcoin Model	2.77	Bitcoin risk	-1.51
14	Bitcoin reality	2.73	What is Bitcoin used for	-1.47
15	Coinbase	2.72	B2B payments	-1.46
16	Price of Bitcoin in USD	2.71	Reddit Bitcoin Markets	-1.38
17	creator of Bitcoin	2.68	Bitcoin chart live	-1.34
18	Bitcoin block time	2.41	Money laundering	-1.29
19	Digital Coin Bank	2.36	Bitcoin currency converter	-1.28
20	Bitcoin value graph	2.29	Little bitcoin	-1.25
21	taking bitcoin	2.28	Internal Revenue Service	-1.24
22	Bitcoin Group stock	2.27	Betting on Bitcoin	-1.23
23	Digital Currency Bitcoin	2.20	Bitcoin Experience	-1.21
24	Bitcoin storage	2.19	Bitcoin mining sites	-1.20
25	Bitcoin atm	2.13	Rise of Bitcoin	-1.20
26	Bitcoin Circulation	2.06	Coding errors	-1.17
27	Virtual currency exchange	2.02	Trading Bitcoin online	-1.16
28	Bitcoin investors	2.00	Buy Bitcoin with a credit card	-1.15
29	Bitcoin rate	1.97	Scam artists	-1.14
30	Bitcoin news reddit	1.93	Demand bitcoin	-1.13

Source: Authors' estimation.
Note: This table displays the top 30 search terms related to Bitcoin sentiment. Descending order based on their corresponding T-statistic values. Panel A displays all positive t-statistic values, while Panel B shows all negative t-statistic values.

TABLE 2

Optimal Selection of the Bitcoin Sentiment Index (BSI)

Model	**Panel A** Positive t-statistic value of BST				**Panel B** Negative t-statistic value of BST			
	Top15	Top20	Top25	Top30	Top15	Top20	Top25	Top30
Intercept	0.0205^{***}	0.0200^{***}	0.0199^{***}	0.0198^{***}	0.0212^{***}	0.0215^{***}	0.0217^{***}	0.0210^{***}
t-stat	9.70	9.49	9.45	9.34	10.18	10.42	10.54	10.24
Std. Err	0.002115	0.002113	0.002112	0.00212	0.002086	0.002066	0.002059	0.002055
SPR	0.00841^{*}	0.01036^{***}	0.0114^{***}	0.0115^{***}	-0.0104^{***}	-0.0142^{***}	-0.01622^{***}	-0.01786^{***}
t-stat	6.46	7.03	7.23	6.95	-7.88	-9.2	-9.65	-10
Std. Err	0.001	0.001	0.002	0.002	0.001	0.002	0.002	0.002
Obs	1179	1179	1179	1179	1179	1179	1179	1179
R2	0.1131	0.1187	0.1208	0.1179	0.1277	0.1433	0.149	0.1537
Adj R2	0.1109	0.1165	0.1185	0.1157	0.1255	0.1411	0.1468	0.1515

Source: Authors' estimation.
Note: This table outlines the selection criteria for the optimal Bitcoin Sentiment Index among all eight indices. The dependent variable in all regression models is the daily S&P returns; the model also includes S&P volume and the Volatility Index as control variables. Each column in the contemporary model uses BSI as the independent variable. The average number of terms varies, ranging from 15 to 30 t-statistic values in both panels, Panel A and Panel B. *** and * represent significance at the 1 and 10 percent levels, respectively.

these pessimistic sentiments, and they ultimately shift their investments towards stock returns. The direction of the relationship between dependent and independent variables is determined through the correlation coefficient. Table 1 shows that there are strong negative correlations in most cases. Descriptive Statistics and a correlation matrix of all variables are presented in Tables 3 and 4, respectively.

TABLE 3

Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
SPR	1510	0.0010621	0.0137516	-0.1075206	0.0395479
BSI	2184	9.97E-10	0.2246659	-0.8275557	0.9621106
SPV	1510	-0.0144952	0.5912234	-22.03231	1.069681
VIX	1509	14.75968	3.942591	9.14	40.74

Source: Authors' estimation.
Note: This table presents relative descriptive statistics for the daily frequency of all dependent, independent, and control variables. SPR stands for the log difference of S&P index returns. The Bitcoin Sentiment Index (BSI) serves as a proxy for search sentiments, SPV is a proxy for the S&P volume traded (log difference), and VIX is a proxy for the volatility index.

TABLE 4

Correlation Matrix

	SPR	BSI	SPV	VIX
SPR	1			
BSI	-0.2889***	1		
	0			
SPV	-0.0692***	0.0602**	1	
	0.0174	0.0195		
VIX	-0.2346***	0.0159	-0.1085***	1
	0	0.5383	0	

Source: Authors' estimation.
Note: This table presents the correlation matrix of daily frequency variables, including S&P returns, the Bitcoin Sentiment Index, S&P volume traded, and the volatility index. Here, ***, and ** represent significance levels of 1, and 5 per cent, respectively.

True investors' sentiments can be assessed through an investor-driven index. In this study, the BSI is used to measure stock market attention and track investors' sentiments. Previous studies, such as Da et al. (2015), Klemola et al. (2016b), Mao et al. (2011), Mondria (2010), and Takeda & Wakao (2014), have explored ways to quantify sentiments and have yielded significant results. The relationship between Bitcoin sentiment and the stock market, as reflected in the constructed sentiment index, is rather a gap to be filled. This study has drawn the attention of bitcoin investors to the returns of the stock market. Whether such sentiments may have an impact on the future returns of the stock market, this leads to the following hypothesis:

H1: The BSI terms index has a negative impact on stock returns.

In recent years, various authors have explored the relationship between the terms 'index' and 'stock market returns' using simple regression models. Notable studies include those conducted by Habibah et al. (2017), Shah and Zhang (2014), and Feng et al., (2018). These researchers employed statistical techniques to analyse how fluctuations in the terms index—an important indicator of financial performance—correlate with changes in stock market returns. Their findings contribute to a better understanding of the dynamics between macroeconomic indicators and equity market performance, highlighting the significance of the term index in predicting stock market behaviour. The relation between S&P 500 index returns and BSI can be determined through the Ordinary Least Squares (OLS) model. To test this assumption, the following OLS model is applied in Equation (4):

$$SPR_t = \beta_{i0} + \beta_1\, {}^{o}BSI_t + \textstyle\sum_{i=1}^{4}\ \beta_{in} SPR_{t-n} + \mu_{1t} \tag{4}$$

The Bitcoin sentiment index is the explanatory variable, and stock market returns are the dependent variables in this study. Stock returns are not only affected by sentiments, but also they are affected by the volume traded (Klemola et al., 2016a). Therefore, Volume traded and VIX, which is the Chicago Board Options Exchange (CBOE) daily market volatility index (Da et al., 2015). There are two additional variables in the model, as presented in Equations (5) and (6).

$$SPV_t = \gamma_{i0} + \gamma_1\, {}^{o}BSI_t + \textstyle\sum_{i=1}^{4} \gamma_{in} SPV_{t-n} + \mu_{2t} \tag{5}$$

$$VIX_t = \delta_{i0} + \delta_1\, {}^{o}BSI_t + \textstyle\sum_{i=1}^{4} \delta_{in} VIX_{t-n} + \mu_{3t} \tag{6}$$

Where SPR represents the log-returns of the S&P500 index, BSI is the constructed index, whereas ΔSPV is the volume of the S&P500 index, and VIX is the volatility index. Four lags of dependent variables in each case are taken as control variables.

The results of Equations (4), (5) and (6) are given in Table 5. According to regression results, there is a significant negative impact of BSI on stock market returns. Siriopoulos & Fassas (2012) used the VAR model and Granger causality tests to measure sentiments and the relation between the Greek Implied Volatility Index (GRIV) and the Underlying Equity Index (VDAX). In addition to these results, it is also necessary to determine the causal relationship between BSI and S&P returns. Here, a change in stock returns may lead to an increase in the sentiments of Bitcoin investors. Therefore, in this study, the effect of the opposite direction is also considered. Based on this assumption, the second hypotheses state:

H2a: BSI can cause S&P returns.

H2b: S&P returns can cause BSI.

To support the above statement, a vector autoregressive model is employed to predict the results in Equations (7), (8), (9), and (10).

$$SPR_t = a_0 \textstyle\sum_{l=1}^{2} a_{1l} SPR_{t-1} + {}^{o}\sum_{m=1}^{2} a_{2m} BSI_{t-m} + {}^{o}\sum_{n=1}^{2} a_{3n} SPV_{t-n} + {}^{o}\sum_{n=1}^{2} a_{4o} VIX_{t-n} + {}^{o}e_{1t} \tag{7}$$

$$BSI_t = b_0 \textstyle\sum_{l=1}^{2} b_{1l} SPR_{t-1} + {}^{o}\sum_{m=1}^{2} b_{2m} BSI_{t-m} + {}^{o}\sum_{n=1}^{2} b_{3n} SPV_{t-n} + {}^{o}\sum_{n=1}^{2} b_{4o} VIX_{t-n} + {}^{o}e_{2t} \tag{8}$$

$$SPV_t = c_0 \textstyle\sum_{l=1}^{2} c_{1l} SPR_{t-1} + {}^{o}\sum_{m=1}^{2} c_{2m} BSI_{t-m} + {}^{o}\sum_{n=1}^{2} c_{3n} SPV_{t-n} + {}^{o}\sum_{n=1}^{2} c_{4o} VIX_{t-n} + {}^{o}e_{3t} \tag{9}$$

The null hypothesis in Equation (7) states that BSI, SPV, and VIX do not cause SPR. Likewise, the null hypothesis for Equation (8) defines that SPR, SPV, and VIX do not cause BSI.

IV. Empirical Results and Discussion

Investors exhibit constraints in their cognitive capacities when evaluating future investment choices (Tversky & Kahneman, 1973). In behavioural finance, Google search volume serves as a proxy for investor attention (Mondria, 2010). Each search query is analysed in conjunction with financial market price and volume data to assess its significant impact on the market (Baker and Wurgler 2006; Habibah et al., 2017; Mao et al. 2011; Vozlyublennaia 2014). In this study, the BSI (a measure of the top 30 negative terms) is used to analyse and compare with stock market data (S&P 500 index). The results of the Ordinary Least Squares (OLS) model, as shown in Table 5, confirm the first hypothesis (H1) of the study.

According to the results of the regression analysis, the Bitcoin Sentiment Index (BSI) can accurately forecast volatility and S&P returns. The correlation between investor mood and stock market performance, however, is negative. This suggests that investors perceive a general trend of declining stock market returns as the number of search phrases mentioning Bitcoin increases. The results show that stock market returns fall by up to 0.112 per cent for every 1 per cent rise in sentiment variations among bitcoin investors. When examining the VIX, a similar pattern emerges.

A strong inverse correlation between BSI and the volatility index is demonstrated in the third column in Equation (6). Therefore, it seems that the volatility drops as the number of search phrases mentioning Bitcoin goes up (Lee et al., 2002). The second

TABLE 5

Regression Analysis (OLS)Results

SPMr	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
mLNM30	-0.007	0.001	-5.58	0.000	-0.009	-0.004	***
L.SPMr	0.759	0.020	37.94	0.000	0.719	0.798	***
VIX	0.000	0.000	03.27	0.001	0.000	0.000	***
SPV_previous	-0.008	0.002	-4.55	0.000	-0.012	-0.005	***
Constant	-0.002	0.001	-2.17	0.030	-0.004	0.000	**
Mean dependent var		0.001		SD dependent var		0.013	
R-squared		0.613		Number of obs		1179	
F-test		465.809		Prob > F		0	
Akaike crit. (AIC)		-7930.363		Bayesian crit. (BIC)		-7905.001	

Source: Authors' estimation.
Note: This table reports regression results (Ordinary Least Squares) of three different models in each column. The log differences of S&P returns (SPR), the volume of S&P traded (SPV), and the Volatility Index (VIX) are dependent variables in their respective models. The Bitcoin Sentiment Index (BSI) is a primary independent variable in all of the models, along with the first five lags of the dependent variables. Here, ***, and ** represent significance levels of 1, and 5 per cent, respectively.

model of OLS from Equation (5) indicates a negative and significant relationship between BSI and the stock market volume, as traded at its first and third lags. The influence of BSI reduces the trading volume of stock market returns, as evidenced by significant findings from its first, second, and third lag results. The results obtained are contrary to those reported by Guo et al. (2017).

The Vector Autoregressive (VAR) model is a multi-equation system in which all the variables are treated as dependent variables. In this study, the multivariate model is used. Before moving towards the final analysis, it is necessary to confirm that all the variables of the model are stationary at a level. The results of the unit root are given in Table 6. The table indicates that all variables are stationary both at the level and in first differences.

TABLE 6

Variables with Stationarity

	T-statistics at the level			T-statistics at first difference		
Variables	ADF	PP	Results	ADF	PP	Results
BSI	-32.387	-1417.829	S	-27.615	-1430.469	S
SPR	-32.605	-1141.676	S	-19.421	-1157.713	S
SPV	-8.968	-1510.7	S	-3.311	-1478.032	S
VIX	-7.464	-93.467	S	-7.843	-88.053	S

Source: Authors' estimation.
Note: The unit root test results are shown in this table. The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests are provided. In this table, 'S' indicates whether the corresponding variable is stationary.

According to Wang Wei, the Granger causality test assesses whether one time series helps predict another time series in the analysis. Several studies support it. (2019), Tantaopas et al. (2016) have conducted a Granger causality test using a VAR model as a robust check. This section presents the results derived from the VAR model. Granger causality is employed to ascertain whether BSI influences S&P returns or vice versa. Table 7 displays the model using two lags. The values in the first column of the table represent the 2nd hypothesis of the study. The 'BSI→SPR' statement signifies the null hypothesis that investor sentiment, as measured by BSI, does not contribute to predicting SPR. The results are insignificant, as evidenced by the first row. Therefore, we may reject H2a. The null hypothesis of the 'SPR→BSI' posits that S&P returns cannot predict or influence BSI sentiments. The results demonstrate significance at the first lag for the second statement. Consequently, it can be concluded that H2b is acceptable. It has been significantly proven that a positive change in stock market returns elicits a positive response to bitcoin sentiments among investors. VIX has explained S&P returns in a more significant way at its second lag.

TABLE 7

Granger Causality Model for two lags

	Lag 1	Lag 2
BSI→SPR	0.00136	-0.00123
BSI→SPV	-0.0471	0.07***
BSI→VIX	0.3232	-0.2504
SPR→BSI	0.92***	0.5637
SPR→SPV	-1.68***	2.27***
SPR→VIX	-4.0592	-43.5418
SPV→SPR	-0.00367	-0.00383
SPV→BSI	0.0699	0.0015
SPV→VIX	0.42***	2.09***
VIX→SPR	-0.00***	0.00***
VIX→BSI	-0.0044	0.003
VIX→SPV	0.0031	-0.0011

Source: Authors' estimation.
Note: This table shows two lag data points for all four variables. The arrow represents the statement 'Can Predict.' Values with ***, represent whether the coefficient is significant at the 1 percent.

TABLE 8

Vector Autoregressive Model for two lags

Variables	SPR	t-stat.	BSI	t-stat	SPV	t-stat.	VIX	t-stat.
SPR(-1)	0.90483	20.9	0.9273	-3.48	-1.6859	-2.25	-4.0592	-0.76
SPR(-2)	-0.16853	-3.71	0.5637	0.58	2.2714	2.88	-43.5418	-7.74
BSI(-1)	0.00136	0.69	0.211436	5.00	-0.0471	-1.37	0.3232	1.32
BSI(-2)	-0.00123	-0.64	0.1486	3.63	0.0706	2.13	-0.2504	-1.06
SPV(-1)	-0.00367	-0.95	0.0699	0.85	-0.2753	-4.11	0.4255	4.84
SPV(-2)	-0.00383	-1.09	0.0015	0.02	0.0035	0.06	2.0966	22.06
VIX(-1)	-0.00076	-3.19	-0.0044	-0.87	0.0031	0.76	0.6482	22.06
VIX(-2)	0.00096	4.21	0.003	0.61	-0.0011	-0.28	0.2006	7.11
C	-0.00232	-1.48	0.0473	1.41	-0.0311	-1.14	2.1152	10.89
Adj. R2	0.6263		0.1646		0.0514		0.9273	
AIC	-5.513844							
SIC	-5.233695							
Obs	555							

Source: Authors' estimation.
Note: This table displays two lag data points for all four variables.

The VAR (Vector Autoregressive) model is employed to characterise the dynamic behaviour of variables. Investor sentiment has a significant influence on investment decisions, and the VAR model helps predict future returns. In 1980, Sims proposed vector autoregressive models in his publication, which have since become an essential instrument in macroeconomic research. The results of this study differ from those of previous studies (Dizaji, 2014; Panagiotidis et al., 2019; Shen et al., 2019; Vozlyublennaia, 2014). Table 8 presents the VAR results corresponding to Equations (7) through 10. The table demonstrates that alterations have a substantial impact on the first lag of BSI in S&P returns, whereas S&P returns do not exhibit a significant response to BSI.

V. Conclusion and Recommendations

Changes in attention can positively or negatively affect returns, and attention is likely to influence changes in index returns. As a measure of sentiment, the Bitcoin sentiment Index negatively impacts index returns and volatility. Moreover, from the causal relation, it is also proved that S&P returns can cause BSI to fluctuate. The study's primary aim, to determine the sentimental impact of Bitcoin investors on stock markets, is achieved. In the OLS model, the research found a significant but negative impact of BSI on S&P returns. The coefficient of this impact allows us to assess both the causality and autoregressive effects using the VAR model. The findings indicate that the BSI does not cause fluctuations in S&P returns; rather, it is the S&P returns that cause variations in the BSI. Therefore, it may be concluded that hypotheses 1 and 2b are accepted, but hypothesis 2 is rejected.

The impact of the newly constructed term list can be investigated on different sectors of the American stock market to measure the exact industry impact. Also, this (BSI) index can be used to determine the asymmetric impact on the USA stock markets, like the results of Habibah et al. (2017), which also demonstrates that VIX explains a more robust predictability of returns than BSI. The construction of the Bitcoin sentiment index for measuring sentiments was the main finding of this research. The impact of BSI on S&P returns was found to be negative. The above results are in support of hypotheses 1 and 2b, but not in support of 2a that BSI causes changes in S&P returns.

The findings suggest that cryptocurrency investors respond to the same macroeconomic and financial signals as traditional investors. This supports the idea that Bitcoin is increasingly viewed as a risk-on asset, meaning it performs well in a favourable risk environment rather than acting as a hedge against risk. In the United States, the S&P 500 represents the large-cap stocks of domestic companies. When the stock market experiences positive returns, it often boosts investor confidence, which can subsequently influence more speculative markets, such as the cryptocurrency market. This suggests a unidirectional causal relationship in which traditional equity markets have an influence on cryptocurrency sentiment.

In economic terms, the unidirectional causality from S&P 500 returns to the Bitcoin sentiment index suggests that crypto markets respond to traditional markets without yet exerting a significant influence over them. This relationship indicates that Bitcoin is integrated into the broader financial ecosystem, revealing a greater interconnectedness in investor behaviour across different asset classes than previously understood. Therefore, it may be concluded that Bitcoin is not yet fully decoupled from traditional financial markets and is influenced by broader macroeconomic conditions.

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