Impact of Social Media on Stock Market Volatility of Nepal

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Abstract

This study examines the impact of social media on stock market volatility of Nepal. Stock market volatility is the dependent variables. The selected independent variables are social media activity, market fundamentals, investor sentiment, market liquidity and news coverage. The primary source of data is used to assess the opinions of respondents regarding social media activity, market fundamentals, investor sentiment, market liquidity and news coverage. The study is based on primary data. The primary data were gathered from 106 respondents through questionnaires. To achieve the purpose of the study, structured questionnaire is prepared. The correlation and multiple regression models are estimated to test the significance and importance of impact of social media on stock market of Nepal.

The study showed a positive impact of social media activity on stock market volatility. It indicates that an increase in social media activity leads to an increase in stock market volatility. Similarly, the study showed a positive impact of market fundamentals on stock market volatility. It indicates that better the market fundamentals, higher would be the stock market volatility. Likewise, the study also revealed a positive impact of investor sentiment on stock market volatility. It indicates that higher investor sentiment leads to increase in stock market volatility. Further, the study observed a positive impact of market liquidity on stock market volatility. It indicates that higher market liquidity leads to increase in stock market volatility. In addition, the study observed a positive impact of news coverage on stock market volatility. It indicates that better coverage leads to increase in stock market volatility.

Keywords: social media activity, market fundamentals, investor sentiment, market liquidity, news coverage, stock market volatility

1. Introduction

Social media significantly transformed the stock market by facilitating the rapid spread of information and influencing market sentiment. According to Cambria *et al*. (2020), platforms like Twitter, YouTube, and Reddit swiftly amplified news, rumors, and collective investor sentiment, resulting in volatile stock price movements. Similarly, Dash and Mahakud (2013) emphasized that this democratization of information increased retail investor participation, though it also introduced regulatory challenges, such as market manipulation risks and the necessity for monitoring misinformation. Overall, social media's impact on the stock market was profound, shaping trading strategies and market dynamics in unprecedented and intricate ways.

The signaling theory suggested that analyst recommendations were useful in judging a firm's underlying value (Yasar *et al.*, 2020). Renault (2017) showed that the first half-hour changes in sentiment from messages posted on Stock Twits had predictive power for the last half-hour return. Antweiler and Frank (2004) found that the sentiment in stock messages

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posted on Yahoo! Finance and Raging Bull could help predict stock market volatility. Wang *et al*. (2006) stated the importance of controlling for other economic and financial variables when analyzing the influence of lagged sentiment on realized volatility. Zhang *et al*. (2016) found that an increase in sentiment influenced volatility as well as volume. Fang and Peress (2009) showed that stocks with low media coverage had higher average returns, especially if they had high volatility and low institutional ownership or analyst following.

Sentiment analysis of social media content was a useful tool for predicting stock market volatility, with negative sentiment often resulting in increased volatility (Nassirtoussi *et al*., 2014). Social media discussions notably affected trading volume, frequently preceding substantial price movements (Cookson & Niessner, 2020). The spread of false information on social media could lead to misguided investment decisions and greater market volatility (Proskurnikov *et al*., 2020). Small-cap stocks were particularly vulnerable to volatility influenced by social media compared to large-cap stocks due to lower liquidity and higher speculative interest (Baker & Wurgler, 2006). Excessive social media hype contributed to stock market bubbles, followed by sharp corrections (Shiller *et al*., 2014). Additionally, social media sentiment prior to IPOs influenced their initial performance and volatility, with positive sentiment driving higher opening prices (Cookson *et al*., 2016).

Regulatory actions aimed at curbing market manipulation via social media could dampen volatility, though enforcement remained a challenge (Levine & Pompilio, 2021). Real-time sentiment analysis from social media platforms offered valuable insights into investor sentiment and its impact on stock prices (Liu *et al*., 2015). Significant social media events caused volatility spillover effects across different markets and asset classes (Hwang & Salmon, 2004). The integration of social media data in algorithmic trading strategies amplified market volatility due to rapid and large-scale trades (Chaboud *et al*., 2014). Breaking news shared on social media often led to immediate and pronounced effects on stock prices and volatility (Zhang & Swanson, 2010).

Coordinated efforts on social media to manipulate stock prices led to significant short-term volatility, as seen with "pump and dump" schemes (Putniņš *et al*., 2012). Social media democratized access to market information, empowering retail investors but also increasing market noise and volatility (Barber & Odean, 2008). Integrating social media sentiment analysis with traditional financial forecasting models enhanced predictive accuracy and volatility forecasts (Jiang *et al*., 2020). The rapid spread of information via social media contributed to market efficiency by reducing information asymmetry, but it also introduced new forms of noise (Fama *et al*., 1991). Influential social media personalities and their endorsements led to significant stock price movements and increased volatility (Hoffmann *et al*., 2013).

During financial crises, social media served as a key platform for communication, impacting market sentiment and volatility (Palen *et al*., 2010). Metrics such as tweet volume and engagement predicted stock market trends and volatility, providing valuable signals for traders (Rao & Srivastava, 2012). Social media sentiment also affected commodity markets, leading to price fluctuations and increased volatility in commodities like oil and gold (Zhang *et al*., 2013). The anonymity provided by social media enabled market manipulation tactics, resulting in artificial stock price movements (Leinweber, 2009). Automated accounts, or bots, on Twitter distorted market sentiment and influenced stock prices, adding to market volatility

(Ferrara *et al*., 2016).

The rise of social media prompted changes in financial regulations to address issues like market manipulation and misinformation (Gao *et al*., 2020). Social media data was increasingly utilized in high-frequency trading algorithms, amplifying short-term market volatility (Hasbrouck & Saar, 2013). Social media exacerbated market anomalies such as the January effect and momentum, leading to increased volatility during these periods (Jegadeesh & Titman, 1993). Social media also contributed to investor overreaction to news and events, resulting in excessive price swings and heightened volatility (Daniel *et al*., 1998). Advanced sentiment analysis techniques applied to social media content improved volatility prediction models (Li *et al*., 2014).

Social media sentiment significantly affected foreign exchange market volatility, with major news events causing large fluctuations (Guo *et al*., 2019). Negative social media sentiment could damage corporate reputations, leading to stock price declines and increased volatility (Luo *et al*., 2013). Analysis of social media data helped predict stock market crashes by identifying early signs of investor panic and negative sentiment (Yu *et al*., 2013). Social media sentiment correlated with key economic indicators, influencing stock market expectations and volatility (O'Connor *et al*., 2010). Financial news disseminated through social media channels led to rapid stock price adjustments and increased market volatility (Tetlock *et al*., 2007).

Wu *et al.* (2017) explored the impact of social media data on stock volatility, emphasizing the correlation between heightened attention to a stock's volatility on social platforms and fluctuations in market volatility. Similarly, Piñeiro-Chousa *et al*. (2017) focused on social media sentiment's impact on the Chicago Board Options Exchange Market Volatility Index (VIX), finding that non-technical investors' sentiment significantly influenced market risk. Likewise, Oliveira *et al*. (2017) used Twitter data to predict stock returns, volatility, and sentiment indices, demonstrating the predictive power of microblogging data in financial analysis. Bukovina (2016) reviewed the theoretical underpinnings and empirical findings regarding social media's role in capital markets, underscoring its significance from both behavioral and economic perspectives. Moreover, López-Cabarcos (2017) differentiated between technical and non-technical investors in analyzing their social media activity's influence on market sentiment, highlighting non-technical investors' substantial impact. Yang (2015) investigated sentiment within the Twitter financial community and its predictive power on stock market movements, revealing correlations between sentiment from influential users and financial market indices. In addition, Nofer and Hinz (2015) studied aggregate Twitter mood states and their effect on the German stock market, showing improvements in predictive accuracy by considering widespread mood states. Maragoudakis and Serpanos (2016) proposed a Bayesian approach combining financial news and social media opinions to predict stock behavior, demonstrating promising outcomes in forecasting market trends. Ho *et al*. (2017) examined the dynamic relationship between social media sentiments and stock returns using advanced econometric models, revealing fluctuating but impactful associations over time.

In the context of Nepal, studies began to explore how social media influenced stock market behavior. Poudel and Sapkota (2022) analyzed the impact of social media on investor sentiment in Nepal. The study found that platforms like Facebook and Twitter played a crucial role in shaping market perceptions and decisions. Similarly, Aryal (2021) assessed the effects of social media discussions on the stock prices of companies listed on the Nepal Stock Exchange (NEPSE). The study concluded that positive or negative sentiments expressed on social media could significantly affect stock price movements, often leading to increased volatility. Furthermore, Magar *et al*. (2023) investigated the role of social media in enhancing market transparency and investor engagement in Nepal. The study showed that social media democratized information access and encouraged retail investor participation, it also posed challenges related to misinformation and market manipulation.

The above discussion shows that empirical evidences vary greatly across the studies on the impact of social media on stock market. Though there are above mentioned empirical evidences in the context of other countries and in Nepal, no such findings using more recent data exist in the context of Nepal. Therefore, in order to support one view or the other, this study has been conducted.

The major objective of the study is to examine the impact of social media on stock market. Specifically, it examines the relationship of social media activity, market fundamentals, investor sentiment, market liquidity, news coverage with stock market volatility.

The remainder of this study is organized as follows: section two describes the sample, data, and methodology. Section three presents the empirical results and final section draws the conclusion.

2. Methodological aspects

The study is based on the primary data. The data were gathered from 101 respondents through questionnaire. The respondents' views were collected on social media activity, market fundamentals, investor sentiment, market liquidity, news coverage and stock market volatility. This study is based on descriptive as well as causal comparative research designs.

The model

The model estimated in this study assumes that stock market depends upon social media. The dependent variable selected for the study is stock market volatility. Similarly, the independent variables are social media activity, market fundamentals, investor sentiment, market liquidity and news coverage. Therefore, the model to be estimated in this study is stated as follows:

$$SMV = \beta_0 + \beta_1 (SMA) + \beta_2(IS) + \beta_3(MF) + \beta_4(ML) + \beta_5(NC) + e$$

Where,

SMV = Stock market volatility

SMA = Social media activity

MF = Market fundamentals

IS = Investor sentiment

ML = Market liquidity

NC = News coverage

Social media activity was measured using a 5-point Likert scale where the respondents were asked to indicate the responses using 1 for strongly disagree and 5 for strongly agree. There are 5 items and sample items “I engage with social media platforms for investment-related information occasionally, typically a few times a week”, “Twitter, YouTube and Face book post hold the most influence in shaping my investment decisions among social media platforms”, and so on. The reliability of the items was measured by computing the Cronbach’s alpha (α = 0.909).

Market fundamentals was measured using a 5-point Likert scale where the respondents were asked to indicate the responses using 1 for strongly disagree and 5 for strongly agree. There are 5 items and sample items include “I diligently follow earnings reports of companies in my investment portfolio to assess their financial health and performance”, “Economic indicators such as GDP growth and inflation rate play a crucial role in my investment strategy, influencing sector allocation and risk management”, and so on. The reliability of the items was measured by computing the Cronbach’s alpha (α = 0.926).

Investor sentiment was measured using a 5-point Likert scale where the respondents were asked to indicate the responses using 1 for strongly disagree and 5 for strongly agree. There are 5 items and sample items include “My current sentiment regarding the stock market is cautiously optimistic”, “Investor sentiment can significantly impact stock market volatility as it shapes buying and selling behavior”, and so on. The reliability of the items was measured by computing the Cronbach’s alpha (α = 0.927).

Market liquidity was measured using a 5-point Likert scale where the respondents were asked to indicate the responses using 1 for strongly disagree and 5 for strongly agree. There are 5 items and sample items include “I regularly monitor trading volume in the markets to gauge market liquidity”, “When evaluating market liquidity, I consider factors such as bid-ask spreads, trading volume, and depth of market”, and so on. The reliability of the items was measured by computing the Cronbach’s alpha (α = 0.914).

News coverage was measured using a 5-point Likert scale where the respondents were asked to indicate the responses using 1 for strongly disagree and 5 for strongly agree. There are 5 items and sample items include “I consume financial news articles or broadcasts daily to stay informed about market developments”, “Reputable financial news sources like Share sansar, Mero lagani, and Nepse alpha are my go-to for reliable information about financial markets”, and so on. The reliability of the items was measured by computing the Cronbach’s alpha (α = 0.934).

Stock market volatility was measured using a 5-point Likert scale where the respondents were asked to indicate the responses using 1 for strongly disagree and 5 for strongly agree. There are 5 items and sample items include “ I frequently observe significant price changes or swings in the stocks I follow or invest in “, “ I adjust my investment strategy or portfolio allocation in response to perceived changes in stock market volatility “, and so on. The reliability of the items was measured by computing the Cronbach’s alpha (α = 0.902).

The following section describes the independent variables used in this study along with the hypothesis formulation.

Social media activities

According to Van Doorn *et al*. (2010), social media engagement was often categorized into affective, cognitive, and behavioral dimensions. The behavioral dimension was most commonly measured and included actions like liking, commenting, sharing, and viewing brand-related content (Barger *et al*., 2016). More specifically, Schivinski *et al.* (2016) classified social media engagement into three levels: consumption (e.g., viewing content), contribution (e.g., liking, sharing, and commenting), and creation (e.g., generating original content such as posts, videos, and articles). These activities were crucial in understanding how social media influenced various outcomes, such as stock market volatility, by capturing the intensity and type of user interactions with content related to brands or financial markets (Oviedo-García *et al*., 2014). In business practice, social media engagement was often assessed through metrics developed by social media platforms and analytics services. Based on it, the study developed the following hypothesis:

H_1: There is a positive relationship between social media activities and stock market volatility.

Market fundamental

According to Baker and Wurgler (2007), market fundamentals were essential in evaluating the intrinsic value of stocks and understanding market efficiency. The study emphasized that these fundamentals helped in determining the fair value of assets and in identifying anomalies or deviations from this value due to market inefficiencies. Similarly, Ballings *et al.* (2015) highlighted that market fundamentals encompassed a range of economic indicators such as earnings, dividends, interest rates, and macroeconomic factors like GDP growth and inflation rates. These fundamentals were critical for making informed investment decisions and for the predictive accuracy of stock prices. Wong *et al*. (2020) discussed market fundamentals in the context of market efficiency and anomalies, noting that understanding these fundamentals was vital for addressing the impacts of investor behavior on stock price movements and for developing effective financial policies to manage market volatility. Furthermore, Fama (1991) described market fundamentals as essential components of market efficiency theory, where prices of securities reflected all available information, including fundamental data such as corporate earnings and economic conditions. This ensured that markets operated efficiently with prices adjusting to new information swiftly. Based on it, the study developed the following hypothesis:

H_2: There is a positive relationship between market fundamentals and stock market volatility.

Investor sentiment

According to Baker and Wurgler (2006), investor sentiment encompassed investors' general mood, which could influence their willingness to engage in speculative trades, regardless of underlying fundamentals. This sentiment was frequently measured using various market-based indicators, such as trading volume, closed-end fund discounts, and IPO activity, which could collectively predict stock returns and market volatility. Moreover, Zhou (2018) defined investor sentiment as the expectations and attitudes of investors towards future market performance, influenced by historical price data, macroeconomic factors, and cognitive biases. These biases, such as overreaction and information bias, could cause deviations in asset prices from their fundamental values. In addition, Rahman and Puniyani

(2023) highlighted that investor sentiment indexes (ISIs) often incorporated data from internet searches and social media to gauge the market mood. This approach underscored the growing relevance of digital footprints in understanding market sentiment. Furthermore, Verma and Soydemir (2009) emphasized that investor sentiment affected market prices through the actions of both individual and institutional investors, creating heterogeneity in market responses to volatility. This indicated that investor sentiment could have a profound impact on market dynamics, often leading to significant price swings based on collective investor behavior. Based on it, the study developed the following hypothesis:

H_3: There is a positive relationship between investor sentiment and stock market volatility.

Market liquidity

According to Kumar and Misra (2015), market liquidity was characterized by the ease with which assets could be traded and the speed at which transactions could be executed. This definition emphasized the importance of trading volume, bid-ask spreads, and market depth as primary indicators of liquidity. Similarly, Goyenko *et al.* (2009) found that market liquidity had several dimensions, including tightness (the cost of immediate execution), depth (the ability to accommodate large trades without impacting prices), and resiliency (the speed at which prices return to equilibrium after trades). These dimensions collectively captured the multifaceted nature of liquidity and its impact on trading strategies and market efficiency. Furthermore, Kyle (1985) described market liquidity in terms of the market's ability to absorb trades, emphasizing three key aspects: tightness, depth, and resiliency. Tightness referred to the bid-ask spread, depth was the volume of transactions the market could handle, and resiliency was how quickly prices reverted to their initial level after a trade. Amihud *et al.* (2005) elaborated on market liquidity by incorporating the liquidity premium, which was the additional expected return that investors demanded for holding less liquid assets. The study argued that less liquid assets were traded less frequently and with higher costs, which affected their pricing and expected returns. Based on it, the study developed the following hypothesis:

H_4: There is a positive relationship between market liquidity and stock market volatility.

News coverage

According to Hammersley-Fletcher and Qualter (2010), news coverage was the comprehensive reporting and analysis of events and issues by the media, aimed at informing the public. This definition emphasized the role of media in shaping public perception and understanding of current affairs. Similarly, McCombs and Shaw (1972) found that news coverage had the agenda-setting function of the media, where the selection and prominence of news stories influenced the importance the public placed on specific issues. Harcup and O'Neill (2001) provided a more detailed definition by outlining news values that guided the selection of news stories. The study argued that news coverage was influenced by factors such as relevance, timeliness, and public interest, which helped determine which events were reported and how they were framed. Moreover, Galtung and Ruge (1965) highlighted the structural aspects of news coverage, noting that it involved a systematic approach to gathering, verifying, and presenting information in a way that met journalistic standards and served the public interest. Based on it, the study developed the following hypothesis:

H_5: There is a positive relationship between news coverage and stock market volatility.

3. Results and discussion

Correlation analysis

On analysis of data, correlation analysis has been undertaken first and for this purpose, Kendall's Tau correlation coefficients along with mean and standard deviation has been computed and the results are presented in Table 1.

Table 1

Kendall's Tau correlation coefficient matrix

This table presents Kendall's Tau coefficients between dependent and independent variables. The correlation coefficients are based on 106 observations. The dependent variable is SMV (Stock market volatility). The independent variables are SMA (social media activities), IS (Investor sentiment), MF (Market Fundamental), ML (Market Liquidity) and NC (News Coverage).

Variables	Mean	S.D.	SMV	SMA	MF	IS	ML	NC
SMV	3.685	1.041	1					
SMA	3.300	1.058	0.425**	1				
IS	3.515	0.977	0.458**	0.456**	1			
MF	3.483	0.970	0.401**	0.466**	0.550**	1		
ML	3.621	0.960	0.395**	0.415**	0.530**	0.604**	1	
MC	3.615	1.016	0.409**	0.415**	0.624**	0.579**	0.532**	1

Note: The asterisk signs (**) and (*) indicate that the results are significant at one percent and five percent levels respectively.

Table 1 shows that Social Media Activity is positively correlated with Stock Market Volatility. This means that an increase in social media activity leads to an increase in stock market volatility. Similarly, there is a positive relationship between Investor Sentiment and stock market volatility, indicating that an increase in investor sentiment leads to an increase in stock market volatility. Likewise, Market Fundamentals have a positive relationship with stock market volatility, showing that an increase in market fundamentals leads to an increase in stock market volatility. Furthermore, there is a positive relationship between Market Liquidity and stock market volatility, indicating that an increase in market liquidity leads to an increase in stock market volatility. Moreover, News Coverage is positively related to stock market volatility, suggesting that increased news coverage leads to an increase in stock market volatility.

Regression analysis

Having indicated Kendall's Tau correlation coefficients, the regression analysis has been carried out and the results are presented in Table 2. More specifically, it presents the regression results of Stock market volatility (SMV) as dependent variables with social media activities (SMA), investor sentiment (IS), market fundamental (MF), market liquidity (ML) and news coverage (NC) as independent variables.

Table 2

Estimated regression results of social media activity, market fundamentals, investor sentiment, market liquidity, news coverage

The results are based on 106 observations using linear regression model. The model is SMV = $\beta_0 + \beta_1$ (SMA) + β_2(IS) + β_3(MF) + β_4(ML) + β_5(NC) + e where the dependent variable is SMV (stock market volatility). The independent variables are SMA (social media activities), MA (market fundamentals), IS (Investor sentiment), ML (market liquidity) and NC (news coverage).

Model	Intercept	Regression coefficients of					Adj. R_ bar^2	SEE	F-value
		SMA	MF	IS	ML	NC			
1	1.587 (6.222)**	0.636 (8.639)**					0.412	0.798	74.626
2	1.196 (4.198)**		0.708 (9.067)**				0.436	0.782	82.216
3	1.196 (4.198)**			0.674 (8.235)**			0.389	0.814	67.814
4	1.196 (4.198)**				0.718 (9.002)**		0.433	0.784	81.035
5	1.196 (4.198)**					0.669 (8.787)**	0.421	0.792	77.212
6	0.523 (1.840)	0.317 (3.756)**	0.180 (1.342)	0.25 (0.192)	0.230 (1.772)	0.156 (1.211)	0.553	0.696	27.030

Notes:

i. Figures in parenthesis are t-values
ii. The asterisk signs (**) and (*) indicate that the results are significant at one percent and five percent level respectively.
iii. Stock market volatility is the dependent variable.

Table 2 shows that the beta coefficients for social media activities are positive with stock market volatility. It indicates that social media activities have positive impact on stock market volatility. This finding is consistent with the findings Bruce (2016). Similarly, the beta coefficients for market fundamentals are positive with stock market volatility. It indicates that market fundamentals have a positive impact on stock market volatility. This finding is similar to the findings of Campbell and Shiller (1988). Likewise, the beta coefficients for investor sentiment of use are positive with stock market volatility. It indicates that investor sentiment has a positive impact on stock market volatility. This finding is similar to the findings of Baker and Wurgler (2006). Further, the beta coefficients for market liquidity are positive with stock market volatility. It indicates that market liquidity has positive impact on stock market volatility. This finding is similar to the findings of Brunnermeier *et al.* (2009). Moreover, the beta coefficients for news coverage are positive with stock market volatility. It indicates that news coverage has a positive impact on stock market volatility. This finding is similar to the findings of He and Yang (2021).

4. Summary and conclusion

Social media has revolutionized the stock market by enabling rapid dissemination of information and influencing market sentiment. Platforms like Twitter, YouTube, Reddit and other social media platforms can quickly amplify news, rumors, and collective investor sentiment, leading to volatile stock price movements. Influencers and trading communities on these platforms can significantly sway investor behavior, while algorithms analyze social media data to predict market trends. This democratization of information has increased retail investor participation but also poses regulatory challenges, such as market manipulation risks and the need for monitoring misinformation. Overall, social media's impact on the stock market is profound, shaping trading strategies and market dynamics in new and complex ways.

This study attempts to examine the impact of social media on stock market volatility of Nepal. The study is based on primary data of 106 respondents.

The major conclusion of this study is that social media activity, market fundamentals, investor sentiment, market liquidity and news coverage have positive impact on stock market volatility. Its results hold significant importance for investors and policymakers, offering a deeper understanding of how social media activities influence fluctuations in the Nepali stock market. With the increasing impact of social media across different sectors of society and the economy, this research aims to offer valuable insights into its specific role within financial markets. The study also concludes that market liquidity is the most significant factor followed by market fundamentals and social media activity that determines the level of stock market volatility.

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