Bitcoin Sentiment Index and its Impact on Stock Market Returns: An Evidence from 28 Countries

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Abstract

Investor psychology is one of the determinants of asset pricing according to Behavioral Finance. The tool of diversification is used for increasing returns and avoiding risk. In this study, Bitcoin as a new investment avenue is explored. The main objective of this study is to measure the effect of the Bitcoin investors' sentiments on the stock market returns of developed and developing countries worldwide. This impact is measured through a newly constructed sentiment index for each of the 28 sample countries. For the sample period of 01st Jan 2014 to 30th May 2023 on a daily basis, data, such as an impact, is measured through the ordinary least squares OLS method. The findings suggest that the (negative and positive) Bitcoin Sentiment Index significantly affects the stock market returns of the 28 sample countries. Furthermore, Bitcoin shares characteristics with other financial assets and commodities, making it suitable for inclusion in an ideal portfolio. These findings have crucial empirical implications for investors, policymakers, and cross-border portfolio managers, who must make informed short-term and long-term decisions to plan their diversification strategies and consider including Bitcoin as a financial asset.

Keywords: Behavioural finance; Bitcoin sentiment index; ordinary least square; regression; stock return.

JEL Classification: C10, C22, E44, E71, G15, G40, G41, N2

1. Introduction

In the world of finance, investors' behaviour plays a vital role. Investors' behaviour creates future investment opportunities. Modern finance theory reached its peak in academic circles during the 1970s. It was a time when the rational expectations revolution came into the market and became a part of Economic theory, and grasped the attention of the finance, academic,

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and investment world (Shiller, 2003). However, according to Behavioural Finance, these emotions of investors, commonly known as investor sentiments, are the main component that affects the investment decision. Such investor sentiments are used as an effective proxy to explore the financial markets, like stock market returns, volatility, and trade volume, real estate price, and Bitcoin[1] price, etc. These proxies are part of Behavioural Finance.

The structure of the global financial system has changed because cryptocurrency markets have grown rapidly over the last 12 years. This has also called into question long-held beliefs that underpin modern finance theory. Individual investors, just like institutional investors, invest in different conventional and digital financial markets. Since its launch in 2008(Nakamoto, 2008), Bitcoin's price and popularity have increased. Changes in Bitcoin can make financial and technological news on any given day. Bitcoin prices have reached as high as $ 60,000 since their launch in October 2021[2]. Several renowned financial media outlets, including Bloomberg, Forbes, and CNN, have dubbed cryptocurrencies, particularly Bitcoin, the "New Gold." Bitcoin is the most well-known and important cryptocurrency.

Individual investors are primarily motivated by investor sentiment. These feelings are considered when forecasting how the financial markets might move. In the field of Behavioural Finance Richard Thaler has made tremendous contributions(Kahneman et al., 2019; Lee et al., 1991; Qiu & Welch, 2011; Thaler & Johnson, 1990 & Zhang & Sussman, 2018). Similarly, Barberis and Huang (2001), in their article prospect theory and asset prices, define investor sentiments as preferences made by market participants irrationally. According to the definition given by Long et al. (1990), when expectations of noise traders' (individual investors) asset value systematically deviate, such a phenomenon is called investor sentiments. And these noise traders are great sources of mispricing[3] in the financial markets. Likewise, Lee et al. (1991) say that the investor sentiments are part of the investor assets' future return. The fundamentals are not sufficient to explain the fundamental degree, in which deviation without any reason in their future prices is caused by investor sentiments.

Numerous scholars have recently conducted studies examining the feelings associated with predicting the price of Bitcoin (Figà-Talamanca & Patacca, 2020; Jang & Lee, 2017; Karalevicius, 2018; Matta et al., 2015; Wang & Chen, 2020). The effect of investor sentiments on Bitcoin return, realised volatility, and transaction volume has also been the subject of previous research. (Audrino et al., 2020; Hang & Zhang, 2021; Hu et al., 2020; Zhu et al., 2021). However, more research needs to be done on the attitudes held by potential Bitcoin investors and how they may affect other asset classes in developed, developing,

[1] Bitcoin is a peer-to-peer (p2p) payment cash system and an unregulated digital currency that was created in 2008 but has no legal tender status (Krause & Pham, 2017).
[2] Yahoo.c
[3] Mispricing is the difference between the securitiy's market value and its fundamental value.

and underdeveloped nations. Furthermore, sentiment analysis in cryptocurrency research has often relied on limited proxies, such as social media metrics and aggregated Google search trends, rather than developing comprehensive, country-specific sentiment indices that systematically and theoretically capture investor sentiment. Here, the constructed Bitcoin Sentiment index is the independent variable. However, the dependent variables include the Stock Market return. A Conceptual framework for easy understanding is given in figure 1.

Source: Author's Illustration

Figure 1: Research Conceptual Framework

The study's scope encompasses developed and underdeveloped countries worldwide. This study includes a list of the top 28 countries (Table 1) selected based on Bitcoin mining Volume on online exchanges (Mohsin et al., 2020). These countries were selected based on their awareness and ownership of Bitcoin. Secondly, these countries account for more than 50% of Google's worldwide search traffic. The study period is from January 01, 2014, to May 30, 2023.

Table 1

Bitcoin Mining Volume and Google Share of Search Traffic

Sr. No.	Country	Bitcoin Mining Volume on online exchanges in various countries worldwide in 2020 in a million US dollars	Google Share of Search traffic worldwide
1	United States	1523.6	88.83%
2	Russia	421.38	48.78%
3	Nigeria	400.08	98.81%
4	China	198.26	5.03%
5	UK	193	85.70%
6	Colombia	147.49	64.47%
7	Kenya	91.96	98.10%
8	South Africa	87	95.44%
9	Canada	65.56	88.38%
10	India	63.72	95.45%
11	Australia	54.78	90.23%
12	Argentina	47.85	97.62%
13	Peru	44.69	97.09%

Table to be continued...

14	Philippines	30.77	95.31%
15	Thailand	27.23	99.33%
16	Brazil	25.22	92.58%
17	Chile	23.81	92.65%
18	Mexico	23.47	96.44%
19	Sweden	23.38	90%
20	Hong Kong	20.09	91.12%
21	Ukraine	18.02	93.63%
22	Malaysia	17.04	98.32%
23	Pakistan	12.4	98.39%
24	Vietnam	12.12	93.15%
25	Singapore	10.64	96.19%
26	New Zealand	9.92	94.77%
27	Indonesia	8.84	98.19%
28	Morocco	8.28	97.85%

Note: The table lists all selected countries (i) as of 30/05/2021. The sources of data for the third column are https://www.statista.com/statistics/1195753/bitcoin-trading-selected-countries/ and for the fourth column, it is https://www.statista.com/statistics/220534/googles-share-of-search-market-in-selected-countries/

Source: Estimated by the authors

This research fills those gaps by analyzing the influence of Bitcoin investor sentiment on stock market returns across 28 Bitcoin-active nations, utilizing an innovative, text-based Bitcoin Sentiment Index (BSI) developed for this purpose. Based on behavioural finance theory, this study examines whether sentiment-driven behaviour in cryptocurrency markets exerts a statistically significant impact on stock markets worldwide. With the help of the constructed Bitcoin Sentiment Index, this objective will be achieved. The Bitcoin Sentiment Index is made up of news-based text data and Google search frequency metrics. This gives a more detailed and accurate picture of investor sentiment than traditional market-based indicators.

2. Theoretical Background and Literature Review

Stock prices are influenced by fundamental factors such as earnings, dividends, and growth prospects, and any deviations caused by investor sentiment are swiftly corrected by rational market participants, according to the Efficient Market Hypothesis (EMH). Traditional finance theory is challenged by Behavioural finance assumptions, which assume that investors always move according to their mental prospect. Moreover, according to Thaler (2005) investors' decisions are based on the fundamental information as well as on their psychological biases. Such emotions can impact asset prices. However, such behavioural effects are more pronounced in cryptocurrency markets (Shrotryia & Kalra, 2021). The psychological biases include herding behaviour, overconfidence bias, loss aversion and representativeness Heuristic, which directly affect Bitcoin returns.

A new and emerging field in finance is cryptocurrency, and among the numerous cryptocurrencies, the Bitcoin currency has captured unusual attention. The price of Bitcoin is mostly driven by public interest, media coverage, and consumer confidence among financial assets like equities, bonds, commodities, and currencies (Bartholomae & Rafih, 2020). Like in different stock markets, Bitcoin (a digital market) also gets affected due to the unusual sentiment created by individual or institutional investors. However, Urquhart and Zhang (2018) analyzed the relationships between Bitcoin attention and realized volatility and returns of Bitcoin using Google Trends data and reported an absence of predictive power for next day Bitcoin returns.

The need to ascertain Bitcoin's co-movement with other asset classes arises from the fact that the volatility of Bitcoin return looks much larger than that of other assets like stock when the topic of volatility of Bitcoin return arises. The total number of cryptocurrencies in circulation is around 16,203. To date, there are 450 exchanges where these cryptocurrencies may be bought and sold. According to the data[4] available as of 30th December 2021, the total market capitalization of the cryptocurrency market is $221.42Billion with a total volume of $9.740Billion. Bitcoin holds the largest market share at 40.17%, followed by Ethereum with 19.9%. In the same way, the influence of sentiments on realised volatility, volume, and return is uncovered through news, social media, Twitter, and social media searches and comments. However, optimistic views correlate positively with stock performance, whereas pessimistic views have a negative effect (Hassanein et al., 2021). Volatility and volume were shown to be influenced by shifts in sentiment; however, no correlation between sentiment and bitcoin returns was established. Negative correlations between stock market returns and volatility and text-based investor attitudes have been shown in a few previous studies (Brown & Cliff, 2004; Statman, 1999). Conversely, a plethora of recent studies have found a positive correlation between investor attitude and stock returns, leading researchers to the conclusion that investor emotions can help to explain stock price fluctuations. (Koshoev, 2020; Takeda & Wakao, 2014; Vozlyublennaia, 2014).

Several studies elucidate the role of Bitcoin-related views and their consequences for social groups worldwide. Investors pay close attention to the market whenever asset values fluctuate widely, which can set off a positive feedback loop in which increased attention and price movements further drive-up asset prices. Speculative investment demand is primarily determined by investor attitude, which can be viewed as a propensity to speculate. Such demand results in cross-sectional impacts even if the arbitrage forces are uniform across the stock. Simply put, investors want to buy companies that they believe have several key traits that align with their values. Small stocks, young stocks, stocks with significant volatility, unproductive stocks, companies that do not pay dividends, stocks with extraordinary growth,

[4] https://coinmarketcap.com/

stocks in distress, and stocks that do not pay dividends all have poor investor sentiment, according to Baker and Wurgler (2006). The ensuing returns on these types of stocks are poor when sentiment is high. Table 2 gives a summary of a few studies among several research articles on this topic.

Table 2
Summary Table Mapping Major Studies on Sentiment Index

Sr. No	Research Study	Variables	Methods	Findings
1	Internet search-based investor sentiment and value premium by Antti Klemola, 2020	Internet search-based investor sentiment effects U.S. stock market	Cross-Sectional Effect	An unexpected increase in optimism (pessimism) in the sentiment predicts a positive (negative) subsequent value premium in the U.S stock market.
2	Sentiment-Induced Bubbles in the Cryptocurrency Market by Cathy Yi-Hsuan Chen, 2019	Sentiment and market bubbles in cryptocurrencies	Case studies of market events	Sentiment-driven trading can lead to significant price bubbles in cryptocurrency markets.
3	In Search of Attention by Zhi Da et al. 2011	Search volume index	Correlation, VAR,	Increased attention leads to higher stock returns in the short term.
4	Google search intensity and its relationship with returns and trading volume of Japanese stocks, Fumiko by Famiko Takeda 2014	Google search intensity and trading volume	Portfolio analysis on the factor model and Regression	Higher search intensity correlates with increased trading volume and stock returns in the Japanese market.
5	Stock market return predictability: Google pessimistic sentiments versus fear gauge by Ume Habibah 2017	Pessimistic sentiments and fear gauge	ARDL and NARDL method	Pessimistic sentiments can predict lower stock returns, highlighting the role of investor fear in market dynamics.
6	Bitcoin is not the New Gold – A comparison of volatility, correlation, and portfolio performance by Tony Klein 2018	Bitcoin volatility, correlation with gold	Comparative analysis	Bitcoin shows higher volatility compared to gold and does not serve as a stable store of value.

There is a strong need to investigate potential investors' sentiments toward Bitcoin and how they could affect the stock market. Such impact of investor sentiment on Bitcoin returns, volatility, and trade volume (D'Alfonso et al., 2016; Shen et al., 2019; Wołk, 2020) and its use in predicting Bitcoin's future price (Karalevicius et al., 2018; Prajapati, 2020) have all been the subject of prior research. A text-based sentiment analysis approach for potential Bitcoin investors has yet to be explored. Secondly, with the help of such an index, the impact of Bitcoin investor sentiment on the stock market returns of different countries worldwide is another broad area of financial markets. Where such an impact is explored to assess Bitcoin's potential impact on investor sentiment. In addition, this research study differs from others in that it uses a newly developed Bitcoin Sentiment Index to examine the effect of Bitcoin-related sentiment on other financial system assets.

The uniqueness of this is that it provides a new dimension of investigation for policymakers, risk managers, and international investors to diversify and hedge using Bitcoin. Studies on Bitcoin sentiment (Burggraf et al., 2020; Hu et al., 2020; Kapar & Olmo, 2021; & Karalevicius, 2018) have been investigated earlier. However, this study differs from all such literature. Exploring assets based on the sentiments of Bitcoin investors, which is the most volatile asset, is vital for the future benefit of diversifying risk and enhancing returns, given the dynamism between Bitcoin and stocks and their co-movement with each other.

3. Research Methodology

3.1 Overview

This article explores the impact of Bitcoin investor sentiment on the stock markets of 28 different countries. Here, research follows the methodology used by(Ali Soomro et al., 2025; Da et al., 2015; Klemola, 2020; Rajput et al., 2020) to construct a Bitcoin sentiment index for each country from the sample frame.

3.2 Sample Size and Selection Criteria of the Sample

The main objective of the study is to provide evidence from worldwide data. Therefore, the sample of this study is selected from all developed, emerging, and underdeveloped countries worldwide (Table 1). The criteria for sample selection are derived from the study of crypto trade volume by Mohsin et al. (2020). The study sample is selected based on the top Bitcoin-mining countries, with a top-priority focus on Google search engine usage. The study's sample size comprises 28 developed, emerging, developing, and underdeveloped states. These sample nations provide this research project with a wide-ranging and international perspective.

3.3 Sources of Data

The data sources are secondary to this research. The data is initially collected from each country's top finance online newspapers and magazines (Schumaker et al., 2012; Pyo & Kim, 2021; Agoraki et al., 2022). Then, the frequency data is collected from Google Trends. Further, Bitcoin price data and stock market data for each country throughout the sample period of 01 January 2014 to 30 May 2023 are collected daily from Yahoo. Finance and Data Stream Portal. Here, BSI(i) is the independent variable, and the Stock market index of each sample country is the dependent variable of this study. The one for all sample countries Volatility Index (VIX) and the Risk-free rates, separate for each sample country, are the control variables.

3.4 Data Analysis Strategies

The main objective of this study is to analyses the impact of the Bitcoin sentiment index (constructed from Bitcoin sentiment data) on the stock returns of the top Bitcoin-mining countries worldwide.

3.5 Construction of Bitcoin Sentiment Index

The Finance and Economics-related news articles from top finance and economics Magazines and Newspapers[5] available online were examined to determine the Bitcoin-related terms. This method prepares a word glossary for the final index. The initial search returned only 138 terms after duplicates were removed. Further, a top-ten list of Google search results was compiled to determine the search frequency of Bitcoin-related terms.

The list of 138 terms increased to 1038 terms after adding the top 10 searches for each term. The duplicates were removed as deemed necessary. Then, for yearly data from the sample period of 2014 to 2023, all terms in the list were downloaded, and those with the lowest frequency or no significant data were excluded. Now, this reduced list of Bitcoin search terms (BST) is checked on Google Trends for the frequency of daily data over the sample period of 9.5 years. In this way, the frequency data of each term is downloaded one by one. Before going for regression to get the final list, "1" is added to all terms to avoid the error created by negative and zero frequencies. With its first lag, the bitcoin search term (BST) is taken from the data available in Equation 01. This model includes a log of all Bitcoin search terms at the first lag, subtracted from the log return of those search terms. The entire dataset is winsorised at a 5% level and then standardized to have a mean of "0" and a standard deviation of "1". Finally, the data available for analysis is winsorised, standardized, and adjusted to

[5] For Russia the list included Vedomosti, RBK Daily newspaper, Kommersant, Vremya Novostei, Delovoy Peterburg, The Kazan Herald, Forbes Russia, and so on.

minimize errors. In the second step, each word in the list is regressed individually against Bitcoin's log-returns (daily prices from 2014 to 2023) to obtain t-statistic values. through Equation 02 (Da et al., 2011, 2015; Klemola et al., 2016). Lastly, 60 terms (top 30 positive t-statistics values and top 30 negative t-statistics values) and eight sentiment indices (top 15, 20, 25, and 30 most positive and most negative terms) with highly significant t-statistics are constructed (Rajput et al., 2020). These 60 terms are selected based on their top t-stat values on the positive side (indicating the largest positive correlation between BSI and the stock market) and on the negative side (indicating the largest negative correlation between BSI and the stock market).

$$(\Delta BST_{it}) = lnBST_{i,t} - \ln BST_{i,t-1} \tag{1}$$

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

A robust check is performed to select the optimal index from among eight indices generated by this process. For the final selection of BSI(i) (where "(i)" denotes each country in the sample), each BSI model is regressed on daily Bitcoin returns to determine how well this sentiment index explains Bitcoin returns given in Equation 3.

$$BTCr_t = \alpha_{i0} + \beta_{i,t}\, BSI_{i,t} + \delta_{i,n} BTCr_{i,t-n} + \theta_{i,t} VIX_{i,t} + e_{i,t} \tag{3}$$

In Equation 3, BTC denotes the daily Bitcoin prices, and VIX denotes the volatility index. At this stage, the index is finally ready for analysis. The next phase is to determine the main objective of the study, which states that BSI(i) has an impact on stock market(i) returns[6]. This can be determined through the ordinary least squares (OLS) model given in Equation 04.

$$STr_{i,t} = b_{i,0} + \beta_{i,t}\, BSI_{i,t} + \theta_{i,t} VIX_{i,t} + \delta_{in} RF_{i,t} + e_{i,t} \tag{4}$$

The corresponding stock returns are denoted by $STr_{i,t,}$ BSI denotes the Bitcoin Sentiment Index, whereas VIX represents the fear gauge, and RF gives the risk-free rate. Moreover, $b_{i,0,}$ and e_t a constant and an error term, respectively.

4. Empirical Results and Discussion

The Bitcoin price dynamics can be influenced by a range of news factors, including macroeconomic and COVID-19 news, as well as social media sentiment. Consequently, a thorough understanding of Bitcoin sentiment and its correlation with news indicators may be

[6] Where (i) denotes each country in the list of top Bitcoin mining countries.

achieved by incorporating these findings from credible studies (Chen et al ., 2020; Kapar & Olmo, 2021). Based on the model given in Equation (1), a list of ΔBST terms is constructed for each sample country. Such a Table is provided in Appendix A, Table 1, for each sample country. In a second step, the list of words was regressed with the daily Bitcoin price (log returns) for the sample period of 2014 to 2023. This was done to determine the t-statistic values explained by the model given in Equation 02 (Da et al., 2011, 2015; Klemola et al., 2016).

Further, eight indices M15, M20, M25 and M30 from the positive side and NM 15, NM20, NM25 and NM30 from the negative side of the BST list were generated with highly negative and highly positive significant t-statistics (Rajput et al., 2020). The selection of these eight indices for each country was based on the list of 60 terms in Tables 1for each sample country (Appendix A). These eight indices are further regressed with stock returns (of their respective country) to determine the most appropriate index based on t-statistics, R-squared, and standard error (Burggraf et al., 2020; Da et al., 2015; Nakagawa & Schielzeth, 2013). Out of these 8 models, one index model has been finalized. Descriptive statistics of these variables are presented in the 3rd Table of each country in Appendix A. Such a model is the Bitcoin Sentiments Index, the main index, determined by the ordinary least squares (OLS) model given in Equation 04 for each sample country. This study has employed simple ordinary least squares (OLS) regression. It is an appropriate model for measuring the relationship between time-series variables when integrated at the level, especially in a bivariate model. In the optimal model selection table of each country, the residual sum of squares R2 is the most useful measure for model fitness, and the maximum value of R2 in a regression model represents the probability of a satisfactory model. However, the correlation between the dependent and independent variables is presented in the 4th Table of each sample year. A consolidated list of all 28 sample countries and their highest OLS t-stat values is provided in Table 3 below.

Table 3
Bitcoin Sentiment Index Details

CONTINENTS	Sr. No	Country	Symbol	Bitcoin Sentiment Index Symbol	Model-BSI	OLS t-stat Value	Stock Market
	1	China	CN	BSI-CN	NM30	-7.36	Price Hang Seng CSI
	2	India	IN	BSI-IN	M30	8.65	Price BSE
	3	Philippines	PH	BSI-PH	M30	9.47	PHS ALL
	4	Malaysia	MY	BSI-MY	M30	8.81	Price KLCI
	5	Pakistan	PK	BSI-PK	NM30	-8.45	Price KSE-100
	6	Vietnam	VN	BSI-VN	NM30	-7.84	FTSE All

Table to be continued...

	7	Singapore	SG	BSI-SG	M30	6.91	FTSE Singapore
	8	Indonesia	IO	BSI-IO	NM30	-7.2	Price Jakarta
	9	Hong Kong	HK	BSI-HK	M25	7.7	HKG
ASIA	10	Thailand	TH	BSI-TH	NM30	-9.46	Price FTSE set
	11	Kenya	KE	BSI-KE	NM25	-8.1	Price Nairobi
	12	Nigeria	NG	BSI-NG	NM30	-7.85	NGX-All share
	13	South Africa	ZA	BSI-ZA	M30	9.42	Price S.AF
AFRICA	14	Morocco	MA	BSI-MA	M30	4.77	Price Moroccan All share
	15	Russia	RU	BSI-RU	M30	9.38	Price MOEX
	16	United Kingdom	GB	BSI-GB	NM25	-9.7	Price FTSE UK
	17	Ukraine	UA	BSI-UA	M25	7.58	PFTS stock index
EUROPE	18	Sweden	SE	BSI-SE	M30	8.96	Price OMX
	19	USA	US	BSI-US	M25	10.14	S&P 500
NORTH AMERICA	20	Mexico	MX	BSI-MX	NM30	-7.33	S&P/BMV IPC
	21	Canada	CA	BSI-CA	M30	9.73	Price TSX
	22	Brazil	BR	BSI-BR	NM30	-7.71	Price Bovespa
	23	Colombia	CO	BSI-CO	NM30	-8.01	Price COLCAP
	24	Argentina	AR	BSI-AR	M30	8.85	PriceBYMA
SOUTH AMERICA	25	Chile	CL	BSI-CL	NM30	-6.83	Price CLX IPSA
	26	Peru	FE	BSI-FE	M25	6.92	Price PSEi
	27	New Zealand	NZ	BSI-NZ	M30	8.05	Price NZX
AUSTRALIA	28	Australia	AU	BSI-AU	M30	10.19	Price ASX

Note: The Table represents the list of all sample countries (i) as of 30/05/2021. This list denotes essential symbols and stock markets from which data is collected. The second-to-last column presents the t-statistic for each BSI model, calculated via OLS. The source of the stock market return data is https://www.investing.com/, and the data stream is provided by https://www.investing.com/.

Source: Estimated by the authors

The 3rd last column on model BSI in Table 3 shows that 12 out of 28 countries have negative or pessimistic Stock returns, as indicated by a negative list of terms, suggesting a pessimistic outlook. Such a negative list implies that Bitcoin investors contribute to these negative sentiments, ultimately shifting their investments towards stock returns. These countries include China, Pakistan, Vietnam, Indonesia, Thailand, Kenya, Nigeria, the United Kingdom, Mexico, Brazil, Colombia and Chile. These results are the same as those reported by (Ali Soomro et al., 2025). On the other hand, the remaining 16 countries have shown an optimistic Bitcoin sentiment index, indicating that BSI has a positive impact on stock market returns. These countries include Malaysia, Singapore, Hong Kong, India, the Philippines, South Africa, Morocco, Russia, Ukraine, Sweden, the USA, Canada, Argentina, Peru, New Zealand and Australia. The optimistic BSI suggests that Bitcoin investors in these countries create positive sentiment and increase their investment in Bitcoin assets. When people become optimistic about Bitcoin, they invest in it, which ultimately drives its value higher. These results match those reported by (Rajput et al., 2020).

5. Conclusion

Traditional finance theories often assume that markets are efficient. However, according to behavioural finance, it is essential to consider the impact of investor sentiment, which indicates that markets can sometimes be imperfect and influenced by investors' emotions. The main objective of this study is to examine the impact of the newly constructed Bitcoin Sentiment Index on stock market returns across 28 sample countries, to provide a more comprehensive understanding and prediction of market behaviour. Here daily average Bitcoin returns are employed. The sample starts from January 01, 2014, to May 30, 2023. It was predicted that Bitcoin sentiment varies in both developed and emerging economies. A positive Bitcoin Sentiment Index is associated with higher stock market returns. However, in some economies, negative or pessimistic sentiment toward Bitcoin has an adverse effect on equity returns, leading investors to shift their investments toward stock markets. These findings show that investors and markets behave differently in different parts of the world. Further, it can be inferred that Bitcoin possesses asset-like attributes similar to those of shares, commodities, and currencies, thereby reinforcing its increasing integration into the global financial system. The study enhances the behavioural finance literature by offering a thorough, cross-national examination of sentiment-driven interactions between Bitcoin and stock markets. The development of a country-specific Bitcoin Sentiment Index represents a methodological development that deepens understanding of sentiment-driven mispricing.

The major implications for investors, portfolio managers, policymakers, and financial regulators indicate that Bitcoin sentiment can be a significant informational signal for investors and portfolio managers in developing trading and diversification strategies. Integrating sentiment indicators with conventional financial metrics may enhance portfolio performance, especially during periods of heightened market volatility. The data indicating that Bitcoin sentiment influences stock market outcomes suggests that ignoring behavioural signals may result in inefficient investment choices. Regulators may therefore benefit from observing sentiment-based indicators as signals of market stress and speculative bubbles. Moreover, the study provides empirical evidence for incorporating behavioural indicators into economic supervision frameworks.

This research also supports the inclusion of behavioural finance in models of market interconnectivity and asset pricing. The research fills a gap between traditional financial economics and cryptocurrency research by showing how sentiment-driven behaviour in a highly volatile asset like Bitcoin can affect equity markets worldwide. Although this study provides several significant findings, it also offers numerous opportunities for further investigation. Researchers can further utilize explanatory value relative to text-based news sentiment, which can be evaluated; future research could first expand the analysis by including additional sentiment measures from social media platforms, discussion forums, or blockchain-based data. Such an approach may capture investor emotions in real time more effectively. Further, the qualitative research method may be used as a mixed method to interpret the quantitative models. Moreover, it would be worthwhile to examine how Bitcoin sentiment shifts in response to extreme market events, such as financial crises or geopolitical shocks. Finally, researchers could explore whether the observed sentiment effects are unique to Bitcoin or reflect broader trends within the cryptocurrency ecosystem.

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