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RESEARCH PAPER

The Impact of Tweet Risks on Global Financial Markets Using the Quantile VAR Model

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Abstract

This study examines how tweets influence the emotions of investors and how these emotions impact global financial markets. The study applies the Quantile VAR model, a method that captures the dynamics of different quantiles of the conditional distribution, to analyze the data of weekly returns for five financial variables: the U.S. dollar, gold, oil, NASDAQ index, and S&P index, from 2019 to 2023. The study also constructs weighted indices of emotions based on tweets from the US and England, using a sentiment analysis tool. The results reveal a high correlation (95%) between the emotions and the average conditional distribution, indicating that emotions have a significant effect on financial markets. The study also finds that gold and the U.S. dollar are the most vulnerable to emotional shocks, especially during the peak of the COVID-19 pandemic, when fear and uncertainty were widespread. The study emphasizes the importance of addressing the direct impact of emotions on financial markets and urges policymakers and legislators to implement regulations that can protect investors and ensure market stability.

Keywords: Financial Markets, Investor Emotions, Quantile VAR, Risks, Tweets.
JEL Classification: G01, G14, G15, G17, G18.

1. Introduction

Twitter is a valuable source of information for predicting and detecting stock market events and news. However, extracting useful insights from Twitter data is not a trivial task. It requires sophisticated econometric and machine-learning methods that can create Twitter networks that accurately anticipate market movements (Bouri et al., 2021). Moreover, it involves social media analysis that can track key events in the stock market, such as “COVID-19” or “mergers” by using keywords as indicators. For example, a surge in merger-related keywords may signal an impending merger (Karampatsas et al., 2023). Additionally, it entails transactional analysis that can monitor corporate news and rumors, and Twitter and stock market APIs that can provide real-time market updates. With market alerts, managers can keep up with vital market conditions (Reboredo and Ugolini, 2018). The main challenge of Twitter and social media analysis is the quality and reliability of the data. Many tweets are irrelevant, and fake accounts can disseminate false information, affecting investors' behavior (Sul et al., 2017; Teti et al., 2019). Furthermore, stock prices are influenced by social networks. Twitter user sentiments can sway public opinion and financial responses, and user content can support market surveillance and decision-making (Guo et al., 2025). News and tweets from CEOs, policymakers, journalists, and analysts have a significant impact on stock prices. Network and statistical analysis can identify news or rumors that affect stock prices. An alert system can give specific users immediate access to trustworthy information (Zeitun et al., 2023).

This research aims to develop a comprehensive framework for analyzing Twitter and social media data for stock market prediction and detection. The objectives of this research are:

- To review the existing literature on Twitter and social media analysis for stock market prediction and detection.

- To propose a novel methodology for creating Twitter networks that can precisely forecast market events using econometric and machine-learning methods.

- To design and implement algorithms for assessing key stock market events using keywords as indicators.

- To evaluate the performance and accuracy of the proposed methodology and algorithms using real-world data.

- To develop an alert system that can provide specific users with instant access to reliable information based on network and statistical analysis.

So the main problem of this research is how Twitter risks affect global financial markets, and the research questions of this paper are as follows:

How do tweets influence the emotions of investors in the context of global financial markets?

What is the impact of investor emotions, influenced by tweets, on global financial markets?

To what extent do emotions, as captured by weighted sentiment indices derived from tweets, affect the dynamics of financial variables, including the U.S.

dollar, gold, oil, NASDAQ index, and S&P index?

Which financial variables exhibit the highest vulnerability to emotional shocks, particularly during periods of heightened fear and uncertainty, such as the peak of the COVID-19 pandemic?

2. Literature Review

In 1936, John Maynard Keynes used the term “Animal spirits” in his book for the first time in the economic context. Since that time, researchers and economists have been searching for the determinants of the wild price movements and volatility on the stock market that cannot be explained by the fundamentals of the companies.

Over the last 10 years, a new type of media has become the most important source of data for investors and businesses: social media (Fan and Gordon, 2014). This development has led to a lot of new studies regarding the effect of social media on the stock market. The most interesting social media platform for researchers is Twitter, due to its fast growth and real-time nature. Social media is similar to other news outlets in the sense that it can also help with the information asymmetry of investors. Blankespoor et al. (2014) show that firms that use Twitter can decrease the information asymmetry and lead to an increase in liquidity, if the firms are not covered much in the other news outlets. Mao et al. (2012) investigated the effect of the daily number of tweets mentioning the S&P 500 on the stock indicators of the S&P 500. The authors find evidence that the Twitter data is correlated with the stock indicators for the S&P 500. Also, they found a predictive nature in the Twitter data, since the Twitter data could help predict whether the closing price would go up or down. Another interesting subject in the previous literature is the effect of the sentiment of the tweets, since Tetlock (2008) already showed that negative words in firm-specific news stories can forecast low firm earnings and returns.

William et al. (2023) argue that despite the utility of stock market social network analysis, it should not be solely relied upon without survey data. Their research focuses on the impact of social media news on stock prices. Twitter content analysis reveals user behavior and collective insights despite irrelevant posts. Companies like Bloomberg use Twitter sentiment analysis for predicting stock returns, although its use in investment systems is debated (Groß-Klußmann et al., 2019). Checkley et al. (2017) discovered that Twitter sentiment-based investment strategies are efficient yet ephemeral due to rapid information spread and decay. Garcia (2013) asserts that these indicators predict stock prices in recessions. Negative market views favor short positions. Ranco et al. (2015) found significant yearly Twitter data for major stock indices despite low individual stock tweets. Capital market analysis uses machine learning and game theory, leading to the development of behavioral finance, which blends behavioral economics and game theory. Twitter's extensive archives and diverse views are valuable for assessing tweet risks. In 2021, Twitter allowed academics to access its archive for risk studies (William et al., 2023).

Timmermann (2008) discovered that Twitter sentiment can forecast stock returns. Atkins et al. (2018) noted that few studies used these signals for equity index performance in trend-following strategies. Neri et al. (2012) found that financial decisions and global markets are swayed by social media sentiment, which is crucial for forecasting market trends, particularly in cryptocurrency. Shokri et al. (2021) investigated volatility spillovers from Bitcoin to other digital currencies using multivariate GARCH, noting significant impacts on Dogecoin and Dash that contribute to market irrationality, which can be amplified by tweet-driven sentiments influencing crypto prices. Similarly, Hajilo Moghadam et al. (2023) analyzed spillover effects of digital currencies on gold via wavelet coherence, identifying Bitcoin's strong influence on Litecoin, Ethereum, and Dash while affirming gold's safe-haven role, potentially exacerbated by social media volatility during crises like COVID-19. Shokri and Roshanfekr (2023) explored Bitcoin's fluctuation spillovers to other cryptocurrencies, highlighting interconnected risks that tweets from influential figures can intensify, as seen in market swings from high-profile endorsements. Complementing this, Dorouzi and Shokri (2020) examined Bitcoin's effects on international law, underscoring legal challenges from its volatility, which social media discussions and rumors can further propagate across global financial markets. Garcia and Schweitzer (2015) explored the correlation between social signals and Bitcoin algorithmic trading, showing social media's impact on Bitcoin trading.

There is a close relationship between financial markets, risk, and the performance of individual financial assets. Financial markets are inherently susceptible to various risks arising from economic, political, social, and technological factors. When uncertainties or unforeseen events materialize, they can significantly impact market sentiment and volatility. Prior research has shown that periods of heightened risk and uncertainty, such as economic downturns and financial crises, tend to negatively affect the prices and returns of various asset classes. Assets like stocks, currencies, commodities, and cryptocurrencies exhibit different levels of vulnerability to market fluctuations and risks. For example, gold has traditionally served as a safe-haven asset during times of market turmoil. The literature also indicates that non-fundamental factors like social media sentiment can influence the risk profiles of individual assets. By examining how tweet sentiment shapes investor emotions, which then feed back into market dynamics, this study aims to provide a more nuanced understanding of the relationship between overall market conditions. Such insights are crucial for improving risk management strategies and investment decisions. Also, no studies have used sentiment and volatility measures from quantile analysis to predict returns.

Twitter signals are a rich but untapped source of information for understanding the interplay between emotions and financial markets. This research explores this novel and timely topic using cutting-edge methods. The study measures how Twitter influences financial markets across different countries and sectors using market spillovers and Quantile VAR models. The study also uses tweets as sentiment indicators to capture the emotional states of investors and their impact on market outcomes.

3. Methods and Materials

This study uses the variance decomposition approach proposed by Diebold and Yilmaz (2012). This approach is based on the forward stepwise decomposition of the variance of the prediction errors for each variable in an N-variable vector autoregression. Using this approach, a portion of the variance in the prediction error of variable i, which can be attributed to shocks from variable j, was examined. The spillover index was calculated by adding the effects.

3.1 Quantile VAR Model

A quantile estimation of the conditional measurement of y_t on x_t is performed for each quantile τ of the conditional dependency of y_t/x_t as follows:

$$Q_\tau\left(y_t \,|x_t\right) = x_t\beta(\tau) \tag{1}$$

where Q_τ represents the τth conditional quantile function of y_t and τ is a number between zero and one. x_t is the vector of variables and β(τ) is the determinant of the mutual dependency between x_t and the conditional quantiles of y_t. Coefficient β(τ) represents the τth conditional quantile as follows:

$$\hat{\beta}(\tau) = \frac{a}{\beta(\tau)}\sum_{i=1}^{T}(\tau - 1_{\{y_t<x_t\beta(\tau)\}})\,|y_t - x_t\beta(\tau)| \tag{2}$$

The multivariate quantile VAR with p lags is defined as follows:

$$y_t = c(\tau) + \sum_{i=1}^{p} \beta(\tau) y_{t-i} + e_t(\tau)\,, t = 1, \dots, T \qquad (3)$$

In this equation, y_t represents the vector of dependent variables, c(τ) and $e_t(\tau)$ represent the model constant and residual, respectively, and β(τ) represents the coefficient matrix of dependence in the τ-th quantile.

Assuming i=1,…,p, the values of $\hat{\beta}(\tau)$ and ĉ(τ) are estimated under the assumption that the residuals are independent of the lagged dependent variables, that is,

$$Q_t(e_t(\tau) \big| y_{t-1}, \dots, y_{t-p}) = 0 \qquad (4)$$

The estimation of conditional quantile y is given by the following equation, through which each quantile τ can be estimated:

$$Q_t(y_t \big| y_{t-1}, \dots, y_{t-p}) = c(\tau) + \sum_{i=1}^{p} \hat{\beta}(\tau)\, y_{t-i} \qquad (5)$$

In this section, we present a method based on multivariate dependencies. This method, proposed by Ando et al. (2022), uses a Quantile Connectedness framework based on the Diebold-Yilmaz model. Initially, Eq. (3) can be written as a moving average process.

$$y_t = \mu(\tau) + \sum_{s=0}^{\infty} A_s(\tau) e_{t-s}(\tau)\,, t = 1, \dots, T \qquad (6)$$

Furthermore, μ(τ) represents

$$\mu(\tau) = \left(I_n - B_1(\tau) - \cdots - B_p(\tau)\right)^{-1} c(\tau) \text{ و } A_s(\tau) = \begin{cases} 0. s < 0; I_n\,, s = 0 \\ B_1(\tau) A_{s-1}(\tau) + \cdots B_p(\tau) A_{s-p}(\tau), s > 0 \end{cases} \qquad (7)$$

Variable yt was obtained using the sum of residuals. In addition, generalized forecast error variance decomposition (GFEVD) is used to measure the shock structure of different variables, which provides an advantage over the simple Diebold-Yilmaz model (which uses the VAR structure). The GFEVD structure for H-step-ahead decomposition is defined as follows:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{ij}^{-1} \sum_{h=0}^{H-1} (e_i' A_s \sum e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_s \sum e_j)} \qquad (8)$$

where $\theta_{ij}^{g}(H)$ represents the jth variable's gth forecast error for the ith variable at the H-steps ahead, ∑ is the variance matrix of the error vector, σjj is the jth diagonal element of the ∑ matrix, and e_i is a vector with values of one for the ith variable and zero for other values. The variance decomposition matrix was normalized as follows:

$$\tilde{\theta}_{ij}^{g} = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{9}$$

Finally, four measures were calculated for each variable using the GFEVD structure. These, in order, are:

1. Total Connectedness Index (TCI): This represents a measure of market risk. For example, a higher TCI indicated a higher degree of overall network connectivity. This was calculated as follows:

$$TCI(\tau) = \frac{\sum_{i=1}^{N}\sum_{j=1, i\neq j}^{N} \tilde{\theta}_{ij}^{g}(\tau)}{\sum_{i=1}^{N}\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(\tau)} \tag{10}$$

2. Total overflow index from variable i to variable j (TO[1]): This calculates the overall impact of variable i on all other variables j, providing information on the general influence of variable i. This was calculated as follows:

$$TO = SI_{i\rightarrow j}(\tau) = \frac{\sum_{j=1, i\neq j}^{N} \tilde{\theta}_{ij}^{g}(\tau)}{\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(\tau)} \tag{11}$$

3. Total Inflow Index of Variable j to Variable i (FROM[2]): This evaluates the overall impact of shocks from all other variables j on Variable i in a directional manner, capturing the direction of influence.

$$FROM = SI_{i\leftarrow j}(\tau) = \frac{\sum_{j=1, i\neq j}^{N} \tilde{\theta}_{ij}^{g}(\tau)}{\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(\tau)} \tag{12}$$

4. The difference between the total outflow (TO) and total inflow (FROM) and other variables results in net directional connectivity (NET[3]).

$$NET_i(\tau) = SI_{i\rightarrow j}(\tau) - SI_{i\rightarrow j}(\tau) \tag{13}$$

We used weekly financial market data for the variables described in Table1 for the period 2019 to 2023. Additionally, we used data related to various tweets that indicate sentiments in financial markets. Twitter data provides some attractive features for studying the effects of sentiments. The volume of available tweets is very high, with 0.22 of adults in the United States using Twitter, and approximately 500 million messages sent on this platform daily. Twitter enables the depiction of beliefs and opinions on various social media platforms. Tweets have precise timestamps that allow the exact publication time for each tweet to be known. The impact or correlation of each tweet is obtained from the number of retweets received. In January 2021, Twitter opened archives for academic researchers. To

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[1]. Total directional connectedness to others
[2]. Total directional spillover index FROM indices j to index i
[3]. The net total directional spillover

extract all tweets published about financial markets, a data extraction algorithm containing keywords such as "uncertain", "ambiguous", "uncertainties", and "uncertainty" has been applied to each tweet. The Economic Uncertainty (TEU) indices are based on Twitter and span the period from June 2015 to the present. The TEU indices were developed by Thomas Renault (University of Paris 1 Panthéon-Sorbonne) in collaboration with Scott R. Baker (Northwestern), Nicholas Bloom (Stanford), and Steve Davis (University of Chicago). The text explains how the researchers extracted all the tweets that contained keywords related to uncertainty and the economy since June 2015. The uncertainty terms are ‘uncertain’, ‘uncertainly’, ‘uncertainties’, and ‘uncertainty’. The economic terms are ‘economic’, ‘economical’, ‘economically’, ‘economics’, ‘economies’, ‘economist’, ‘economists’, and ‘economy’. Using this database of tweets, they constructed four TEU indices. The first one, TEU-ENG, consists of the total number of daily English-language tweets that contain both uncertainty and economic terms. The second one, TEU-USA, isolates the number of these tweets that originate from users in the United States using a geo-tag-based classifier. US users make up about 50 percent of the English-language Twitter population in this sample. The financial data in this paper were collected from Investing.com[1].

Table 1. An Introduction to Research Variables

Variables	Descriptions
Item1	End-of-day price of gold
Gold	End-of-day price of oil
Oil	Weekly S&P Index
S&P Index	Weekly Nasdaq Index
Nasdaq Index	End-of-day price of Bitcoin
Bitcoin	Weekly Dollar Index
Dollar Index	The total number of daily tweets in English
TEU.ENG	The total number of tweets by Americans
TEU.USA	Weighted variable where retweets are given weight
TEU.WGT	Individuals residing in the United States of America
TEU.SCA	End-of-day price of gold

Source: Research finding.

In this model, the performance of the indices is first calculated using (14), and then the model is applied. The variables are generally calculated as follows: P_t represents the closing price and R_t represents the returns of the indices. These

[1]. Investing.com - Stock Market Quotes & Financial News https://www.investing.com/

variables have been applied to financial indicators such as gold, oil, S&Pthe index,the NASDAQ index, the dollar index, and Bitcoin.

$$R_t = Ln(\frac{P_t}{P_{t-1}}) \times 100 \quad (14)$$

4. Results

The descriptive statistics and data returns are shown in Table 2.

Table 2. Descriptive Statistics of Research Variables

	Gold	Oil	S&P	Nasdaq	DJI	USD	TEU.ENG	TEU.USA	TEU.WGT	TEU.SCA
Mean	22.04	2.387	49.942	183.624	414.121	0.7	22.508	24.141	26.051	18.461
Variance	449.356	6.1	3288.202	45081.26	206905.629	0.405	1283.711	1527.192	1803.457	1328.177
Skewness	2.302***	2.912***	2.563***	2.308***	2.953***	2.079***	6.664***	5.944***	6.186***	8.808***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ex. Kurtosis	8.784***	12.919***	8.687***	7.184***	13.368***	7.235***	62.592***	46.137***	50.059***	99.127***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	1729.596***	3530.960***	1788.883***	1282.152***	3755.475***	1224.422***	72011.372***	39913.321***	46753.301***	178231.922***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-7.349***	-3.862***	-3.441***	-2.458**	-4.617***	-4.687***	-6.226***	-7.170***	-7.253***	-6.548***
	(0.000)	(0.000)	(0.001)	(0.014)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q(10)	30.354***	150.612***	179.023***	236.540***	143.141***	18.229***	114.188***	143.257***	140.408***	189.772***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Q2(10)	66.341***	135.514***	94.095***	111.766***	119.149***	14.864***	86.074***	53.109***	57.624***	108.864***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)

Source: Research finding.

Note: The sign *** shows a statistical significance level of 0.99.

Table 3. Results of 0.95 Quantile level

Q=0.95	Gold	Oil	S&P	Nasdaq	DJI	USD	TEU-ENG	TEU-USA	TEU-WGT	TEU-SCA	FROM
Gold	7.02	9.36	10.74	9.33	9.95	9.32	10.61	10.80	11.43	11.45	92.98
Oil	6.90	9.98	9.60	9.16	10.17	10.02	9.65	11.55	11.93	11.05	90.02
S&P	6.61	9.41	9.83	9.02	9.79	8.99	10.39	11.93	12.18	11.85	90.17
Nasdaq	6.41	9.00	10.35	9.19	9.54	9.24	10.48	11.49	12.07	12.23	90.81
DJI	6.32	9.33	10.31	8.57	10.17	9.42	10.16	11.71	12.14	11.88	89.83
USD	6.27	9.38	10.07	8.67	9.83	9.71	10.26	11.69	11.90	12.22	90.29
TEU-ENG	6.32	9.44	9.38	8.55	9.65	9.16	10.41	12.17	12.34	12.58	89.59
TEU-USA	6.06	9.31	8.80	8.76	9.83	9.01	10.63	12.62	12.59	12.41	87.38
TEU-WGT	6.07	9.61	8.95	9.06	10.14	8.94	10.33	12.50	12.34	12.06	87.66
TEU-SCA	6.09	9.35	9.04	8.63	9.71	8.90	10.64	12.38	12.39	12.86	87.14
TO	57.04	84.19	87.25	79.76	88.60	82.99	93.16	106.20	108.97	107.72	895.88
NET	-35.94	-5.83	-2.92	-11.06	-1.23	-7.30	3.56	18.82	21.31	20.58	TCI=89.59

Source: Research finding.

Table 4. Results of 0.05 Quantile level

Q=0.05	Gold	Oil	S&P	Nasdaq	DJI	USD	TEU-ENG	TEU-USA	TEU-WGT	TEU-SCA	FROM
Gold	27.21	8.66	7.15	7.47	8.50	11.96	7.64	7.34	7.39	6.70	72.79
Oil	7.25	25.49	11.68	10.87	11.59	8.49	6.58	6.13	6.01	5.92	74.51
S&P	5.04	10.12	20.85	17.50	18.52	6.80	5.39	5.45	5.38	4.95	79.15
Nasdaq	6.35	10.11	18.28	22.05	16.04	8.08	5.18	4.81	4.81	4.30	77.95
DJI	5.64	9.81	18.10	15.05	21.09	7.45	5.82	5.94	5.76	5.33	78.91
USD	10.99	8.58	8.26	8.52	9.21	26.51	7.80	6.86	6.94	6.33	73.49
TEU-ENG	4.92	5.29	4.59	4.03	5.62	6.04	20.74	16.59	16.24	15.95	79.26
TEU-USA	4.49	4.64	4.36	3.60	5.55	5.12	15.74	19.73	19.03	17.73	80.27
TEU-WGT	4.54	4.67	4.31	3.59	5.45	5.19	15.58	19.22	19.99	17.47	80.01
TEU-SCA	4.17	4.68	4.24	3.33	5.26	4.87	15.94	18.63	18.22	20.64	79.36
TO	53.39	66.54	80.98	73.96	85.74	63.99	85.68	90.97	89.79	84.68	775.72
NET	-19.40	-7.98	1.83	-3.99	6.83	-9.50	6.41	10.70	9.77	5.32	TCI=77.57

Source: Research finding.

Table 5. Results of 0.5 Quantile level

Q=0.5	Gold	Oil	S&P	Nasdaq	DJI	USD	TEU-ENG	TEU-USA	TEU-WGT	TEU-SCA	FROM
Gold	48.82	3.64	4.24	2.49	5.75	8.99	6.41	6.66	7.78	5.21	51.18
Oil	1.87	47.99	10.35	8.24	9.25	2.94	4.73	5.26	5.24	4.11	52.01
S&P	0.72	5.88	29.49	22.25	25.55	2.35	3.39	3.81	3.53	3.03	70.51
Nasdaq	0.89	5.33	26.65	36.65	21.05	2.35	1.78	1.90	1.95	1.44	63.35
DJI	1.06	5.83	24.71	17.23	29.84	3.23	4.16	5.06	4.84	4.04	70.16
USD	6.55	3.39	4.19	3.33	5.42	52.24	6.31	6.92	7.15	4.51	47.76
TEU-ENG	1.57	2.64	3.18	1.05	4.47	3.29	27.31	19.57	19.09	17.83	72.69
TEU-USA	1.11	2.45	3.14	1.15	4.43	2.71	17.17	24.13	22.83	20.87	75.87
TEU-WGT	1.33	2.28	2.85	0.93	4.20	3.00	17.06	23.31	24.66	20.37	75.34
TEU-SCA	0.90	2.40	2.67	0.75	3.85	1.93	16.92	22.70	21.95	25.93	74.07
TO	16.01	33.85	81.98	57.43	83.97	30.79	77.92	95.19	94.37	81.41	652.94
NET	-35.17	-18.16	11.47	-5.92	13.82	-16.97	5.23	19.32	19.04	7.33	TCI=65.29

Source: Research finding.

Based on the descriptive statistics of the research variables in Table 2, the time series of the index returns exhibits higher kurtosis than that of a normal distribution (kurtosis statistic > 3). Additionally, the Jarque-Bera test rejects the assumption of normality for the return time series. Furthermore, the skewness statistic is positive, indicating that the return time series has a longer right tail than the left tail. ERS[1] was used to examine and confirm the validity of the data. Continuing the analysis, we present measures of the average correlation of the research findings (the transmission of sentiment). The results presented in Table 2 show the average values for the entire study period. To this end, we consider the results obtained from the three quantiles (0.05, 0.5, and 0.95) to determine whether severe shocks resulting from sentiment play a prominent role in the relationship between the network variables. Note that all numbers in Table 2 are presented as percentages and correspond to the average connectivity values. In addition, please note that the magnitude of the shock received (FROM) and the magnitude of the shock transmitted by others (TO) are indicated. To indicate the sender variable in the network, if a variable is a shock sender, it is denoted by a (+) sign; if it is a shock receiver, it is denoted by a (-) sign. The overall correlation index (TCI) was used to determine the relationships between variables.

Based on the results obtained from Table 3 at the 0.95 quantile level, the number of English retweets discussing market uncertainty, tweets from US residents, and the total number of tweets from individuals of American nationality had the highest impact and spillover shocks on the markets. Additionally, the TCI statistic indicated the connectivity and correlation of the data with a value of 89.59, suggesting a strong relationship between the available data.

Figure 1 shows the overall correlation index (TCI), an overflow market indicator used to measure market risk. This indicates the level of correlation between the returns of each index and the overall returns of the variables.

[1]. Elliott, Rothenberg and Stock Unit Root Test

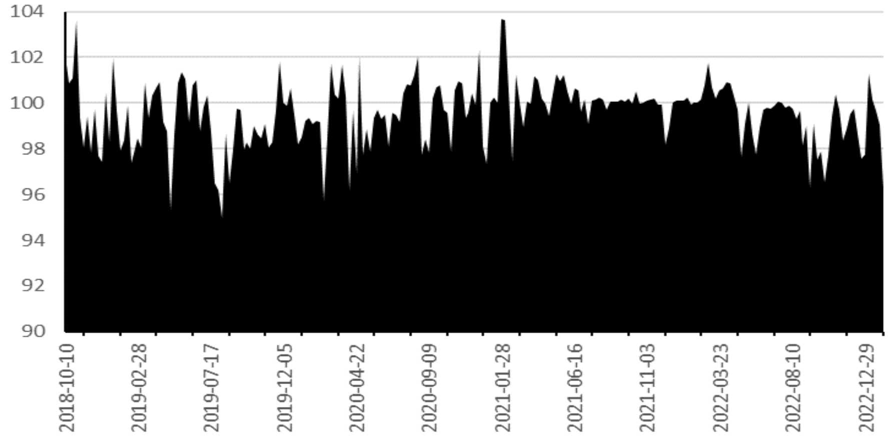

Figure 1. Overall Correlation Index
Source: Research finding.

Furthermore, considering the connectivity network shown in Figure 2, the gold market and dollar index had the highest receiver effects. Generally, the higher the TCI, the greater the coordination and correlation among the indices.

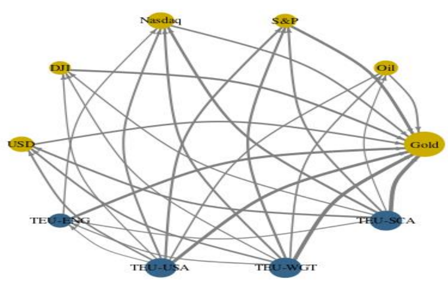

Figure 1. Network Analysis between Variables at the 0.95 quantile level
Source: Research finding.

TCI is a useful tool for analyzing index relationships. Trends and directions should be examined to interpret the TCI chart. If the TCI rises, it may mean that the market is more interconnected and sentiment spillover effects are more likely. A decreasing TCI may indicate less interrelatedness and lower sentiment spillover. Figure 1 shows periods of higher correlation, such as the COVID-19 pandemic in 2019 and the Ukraine-Russia war in 2022. Table 4 shows that at a 0.05 significance level, the most influential tweets were total tweets by Americans, retweets in

English about market uncertainty, and English tweets. The TCI statistic (77.57) showed a strong connection between the data. NET statistics revealed that English retweets discussing market uncertainty, American tweets, and English tweets had the most influence on emotional shock transmission.

Figure 3 illustrates the correlation between the indices, which showed a sudden increase after the onset of the COVID-19 pandemic in December 2019.

Figure 3. Overall Correlation Index
Source: Research finding.

According to the connectivity network shown in Figure 4, the gold market and dollar index were the most influential receivers of impact, similar to the 95th percentile level. Furthermore, considering the connectivity network shown in Figure 4, the gold market and dollar index are the most influential factors, similar to the 0.95 quantile level.

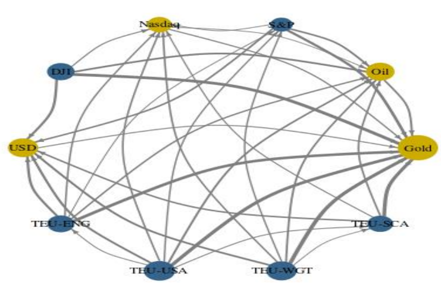

Figure 2. Network Analysis between Variables at the 0.05 Quantile Level
Source: Research finding.

Based on the NET statistics among the available data in Table 5, at the 0.5th percentile level, the total number of tweets by individuals of American nationality and English retweets discussing market uncertainty had the highest impact on transmitting emotional shocks among other tweets. Additionally, the TCI statistic indicated the connection and correlation of the data with a value of 65.29, suggesting a strong relationship between the available data.

In Figure 5, an important factor to consider when analyzing the TCI index is the trend and direction of the index over time. If the TCI increases over time, this may indicate that the market is becoming more interconnected, posing a greater risk of spillover effects among companies. For example, if a company experiences a significant event, such as bankruptcy or a major product recall, it may have ripple effects on other companies in the market that are connected to it through supply chains or business partnerships. Figure 5 shows an upward jump corresponding to the COVID-19 pandemic of December 2019. From that date onwards, the index shows an upward trend, indicating the impact of the pandemic on the correlation and connectivity among these markets. This could be due to various factors, such as changes in industry structure, consumer preferences, or regulatory changes that affect certain companies more than others.

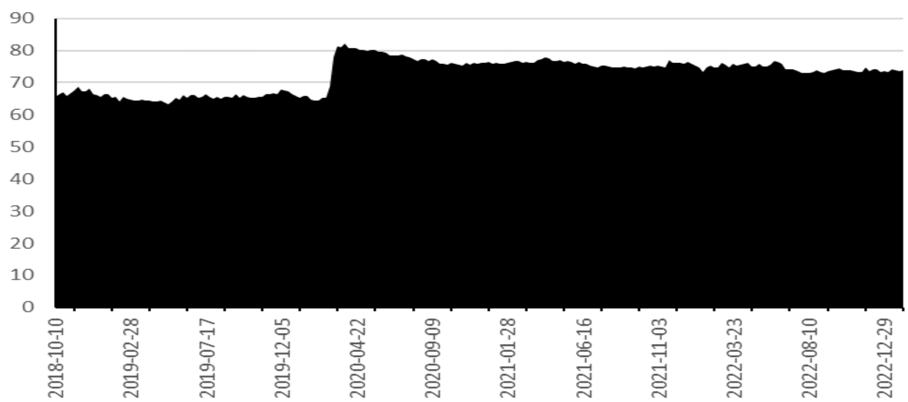

Figure 5. Overall Correlation Index
Source: Research finding.

Furthermore, considering the network connectivity shown in Figure 6, the gold market and dollar index are the major recipients of impacts, similar to the 0.95th percentile level.

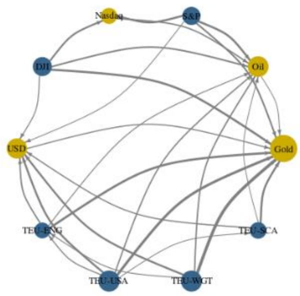

Figure 3. Network Analysis between Variables at the 0.5 Quantile Level
Source: Research finding.

TCI is only one measure of market interconnectivity and should be considered with other metrics and external factors. Global economics, politics, and technology can affect market connectivity and TCI. Results show that tweets about market fluctuations have short- and long-term effects on these markets. The dollar index and gold are most impacted by emotional waves. Other variables affect market fluctuations, but emotion in virtual spaces such as Twitter is a major factor. Research models show that tweet indices influence other markets, with gold and the dollar index having the greatest impact. In summary, tweets from American citizens or residents are the main drivers of emotions in markets. When an influential investor or analyst tweets about market movements or worries about an asset or market, it can influence other market participants, especially if the tweet is widely seen. The effect of tweets depends on many factors, such as the source's credibility, the timing of the tweet, and the emotions expressed. A tweet from a reliable, knowledgeable person with many followers can significantly influence market sentiment and cause selling. If a tweet is released during a period of market instability, it can amplify investor fear and cause sales.

Tweets can become viral and widely shared, amplifying their effect. This can cause market fluctuations or harm vulnerable assets, especially if the tweet is seen as reliable and from a reliable source. For instance, a tweet expressing optimism about an asset or market can boost investor confidence and increase buying. Pessimistic tweets can damage investor confidence, leading to more selling. Tweets may not be the only cause of market movements, but they can affect market sentiment and short-term trends. Twitter has become a popular platform for investors to share news and opinions on financial markets. Twitter emotions can influence stock prices and other financial metrics. Corea (2016) explores whether Twitter can serve as a proxy for investors' sentiment in stock market predictions within the technology sector, focusing on Apple, Facebook, and Google over two months in 2014. The researchers collected English tweets and stock data, applying sentiment scoring and volume metrics to build OLS and logistic probability models for price and trend forecasting on a minute-by-minute basis. The results indicate that Twitter posting volume enhances the model's explanatory power more than average tweet sentiment, suggesting social media's potential in financial forecasting. Bollen et al. (2011) found that Twitter emotions accurately predicted Dow Jones changes.

Although social media sentiment and financial market movements appear to be linked, caution is necessary when interpreting these results. Correlation does not always imply causation; other factors may also influence market movement. The relationship between social media sentiment and financial market movements is complex, and it is unclear if emotions are the primary drivers or just a reflection of economic conditions. Government policies, geopolitical events, and interest rate changes can also affect financial markets; therefore, attributing causality to the relationship between social media sentiment and market movement should be done with caution. This study found that emotions from tweets on Twitter significantly influence financial markets and market performance. Alomari et al. (2021) also showed this effect. It confirms Kranefuss and Johnson's (2021) and Al-Nasseri et al. (2021) findings in Twitter emotions effect on Dow Jones and S&P market fluctuations. Also, this research agrees with Ranco et al. (2015) and Sprenger et al. (2014)'s research on tweets' stock market influence, as these markets are more affected by emotions and negative news on virtual platforms like Twitter.

5. Conclusion

This study investigates how emotions expressed on Twitter, a major social network, influence financial market movements. Emotions and behaviors of humans have always played a significant role in their decisions and actions, especially in economic and investment domains. With the advent of social media platforms such as Twitter, emotions and behaviors can spread rapidly and widely, affecting investor behavior and market fluctuations. This study aims to measure the impact of Twitter emotions on different financial markets and assets, using the Twitter Connectivity Index (TCI) as a proxy for market interconnectivity. The study hypothesizes that Twitter emotions have a positive correlation with market movements, and that English and American tweets have a stronger effect than other languages or regions. The study analyzes the data from summary tables and uses machine learning models to test the hypotheses. The results confirm the hypotheses and show that Twitter emotions have a substantial effect on financial market emotions, particularly in the oil, gold, NASDAQ, and S&P markets. The results also suggest that Twitter emotions can cause market fluctuations, high returns, and small-scale investors. The study contributes to the literature on social media sentiment and financial market movements by using a novel measure of market interconnectivity, TCI, and by examining the effects of tweets on different markets and assets. The study also has practical implications for investors, policymakers, and researchers who want to understand and predict the behavior of financial markets. The study recommends using machine learning models to anticipate tweet effects, helping investors adjust portfolios and governments prepare for crises. The study also suggests using data science and platforms like Facebook to create indices like Twitter indices for future studies. This approach offers a more precise view of the effects of these platforms as financial indicators.

In conclusion, this paper shows that Twitter emotions have a significant impact on financial market movements and that TCI is a useful measure of market interconnectivity. Our paper adds to the growing body of literature on social media sentiment and financial market movements and offers practical implications for investors, policymakers, and researchers. Our paper also points out some limitations and suggests some avenues for future research. We hope that our research will stimulate further research on this topic and advance our understanding of the role of social media in financial markets.

Statements and Declarations

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- Conflict of interest: The authors declare that there is no conflict of interest.

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