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Twitter sentiment analysis and bitcoin price forecasting: implications for financial risk management

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Abstract

Purpose – The present study distinguishes itself by pioneering an innovative framework that integrates key elements of prospect theory and the fundamental principles of electronic word of mouth (EWOM) to forecast Bitcoin/USD price fluctuations using Twitter sentiment analysis.

Design/methodology/approach – We utilized Twitter data as our primary data source. We meticulously collected a dataset consisting of over 3 million tweets spanning a nine-year period, from 2013 to 2022, covering a total of 3,215 days with an average daily tweet count of 1,000. The tweets were identified by utilizing the "bitcoin" and/or "btc" keywords through the snscrape python library. Diverging from conventional approaches, we introduce four distinct variables, encompassing normalized positive and negative sentiment scores as well as sentiment variance. These refinements markedly enhance sentiment analysis within the sphere of financial risk management.

Findings – Our findings highlight the substantial impact of negative sentiments in driving Bitcoin price declines, in contrast to the role of positive sentiments in facilitating price upswings. These results underscore the critical importance of continuous, real-time monitoring of negative sentiment shifts within the cryptocurrency market.

Practical implications – Our study holds substantial significance for both risk managers and investors, providing a crucial tool for well-informed decision-making in the cryptocurrency market. The implications drawn from our study hold notable relevance for financial risk management.

Originality/value – We present an innovative framework combining prospect theory and core principles of EWOM to predict Bitcoin price fluctuations through analysis of Twitter sentiment. Unlike conventional methods, we incorporate distinct positive and negative sentiment scores instead of relying solely on a single compound score. Notably, our pioneering sentiment analysis framework dissects sentiment into separate positive and negative components, advancing our comprehension of market sentiment dynamics. Furthermore, it equips financial institutions and investors with a more detailed and actionable insight into the risks associated not only with Bitcoin but also with other assets influenced by sentiment-driven market dynamics.

Keywords Twitter, Sentiment analysis, Loss aversion, Status quo, Electronic word of mouth, Prospect theory

Paper type Research paper

1. Introduction

Sentiment analysis has emerged as a popular tool in social media and business analytics. Numerous researchers and academic practitioners are exploring the diverse applications and complexities of sentiment analysis across various disciplines (Dash and Maitra, 2019; Ilyas *et al.*, 2020). In recent years, sentiment analysis has gained substantial traction in financial risk management. Within this domain, a subject that has generated significant interest is the application of sentiment analysis for forecasting price fluctuations in Bitcoin and other cryptocurrencies (Karalevicius *et al.*, 2018; Ramani *et al.*, 2023).

Notably, the emergence of Bitcoin as an exclusively digital asset, disconnected from tangible properties and existing solely within the realm of the Internet, has propelled the prominence of sentiment analysis in forecasting price movements in bitcoin (Jagini *et al.*, 2023). It has become an invaluable tool in the arena of financial risk management, offering valuable insights into market dynamics and investor behavior related to Bitcoin. Through

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sentiment analysis, financial professionals can harness the collective sentiment expressed on social media platforms to make informed decisions and implement effective risk management strategies that carries insightful implications in the realm of financial risk management.

Given this significance, the utilization of sentiment analysis for predicting Bitcoin's price movements has become increasingly important. Undoubtedly, numerous researchers have made commendable contributions to this domain, but the present study distinguishes itself by employing a more robust and comprehensive approach to conducting sentiment analysis for predicting Bitcoin's price movements. The present study stands out as a unique exploration that aims to offer an alternative framework by combining key elements of prospect theory with the fundamental principles of electronic word of mouth (EWOM). This framework is employed to predict Bitcoin price fluctuations through Twitter sentiment analysis.

Our methodology deviates from conventional approaches by incorporating distinct positive and negative sentiment scores instead of relying on a singular compound score. This nuanced approach facilitates a more intricate examination of sentiment's relationships with Bitcoin's price movements. Moreover, we underscore the significance of normalizing the entire dataset, enabling precise measurement and cross-time period comparisons while mitigating potential biases and distortions. Additionally, we introduce the concept of sentiment variations as a metric to assess the consistency of Twitter sentiments pertaining to Bitcoin. This enhancement to the sentiment analysis model is further elucidated within the context of EWOM, a well-established factor in impulsive purchasing and persuasive communication, extensively explored in previous research (Chang *et al.*, 2014; Shankar *et al.*, 2020). Lastly, we undertake a comparative analysis between the redesigned sentiment analysis model and the traditional model, which relies solely on compound sentiment scores. Our empirical findings demonstrate superior performance of the redesigned model.

The current study holds significant implications in the context of financial risk management, particularly concerning Bitcoin investments. By incorporating sentiment analysis techniques, this study gives insights into the dynamics of sentiment and its relationship to risk mitigation. This understanding of sentiment variations allows for a more comprehensive assessment of risk and potential market outcomes. Our research emphasizes the importance of considering sentiment analysis in financial risk management, as sentiment plays a crucial role in driving market trends. By integrating sentiment analysis, decision-makers can make more informed choices and develop effective risk mitigation strategies.

The structure of the remaining study is organized as follows: Section 2 critically examines the existing literature and provides a comprehensive review of prior research relevant to the topic. Section 3 outlines the methodology employed in this study. Section 4 presents and discusses the empirical findings derived from the analysis, providing detailed insights and interpretations. Section 5 concludes the study by summarizing the key findings, discussing their implications for policies and practices and proposing avenues for future research.

2. Literature review

Behavioral economists have posited that financial systems are not solely driven by objective factors such as capital value, but also by subjective elements such as emotional ethics (Wołk, 2020). Dolan and Edlin (2002) have advanced the argument that decision-making processes are significantly influenced by emotions, challenging the previous notion of rationality as the sole driver. Consequently, recognizing the significance of human emotions and sentiments becomes imperative, thereby underscoring the necessity for tools such as sentiment analysis. In situations where emotions play a significant role, implying sentiment analysis becomes crucial to attain a more profound understanding of individuals' emotional states and sentiments. Sentiment analysis identifies people's reactions and opinions expressed toward a particular topic by processing raw text (Rao *et al.*, 2020).

Twitter has emerged as a prevalent source of sentiment data, enabling analysis in various domains such as political discourse (Ilyas *et al.*, 2020), public discussion after a natural disaster (Wang and Zhuang, 2017), information dissemination in health crises (Van Lent *et al.*, 2017) and stock price prediction (Bollen and Mao, 2011). Among the notable applications of sentiment analysis on Twitter, the examination of Bitcoin-related sentiment stands out as a prominent use case.

Bitcoin, a widely recognized digital currency introduced by Nakamoto in 2008, has been a central focus of numerous research papers examining its price dynamics. Several researchers have dedicated their efforts to comprehending the factors influencing Bitcoin's price movements (Aggarwal *et al.*, 2020; Bouoiyour and Selmi, 2017; Nagula and Alexakis, 2022). Researchers have also investigated the effects of sentiments on Twitter on cryptocurrency prices, specifically Bitcoin (Georgoula *et al.*, 2015; Kraaijeveld and De Smedt, 2020). Pant *et al.* (2018) employed recurrent neural networks for this purpose, while Rather *et al.* (2015) utilized a combination of multiple linear regression and neural networks. Researchers have shown that twitter serves as a significant information source for predicting Bitcoin prices (Nie and Ji, 2014).

However, it is worth mentioning that the foundation of sentiment analysis lies in the model that generates sentiment scores from a given body of text. There are various models in use such as VADER, SentiWordNet and machine learning-oriented techniques relying on Naive Bayes and support vector machine (SVM) algorithms. Notably, in the existing academic disclosure, two distinct approaches to Twitter sentiment analysis models have been observed concerning the utilization of sentiment scores as predictors of Bitcoin price. These approaches can be categorized as: "Models employing only the compound sentiment score" and "Models based on the count of positive and negative tweets" which have been widely employed by the researchers. For instance, Abraham *et al.* (2018) adopted the former approach, wherein the average compound sentiment score of daily tweets was considered. In contrast, Pant *et al.* (2018) and Cakra and Trisedya (2015) pursued the latter strategy, relying on a simple count of positive and negative tweets per day. However, both approaches possess some limitations and inadequacies. For instance, by using a simple count of negative or positive tweets, we lose the opportunity to understand the varying effect of sentiments according to the degree of positivity or negativity in the text. For example, if only the count of positive and negative tweets are considered, then "Bitcoin is the best invention after the wheel" and "Bitcoin is good" will seem to have the same effect because both are positive, whereas we expect the former to be much more effective due to stronger sentiments.

On the other hand, using a single compound sentiment score may lead to the loss of valuable insights into the distinct impacts of positive and negative sentiments on Bitcoin's price. This occurs because both effects are amalgamated into a singular coefficient within the composite sentiment score. This observation is supported by research papers that have examined separate counts for positive and negative tweets, revealing significant disparities in the influence of positive and negative sentiments. For instance, Tetlock (2007) focused on the pessimism conveyed in articles, rather than optimism or positivity, to forecast stock prices. Pant *et al.* (2018) discovered a more substantial correlation (0.41) between negative sentiments and price declines compared to positive sentiments and price increases (0.26). Additionally, Cakra and Trisedya (2015) reported similar findings. This divergence in the impact of positive and negative tweets can be attributed to a widely recognized phenomenon in behavioral economics called loss aversion (Kahneman and Tversky, 2013). The idea of loss aversion is well-documented and has been utilized frequently in behavioral finance (Barberis *et al.*, 2001; Berkelaar *et al.*, 2004; Roger, 2003).

To address this issue, it is advisable to incorporate a more nuanced approach to sentiment analysis by using separate continuous scores for positive and negative sentiments, as generated by models such as VADER. VADER was specifically developed for analyzing sentiments expressed on social media, but its applicability extends to several types of text data (Hutto and Gilbert, 2014). Notably, VADER has been widely adopted in academic literature, including studies by Wołk (2020) for short-term cryptocurrency price prediction, Abraham *et al.* (2018) for cryptocurrency price prediction and Ilyas *et al.* (2020) for the analysis of Twitter discussions related to Brexit.

Nevertheless, it is noteworthy that a crucial question, which has not been sufficiently addressed in previous Twitter sentiment analysis models, concerns the use of polarity scores without considering the cultural, social and economic context of the given period. For instance, when VADER assigns a text a compound sentiment score of 0.4, should we simply adopt this value without assessing its appropriateness in the real-world context? This inquiry carries substantial importance as it challenges a foundational assumption in the realm of Twitter sentiment analysis. The existing literature on Twitter sentiment analysis has implicitly assumed that scores provided by models, such as VADER should be applied without rigorous further examination. Within the framework of prospect theory, this assumption may be unwarranted. Prospect theory suggests that gains and losses should be assessed relative to a reference point, which could be one's current asset position, aspirations, or the status quo, referred to as the status quo effect (Kahneman and Tversky, 2013). Applying this concept to sentiments, we should also consider measuring shifts in sentiment in relation to a status quo when seeking to establish a connection between sentiments and Bitcoin's price. Consequently, the question of how to effectively incorporate sentiment scores generated by VADER into a sentiment analysis model becomes increasingly pertinent.

Another notable gap in prior studies is the absence of sentiment variation integration into existing models within the literature concerning Bitcoin price prediction through Twitter sentiment analysis. The rationale for introducing this variable stem from the notion that even when average sentiment scores are identical in two scenarios, the impact may differ depending on sentiment consistency. This concept is more comprehensively explored in the realm of word-of-mouth communication. Several studies have underscored the significance of consistency in electronic word of mouth for achieving desired outcomes, such as increased purchases or enhanced persuasion (Shankar *et al.*, 2020). Considering these findings, sentiment variation can be construed as a proxy for the consistency of word of mouth on Twitter. Consequently, to account for the effects of sentiment consistency and word of mouth, we have integrated sentiment variation into our model. Thus, based on the aforementioned academic considerations, we formulate the following hypotheses.

H1. Does the adoption of separate scores for positive and negative sentiment scores enhance the performance of Twitter sentiment analysis models?

H2. Can incorporating variations in sentiment analysis improve the effectiveness of Twitter sentiment analysis models?

H3. Do normalizing average sentiments and sentiment variations in sentiment analysis lead to improved results in Twitter sentiment analysis models?

3. Econometric methodology

3.1 Data collection

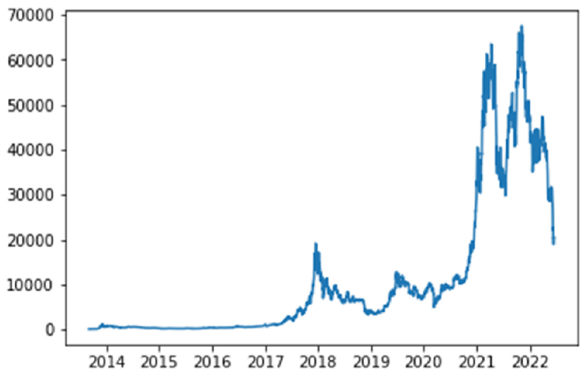
To achieve the intended study objectives, we curated a dataset consisting of 3,215,000 tweets. This dataset spans from September 1, 2013, to June 27, 2022, covering a total duration of 3,215 days, with an average of 1,000 tweets per day. We chose this period for our analysis because it effectively spans the entire history of Bitcoin. While Bitcoin was launched in 2009, it is important to note that initially, the digital asset had no assigned price and was not accessible for purchase on exchanges.

The tweets for this study were identified by utilizing the "bitcoin" and/or "btc" keywords through the snscrape python library [1]. Unlike some previous studies (Pant *et al.*, 2018), we did not restrict our tweet collection to specific Twitter accounts, as this approach might have yielded a dataset that did not adequately represent broader Twitter population. We aimed for a more comprehensive and representative dataset. Additionally, we gathered data on the exchange rate between Bitcoin and USD for the same time period [2] from Binance exchange. This Bitcoin USD price comparison is shown in Figure 1.

3.2 Data cleaning

The tweets were subsequently processed to eliminate hashtags, mentions and https links, following a similar method as employed by (Abraham *et al.*, 2018). This process led to the identification of a few empty tweets, which were consequently excluded from our dataset. We emphasize that the treatment of neutral tweets differed from that of positive and negative tweets in prior literature. For instance, Cakra and Trisedya (2015) chose to delete neutral tweets before conducting sentiment analysis. However, neutral tweets, although devoid of explicit sentiment, can still play a role in disseminating information about Bitcoin, potentially influencing price dynamics. Thus, it becomes imperative to include neutral tweets in our analysis and assess how the dissemination of information through these tweets impacts Bitcoin prices. Moreover, when we separately consider positive and negative sentiments, we inadvertently account for the influence of neutral tweets as well. This aspect will be further explored in the discussion section of this paper.

Lastly, the snscrape tool provides a wealth of metadata for each tweet, yet for the purposes of this research, we only needed the date and the content of the tweet. Consequently, all other extraneous information was discarded. Additionally, it is essential to note that collecting user IDs and names would raise ethical concerns, as individuals posting tweets may not have anticipated their personal information being used in such analyses (Abraham *et al.*, 2018).



Source(s): Author's own creation

Figure 1. Bitcoin to USD exchange rate trend from September 1, 2013, to June 27, 2022

Therefore, we made a conscious decision not to collect names and user IDs during the data gathering process.

3.3 Data pre-processing

After cleaning the data, we converted the text to lowercase to ensure that the model does not treat words with different cases as distinct. Subsequently, stop words, such as "a," "her," and "his," along with punctuation marks, were eliminated using NLTK's corpus of stop words. Following this, the text underwent tokenization, which involves breaking it into sentences and then further into words. This process was succeeded by lemmatization, wherein third-person words were transformed into first person and future tenses were converted to present tense. This text preprocessing not only enhances the clarity of our data but also reduces the computational complexity of our models.

3.4 VADER polarity scores

After completing the data cleaning process, we utilized VADER to generate sentiment analysis scores for each cleaned individual tweet. VADER is a rule-based model developed using a dataset of texts that were assessed for sentiments by ten independent human raters, all of whom were pre-screened, trained and rigorously quality-checked to ensure optimal inter-rater reliability. VADER delivers four numerical outputs, ranging from 0 to 1 to quantify neutral, positive and negative sentiments, and it provides a scale from -1 to $+1$ for the compound sentiment (Hutto and Gilbert, 2014).

Given that VADER is designed to handle short texts, it is essential to tokenize the tweets into smaller sentences before conducting sentiment analysis to prevent the generation of misleading sentiment values. This practice aligns with industry standards, and several research papers have adopted a similar tokenization approach (Zaman *et al.*, 2022; Cakra and Trisedya, 2015; Katayama *et al.*, 2019). Finally, the overall sentiment of each tweet is determined by computing the average sentiment score of the individual sentences that compose the tweet.

4. Empirical results

4.1 Exploratory data analysis

After conducting sentiment analysis, we proceeded to group the dataset by days to calculate several daily metrics, including the daily average positive and negative sentiment scores, as well as the daily variance in positive and negative sentiment scores. In total, this process yielded four (4) variables. The distribution of compound sentiment is illustrated in Figure 2, displaying a unimodal smooth curve, as observed by Abraham *et al.* (2018) and Katayama *et al.* (2019). Both studies observed that the majority of tweets typically express a neutral sentiment and occurrences of negative values are relatively rare. From the results of Figure 3, it becomes evident that the average negative score is notably lower than the average positive score. This suggests that, on average, Twitter tends to express a more optimistic sentiment towards Bitcoin rather than a critical one. It's also worth noting the spread of the two curves in Figure 3 and the daily variance observed in the two daily averages shown in Figure 4, positive sentiment scores exhibit a broader distribution compared to negative sentiments. This implies that while Twitter may not frequently criticize Bitcoin, when it does, the criticism tends to be more consistent than the praise.

Finally, all four variables were normalized, and the data were divided into training and testing sets. The testing set comprises of 20% randomly selected data points from the original dataset.

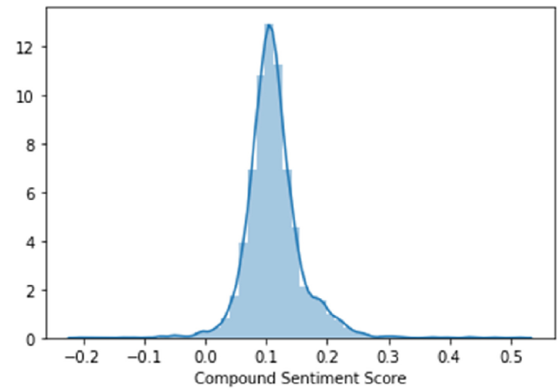


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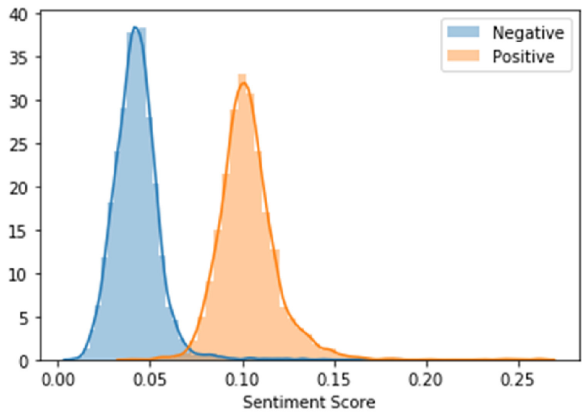
Figure 2. Histogram depicting compound sentiment scores reveals that the majority of tweets express a positive sentiment



Source(s): Author's own creation

Figure 3. Histogram of daily average of positive and negative sentiment scores of tweets

4.2 Logistic regression model

A multitude of researchers have employed linear regression for predicting Bitcoin prices through Twitter sentiment analysis (Skuza and Romanowski, 2015). However, this approach presents two significant issues. Firstly, if the predicted variable (Bitcoin price) lacks stationarity, the regression results can be unreliable. Secondly, even when ignoring the stationarity of Bitcoin prices, creating a model to predict the precise Bitcoin price is both academically and practically unnecessary (Noriega and Ventosa-Santaulària, 2007). Considering these factors, a more practical and theoretically sound alternative is to utilize a logistic regression model for predicting the direction of Bitcoin price movement – whether it will rise or fall – rather than attempting to predict a non-stationary price time series. Therefore, the present study has adopted the use of a logistic linear regression model, which has entailed transforming the continuous time series data of Bitcoin prices into a binary categorical variable representing rises and falls. The distribution of these rises and falls in the Bitcoin-USD exchange rate is depicted in Figure 5. Notably, it's worth acknowledging that the dataset is not perfectly balanced, with the Bitcoin-USD exchange rate experiencing increases 52.8% of the time.

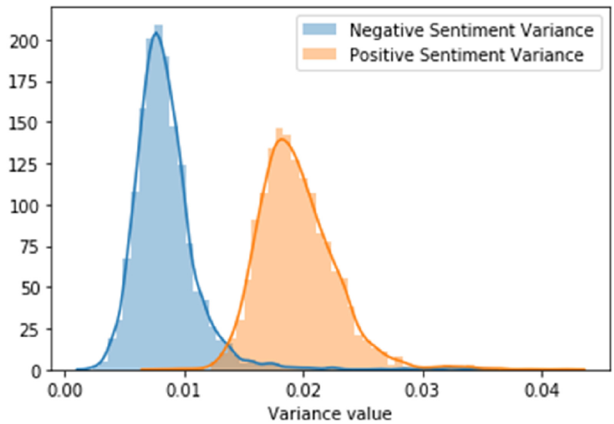


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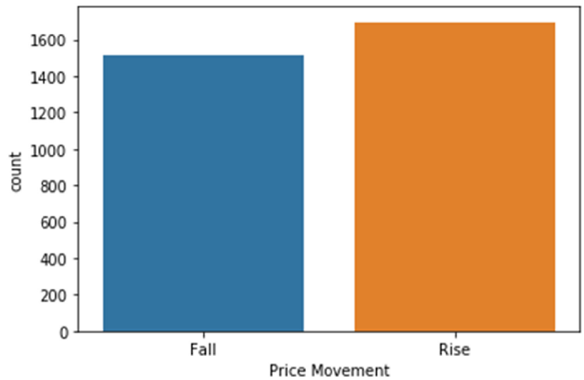
Figure 4. Histogram of daily variance in positive and negative sentiment scores of tweets



Source(s): Author's own creation

Figure 5. Distribution of rises and falls of Bitcoin-USD exchange rate

The logistic regression has bitcoin price movement as predicted variable and normalized positive and negative sentiment scores, normalized variance in positive and negative sentiment score as predictor variables. The final logistic regression equation for our proposed model is as follow:

$$probabilty\ of\ rise = \frac{1}{1+e^{-x}}$$

$$\begin{aligned} x = a &+ b(normalized\ postive\ score) + c(normalized\ negative\ score) \\ &+ d(normalized\ variance\ in\ postive\ score) + e(normalized\ variance\ in\ negative\ score) \end{aligned}$$

This model will be compared against the most commonly used model, using only the compound sentiment score. The logistic regression equation for this commonly used model is as follows:

$$probabilty\ of\ rise = \frac{1}{1 + e^{-(constant + a*compound\ sentiment\ socre)}}$$

To comprehensively assess and compare model performances, it is imperative to establish key definitions upfront. Our evaluation metrics encompass training accuracy, testing accuracy, weighted average F1 score, weighted average precision and weighted average recall, which collectively enable effective evaluation. Training accuracy evaluates how well the model classifies price movements during training on familiar data, while testing accuracy assesses its performance on unseen data. Recall measures the model's ability to identify relevant cases in a dataset, while precision gauges its capability to accurately identify pertinent data points. Weighted average recall and precision account for sample imbalances in different label categories provide a balanced assessment.

The sentiment analysis model using a single variable of compound sentiment score, which is the most often used mathematical model, has a training accuracy of 54%, a testing accuracy was just 51% and a small weighted F1 score of 0.36. Note that about 52.8% of the price movement is rising, hence the testing accuracy of traditional method is worse than random prediction. No considerable difference was seen in the performance of the model by, first, replacing compound sentiment scores with normalized compound sentiment score and then by separate positive and negative sentiment scores. But there is a considerable jump in the testing accuracy and F1 score of models with predictor variables as normalized positive and negative sentiment scores. The results are summarized in Table 1.

In Table 2, we have compiled the constant and coefficient values for the final model. The interpretation of these values will be elaborated upon in the following section.

Our findings reveal a smaller coefficient (0.0225) for positive sentiments in comparison to negative sentiments (0.3029). This suggests that positive tweets may not be as influential as negative ones, or it points to a stronger correlation between negative sentiments and price declines, contrasting with the weaker association between positive sentiments and price increases. This observation aligns with (Pant *et al.*, 2018), where they reported a higher

Number of variables	Independent variables	Training accuracy (%)	Testing accuracy (%)	Weighted average precision	Weighted average recall	Weighted average F1-score
1	Compound Sentiment Score	54.55	51.32	0.75	0.51	0.36
1	Normalized Compound Sentiment Score	53.83	51.47	0.61	0.51	0.37
2	Positive and negative sentiment scores	53.36	50.69	0.75	0.51	0.34
2	Normalized positive and negative sentiments scores	54.99	55.36	0.60	0.55	0.49
4	Normalized positive and negative sentiment scores and normalized variance in positive and negative sentiment scores	55.15	55.21	0.59	0.55	0.50

Source(s): Authors' own creation

Table 1. Performance matrices of models

correlation (0.41) between negative sentiments and price drops compared to the correlation (0.26) between positive sentiments and price gains. Additionally, Cakra and Trisedya (2015) found that an increase in the percentage of positive tweets resulted in a decreased R2 value in their model, further supporting the notion that negative sentiments play a more significant role in driving down Bitcoin prices.

Furthermore, it is important to note that the coefficient value for variance in positive sentiment scores is negative (−0.0462), while the coefficient for variance in negative sentiment scores is positive (0.1663). This implies that greater variation in positive sentiment scores reduces the likelihood of price increases, whereas greater variation in negative sentiment scores increases the likelihood of price appreciation. This underscores the importance of consistency in tweets' sentiment patterns. Variations in sentiment, in conjunction with the actual sentiment values, can be interpreted as a proxy for trust or word-of-mouth sentiment, reflecting how the general population perceives Bitcoin. When sentiments are consistently positive with low variation, it indicates trust or positive word of mouth, signifying a consensus among the population regarding Bitcoin's favorability. Conversely, when sentiments are consistently negative with low variation, it signals mistrust or negative word of mouth, reflecting a consensus on Bitcoin's unfavorable perception. Higher variation values indicate confusion or mixed opinions, denoting a lack of consensus in sentiment, which carries its own implications.

During the data pre-processing phase, we noted a distinction between the patterns of daily positive and negative sentiment scores, as well as in the distribution of daily variance in positive and negative sentiment scores. However, this disparity vanishes when we normalize the data, as depicted in Figures 6 and 7. After normalization, the distinctions in the distributions become inconsequential. In our model's context, sentiment is evaluated relative

Table 2.
Results of the final model

Constant	Normalized positive sentiment scores	Normalized negative sentiment scores	Normalized variance of positive sentiment scores	Normalized variance of negative sentiment scores
0.1341	0.0225	−0.3029	−0.0462	0.1663

Source(s): Authors' own creation

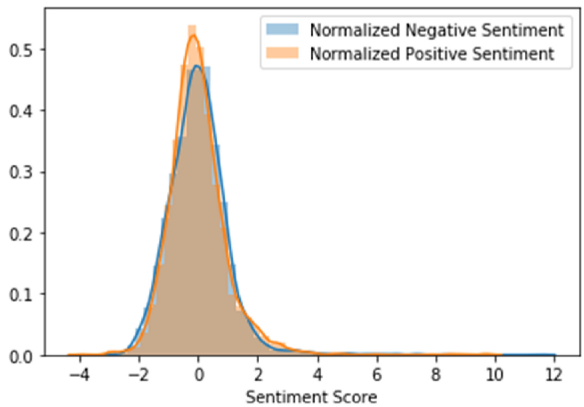
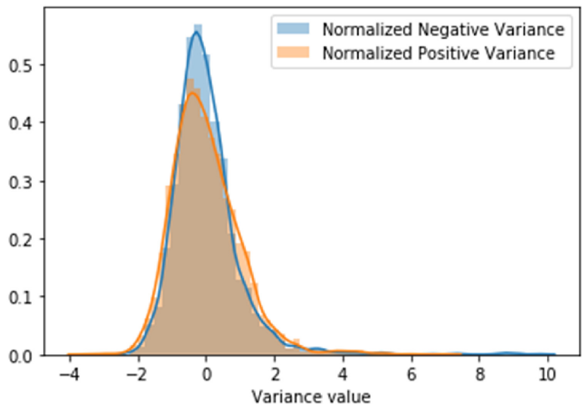


Figure 6.
Normalized sentiment scores

Source(s): Author's own creation



Source(s): Author's own creation

Figure 7.
Normalized variances

to the status quo, which we assume to be the average in this study. Consequently, the absolute value of daily positive sentiments being higher or the absolute variance (indicating inconsistency) of negative sentiments being lower becomes irrelevant. What holds significance is their relative value and we observe that there is no discrepancy between the two concerning their relative value.

In our model, the constant term also bears significant importance. It represents a scenario where all variables are set to zero, indicating that they are at their expected or status quo values. This suggests that even in scenarios where there is no active Twitter discussion about Bitcoin, or when predominantly neutral tweets are prevalent, as observed per Abraham *et al.* (2018), there still exists a 53.34% likelihood of Bitcoin price increasing. This closely aligns with the proportion of data points corresponding to rising Bitcoin prices in our dataset (52.8%). Therefore, it's plausible that the constant merely signifies the baseline expectation for Bitcoin price movement, irrespective of Twitter sentiment. Another interpretation of the constant's value is that it reflects Twitter's capability to disseminate information effectively. This, in turn, stimulates greater participation in the Bitcoin market and contributes to price increases.

In conclusion, although the model does not provide an exceptional accuracy, something that has been noted by literature on sentiment analysis and Bitcoin price such as Abraham *et al.* (2018), the model proves to be better than traditionally used models on the same dataset and provides a novel and better perspective into the relationship between sentiments and Bitcoin price. The model demonstrates that there is an asymmetry between the effects of positive and negative sentiments, providing an example of loss aversion as described by Kahneman and Tversky (2013), and aligning with the findings of previous literature on this topic which also dealt with positive and negative sentiments separately such as Pant *et al.* (2018) and Cakra and Trisedya (2015). Furthermore, the model also demonstrates that variation in sentiments dampens its effect something which has been discussed widely in literature related to EWOM such as Chang *et al.* (2014) and Shankar *et al.* (2020). Lastly, the model demonstrates that normalizing the variables considerably improves the results of the model and provides a clear demonstration of the status quo effect of the prospect theory proposed by Kahneman and Tversky (2013).

5. Conclusion, policy implications and future research avenues

This study takes a unique and noteworthy approach by carefully reassessing models used for sentiment analysis in the context of financial risk management. We propose an alternative framework that combines prospect theory and the fundamental principles of EWOM to predict Bitcoin price changes through Twitter sentiment analysis. Our approach differs from traditional methods by incorporating separate positive and negative sentiment scores, moving away from the reliance on a single compound score.

Our findings highlight the divergent effects of positive and negative sentiments on Bitcoin's price movements. Specifically, we observe that negative sentiments exert a significantly greater impact than positive sentiments. This suggests that the sentiment expressed in social media and other channels can have a substantial influence on the market perception and subsequent pricing of Bitcoin. Furthermore, our study establishes the significance of sentiment fluctuations as a mechanism that can counteract the impacts of both positive and negative sentiments, thereby assuming a central role in either amplifying or dampening the likelihood of Bitcoin price appreciation. Our study provides valuable insights for financial risk management, enabling financial institutions and investors to make more informed decisions, anticipate potential price fluctuations and develop tailored risk mitigation strategies.

It's important to note that this study introduces an innovative sentiment analysis framework. By breaking down sentiment into distinct positive and negative components, our research not only advances our comprehension of market sentiment dynamics but also provides financial institutions and investors with a more detailed and actionable insight into the risks tied to Bitcoin and potentially other assets affected by sentiment-driven market forces. The revelation that negatives sentiments exert a notably greater impact on Bitcoin's price movements than positive sentiments carry profound implications for risk assessment and mitigation strategies. This knowledge empowers risk managers and investors to gauge and respond to market sentiment shifts, enhancing their ability to anticipate and prepare for potential price fluctuations more effectively. Furthermore, by including the effects of variations in sentiments, the study equips risk managers and investors with a tool to tackle the most common obstacle in predicting the price of sentiment-driven assets, high levels of variations in sentiments. Lastly, the study serves to be a bridge between risk management and behavioral economics as it predominantly builds on literature from behavioral economics. Equipping financial institutions and investors with knowledge of behavioral economics can help them understand the market from a novel perspective and hence enable them to make better decisions in the face of high uncertainty. However, notwithstanding the considerable advancements made by the present study in the realm of sentiment analysis within financial risk management, it remains subject to some limitations which warrant further investigation and open avenues for further exploration. First and foremost, the study's primary focus on English-speaking Twitter users may inadvertently neglect the sentiments of non-English speakers and individuals with limited Twitter engagement. This narrow scope potentially provides an incomplete perspective on the impact of sentiments on Bitcoin prices within the context of financial risk management. Secondly, the current study does not incorporate geographical data into its sentiment analysis, overlooking a crucial aspect of understanding regional sentiment variations and their relevance to financial risk assessment. It is essential for future research to address this geographical dimension comprehensively. Thirdly, the descriptive nature of the model employed in this study prevents it from predicting price changes. This limitation stems from its reliance on historical averages of sentiments and retrospective variations. To enhance risk management strategies, upcoming studies should explore predictive models that integrate real-time sentiment data. Lastly, the analysis primarily focuses on long-term trends, leaving short-term dynamics unexplored. Given the potential for sentiment dynamics to behave differently on shorter time scales, it is imperative that further research investigates the applicability of sentiment analysis at daily or hourly intervals. This will provide a more comprehensive understanding of sentiment-driven dynamics in cryptocurrency markets and its implications for effective financial risk management.

Notes

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2. www.cryptodatadownload.com/data/binance/

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