



Article

The Interplay of Macroeconomic Sentiments at Financial Markets: A Comparison of S&P Stock and Cryptocurrency Index

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Abstract

The global financial system is constantly evolving through technological integration. This has led to the inception and rise in the cryptocurrency market, opening new avenues of comparative studies on market behavior. Therefore, the current study aimed to identify nuances in stock and cryptocurrency behavior. Based on the socioeconomic theory of finance, the study is a pioneer in considering the interplay of economic, market, and social media sentiments while providing a comparative view of cryptocurrencies and stocks. The study utilizes data of economic news sentiments, cryptocurrency fear and greed index, CNN fear and greed index, and Twitter sentiments against the movement of S&P Cryptocurrencies and S&P 500 stock index return spanning from 2018 to 2023. The study applied a vector autoregressive-based spillover model to assess the theorized linkage and applied robustness measures, including linear regression and the Granger causality test, for validation. The findings unveil distinct weak and moderate associations of sentiments across cryptocurrencies and stocks, respectively. The former is primarily driven by market sentiments while shaping economic news and social media sentiments. Meanwhile, the findings for stock return movements are found to be significantly associated with economic and market sentiments. This led to the inference that the cryptocurrency environment is an isolated system driven by internal sentiments, while stock markets are more economically integrated, and in both cases, social media sentiments are found to be the receiver of market spillover, weakly influencing economic news. The study is pioneering in its exploration of the interlinkage between selected macroeconomic sentiments; additionally, the comparative findings further add to the existing debate on influence of sentiment across financial markets. The varying realities identified in the findings hold significant practical implications for portfolio optimization, risk assessment and policy making.

Keywords: stock index; cryptocurrency index; economic news; social media; market sentiments; spillover



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1. Introduction

In today's world, technology has transformed financial markets beyond their traditional roles and boundaries. The global financial system is constantly innovating and evolving into an interconnected financial hub (Hsiao & Chiu, 2024). The rise in cryptocurrencies and decentralized financial assets has brought it further beyond traditional

economic underpinnings and theories. On the other hand, improved communication technologies have brought a shift from the era of informational scarcity and market friction towards overload of real-time data (Zhao & Gan, 2024). This increased interconnectivity and informational overload have led financial markets towards elevated volatility, and financial contagion threatening its long-term sustainability (Li et al., 2025; Tan et al., 2024). These unprecedented levels of market sensitivity and complexity amongst modern global financial systems necessitate the rediscovery of market subtleties, bringing newfound interest from researchers to understand the behavior of modern financial markets.

The inception of Bitcoin through the pioneering work of Nakamoto (2008) became the precursor of the cryptocurrency financial market (Almeida & Gonçalves, 2023). Cryptocurrencies are based on decentralized networks, and currently, there are more than ten thousand cryptocurrencies in circulation around the globe (Ballis & Verousis, 2022). As of March 2025, the cryptocurrency ecosystem is valued at around 3 trillion US dollars, making it an attractive and lucrative avenue for investment. The rapid development and exponential rise in cryptocurrencies also made it a critical avenue for academic research (Almeida & Gonçalves, 2023). Given the lack of any fundamental information for traditional evaluation models, the value of cryptocurrencies like Bitcoin is essentially zero. This invalidates the application of traditional financial models across the cryptocurrency market. The existing empirical evidence also invalidates the application of traditional asset and risk models to explain cryptocurrencies (Chen et al., 2019; Y. Liu & Tsyvinski, 2021), hence necessitating a need to develop a distinct and contextualized understanding of cryptocurrency markets for the stakeholders. According to Chen et al. (2019), given the speculative nature of cryptocurrencies, behavioral sentiments should play a key role in determining the market value of a cryptocurrency. Anamika et al. (2023) found significant influence of investor sentiments across the cryptocurrency market, but this impact is not uniform and varies across types of sentiments (Burggraf et al., 2021).

The rising acceptance of cryptocurrencies as a financial ecosystem and validation from institutional investors is making it a vital component of modern financial reality while regulatory challenges still hinder their global outreach, and overall, their distinct nature from the traditional financial ecosystems is making researchers focus on the comparative analysis of stock and cryptocurrency assets. The efforts aim to explore their connectedness, discover unique market dynamics, and develop market models to identify implications for investors and stakeholders. The existing literature compared the cryptocurrency market with decentralized financial assets (Mensi et al., 2024), real estate investment trusts (Abdullah et al., 2023), renewable energy stocks, and other assets classes like Oil, Gold, Forex (Yousaf et al., 2024), etc. but none of the earlier literature focused on examining the comparison of sentiments across stock and cryptocurrency markets. Therefore, the current study also aims to uncover and compare the varying dynamics of market sentiments, economic news sentiments, and social media sentiments across stock and cryptocurrency markets, thereby filling this theoretical gap in the existing literature by focusing on pertinent sentiment types across Standard and Poor's (S&P) 500 stock index and Standard and Poor's (S&P) cryptocurrency index of the top 10 cryptocurrencies (C10).

The traditional financial theory views market behavior through the lens of market efficiency (Bianchi et al., 2023). Efficient market structure is based on rational behavior and bound to follow a random walk in prices, but consistent market predictability across the global markets indicates otherwise (Rasheed et al., 2021). Apart from that, the history of the financial market is already filled with financial crises leading to substantial changes in stock prices, defying the traditional view (Ain et al., 2021), where rational investors force markets towards intrinsic stock valuations (Baker & Wurgler, 2007). This has led to an alternate explanation of market dynamics through behavioral models pioneered

by [Kahneman and Tversky \(1979\)](#). The model posits that market movements are rooted in the psychology of market participants ([Ying et al., 2020](#)), which is not rational and is predominantly influenced by behavioral biases and cognitive limitations ([Rasheed et al., 2020](#)). The socionomic theory of financial behavior states that these individual irrationalities are exhibited through collective market mood, i.e., market sentiments ([Nofsinger, 2005](#); [Rasheed et al., 2023](#)).

Existing literature indicates that market sentiments play a critical role in shaping financial market behavior across the globe ([Heydarian et al., 2025](#); [Rasheed et al., 2023](#)). Widespread empirical support has now shifted the focus from whether sentiments impact market movements towards uncovering, measuring, and quantifying their impacts ([Baker & Wurgler, 2007](#)). The existing literature established significant influence of varying sentiments across the stock ([Gong et al., 2022](#); [Rasheed et al., 2021](#); [Tan et al., 2024](#)) and cryptocurrency markets ([Gurdgiev & O'Loughlin, 2020](#); [Karaa et al., 2024](#)) utilizing a diverse set of sentiment proxies including trading volume ([Rasheed et al., 2023](#)), media news ([Fraiberger et al., 2021](#); [Tan et al., 2023](#)), social media ([Al-Qablan et al., 2023](#)), Google trends ([Ito et al., 2021](#)) and multifactor regression models of sentiments ([Gong et al., 2022](#); [Hu et al., 2021](#)), etc., but despite significant focus from the existing literature, it often fails to distinguish underlying distinctions across sources of sentiments ([Aggarwal, 2019](#)).

Therefore, the current study is aimed at exploring the spillover dynamics of market sentiments, economic news sentiments, and social media sentiments and their spillover towards stock and cryptocurrency markets. The traditional view of financial markets dictates that economic news and their sentiments are primary drivers of stock market movements. Similarly, behavior of modern societies is found to be significantly influenced by social media perceptions creating roles like social media influencer. Hence the current investigation explored the dynamics and flow of these sentiments to develop a deeper understanding of the market movement and identify divergence amongst traditional and cryptocurrency market movements.

1.1. Market Sentiments and Financial Markets

The current study draws its definition of market sentiments from the socionomic theory of finance ([Prechter, 1970](#)) and considers market sentiments as the collective mood, attitude, and tone of market participants, thereby relying on market-specific indicators of sentiments from the existing literature. One such recent and specific multifactor indicator is the fear and greed index across stock and cryptocurrency markets ([Ahadzie et al., 2025](#); [Wang et al., 2024](#)). [Xue and Zhang \(2017\)](#) and [Rasheed et al. \(2021\)](#) utilized trading volume as a proxy for market sentiments and concluded a significant variation in market behavior during bullish and bearish trends. [Tan et al. \(2024\)](#) explored the determinants of market sentiments and attributed them to the underlying behavioral patterns. Similarly, studies also analyzed the influence of market sentiments across stock markets. ([Ahadzie et al., 2025](#)) and cryptocurrency markets ([Wang et al., 2024](#)) concluding a nonlinear but significant impact, but the existing literature has yet to explore the avenue of comparative analysis across the stock and cryptocurrency markets. Therefore, the current investigation aims to address this research gap by applying the vector autoregressive (VAR) spillover model by [Diebold and Yilmaz \(2012\)](#) to uncover temporal association and variation across these markets.

1.2. Economic News Sentiments and Financial Markets

Economic news sentiments refer to the overall tone of the daily news reported. It uses the lexical approach to calculate sentiment score through natural language processing ([Shapiro et al., 2022](#)). The conventional school of financial literature posits that rational

analysis based on relevant economic factors is the sole determinant of market movements (Rasheed et al., 2021; Tan et al., 2023). Therefore, economic news sentiments are expected to significantly shape stock and cryptocurrency markets. Gan et al. (2020) reported the significant influence of news sentiments on S&P 500 companies. Similarly, Verma and Verma (2025) explored of US stock markets and found a significant positive influence of news sentiments to predict stock returns. Tan et al. (2023) have further expanded the influence of news sentiments across Asian Pacific markets and reported a moderately significant and time-varying association across regional stock markets. Similarly, Rognone et al. (2020) analyzed and validated cryptocurrency and forex markets for the influence of news sentiments, but the existing literature still uncovers the similarities and differences across stock and cryptocurrency markets. Therefore, the current study intends to address this empirical gap in the existing literature.

1.3. Social Media Sentiments and Financial Markets

Social media sentiments refer to the sentiment score generated from various social media platforms (Nyakurukwa & Seetharam, 2023). The behavioral school of financial literature is of the view that the market participants are biased and emotional (Rasheed et al., 2018). Investors tend to react to irrelevant information (Shiller, 2017), and therefore the excessive and real-time information from social media platforms is expected to exacerbate these irrational tendencies. Leading researchers like Chai et al. (2023) are attempting to utilize social media data like geotagged Twitter data to create daily global, regional, and country-wide Twitter sentiment scores through natural language processing (NLP). Gan et al. (2020) explored the influence of social media sentiments across the S&P 500 and discovered time-varying association with stock movements; similarly, Verma and Verma (2025) concluded a distinct association between social media sentiments and stock returns across US stock markets during bearish and bullish trends. Q. Liu et al. (2023) found a significant influence of social media sentiments on Chinese stocks. Similarly, Kyriazis et al. (2023) extended the impact of social media sentiments to the realm of cryptocurrency market, but the existing literature has yet to address the association and variation across stock and cryptocurrency markets. Therefore, the current investigation aims to address this avenue to further expand current understanding of the topic of sentiments and market behavior.

Overall, the study aims to distinguish the influence of various sources of macroeconomic sentiments in the existing literature through theoretical and empirical support. Furthermore, the findings of the study are expected to uncover the interlinkage between these sentiments, and lastly, a deeper understanding of conventional stock markets and cryptocurrencies. The findings of the study indicate the presence of an overall weak spillover from select sentiments across the stock and cryptocurrency indices. The most relevant and significant sentiment determining market behaviors is found to be the market sentiment itself, while economic news and social media sentiments do have a weak influence across time. The causality analysis reveals that apart from its bidirectional association with market sentiments, social media is also influencing economic news. Meanwhile, the causality analysis for the stock market index reveals that it has a significant bidirectional association with market and economic news sentiments, while social media is found to be linked with economic news, which then influences market sentiments and the stock indices. Hence, the findings reveal that the stock market is highly integrated with different sentiments, while the cryptocurrency market is an isolated and closed system with sentiments generated from within.

The remaining structure of the article is followed by a data and methodology section, subsequently reporting and discussing the findings of the study, paving the way to the conclusion of the investigations.

2. Data and Methodology

The data of the study consisted of daily index values for the stock and cryptocurrency markets. The current study is focusing on the S&P 500 index to represent the behavior of the stock market. Ample existing literature focused on the S&P 500 index to study the behavior of the stock markets (Ahadzie et al., 2025; Gong et al., 2022). The financial integration and influence of US stocks across the global financial ecosystem and data availability further justify their selection (Hsiao & Chiu, 2024; Tan et al., 2024). Similarly, for the cryptocurrency market, the study has considered the S&P Cryptocurrency Top 10 Equal Weight Index (USD). These cryptocurrencies represent more than 80% of the cryptocurrency market share. (Häusler & Xia, 2022; Neslihanoglu, 2021). Therefore, the index is suited for representing overall cryptocurrency market behavior. The final dataset ranges from 2018 to 2023, covering adequate observation for valid statistical analysis and inferences. The data is limited till 2023 due to the availability of data about social media for sentiment analysis. The final dataset is attained after removing any missing values, and Figure 1 below presents the temporal display of the final dataset included in the sample.

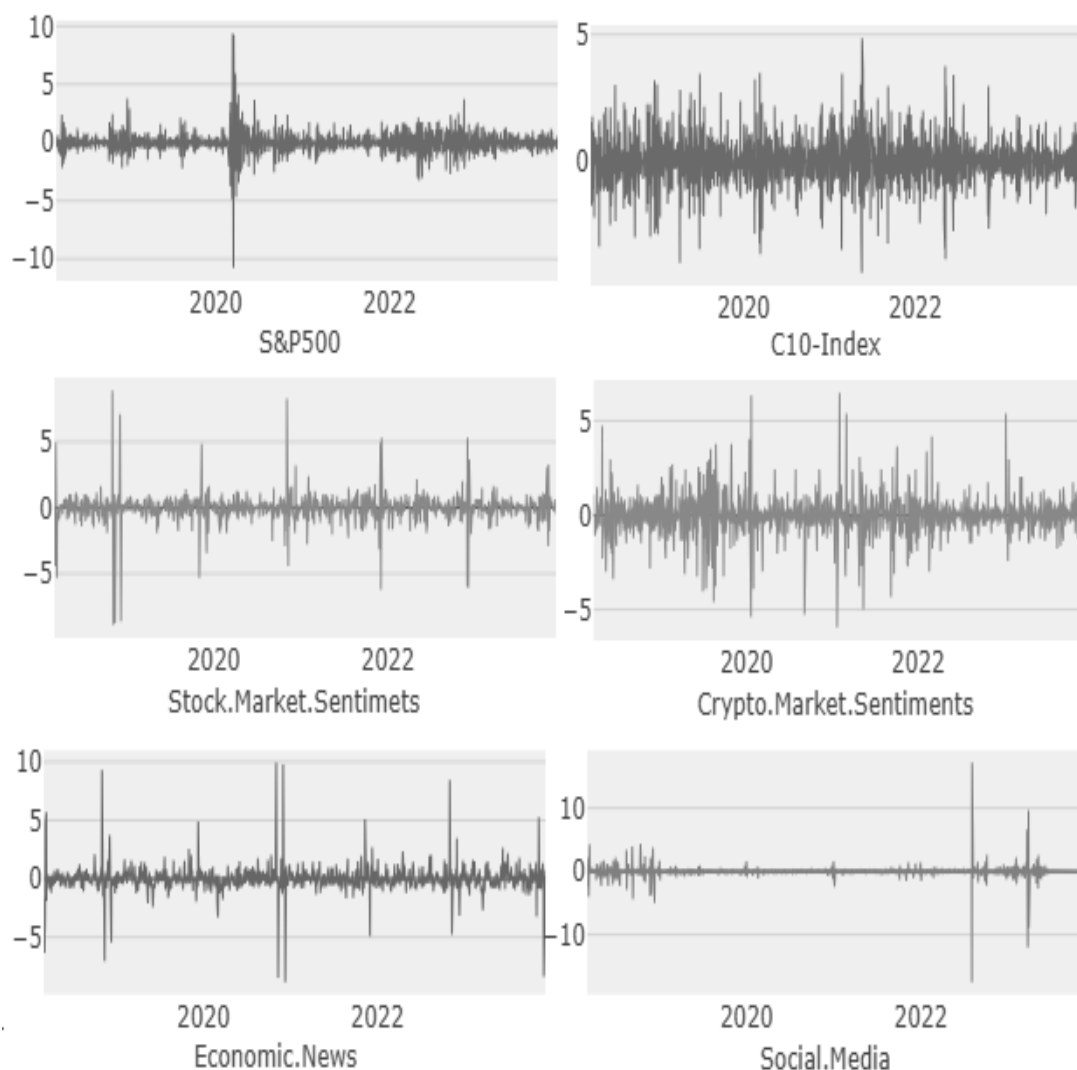


Figure 1. Transformed data. Source: Study findings from sampled data.

2.1. Operationalization of Variables

One of the cornerstones of a reliable and valid scientific inquiry lies in the appropriateness and suitability of instruments utilized to measure the constructs considered in the model. The current model comprises market movement, market sentiments, economic news sentiments, and social media sentiments. The current study relied on the existing literature to identify the already-established and validated proxies to measure these constructs.

2.1.1. Market Return

The current study utilized the log return of the market index to generate a time series for market return. This proxy is widely utilized and accepted in the existing literature of financial market movements (Rasheed et al., 2023) and also aids in overcoming underlying issues in time series data, like stationarity (Bianchi et al., 2023).

2.1.2. Market Sentiments

The current models consider market sentiments as crowd psychology and are defined as the collective behavior of market participants in the financial market. The current model relies on the fear and greed index as a representative of market sentiments. The index is gaining acceptability in the recent literature as a market-specific multifactor representation of sentiments (Ahadzie et al., 2025; Wang et al., 2024). The index ranges from 0 to 100, where a value close to 0 represents extreme fear and a value near 100 represents extreme greed, covering both bearish and bullish spectrums of the market.

To measure stock market sentiments against the S&P 500 index, the study relies on the CNN Fear and Greed Index (Farrell & O'Connor, 2025). The index comprises seven subcomponents, including “market momentum (MM), stock price strength (SPS), stock price breadth (SPB), put and call options (PCO), junk bond demand (JBD), market volatility (MV), and safe haven demand (SFD)”.

Similarly, to capture cryptocurrency market sentiments, the study utilized a similar measure of the cryptocurrency fear and greed index. This index also ranges from 0 to 100, ranging from extreme fear to extreme greed, but comprises five slightly different representations of the market including “market volatility (MV), market momentum (MV), social media sentiment (SMS), bitcoin dominance (BD), and search trends (ST)”. The index is calculated using a weighted average method and is found to significantly capture the market movements (Gurdgiev & O'Loughlin, 2020; Wang et al., 2024).

The market-specific nature of these indicators makes them an ideally suited proxy for analysis of market-specific behavior in the current model and to isolate overall economic and societal mood.

2.1.3. Economic News Sentiments

Traditional models of market behavior, like efficient market hypothesis, posit that the market participants are rational agents and act solely on relevant economic news to evaluate stock (Fama, 1970). Therefore, current-day economic news is expected to be highly related to market returns, based on which the current study is utilizing economic news sentiments derived from the work of Shapiro et al. (2022). The news index is an aggregated measure of individual article scores and is calculated using natural language-based lexical processing of daily economic news articles from 24 major newspapers across the United States of America. To address the noise in the data, the index used a moving weighted average methodology to arrive at the daily final scores (Verma & Verma, 2025).

2.1.4. Social Media Sentiments

Behavioral models of financial literature attribute market movements to the social mood originating from irrational behavioral and emotional factors (Kahneman & Tversky, 1979; Tan et al., 2024). Thereby, the overall social media sentiments are expected to be highly correlated with market movements across the stock market, and this influence is expected to be even higher amongst the speculative cryptocurrency market (Kyriazis et al., 2023). Therefore, the study is considering Chai et al.'s (2023) Twitter sentiment geographic index (TSGI) as a proxy of global social media sentiments. The proxy is generated through a comprehensive set of geotagged tweets across the globe through natural language processing. The dataset is limited till 2023 when twitter stopped the provision of free datasets through API processing, while this factor is also acting as a bottleneck for sample selection for the current model.

2.2. Descriptive Statistics

This section focuses on the descriptive exploration of the final dataset included in the study. Descriptive statistics are aimed at uncovering the underlying dynamics of similarities and dissimilarities across selected indices and sentiment types. The results are reported in Table 1 below, and the findings affirm the speculative nature of the cryptocurrency market as the average daily return of the cryptocurrency index is found to be almost (0.000444/0.000373) 20% higher than the S&P500 index while risk is also exponentially higher at 384% (0.050476/0.013129). The value of the Jarque–Bera test is all significant, indicating a lack of normal distribution in the dataset, which is expected with a time series dataset, whereas the stock and cryptocurrency sentiments exhibit similar patterns of mean, range, and standard deviation. Lastly, economic and social media sentiments vary significantly, where economic news exhibits much larger fluctuations of emotional scores, and social media posts remain within a limited spectrum of sentimental scores.

Table 1. Descriptive statistics.

	S&P500	C-10	SS	CS	ENS	SMS
Mean	0.000373	0.000444	47.61856	44.2388	−0.097854	0.594550
Median	0.000819	0.001983	50.00000	41.0000	−0.066776	0.589945
Max	0.089683	0.184481	97.00000	95.0000	0.290519	0.742645
Mini	−0.127652	−0.303534	02.00000	05.0000	−0.673245	0.262517
S.D.	0.013129	0.050476	20.12621	21.7206	0.177013	0.023341
JB	11,855.67	1176.951	35.17681	78.11629	451.2504	62,643.81

Source: Study findings from Sampled Data. Bold: Significant @ ($p < 0.01$) SS = Stock Sentiments, CS = Crypto Sentiments, ENS = Economic News Sentiments, SMS = Social Media Sentiments.

2.3. Correlational Analysis

A correlational analysis is also a useful statistical tool for pre-assessment linkage among sampled variables. A two-step analysis is conducted for the stock and cryptocurrency markets, and the results are reported in Table 2. Findings related to the S&P cryptocurrency index revealed that it weakly correlated with market, news, and social media sentiments, with the latter having the weakest and negative association. Similarly, economic news sentiments are negatively associated with index behavior, while market sentiments flow in the direction of market movement. The findings for the S&P500 stock index the findings affirm the impact of market direction, but the impact of economic and market sentiments is found to be higher and lower for social media sentiments. While the intersection of sentiments with each other indicates that economic news is positively related to market and social media, and while social media sentiments are negatively correlated with market sentiments.

Table 2. Correlational analysis.

	C10	ENS	CS	SMS
C10_INDEX	1			
ECONOMIC_NEWS	−0.023858547	1		
CRYPTO_SENTIMENTS	0.127349103	0.04847606	1	
SOCIAL_MEDIA	−0.071823886	0.162442019	−0.165261224	1
	S&P500	ENS	SS	SMS
S&P500	1			
ECONOMIC_NEWS	−0.053841166	1		
STOCK_SENTIMENTS	0.141003732	0.016902867	1	
SOCIAL_MEDIA	−0.040298211	0.175502995	−0.193899791	1

Source: Study findings from sampled data.

Before proceeding with the final model, a test for stationarity of the time series is conducted and reported in Table 3. Although the final analysis is conducted on logged returns of stock indices and a log differential on raw sentiment scores, the transformation is expected to overcome the issue of nonstationary of data; still, to ensure the validity of the model, final spillover analysis is conducted, and still the Augmented Dickey–Fuller (ADF)-based indicators for the common sample series are obtained and the results are reported. The findings are significant and indicate stationarity in the sample.

Table 3. Augmented Dickey–Fuller Test for Stationarity.

Variables	Statistic	Prob
S&P500 Index	−11.50907	0.0000
C-10 Index	−37.69902	0.0000
Stock Market Sentiments	−22.66854	0.0000
Crypto Market Sentiments	−2.358653	0.0178
Economic News Sentiment	−2.890401	0.0038
Social Media Sentiments	−16.08796	0.0000

Source: Study findings from sampled data.

2.4. Methodology

Appropriateness of the statistical model in a study is a key factor in determining the validity of theoretical and empirical inferences determined in the study. Therefore, a solid foundation and alignment are vital. The model of the current study is aimed at uncovering the time-varying association between sentiments and market behavior. Therefore, a time-series model aimed at establishing integration or spillover is appropriate. The modern literature on economic integration and financial spillover uncovered that the model of [Diebold and Yilmaz \(2009\)](#) is widely utilized and appropriate to study such an association. The model initially proposed to study stock prices but was later extended by [Diebold and Yilmaz \(2012\)](#) to incorporate other time-series variables. Their model is based on the vector autoregressive model (VAR), enabling researchers to analyze spillover within and across assets, asset classes, asset markets, and regions. The model and its measures are reported in Table 4 and are widely utilized in the field of spillover and connectedness comparison of cryptocurrencies and the stock market ([Yen, 2023](#)) cryptocurrency, and cryptocurrency-related stocks ([Frankovic et al., 2022](#)), Artificial Intelligence (AI) tokens and Artificial Intelligence stocks ([Jareño & Yousaf, 2023](#)), real estate tokens and REITs ([Abdullah et al., 2023](#); [Yousaf et al., 2024](#)), meme tokens and meme stocks ([Yousaf et al., 2023](#)), and fan tokens and football club stocks ([Ersan et al., 2022](#)), with avenues further growing exponentially. Recently, [Tan et al. \(2023\)](#) expanded this model to study the influence of

climate, security, and economic time series across Asian Pacific markets. Therefore, the acceptability and relevance of the model in the current study are also utilizing the model for studying time-varying inferences. The study relied on a basic VAR model, and analysis was conducted by using the Akaike Information Criterion (AIC) for lag length criterion while considering a rolling window size of two hundred.

Table 4. Statistical model.

1—Variance share of each asset	4—Spillover from an asset
$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^N \theta_{ij}^g(H)}$	$\sum_{j=1}^N \tilde{\theta}_{ji}^g(H)$ $FROM_{.i}^g(H) = \frac{j \neq i}{N} \cdot 100$
2—Total average spillover	5—Net average spillover from an asset
$\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H)$ $TCI^g(H) = \frac{i \neq j}{N} \cdot 100$	$NET_i^g(H) = FROM_{.i}^g(H) - TO_i^g(H)$
3—Spillover to an asset	6—Net pairwise spillover from an asset
$\sum_{j=1}^N \tilde{\theta}_{ij}^g(H)$ $TO_{.i}^g(H) = \frac{j \neq i}{N} \cdot 100$	$PAIR_{ij}^g(H) = \frac{(\tilde{\theta}_{ji}^g(H) - \tilde{\theta}_{ij}^g(H))}{N} \cdot 100$
Source: Diebold and Yilmaz (2009) and Diebold and Yilmaz (2012)	
Simple Linear Regression	Granger Causality Analysis
$y_t = \alpha + \beta_1 X_{1t} + \beta_2 X_{2t} + \dots \beta_n X_{nt} + \varepsilon_t$	$y_t = \sum_{j=1}^p \alpha_j y_{t-j} + \beta_j x_{t-j} + \mu_t$ $x_t = \sum_{j=1}^p \gamma_j x_t + \delta_j y_{t-j} + \omega_t$

Note: “ θ = Variance of Time Series; FROM = Spillover from Time Series; TCI = Total Connectedness Index; NET = Net Spillover; TO = Spillover to Time Series; PAIR = Pairwise Spillover”. Source: [Durbin \(1960\)](#), [Granger \(1969\)](#), [Jordaan and Eita \(2007\)](#), [Kónya \(2006\)](#), and [Shojaie and Fox \(2022\)](#).

2.5. Robustness Measures

Sub-analyses are conducted to validate the findings of the model further and establish the robustness of the findings, while uncovering new insights from the dataset. Firstly, the study applied a simple linear regression model to assess the significance of the association between sentiment type and index return ([Durbin, 1960](#); [Peck et al., 2015](#)). Subsequently, the study also applied a two-way Granger single-factor causality test to validate the findings of VAR-based spillover assessment and evaluate the significance of these associations. The test was initially proposed by Granger in 1969. The traditional method is based on VAR-based F statistics and is widely utilized in economic research ([Durbin, 1960](#); [Granger, 1969](#); [Jordaan & Eita, 2007](#); [Kónya, 2006](#); [Shojaie & Fox, 2022](#)). The findings of this robustness are expected to further enhance the significance of the current model, and the underlying models are also reported in Table 3.

3. Results and Discussion

This part is dedicated to the analysis and subsequent findings of the study. [Diebold and Yilmaz \(2012\)](#) VAR-based dynamic connectedness approach is utilized to obtain the final results. The results of the findings are reported in the next section and comprise network plot, static or average connectedness, and temporal or dynamic connectedness measures generated from the series.

3.1. Network Plot

The findings of the network plot are aimed at uncovering the intervariable association between the constructs included in the model. The findings of the network plot are reported in Figure 2a,b for S&P cryptocurrency and the S&P 500 index. The plot not only shows direction but also the degree of association between the variables. The blue indicators represent net transmitters, and the yellow color represents net receivers in the model, while the magnitude of the relationship is represented through the thickness of the link.

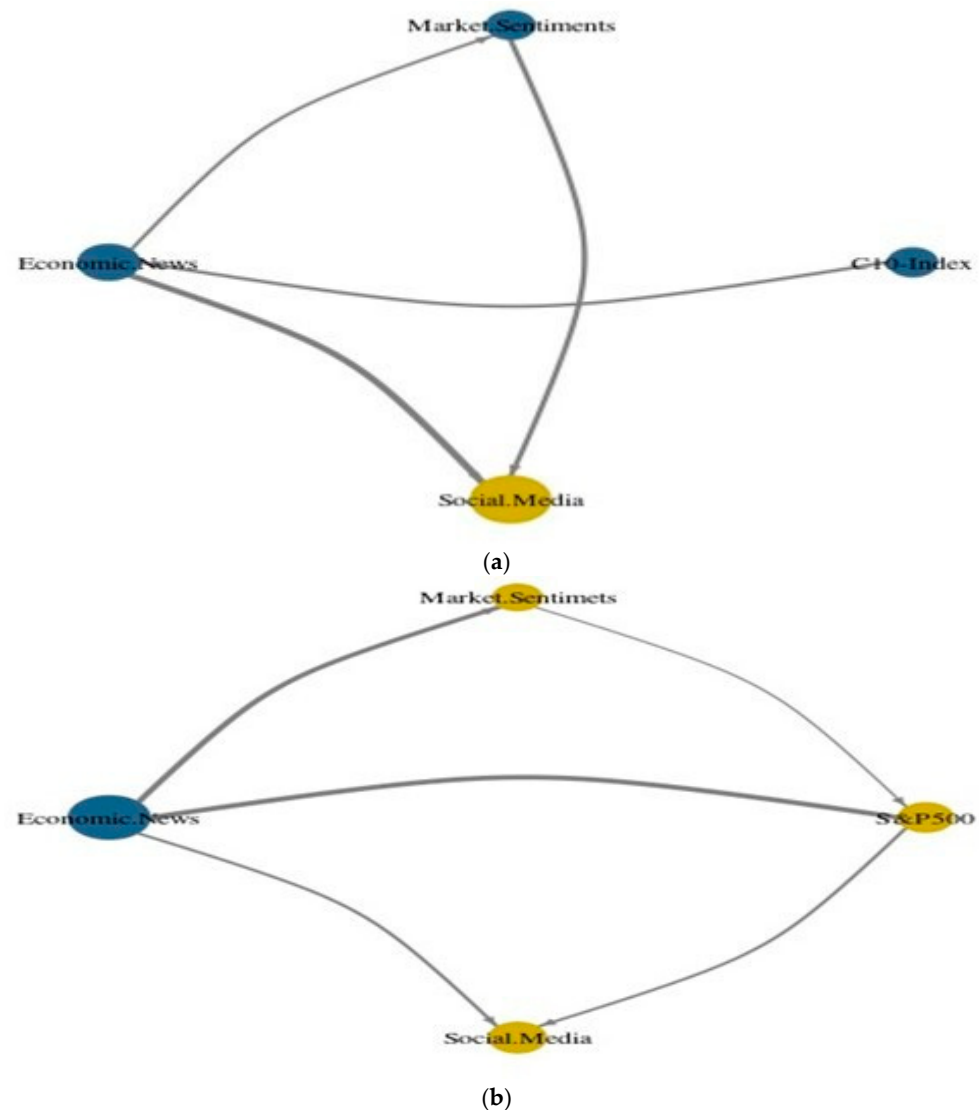


Figure 2. (a) Network between C-10 index, crypto market sentiments, economic news sentiments, and social media sentiments. Source: Study findings from Table 5a. (b) Network between S&P 500 index, stock market sentiments, economic news sentiments, and social media sentiments. Source: Study findings from Table 5b.

Figure 2a uncovers the relationship of the S&P cryptocurrency index with market, economic news, and social media sentiments. The analysis uncovers that the cryptocurrency index is weakly associated with economic news sentiments, whereas no visible association exists for market and social media sentiments towards cryptocurrencies. These findings are aligned with the study of Rognone et al. (2020) who found a significant association of cryptocurrencies with economic news, and are unable to validate the findings of Kyriazis et al. (2023) and Wang et al. (2024) regarding market and social media sentiments. This can be attributed to the interlinkage between different types of sentiments. This interlinkage

can also be observed from Figure 2a, where economic news (market sentiments) is found to be a strong (weak) driver of social media sentiments, while economic news is also found to be weakly influencing the market sentiments, thereby establishing that the cryptocurrency market and related sentiments are highly sensitive to the variation in economic sentiments.

Table 5. (a) Average connectedness of C-10 index, crypto market sentiments, economic news sentiments, and social media sentiments. (b) Average connectedness of S&P 500 index, stock market sentiments, economic news sentiments, and social media sentiments.

(a)					
	C10-Index	Market Sentiments	Economic News	Social Media	FROM
C10-Index	086.50	009.57	002.08	001.84	013.50
Market Sentiments	009.22	086.25	002.38	002.14	013.75
Economic News	003.02	001.60	093.15	002.23	006.85
Social media	001.88	003.14	003.79	091.19	008.81
TO	014.12	014.32	008.25	006.22	042.90
Inc. Own	100.62	100.57	101.40	097.41	cTCI/TCI
NET	000.62	000.57	001.40	−002.59	14.30/10.73
(b)					
	S&P500	Market Sentiments	Economic News	Social Media	FROM
S&P500	065.58	020.62	010.01	003.79	034.42
Market Sentiments	018.92	063.43	012.70	004.94	036.57
Economic News	005.04	007.34	083.37	004.25	016.63
Social media	006.58	005.50	007.16	080.75	019.25
TO	030.55	033.46	029.88	012.98	106.86
Inc. Own	096.13	096.89	113.25	093.73	cTCI/TCI
NET	−003.87	−003.11	013.25	−006.27	35.62/26.72

Source: Study findings from sampled data.

Figure 2b is associated with the return of S&P500-selected types of sentiments in the model. The findings uncovered that all economic news and stock market news plays a significant role in determining the behavior of S&P500 return, whereas the former dominates this association with a much higher association, while the latter has a weak influence. These findings are aligned with existing studies of Farrell and O'Connor (2025), Gong et al. (2022), Q. Liu et al. (2023), Tan et al. (2023), and Verma and Verma (2025). These findings validate that investors in stock markets are much more influenced by sentiments and act irrationally, leading these sentiments to predict stock markets. The study also established that market behavior alongside economic and market sentiments act as a driving agent for social media sentiments. The interlinkage between these sentiments established and affirmed economic news sentiments as the sole dominating force in the stock market.

3.2. Static Connectedness Analysis

This section focuses on presenting the average connectedness among the returns of the market index and selected types of sentiments. The section is divided into two categories to present findings related to cryptocurrency and stock market analysis in Table 5a,b. The dominance of diagonal values of each variable indicates that the highest influence on prices and sentiments is self-driven and is attributable to their shocks and movement, and is consistent with the existing literature on spillover (Abakah et al., 2023; Frankovic et al., 2022; Yousaf et al., 2023).

The findings related to the S&P cryptocurrency index and sentiments are reported in Table 5a. The findings of the total connectedness index (TCI) revealed a weak association between sentiments and cryptocurrency returns at 14.30%. The findings suggest that

economic news sentiments act as a driving factor for spillover across cryptocurrency returns (Philander, 2023; Rognone et al., 2020; Umar et al., 2021). The findings of the study align these findings with the work of Karaa et al. (2024) showing that associated investors' behavior relies on behavioral patterns and trends reflected by investors' sentiments, hence affirming the presence of irrational and noise trading derived from biased behavioral factors. Conclusively, variation in behavioral market sentiments is found to shape the cryptocurrency returns (Caferra, 2020). The findings uncover that economic news is the sole dominating factor in the cryptocurrency environment, which shapes market and social media sentiments to shape cryptocurrency behavior. In a speculative market like cryptocurrency, where the market valuation of an asset is solely driven by investors' sentiments, they became a vital indicator for investors, managers, practitioners, initial coin offerings, and regulators (Domingo et al., 2020). Stakeholders should carefully consider trends and persistent economic sentiments to plan and execute their financial decisions to gain optimal results.

Similarly, the findings related to the S&P 500 stock indices and sentiments are reported in Table 5b. The findings of the evaluation established moderate spillover between market returns and sentiments at 35.62%. The findings suggest that economic and market sentiments act as a driving force for stock market movements (Farrell & O'Connor, 2025; Verma & Verma, 2025) while economic news acts as the primary factor influencing market and social media sentiments and hence establishes itself as the driving force for the stock market movements. The findings of the study highlighted that social media sentiments do not determine stock market, but instead they are generated in consequence of the economic sentiments, market sentiments, and stock movements. Therefore, a more appropriate measure to consider for investors is economic news and stock market movements. Given that existing literature like Rasheed et al. (2023) and Tan et al. (2024) posits that the driving force behind economic and market sentiments are also biased and resulted from investor over- or underreaction to information, investors can utilize this nexus among sentiments to determine the market direction and expected valuation for return optimization.

3.3. Temporal Analysis

Lastly, an analysis to uncover the time-varying association between cryptocurrency and stock market index with selected sentiments is conducted and reported below. The analysis aims to uncover any temporal variations and changes in dynamics during the sampled period. The analysis will also aid in understanding the variation in spillover and association amongst these factors during different phases of the economic cycle.

3.3.1. Dynamic Total Connectedness

The first measure of temporal analysis is the dynamic total connectedness, which focuses on average spillover among model variables across the sampled period. The result of dynamic total connectedness is also divided into two parts to present findings related to cryptocurrency and stock-related analysis. The findings are presented in Figure 3a,b for cryptocurrency and stock market analysis, respectively.

The temporal analysis of cryptocurrency and sentiment analysis indicates that connectedness across these factors varied significantly from 10% to its highest point of 40%, uncovering diverse dynamics of association that the average static findings failed to uncover. The figure indicates high points of association between 2019 and 2020, and this variation in spillovers reduced significantly after that. This high spillover can be attributed to the cryptocurrency resurgence (Gandal et al., 2021) and COVID-19 pandemic (Yen, 2023). This elevated existence of spillover is aligned with existing literature, which posits that markets become more connected during the tenure of extreme financial conditions, and behavioral theory already attributes financial bubbles and crashes to sentiments generated

from biased behavior (Tan et al., 2024). Therefore, the findings of the study establish that during the financial extremes, the spillover association and predictability through sentiments will be much higher and should be considered during similar phases of economic cycles. The relevance of sentiments for the cryptocurrency market in the absence of fundamental factors makes it the sole significant factor to be considered for evaluation and prediction.

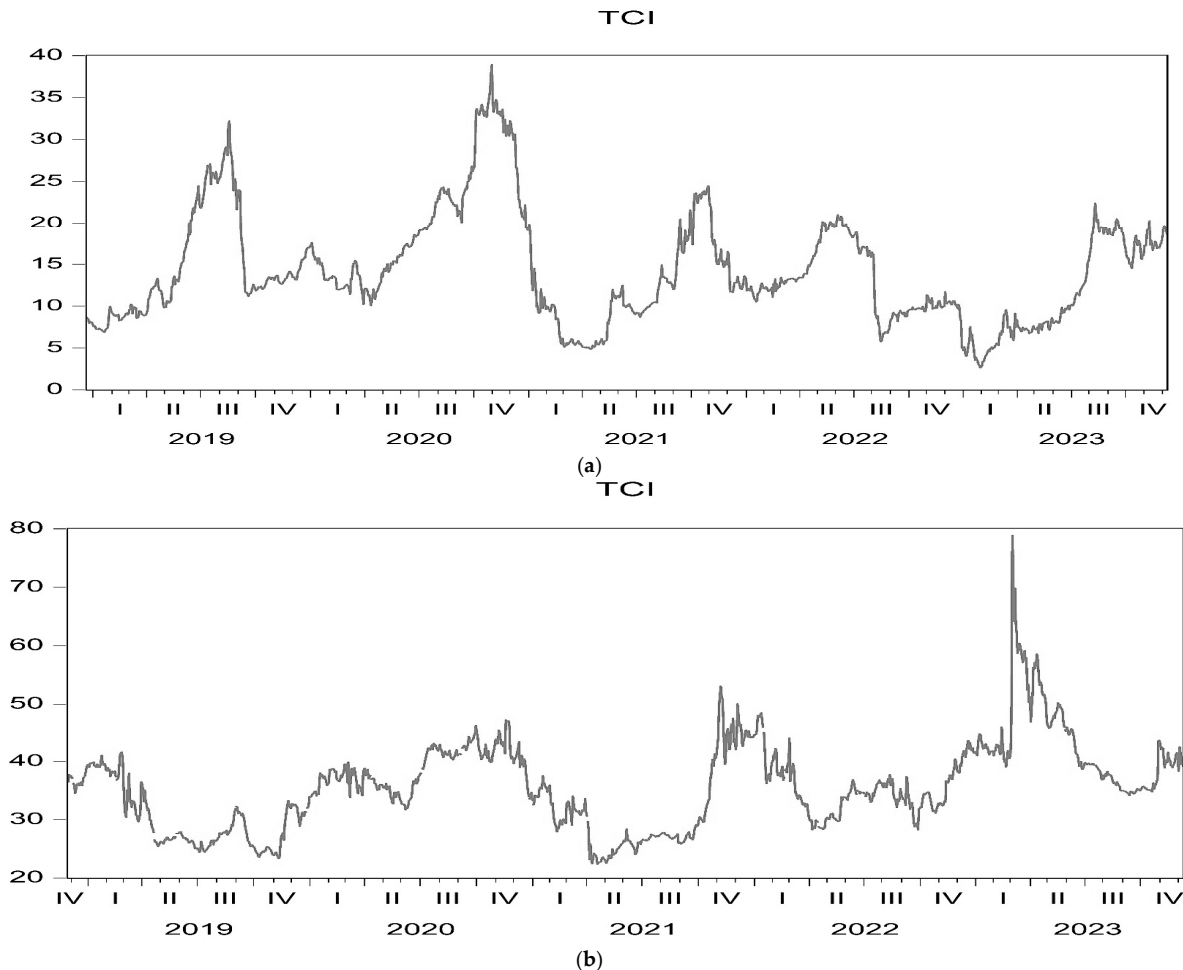


Figure 3. (a) C-10 index, crypto market sentiments, economic news sentiments, and social media sentiments. (b) S&P 500 index, stock market sentiments, economic news sentiments, and social media sentiments. Source: Study findings from sampled data.

Similarly, the dynamic temporal findings of the S&P 500 are presented in Figure 3b. The findings indicate a comparatively smooth spillover ranging from 45% to 25%, with an average value revolving around 35%, significantly jumping to around 80% during mid-2022. This high association can also be attributed to global economic turbulence during 2022. The market observed significant bearish trends with high global interest rates and inflation, raising concerns about economic recession. Other geopolitical issues like the Russia–Ukraine war further elevated this uncertainty. Hence, the elevated spillover is, as per the earlier literature, associated with a period of economic uncertainties (Yen, 2023; Yousaf et al., 2023). Overall, the findings revealed that the association of stock markets is higher than that of cryptocurrencies. These findings are against the traditional belief that sentiments drive cryptocurrencies and affirm the purely speculative nature of the cryptocurrency market.

3.3.2. TO, FROM, and NET Connectedness

Lastly, the dynamic temporal findings for individual variables are obtained and presented in this section. The time-varying assessment comprises spillover from each variable

to the other variables, from other variables, and net connectedness through sampled tenure. This part is also further divided into two distinct categories of cryptocurrency-related variables and stock market-related variables and discussed to provide a comparative overview of the underlying cryptocurrency and stock market.

The results for spillover to each variable across cryptocurrency analysis are reported in Figure 4a. The results validate that there exists significant spillover towards the S&P cryptocurrency index return from various sentiments, which become significantly higher during times of financial uncertainties towards a bubble or crash. The behavior of sentiments across time uncovers unique insights into their dynamics. Economic news sentiments indicate consistent variation across time from market movement and other sentiments. The behavior is consistent with the comprehensive nature of economic news sentiments influenced by economy-related social media and market trends, while also covering economic news unrelated to market behavior. The results for market sentiments are very convergent with market and social media behavior, with elevation during the time of financial extremes, whereas the trend of social media sentiments is found to overlap with market sentiments, either over or underreacting to the trends in the market.

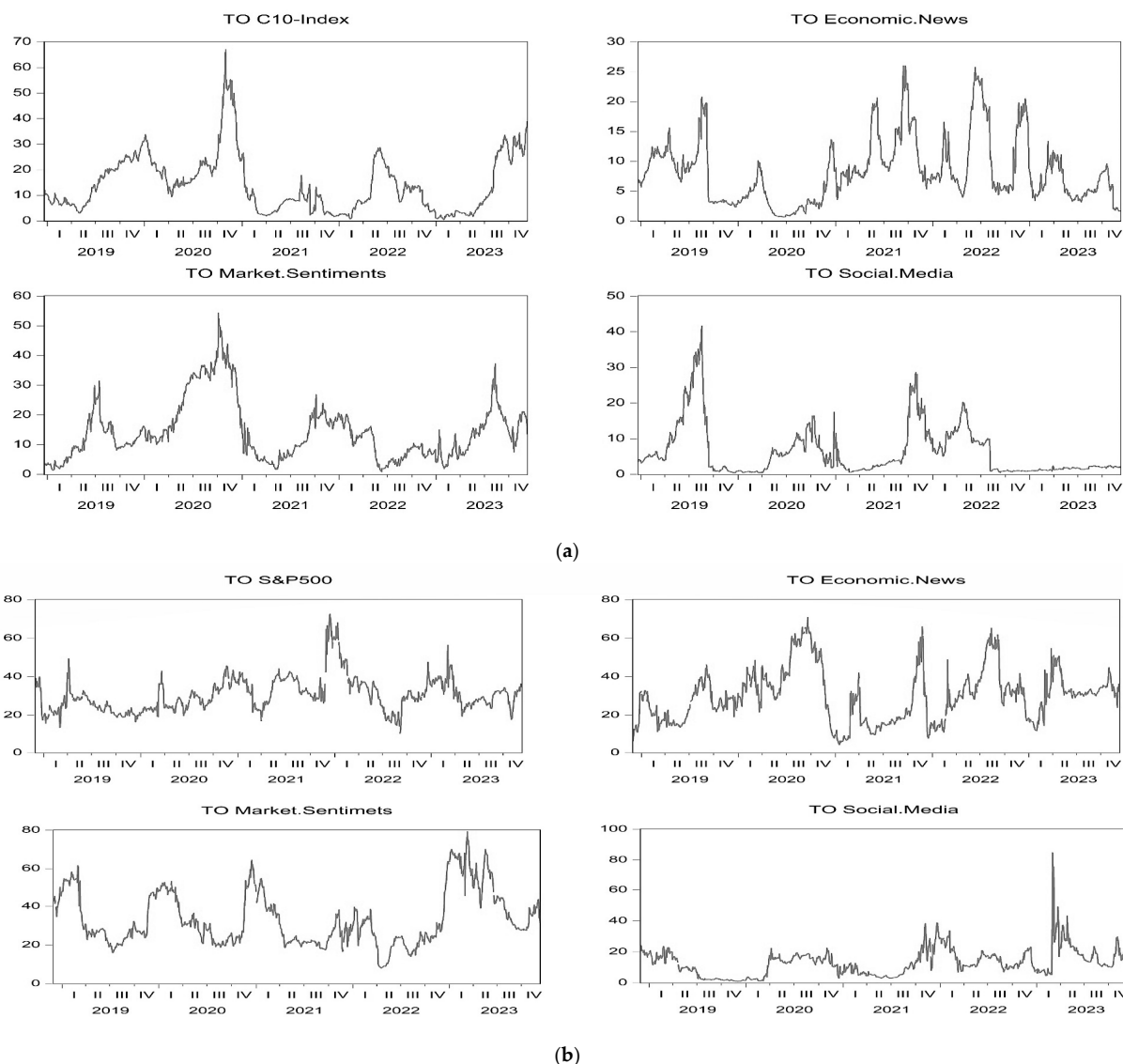


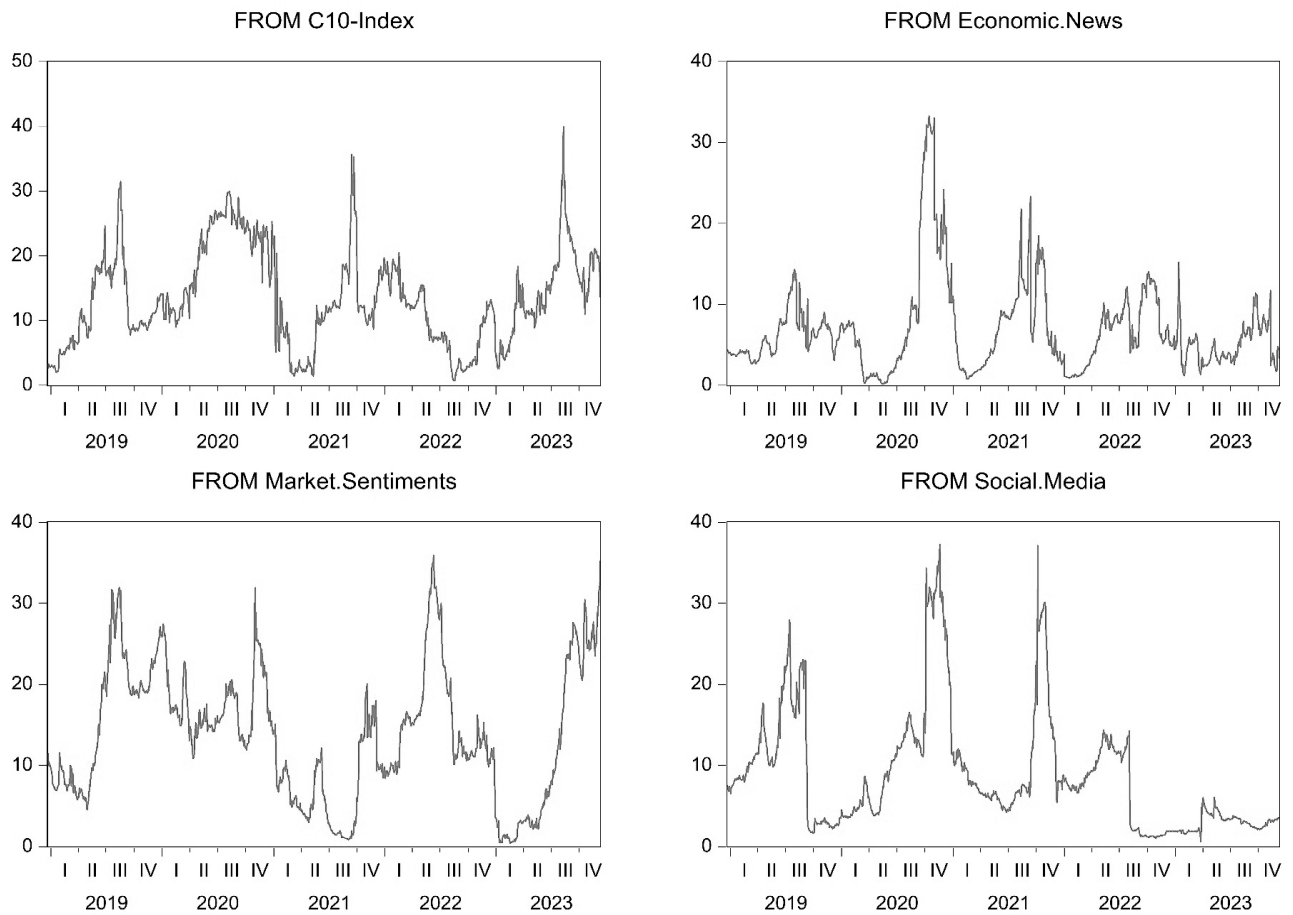
Figure 4. (a) TO for C-10 index, crypto market sentiments, economic news sentiments, and social media sentiments. (b) TO for S&P 500 index, stock market sentiments, economic news sentiments, and social media sentiments. Source: Study findings from Sampled Data.

Figure 4b represents spillover towards variables against stock-related variables. The findings revealed that there exist much higher and consistent spillovers of sentiments across S&P 500 index returns. This indicates that stock markets are much more prone to emotional response as compared to the cryptocurrency market. Meanwhile, the overlap of economic news sentiments against stock return movement validates the earlier observation of heavy overlap during times of financial extremes. The findings for market sentiments revealed that stock market sentiments are aligned with both stock market and economic behavior, while social media sentiments are found to be unrelated and consistent throughout the period, hinting at their isolation from the market.

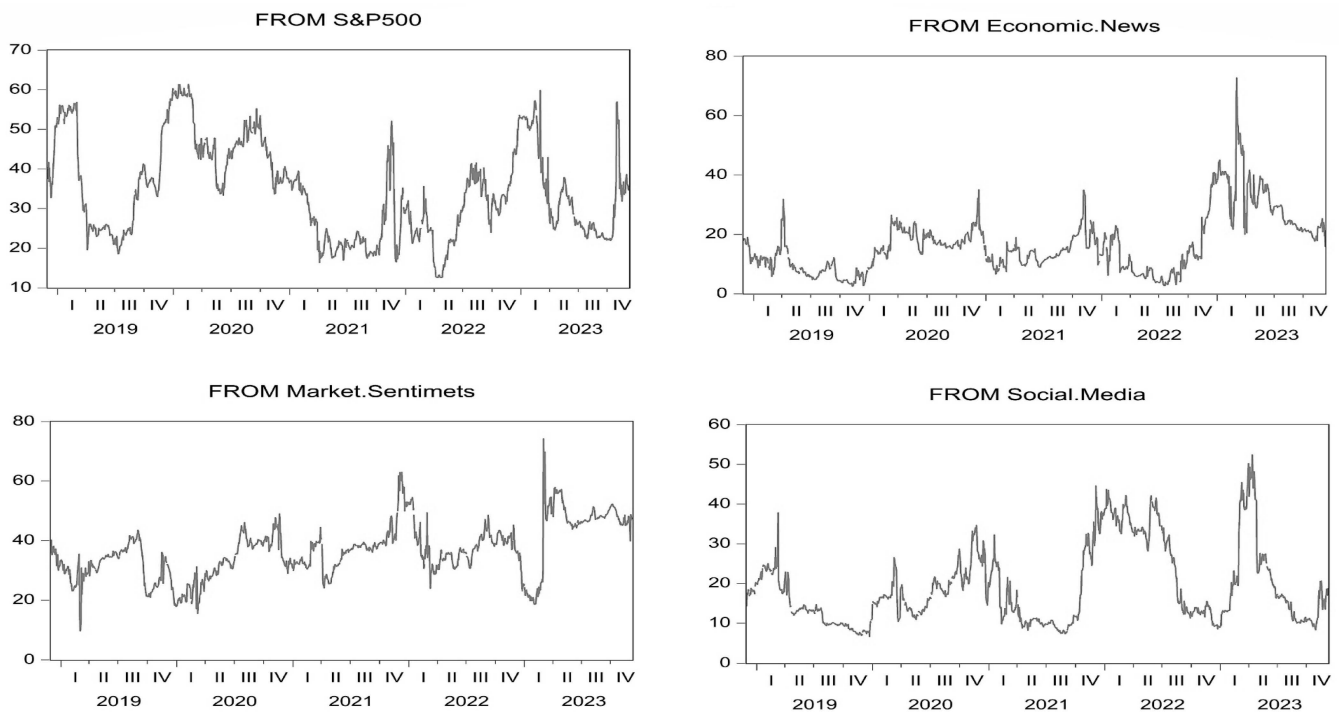
Subsequently, the findings related to spillover from each variable towards other variables in the analysis are presented. First, the spillovers from variables in the cryptocurrency model are reported in Figure 5a. The findings reveal that spillovers from the cryptocurrency index are increasing across the sampled period. Here again, the spillover is elevated during the period of financial extremes. This hints at the increased relevance of the cryptocurrency space globally, shaping economic and social media sentiments. Meanwhile, results about sentiments exhibit mixed behavior. The spillover from economic news sentiments is weak but becomes significantly higher during a financial crisis; meanwhile, market sentiments tend to almost perfectly overlap with the market behavior. This can be attributed to the closed, speculative nature of the cryptocurrency market. Lastly, the spillover from social media sentiments tends to be highly overlapped with economic news sentiments, establishing economic news sentiments as the driving force for social media sentiments.

The findings related to stock market and related sentiments are reported in Figure 5b. The stock market exhibits consistent and moderately significant influence across the sampled period, making it a much more pertinent part of the financial environment. Across the sentiments, the market sentiments are predominantly overlapping with market movements, and only significant deviations occur during extreme changes in economic sentiments, whereas social media sentiments are found to revolve around economic news sentiments. This validates earlier findings that economic news sentiments act as a driving force for social media sentiments and significantly influence market sentiments during extremes of economic sentiments.

Finally, results for net transmission through each variable across time are obtained and reported. This part will help evaluate the role of each variable as either transmitter or receiver of spillover from other variables. Figure 6a discusses the net spillover for the variables included in cryptocurrency analysis. The findings indicate that overall, the S&P cryptocurrency index return acted as a net receiver of the spillover from existing sentiments; only once during the timeline it acted as a weak transmitter of spillover during 2021, which as we already discussed, is aligned with the resurgence of cryptocurrencies. Meanwhile, economic news sentiments are found to be consistently acting as a net transmitter of spillover and once acted as a receiver during the same period of 2021. The social media sentiments are also found to be highly overlapped with economic news sentiments while remaining a net receiver of spillover, establishing economic news as the origin of social media sentiments. Meanwhile, market sentiments tend to present mixed behavior to the transmitter and receiver during the sampled period. The analysis reveals that during extreme market movement, it became a net transmitter while remaining a net receiver during average market conditions.



(a)



(b)

Figure 5. (a) FROM for C-10 index, crypto market sentiments, economic news sentiments, and social media sentiments. (b) FROM for S&P 500 indices, stock market sentiments, economic news sentiments, and social media sentiments. Source: Study findings from sampled data.

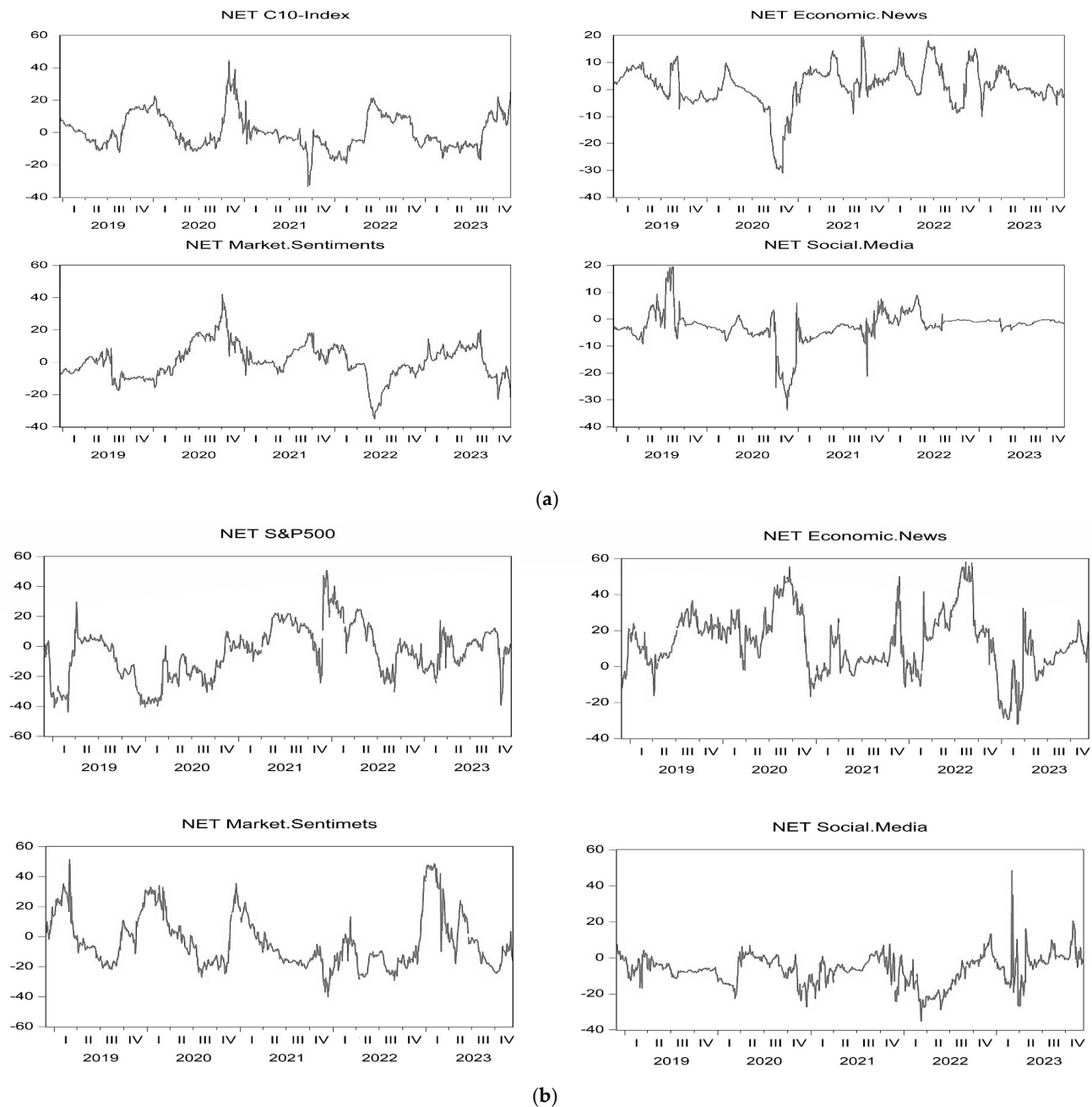


Figure 6. (a) Directional spillover for C-10 index, crypto market sentiments, economic news sentiments, and social media sentiments. (b) Directional spillover for S&P 500 index, stock market sentiments, economic news sentiments, and social media sentiments. Source: Study findings from sampled data.

Finally, Figure 6b is attributable to the net spillover findings related to stock returns and sentiments. The findings of the S&P 500 index return uncovered that the behavior of stock return is much more dynamic than compared of the cryptocurrency index. The index predominantly remained a net receiver of spillovers from the sentiments, but on several occasions, it acted as a net transmitter of spillover. This establishes the increased relevance of the stock market to the economic ecosystem as compared to the cryptocurrency market. Meanwhile, the findings of economic news sentiments also unveil that it has a significantly higher overlap with stock market movements as a transmitter of spillover, while at a couple of points of extreme market movement, it received spillover from the market. Similarly, the association and overlap of market sentiments as the transmitter is also much higher

for stock market movements as compared to its cryptocurrency counterpart. Meanwhile, social media sentiments are found to be net receivers of spillovers from market returns, sentiments, and economic news.

Overall, the study is unique in highlighting and distinguishing nuances across cryptocurrency and stock market behavior about the influence of sentiments. The study is the pioneer in elaborating and establishing that cryptocurrency has a weak association with sentiments but is much more prone to its own market sentiments and social media, while economic news has a consistent but weak influence on cryptocurrency market return. This affirms the speculative nature of cryptocurrency market, and similar to a betting club the return behavior of the cryptocurrency market is like an isolated closed system, where participants are risking their investment for higher returns without any fundamentals. This also validates the high variation across cryptocurrency spillover. On the other hand, stock market returns are highly and consistently related to sentiments. In the stock market environment, economic news sentiments act as a driving force for market sentiments and movement. While social media sentiments are found to be merely reacting to economic and market trends. These findings are also aligned with the time-varying behavior of social media sentiments established by Gan et al. (2020), where the changing dynamics of social media sentiments were recorded to act as a receiving agent from news, followed by a transition period of two-way causality, and later, from 2016, the social media activity seems to influence news movements. The consistent role of sentiments also hints at the role of behavioral factors, which shape these sentiments to create such predictability in the stock market (Tan et al., 2024), opening new avenues and associations for the future.

3.4. Robustness Analysis

To further validate the findings of the study and uncover further insights from the dataset, a simple linear regression model and Granger causality analysis are applied as robustness measures. Two separate regression models are applied against the S&P cryptocurrency index return and S&P 500 stock returns through E-Views.

The results for cryptocurrency returns are reported in Table 6a; the overall fitness of the model is assessed using the significance of F statistics. The Durbin–Watson test for multicollinearity and unit root test for stationarity of series is applied and reported. The findings indicate that models have sufficient statistical validity and reliability. The inferential findings indicate that only market sentiments are a significant determinant of cryptocurrency returns at ($p < 0.01$), while results regarding economic sentiments and social media sentiments are statistically insignificant. This validates the earlier inference that the cryptocurrency market is an isolated environment with self-driving sentiments and remains alienated from outside macroeconomic factors.

Subsequently, an analysis of S&P 500 stock returns is reported in Table 6b. The model indices comprising F statistics, Durbin–Watson statistics, and unit root analysis reveal reliability and validity of the statistical model. The findings of the analysis uncovered that market sentiments are a significant driver of market return at ($p < 0.01$) while the findings related to economic news sentiments are also significant but at ($p < 0.1$). The influence of social media sentiments on the stock market is also insignificant, thereby establishing that stock markets are more influenced by overall economic and market sentiments and are much more prone to fluctuations in external factors.

Lastly, to further extend the analysis into the significance of the two-way association among each set of variables, Granger causality tests are applied based on F-statistics and results are reported in Table 7 for both cryptocurrency- and stock-related variables. The findings related to cryptocurrency-related variables validate the findings of spillover and regression analysis and establish that there exists two-way causality among market

sentiments and index returns. Apart from that, causality between sentiments and market returns is not significant.

Table 6. (a) Regression analysis crypto market; (b) Regression analysis stock market.

(a)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
ECONOMIC_NEWS	−0.008604	0.007342	−1.171870	0.2414
MARKET_SENTIMENTS	0.000299	0.000060	5.015706	0.0000
SOCIALMEDIA	−0.082222	0.067180	−1.223897	0.2212
C	−0.013656	0.003060	−4.462789	0.0000
R-squared	0.018108	Mean dependent var		0.000444
Adjusted R-squared	0.016133	Durbin–Watson stat		2.005107
F-statistic	9.165795	Prob (F-statistic)		0.000
(b)				
Variable	Coefficient	Std. Error	T-Statistic	Prob.
ECONOMIC NEWS	0.002541	0.001817	−1.398458	0.0922
MARKET SENTIMENTS	0.000599	0.000041	14.66358	0.0000
SOCIAL MEDIA	−0.003648	0.016322	−0.223523	0.8232
C	0.000125	0.000367	0.341451	0.7328
R-squared	0.131593	Mean dependent var		0.000373
Adjusted R-squared	0.129798	Durbin–Watson stat		2.459387
Log likelihood	4342.993	Hannan–Quinn criteria		−5.958833
F-statistic	73.29207	Prob (F-statistic)		0.000

Source: Study findings from sampled data.

Table 7. Granger causality analysis.

Causality in Crypto Market		Causality in Stock Market	
Null Hypothesis	F Stat.	Null Hypothesis	F Stat.
C10 INDEX does not Granger Cause MARKET SENTIMENTS	244.217	S&P500 does not Granger Cause MARKET SENTIMENTS	8.25698
C10 INDEX does not Granger Cause ECONOMIC NEWS	2.53450	S&P500 does not Granger Cause ECONOMIC NEWS	8.98435
C10 INDEX does not Granger Cause SOCIAL MEDIA	0.01595	S&P500 does not Granger Cause SOCIAL MEDIA	0.27839
MARKET SENTIMENTS do not Granger Cause C10 INDEX	8.21264	MARKET SENTIMENTS do not Granger Cause S&P500	7.02102
ECONOMIC NEWS does not Granger Cause C10 INDEX	0.83839	ECONOMIC NEWS does not Granger Cause S&P500	7.24013
SOCIAL MEDIA does not Granger Cause C10 INDEX	0.19689	SOCIAL MEDIA does not Granger Cause S&P500	0.95484
ECONOMIC NEWS does not Granger Cause MARKET SENTIMENTS	0.00383	ECONOMIC NEWS does not Granger Cause MARKET SENTIMENTS	9.98759
ECONOMIC NEWS does not Granger Cause SOCIAL MEDIA	0.04237	ECONOMIC NEWS does not Granger Cause SOCIAL MEDIA	0.00668
MARKET SENTIMENTS do not Granger Cause ECONOMIC NEWS	1.51853	MARKET SENTIMENTS do not Granger Cause ECONOMIC NEWS	8.74912
SOCIAL MEDIA does not Granger Cause ECONOMIC NEWS	3.64543	SOCIAL MEDIA does not Granger Cause ECONOMIC NEWS	3.31767
MARKET SENTIMENTS do not Granger Cause SOCIAL MEDIA	0.03805	MARKET SENTIMENTS do not Granger Cause SOCIAL MEDIA	2.04162
SOCIALMEDIA does not Granger Cause MARKET SENTIMENTS	0.08524	SOCIAL MEDIA does not Granger Cause MARKET SENTIMENTS	1.44991

Source: Study findings from Sampled Data. Bold: Significant @ ($p < 0.1$).

Similarly, for the casualty of S&P500 index return and market sentiments, similar bidirectional and significant outcomes are revealed, but similar to spillover and regression analysis, it additionally reported significant bidirectional influence of economic news sentiments on stock index return. Meanwhile, economic news and market sentiments are also significantly affecting each other. These unique findings affirm the insights uncovered during earlier analysis regarding the greater sensitivity of the stock market against sentiments as compared to the cryptocurrency market. The bidirectional significant influence validates that the S&P500 index is a significant and integrated part of the overall economic system, with a change in one influencing the other significantly.

Social media sentiments are found to be consistently influencing economic news sentiments, a findings aligned with the earlier findings of [Gong et al. \(2022\)](#) which determined that social media has influenced economic news in recent times. The pioneering nature of this particular avenue makes it a significant theoretical and practical contribution for all the relevant stakeholders while also opening new behavioral avenues for future researchers.

These results reveal the way that sentiments are distributed among various information sources and how these sentiments are associated with the movements of stock and cryptocurrency markets.

Cryptocurrency results and analysis reveal that there is substantial bidirectional causality between the market sentiments and cryptocurrency index returns for cryptocurrencies. The past market sentiment drives returns of cryptocurrencies at the same time that past returns of cryptocurrencies drive future market sentiment. The cryptocurrency market is very dynamic, with investors reacting on their emotional and speculative instincts, driving the market as much as the market drives them. Volatile cryptocurrency prices can cause investors to change their expectations of the markets, and these are reflected in their subsequent actions. The cryptocurrency markets thus seem to be in what looks like a feedback loop of sentiment returning. With the exception of the relationship between market sentiments and cryptocurrency returns, the causality between other sentiment variables and cryptocurrency returns seems negligible. These indicate, in a sense, that the economic news sentiment and social media sentiment have less direct impacts on the returns of cryptocurrencies. The reason may be that the cryptocurrency markets tend to react more to internal market indicators, investor sentiment, market liquidity, investor speculation, and the narratives built around certain platforms rather than to official economic data. For this reason, although sentiment does matter in the cryptocurrency market, the results suggest that the market-level sentiment metric is more predictive than other economic indicators or sentiment measures based on social media.

As far as the findings relating to S&P 500 are concerned, they provide much-interconnected dynamics. The association of return and market sentiments is found to be similar to the cryptocurrency market. This uncovers investor sentiment as the driving force for stock market returns, and that changes in stock market sentiment help explain future movements in stock returns. In such a feedback relationship, stock market actors react to price signals as well as to investor sentiment or collective investor expectations. When returns rise, it boosts investor confidence; however, if a company performs poorly, investor confidence will decline, changing investors' future expectations for that company. One of the major discrepancies seems to lie in the power of economic news sentiments. The S&P 500 index return has much stronger bidirectional causality relations with economic news sentiments, unlike the cryptocurrency market. This result indicates that the behavior of the stock market is more sensitively influenced by economic news. Companies included in the S&P 500 are heavily linked to the broader economy, so investors are paying attention to related indicators like inflation, interest rates, employment, GDP growth, monetary policy, and other aspects of the economy. Meanwhile, financial markets are also impacting the way

economic conditions are reported in the public and financial media. When the stock market climbs, it bolsters the positive economic outcomes, and when the stock market drops, the negative news framing boosts.

The Granger causality results overall show a generally stronger sentiment transmission in the stock market than in the cryptocurrency market. The impact of sentiment on social media is found to have important links to economic news sentiments, which have spillovers to market sentiment; and both economic news sentiment and market sentiment have connectedness to the returns of the S&P 500. This trend indicates that peoples' sentiment moves via a series of interlinked channels and influences stock market behavior. The cryptocurrency market, by contrast, has a more restricted causal network, predominantly focused on the causality between market sentiments and cryptocurrency returns.

The results reveal a significant disparity in the two markets, stock versus cryptocurrencies. The stock market is more influenced by the informational and economic outlooks because the stock market is still linked to the real economy, and the performance of companies, business expectations and the investments that institutions are making. The cryptocurrency market, on the other hand, seems more sentiment-driven at the market level, with weaker direct one-to-one relationships between the economic news sentiments.

The bi-directional relationships in this study also warrant that sentiments and returns should not be considered as one-directional relationships. Sentiments are not the only factor driving market movements. They also influence opinion in the long run. The feedback process is significant to investors, policymakers, analysts, and researchers because it demonstrates market behavior developing via the ongoing exchange of information, interpretation, and price change.

Overall, the Granger causality findings reaffirm that there is dynamic sentiment transmission among financial markets and support the notion of significant differences between the behavior of stock and cryptocurrency markets. The S&P 500 is well-integrated with economic news and market sentiments as it is closely aligned with the overall economic system. There is a smaller causal structure around cryptocurrency returns, primarily associated with market sentiment. This finding, in turn, confirms that it is the sentiment and informational breadth that dominates the behavior of stock markets while sentiment-return dynamics continue to have a stronger impact in cryptocurrency markets.

4. Conclusions

The current investigation took a top-down approach to investigate the influence of various proxies of macroeconomic sentiments on financial market movements. Furthermore, the current investigation also focused on identifying similarities and differences between traditional stock markets and cryptocurrency movements. The latter has emerged as a new decentralized form of financial assets, attracting investors and researchers. Given a lack of any traditional fundamentals, the behavior of the cryptocurrency space is expected to vary significantly from the conventional stock market. Therefore, the current study focused on both of these avenues to analyze the significance, flow, and direction of economic news, market, and social media sentiments, while highlighting their association with each other to provide stakeholders with contextualized insights.

The study initially applies a VAR-based spillover model to study the association among sampled cryptocurrency index, stock market index, economic news sentiments, market sentiments, and social media sentiments. Later, linear regression and Granger causality analysis are applied as robustness measures. The findings uncovered unique and contrasting behavior attributable to each market, with the cryptocurrency market index and stock market index having weak and moderate overall spillover from the sentiments. The detailed findings related to cryptocurrencies' association with selected sentiments

revealed that the cryptocurrency market is primarily driven by market sentiments. The subsequent analysis reveals that market sentiments play a significant role in determining economic news and social media sentiments. Economic news, in turn, influences social media and the market index. Meanwhile, no significant causal association of social media sentiments with market movement is observed. The findings about the stock market index reveal that there is a significant association of economic and market sentiments with stock market returns, while the association of social media sentiments with market returns lacks significance. Social media sentiments are found to be weakly shaping economic news sentiments. Hence, the study fails to establish its role as a direct significant determinant of cryptocurrency or stock returns, but the temporal analysis reveals that the influence of every sentiment increases exponentially. Thereby making economic news, market, and social media sentiments a significant determinant of market movement.

The findings hold particular significance both at the theoretical and practical levels. Theoretically, it fills a gap in the existing literature to uncover the difference in behavior across cryptocurrency and the stock market. Furthermore, it adds to the existing debate on the relevance of macroeconomic sentiments for market prediction and opens new avenues to solicit and validate the most relevant macroeconomic sentiments for investors, practitioners, and policymakers. Practically, the study highlighted the need to consider contextualized sentiments for their investments. The study highlighted the weak association of sentiments against cryptocurrency movements, but stakeholders can still rely on market sentiments to predict cryptocurrency movements instead of relying on economic news or social media sentiments. Meanwhile, the stock market stakeholders show a persistent and significant association with economic and market sentiments. Thereby, an increased reliance on sentiments can aid in gaining above-market returns and better identify risks associated with each stock. Finally, the ability of social media to generate influence on economic news can help stakeholders focus on significant social media events, which can influence both cryptocurrency and stock markets through economic news and market sentiments.

The current investigation highlights some uncharted avenues and contributes significantly to the current understanding of the debate on macroeconomic sentiments and financial market behavior. Still, one of the limitations of the current model is that it is limited to traditional stocks, while future researchers can extend its application to other asset classes like forex and commodities. Furthermore, the study is limited to a single social media platform, i.e., Twitter, which may not fully capture the influence of overall social media. Therefore, future investigations can focus on other social media platforms to validate the findings of the model. The lexical-driven economic and social media sentiments comparison with market-driven sentiments can further be validated by introducing other proxies of market and macroeconomic sentiments. The dataset of the model is also limited to 2023 due to data availability, which can further be extended to uncover new insights. Lastly, after identifying the varying association of sentiment categories, researchers can build a theoretical model to test the mediating and moderating nature among economic news, market, and social media sentiments, thereby providing deeper insights into the actual flow of influence from these sentiments towards market behavior.

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