International Journal of Economics, Management and Accounting 34, no. 1 (2026): 155-180

INFLUENCE OF TRADE WAR SENTIMENT ON STOCK MARKET AND BITCOIN: A WAVELET COHERENCE APPROACH

Raja Solan Somasuntharam[a], Fathin Faizah Said[b,c*], Tamat Sarmidi[b,d], and Mohd Ridzwan Yaakub[e]

[a]*Faculty of Business and Communications, INTI International University, Nilai, Malaysia. (Email: raja.somasuntharam@newinti.edu.my)*

[b]*School of Economics, Faculty of Economics and Management, Universiti Kebangsaan Malaysia, Selangor, Malaysia. (Email: [c]fatin@ukm.edu.my, [d]tamat@ukm.edu.my)*

[e]*Faculty of Information Science and Technology, Universiti Kebangsaan Malaysia, Selangor, Malaysia. (Email: ridzwanyaakub@ukm.edu.my)*

ABSTRACT

The massive amount of information shared on social media regarding certain issues could influence user sentiments. This study examined the importance of users' sentiments in Twitter platform regarding the trade war related to the S&P 500, MSCI China, and Bitcoin returns. The wavelet coherence method was utilized to examine the issue, which involved daily data observation spanning 4 March 2020 to 20 January 2021. The estimations revealed that users' sentiments showed significant co-movement with the returns on S&P 500, MSCI China, and Bitcoin. The finding may be useful for both policymakers and investors in their efforts to create strategies to reduce market volatility, particularly in navigating through undesired future events. It can particularly assist investors in developing profitable investment strategies for volatile markets.

JEL Classification: E70, E71, G11, G14, G15, G41

Keywords: Trade war, Twitter, Sentiment analysis, Wavelet coherence, Stock return

Submitted: 29/07/2024 Accepted: 11/11/2024 Published: 28/06/2026

*Corresponding author: fatin@ukm.edu.my

1. INTRODUCTION

Trade war refers to a nation's initiative in imposing tariffs or trade quotas on imported goods from other countries with the intention of protecting the domestic market. By implementing this, the competitive advantage of domestic product manufacture can be increased thus boosting the potential to generate more local job opportunities. The United States (US) trade war not only disrupts international trade but also affects the international financial market performance. In 2018, the stock market of several countries experienced a very steep decline in the last decade. The S&P 500 stock for example recorded a decline of greater than 6%, followed by the Hang Seng and Shanghai indices which also declined by 13% and 25% respectively (Huynh and Burggraf, 2020). This situation was exacerbated when the former US president Donald J. Trump recorded on Twitter every intended political and trade war moves, prior to the official announcement. Unsurprisingly, Trump's official Twitter account (@realdonaldtrump) was selected as the world's most influential Twitter user in 2020[1].

The Office of the US Trade Representative, in 2017, had accused China of engaging in unfair trade practices and stealing intellectual property. Tensions between the two countries further escalated with the imposition of trade sanctions by the US when Trump signed a memorandum in the World Trade Organization (WTO) on 22nd March 2018, to file a case against China that restricted her investment in crucial technology areas (Yujie Shi, Liming Wang and Jian Ke, 2021). The situation was further exacerbated with Trump's frequent tweets that influenced shareholder sentiments which also carried adverse implications on the global stock market. On 5th May 2019, for example, the president posted his tweet announcing an increase in tariffs amounting to 200 billion USD of imported goods from China which caused a loss of 1.36 trillion on the global stock market (Burggraf, Fendel and Huynh, 2019). In consequence, investors refrained from investing in the stock market for fear of adverse potential impact from the ensuing trade war and were thus forced to look for alternative investment opportunities (Xiaofan Peng, 2019). Accordingly, many investors chose to invest in Bitcoin to protect their profits (Plakandaras, Bouri and Gypta, 2019). Bouri et al. (2020) however stated that the trade conflicts between the two countries could affect the Bitcoin market as well. Bitcoin nevertheless became popular among investors, and its price peaked in December 2017 at 19, 343.04 USD[2]. Nearly 70% of the USD currency was used in Bitcoin transaction since 2017[3] which indicated that investors were beginning to structure new investment strategies and give high priority to cryptocurrency.

According to earlier research on behavioral economics (Bheenick et al., 2022; Anastasiou, Ballis, and Drakos, 2021; Ding et al., 2020; Kraaijeveld and De Smedt, 2020; Reis and Pinho, 2020) human sentiment can significantly influence their behavior and decision-making process. Such sentiment most undoubtedly resulted in the cryptocurrency prices spike around the middle of 2017. At the same time, the frequency of user access to Twitter and Google searches for cryptocurrency news also increased dramatically[4]. Twitter was launched in 2006 and this platform has provided a space for people worldwide to share their thoughts and emotions through short messages known as "tweets". The Twitter platform has become a vital source for obtaining the latest information[5]. In recent times, Twitter was increasingly used in many studies on predictions of cryptocurrency (Öztürk and Bilgiç, 2021; Kraaijeveld and De Smedt, 2020) and election results (Sprenger et al., 2014; Bermingham and Smeaton, 2011). Furthermore, sentiment analysis from Twitter data might enhance prediction of stock market movement (Raja Solan et al., 2023a; Soudeep, 2021; Ranco et al. 2015).

Yuexin et al. (2012) found a significant relationship between daily volume of tweets mentioning "S&P 500" and the S&P 500 stock price. Besides that, Kraaijeveld and De Smedt (2020) state that Twitter may potentially reflect investor emotions because, before the news became formally published, it would go viral on the platform, instantly affecting the financial markets. The rise in Twitter user access indicated that they tend to respond swiftly to an event by tweeting their views. These actions have impacted investor behaviour in an indirect way when it comes to investing decisions. Huerta et al. (2021) emphasized that researchers may be able to predict more accurately the users' thoughts and feelings through their tweets, especially during a crisis. Ensuing public feelings toward specific problems could thus be ascertained by policymakers, enabling them to quickly formulate a framework to address the problems. Additionally, Kraaijeveld and De Smedt (2020) pointed out that Twitter may also effectively reflect investor views since news that becomes viral on Twitter, before its formal posting, would have an instantaneous impact on financial markets.

To develop valuable management strategies in future, it is crucial to comprehend the relationship between investor sentiment on particular issues and the financial markets. On this cognizance, the impact of user sentiment on Twitter platform on the returns of the S&P

500, MSCI China, and Bitcoin, during the trade war, was examined in this study. Currently, Americans are the most active Twitter users with a usage rate of 24.32%, the highest globally[6]. Among the top 100 cryptocurrencies in the market, Bitcoin was chosen for this study since it comprised 48% in market capitalization, the largest component.

The structure of this paper begins with an introduction in section one. Section two then presents the literature review, while section three describes the data and methodology. Section four analyses the results, and a conclusion appears in section five.

2. LITERATURE REVIEW

The behavioral science theory describes how individuals and their surroundings influence behavior. The financial behavior field was pioneered by Amos Tversky, Daniel Kahneman, and Richard Thaler (Thaler, 1980; Kahneman and Tversky, 1979). In this particular science, investors' decision-making processes are scrutinized, in their reaction to different financial market conditions, and the implications of their actions. Without inclusion of the consumer behavioral elements in the rational pricing model, the estimation of securities performance may tend to be overestimated or underestimated (Baker and Wurgler, 2006). Anastasiou et al. (2021) also pointed out that financial behavior was able to expose investor irrational behavior. Further, this sentiment factor can anticipate price discrepancies when a stock's price deviates from its initial value (Reis and Pinho, 2020). Conversely, the Efficient Market Hypothesis (EMH) presumes that stock prices mirror all pertinent information and signals for resource allocation (Fama, 1970). Ultimately, when an event occurs in the market that provides new knowledge to the public, the stock price will naturally revert back to its original price without producing any shock. Ding et al. (2020) stated that in real situations, investors frequently overreact and disregard historical stock price information when a negative event exerts its short-term influence on financial markets. Moreover, Kraaijeveld and De Smedt (2020) observed that the EMH is a well-known neoclassical financial markets theory which however downplays the important aspect of user behavior. Furthermore, this particular behavior is the primary focus of financial behavior theory and is recognized as a non-fundamental variable (Bourghelle, Jawadi and Rozin, 2022). Investor behavior along with psychological elements tend to impact investment decisions as well as market economic factors.

Trump, who was elected as the 45th president of the US on 8th November 2016, often used the Twitter social media platform as his main communication tool. Burggraf et al. (2019) studied the effect of Trump's political news, expressed via his 3,200 tweets, on the returns and volatility of S&P 500 stocks, between 14th September 2018 and 28th May 2019. Their predictions on the impact of trade war news on the returns and volatility of the S&P 500 were ~~as~~ respectively negative and positive. Tweets made by Trump, prior to his swearing-in ceremony on 20th January 2017 (Ge, Kurov and Wolfe, 2019), impacted the financial market through increasing volatility of stock prices and generally attracting investor attention. The trade war between the US and China had a profound impact on the global economy which largely changed shareholder investment strategies. The crisis raised world economic uncertainty between the two competitors (He, Rui and Ying, 2022) leading to decline in global economic growth and trade (Tsiaplias and Jiao, 2020).

Further, policy announcements on the economic uncertainty became the underlying reason for most businesses to elude commitment in long-term investments and expenditures. Such actions have led investors to avoid risky stocks, especially those likely affected by the tariff policy, thus motivating them to seek safer investment assets. This finding concurs with Xiaofan Peng (2019), who demonstrated that valuable metal assets in China act as safe investment during market turmoil. Furthermore, in the third quarter of 2018, demand for gold increased by 25% in China followed by jewelry which rose by 10%. This development proves that investors are starting to choose gold assets as a safe investment and are reluctant to invest in stocks that experienced significant trade war impact. Likewise, the study by Gjerstad et al. (2021) further strengthened the finding of Xiaofan Peng (2019) who emphasized the importance of Trump's 8,686 tweets. The results verified that the S&P 500 (US) and Hang Seng Index (China) reacted negatively to the mention of "Trade War" in his tweets as indicated by the decrease in stock prices whereas the price of gold reacted positively. The reaction proves that investors are influenced by sentiment related to the trade war in the stock market as a contrarian signal for all financial markets to help them identify the directional biases and potential trends (Bheenick et al., 2022).

The trade war sentiment ultimately entered the limelight among investors and shareholders. Shleifer and Vishny (1997) also pointed out that sentiment related to trade noise may also exert a great impact on stock prices which can significantly skew prices away from the fundamentals.

The ongoing trade war between China and the US not only impacted a country's stock market but also affected cryptocurrency. Bouri et al. (2020) examined trade war implication on Bitcoin volatility from 1st July 2017 to 30th June 2019 using the Heterogeneous Autoregressive Realized Volatility model (HAR-RV) approach. The study used Google trend data as indicator of users' sentiment via the keywords "Tariffs War" and "Tariff War US-China". It established a significant relationship between Google trends and the Bitcoin market. Conversely, AlKhatib et al. (2020) used the variable of user sentiment in Twitter on the trade war to analyze from the users' perspective. Tweet statements were collected from the Twitter API through the keywords "5G-TradeWar" and "Tariffsman". The study provided policymakers with a comprehensive understanding of users' views on the stated issues. If negative sentiments were to be dominant among the public, policymakers should be able to take appropriate action. Alkhatib et al. (2020), however, was unable to relate users' sentiment on Twitter to stock market dynamics and cryptocurrency. The study was able to demonstrate in greater detail the effect of users' sentiment regarding the trade war on the stock market and cryptocurrency.

Huynh (2021) analyzed the sentiment spillover effect of Trump's tweet statements on the Bitcoin market through examining 13,918 tweets from January 2017 to January 2020. The findings revealed that the negative sentiment on tweets was a predictive factor for Bitcoin returns, volatility, and trading volume. Further, the sentiments of Trump's tweets can act as a forecasting tool for the market even during the Covid-19 pandemic. This study can be further strengthened by taking into account the users' perception of trade war and relating it to the financial market in line with some earlier studies (Alkhatib et al., 2020; Bouri et al., 2020). It should be noted, however, that the analysis of users' sentiments on Trump's tweets is different from evaluation of the sentiments alone.

Some past studies (Ge et al., 2019; Born, Myers, and Clark, 2017) revealed the overall consequence of Trump's tweet sentiments on the stock market. Other studies (Gjerstad et al., 2021; Burggraf et al., 2019) mainly focused on the sentiment of the trade war as mentioned in Trump's tweets and its proven relationship with the stock market. In addition, studies also emphasized the importance of users' perception regarding the trade war on the Bitcoin market. Bouri et al. (2020) for example, only used Google trend data as investor sentiment and Huynh (2021) analyzed the implication of sentiment spillover of Trump's tweets on the Bitcoin market. Alkhatib et al. (2020) examined users' sentiment on Twitter related to a trade war but did not demonstrate its consequence on the stock market nor cryptocurrency. Some studies however (Huynh, 2021; Alkhatib et al., 2020; Bouri et al., 2020; Burggraf et al., 2019; Ge et al., 2019; Born et al., 2017) can be further strengthened and made comprehensive through analyzing the relationship between users' sentiment on the stock market and cryptocurrency from the trade war perspective.

This study thus aimed at filling the knowledge gap associated with the implication of user sentiments on Twitter on the rate of return of S&P 500, MSCI China, and Bitcoin in relation to a trade war. This is in cognizance that user discussion regarding an issue on Twitter exerts an impact on investor behavior (Huerta et al., 2021). By analyzing the consequences, policymakers and investors may obtain a clearer view on the possibility of user perceptions on certain issues related to Twitter influence on the stock market and Bitcoin. If negative sentiment predominates among users over the issue. the financial market may possibly experience a negative rate of return. Thus, forewarned policymakers can consider implementing appropriate actions to change users' perceptions and thus foster a good image of government policies. In addition, investors are able to design profitable investment portfolios through observing this relationship, especially during economic crises (Huynh and Burggraf, 2019).

3. DATA AND METHODOLOGY

This study employed the wavelet coherence method of Grinsted, Moore and Jeyrejeya (2004) for daily observations from 4th March 2020 to 20th January 2021. This particular span was chosen since the administration of President Trump ended on 20th January 2021. Furthermore, various changes in US trade policies took effect following his term. The historical closing price data for S&P 500 and MSCI China were sourced from investing.com[7] and for Bitcoin from coinmarketcap.com. Using the term "Trade War" in the Rapidminer software[8], a total of 64, 419 tweets were collected via the Twitter Application Programming Interface[9].

3.1 SENTIMENT ANALYSES AND RETURN

The Valence Aware Dictionary for Sentiment Reasoning (VADER) was used to analyze user sentiments (Hutto and Gilbert, 2004). This dictionary was also able to evaluate certain punctuations, symbols, and numbers in tweets. In addition, our study followed the data cleaning steps shown by Öztürk and Bilgiç (2021), which also employed the

VADER dictionary. Data cleanup processes included removal of all punctuation from tweets, other than #, $, @, ‘, ’, !, “, ?, ., and webpage links and the changing of all capital letters to lowercase letters. Following this, sentiment analysis was conducted on the cleaned tweet content. According to some studies (Kraaijeveld and De Smedt, 2020; Elbagir and Jing, 2019), the VADER technique is a lexicon and rule-based sentiment analysis specifically designed and suitable for sentiments expressed on social media. When compared to machine learning techniques, VADER has several additional advantages, including the ability to analyze tweet content and extract sentiment values from emotions, emojis, punctuations, grammatical usage, slang, and acronyms (Valencia, Gómez-Espinosa and Valdés-Aguirre, 2019). In addition, three types of sentiments, namely positive sentiment, negative sentiment, and neutral sentiment, were produced by the VADER dictionary. Based on the compound score obtained for cleaned tweets from the dictionary, each tweet statement was classified into the three types of sentiment as stated. A tweet with a compound score of -1 (+1) was categorized as a negative (positive) sentiment.

Hutto and Gilbert (2014) also stated that compound scores of ≥ 0.05 show positive sentiments, while neutral sentiments ranged between > -0.05 and < 0.05, and ≤ -0.05 for negative sentiments. These score ranges were also used in earlier studies that adopted the VADER dictionary (Öztürk and Bilgiç, 2021; Kraaijeveld and De Smedt, 2020). Then the total number of positive, negative, and neutral sentiments was computed daily for gathered tweets. The Python software[10] was used for cleaning procedures and sentiment analysis.

We used the price (P_t) of S&P 500, MSCI China, and Bitcoin to compute the return, and t is referred to time;

$$(1) \qquad Return_t = \frac{P_t - P_{(t-1)}}{P_{(t-1)}}$$

We standardized all the time series by using the Z-transformation: $Z_t = (X_t - \mu_x)/\sigma_x$, where μ_x and σ_x are defined respectively as the mean and standard deviation of each series. This normalization is necessary since data on sentiment were rather noisy and fluctuated widely. Through transformation, all data will have a similar scale and variance, thus facilitating researchers in estimating their impact differences through numerical analysis (Garcia et al., 2014; Raja Solan et al., 2023a, 2023b).

Table 1 presents the descriptive statistics on the datasets for the S&P 500, MSCI China, and Bitcoin. This study adopted the

Augmented Dickey Fuller (ADF) (Fuller 2009) to test the stationarity of each time series. The time series is stationary when the p-value is below 0.05. Accordingly, the results indicate that all the variables are stationary at level. The unit root test for each dataset of S&P 500, MSCI China, and Bitcoin are shown in Table 2.

TABLE 1
Descriptive Statistics

Variable	S&P 500	MSCI China	Bitcoin
Return			
Mean	2.09E-17	-3.84E-18	1.29E-19
Median	0.0769	0.0239	-0.0368
Maximum	3.9403	3.0761	4.0836
Minimum	-5.7289	-4.0486	-8.3488
Std. Dev	1	1	1
Skewness	-0.9277	-0.5774	-1.3845
Kurtosis	11.5503	4.7479	18.7938
Positive Sentiment			
Mean	4.62E-16	-5.62E-16	-5.69E-16
Median	-0.2835	-0.2819	-0.2454
Maximum	4.2272	4.1100	4.2058
Minimum	-1.3407	-1.3113	-1.3759
Std. Dev	1	1	1
Skewness	1.7561	1.8083	1.6929
Kurtosis	6.4123	6.6298	6.3708
Negative Sentiment			
Mean	-4.39E-16	3.43E-16	1.10E-15
Median	0.1819	0.1590	0.1462
Maximum	1.8570	1.8360	1.8852
Minimum	-3.1398	-3.0833	-3.7594
Std. Dev	1	1	1
Skewness	-0.6911	-0.6824	-0.7259
Kurtosis	3.2832	3.2372	3.5497
Neutral Sentiment			
Mean	3.04E-16	-7.57E-16	2.14E-16
Median	-0.1527	-0.1565	-0.1914
Maximum	6.1707	6.1117	7.4631
Minimum	-1.1842	-1.1790	-1.1537
Std. Dev	1	1	1
Skewness	2.4991	2.4310	3.0355
Kurtosis	13.2450	12.5859	18.4393

TABLE 2
Augmented Dickey Fuller Unit Root Test

Variable	ADF			
	Level		1 st diff	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept
S&P 500				
Return	-5.7847***	-5.7670***	-10.7734***	-10.8528***
Positive Sentiment	-12.9738***	-13.6340***	-12.3909***	-12.3594***
Negative Sentiment	-11.7804***	-13.1680***	-11.4176***	-11.3855***
Neutral Sentiment	-12.5529***	-13.4312***	-10.4575***	-10.4305***
MSCI China				
Return	-15.1853***	-15.2479***	-9.1781***	-9.1687***
Positive Sentiment	-13.0632***	-13.8763***	-12.7864***	-12.7546***
Negative Sentiment	-12.0552***	-13.6799***	-11.2776***	-11.2493***
Neutral Sentiment	-13.0340***	-13.9654***	-12.5134***	-12.4849***
Bitcoin				
Return	-17.5399***	-17.7732***	-12.2555***	-12.2409***
Positive Sentiment	-14.8121***	-15.8084***	-11.1729***	-11.1551***
Negative Sentiment	-13.5004***	-15.3106***	-14.5982***	-14.5732***
Neutral Sentiment	-14.5561***	-15.4493***	-15.1165***	-15.0919***

Note: *Null hypothesis rejection at 10%, **Null hypothesis rejection at 5%, *** Null hypothesis rejection at 1%.

3.2 WAVELET COHERENCE

The wavelet coherence approach uses the bivariate framework which is introduced under the continuous wavelet transform method. This allows the approach to demonstrate the movement between two-time series in a different time period and frequency compared to traditional econometric methods (Rua and Nunes 2009). In addition, studies (Dowling, 2022; Goodell and Goutte, 2021) have utilized the wavelet coherence approach in analyses related to cryptocurrency and the stock market.

Torrence and Compo (1998) introduced the Cross Wavelet Transform (CWT) approach for two time series X_t and Y_t that defined their own CWT $W_n^x(a,b)$ and $W_n^y(a,b)$ as:

(2) $$W_n^{xy}(a,b) = W_n^x(a,b) * W_n^y(a,b)$$

Where, a is defined as the time period and b is referred to as the frequency. The * indicates the complex conjugate. Additionally, CWT displays the time period components that have significant movement between X and Y time series at each scale (frequency). In this study, the time series X represents the variables such as positive sentiment of trade war, negative sentiment of trade war, and neutral sentiment of trade war while the Y time series is the returns of S&P 500, MSCI China, and Bitcoin.

In accordance with Torrence and Webster (1999), we explain the wavelet coherence that shows the movement between time series X and Y as follows:

(3) $$R^2(a,b) = \frac{(S(s^{-1}W^{xy}(a,b)))^2}{S\left(s^{-1}\left(W^x(a,b)\right)^2\right) S\left(s^{-1}\left(W^y(a,b)\right)^2\right)}$$

Where S is a smoothing operator over time as well as scale and time period between time series X and Y and $0 \leq R^2(a,b) \leq 1$ (Rua and Nunes, 2009). Besides, the quantity $R^2(a,b)$ represents the square of wavelet coherence and its value ranges from 0 to 1. The higher value shows the movement between two time series is high and vice versa. Unlike the classical correlation approach of two-time series, however, the squared wavelet coherence is limited to positive values only. Thus, at this stage the methodology is unable to distinguish between positive and negative co-movement or correlation. This problem can be overcome by using the phase difference approach of Terrence and Compo (1998) to show the positive and negative co-movement between two time series. By following this, the square wavelet coherence diagram displays the causal relationships between the two-time series. Wavelet coherence phase difference is shown as:

$$\varphi_{xy}(a,b) = tan^{-1}\left(\frac{lm\{S(s^{-1}W^{xy}(a,b))\}}{Re\{S(s^{-1}W^{xy}(a,b))\}}\right) \tag{4}$$

Where lm is the imaginary part while Re shows the real parts of the smoothed-CWT.

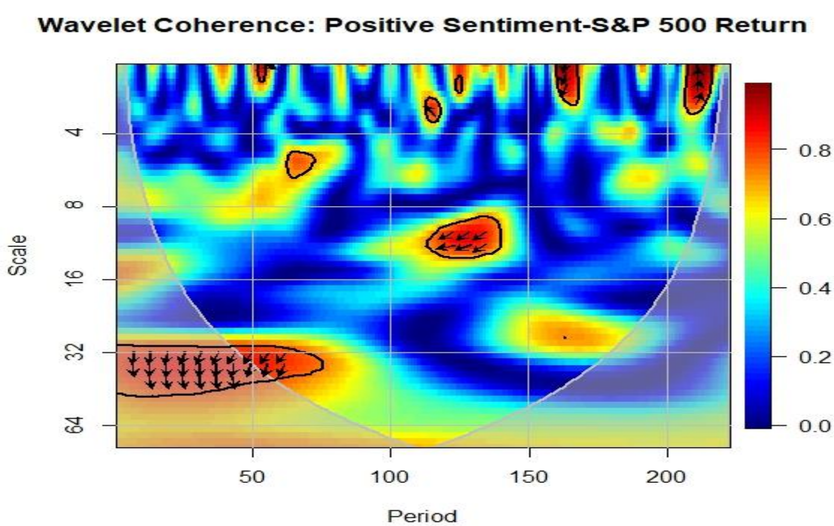
4. RESULTS

The absolute value of the square of the wavelet transformation is referred to as the wavelet power spectrum. This shows the time series variance measure for each period and scale (frequency). Accordingly, the horizontal axis presents the period (days) and the vertical axis depicts the scale (frequency). The frequency component ranges from a scale 1 (one day) to a scale of 64 (more than 64 days). The scale is divided into four levels: 1-4 days, 4-8 days, 8-16 days, 16-32 days, and scale more than 64 days. In addition, the black contours in the wavelet coherence diagram demonstrate the significant area at the 5% level. This is estimated by Monte Carlo simulation with a phase-randomized surrogate series. Furthermore, the solid white bell-shape line in the wavelet coherence plot is the cone of influence, where arrows inside (outside) of the cone are explicable (not explicable). A zero-phase difference indicates that the first and second time series move in an inhomogeneous direction.

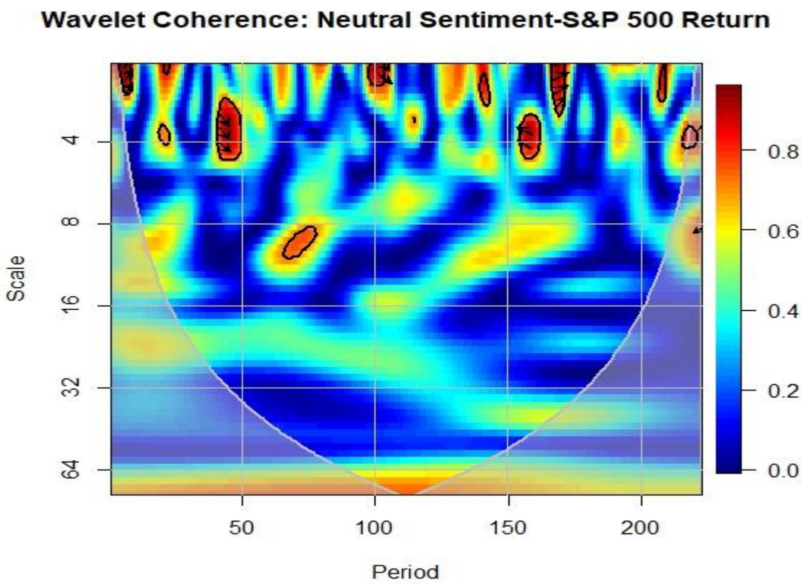
The correlation (coherency band) ranges from red (high coherence) to blue (low coherence) colors which indicates the amount of co-movement between the two variables displayed on the right side of the figure. The red color (1.0) illustrates that the co-movement between variables is strong while the blue color (0.0) shows that the co-movement is weak, thus indicating the highest and lowest correlation value (R^2). There are eight unique arrows (→, ←, ↑, ↓, ↗, ↙, ↘, ↖) that explain the relationship between users' sentiment and the return of the stock market and Bitcoin on the black contour. Meanwhile, users' sentiment on trade war is considered as the first time series while the returns of the S&P 500, MSCI China, and Bitcoin is considered as the second time series. The right side (→) arrow and the left side (←) arrow indicate that users' sentiment and rate of return are in phase and out of phase respectively. Being in phase (out of phase) shows a positive (negative) relationship between users' sentiment and rate of return. Further, the upward ↑ and (downward ↓) pointing arrow shows the sentiment (return) series leads the return (sentiment) series. Also, the forward downward (upward) arrows ↘ (↗) display a positive co-movement between two-time series where the return (sentiment) series leads the sentiment (return) series by $\pi/2$. On the other hand, backward upward (downward) arrows ↖ (↙) indicate that a negative co-movement between two-time series where the return (sentiment) leads the sentiment (return) by $\pi/2$.

Figure 1 displays the wavelet coherence of trade war sentiment and S&P 500 return. The vertical axis shows the scale while the horizontal axis indicates the period covering from 4/3/2020 (1-day) to 20/1/2021 (223-days). Based on Figure 1, we found that positive sentiment leads and has a negative relationship (↙) with the S&P 500 return at two different periods. Starting from 13/5/2020 until 11/6/2020 on 32-40-day scales at the beginning, and later from 21/8/2020 to 21/9/2020 on 8-12 day scales the sentiment was positive and significant as indicated with light red color. Further, positive sentiment was lagging (leading) and significant with S&P 500 return from 12/10/2020 to 19/10/2020 (22/12/2020 to 30/12/2020) on 1–3-day scales as indicated in dark red.

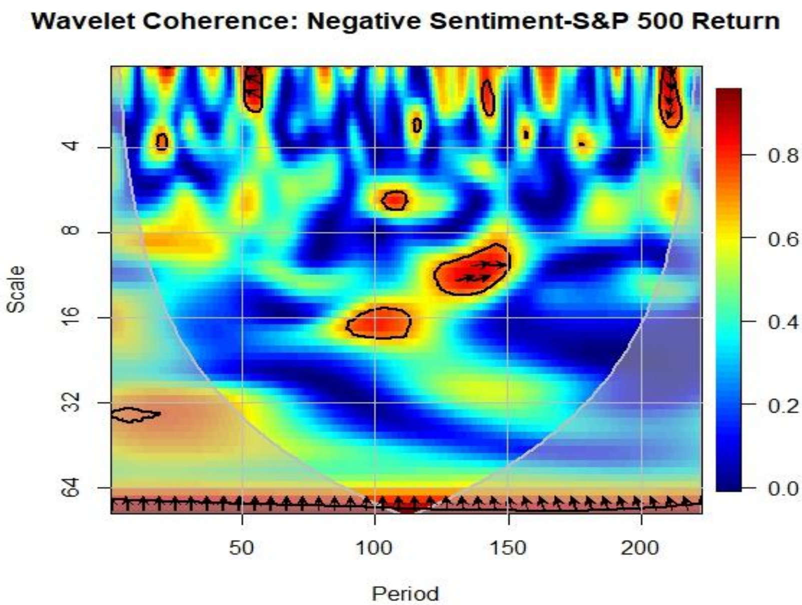
FIGURE 1
Wavelet Coherence of Trade War Sentiments and S&P 500 Return



(a)


Wavelet Coherence: Neutral Sentiment-S&P 500 Return
Scale
4
8
16
32
64
50
100
150
200
Period
0.8
0.6
0.4
0.2
0.0

(b)

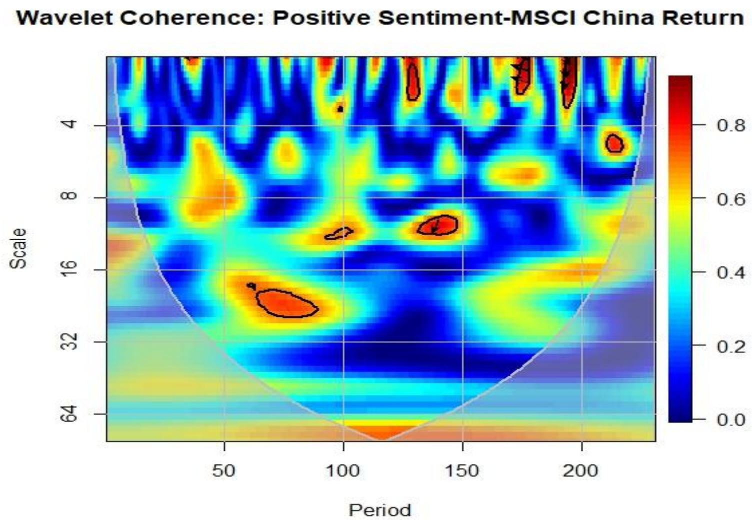

Wavelet Coherence: Negative Sentiment-S&P 500 Return
Scale
4
8
16
32
64
50
100
150
200
Period
0.8
0.6
0.4
0.2
0.0

(c)

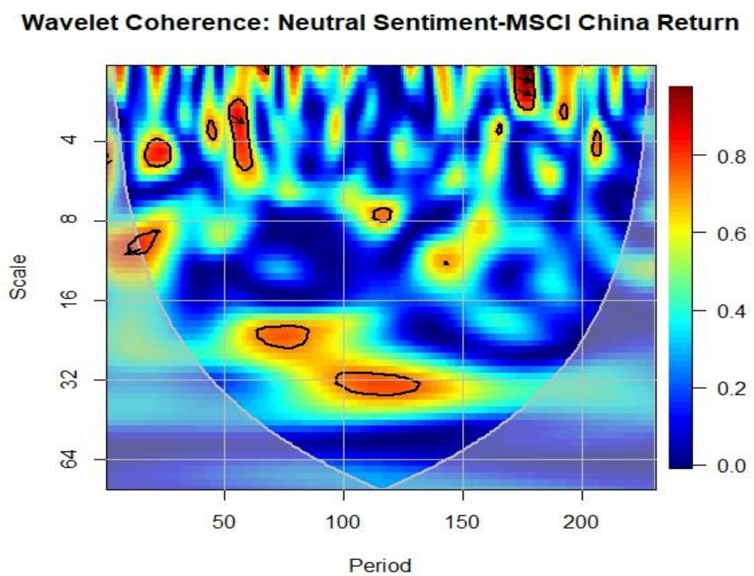
In addition, neutral sentiment has a positive and backward (positive and leading) co-movement with a return on 6/5/2020 to 13/5/2020 (2/11/2020 to 9/11/2020) on a 2-5 day (1-3 day) scales shown in dark red. On the other hand, there is a positive co-movement (→) between negative sentiment and return for the period 4/9/2020 to 5/10/2020 on 9-15-day scales with light red. Meanwhile, negative sentiment lagging (↓) was significant with return from 22/12/2020 to 7/1/2021 on 1-3 day scales as shown in dark red. This finding is consistent with Gjerstad et al. (2021) who documented that S&P 500 stocks reacted to Trump's tweets on the trade war topic with prices on the decline. Moreover, not only did the US economy face the consequences of lifting the tariffs but so too the international financial market (Bheenick et al. 2022). This indicates that a trade war generates an insecure investment atmosphere in the financial market. Yong Chen, Jing Fang and, Dingming Liu (2023) also discovered that the trade war shock produced an impact on the S&P 500 index mainly through news of the event which significantly influenced investors' investment decision.

The wavelet coherence analysis of trade war sentiment and MSCI China return, from 4/3/2020 (1 day) to 20/1/2021 (231 days), is described in Figure 2. The vertical axis is the frequency component and the horizontal axis shows the period. There is a significant negative co-movement and positive sentiment leads (↙) return, from 8/9/2020 to 29/9/2020 on 10-13 day scales, shown in red color. Furthermore, positive sentiment displays a negative co-movement (←) with a return from 27/10/2020 to 3/11/2020 on 1-2 day scales, shown in dark red. Neutral sentiment shows a significant positive and backward relationship (↘) with returns at two different periods; from 12/5/2020 to 19/5/2020 on a 2-6 day frequency band with red color and, from 27/10/2020 to 3/11/2020 on 1-3 day scales, with dark red color. Next, there is a significant negative co-movement (←) between negative sentiment and return from 21/7/2020 to 4/8/2020 on 5-8 day scales, shown in dark red color. The result is consistent with Hasuike and Mehlawat (2018) who indicated that investors are typically risk-averse and try to avoid negative market downturns by diversifying asset portfolios. As such, public worry over the US-China trade war may have affected investments in Chinese stock markets.

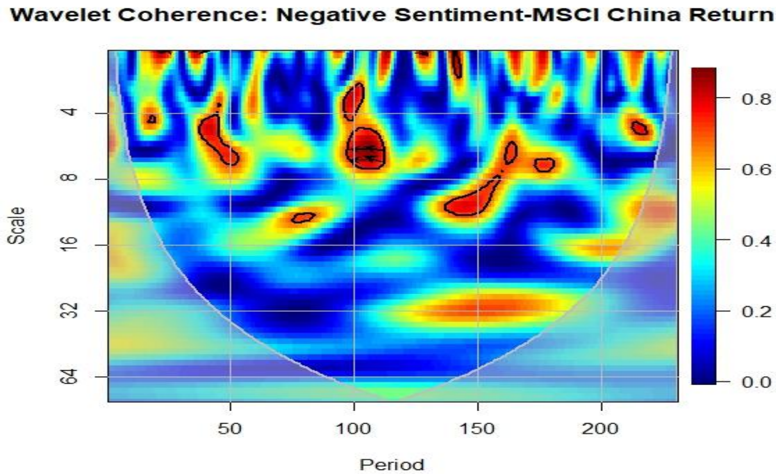
FIGURE 2
Wavelet Coherence of Trade War Sentiments and MSCI China Return



(a)



(b)



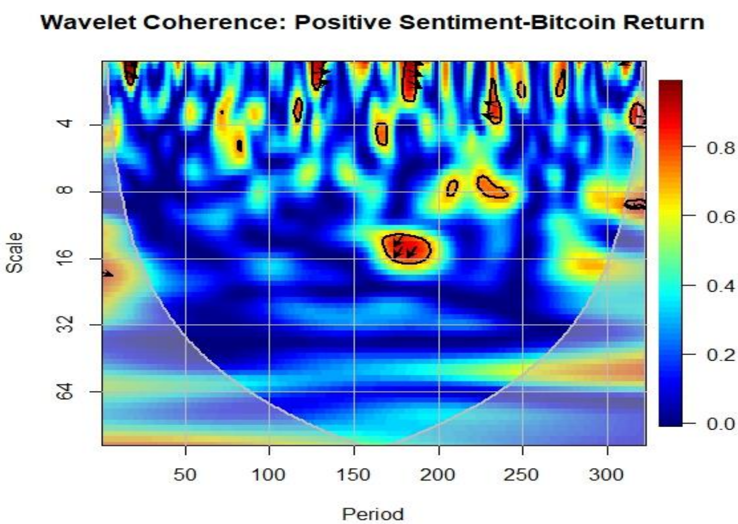
(c)

Figure 3 explains the wavelet coherence co-movement between trade war sentiment and Bitcoin return from the period 4/3/2020 (1 day) to 20/1/2020 (323 days). The vertical axis shows the frequency component and the horizontal axis illustrates the time period. There is a positive co-movement (→) positive sentiment and return from 13/3/2020 to 17/3/2020 on 1-2 day scales. The positive co-movement was similarly shown twice, on 11/7/2020 to 21/7/2020 and from 20/8/2020 to 25/8/2020 on 1-3 day scales. Conversely, we have a negative relationship (←) between the positive sentiment and return from 19/10/2020 to 24/10/2020 on a 2-4 day scale. All the stated movements are shown in black contours with dark red color which confirms that they strong at the 5% significance level. Although, there is a positive and negative co-movements between the stated time series, the positive co-movement is stronger than the latter and has a positive relationship at three different periods. Additionally, there is a negative co-movement and positive sentiment leads (↙) return from 21/8/2020 to 9/9/2020 on 12-16 day scales, shown as black contour filled with light red color indicating that the movement is modest at the 5% significance level.

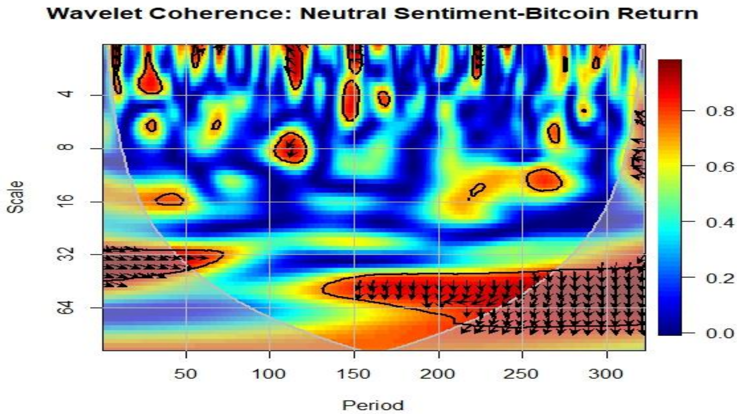
In addition, there is a significant positive co-movement (→) between neutral sentiment and return from 22/4/2020 to 12/5/2020 on 32-40 day frequency cycles shown in light red color. Further, there is also neutral sentiment leads and negative co-movement ↙ (lagging ↓) with return for the period 16/6/2020 to 21/6/2020 (31/7/2020 to 8/11/2020) on 6-10 day (40-64 day) scales, given in light red color.

Apart from that, negative sentiment shows negative co-movement and leading (↙) with return from period 31/7/2020 to 10/8/2020 on 6-10 day scales in light red color. There is a positive relationship (→) between negative sentiment and return from 24/10/2020 to 29/10/2020 on a 1-3 day frequency band, in dark red color. However, the significance level of positive co-movement between negative sentiment and return is higher than that for the negative co-movement as indicated by the color intensity. This result is supported by Bouri et al. (2020) who showed a significant relationship between users' search interest in the trade war in Google and Bitcoin volatility. However, the authors only analyzed the overall user interest and didn't emphasize on users' perceptions of the trade war on Twitter, although Trump exclusively used the platform as the main channel to announce the news on trade policy. Huynh (2021) on the other hand had shown that negative sentiment found in 13, 918 tweets from Trump as a whole proved to be a predictive factor for the rate of return and volatility of Bitcoin. Nevertheless, Huynh (2021) only focused on the sentiments of Trump's tweets but did not take into account the importance of users' perceptions on policies specifically introduced by him.

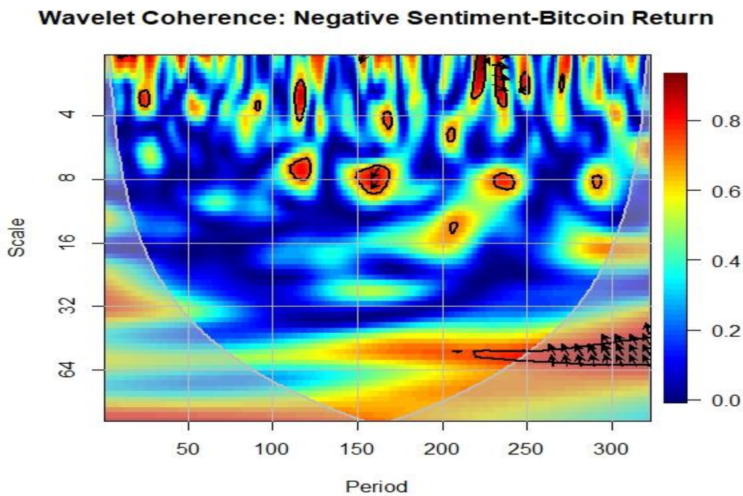
FIGURE 3
Wavelet Coherence of Trade War Sentiments and Bitcoin Return



(a)



(b)



(c)

5. CONCLUSION

This study elucidated the consequence of users' sentiment regarding the trade war, using the Twitter social media, on the return of the S&P 500, MSCI China, and Bitcoin. Altogether, the findings have revealed that positive sentiment, neutral sentiment, and negative sentiment on the trade war have produced positive and negative co-movements with Bitcoin return at different periods. Besides this, the positive sentiment has a negative co-movement with the return of the S&P 500 and MSCI China. In addition, the neutral sentiment boosted the returns of both stocks. On the other hand, negative sentiment has a positive (negative) co-movement with S&P 500 (MSCI China) returns. This finding is supported Burggraf et al. (2019) and Gjerstad et al. (2021) who documented empirical evidence that Trump's tweets on the trade war have implications for financial markets. Burggraf et al. (2019) reported that Trump's tweets affected the S&P 500 return negatively in the first lag and positively in the second lag. The financial market accordingly reacted to these tweets but changed in the following period. Hence, the effect of sentiment on the financial market is only temporary but it did react to user sentiment. The finding strengthens the results of some past studies (Alkhatib et al., 2020; Born et al., 2017; Bouri et al., 2020; Huynh, 2021; Ge et al., 2019). Ge et al. (2019) specifically revealed that there is a one-way relationship between Trump's tweets and the financial market, which is directed from the tweets to the markets. This study has thus established that user perceptions of trade war have an impact on stock markets and Bitcoin.

The recent study by Alkhatib et al. (2020) only examined user sentiment on the trade war but did not analyze the consequence of user perceptions on the financial markets. The US stock market furthermore tended to have a spillover effect on the stock markets of other countries (Georger, 2014; Zhang and Li, 2014); thus implementation of the policy will not only affect its domestic stock market but also has the potential to influence stock markets in other nations. Accordingly, US policymakers found that the tariff policy implementation produced a mixed result on Bitcoin return. Additionally, user sentiments showed a negative (positive) impact on the overall Chinese (US) stock market. This outcome indicates that the purpose of implementing the trade war policy has been achieved, which is to stimulate the US economic growth. Even though the positive sentiment has a negative effect on S&P 500 return, in reality most of the users harbor a negative feeling on the tariff policy especially those from countries adversely affected by the trade war. This was proven by Huynh (2019) who pointed out that Trump's tweets regarding tariffs triggered a huge loss to the global stock market.

Against this development, policymakers in the US and China should consider user perceptions of policy on Twitter platform, that policy implementation tends to indirectly influence investor behavior (Huerta et al., 2021). This is more apparent nowadays given that financial markets are easily influenced by current issues and information announced on social media (Beckers, 2018). In addition, Xiaowei Kong et al. (2023) and Siriopoulos, Svingou, and Dandu (2021) maintained that policymakers have to understand the real reason for the fluctuation in stock market return in order to restabilize the market through taking the necessary action. By observing the user opinion on Twitter, the policymakers and government authorities may gain quick access on users' perceptions, via the Twitter platform, as related to the implementation of current government policies thus enabling them to identify extreme negative feelings that may lead to problematic situations or even acts of terrorism (Alkhatib et al., 2020).

The increasing facility of social media access by the public makes it easier for them to express their emotions and opinions on issues or government policies. Thus, monitoring public opinion expressed on social media can be considered an important initial step to problem solving. Through this means, policymakers have the potential to quickly react and galvanize the appropriate actions to problem solve. Furthermore, investors also need to diversify their investments during economic turmoil (Huynh and Burggraf, 2019), and as such they need to identify the stocks and assets that are ~~not~~ unaffected by prevailing financial crises. Moreover, such information can also be used by stockholders to formulate profitable investment strategies (Hasan, 2022). Evidently, psychological and sentiment elements can exert a big impact on investment decisions, in line with the behavioral science theory (Bheenick et al., 2022; Kraaijeveld and De Smedt, 2020). In consequence, Bitcoin and S&P 500 are positively affected by trade war sentiment during specific time period relative to the MSCI China. This study has empirically proven the relationship between user sentiments and the financial market. As such, investors cannot dismiss users' sentiment on Twitter as merely noise factor (Gjerstad et al., 2021).

ACKNOWLEDGMENT

The authors much appreciated the financial assistance provided by the Faculty of Economics and Management, Universiti Kebangsaan Malaysia and the anonymous reviewers for helpful comments on earlier drafts of the paper presented at the 2nd Finance and Business Analytics Conference 2024, Athens, Greece.

ENDNOTES

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