Jurnal Ekonomi Malaysia 57(2) 2023 81-95
http://dx.doi.org/10.17576/JEM-2023-5702-06

Impact of Twitter and Google Searches on Bitcoin Rate of Return

(Kesan Twitter dan Pencarian Google terhadap Kadar Pulangan Bitcoin)

Raja Solan Somasuntharam
Universiti Kebangsaan Malaysia
Fathin Faizah Said
Universiti Kebangsaan Malaysia
Tamat Sarmidi
Universiti Kebangsaan Malaysia
Mohd Ridzwan Yaakub
Universiti Kebangsaan Malaysia

ABSTRACT

This paper investigates the importance of user emotions in social media Twitter and Google searches on the Bitcoin rate of return. The analysis is based on daily data frequency from 17 August 2021 until 17 December 2021 and the study adopted the Vector autoregression (Var) method for analysis. Findings on the impulse response function revealed that disgust emotion and Google trend YouTube search influenced Bitcoin return. In addition, these results are also supported by the variance decomposition test which is a Google trend, YouTube search and disgust emotion variables that explain most of the forecast error variance decomposition for Bitcoin return. This study shed some light for policymakers concerning the implication of user emotions from Twitter on the Bitcoin rate of return. Finally, this study provides a highlight to investors the importance of Google searches in Bitcoin return and in building a profitable investment portfolio.

Keywords: Bitcoin; return; emotions analysis; Google searches; Twitter; social media

ABSTRAK

Makalah ini mengkaji peranan emosi pengguna di media sosial Twitter dan pencarian Google terhadap kadar pulangan Bitcoin. Analisis ini adalah berdasarkan kekerapan data harian dari 17 Ogos 2021 hingga 17 Disember 2021 dan menggunakan kaedah Vektor autoregresif (Var) untuk menganalisis isu tersebut. Penemuan kajian yang menggunakan fungsi tindak balas impulse menunjukkan bahawa emosi meluat dan Google trend pencarian YouTube mempengaruhi kadar pulangan Bitcoin. Di samping itu, dapatan kajian turut disokong oleh kaedah penguraian varians ralat ramalan yang menjelaskan emosi meluat dan Google trend pencarian YouTube menerangkan kebanyakan ralat penguraian kadar pulangan Bitcoin. Kajian ini memberi penerangan penting kepada pembuat dasar mengenai implikasi emosi pengguna daripada Twitter terhadap kadar pulangan Bitcoin. Akhir sekali, kajian ini juga memberikan pendedahan kepada pelabur mengenai kepentingan pencarian Google terhadap kadar pulangan Bitcoin dan membina portfolio pelaburan yang menguntungkan.

*Kata kunci***:** *Bitcoin; kadar pulangan; analisis emosi; pencarian Google; Twitter; media sosial*
JEL: E70, E71, G11, G14, G15, G41
Received 21 December 2022 ; Revised 7 August 2023; Accepted 25 August 2023; Available online 7 September 2023

INTRODUCTION

The advances of borderless technology through applications such as Twitter and Google causes information to spread quickly without borders. In the era of digitalization, information is already at the fingertips, and this will influence investment decisions. In addition, Nouri et al. (2017) stated that behavioral science theory illustrates the reason for trading in financial markets is due to internal and external psychological factors. This argument was further strengthened by studies (Anastasiou et al. 2021; Ding et al. 2020; Kraaijeveld & De Smedt 2020; Reis & Pinho 2020) which suggested that user sentiment has the potential to influence individual behavior and decision-making. Furthermore, external influences are also one of the main causes of price fluctuation in the digital assets market. Reportedly, in mid-2017 most digital assets had shown drastic changes in prices[1] and at the same time user responses on Twitter social media and Google searches concerning digital assets also increased simultaneously (Bitinfocharts 2021[2]; Google Trend 2021[3]). Moreover, the Twitter platform which is known as one of the social media has become reference sources for users to gather the latest information[4]. Also, Kraaijeveld and De Smedt (2020) pointed out that Twitter stands for investor sentiment as a consequence of news becoming viral on the platform before it was officially announced and this will exert an immediate impact on financial markets. In addition, the spread and fatality rate of Coronavirus-2019 (Covid-19) influenced user emotions strongly (Ding et al. 2020). The Covid-19 pandemic will stimulate fear and anxiety among the populace and this will impact investment decisions and reduce attention on previous historical price data (Del Lo et al. 2022; Siriopoulus et al. 2021). In May 2020, while the US interest rate was dropping to almost zero level the financial market still faced turbulent conditions (Gao et al. 2021). Understanding the implication of user emotions on digital assets will thus help to formulate efficient management strategies in the future.

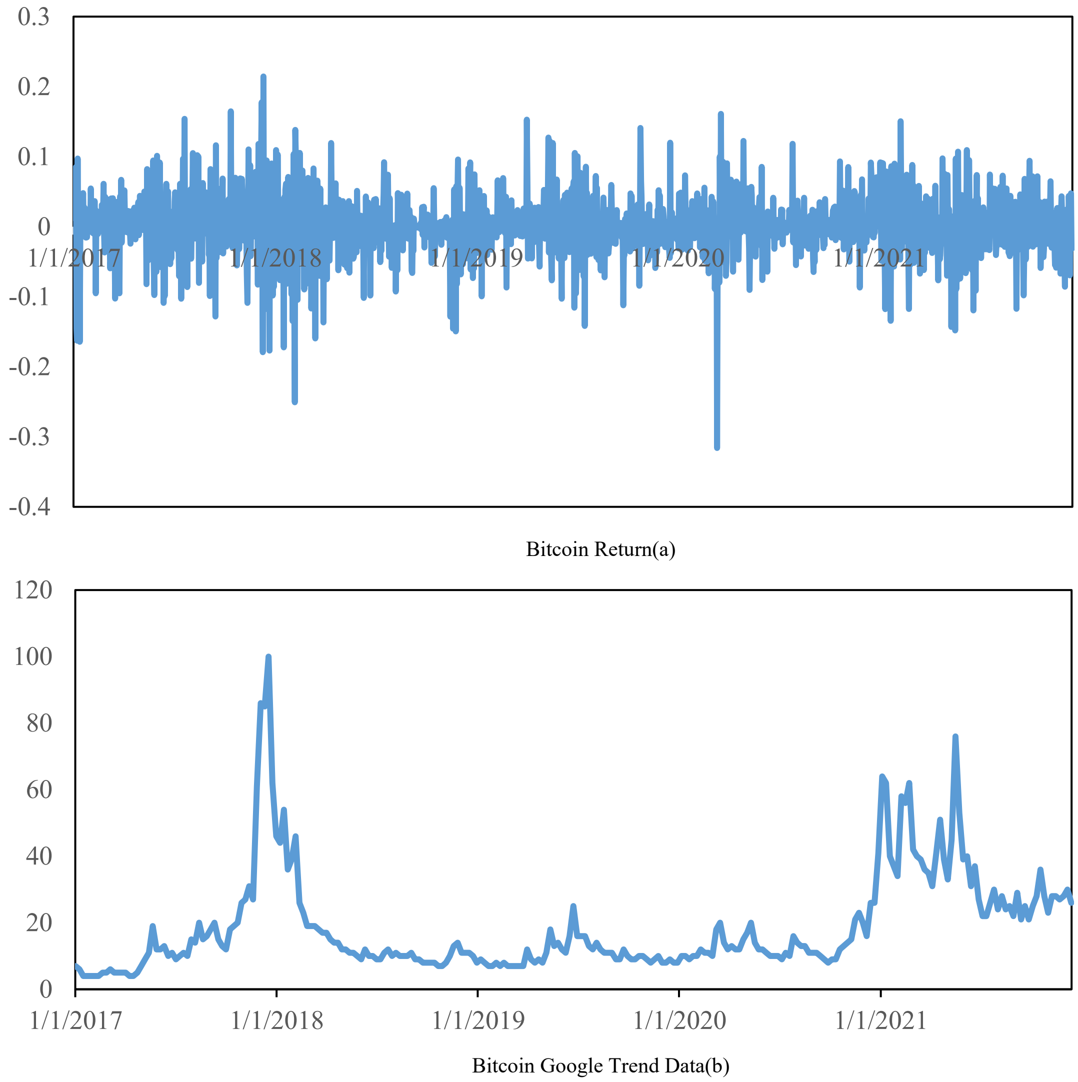


FIGURE 1. Bitcoin Market and Google Trend.
(a) Bitcoin return; (b) Investor attention on Bitcoin
Source: Author's calculation from the historical Bitcoin price and Google trend data. https://coinmarketcap.com and https://trends.google.com

Figure 1 illustrates Bitcoin's return from January 2017 until December 2021, together with users' web search interest in the keyword "Bitcoin". It showed that there is a positive relationship between Bitcoin return and Google trend data especially in the beginning of 2018 and also 2021. In addition, Preis et al. (2013) also stated that there was an increase in Google search activity related to financial market keywords before the stock market crash. A similar situation also occurred in the Bitcoin market. Based on Google trend data (2019)[5], searches on websites, news and YouTube as related to the digital currency, rose sharply before the fall in prices. This was attributed to users' Google search activity responding more quickly towards negative events, such as the law introduced to prohibit Bitcoin trading (Garcia et al. 2014). In addition, the author also noted that the increase in search activity was a hint on the decline in digital asset prices.

In cognizance of the above development this study will attempt to interpret the role of user emotion in Twitter and Google search activities with respect to the return in Bitcoin. This study focuses on Bitcoin since the currency covers 48 percent of market capitalization comprising the top 100 digital market assets[1]. There are two research gaps identified in the digital market related to the relationship between user sentiment on Bitcoin and its market. These gaps will be addressed in this study. Firstly, the emotional impact of Twitter users on the Bitcoin rate of return will be analyzed. Eight emotions can be identified such as joy, trust, fear, surprise, sadness, disgust, anger, and anticipation. At the same time, we also incorporated macroeconomic and Google search variables in the study with the aim of showing more clearly the priority of Twitter user emotions in the Bitcoin market. Most of the earlier studies have only been concerned with the number of tweets and have classified users' sentiments into positive, negative or neutral. In reality, there are other additional emotions shown in user tweets. In addition, measuring the impact of these emotions such as fear, sadness, and surprise apparent in user comments relating to the Bitcoin market, may produce results that are potentially beneficial to investors and policymakers. Grgic and Podobnik (2021) explained that emotions were able to indicate investor behavior as a whole towards a particular market. Some studies (Ahn & Kim 2021; Bartolucci et al. 2020) have also examined the influence of emotions on Bitcoin but not from the platform of Twitter social media. As we explained earlier, the Twitter platform is becoming an important source in the digital assets market and this has been proven in previous studies.

The second research gap in the digital market concerns the implication of Google search activity in the Bitcoin rate of return. A large number of past studies related to such implication on the digital assets market used Google trend data as a whole. However, these data can be divided into three elements, specifically the YouTube search, web search, and news search on a particular term. Further, users do not only depend on a certain Google search but also tend to browse through other searches to source enough information. Based on Google trend data (2019)[4], Google searches on news and YouTube related to Bitcoin increased in accordance with Bitcoin price. This study is accordingly motivated to close the literature gap by identifying the implications of searches on websites, news, and YouTube on Bitcoin rate of return. Through this approach, this study is able to compare the elements of Google searches of websites, news and YouTube to identify sources that may have a significant impact on Bitcoin rate of return. This should assist policymakers and investors obtain a clearer picture regarding the value of user emotions and Google searches on the Bitcoin market. As an illustration, the result of this study may be very useful to policymakers of the Federal Reserve US central bank given that the USD currency is widely used in Bitcoin transactions. This is consistent with Huerta et al. (2021) who pointed out that such analysis is very useful to national policymakers since the public conversation on Twitter regarding a particular issue will exert an impact on user sentiment. In addition, policymakers may obtain a clearer picture of user emotions and formulate a prudent framework to mitigate the issue in the future. Investors will also be able to structure a profitable investment portfolio by identifying the right time for asset investment (Chuffart 2021; Siriopoulos et al. 2021).

Following an introduction in section one, the paper continues with a literature review in section two and followed with the methodology in section three. Study results are given in section four and the conclusion is presented in section five.

LITERATURE REVIEW

Behavioral science theory identifies the nature of individuals and their environment with their behavior. Amos Tversky (Kahneman & Tversky 1979), Daniel Kahneman and Richard Thaler (Thaler 1980) are known as pioneers of financial behavior who studied the decision-making processes of investors and their response to various financial market conditions as well as the implication of their decisions on these markets. Neglecting consumer behavioral aspects in the rational pricing model may potentially incur an adverse influence on the estimation of securities performance (Baker & Wurgler 2006). Furthermore, financial behavior is able to explain investors' irrational behavior (Anastasiou et al. 2021). The element of sentiment can help clarify price differences due to stock price deviation from its original price (Reis & Pinho 2020). Hence, when stock prices show fluctuating patterns of movement, investor's behavior may be one of the reasons that influence changes in the rate of return of assets. This is contrary to the Efficient Market Hypothesis (EMH) theory which assumes that stock market prices reflect all the appropriate information and signals for resource allocation (Fama 1970). The stock price will return to its normal price without the occurrence of any shock in the market and with the dissemination of new information to the public. However, according to Ding et al. (2020), in a realistic scenario, investors tend to overreact to a negative event that leaves an impact on the financial market in the short term and consequently display a tendency to ignore past stock price data. Moreover, Kraaijeveld and De Smedt (2020) also emphasized that the EMH theory is a standard neoclassical theory of financial markets that pays little attention to the behavior and emotion shown by investors. In addition, Bourghelle et al. (2022) stated that the financial behavior theory focuses on consumer behavior which is accepted as a non-fundamental variable. Consequently, investors' sentiment and psychology tend to influence investment decisions which is separate from the economic aspects of the market. This issue has been proven by Wu and Hock Ow (2021) who revealed that news sentiment from the Organization of the Petroleum Exporting Countries (OPEC) influences the stock market prices of oil and gas companies, and also assists market participants in making better investment decisions. In addition, some safety precautions during the pandemic Covid-19 such as lockdowns, border closures, social distancing, and other health interventions have triggered an uncertainty condition in the world stock market that exerts serious impact on investors (Tanveer 2021).

Steinert and Herff (2018) predicted the rate of return of digital assets apart from Bitcoin by taking into account the number of tweets and user feelings recorded on tweets concerning digital assets. The study established that Twitter is an essential social media channel and a good indicator to depict user feelings. In addition, Twitter provides beneficial signals that can assist in predicting digital asset rates of return. Besides user sentiments, there are various emotions expressed by users on Twitter. For illustration, consumer sentiments can be categorized into three types which are either positive, negative and neutral. Each comment or tweet from users are classified accordingly. Similarly, user emotions can be assessed by the words used in their comments. There are eight main types of emotions recognized on Twitter, namely joy, trust, fear, surprise, sadness, disgust and anger. Following this, Grgic and Podobnik (2021) suggested that emotion is an indicator that should be emphasized in analysing the behavior of certain markets especially concerning investor sentiment. This sentiment and emotion are considered a measure of overall investor behavior and this indicator is important in analysing future market risk and rate of return.

User emotion on social media has the potential to influence the Bitcoin market. This was proven by Bartolucci et al. (2020) who analysed the emotional implication of Github developers on Bitcoin and Ethereum asset prices in a study from December 2010 to August 2017. The study showed that Grangers' causal relationship exists between developer emotions and assets' price. Further, Ahn and Kim (2021) measured the emotional impact on the Bitcointalk.org online forum by collecting 2,050,280 comments on Bitcoin price changes spanning the period from November 2009 to September 2020. In addition, they also included macroeconomic and Google search variables as control variables to disclose the importance of emotions in the Bitcoin market.

In comparison, Bartolucci et al. (2020) were only concerned with the emotional impact of developers on the digital market. The study by Ahn and Kim (2021) however indicated that the emotion indicator influences the Bitcoin market. They also highlighted that the emotional aspect can drive substantial Bitcoin price changes. Typically though not all users are active on Github and online fora but they tend to be active on Twitter[6]. Both studies nevertheless did not take into account the emotional impact of users on Twitter on the Bitcoin market. Thus, emphasizing the emotional importance of users on social media can add value to the importance of individual behavior in the Bitcoin market. As with Twitter, the Google platform also provides a major reference source for users to obtain the latest information on digital assets. Most researchers have studied the implication of Google search on the digital asset market (Aslanidis et al. 2021; Chang et al. 2021; Chuffart 2021; Pinto-Gutiérrez et al. 2022; Katsiampa et al. 2019; Süssmuth 2022; Smales 2022; Tripathi et al. 2022; Zhang et al. 2018; Zhang et al. 2021). Specifically, the findings of Chuffart (2021) showed that Google search is a good predictor of correlation between the stated digital assets and provides useful input for portfolio management. The researchers also explained that the large changes in the correlation dynamics between digital assets following the bubble burst in 2017 could be explained through Google search activity.

Some studies have examined the impact of Twitter user sentiment on the digital assets market (Zhang & Zhang 2022; Kraaijeveld & De Smedt 2020; Öztürk & Bilgiç 2021; Suardi et al. 2022; Steinert & Herff 2018; Shen et al. 2019). They have subsequently established the importance of Google search in their studies (Aslanidis et al. 2021; Chuffart 2021; Pinto-Gutiérrez et al. 2022; Katsiampa et al. 2019; Koch & Dimpfl 2023; Li et al. 2021; Rutkowska & Kliber 2021; Süssmuth 2022; Smales 2022; Tripathi et al. 2022; Urquhart 2018; Zhang et al. 2021). In addition, several studies (Garcia et al. 2014; Garcia & Schweitzer 2015; Li et al. 2021) have highlighted the combined importance of Google search activity and Twitter as effective indicators to describe investor sentiment, based on their research findings. Similarly, macroeconomic elements also play an important role in the digital assets market that should be recognized. Some researchers (Baig et al. 2020; Baur & Dimpfl 2021; Chen et al. 2021) have explained the consequence of macroeconomic variables to the digital assets market. Indeed, the emphasis given to social media in combination with macroeconomics, has the potential to produce more accurate research findings in determining the rate of return on digital assets. Chang et al. (2021) and Lin (2020) had examined the implication of macroeconomic and Google search factor on the digital assets markets. They revealed that Google search activity still has significant relationship with the market even with the inclusion of macroeconomic variables. Briefly, this paper examines the consequence of user emotions in Twitter and Google search activities, namely the YouTube, web, and news search, on the rate of return of Bitcoin.

METHODOLOGY

This section explains the steps carried out in the methodology. The initial step was data collection, followed with estimate of Bitcoin return and associated volatility. The subsequent steps include the tweets cleaning process, emotion analysis, datasets preparation, and finally model estimation using the Var method.

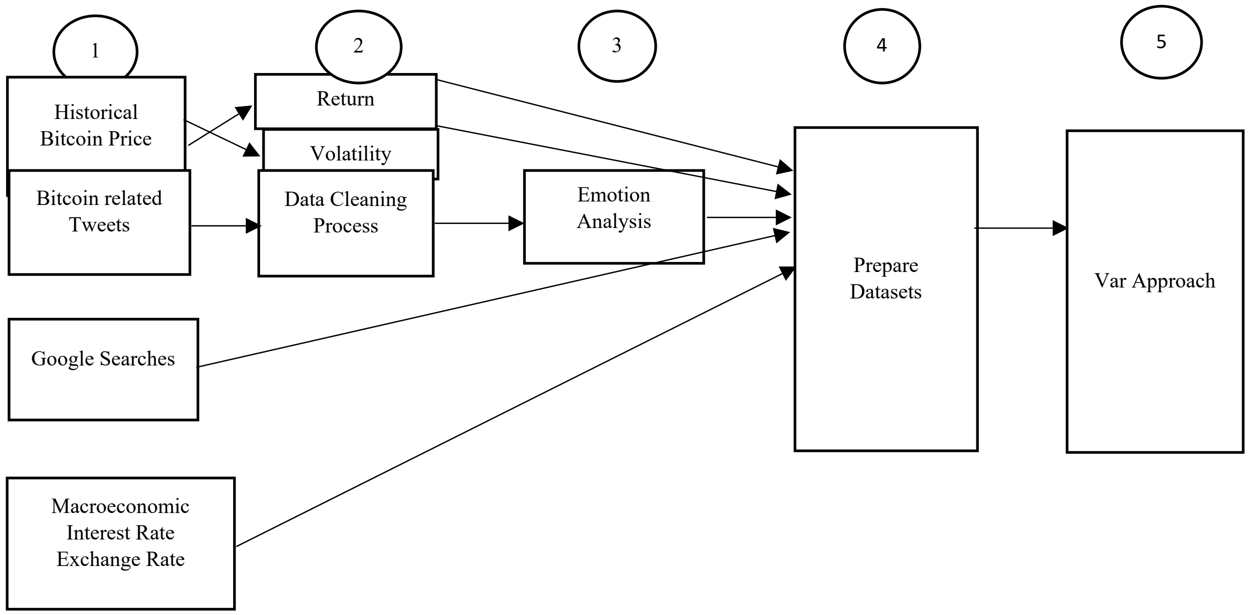


FIGURE 2. A general sketch of the various stages of the methodology
Source: Author's sketch

Figure 2 explains an overview of the steps involved in the methodology. Step one was data collection comprising data set of daily observations over the study period, from 17 August 2021 until 17 December 2021. Data were sourced using the RStudio software which only extracted real-time data but not historical data. The daily four-monthly data collated were considered sufficient for sentiment analysis. The majority of past studies (Feng Mai et al. 2018; Kraaijeveld & De Smedt 2020; Steinert & Herff 2018; Shen et al. 2019) by comparison only included two- or three-month daily data using Twitter platform for sentiment analysis. In addition, some studies (Katsiampa et al. 2019; Koch & Dimpfl 2023; Shen et al. 2019; Urquhart 2018) employed the Var method for daily data observation related to digital asset markets. The actual closing price data for Bitcoin were collected via coinmarketcap.com. Tweets were gathered from Twitter Application Programming Interface[7] (API) by using the keywords "Bitcoin" in RStudio software. A total of 2,155,210 tweets were collected this way. Subsequently, Google trend data[7] were sourced from a website in Google that displayed the search popularity of certain keywords from various countries. The value of Google trend data ranges from 0 to 100. This study, used a similar keyword with Twitter to gather Google search data separately for the web, news, and YouTube by using the RStudio software. In addition, we also sourced Google search data for the keyword "Covid" since the analysis was carried out during the pandemic time frame. The vast spread in Covid-19 exerted a significant impact on most financial assets globally. Therefore, the inclusion of such variables may illustrate the significance of Covid-19 on Bitcoin.

Additionally, the present study employed the interest rate (Effective Federal Fund Rate) and exchange rate (USD/EUR) of the US as macroeconomic data which was sourced from Investing com[8] and Fred[9]. USD currency captured almost 70 percent of Bitcoin transactions in 2021[10]. At the same time the US also maintained a massive number of Twitter users totaling 69.3 million in 2022[4], much more than any other countries. Furthermore the US central bank which is the Federal Reserve was active in using a Twitter channel to announce current economic changes in the country. The Federal Reserve also had an official Twitter account containing 768.9 thousand followers until July 2021[4].

The second step involved the historical Bitcoin price data and Bitcoin tweets. Beginning with Bitcoin market data, we used the Bitcoin price P_t to compute the return (Ret), with t as time;

$$Ret_t = \frac{P_t - P_{(t-1)}}{P_{(t-1)}} \tag{1}$$

After computing the return, the Garch (Generalized autoregressive conditional heteroskedasticity) approach is used to obtain the Bitcoin return variance. The conditional mean and variance specifications are as follows;

$$Ret_t = \beta_0 + \beta_1 Ret_{t-1} + \varepsilon_t$$
$$\varepsilon_t = \eta_t \sqrt{h_t}, \ \eta_t \sim N(0,1) \tag{2}$$
$$\sigma_t^2 = x + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{3}$$

where, Ret_t and Ret_{t-1} are the rates of return of Bitcoin at the time t and t-1 respectively, ε_t is the error term, $x>0$, $\alpha \geq 0, \beta \geq 0$, and η_t is independent. Similar random variables are distributed with zero mean and unit variance. h_t is the variance-covariance matrix and σ_t^2 is the variance. In subsequent, is data cleaning on collected Tweets and the process of filtering out the noise element from the Tweet text. This activity also adds value to the analysis conducted later. The data cleanup process involved the deletion of all types of punctuation, numbers and words that did not have any information value pertaining to user emotions (stopwords) and website addresses in Tweets. All uppercase letters were converted to lowercases and all spaces between the words were erased on completion of the cleaning process.

The third step is the emotional analysis section for cleaned tweets. By using the get-nrc-sentiment package found in RStudio software, we obtained eight types of emotions namely joy, trust, fear, surprise, sadness, disgust, anger, and anticipation. The research method of Ahn & Kim (2021) was adopted to determine the value of emotion. As an example, for trust emotion, we will sum the number of emotion trust words for every day and the same process was repeated for other emotions. In step four, we prepared data set for Bitcoin. The emotional data fluctuated considerably compared with other variables. To renormalize the variables, we standardized all the time series by Z-transformation $Z_t = (X_t - \mu_x)/\sigma_x$, where μ_x and σ_x were respectively defined as the mean and standard deviation of each time series. Following standardisation, all data have similar scale and variance and their impact differences in numerical analysis can be calculated (Garcia et al. 2015). The descriptive statistics of the data set for Bitcoin is shown in Appendix, Table A1. Before conducting the Var (Vector autoregressive) analysis, we evaluated the stationary of each time series by using the Augmented Dickey Fuller (ADF) test (Fuller 2009). The time series is stationary when the p-value is below 0.05. Following this, we implemented the differentiation method $\Delta X_t = X_t - X_{(t-1)}$ for time series which was not stationary at levels. The ADF results indicated that all the variables were stationary at the level except for the exchange rate stationary at first difference. In subsequent, we apply the differentiation method to exchange rate data. This was supported by Pinto-Gutiérrez et al. (2022), who employed the Var method to investigate the effect of users' attention on Non-Fungible Tokens. This produced the first difference to the variable which was not stationary at level. The unit root test for the Bitcoin data set is presented in Appendix, Table A2.

The Var estimation approach was adopted to analyse the implication of user emotions and Google searches on Bitcoin rate of returns. The same approach was also used by several authors in analysis the relationship between Google search, Twitter, and digital asset market (Pinto-Gutiérrez et al. 2022; Katsiampa et al. 2019; Koch & Dimpfl 2023; Shen et al. 2019; Urquhart 2018). The method is suitable for the high-frequency and extremely noisy data structure of Google trend, Twitter, and digital assets prices. Conversely the Autoregressive Distributed Lag (ARDL) method was not applied in this study since the ARDL diagnostic test, such as cumulative sum test (cusum), cumulative sum of square test (cusumsq), and heteroscedasticity test, cannot be implemented. The Var model used is in the following form:

$$Y_t = a + BX_{t-1} + \varepsilon_t \tag{4}$$

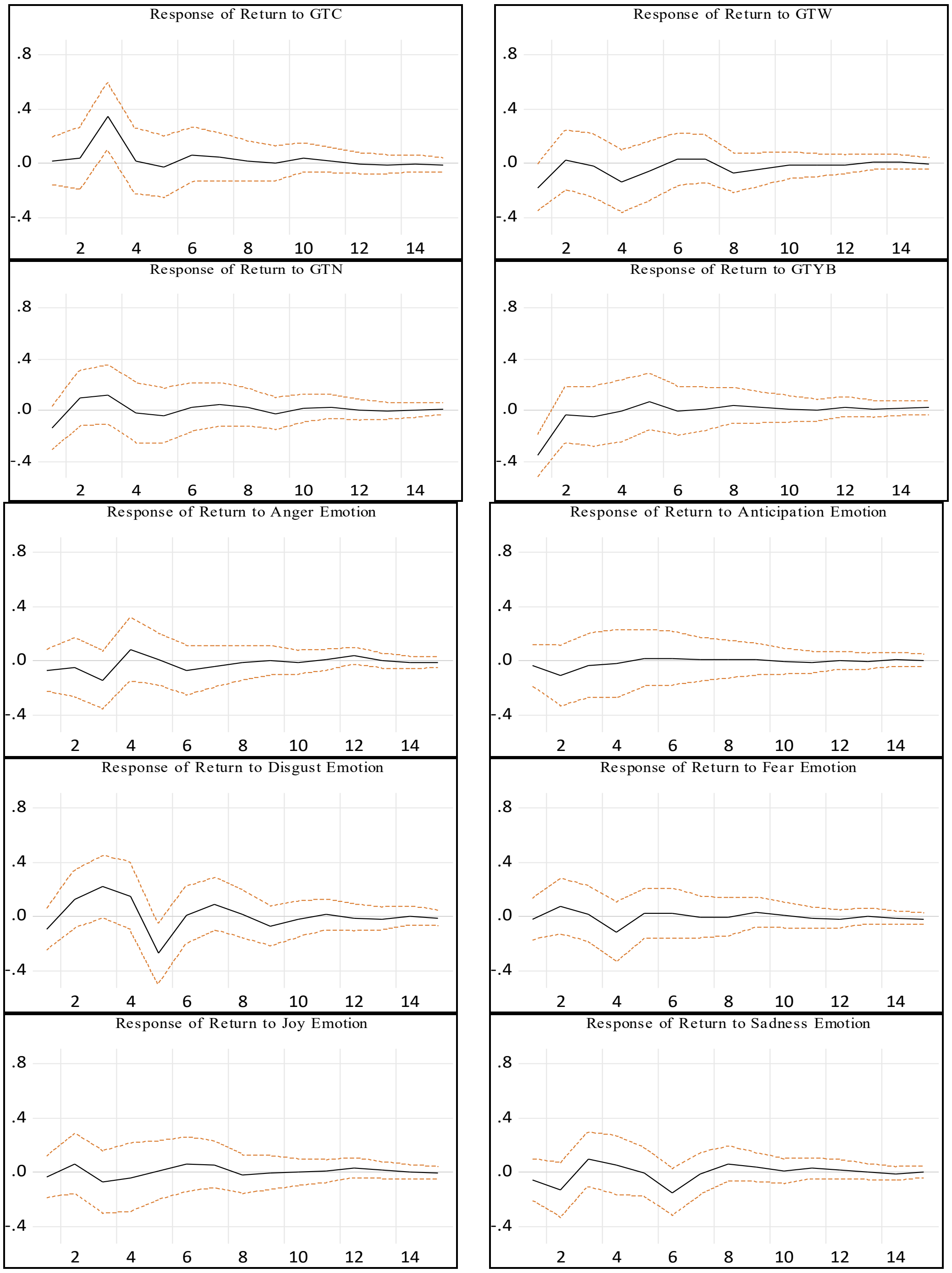
where, Y_t is the vector containing vectors y of variables such as Bitcoin Return (Ret). BX_{t-1} represent the variables such as Google Trend Covid (GTC), Google Trend Web (GTW), Google Trend News (GTN), Google Trend YouTube (GTYB), anger emotion, anticipation emotion, disgust emotion, fear emotion, joy emotion, sadness emotion, surprise emotion, trust emotion, interest rate and exchange rate, volatility and return. We applied two methods under the Var model which were Impulse Response Function (IRF) and Variance Decomposition (VDC). These are vital methods in the Var model (Dizaji 2019; Siriopoulos et al. 2021). IRF illustrates how the Bitcoin return reacts to a shock in GTC, GTW, GTN, GTYB, anger emotion, anticipation emotion, disgust emotion, fear emotion, joy emotion, sadness emotion, surprise emotion, trust emotion, interest rate, exchange rate, volatility, and return. The vertical line in impulse response functions indicates the magnitude of response to shocks and the horizontal line shows the period after the initial shock. The solid lines show the impulse response and the dotted lines represent 95% confidence intervals. The impulse response is not statistically significant when the horizontal line in the IRFs falls between confidence bands. On the other hand, VDC explains how much of the forecast error variance decomposition of Bitcoin return can be interpreted by shocks to stated variables such as in IRFs. The Var system variable ordering is crucial for computing IRF and VDC analyses. The outcome of IRFs and VDCs may alter depending on this ordering. An economic theory should ideally assist us in determining the most reliable ordering which from the most exogenous variables toward the most endogenous ones (Dizaji 2019). Google trend data were ordered as the first variable being the most exogenous in our model. The first variable in the Cholesky ordering was followed by emotions and macroeconomic variables. Finally, volatility and return were the two most endogenous variables in the Var system.

In addition, the lag selection was based on Schwarz (SC), Akaike (AIC), and Hannan-Quinn (HQ). However, the suggested lag for Bitcoin had an autocorrelation problem. To solve this we selected lag apart from the suggested lag for Bitcoin. We also examined the diagnostic test of the estimated Var model by inverse roots of AR characteristic polynomial (Var stability) and Var residual serial correlation LM test. From stability results of the Var test we found that the absolute values of Eigen value were less than one (1) and all points were located in the circle. In addition, the Var residual serial correlation LM test indicated that there was no serial correlation problem in Var estimation. As a result, the diagnostic criteria showed that the estimated Var model was stable and satisfactory. The diagnostic tests are reported in Appendix, in Figure A1 (Eigen Value Stability) and also Table A3 (LM Autocorrelation).

RESULTS

IMPULSE RESPONSE FUNCTION

This section explains the response of Bitcoin return to shock derived from the variables of Google search, emotions, interest rate, exchange rate, volatility, and return.



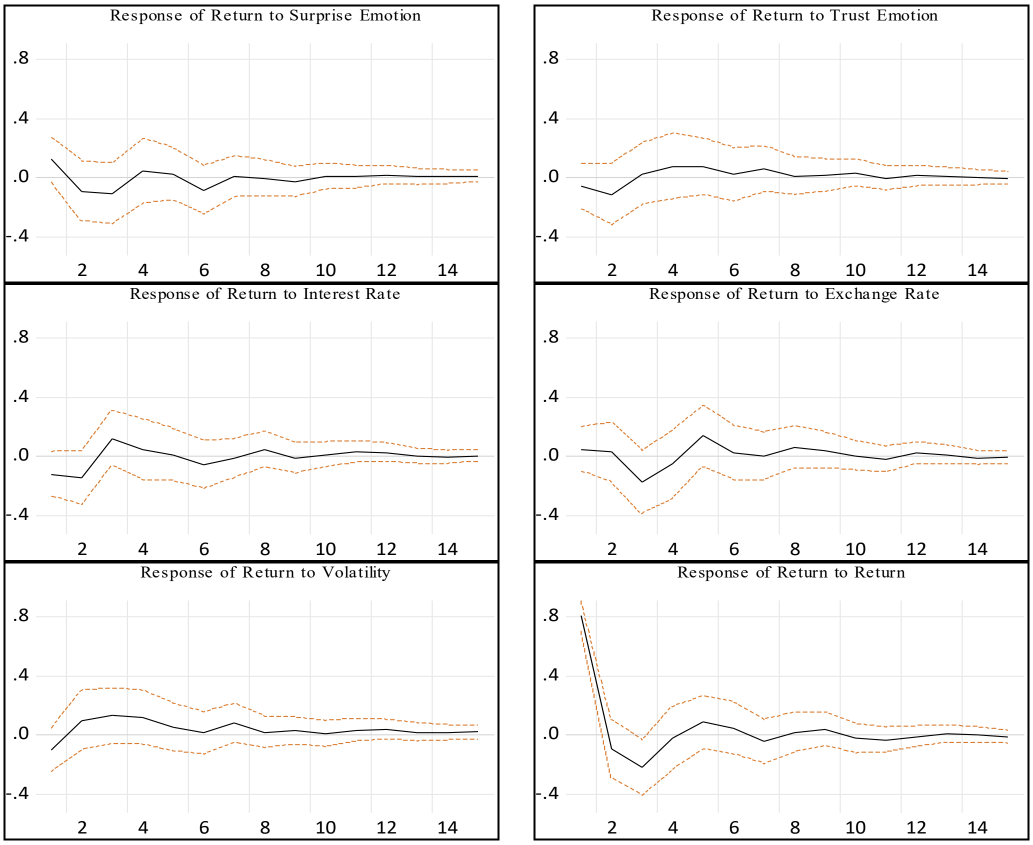


FIGURE 3. Impulse response function Bitcoin

Source: Author's calculations

Note: Google Trend Covid (GTC), Google Trend Web (GTW), Google Trend News (GTN), Google Trend YouTube (GTYB)

Figure 3 illustrates the impulse response of Bitcoin return when an innovation of other variables takes place over the next 15 days (period). Based on this the return response was significant for GTC which indicates that one unit shock in the standard deviation of the GTC variable influences the Bitcoin return positively and significantly on the third day. This outcome is consistent with some past studies (Chen et al. 2021; Chundakkadan & Nedumparambil 2021; Ding et al. 2020; Reis & Pinho 2020) that documented the impact of investor sentiment measured by Google trend data against the stock market as well as the digital asset market. Furthermore, it defines the user perception of Covid-19 as a positive impact on Bitcoin return as evidenced by the increase in its demand as well as pricing during the peak period of the pandemic season. In addition, among the Google search variables, the Bitcoin return response was negative and significant towards shock arising from GTYB until day 1. On the other hand, the response of Bitcoin return was not significant towards any shock arising from variables of GTW, GTN, interest rate, exchange rate, and also volatility. This may have transpired due to public concern on Covid-19 and Bitcoin rather than on other issues during the study period, as evidenced by the positive relationship result shown between GTC and Bitcoin return.

Although there are eight types of user emotions, not all are influential on the Bitcoin market. Further, the response of its return was not significant to emotion shock such as anger, anticipation, fear, joy, sadness, surprise, and trust. The result showed that a one-unit standard deviation shock in the disgust emotion negatively and significantly affect Bitcoin return on day five. This finding suggests that users' negative emotions on the Twitter social media have the potential for negative influence on the Bitcoin market. Furthermore, positive shocks that occur in Bitcoin return produce a significant positive response. A one-unit standard deviation shock in Bitcoin returns lead to an increase that lasts until the second day. However, between day 3 and 4 the response towards the return shock was significantly negative.

VARIANCE DECOMPOSITION METHOD

The forecast error variance decomposition of Bitcoin return was evaluated and shown in Table 1 which describes the influence of variables on the forecast error variance (fev) of Bitcoin return on a 15-day horizon period.

TABLE 1. Variance decomposition of return

Days	S.E.	GTC	GTW	GTN	GTYB	Anger	Anticipation	Disgust	Fear
1	0.95	0.03	3.55	2.15	13.90	0.54	0.14	0.99	0.06
2	1.01	0.15	3.15	2.73	12.23	0.73	1.31	2.38	0.64
3	1.17	8.82	2.39	3.12	9.33	2.08	1.06	5.32	0.50
4	1.21	8.28	3.48	2.95	8.74	2.40	1.02	6.48	1.38
5	1.26	7.69	3.42	2.83	8.36	2.23	0.97	10.58	1.31
6	1.28	7.69	3.36	2.78	8.10	2.47	0.96	10.25	1.31
7	1.29	7.69	3.35	2.84	7.95	2.55	0.95	10.57	1.29
8	1.30	7.62	3.62	2.84	7.95	2.53	0.94	10.46	1.27
9	1.31	7.54	3.71	2.86	7.90	2.51	0.94	10.67	1.33
10	1.31	7.62	3.71	2.87	7.88	2.51	0.94	10.66	1.33
11	1.31	7.61	3.71	2.90	7.85	2.50	0.95	10.64	1.33
12	1.31	7.58	3.70	2.89	7.86	2.56	0.95	10.60	1.35
13	1.31	7.58	3.70	2.89	7.86	2.56	0.95	10.61	1.35
14	1.32	7.58	3.70	2.88	7.86	2.57	0.95	10.60	1.35
15	1.32	7.57	3.70	2.89	7.88	2.58	0.95	10.59	1.37

cont...

Days	S.E.	Joy	Sadness	Surprise	Trust	Interest Rate	Exchange Rate	Volatility	Return
1	0.95	0.14	0.39	1.68	0.37	1.62	0.24	1.12	73.07
2	1.01	0.51	2.05	2.28	1.60	3.52	0.28	1.91	64.54
3	1.17	0.78	2.18	2.57	1.25	3.72	2.39	2.69	51.82
4	1.21	0.85	2.22	2.55	1.57	3.63	2.41	3.49	48.55
5	1.26	0.79	2.05	2.39	1.81	3.36	3.45	3.39	45.37
6	1.28	0.96	3.34	2.77	1.78	3.47	3.37	3.30	44.09
7	1.29	1.12	3.29	2.72	1.95	3.42	3.31	3.64	43.37
8	1.30	1.13	3.49	2.69	1.94	3.51	3.50	3.62	42.89
9	1.31	1.12	3.53	2.71	1.94	3.49	3.56	3.63	42.57
10	1.31	1.12	3.52	2.71	1.99	3.48	3.55	3.63	42.48
11	1.31	1.12	3.55	2.70	1.99	3.52	3.57	3.68	42.38
12	1.31	1.17	3.56	2.71	1.99	3.54	3.58	3.75	42.21
13	1.31	1.18	3.56	2.71	2.00	3.54	3.59	3.77	42.18
14	1.32	1.18	3.57	2.71	1.99	3.54	3.59	3.78	42.14
15	1.32	1.18	3.56	2.71	1.99	3.53	3.59	3.80	42.10

Source: Author's calculations

Note: Standard Error (S. E), Google Trend Covid (GTC), Google Trend Web (GTW), Google Trend News (GTN), Google Trend YouTube (GTYB)

As shown in Table 1, Bitcoin return elucidates most of the fev in the following days but in a decreasing trend. As illustration, on the first day the Bitcoin return variable explains 73.07 percent of fev. However, by the fifteenth day it only contributes around 42.10 percent. As expected, apart from Bitcoin return shock, Google search and emotional variables shock, especially Google trend, YouTube search and disgust emotion, showed dominance in explaining the fev of the currency return. Google and YouTube search explained for 13.90 percent fev of Bitcoin return on day 1 and this amount is still maintained at above 7.00 percent until the fifteenth day. Further, disgust emotion shows more than 10.00 percent fev on the fifth day and this value was consistent until the fifteenth day. These findings are in agreement with the impulse response function results which proved significantly the relationship between GTYB, disgust emotion and Bitcoin return. In comparison, other emotional variables only illustrate no more than 4.00 percent fev of return. Results of the study again confirmed the influence of user emotions and Google searches on the Bitcoin market.

Further to this, GTC search variable also explained the highes t amount of fev Bitcoin return which was 8.82 percent on day 3. This indicates that user attention on the spread of the Covid-19 pandemic exerts an impact on Bitcoin return and this is also consistent with impulse response function findings. Conversely, GTW showed the fev of Bitcoin return of more than 3.00 percent for most of the days except for day 3 which registered 2.39 percent. Similarly, GTN interpreted fev of more than 2.00 percent on most days. Subsequently, it was found that the shock of the exchange rate variable showed fev to have exceeded 3.00 percent of return from the fifth day onwards until the fifteenth day, whereas both the interest rate and volatility variables explained for more than 3.00 percent fev of return during most of the time. Based on this result we informed that besides the influence of return variable, the GTYB and disgust emotion variables were also important to the fev of Bitcoin return relative to other indicators.

This study andeavours to explain the influence of user emotions from Twitter and Google search activities as related to Bitcoin return. Initially, we begin with the role of user emotions shown in the Bitcoin markets. The findings of impulse response function and variance decomposition reveal that user emotions, specifically disgust emotion, affect Bitcoin return. This outcome is consistent with Ahn & Kim (2021) and Bartolucci et al. (2020) who demonstrated the importance of the aspect of emotions in the Bitcoin market. In addition, some studies (Kraaijeveld & De Smedt 2020; Öztürk & Bilgiç 2021; Suardi et al. 2022; Steinert & Herff 2018; Shen et al. 2019) have also demonstrated the influence of user sentiment from the Twitter platform, on digital assets market. Psychological and sentiment elements do play a meaningful role in investment decisions as consistent with behavioral science theory (Kraaijeveld & De Smedt 2020). Such analysis is beneficial to policy makers, particularly in knowing the significance of user emotion from Twitter and in identifying the real factors causing Bitcoin market fluctuation. This suggestion is supported by other authors (Huerta et al. 2021; Siriopoulos et al. 2021) who argued that it was crucial for policymakers to identify the real causes of financial market fluctuation in order to stabilize the market through implementing the appropriate steps.

We have shown earlier that the GTYB, among the Google search variables, has significantly influenced Bitcoin return, although many earlier studies (Aslanidis et al. 2021; Chuffart 2021; Chang et al. 2021; Pinto-Gutiérrez et al. 2022; Katsiampa et al. 2019; Lin 2020; Li et al. 2021; Rutkowska & Kliber 2021; Süssmuth 2022; Smales 2022; Tripathi et al. 2022; Urquhart 2018; Zhang et al. 2021) had indicated the importance of Google search activity in the digital assets markets. However, our findings are different from those of previous studies since we specifically focused on searches in YouTube, web and news in the Google trend and analysed their implications on Bitcoin return. The investor can thus refer to the GTYB trend before deciding to invest in the Bitcoin market since its return response to the GTYB shock is negative and significant. As a result, investors are able to build profitable investment strategies and minimize the risk. For instance, Google searches with keywords on the financial market may discern increasing trends prior to the crash in the stock market (Preis et al. 2013). Chuffart (2021) further demonstrated that Google searches are known to be a useful predictor for cryptocurrencies and provide profitable information to portfolio management.

ROBUSTNESS TESTS

Initially, we arrange the variables from the most exogenous to the endogenous (GTC, GTW, GTN, GTYB, anger emotion, anticipation emotion, disgust emotion, fear emotion, joy emotion, sadness emotion, surprise emotion, trust emotion, interest rate, exchange rate, volatility, and return). The IRFs show that the response of Bitcoin returns to the shock arising from GTC, GTYB, disgust emotion, and return, is significant. The IRFs result is however different when we reverse the order of the variables from most endogenous to exogenous (return, volatility, exchange rate, interest rate, anger emotion, anticipation emotion, disgust emotion, fear emotion, joy emotion, sadness emotion, surprise emotion, trust emotion, GTC, GTW, GTN, and GTYB). The findings hence indicate that the response of Bitcoin is significant to the shock coming from return and GTC only. Thus, the ordering of variables is important in IRFs and VDC since the dependent variable will respond more towards endogenous variable shock if the endogenous to exogenous arrangement is adopted. Results of the robustness tests are shown in Appendix of Figure A2.

CONCLUSION

User attention is one of the important factors for Bitcoin market fluctuation and deviation from Bitcoin mean price. This study highlights the significant role of user emotions and Google searches in Bitcoin market performance. We documented empirical evidence that Bitcoin return is significantly associated with emotional factors among users and Google searches. We further advance the literature with new information by illustrating the importance of user emotion element in analysing Bitcoin market performance as well as the economic aspects. Thus, we assist the policy makers of the country, which has extensively adopted the Bitcoin digital currency in their trading activities, in drawing up strategies to reduce currency price fluctuation through identifying the significant influence of user emotion factors in the Bitcoin market. Additionally, investors can make investment decisions from observing the relationship between Google trend YouTube search data and Bitcoin markets especially during the periods of market turbulence. Further research should be considered on the implication of user emotions on the stock market and comparing these with the digital asset markets. Through its implementation we should be able to identify the markets that receive greater impact from user emotions.

NOTES

[1] https://coinmarketcap.com
[2] https://bitinfocharts.com
[3] https://trends.google.com
[4] https://www.statista.com/topics/737/twitter
[5] https://trends.google.com/trends
[6] https://twitter.com
[7] https://developer.twitter.com/en/docs/twitter-api
[8] https://www.investing.com
[9] https://fred.stlouisfed.org
[10] https://bitcoinity.org/markets

ACKNOWLEDGEMENT

This work if funded by *Geran Kursi Yayasan Tun Ismail Ali* (YTI-UKM)-grant number EP-2018-009.

REFERENCES

Ahn, Y. & Kim, D. 2021. Emotional trading in the cryptocurrency market. *Finance Research Letters* 42: 101912-10921.

Anastasiou, D., Ballis, A. & Drakos, K. 2021. Cryptocurrencies' price crash risk and crisis sentiment. *Finance Research Letters* 42: 101928-101938.

Aslanidis, N., Bariviera, A.F. & G. López, Ó. 2021. The link between Bitcoin and Google trends attention. *SSRN Electronic Journal* (2019): 1–9.

Baker, M. & Wurgler, J. 2006. Investor sentiment and the cross-section of stock returns. *Journal of Finance* 61(4): 1645-1680.

Baig, A.S., Butt, H.A., Haroon, O. & Rizvi, S.A.R. 2020. Deaths, panic, lockdowns and US equity markets: The case of COVID-19 pandemic. *Finance Research Letters* 38: 101701-101710.

Bartolucci, S., Destefanis, G., Ortu, M., Uras, N., Marchesi, M. & Tonelli, R. 2020. The butterfly "Affect": Impact of development practices on cryptocurrency prices. *EPJ Data Science* 9: 21-39.

Baur, D.G. & Dimpfl, T. 2021. The volatility of Bitcoin and its role as a medium of exchange and a store of value. *Empirical Economics* 61: 2663-2683.

Bourghelle, D., Jawadi, F. & Rozin, P. 2022. Do collective emotions drive Bitcoin volatility? A triple regime-switching vector approach. *Jornal of Economic Behavior & Organization* 196: 294–306.

Chang, C.Y., Lo, C.C., Cheng, J.C., Chen, T.L., Chi, L.Y. & Chen, C.C. 2021. Relationship between Bitcoin exchange rate and other financial indexes in time series. *Mathematical Problems in Engineering* 8842877: 1-9.

Chuffart, T. 2021. Interest in cryptocurrencies predicts conditional correlation dynamics. *Finance Research Letters* 46: 102239-102249.

Chen, T.H., Chen, M.Y. & Du, G.T. 2021. The determinants of Bitcoin's price: Utilization of GARCH and machine learning approaches. *Computational Economics* 57(1): 267–280.

Chundakkadan, R. & Nedumparambil, E. 2021. In search of Covid-19 and stock market behavior. *Global Finance Journal* 54: 100639-100649.

Del Lo, G., Basséne, T. & Séne, B. 2022. COVID-19 and the African financial markets: Less infection, less economic impact? *Finance Research Letters* 45: 102148-102155.

Dizaji, F.S. 2019. Trade openness, political institutions, and military spending (evidence from lifting Iran's sanctions). *Empirical Economics* 57(6): 2013–2041.

Ding, D., Guan, C., Chan, C.M.L. & Liu, W. 2020. Building stock market resilience through digital transformation: Using Google trends to analyze the impact of COVID-19 pandemic. *Frontiers of Business Research in China* 14: 21-42.

Fama, E.F. 1970. Efficient capital markets: A review of theory and empirical work. *The Journal of Finance* 25(2): 383–417.

Feng Mai, Zhe Shan, Qing Bai, Xin Wang & Roger H.L. Chiang. 2018. How does social media impact Bitcoin value? A test of the silent majority hypothesis. *Journal of Management Information Systems* 35(1): 19–52.

Fuller, W.A. 2009. *Introduction to Statistical Time Series, Vol. 428*. New York, NY: John Wiley and Sons.

Garcia, D., Tessone, C.J., Mavrodiev, P. & Perony, N. 2014. The digital traces of bubbles: Feedback cycles between socio-economic signals in the Bitcoin economy. *Journal of the Royal Society Interface* 11(99): 20140623-20140631.

Garcia, D., Schweitzer, F. & Garcia, D. 2015. Social signals and algorithmic trading of Bitcoin Subject Category: Subject areas: Author for correspondence. *Royal Society open science* 2(9): 1–19.

Raja Solan Somasuntharam
Faculty of Economics and Management
Universiti Kebangsaan Malaysia
43600 UKM Bangi, Selangor, MALAYSIA.
E-mail: P94772@siswa.ukm.edu.my

Fathin Faizah Said*
Center for Sustainable and Inclusive Development Studies (SID)
Faculty of Economics and Management
Universiti Kebangsaan Malaysia
43600 UKM Bangi, Selangor, MALAYSIA.
E-mail: fatin@ukm.edu.my

Tamat Sarmidi
Center for Sustainable and Inclusive Development Studies (SID)
Faculty of Economics and Management
Universiti Kebangsaan Malaysia
43600 UKM Bangi, Selangor, MALAYSIA.
E-mail: tamat@ukm.edu.my

Mohd Ridzwan Yaakub
Center for Artificial Intelligence Technology (CAIT)
Faculty of Information Science and Technology
Universiti Kebangsaan Malaysia
43600 UKM Bangi, Selangor, MALAYSIA.
E-mail: ridzwanyaakub@ukm.edu.my

*Corresponding author

APPENDIX

TABLE A1. Descriptive Statistics

	Variables							
	Return	Volatility	Anticipation	Anger	Disgust	Fear	Joy	Sadness
Mean	-5.10E-17	1.26E-17	-3.60E-16	-5.20E-16	3.54E-16	-3.90E-16	-2.20E-16	-1.30E-16
Median	0.066	-0.24	-0.0036	-0.0723	-0.1714	-0.1291	-0.0478	-0.1681
Max	2.665	2.757	3.7573	4.3316	4.6108	2.8753	3.0742	2.7926
Min	-3.318	-1.5501	-2.3488	-1.7181	-1.32	-2.008	-2.0437	-1.9215
Std.Dev	1	1	1	1	1	1	1	1
Skewness	-0.357	0.8505	0.9377	1.2864	1.9257	0.5961	0.5826	0.7835
Kurtosis	3.729	3.1845	5.7182	6.1684	7.8108	3.0443	3.5819	3.4697
	Variables							
	Surprise	Trust	GTC	GTN	GTW	GTYB	Interest Rate	Exchange Rate
Mean	2.98E-16	-3.10E-16	-2.60E-16	-1.50E-16	-2.10E-16	1.41E-16	-9.10E-16	9.82E-16
Median	-0.0813	0.0025	-0.0854	-0.1912	-0.185	-0.198	-0.0705	-0.1651
Max	4.3808	3.7453	2.7658	2.7265	2.2744	2.2205	4.494	1.9346
Min	-2.0636	-2.578	-2.122	-1.4481	-1.6879	-1.9256	-4.635	-1.5694
Std.Dev	1	1	1	1	1	1	1	1
Skewness	0.9235	0.1992	0.4122	1.1413	0.5322	0.5771	-0.3358	0.3726
Kurtosis	5.2226	4.3009	3.5083	3.9362	2.5247	2.6232	13.3212	1.8934

Source: Author's calculations
Note: Google Trend Covid (GTC), Google Trend Web (GTW), Google Trend News (GTN), Google Trend YouTube (GTYB)

TABLE A2. Augmented Dickey Fuller (ADF)

Variable	ADF					
	Level			1st diff		
	Intercept	Trend and Intercept	None	Intercept	Trend and Intercept	None
Return	-9.4388***	-9.6187***	-9.4783***	-10.6463***	-10.6001***	-10.6884***
Volatility	-3.7242***	-3.718**	-3.7399***	-11.6701***	-11.6212***	-11.7178***
Anticipation	-7.8948***	-7.8630***	-7.9274***	-9.3672***	-9.3742***	-9.4002***
Anger	-7.0294***	-7.3991***	-7.0589***	-10.1712***	-10.1292***	-10.2010***
Disgust	-10.2443***	-10.4069***	-10.2866***	-10.7062***	-10.6658***	-10.7464***
Fear	-8.1274***	-8.4253***	-8.1603***	-10.6192***	-10.5726***	-10.6548***
Joy	-6.7912***	-6.7579***	-6.8188***	-11.4800***	-11.4571***	-11.5239***
Sadness	-4.5284***	-4.6443***	-4.5529***	-11.0230***	-10.9744***	-11.0600***
Surprise	-3.2692***	-7.3995***	-3.2649***	-11.2656***	-11.2771***	-11.3027***
Trust	-7.0905***	-7.1258***	-7.1188***	-11.4587***	-11.4407***	-11.4958***
GTC	-4.5694***	-4.5510***	-4.5885***	-12.2557***	-12.2040***	-12.3067***
GTN	-9.3009***	-9.3740***	-9.3385***	-10.7278***	-10.6770***	-10.7754***
GTW	-4.7603***	-4.7495***	-4.7820***	-9.8086***	-9.7668***	-9.8336***
GTYB	-5.6095***	-5.8771***	-5.6346***	-9.4381***	-9.3965***	-9.4591***
Interest Rate	-7.2793***	-7.3833***	-7.3020***	-9.5047***	-9.5521***	-9.5175***
Exhange Rate	-0.3484	-2.9206	-0.3655	-12.4644***	-12.4917***	-12.3347***

Source: Author's calculations
Note: *Null hypothesis rejection at 10%, **Null hypothesis rejection at 5% and *** Null hypothesis rejection at 1%. Google Trend Covid (GTC), Google Trend Web (GTW), Google Trend News (GTN), Google Trend YouTube (GTYB)

TABLE A3. Var residual serial correlation LM test

Bitcoin	Lags	LM test	P-Value
	1	0.9332	0.7317
	2	1.3597	0.0021
	3	1.0519	0.3174
	4	1.0447	0.3404

Source: Author's calculations
Note: *Ho no serial correlation at lag order h

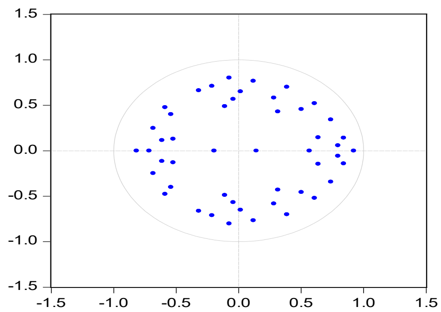
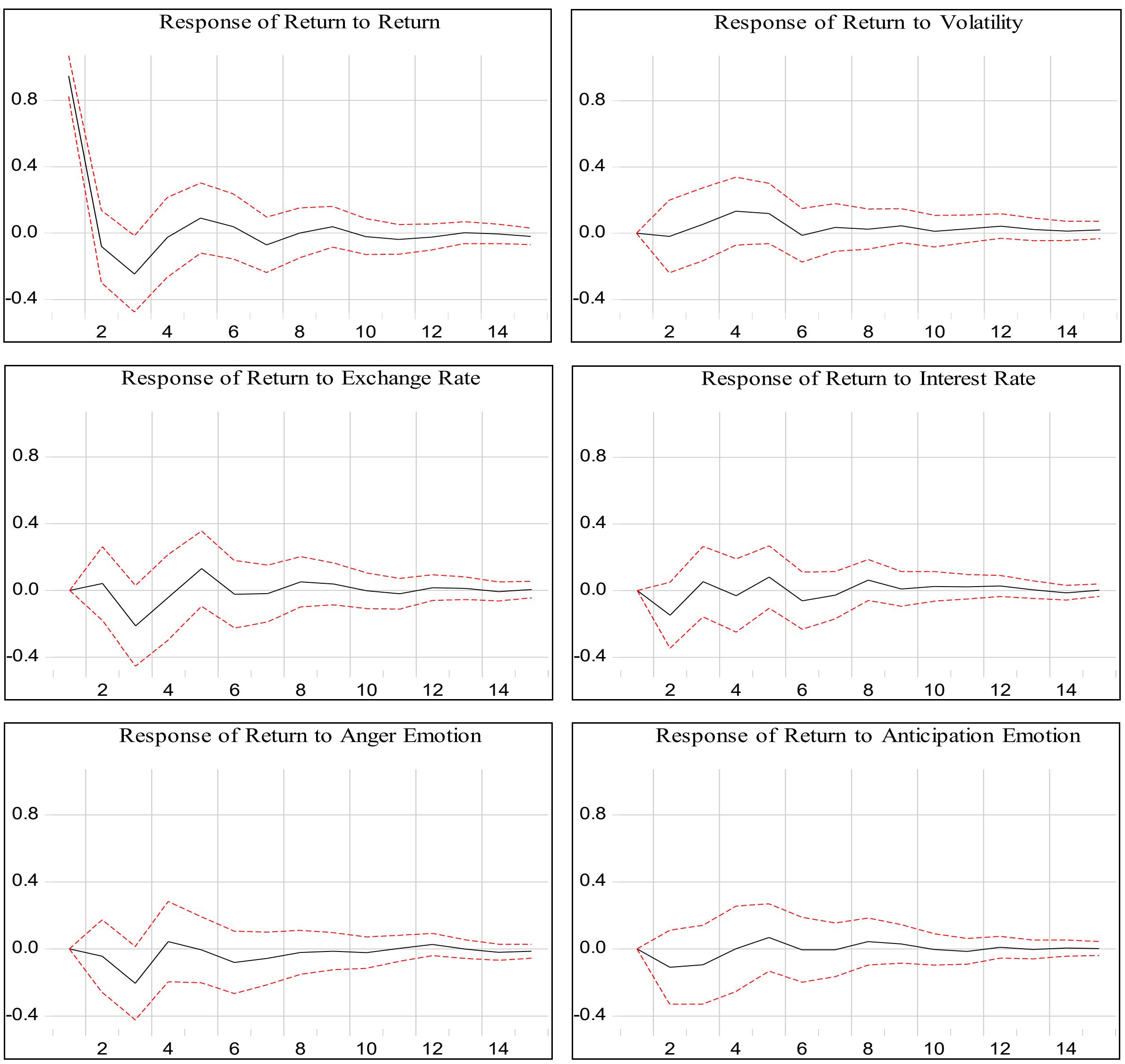
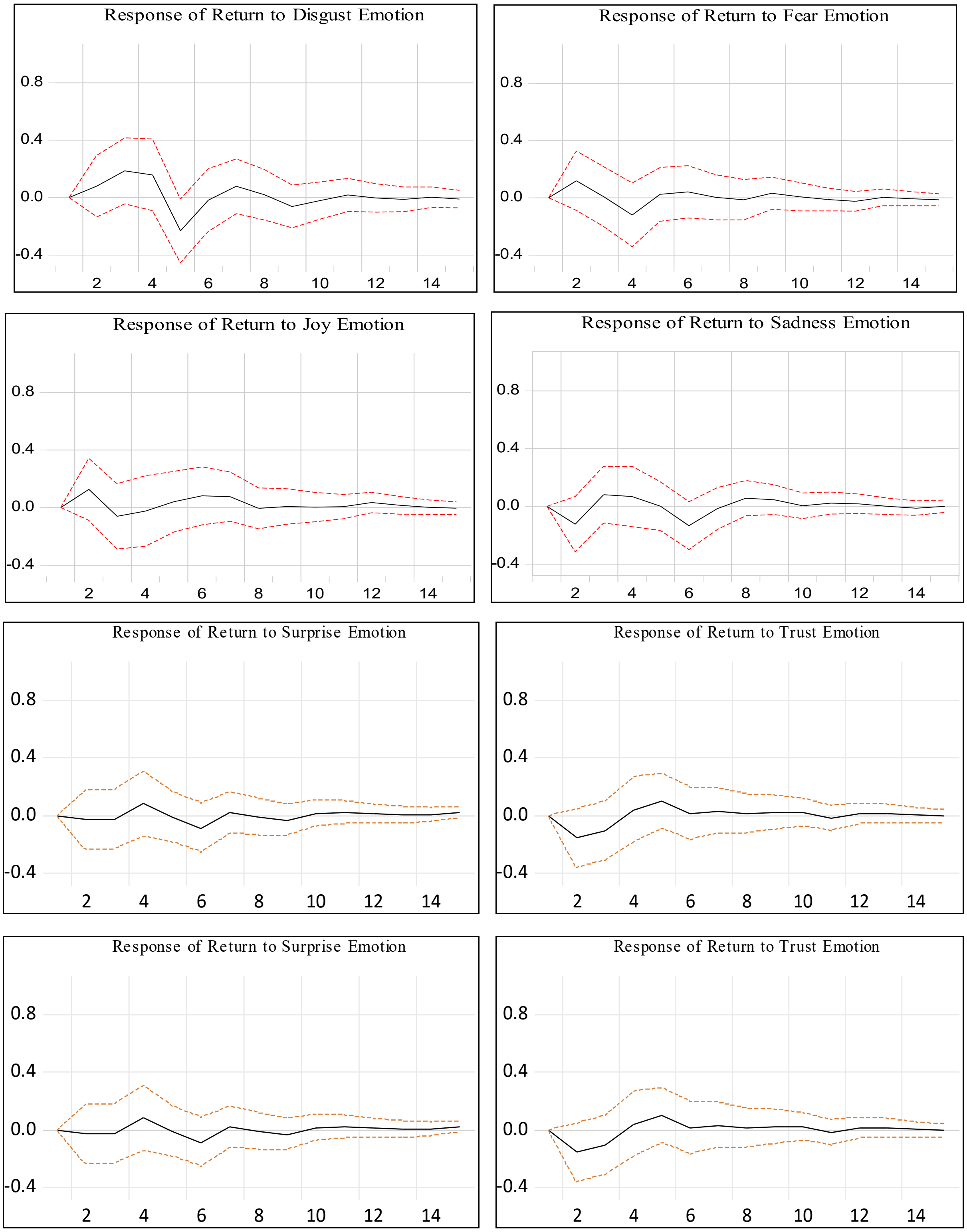


FIGURE A1. Inverse roots of AR characteristic polynomial
Source: Author's calculations




Response of Return to Disgust Emotion
Response of Return to Fear Emotion
Response of Return to Joy Emotion
Response of Return to Sadness Emotion
Response of Return to Surprise Emotion
Response of Return to Trust Emotion
Response of Return to Surprise Emotion
Response of Return to Trust Emotion
0.8
0.4
0.0
-0.4
2 4 6 8 10 12 14

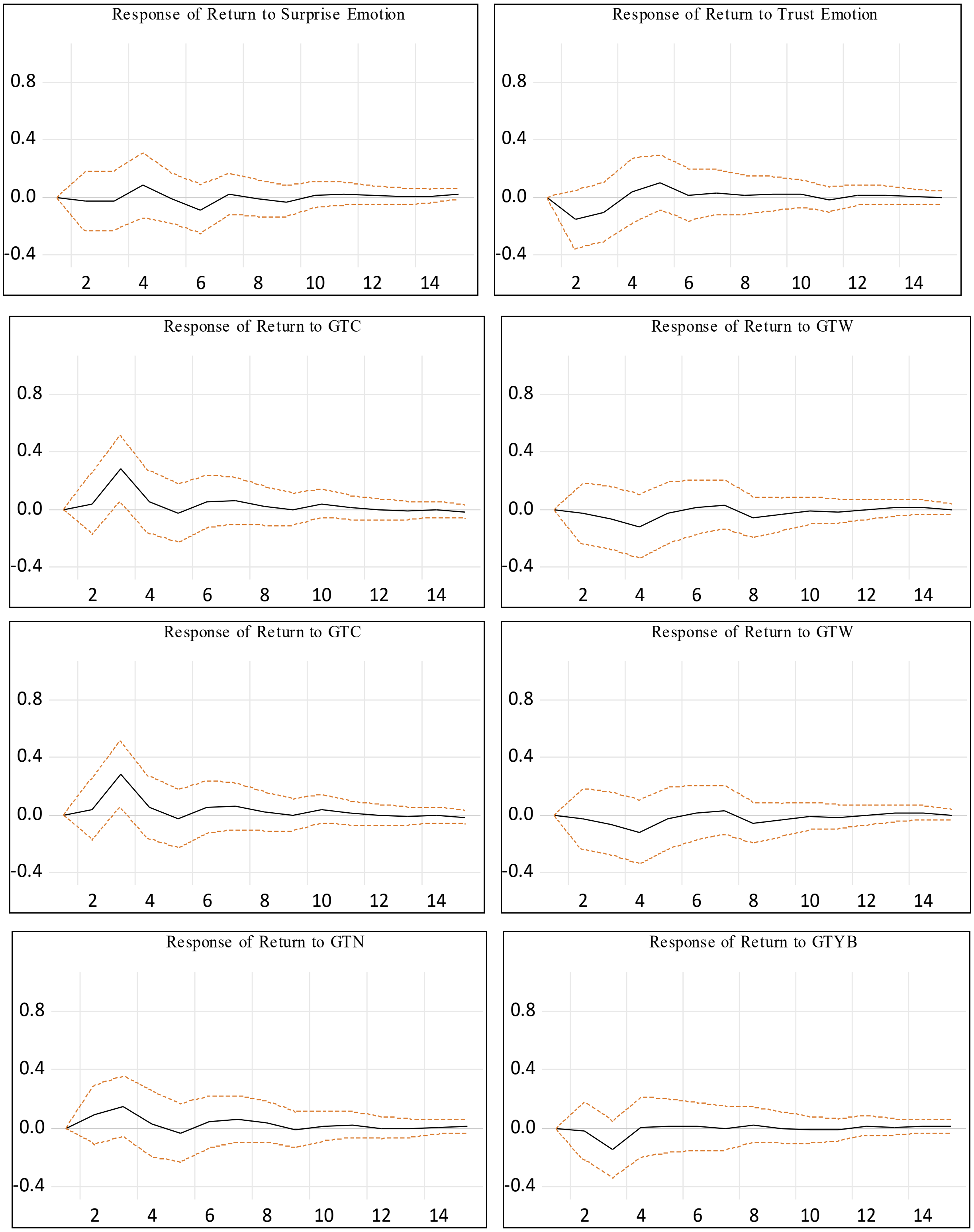


FIGURE A2. Impulse response function Bitcoin.

Source: Author's calculations

Note: Google Trend Covid (GTC), Google Trend Web (GTW), Google Trend News (GTN), Google Trend YouTube (GTYB)