Financial Markets, Institutions and Risks, Volume 7, Issue 4, 2023
ISSN (online) 2521-1242; ISSN (print) – 2521-1250

The Impact of Social Media Related Events on the Price Volatility of Mega-Cap Technology Stocks

http://doi.org/10.61093/fmir.7(4).14-23.2023

Halil D. Kaya, https://orcid.org/0000-0002-7535-9857

Department of Accounting and Finance, College of Business and Technology, Northeastern State University, USA

Abhinav Maramraju

West Windsor-Plainsboro High School South, USA

Anish Nallapu

Green Hope High School, USA

Corresponding author: kaya@nsuok.edu

Abstract. *This paper summarizes the arguments and counterarguments within the scientific discussion on the issue of the impact of social media events on stock price volatility. The main purpose of the research is to examine the impact of the Reddit posts from January 2022 through July 2023 on the price volatility of the six U.S. mega-cap technology stocks. Unlike most of the previous studies that focus on Twitter, this study focuses on Reddit. This study not only examines how Reddit posts relate to volatility but also how trading volume and stock price relate to volatility. Therefore, while focusing on the impact of social media events on volatility, the study controls for the effects of trading volume and price. Based on the previous research on social media events on different platforms, it is expected that Reddit events significantly affect stock price volatility. Again, based on the previous research on social media events on different platforms, higher trading volume and higher stock prices are expected to have a positive relationship with stock price volatility (i.e. higher volumes and higher prices are associated with higher volatility). Overall, the findings in this paper support these expectations. First, the ANOVA test results reject the null hypothesis of no predictive relationship between the three independent variables (i.e. "Socialmedia", "Price", and "Volume") and the stock price volatility of the six mega-cap stocks. For the whole group of firms, the regression analyses show that the positive Reddit events are associated with lower volatility when compared to negative Reddit events, and that higher trading volumes and prices are associated with higher volatility. Therefore, for the group of six mega-cap stocks, the results support our hypothesis. When individual regressions are performed for each stock, the results are mixed. The results for Alphabet (i.e. Google), Tesla, Meta, and Microsoft are more in line with the expectations, while the results for Apple and Nvidia are not. For Google and Tesla stocks, when there is a positive social media event, the volatility is lower. This finding indicates that a positive event calms the investors of these stocks. For Meta and Microsoft stocks, when there is a positive social media event, the volatility is higher. This finding may imply that increased volatility due to a positive event possibly stems from the extra demand for these stocks in a very short period. For Apple and Nvidia stocks, there is no significant relationship between social media events and volatility. Overall, we conclude that, a prospective investor who wants to invest in a pool of "mega-cap technology stocks", social media events should be a factor when making an investment decision. On the other hand, a prospective investor who is a "stock picker", needs to evaluate each individual regression result when making an investment decision.*

Keywords: *social media events, volatility, mega-cap stocks, ANOVA, regression analysis, individual stock analysis.*

JEL Classification: *G12, G14, G15.*

Received: 5.09.2023 **Accepted:** 24.12.2023 **Published:** 31.12.2023

Funding: There is no funding for this research.

Publisher: Academic Research and Publishing UG (i. G.) (Germany)

Cite as: Kaya, H., Maramraju, A. & Nallapu, A. (2023). The Impact of Social Media Related Events on the Price Volatility of Mega-Cap Technology Stocks. *Financial Markets, Institutions and Risks*, *7*(4), 14-23. http://doi.org/10.61093/fmir.7(4).14-23.2023

Introduction. In this paper, we explore the effects of social media events (i.e. mass viewed social media posts on Twitter, Reddit, etc.) on the volatility of mega-cap stocks (i.e. VIX Beta value of each company on its respective date). Specifically, we investigate how negative and positive social media events impact volatility, trading volume, and stock prices for a sample of six mega-cap stocks.

In the realm of understanding the impact of social media sentiment on market volatility, one pivotal research paper stands out. Titled "The Influence of Twitter Sentiment on Financial Markets: Evidence from Indian Stock Market," the study by Agarwal, Kumar, and Goel (2021) delves into the relationship between Twitter sentiment and the performance of the Indian stock market. By analyzing a vast corpus of tweets related to various Indian stocks, the researchers sought to identify patterns in sentiment and their effects on financial sector indexes. Their comprehensive analysis revealed a significant correlation between sentiment expressed on Twitter and fluctuations in market indexes. Positive or negative sentiment expressed on the platform was found to sway individual attitudes towards specific stocks, ultimately influencing market volatility. Moreover, the research highlights the potential role of Twitter as a driver of investor emotions and perceptions, shedding light on how social media events can shape market dynamics. This study's findings hold valuable insights not only for the Indian stock market but also for understanding the broader implications of social media sentiment on financial markets worldwide. As we explore the impact of social media events on the volatility of mega-cap technology stocks in our current research, such seminal works contribute to the growing body of knowledge in this field and underscore the significance of considering social media dynamics in investment and policy decisions.

In this research, we gathered data from diverse sources, including popular discussion platforms like Reddit, various news outlets, and credible financial websites such as Yahoo Finance. Our focus was to study the impact of large social media events on the volatility of six mega-cap technology stocks: Apple, Google, Meta, Microsoft, Nvidia, and Tesla. The dataset comprised 1,199 distinct social media events, spanning from January 2022 to July 2023, meeting specific criteria, including direct references to the technology stocks and clear displays of positive or negative attention towards each firm. We closely monitored the VIX Beta Value, stock price, and stock volume to ascertain their influence on market volatility within the context of social media events. By examining the dynamics between social media events and financial metrics, we aimed to evaluate their collective impact on the volatility of the selected mega-cap technology stocks, providing valuable insights for investors, policymakers, and market participants in navigating the dynamic landscape of social media-driven market dynamics.

Our analysis reveals intriguing findings regarding the impact of social media events on the volatility of these mega-cap technology stocks. Negative events were associated with higher mean values of VIX betas and trading volumes, indicating heightened market volatility during such occurrences. Conversely, positive events exhibited higher mean stock prices, suggesting positive sentiments and market optimism. The ANOVA results further underscore the significance of social media events, as we found a statistically significant difference between the means of positive and negative events, substantiating the distinct impacts of social media dynamics on market volatility. Through regression analysis, we uncover the specific effects of social media events, trading volume, and stock price on volatility. Positive social media events were found to reduce volatility, while higher trading volumes and increasing stock prices contributed to increased volatility.

However, the individual stock analyses revealed variations in the effects of these variables, highlighting the importance of considering stock-specific dynamics when making investment decisions. Our research contributes essential insights to investors, policymakers, and market participants seeking to navigate the dynamic and interconnected landscape of social media-driven market dynamics. By understanding the relationships between social media events and market volatility, this study empowers readers with crucial knowledge to make informed decisions in today's fast-paced financial markets.

The rest of this paper is organized as follows. Section 2 reviews prior literature. Section 3 explains the data and methodology while empirical findings are discussed in Section 4. Section 5 concludes the paper.

1. Literature Review

Our review of prior literature indicates that social media sentiment has the power to cause the volatility of many mega-cap tech stocks to rise. These sentiments were exchanged primarily through Twitter, however there were a few outliers highlighted by the following services. Chen, De, Hu, and Hwang (2011) investigate the relationship between mood expressed in traditional and social media and its effect on the stock market. Their research reveals that social media sentiment has a significant link with present and future stock returns, even after accounting for sentiment in traditional media. Notably, they examine articles from reputable sources like the Wall Street Journal and Seeking Alpha to draw these conclusions, and the effect is particularly pronounced for publications that attract more interest from market players and for businesses that garner attention from retail investors. These findings highlight the growing significance of social media as a crucial medium for the communication of news that influences stock prices. Similarly, Zhang and Liu (2021) focus on how the market responds to recommendations on official WeChat accounts (OWA) in China. Their results support the price pressure hypothesis, with significantly positive abnormal returns and excess trading volume on the publishing day. Importantly, they rule out other potential causes for market reactions, such as secondary dissemination of analyst recommendations, firm-specific news releases, media attention, and prior significant abnormal returns. This research demonstrates that social media platforms like WeChat, in addition to more traditional sources, play a pivotal role in influencing stock market volatility for tech stocks.

Numerous studies have delved into the examination of Twitter posts as a means to gauge the influence of social media-related events on volatility in the financial markets. These investigations shed light on how Twitter sentiment can sway individuals' emotions and perceptions towards specific stocks. For instance, the study by Agarwal, Kumar, and Goel (2021) explores the impact of Twitter sentiment on the performance of the Indian stock market and identifies a significant correlation between sentiment expressed on Twitter and the financial sector indexes. It is evident from their findings that positive or negative sentiment expressed on Twitter can prompt individuals to develop distinct feelings and attitudes towards particular stocks, thereby potentially impacting market volatility. Similarly, the research conducted by Paniagua and Sapena (2014) reveals the importance of “followers” and “likes” on Twitter in positively influencing a firm's share value. These findings collectively illustrate the critical role Twitter sentiment plays in shaping individual perceptions and sentiments towards stocks, and how such sentiments can contribute to fluctuations in market volatility.

In a similar fashion, several studies have explored the utilization of Twitter to construct models that assess sentiments and their impact on stock market volatility. Dogan, Metin, Tek, Yumusak, and Oztoprak (2020) adopt sentiment analysis and machine learning algorithms to identify influential Twitter speculators and influencers who significantly influence stock prices of major corporations like Google, Amazon, Apple, Tesla, and Microsoft. On the other hand, Chahine and Malhotra (2018) employ event history analysis to investigate the market response when Fortune 500 companies launched Twitter platforms. The study finds that companies engaging in two-way interactions experienced a stronger market response, emphasizing the importance of reciprocal engagement with stakeholders. Moreover, Lehrer, Xie, and Zhang (2021) focus on forecasting volatility using a sentiment index derived from Twitter tweets at the 1-minute level. They incorporate social media sentiment into the heterogeneous autoregression (HAR) model, demonstrating that it significantly enhances the forecasting accuracy of a popular volatility index, especially over short time horizons. These studies collectively demonstrate the diverse approaches adopted by researchers to leverage Twitter data in modeling sentiments and understanding the dynamic relationship between social media, sentiments, and stock market volatility.

Many studies have investigated the relationship between social media and traditional news spread and its impact on stock market volatility, particularly focusing on tech stocks. Jiao, Veiga, and Walther (2020) explored the effects of news coverage in traditional news media and social media on volatility and turnover. They found that while coverage in social media predicts increases in volatility and turnover, traditional news media predicts decreases in subsequent volatility and turnover. This difference suggests that social media and news media play distinct roles in the stock market, with news media acting as a leading signal for social media. Their theoretical model of "echo chambers" proposes that social networks re-post news, leading some investors to mistakenly believe that repeated signals represent new information, contributing to increased volatility. Jin, Fang, Chakraborty, Self, Chen, and Ramakrishnan (2017) delved into the use of various sources, including social media, news, Google search volumes, and Twitter, to model and predict financial market patterns in real time. Their findings indicated that multi-source forecasts consistently outperformed single-source predictions, underscoring the importance of integrating data from multiple channels to better understand and predict stock market volatility effectively.

Further evidence to the complex and dynamic relationships between traditional and credible news spread through social media rather than random figures are provided by, Chen, De, Hu, and Hwang (2011) examined the connection between sentiment expressed in traditional and social media and its effect on the stock market. Their study revealed that social media sentiment significantly influenced present and future stock returns, even after accounting for traditional media sentiment. The effect was particularly pronounced for publications that garnered more attention from market players and for companies that attracted more retail investors, demonstrating the growing influence of social media as a medium for news dissemination that impacts stock prices. Khan, Gazhanfar, Azam, Karami, Alyoubi, and Alfakeeh (2022) employed machine learning classifiers and data from social media and financial news to predict stock market indexes. Their experiments highlighted that social media and financial news provided the best prediction accuracy, with the Random Forest classifier achieving the highest accuracy of 83.22% through ensemble learning. This emphasized the significance of social media and news as valuable sources of information for predicting stock market behavior, particularly in the context of tech stocks.

2. Hypotheses

The previous studies show that social media influences investors’ sentiment whether in the positive direction or in the negative direction. For example, Agarwal, Kumar, and Goel (2021) examines the impact of Twitter sentiment on the performance of the Indian stock market. Their findings indicate that positive or negative sentiment expressed on social media (i.e. most papers focus on Twitter) can prompt individuals to develop distinct feelings and attitudes towards particular stocks, thereby potentially impacting these stocks’ volatility. These sentiments can sometimes affect the whole market’s volatility. Similarly, Lehrer, Xie, and Zhang (2021) and Wu et al. (2017) show that social media sentiment significantly explains stocks’ volatility.

Therefore, our hypothesis on the relationship between social media events and price volatilities of mega-cap technology stocks is as follows:

Hypothesis 1: “Social media events significantly affect the price volatilities of the six mega-cap technology stocks”.

As our control variables, we use trading volume and price levels of the sample stocks. Li and Bing (2017) use daily stock prices in their analysis of volatility and argue that daily stock prices influence the volatility of a stock. Therefore, in this study, we control for the impact of the six mega-cap stocks’ prices. Wu et al. (2017) argue that trading volume has the biggest effect on the volatility of a stock. Therefore, we include the trading volume as a second control variable.

3. Data and Methodology

We use data from the mega popular discussion website Reddit to gather a dataset of 1,199 posts. The posts that we select have to follow the following criteria: it has to be relevant to at least one of the six mega cap technology stocks included in this paper, it has to bring either negative or positive attention to that firm, and the post can only be from January 2022 until July 2023. An instance of a positive event for Apple would include a post from the twenty third of September, 2022. The caption of this post reads, “Apple Music Replaces Pepsi as the Sponsor of Super Bowl Halftime Show”. On the contrary, on the 12th of July, 2023 where he or she writes sarcastically, “Elon? Under Investigation? Financial malfeasance? You don’t say.” This post includes a screenshot of a Tweet that discusses the investigation on the Tesla CEO. This would classify as a negative social media event for Tesla. In total there are 891 positive events and 308 negative events. The ratio of positive to negative events varies drastically from firm to firm. For Apple, there are 110 positive events and 53 negative events. For Google, there are 283 positive events and 33 negative events. For

ISSN (online) 2521-1242; ISSN (print) – 2521-1250

Microsoft, there are 243 positive events and 26 negative events. For Meta, there are 111 positive events and 95 negative events. For Tesla, there are 81 positive events and 62 negative events. For Nvidia, there are 59 positive events and 37 negative events.

The regression equation that we use is as follows:

$$\text{VIX Beta} = c_0 + c_1(\text{Socialmedia}) + c_2(\text{Price}) + c_3(\text{Volume}) \quad (1)$$

The "Socialmedia" dummy variable is "1" when the event is positive and is "0" when the event is negative. We run this regression for all six firms as a whole and individually for the six firms. The other three variables come from Yahoo Finance's "Historical Prices & Data" page. The trading volume and stock price act as control variables in this regression formula. The purpose of this is so we can limit the external variables affecting the volatility of the stock; to solely focus on a possible correlation between the social media event and the beta value.

Based on the findings of the previous studies, we expect positive social media events to negatively affect the VIX beta (i.e. reduce volatility). We also expect higher volumes and higher prices to positively affect the VIX beta (i.e. increase volatility).

4. Empirical Results

Table 1 shows the summary statistics for our sample of six mega cap stocks. Panel A shows the statistics when the social media events are negative, and Panel B shows the statistics when the social media events are positive. In total, there were 308 negative events and 891 positive events.

Panel A shows that, for the negative events, the mean VIX beta value for the related firms was 1.2646. The corresponding value for the positive events was 1.1226. For the negative events, the mean trading volume for the related firms was 74,036,462 shares. The corresponding value for the positive events was 48,921,113. For the negative events, the mean stock price for the related firms was $179.8568. The corresponding value for the positive events was $193.7135.

Table 1. Summary Statistics

Panel A. Socialmedia=negative						
Variable	**Label**	**N**	**Mean**	**Std Dev**	**Minimum**	**Maximum**
VIXbetavalue	VIXbetavalue	308	1.2646	0.3765	0.5800	3.0200
Volume	Volume	308	74,036,462	53,151,573	1,235,841	306,590,613
Price	Price	308	179.8568	65.9062	88.4900	410.2200
Panel B. Socialmedia=positive						
Variable	**Label**	**N**	**Mean**	**Std Dev**	**Minimum**	**Maximum**
VIXbetavalue	VIXbetavalue	891	1.1226	0.2744	0.6400	2.7800
Volume	Volume	891	48,921,113	41,539,056	1,070,906	234,815,090
Price	Price	891	193.7135	82.2567	83.4300	484.7200

Source: Authors' own work

Overall, we are seeing that the mean values of VIX betas and trading volumes for the negative events were higher than those for the positive events. On the other hand, the mean value of stock prices for the negative events was lower than that for the positive events. These findings were what we were expecting.

In terms of standard deviations, we are seeing that the deviations were higher for all three variables for the negative events, when compared to the positive events. The standard deviation for the VIX beta is 0.3765 for the negative events and 0.2744 for the positive events. The standard deviation for the trading volume is 53,151,573 shares for the negative events and 41,539,056 shares for the positive events. The standard deviation for the stock price is 65.9062 for the negative events and 82.2567 for the positive events.

When we look at the min and max values, we are seeing that the range was narrower for the VIX beta and Volume, and wider for the Price for the positive events.

Table 2 shows the results of our ANOVA. The F-value is 58.39 and it is statistically significant at the 0.01% level (p<0.0001). We reject the null hypothesis of no predictive relationship between the three independent variables (i.e. "Socialmedia", "Price", and "Volume") and the stock price volatility of the six mega-cap stocks.

Table 2. Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	14.72	4.91	58.39	<0.0001
Error	1195	100.43	0.08		
Corrected Total	1198	115.15			

Source: Authors' own work.

Table 3 shows the results of our regression analysis where the VIX beta value (i.e. volatility) is the dependent variable and the social media event, trading volume, and stock price are the explanatory variables. The table shows the regression coefficient for each variable as well as its sign, p-value, significance, and whether the result was expected.

Table 3. VIX Beta Value for the Six Mega Cap Stocks Sample

	Dependent Variable: VIX Beta				
Model	**Coef.**	**Sign**	**p-value**	**Signif.**	**Expected?**
Intercept	1.0607	positive	<0.0001	yes	yes
Social media	-0.0961	negative	<0.0001	yes	yes
Volume	1.996E-09	positive	<0.0001	yes	yes
Price	0.0003	positive	0.0036	yes	yes
R^2	0.1279				
N	1,199				

Source: Authors' own work.

The table shows that, for our sample of six mega cap stocks, the coefficient for the Social Media variable is -0.0961 and it is negative and significant at the 0.01% level (p<0.0001). In other words, when the social media event is positive, the VIX beta value (i.e. volatility) goes down. This finding was expected, because we expected to see that a positive (negative) event lowers (increases) the volatility of these stocks (i.e. calms the investors). Therefore, these results fail to reject our hypothesis of a significant relationship between social media events and stock volatility.

The table shows that the coefficient for the Volume variable is 2E-09 and it is positive and significant at the 0.01% level (p<0.0001). In other words, when trading volume goes up, the VIX beta value goes up. This finding was expected, because we expected to see that in periods of higher trading volume, the volatility is higher.

Finally, the table shows that the coefficient for the Price variable is 0.0003 and it is positive and significant at the 1% level (p=0.0036). In other words, when the stock price goes up, the VIX beta value goes up. This finding was expected, because we expected to see that in periods of higher prices, the volatility is higher.

Table 4 shows the results of our individual regressions where we ran the same regressions for each stock individually. The first column shows the results for AAPL. We are seeing that AAPL's results do not conform to our overall sample results. For AAPL, "Socialmedia" is negative but insignificant. The coefficient for "Socialmedia" is -0.0152 and its p-value is 0.5784. With regard to the control variables, the coefficients for Volume and Price are both negative and significant. The coefficient for "Volume" is -1.3E-9 and its p-value is 0.0076. The coefficient for "Price" is -0.0015 and its p-value is 0.0722. In the overall sample, these two variables were positive and significant.

Table 4. VIX Beta Value for Each Mega Cap Stock

	Dependent Variable: VIX Beta					
Model	**AAPL**	**GOOGL**	**META**	**MSFT**	**NVDA**	**TSLA**
Intercept	1.4548	0.9245	1.1124	0.9707	0.0218	1.6529
	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Social media	-0.0152	-0.0571	0.2588	0.0473	0.0135	-0.2235
	0.5784	0.0006	<0.0001	<0.0001	0.9968	0.0018
Volume	-1.3E-9	2.3E-9	2.3E-10	-7E-10	3E-10	-5.6E-10
	0.0076	<0.0001	0.7445	<0.0001	0.1998	0.4553
Price	-0.0015	0.0002	0.0006	0.0000	0.0001	0.0000
	0.0722	0.5632	0.1331	0.5255	<0.0001	0.9462
R^2	0.0580	0.2839	0.1114	0.2304	0.4839	0.0774
N	163	316	206	269	96	143

Source: Authors' own work.

The second column shows the results for GOOGL. We are seeing that GOOGL results confirm our hypothesis of a significant relationship between social media events and volatility. The coefficient for "Socialmedia" is negative and significant. The coefficient is -0.0571 and its p-value is 0.0006. This finding confirms our hypothesis for GOOGL stock. The coefficient for "Volume" is positive and significant. The coefficient for "Price" is positive but insignificant.

The third column shows the results for META. We are seeing that META's results confirm our hypothesis of a significant relationship between social media events and volatility. The coefficient for "Socialmedia" is positive and significant (coef.=0.2588, p<0.0001). The coefficients for both "Volume" and "Price" are positive but insignificant.

The fourth column shows the results for MSFT. We are seeing that MSFT's results confirm our hypothesis of a significant relationship between social media events and volatility. The coefficient for "Socialmedia" is positive and significant (coef.=0.0473, p<0.0001). The coefficient for "Volume" is negative and significant, and the coefficient for "Price" is positive but insignificant.

The fifth column shows the results for NVDA. We are seeing that NVDA's results do not confirm our hypothesis of a significant relationship between social media events and volatility. The coefficient for "Socialmedia" is positive and significant (coef.=0.0135, p=0.9968). The coefficient for "Volume" is positive but insignificant. The coefficient for "Price" is positive and significant, as expected.

The last column shows the results for TSLA. We are seeing that TSLA's results confirm our hypothesis of a significant relationship between social media events and volatility. The coefficient for "Socialmedia" is negative and significant (coef.=-0.2235, p=0.0018). The coefficient for "Volume" is negative but insignificant. The coefficient for "Price" is positive but insignificant.

Overall, our results indicate that, for the overall sample, social media has a negative effect on volatility, while Volume and Price both have a positive effect on volatility. However, if an investor wants to choose from this basket of stocks, he/she needs to be careful. As Table 4 shows, the impact of these variables on volatility changes from one stock to another. While social media has a significant impact on the volatilities of GOOGL, META, MSFT, and TSLA stocks, it does not have a significant impact on the volatilities of AAPL and NVDA stocks.

Conclusion

In this paper, we study the impact of large social media events, such as, the spread of information on an extensive scale through various news platforms socially, on the volatility of 6 mega-cap technology stocks. This includes the study of whether the stock prices would go up or down along with the volume being traded based on these social media events.

In this research, we derive our data from two primary sources: the popular discussion platform Reddit and various news outlets. Specifically, we focus on posts and articles that pertain to social media events and viral content related to six mega-cap technology companies, namely Apple, Google, Meta, Microsoft, Nvidia, and Tesla. Our sample comprises 1,199 Reddit posts and news articles spanning from January 2022 to July 2023.

To ensure data relevance, each post had to meet specific criteria, including a direct reference to at least one of the mentioned technology stocks and an evident display of positive or negative attention towards the respective firm. Additionally, we closely monitor the VIX Beta Value, stock price, and stock volume to ascertain their impact on volatility within this context. By examining the dynamics of social media events and the associated financial metrics, we aim to evaluate the influence of these factors on the volatility of the selected mega-cap technology stocks.

Our analysis of social media events' impact on volatility for a sample of six mega-cap stocks yielded insightful results. Negative events were associated with higher mean values of VIX betas and trading volumes, while positive events showed higher mean stock prices. These findings support our initial hypotheses, indicating that social media events do influence volatility in distinct ways. Moreover, the ANOVA results confirmed a statistically significant difference between the means of positive and negative events, underscoring the significant impact of social media events on the volatility of the selected mega-cap stocks.

Delving deeper, regression analysis revealed specific effects of social media events, trading volume, and stock price on volatility. Positive social media events were found to reduce volatility, while higher trading volumes and increasing stock prices contributed to increased volatility. However, our individual stock analyses revealed variations in the effects of these variables, emphasizing the importance of considering stock-specific dynamics in investment decisions. For policymakers, this research underscores the importance of monitoring social media-related events to assess their potential impact on market volatility. To enrich our understanding further, future research could explore additional factors that may interact with social media events to influence volatility and extend the study to encompass a broader range of stocks or different sectors.

Overall, we conclude that, a prospective investor who wants to invest in a pool of "mega-cap technology stocks", social media events should be a factor when making an investment decision. On the other hand, a prospective investor who is a "stock picker", needs to evaluate each individual regression result when making an investment decision.

These research results can be useful for portfolio managers that plan on investing in these stocks. During periods when there are positive events for these stocks, volatility tends to be lower as a group. Portfolio managers who focus on certain stocks should examine the individual regression results before making an investment.

Portfolio managers who want to invest in a pool of mega-cap technology stocks should know that in periods of positive social media events regarding these firms, the group's overall volatility tends to be lower when compared to the periods of negative social media events. Portfolio managers who want to invest in GOOGL and TSLA stocks should know that in periods of positive social media events, these stocks' volatility tends to be lower when compared to the periods of negative events. Portfolio managers who want to invest in META and MSFT stocks should know that in periods of positive social media events, these stocks' volatility tends to be higher when compared to the periods of negative events. Finally, portfolio managers who want to invest in AAPL and NVDA stocks should know that there is no significant difference in these stocks' volatility in periods of positive or negative social media events.

Volatility is important in two ways. First, it affects the value of the stock options as well as the trading volume of these options. Second, it signals what is happening with that specific stock. As we are seeing in this study, positive events for GOOGL and TSLA stocks are associated with lower volatility. This finding shows that, for these two firms, positive events tend to calm the investors and because of that, the volatility goes down. On the other hand, positive events for META and MSFT stocks are associated with higher volatility. This finding implies that, for these two firms, positive events tend to increase the excitement around these stocks so much that the volatility increases. For AAPL and NVDA stocks, these two forces (i.e. the "calming effect" versus the "excitement effect") seem to cancel each other, so there is no significant change in volatility. These findings indicate that the trading dynamics for these firms are different from each other. Knowing this difference between the trading dynamics of these stocks is also important for portfolio managers because they can better gauge the direction of the movement for each stock.

References

1. Agarwal, and Shweta. (2021). Social Media and the Stock Markets: An emerging market perspective. *Journal of Business Economics and Management*, *22(6)*, 1614-1632. [Link]
2. Ajjoub, and Carl (2020). Social Media Posts and Stock Returns: The Trump Factor. *International Journal of Managerial Finance*, *17*(2), 185-213. [Link]
3. Berge, and Martin. (2022). Prediction of Stock Market Volatility Utilizing Sentiment from News and Social Media Texts a Study on the Practical Implementation of Sentiment Analysis and Deep Learning Models for Predicting Day-Ahead Volatility M E E A. *Journal of Corporate Finance*, *60*, Article 101514. [Link]
4. Chahine, Salim, and Malhotra K. (2018). Impact of Social Media Strategies on Stock Price: The Case of Twitter. *European Journal of Marketing*, *52*(7/8), 1526-1549. [Link]
5. Chen, and Chen. (2014). Exploiting Social Media for Stock Market Prediction with Factorization Machine. *2014 IEEE/WIC/ACM International Joint Conferences on Web Intelligence (WI) and Intelligent Agent Technologies (IAT)*, 142-149. [CrossRef]
6. Chen, and Hailiang, (2011). Sentiment Revealed in Social Media and Its Effect on the Stock Market. *2011 IEEE Statistical Signal Processing Workshop (SSP),* 25-28. [Link]
7. Derakhshan, Ali, and Beigy, H. (2019). Sentiment Analysis on Stock Social Media for Stock Price Movement Prediction. *Engineering Applications of Artificial Intelligence*, *85*, 569-578. [CrossRef]
8. Dogan, and Mustafa. (2020). Speculator and Influencer Evaluation in Stock Market by Using Social Media. *IEEE Xplore*, *84*(2), 159–180. [Link]
9. Garg, Deepshi, and Tiwari, P. (2021). Impact of Social Media Sentiments in Stock Market Predictions: A Bibliometric Analysis. *Business Information Review*, *38(4)*, 170-182. [Link]
10. Hasselgren, and Ben. (2022). Using Social Media & Sentiment Analysis to Make Investment Decisions. *Future Internet*, *15(1)*, 5. [Link]
11. Javed, A., and Mazhar. (2021). Social Media and Stock Market Prediction: A Big Data Approach. *Papers.ssrn.com*, *67(2)*, 2569-2583. [Link]
12. Jiao, and Peiran, 2020. Social Media, News Media and the Stock Market. *Journal of Economic Behavior & Organization*, *176*, 63-90. [Link]
13. Jin, and Fang, 2017. Tracking Multiple Social Media for Stock Market Event Prediction. *Advances in Data Mining. Applications and Theoretical Aspects*, *10357,* 16-30. [Link]
14. Kalampokis, and Evangelos, 2013. Understanding the Predictive Power of Social Media. *Internet Research, 23(5)*, 544-559. [CrossRef]
15. Kesavan, M. 2020. Stock Market Prediction with Historical Time Series Data and Sentimental Analysis of Social Media Data. *2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS),* 477-482. [Link]
16. Khan, and Wasiat, (2020). Stock Market Prediction Using Machine Learning Classifiers and Social Media, News. *Journal of Ambient Intelligence and Humanized Computing, 13*, 3433-3456. [Link]
17. Lehrer, Xie, and Zhang. (2021). Social Media Sentiment, Model Uncertainty, and Volatility Forecasting. *Economic Modeling, 102*, 105556.
18. Li, and Bing. (2017). Discovering Public Sentiment in Social Media for Predicting Stock Movement of Publicly Listed Companies. *Information Systems, 69*, 81-92. [Link]
19. Li, and Daifeng. (2019). Analyzing Stock Market Trends Using Social Media User Moods and Social Influence. *Journal of the Association for Information Science and Technology, 70(9)*, 1000-1013. [Link]
20. Paniagua, Jordi, and Sapena, J. (2014). Business Performance and Social Media: Love or Hate? *Business Horizons, 57(6)*, 719-728. [Link]
21. Piñeiro-Chousa, and Juan. (2016). Influence of Social Media over the Stock Market. *Psychology & Marketing, 34(1),* 101-108. [Link]
22. Smits, Martin, and Mogos, S. (2013). Association for Information Systems AIS Electronic Library (AISeL) the Impact of Social Media on Business Performance Recommended Citation. *ECIS 2013,* 125. [Link]

23. Trainor, and Kevin, J. (2012). Relating Social Media Technologies to Performance: A Capabilities-Based Perspective. *Journal of Personal Selling & Sales Management, 32(3)*, 317-331. [Link]
24. Tu, and Wenting. (2016). Investment Recommendation Using Investor Opinions in Social Media. *Proceedings of the 39th International ACM SIGIR Conference on Research and Development in Information Retrieval,* 881-884. [Link]
25. Van Dieijen, and Myrthe. (2019). Big Data Analysis of Volatility Spillovers of Brands across Social Media and Stock Markets. *Industrial Marketing Management, 88*, 465-484. [Link]
26. Wang, and Xinjie, 2022. The Causal Relationship between Social Media Sentiment and Stock Return: Experimental Evidence from an Online Message Forum. *Economics Letters, 216*, 110598. [Link]
27. Wang, Yong, and Deng, H. (2018). Expectations, Behavior, and Stock Market Volatility. *Emerging Markets Finance and Trade, 54(14)*, 3235-3255. [Link]
28. Wu, Wang, Ma, and Ye. (2017). The Influence of Social Media on Stock Volatility. *Frontiers of Engineering Management, 4(2)*, 201. [Link]
29. Zhang, Yuzhao, and Liu, H. (2021). Stock Market Reactions to Social Media: Evidence from WeChat Recommendations. *Physica A: Statistical Mechanics and Its Applications, 562*, 125357.
30. Zheludev, and Ilya. (2014). When Can Social Media Lead Financial Markets? *Scientific Reports, 4(1)*, 4213. [Link]