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Morteza Namvar
The University of Queensland, m.namvar@business.uq.edu.au

Jingqi Li
The University of Queensland, jingqi.li@uq.net.au

James Boyce
KPMG australia, jboyce1@kpmg.com.au

Saeed Akhlaghpour
The University of Queensland, s.akhlaghpour@business.uq.edu.au

Marta Indulska
The University of Queensland, m.indulska@business.uq.edu.au

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Research in progress

Morteza Namvar
Business School
The University of Queensland
Brisbane, Australia
Email: m.namvar@business.uq.edu.au

Jingqi Li
Business School
The University of Queensland
Brisbane, Australia
Email: jingqi.li@uq.net.au

James Boyce
KPMG Australia
Brisbane, Australia
Email: jboyce1@kpmg.com.au

Saeed Akhlaghpour
Business School
The University of Queensland
Brisbane, Australia
Email: s.akhlaghpour@business.uq.edu.au

Marta Indulska
Business School
The University of Queensland
Brisbane, Australia
Email: m.indulska@business.uq.edu.au

Abstract

Scholars and practitioners increasingly recognise the importance of microblogs in capturing electronic Word of Mouth (eWoM) and their predictive power for cryptocurrency markets. This research-in-progress paper examines the extent to which microblog messages are related to bitcoin fluctuation. Drawing from information systems and finance literature, we examine the interactions between influencers' extreme sentiment and the bitcoin fluctuation using natural language processing techniques and hypothesis testing. Our preliminary results show when influencers express extreme sentiment, in favour or against bitcoin, it is less likely that their tweets are related to future bitcoin fluctuation. However, when their extreme tweets are in-depth and unique, this negative relationship is moderated. Overall, our findings reveal that influencers' sentiment is an important factor in understanding bitcoin fluctuation, but not all tweets are of equal impact. This study offers new insights into social media and its role in the cryptocurrency market.

Keywords cryptocurrency, bitcoin, microblogs, influencers, extreme sentiment.

1 Introduction

Bitcoin, the most well-known cryptocurrency, has attracted a great deal of interest in recent years due to its growing price and the advancement in the blockchain technology (Li & Wang, 2017). Bitcoin price peaked at more than USD 68,000 in 2021, though it experienced fluctuations and reductions in 2022. Along with bitcoin's growing popularity comes a perplexing dilemma with no obvious answer: What factors influence its value? Whilst financial research tries to explain and predict the movement of bitcoin price using multiple economic factors, due to its unique nature, such as high volatility (compared to the traditional stock market), bitcoin fluctuation remains an unclear but fascinating phenomenon to explore further.

With the emergence and popularity of social media, the power of e-word-of-mouth has drawn much attention from investors and researchers interested in the price fluctuations of assets and stocks. It has been demonstrated that a vicious cycle of word-of-mouth can cause historical underperformance in stock prices to produce more damaging future speculation (Luo 2009). As we all know, widespread negative customer experiences can have a negative impact on a company's reputation and brand equity. Negative word-of-mouth can amplify the spread of negative customer experiences, leading to even more volatile and unstable company cash flow and stock prices. Researchers quantified several socio-economic signals about bitcoin from an extensive dataset and found that the volume of word-of-mouth is a driver of bitcoin price bubbles (e.g., Garcia et al. 2014). Indeed, the bitcoin economy's fixed supply and predictable scarcity are both independent of the user base, which makes a strong connection between public interest, user uptake, and pricing.

Social media literature shows various indicators that hold the predictive power of stock value. Social media content, as a prominent form of big data and a typical representative of e-word-of-mouth, is considered the most significant data source for the public opinion (Yu et al. 2013). Using social media's "crowd wisdom" to forecast social, political, and economic events has become an increasingly promising phenomenon (Deng et al., 2018). Following this trend, researchers bring social media content into play to gain more knowledge of the financial market, such as the bitcoin economy. One specific type of information extracted from social media, sentiment, is found to be an essential feature. Some past research has explored the interconnectedness of sentiment of social media messages and the bitcoin price. For example, Li et al. (2018) investigated the extent to which microblog messages (e.g., tweets) can be linked to financial market indicators and concluded that the sentiment of messages is influenced by daily abnormal stock returns. Despite recent attempts to forecast stock returns using social media sentiment, conversations on the subject are fragmented, and the findings are inconsistent (Deng et al., 2018).

One possible reason for this inconsistency is the quality of the social media content used for the study. Indeed, not everything expressed on social media has an equivalent value. Extant research mostly ignores the underlying impact that different types of users themselves may bring to the study. While some professional forums are updated once or twice a week by a limited number of professional publishers, microblogs are continuously updated in real-time by a larger demographic of users (Deng et al., 2018). Arguably, the impact of the content posted by microblog users is partly shaped by their own popularity and influence. Specifically, a professional financial netizen who posted a message about the bitcoin market will undoubtedly have stirred up a higher wave than an ordinary microblog user. The non-negligible role that different users bring to the impact of social media messages, has been largely overlooked.

Therefore, the objective of our research is to investigate the factors embedded in social media data that are related to bitcoin fluctuation. We examine the following research question: How do factors embedded in influencers' tweets relate to bitcoin fluctuations?

To answer this question, we used natural language processing and machine learning techniques to identify publisher characteristics (e.g., reputation and experience) and text characteristics (e.g., length and uniqueness) to better investigate the impacts of eWoM (electronic word of mouth) on bitcoin price fluctuation. By doing so, we made a novel contribution by incorporating the effect of influencers, which has not addressed in this topic yet. The next section reviews the existing literature on tweet characteristics and influencers' features of how social media plays a role in bitcoin fluctuation. Then we present our conceptual model. We further elaborate on the method and preliminary results of the study. We conclude the paper by elaborating on future work that enhances this research in progress.

2 Background and conceptual model

In recent years, there has been an increase in social media studies using approaches such as opinion mining to extract and process unstructured data from microblogs. Following this trend, researchers and practitioners are increasingly relying on microblogs to capture the market discourse and predict financial movements. Stock microblogs provide a live conversation that updates quickly rather than archival content (Yu et al. 2013). Because of the more interactive live dialogue, investors who utilise stock microblogs are usually exposed to the most recent information about the stocks they follow (Li et al., 2018). The high visibility and information dissemination of microblogs make users more motivated to provide valuable information that affects and reflects financial fluctuation. While the benefits of social media (i.e., tweets) are glaring, they come with some shortages too. Microblog messages commonly include informal language, such as abbreviations, emoticons, and special characters (Li et al., 2012). Also, text on microblogs is often casual and short, and it may not always reflect the correct message. Given these difficulties in extracting useful social media information, researchers have tried to take into account the social influence of the users in addition to focusing on tweet text (Wang et al., 2019). For example, they have tried to include users' social relations to explain the influence of noisy and short texts (Hu et al. 2013), or utilise users' preferences to enhance the sentiment analysis (Ghiassi et al. 2016).

Our work is inspired by those attempts to enrich the value of tweet text and alleviate the limitations imposed by microblogs. To tackle the challenges and answer our research question, we aim to, first, investigate whether influencer sentiment, especially, their extreme sentiment, is related to bitcoin fluctuation. Second, we try to identify tweet characteristics to investigate the relationship between influencer extreme sentiment and bitcoin fluctuation. Figure 1 shows the conceptual model of our study. This model explores the relationship between tweet sentiment and bitcoin fluctuation. It proposes that the value of public opinion, expressed in tweet sentiments, can be moderated by tweet characteristics. Next, we elaborate on this model.

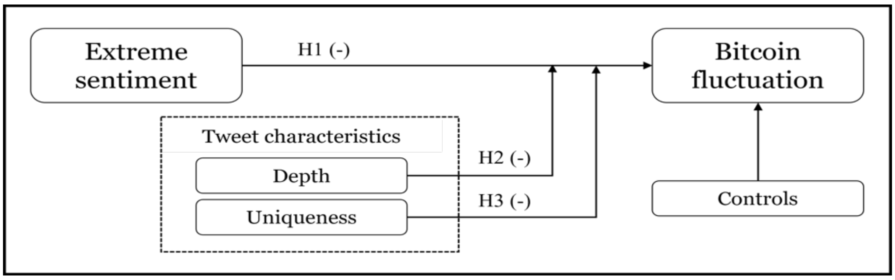

Figure 1: Research model

The investors' sentiment is becoming increasingly visible online thanks to the public's frenzied interest in bitcoin and the investors' obsession with social media (Mai et al. 2018). Prior studies have shown that the emotions of market participants could drive stock fluctuation (e.g., Sun et al. 2020). As bitcoin is very similar to stocks, these findings lead us to the idea that social media sentiment, which reflects public opinion and voice at a high velocity with a large volume, may impact bitcoin price changes.

Various forms of research have investigated the interaction between social media sentiment and stock return with varying foci. Bollen et al. (2011) were among the first to explore whether the Dow Jones Industrial Average's (DJIA) value is associated with the collective mood states derived from large-scale Twitter feeds. They found that adding particular public mood characteristics that measure the sentiment in terms of positive, negative and other six dimensions (calm, alert, sure, vital, kind, and happy) can increase the accuracy of DJIA predictions. Information Systems scholars include Deng et al. (2018), who were one of the first to have examined the association between microblog sentiment and stock return using 18 million microblog messages and discovered that the impact of microblog sentiment on stock return is statistically and economically significant at the hour level. Mai et al. (2018) study the interactions between social media and bitcoin value and show that more bullish posts are linked to increased bitcoin prices in the future. Using text analysis and vector error correlation models (VECM), their results indicate that the social media metrics account for a significant portion of future variations of bitcoin value. In addition, they empirically examined the heterogeneous effects of users by distinguishing the vocal majority and the silent majority and concluded that social media's effect on bitcoin is significantly driven by the majority of inactive users. Xie et al. (2020) posit the existence of noise in social media and explore the role of network cohesion in the relationship between sentiment and bitcoin price changes. As per their findings, investors' sentiments on social media play a significant role in determining bitcoin price fluctuations. However, despite the investigation of the relationship between social media sentiment and stocks, extant research did not address the mechanism of how different social media users' sentiment interact with the bitcoin price.

When tweets related to bitcoin are trending on social media platforms, users and investors can respond to bitcoin market signals in near real-time. These reactions, reflecting investors' mindsets, are then recorded by tweet sentiment. Through this process, bitcoin's demand through eWoM and daily price changes in its market sentiments are factored into the bitcoin price-formation process, further influencing future returns.

Influencers' sentiment is more important than normal users' and can play a more significant role in the bitcoin fluctuations. Not all users provide equal value, and the depth of their content varies (Trusov et al., 2010). Extant literature has shown that if microblog posts are given a larger share of voice based on the social influence of the users, the impact of the tweet and the association between social media sentiment and abnormal returns are much more amplified (Li et al., 2018). Indeed, when influencers post tweets, their sentiment is more related to bitcoin fluctuation, as such tweet messages tend to be more revealing and appealing to other users, influencing the decision-making of other market participants. Hence, the impact of tweets is enhanced by the influencers' own influence.

Compared to ordinary users, more experienced influencers are more cautious in their tweets as they are more aware of the complexities of the bitcoin market. They provide fewer negative or positive comments on social media. They try to stay neutral, mention pros and cons, note the news and provide a fair comparison. The way they act is in contradiction to the ordinary users who try to take a strong side to either fully agree or disagree with the bitcoin market and its future. It seems that inexperienced influencers provide extreme sentiments; therefore, their extreme sentiments are not trustworthy in bitcoin market prediction. Suppose an influencer tweet reveals an overly positive or negative sentiment towards the bitcoin market. In that case, one can assume such an opinion is simply motivated by excessive optimism or negativism. Moreover, the message of extreme sentiment may suggest self-interest from the influencer instead of a reasonable argument from reality. Therefore, if a tweet expresses absolute unconditional favour and confidence in the bitcoin market, we typically question the message's credibility and the influencer's intention. Conversely, suppose a tweet posted by an influencer does not show an extreme sentiment. In that case, the content expressed in the tweet tends to be more trustworthy and is more likely to affect bitcoin prices. Based on the above analyses, extreme influencer sentiment is expected to negatively relate to bitcoin fluctuation. Therefore, we propose that:

Hypothesis 1. The influencer's extreme sentiment is negatively related to bitcoin fluctuation.

We propose two moderators and mention their moderating effects on influencers' extreme sentiment and bitcoin fluctuation. Several studies have discussed factors, such as document length, as an indicator of in-depth social media content (e.g., Namvar, 2020; Namvar and Chua, 2022). It is reasonable to assume that when a tweet has more depth, it has more potential to include more valuable information too. More in-depth tweets from the influencers indicate they tend to be very expressive about bitcoin and have published the tweet after careful consideration. In this case, even if they show extreme sentiment towards the bitcoin market, due to the depth of the tweet, it can be a better signal for market prediction. Consequently, the extreme sentiment expressed in their tweet can be more acceptable and is less likely to be categorised as irrational personal emotions of the influencer. Conversely, though showing an extreme sentiment, when a tweet posted by influencers is less in-depth, it is likely to reflect little reality about the current state of the bitcoin market and more of a personal outpouring of emotion from the influencer. Therefore, we propose:

Hypothesis 2. The negative relationship between influencers' extreme sentiment and bitcoin fluctuation will weaken when the tweet is more in-depth.

The tweets' uniqueness shows influencers' effort to provide original statements carrying unseen information. A unique tweet has a better chance of standing out and being heard since people tend to believe the author has published it after careful reflection and dialectical analysis. Besides, it is reasonable to assume that people are more inclined to trust a unique tweet since it is less likely to be influenced by others' emotions. We, therefore, expect uniqueness to play a moderating role in the relationship between extreme influencer sentiment and bitcoin fluctuation. We believe uniqueness somewhat excludes the potential of the influencer's ideas following the current popular opinion about bitcoin and reflects the outcome of their independent thinking. Hence, even if a tweet posted by an influencer shows an extreme sentiment, it is less likely to be negatively related to bitcoin if it shows uniqueness. Therefore, we propose:

Hypothesis 3. The negative relationship between influencers' extreme sentiment and bitcoin fluctuation will weaken when the tweet is unique.

3 Method

Our collected bitcoin data[1] provided hourly data in an OHLC (Open/High/Low/Close) pricing format. The data provided hourly bitcoin prices from May 2018 to Aug 2022 and was stored in a dictionary <key: value> pair with the key being the date and hour and the value being the respective bitcoin price. We also collected Twitter data[2] containing hashtags #btc or #Bitcoin, resulting in 4,012,401 corresponding tweets. The data provided tweet text along with information on the user (e.g., the number of followers and description). We limited our analysis to date, with the earliest tweet date being in January 2022, resulting in 437,934 tweets.

To operationalise our target variable, bitcoin fluctuation, we applied the following steps. We converted the tweet posted date to a DateTime format to the most current hour. This way, we ensured the correct key and value pair for the bitcoin data dictionary could be matched to a specific tweet. As the bitcoin price can vary rapidly and the frequency of the bitcoin dataset was only hourly, we developed a method to provide a more stable analysis by looking specifically at the time a tweet was posted in an hour interval. We applied a quarter-hour foundation to the tweet posted date. For example, a tweet posted in the first quarter of a specific hour (0-15 minutes) was classified as Q1. Q2 and Q3 were the next 15-minute intervals, and Q4 was the final 15 minutes of an hour. Splitting the hour into quarters allowed us to segment how we handled selecting a bitcoin price to extract from the dictionary. Tweets posted within Q1 may be assumed to relate to the bitcoin price from the hour before, and similarly, a tweet made in the final 15 minutes relates to the price in the following hour. Tweets made in Q2 or Q3 were associated with the price of the current hour they were posted in. To operationalise bitcoin flection, we considered the next 24 hours after the tweet was posted. We calculated the standard deviation of high prices in the next 24 hours. We also calculated the low prices in the next 24 hours. We used the sum of these two deviations as the bitcoin fluctuation.

The sentiment is about the attitude, thought, or judgement expressed in online reviews (Hong et al. 2017). Using the textblob package in Python, we predicted the polarity score. We then used power two of polarity to develop a variable indicating the extreme sentiment. In this way, both extremely negative and positive tweets would be considered as extreme sentiment. Using the textstat library in Python, we calculated tweet complexity and hence its depth. Finally, to develop the index for tweet uniqueness, we multiplied the number of unique words used in a tweet and the average length of their words and then divided them by the tweet length. To demonstrate the robustness of our observations, our proposed research model also considers two control variables, namely, influencers' reputation and experience. We calculated influencers' reputation by measuring the number of their favourites and calculated their experience by the number of days they have been active on Twitter. We then applied Tobit regression to test our proposed hypothesis.

4 Preliminary results

First, we ran a correlation analysis. The highest correlation is between reputation and experience, which stands at 0.17. As our analysis did not indicate any high correlation, there was no need to remove any variables. We developed three models. Model 0 is the base model containing the control variables. Results indicate that tweets from more popular and experienced influencers are less related to bitcoin fluctuation. This can be due to the fact that experienced users understand the uncertainty in the market and they make tweets in highly uncertain times. Model 1 relates to the direct relationship between influencers' extreme sentiment with bitcoin fluctuation and other variables as controls. Model 2 adds the moderating impacts of tweet depth and uniqueness.

Hypothesis 1 postulates that influencers' extreme sentiment negatively relates to bitcoin fluctuation. The results in Model 1 reveal that the coefficient for extreme sentiment is negatively significant (coefficient = -1.92e-02, $p < 0.001$). Therefore, Hypothesis 1 is supported. Hypothesis 2 posits that tweet depth weakens the negative relationship between influencers' extreme sentiment and bitcoin fluctuation. The results in Model 2 indicate a negatively significant coefficient (coefficient = -3.39e-03, $p < 0.01$) for the interaction between tweet depth and influencers' extreme sentiment. Hypothesis 3 proposes that tweet uniqueness weakens the negative relationship between influencers' extreme sentiment and bitcoin fluctuation. The results in Model 2 suggest that the coefficient for the interaction between influencers' extreme sentiment and tweet uniqueness is positive (coefficient = 3.02e-02, $p < 0.001$).

[1] Source: https://www.cryptodatadownload.com/data/bitstamp/
[2] Source: https://www.kaggle.com/datasets/kaushiksuresh147/bitcoin-tweets

		Model 0	Model 1	Model 2
	Reputation	-1.07e-07 *** (1.95-08)	-1.11e-07*** (2.95e-03)	-1.10e-07***(1.95e-08)
	Experience	-5.21e-06 *** (5.00e-07)	-5.56e-06*** (1.95e-08)	-5.58e-06***(5.06e-07)
H1	Extreme sentiment		-1.92e-02*** (2.95e-03)	-1.65e-01*** (2.65e-02)
H2	Extreme sentiment * depth			-3.39e-03** (9.80e-04)
H3	Extreme sentiment * uniqueness			3.02e-02 *** (6.01e-03)
Log-likelihood		14286.31 on 129800 df	14275.51 on 129483 df	14366.39 on 129481 df

Note: Robust standard errors reported in parentheses for coefficients, degrees of freedom (df) for test statistics.
***p < 0.001, **p < 0.01, and *p < 0.05

Table 1. Tobit regression explaining bitcoin fluctuation (n = 64,902)

Figure 2 shows the interaction plots. We employed the spotlight analysis (Aiken et al. 1991) and chose three representative values of tweet depth and tweet uniqueness to estimate the slope of influencers' extreme sentiment. In Figure 2-A, we plotted three lines for influencers' extreme sentiment, one at the mean level of tweet depth, a second at one standard deviation above the mean level of tweet depth, and finally, a third at one standard deviation below the mean level of tweet depth. As shown in Part A of Figure 2, influencers' extreme sentiment has a negative relationship with bitcoin fluctuation. This negative relationship is weaker when the tweet is more in-depth. And as shown in Part B of Figure 2, influencers' extreme sentiment has a negative relationship with bitcoin fluctuation. This negative relationship is weaker when the tweet is unique.

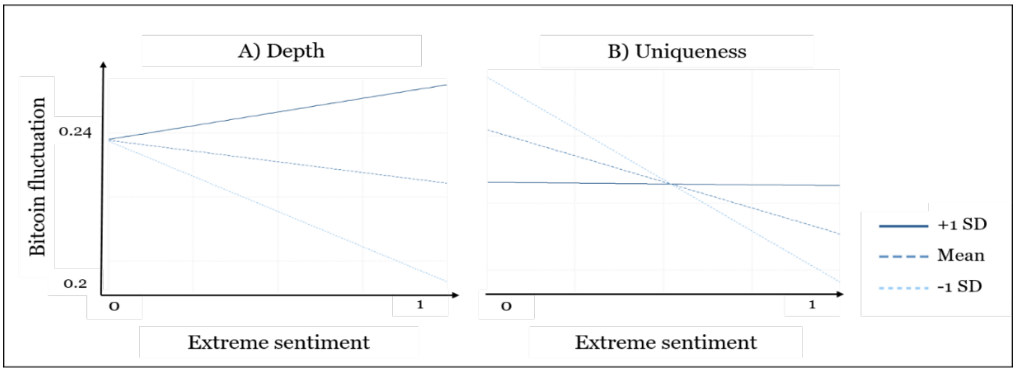

Figure 2: The moderating role of tweet depth and uniqueness on the relationship between influencers' extreme sentiment and bitcoin fluctuation

5 Discussion and future work

Our preliminary findings provided initial insights into the relationship between influencers' extreme sentiment and bitcoin fluctuation. While previous studies have mentioned the importance of users' sentiment in investigating cryptocurrency or stock fluctuation, no study has explored the role of influencers and their content. Our findings show that when influencers express sentiment in favour of or against bitcoin, it is less likely that their tweets are related to future bitcoin fluctuation. This can be due to their bias or self-interest. However, when a tweet is more in-depth and unique, this negative relationship between extreme sentiment and bitcoin fluctuation can be moderated.

Our future work will focus on developing more in-depth tweet characteristics and will use more robust econometrics methods. In this research in progress, we developed tweet depth and uniqueness solely based on the information provided in each tweet. These indexes can be improved by comparing the tweet text to all other tweets in the corpus. Our hourly bitcoin data may not be very informative for the cryptocurrency market. In our future analysis, we will use more frequent intervals, such as 15-minute periods, as one can argue that within a short period the results can be biased, and significant movements cannot be observed. In addition, we will check whether the results are consistent during different periods, especially during COVID-19. Considering our cryptocurrency data, we will also employ well-established econometrics tests used in the stock market (e.g., VECM). We will also test some other concepts in finance literature such as the Asymmetric Effect. As finance literature suggests, stocks react more strongly to bad news than to good news mainly because investors change their sentiments based on past streams of realisations, and discount recent information. We will also apply the leverage effect, which argues that negative returns have a greater influence on future volatility than positive returns. Even though these concepts have been tested in stock and currency markets, investigating them in the cryptocurrency market along with text features extracted using machine learning techniques would provide an interesting insight into this novel field of research.

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