Department of Business and Management

Chair of Advanced Financial Mathematics

Meme Stocks are here to stay?

An empirical analysis on the relationship between investor sentiment and asset performance

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Abstract

Recent trends of financial markets' democratization have led up to the surge of the meme stock phenomenon. Social media and commission free trading platforms have significant role in boosting retail traders' market power, by giving them access to the market and information at lower expense. The objective of this study was to analyze the relationship between investor sentiment and asset performance in the aftermath of meme stock events on the sample of top mentioned stocks on r/wallstreetbets also known as WallStreetBets or WSB, a subreddit where participants discuss stock and option trading on Reddit. (AAPL, AMC, AMD, GME, META, NVDA, TSLA) The Fama-French five-factor model supplemented with momentum was chosen as the model for the regression analyses and sentiment analysis was performed with Valence Aware Dictionary for Sentiment Reasoning natural language processing library. The results of this thesis work reveal varying effects of WSB community sentiment and mentions on daily excess returns and trading volume of stocks. The influence of social media factors is multifaceted and unique for specific time periods and each stock in the sample. This study contributes to behavioral finance underlining growing effects of social media platforms on retail investing and broader markets' performance and efficiency.

Keywords: behavioral finance, retail investing, meme stocks, VADER library, Fama-French model, investor sentiments

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Introduction

The fintech (r)evolution and the diffusion of the online social networks, allowing people to get up-to-date information in real time, laid the foundations for massive paradigm change in financial markets. (Pedersen, 2022) One of the major trends of the recent years is the increasing number of retail investors. Latest JPMorgan data shows that retail trading has reached a record high in 2023 as non-institutional market participation is thriving alongside positive start of the year for equities market. (Investment Outlook for 2023, JPMorgan)

Social media and commission free trading platforms have significant role in boosting retail traders' market power, by giving them access to the market and information at lower expense. (Biancotti and Ciocca, 2021) Recent technological advancements in financial markets gave base for further increasing social nature of retail trading and its impact on prices. The combined effect of financial tech developments and social aspects of retail trading encourages retail investors to join communities and even create mimicking portfolios. (Zetsche et al., 2017)

These trends of financial markets' democratization have led up to the surge of the meme stock phenomenon. According to the Merriam-Webster dictionary, meme is "an amusing or interesting item (such as a captioned picture or video) or genre of items that is spread widely online especially through social media" as well as "an idea, behavior, style, or usage that spreads from person to person within a culture" in a broader sense. Meme stocks are securities that gain popularity among retail investors via social media, they usually have structurally different price formation that mostly does not correspond with fundamentals. (Costola et al., 2021) Meme stocks usually exhibit common stylistic features in dynamics of price, trading volume and user generated content as well as hold higher risk of suspicious trading activity. (Gianstefani et al., 2022)

The meme stock phenomenon started with GameStop short-squeeze events in January 2021 that was triggered by the r/wallstreetbets (further WSB) forum's members on the online social platform Reddit. The share prices of GameStop, American brick-and-mortar video game retailer, surged from $5 in mid-2020 to an intraday maximum of

$483 in January 2021 as a result of coordinated behavior millions of retail investors. (Platt et al., 2021) As a result, several hedge funds that were heavily shorting the stock have suffered irreversible losses. However, it is important to note that thousands of retail investors also have lost their investments in this high risk rally. (GameStop short squeeze will be discussed in detail in the following section) This historic episode has sparked heated debate among policy makers, investors, and business owners, about the power of social media communities and the role of speculative trading withing financial markets.

The most striking aspect of the meme stocks episode is understanding how an ostensibly harmless group of retail investors was able to cause such a significant impact on a market that is typically dominated by the institutional players. These developments show that the interaction of social media and retail trading creates new challenges for the financial markets, necessitating a deeper comprehension of social media role in the formation of asset prices and volatility.

Growing body of literature is focused on the meme stocks and specifically on the topics of investor herding, co-explosivity, and efficiency of financial markets. The effects of social media sentiment on asset performance have gained significant attention from researchers. Costola et al. (2021), Gianstefani et al (2022) and Cuvelier (2022) for instance, demonstrated evidence that dynamics of price, trading volume, and social media activity regarding meme stocks have stylistic features. Moreover, it was found that meme stocks are structurally different from non-meme stocks in their price formation and potentially hold higher risk of market manipulations or suspicious trading activity. By analyzing Reddit data Hu et al (2021) have found that higher traffic, more positive tone of Reddit submissions and discussions, as well as higher connectedness led to higher returns and retail order flow as well as lower shorting flows in the stocks. Cruz et al (2023) have employed machine learning models to predict the stock price movements of GameStop and AMC Entertainment, the findings imply that with the mix of fundamental and technical indicators as well as Reddit sentiment it is possible to predict stocks' next day closing prices.

As it can be seen significant research was done in the field, however the majority of studies are done during the meme stock episodes and cover different variations of sample stocks as the sentiment analysis is labor intensive and requires a lot of data processing. Therefore, the objective of this study is to analyze the relationship between investor sentiment and asset performance in the aftermath of meme stock events, with a focus on wider sample of stocks as well as application of individual approach towards each stock. Number of mentions and compound sentiment were chosen to proxy investor sentiment in the relation to asset performance proxied by daily excess returns and trading volumes of seven most mentioned stocks on WSB subreddit (TSLA, GME, NVDA, AMC, AAPL, AMD, META) during the sample period from July 1, 2022 to June 30, 2023. Main research questions are:

- How strong is the influence of mentions and compound sentiment on the stock performance?
- Does the effect of investor sentiment on social media differ across performances of stocks in the sample?
- Did the effect of WSB user generated content on stock data change in the last year?

The Fama-French five-factor model supplemented with momentum was chosen as the model for the regression analyses as it is recognized to be effective in predicting cross-sectional average returns of stocks. This model was previously used only by Nakstad and Hasle (2022) to analyze the performance of common portfolio built on most mentioned stocks and on the compound sentiment in WSB community. With an individual approach towards each of the stocks in the sample this thesis provides in-depth insights on how investor sentiment affects performance of a particular stock with higher statistical accuracy. For research purposes three datasets were utilized: daily data for Fama-French factors and momentum; daily performance of each stock from Yahoo! Finance; and WSB content - all posts and comments of the subreddit collected using automated scraper. The WSB content dataset accounted 382 670 rows, from which content regarding seven most mentioned stocks was filtered out – 6 284 rows of user generated content. Reprogrammed Valence Aware Dictionary for Sentiment Reasoning (VADER) - natural language processing library was used to analyze the sentiment of WSB content to obtain daily mentions and compound sentiment for each stock. At the last stage of the research all datasets were merged and regression analyses for each stock were performed separately.

The results of empirical analysis have revealed varying effects of WSB community sentiment and ticker mentions on daily excess returns and trading volumes of the stocks, some of them were expected while others were quite surprising. This study contributes to behavioral finance underlining growing effects of social media platforms on retail investing and broader markets' performance and efficiency.

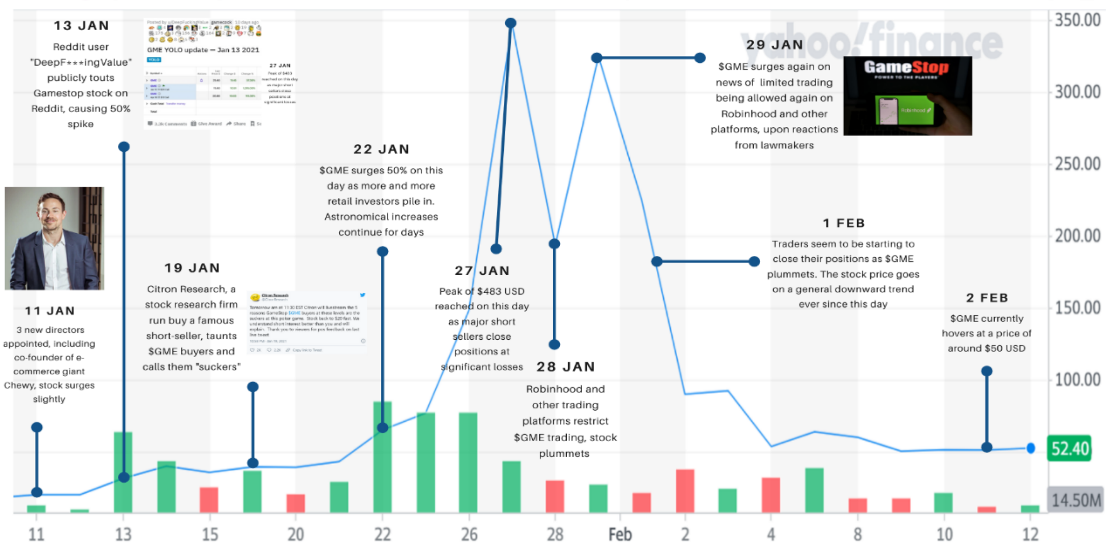
With this thesis I have embarked on a comprehensive journey to explore the phenomenon of meme stocks from various perspectives, so that through the prism of this research I could better understand intricate but fascinating world of financial markets and apply knowledge gained during Advanced Financial Mathematics course. I wholeheartedly hope that the readers will find interesting insights in my work and that this thesis will serve as a valuable resource, offering deeper understanding of the ever-evolving retail investing field.

The first section provides a detailed summary of meme stock frenzy that occurred in the beginning of 2021 to set the context for the readers. Then the Literature Review section initiates with the concepts and current trends of retail investing to provide holistic background to the topic as meme trading is one of the subsets of retail trading. Further in the section existent literature on the influence of social media on financial decision-making is analyzed to discuss the role of social media platforms in shaping investor behavior. In the last part of the Literature Review section, I delve into the exploration of empirical studies that examine aspects of meme stocks within financial markets as well as research the influence of social media (especially Reddit's WSB community) on meme stock price movements. The Methodology section contains description of chosen model and data processing algorithm. In the Results section data regarding WSB community user generated content is dissected with the respective overview of the seven companies constituting research sample; and results of regression analyses are presented. The Discussion section is dedicated to the discussion of research questions in the light of findings and contemplations regarding further research. Ultimately, the Conclusion section wraps up the thesis with conclusive summary and reflection.

GameStop Case

GameStop is an American brick-and-mortar video game retailer listed on NYSE since 2002, that has been struggling in the recent years due to emergence of online retailers in the market. Because of its business model heavily relying on physical points of sales the company was significantly hit by economic effects of COVID-19 pandemic and was forced to close approximately 20% of its stores in the past 3 years. (Tassi, 2020) GameStop revenues have been severely impacted by tightening margins and decreasing sales volume, consequently the stock price of the company has fallen to a low of around 4 USD and remained in 4– 5 USD per share range throughout 2020, which was a significant discount to the price at which it went public. (GameStop Corp. (GME) Stock Price, News, Quote & History - Yahoo Finance, n.d.)

TIMELINE OF GAMESTOP EVENTS



Reddit – Timeline of the Rise and Fall of $GME (stock price info from Yahoo Finance and events from abcNews)
https://www.reddit.com/r/dataisbeautiful/comments/lkz1wm/oc_timeline_of_the_rise_and_fall_of_gme_stock/

Despite company struggles in August 2020, Ryan Cohen (the former CEO of online pet food retailer Chewy) revealed a 9 percent investment in GameStop, which lead to a spread of belief that that the stock was undervalued. Interestingly, even prior to Ryan Cohen’s attention to GameStop Scion Asset Management acquired a 3,3 percent GME shares identifying overlooked value in the company and urging the company board of directors to buy back shares in mid-2019. On 11th of January 2021

GameStop announced appointing three new directors to its board including Ryan Cohen marking a new chapter for GameStop. However, as of 22nd of January the company's public float was shorted 140 percent, meaning that some shorted shares had been re-lent to be shorted again. (Platt et al., 2021)

In the meantime, GameStop was also receiving rising attention over r/wallstreetbets (further WSB) online community on Reddit, forum-based social media that focuses on sub-communities, called subreddits, each with its independent following. The WSB subreddit has always been considered black sheep in the Reddit universe because of its use of foul language, heavy use of memes, crude mechanics for stock evaluations, and encouragement of high-risk stock transactions. However, it is important to note that WSB also has some quality Due Diligence discourse. Since mid-2020 community members were sharing information on their investments in GameStop along with other GME stock enthusiasts, providing regular updates on their investments performance. (WSJ News Exclusive | Keith Gill Drove the GameStop Reddit Mania. He Talked to the Journal., n.d.)

In January 2021, despite the fact that Citron Research predicted the GME value would fall WSB followers have laid the foundations for a short squeeze on GameStop, driving stock price up significantly. According to Dow Jones market data on January 25 more than 175 million GME were traded which was the second highest total in a single day, above its 30-day average volume of 29.8 million shares. On January 26 after GameStop closed up 92.7 percent Elon Musk tweeted "Gamestonk!!" with the reference to the popular "stonks" meme linked to the WSB subreddit. Following Musk's post, the share price experienced a brief, steep increase to over 200 USD. The all-time high intraday stock price for GameStop as of January 28 accounted 483 USD leading GameStop total market capitalization to 33,5 billion USD, temporarily giving it the title of the highest valued Russell 2000 index company. (GameStop Corp. (GME) Stock Price, News, Quote & History - Yahoo Finance, n.d.)

According to the Financial Times in addition to short squeeze "gamma squeeze" also occurred during the episode as traders were as well betting on further increase of the share price by purchasing call options, options sellers hedged their positions through underlying stocks purchases which drove prices even higher. (Powell , 2021)

Short sellers were estimated to have lost a total of $6 billion as a result of the squeeze on January 26. (Nuttall, 2021) Melvin Capital, an investment fund that massively shorted GameStop, has lost 53 percent of its capital by the end of January 2021. Despite significant amount of investment accounting $2,75 billion USD by partner firms to cover its short positions and a short period of gain during February 2021, Melvin Capital has again suffered losses during the GME's continued resurgence in May which ultimately has led the investment fund to close down on May 18, 2022. (Goldstein & Kelly, 2022) Morgan Stanley has reported that the number of hedge funds involved in a short squeeze that had to cover their positions was the greatest in the recent decade

On January 28, Robinhood suspended purchases of GameStop, AMC Entertainment, BlackBerry Limited, Nokia Corporation, and other volatile stocks so users could no longer create new positions in stocks but could still close existing ones. Robinhood and several other brokerage firms have stated that the halt in trading of these stocks was attributed to the fact that clearing houses have raised the required collateral for executing trades and that brokerage firms could not deliver the collateral in time. (Platt & Smith, 2021) Two days later Robinhood has increased the number of restricted stocks to 50, including companies such as Rolls-Royce Holdings and Starbucks Corporation due to high volatility, however, on the next day several of these restrictions were removed so users could only purchase eight securities. The decision of Robinhood to limit the trade on its platform drew criticism and charges of market manipulation from major politicians and businesses from both parties. Multiple class action lawsuits have been filed against Robinhood in the US courts, and the US House Committee on Financial Services has called a hearing on the issue. (Nuttall, 2021)

Because of the halted trading the prices of GameStop shares and other stocks involved in the frenzy started decreasing gradually, on February 1 GameStop has lost 80 percent of its value from its intraday peak price, recorded during the previous week. Reports estimated that about $27 billion in value had been erased in total. (Aliaj et al., 2021) Despite the plummeting prices, some WSB users persuaded other users to hold on to the shares, arguing either that the stock prices will soon rise again or that holding their positions would send a political message. As stock prices fell further, several recent investors held on to their shares and incurred significant losses. Since February 2021 GameStop share prices have been gradually decreasing, exhibiting temporary gains in the beginning of March and first half of May 2021. In 2023 the share price of GameStop is fluctuating between 16 USD and 26 USD.

Literature Review

Rise of retail investors

Due to the fact that meme trading is one of the subsets of retail trading, it is important to provide holistic background to the topic of meme stocks through the concepts of retail investing and current trends in the market

According to U.S. securities and exchange commission "retail investor", also known as an individual investor, is any natural person who does not qualify as an accredited investor" under Rule 501(a) of Regulation D. 17 C.F.R. § 230.50 1(a) (2007) and owns stock by any means. Retail investors trade using traditional or online brokerage firms or other types of investment accounts; they buy assets for their own personal accounts and frequently trade in much lower amounts compared to institutional investors. It is worth noting that meme investors compared to other retail investors tend to exhibit risk-seeking behaviors similar to gambling, choosing high-volatility equities and frequently considering the stock market as a lottery. (Guan, 2022)

Retail investors are typically perceived as unable to influence pricing in traditional models of price discovery. Since the conventional understanding is that majority of retail investors are uninformed traders, whose decision making mostly follows idiosyncratic, individual ways. (Barber and Odean (2000, 2008) As a result, retail investors are as likely to be buying as they are selling at any particular time, meaning that the sum of all of their trades tends to cancel out. (Barber and Odean, 2013)

However, this comprehension falls short of explaining current trading and pricing phenomena. Nowadays retail investors are less prone to behave idiosyncratically and instead, they act in coordinated manner more frequently through online platforms and trading systems that support "social trading." Their trading is therefore stickier and has a greater impact on pricing. (Guan, 2022)

Regardless of the information they possess and awareness they have as market participants, retail investors are currently more likely to influence or anticipate prices through coordination. The chance that retail investors will tend to predict or influence future asset prices increases as the number of retail cohort increases even if the probability that any given single retail trade contains fundamental information about future stock price does not change. (Fong et al. (2014), Kaniel et al. (2012)) and Barrot et al. (2016)) Numerous recent studies support the notion that retail trading has an impact on financial markets and that investor sentiment on social media platforms has predictive powers over returns and trading volume. (Boehmer et al. (2021), Duz et al (2021). Furthermore, data demonstrates that retail investors today have an impact on prices beyond meme stock episodes.

As retail investors' financial decision making is often contaminated by irrational factors recent studies suggest a link between investor sentiment and trading behavior. Wang (2003) has found a positive association between investor sentiment and speculators' net positions. In line with these findings Smales (2016) also suggests that changes in investor sentiment have predictive power over the net positions of retail traders. Kim and Ryu (2021) highlight the finding that individual investors follow a positive feedback strategy, which means that they buy (sell) stocks when the market has bullish (bearish) sentiment.

Social media and social trading platforms have significant role in boosting retail traders' market power. Social media helps retail investors to access information and dramatically reduces their expenses of doing so. (Biancotti and Ciocca (2021); Gomez et al. (2022)). *The effects of social media on financial decision making will be addressed in more detail in the next section.* Moreover, recent technological advancements in financial markets gave base for further increasing social nature of retail trading and its impact on prices. The combined effect of financial tech developments and social aspects of retail trading encourage retail investors to join communities and even create mimicking portfolios. (Zetsche et al., 2017)

Additionally, trading applications promote social trading in more subtle ways as well. For instance, retail investors frequently imitate the trading decisions made by other Robinhood users by trading in accordance with Robinhood's 100 most popular stocks list. Users of Robinhood are five to seven times more likely to purchase newly added stocks to the Robinhood "Top 100" list. (Stein, 2020) However, it is important to note that newly added stocks usually make the list based on short-term gains which are often reversed shortly thereafter.

Trading platforms' influence on decision making of retail investors might spill over to affect asset prices more broadly as trading technology and fintech drastically lower costs of trading and platforms' userbase increases. This could be particularly true since retail investors frequently rely solely on particular apps or social media platforms to gain information as well as that due to the social nature of retail trading that fuels cognitive biases and herding behavior.

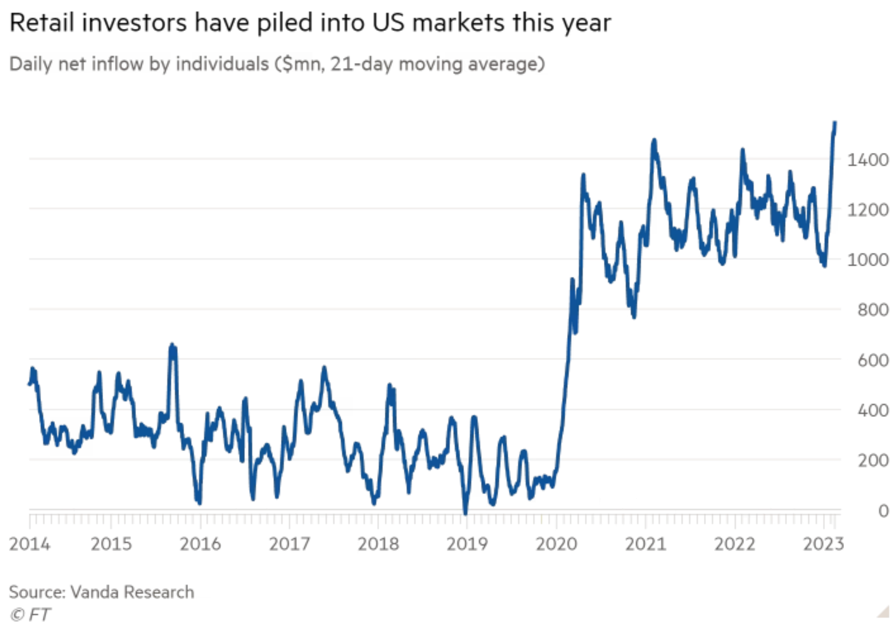
According to Barber et al. (2020), the information shown on the Robinhood trading platform encourages investor herding to the point where it can affect prices. Ozik et al. (2020) have presented evidence that Robinhood users exhibited a tendency to trade attention-grabbing stocks more frequently during Covid-19 lockdown. Additionally, by using intraday data Eaton et al. (2021) have observed that outages of the Robinhood platform were correlated with higher market liquidity in highly popular stocks, meaning that with the presence of zero commission traders the inventory risk of market makers increases.

For instance, Barber et al. (2022) argue that the combination of simplified information display and inexperience encourages attention-driven trading among Robinhood traders. Consequently, attention-driven trading leads to more consolidated retail order flows by Robinhood adding to buy-side herding occurrences, which typically result in negative returns. The top 0.5% of equities purchased by Robinhood traders each day experience negative average returns of nearly 5% while more extreme herding episodes result in negative average returns of over 20%.

Current trends in retail investing

Latest JPMorgan data show that retail trading has reached a record high in 2023 as non-institutional market participation is thriving alongside positive start of the year equities, even exceeding 2021's peak meme stock frenzy rise in day trading. (Investment Outlook for 2023, JPMorgan)

JPMorgan's Peng Cheng reported that total trading volume attributed retail investors was around 23% in the beginning of 2023. This percentage narrowly beats the record share of retail trading during the pandemic driven retail frenzy of 22%. Most importantly, this marks significant increase in retail volumes in comparison to late 2022, which accounted 15%.



Meme-stock 2.0: Wall Street's retail trading boom is back. (2023, February). Financial Times.

This year volumes of retail trading are still concentrated in smaller stocks, while meme stocks like GameStop, AMC, and Bed Bath & Beyond are all up 35% or more. However, JPMorgan's data shows that traders' behaviors are changing. According to Cheng, the share of retail investors in overall trading volume for large cap stocks is increasing. Apple and Amazon were the most popular stocks purchased by non-institutional traders, while Tesla was the most popular stock sold. Moreover, dropping percentage of options trades among private investors was noticed, in the beginning of

February 12% of all trading were high-risk, high-reward options trades, which is down from 17% in early 2021.

Increasing retail investment activity dismisses the belief that the pandemic-era retail trading boom was just a whim caused by government stimulus and lockdown boredom. Retail investors are increasingly driving market upswings rather than chasing them. This trend is anticipated to intensify in the course of next decade as the retail category is believed to represent 60% of global AUM by 2030. It is forecasted that worldwide online trading market will grow at a compound annual rate of 6.4 percent per year, reaching 13.3 billion US dollars in 2026. (Statista, Forecast of the global online trading market 2026, 2023)

Key insights on retail investor market from Nasdaq 2022 report on retail investors profile can be highlighted: There is fierce competition among brokerage platforms. Investing has become more accessible thanks to technological advancements and commission-free trading, especially for younger investors. Fidelity Investments was the most highly used brokerage for Gen X (40%) and baby boomers (32%). However, Gen Z (64%) and Gen Y (50%) have turned to the newer companies on the market as Robinhood. (Nasdaq, 2022)

The report notes that younger investors are more engaged in monitoring their accounts, conducting independent research before investing and their investing activity is more frequent. Financial advisors are believed to be the most trustworthy resource when making investment decisions for all generations of investors. Although Gen Z and Gen Y do their research using a range of sites, such as online discussion forums and social media, financial advisors remain the most essential source of information. Financial experts' content is the most valuable for individuals who utilize social media. (Nasdaq, 2022)

Social media and financial decision making

Behavioral finance enhances the standard model of efficient markets and takes into consideration the influence of less rational human factors like investors' sentiment and overall public mood and emotion on asset pricing and capital market volatility. (Brooks and Byrne, 2008) In particular, behavioral finance proposes that there are factors like animal spirits (Shiller at al., 1984), social mood (Nofsinger, 2005), investor sentiment (Baker and Wurgler, 2007) and psychological factors (Fenzl and Pelzmann, 2012) as a sources of market volatility and anomalies.

In the framework of behavioral finance, the influence of media on financial decision making is significant as media plays crucial role of intermediator between information consumers and information creators. (Tetlock, 2015) Investors have relied on the media through wide range of outlets such as traditional print media, newswires, search engines for repositories of corporate filings, internet-based discussion boards and social media websites for stock-related value information and outlook judgments for many years and, in some cases, the media itself influences how financial decisions are made even beyond the content of the information it transmits.

Even though empirically identifying the causal impact of the media on financial decisions is challenging, there is a vast body of literature that studies effects of media on financial markets. The literature study indicates that media can be useful in financial decision-making: with faster price discovery and less adverse selection wider media coverage enhances market efficiency, as well as it can function as a corporate governance monitor. (Pirami and Singal, 2001, Chan, 2003; Larson and Madura, 2003; Tetlock, 2010;) However, it is undeniable that there are instances in which the media's incentives can result in negative market outcomes, such as market overreactions brought on by false information or slanted media coverage (Shiller's (2000), Frank and Sanati (2018), Dougal et al. (2012))

The advent of social media presents a unique form of information intermediation. Compared to traditional media, the sources of information on social media are interactive, decentralized and relatively unfiltered which allows researchers to explore complexity of investor behavior. Social media provides the chance to obtain direct data about human factors that affect market anomalies present in behavioral finance at the aggregate level such as social mood (Nofsinger 2005), investor sentiment (Baker and Wurgler 2006), and psychological components (Fenzl and Pelzmann 2012).

Early studies on the topic of social media role in financial decision making have been suggesting that message boards (earlier form of social media platforms) posts are able to predict future volatility and volume but exhibit insignificant association with future returns of stocks. For instance, according to Antweiler and Frank (2004) there was no substantial effect of number and sentiment of posts on discussion boards on future returns after accounting for transaction costs, however volume and volatility could still be forecasted, even after controlling for WSJ articles. Similar results are presented in Tumarkin and Whitelaw (2001) and Dewally (2003) using different time periods and platforms.

In contrast, more recent studies indicate that social media posts may predict returns, this can be explained by faster diffusion of information, rapid proliferation of social media channels, emergence of advanced platforms with more complex infrastructure and user-friendly interface. Recent research (Bollen et al., 2011, Mittal and Goel, 2013, Duz and Tan, 2021) suggests that social media can be utilized to predict changes in economic indices and the stock market. Studies show that social media emotion has an impact on the stock market (Ge et al., 2020), confirming that emotionally charged content, especially negative content (Berger and Milkman, 2012), has a tendency to generate more posts (Stieglitz and Dang-Xuan, 2013).

In order to deep dive in illustrating the effects of social media on financial decision making the empirical studies performed on most popular platforms were analyzed and main results of these studies are presented further in the section. The effects of Reddit sentiment effects will be reviewed in detail in the meme stocks section, as this platform influence is meme stock episode specific.

SeekingAlpha

Chen et al. (2014) employs textual analysis of user-generated opinions and articles from Seeking Alpha to discover that the opinions on this website have a significant predictive power of future stock returns and earnings surprises. Dim, C. (2020) has studied the Seeking Alpha social media analysts' behavior and their influence over financial decisions of their followers. The Social media analysts as a group display a behavioral pattern since they tend to herd of views of their peers and extrapolate on past returns. However, it is important to note that these behavioral biases do not seem to result in systematically wrong beliefs, this can be explained by the observation that social media analysts shape their expectations based on fundamental-relevant information.

Farrell et al. (2022) use the delayed release of SeekingAlpha articles to alleviate endogeneity problems, in a context similar to that of Akbas et al. (2018) and Schaub (2018). The trading behavior before and after the publishing of articles was compared and it was found that SeekingAlpha articles lead to more informed trading, particularly when their authors have stronger track records and academic backgrounds. According to Ding, Shi, and Zhou (2022), SeekingAlpha articles are associated with decreased underreaction to earnings shocks, implying that they speed the integration of earnings news into stock prices.

StockTwits

StockTwits platform is designed for sharing ideas among investors, traders, and entrepreneurs and it has a unique feature that allows users to pre-label their posts as either "bullish" (demonstrating positive sentiment) or "bearish" (demonstrating negative sentiment). Oliveira et al. (2016) and Renault (2017) both have built an investor sentiment index using tokenization and a bag-of-words method. The study demonstrates that the investor sentiment indices obtained from StockTwit can predict intraday S&P 500 EFT returns. According to Sun et al. (2016), shifts in the Thomson Reuters sentiment index had a greater impact on the last two hours of trade when predicting market returns. Similar research was conducted by Behrendt and Schmidt (2018), Bloomberg News and Social Sentiment index were used to examine whether changes in the index might be used to forecast intraday stock returns. According to the study despite being statistically significant, the investor sentiment index turned out to be economically insignificant. As mentioned in Renault (2017), utilizing these metrics of investor sentiment is difficult to judge as they are proprietary and hence not "transparent, or replicable." Cookson et al. (2022) have investigated bias in information received by investors on StockTwits. It was discovered that users who showed bullish sentiment on a particular stock are five times more likely to follow another user who is similarly bullish on the stock. Consequently, it makes bullish users see more bullish posts rather than actual representation of the sentiment on the platform. These findings imply that investors are risking trading off financial information accuracy for the utility of conforming reports.

Twitter

There is a rich body of empirical studies investigating the effects of Twitter sentiment on trading activity and individual investors. According to the literature Twitter's large user base has some power to forecast market outcomes: the findings exhibit positive associations between trading volume of stocks and respective posts volume on Twitter as well as between sentiment and stock returns. For instance, positive and negative sentiments on Twitter have been examined by Zhang et al. (2011) and Bollen et al. (2011), who show that sentiments derived from Twitter have the ability to forecast changes in U.S. market indexes.

By using computational linguistics to evaluate daily stock related posts Sprenger et al. (2014) have analyzed S&P 100 companies, the results of the study have shown that there was an association sentiment in tweets and stock returns, number of messages and trading volume. Moreover, it was found that detected disagreement among the stock related twits corresponds with the volatility of the stocks.

In 2015 study of Dow Jones Industrial Average (DJIA) index companies, Ranco et al. discovered a strong correlation between Twitter sentiment and abnormal returns at the moments Twitter posts volume peaks. Later in 2018, Behrendt and Schmidt (2018) also have investigated relation between Twitter sentiment and absolute 5-min individual-level stock return of DJIA index companies the findings suggested that strong feedback effects of return volatility to sentiment were present.

Alternatively, based on Twitter's number of followers mechanism Sul et al. (2017) have investigated S&P 500 companies stock performances, it was discovered that Twitter sentiment of users about a respective company with less than the sample's median has a significant impact on the stock's returns the following day, the following ten days, and the following twenty days. In line with these results Gu and Kurov (2020) by controlling with sentiment from traditional media channels, also have found that that Twitter sentiment has ability to predict a firm's future stock returns over the next day as well as provide analysts with notions regarding quarterly earnings and price targets. Moreover, Bartov et al. (2018) have applied tokenization and bag-of-words approach to build “equity specific investor sentiment index from Twitter” for Russell 3000 firms’ sample. The findings indicate that firms’ quarterly earnings and announcement returns can be predicted by aggregate of opinions in Twitter posts.

Rakowski, Shirley, and Stark (2019) have used Twitter outages to explore a causal influence. The results demonstrate that, regardless of the tone of the Tweets, Twitter increases trading activity and stock returns as compared to times when it is offline. Through residual methodology for attention proxy Wu (2019) has found that high social media attention in Twitter following earnings announcements, even if the news is bad, has a favorable impact on the cumulative abnormal returns. Chawla, Da, Xu, and Ye (2022) have measured the speed of retweeting on Twitter and have discovered that faster diffusion is associated with lower spreads and positive pressure on prices, which is then reversed the next day.

Meme Stocks and financial markets

Growing body of literature is focused on the meme stocks, in this section empirical studies done specifically on meme stocks were analyzed.

Buz and Melo (2021) have aimed to assess the reliability of investment advice encountered on the WSB and determine its potential profitability by analyzing the data from the subreddit from January 2019 to April 2021 associated with the 100 most frequently mentioned stock and ETF tickers. The results shed light on the performance of these stocks in comparison to broader market in this case identified by SPDR S&P500 ETF. Analyzed discussions were revolving around sectors that outperformed the broader market in the course of the last three years, consequently authors come to the conclusion that investing in these sectors and holding positions for an extended period would have yielded superior results compared to the average market growth. Over the last three and a half years, a hypothetical portfolio of the most frequently and regularly mentioned equities outperformed the S&P500 on average. The results' trends are magnified by WSB's strong growth and the success of meme stocks in 2021, but they may still be detected in a lesser form when analyzing data from January 2019 to December 2020, correlating with the aforementioned analytical results.

In line with Pedersen’s model the echo chamber effect can be observed when agents communicate in a closed system, which causes amplification and reinforcement of particular beliefs due to confirmation bias, which in turn might lead to irrational market behavior seen during the GameStop incident. Determining whether the GameStop incident in January 2021 was really an epiphenomenon caused by exogenous variables or the result of routinely irrational behavior (Malz, 2021), amplified by social media and new trading apps, is crucial to map out nature of meme stocks. By investigating the explosivity of meme stocks Aloosh et al. (2021) shed light on this issue because detecting the presence of explosiveness suggests irrational investing (Baker and Ricciardi, 2014), especially during periods of co-explosivity between two or more meme stocks, that do not present justified common economic or financial risk drivers for their reported excessive co-movements. It was determined that meme stock prices have had numerous explosivity periods with substantial duration even after January 2021 event. Therefore, the results suggest that meme stocks price explosiveness are unlikely to be the result of an abnormal event like the GameStop episode, these patterns rather appear to be the result of traders' own irrational behavior facilitated by trading platforms like Robinhood.

Remarkably, it was also found that irrational investing in major cryptocurrencies, like Bitcoin and Ethereum (Baker and Ricciardi, 2014), is equivalent to that in meme stocks markets. Meme stocks and cryptocurrencies both have demonstrated regular price explosivity between 2020 and 2021. Even though, cryptocurrency prices exhibit more frequent and longer periods of explosivity, this was expected considering the peculiar nature of cryptocurrencies: their principal function and absence of fundamentals.

Li, S. (2022) investigated the relationship of meme stocks and Bitcoin, which is also frequently traded by retail investors. The study uncovers a wealth transfer phenomenon from meme stocks to Bitcoin using a VAR (1)-BEKK-AGARCH (1,1) model. When retail investors earn profits from meme stocks they cash out on Bitcoin, pushing the future Bitcoin prices higher. It was that demonstrated meme stocks are prone to higher volatility which further translates into unidirectional short-run volatility spillover from Bitcoin to meme stocks. Ultimately, the research reveals the greater risk in meme stock investments caused by greater extreme returns, higher volatility and strong short-term persistency, prolonged time losing money, and negative spillovers from Bitcoin.

Aloosh et al. (2021) study has tested the hypothesis that meme stocks traders are subject to herd behavior because of their collective and irrational behavior. The findings suggest that meme stock traders tend to herd around specific "viral" stocks that are also beyond the short squeeze events, which implies that meme stocks appear to behave as a separate asset class. Consequently, retail investors who heavily rely social media networks to form their investment strategy might expose themselves to additional risk due to insufficient portfolio diversification. The prevalence of herding in a rising meme stock market should alert policymakers to the potentially destabilizing influence that meme stock traders may have on the economy. Therefore, stricter rules on financial technologies and social media trading are required.

Social media sentiment and meme stocks

Costola et al. (2021) have evidence that the price, trading volume, and social media activity dynamics of meme stocks have stylistic features. Using a regime-switching cointegration model, it was discovered that the "mementum" (when synchronized buying signals originating in social media have an effect on both the price and trading volume of a stock) of meme stocks exhibits distinct characterization in comparison to other stocks with high volumes of buzz (persistent and not) on social media.

In contrast to the literature on sentiment analysis and stock returns that will be addressed further in the section the authors suggest a metric for stock-related meme activity on social media that is neither sentiment nor emotion-based. Three stocks (GME, AMC, KOSS) that were dubbed meme stocks by newspapers and experienced abrupt spikes in mid-January 2021 were taken as sample with the hypothesis that synchronized market effect on volumes and prices was caused by buzz originating in social media. For comparison sample authors have selected Pfizer (PFE), Moody’s (MCO), and Disney (DIS) as these stocks were volatile and the majority of the spikes corresponded to events related to COVD-19 pandemic which on contrary was generating social media buzz.

The research was done with data gathered from Twitter as it is a popular and generalist social platform, differently from Umar et al., 2021, retweets were filtered out. Additionally, authors wanted to stay true to the definition of “meme”, that is, an image with text and/or emojis, therefore only posts that contain images were included in the analysis.

With the use of social media's meme-based coordination mechanisms, retail investors can act as one powerful trader and successfully control prices. The cryptocurrency markets have also seen similar trading tactics, known as "pump-and-dump" schemes, when coordinated social trading mechanisms were used to drive up prices temporarily (Xu and Livshits, 2019).

Gianstefani et al. (2022) have developed alert system detecting users’ disruptive social media activity (extraordinary activity coordinating users to bulk action on Reddit) to assess the echo chamber effects on stock market from Reddit and to evaluate the role of users in trading the meme and non-meme stocks regression was run with the abnormal volume as a dependent variable. The methodology was applied on the sample of two meme stocks (GME and AMC) and two non-meme stocks (AAPL and MSFT). In the flow of the research the alert system has identified episodes of social media buzz for both groups of stocks, however, the regression analysis shows that these episodes have resulted in meme stocks’ abnormal returns, whereas non-meme stocks returns were not sensitive to user generated content regarding them. These results suggest that meme stocks are, indeed, structurally different from non-meme stocks in their price formation and potentially hold higher risk of market manipulations or suspicious trading activity.

Umar et al. (2021) have investigated the correlation between GameStop returns and sentiments of media-wise and media-averse investors through wavelet coherence approach by using number of tweets and news publications, put-call volume ratio and short sale volume as proxies with data span covering January 2020 to January 2021.

The findings imply that during the recent GameStop episode of tension between social media investors and the involved hedge funds, media-wise Reddit investor sentiments may have positively benefited GameStop returns. On the contrary, out-of-phase correlation was detected between the number publications in mainstream media and the GME price, suggesting that media-averse investor sentiments are unlikely to have substantial effect on GameStop returns during the period.

The findings also show that during the period GameStop returns and the put-call volume ratio show a substantial positive co-movement. The investors' derivative trading activity has caused increased put options volume driving the put-call ratio up which in turn was one of the factors of GameStop share price explosion. Moreover, it was observed that at times of rising uncertainty, investors have had a stronger propensity for option trading.

This study also confirms the short squeeze phenomenon as the data exhibits a correlation between the GameStop returns and the volume of short sales during the GameStop episode. The excessive short selling raises demand, prices, and returns, so market inefficiency ultimately stems from a large deviation of market prices from the actual stock value.

By analyzing Reddit data spanning 2020 and 2021 Hu et al (2021) have found that higher traffic, more positive tone of Reddit submissions and discussions, as well asl higher connectedness led to higher returns, higher retail order flow, and lower shorting flows in the stocks. Notably, in the periods when there is increased content traffic or WSB influencer submission is posted the predictive power of retail order flows over future stock returns is stronger. In contrast, shorting flows are more informative and have higher predictive power over lower future returns in the periods when there is more disagreement and higher connectedness on the forum. It is also interesting to note that social media can help retail investors to act in informed manner by alerting them of potential short squeezes and temporary price increases with no fundamentals. Additionally, Hu et al (2021) have also analyzed the Robinhood 50 list stocks, which were under trading restrictions in January 2021. It was found that Reddit sentiment has higher predictive power over future returns of Robinhood 50 stocks compared to other equities.

Cuvelier (2022) have attempted to forecast five meme stocks’ (GameStop, Tesla, AMC Entertainment, BlackBerry, Palantir Technologies) share prices with multiple linear regression models and gated recurrent unit models (recurrent neural network model type) by using WSB user generated content. The results show that the multiple linear regression models have demonstrated stronger results and appear to be applicable, especially in the cases of Tesla, GameStop, and AMC. This implies that WSB sentiment data, can explain the closing prices of stocks on the same day. The gated recurrent unit models were unreliable predictors in the study.

Nakstad and Hasle (2022) have applied the five-factor model supplemented with momentum and combination of data from Reddit data, stock data, and Fama-French factors to analyze how WSB sentiment impacts performance of forty-one most mentioned stocks on the subreddit. The findings support the hypothesis that WSB activity has a significant impact on stock data. The number of mentions had most statistical significance in predicting same day excess returns, but the compound sentiment had weaker relationship with the asset performance.

Long et al. (2023) have developed unique Reddit-specific lexicon with the corresponding sentiment scores in order to explore the impact of Reddit sentiment on GameStop's intraday returns during early 2021. The findings demonstrate that Reddit can amplify positive sentiment when market is bullish but has limited effects when market is bearish.

Similarly, Huang and Shum Nolan (2023) have used Google’s BERT model for natural language processing in order to determine investor sentiment in the sample of 2.4 million WSB posts. In the daily macro attention event study, it was found that in the case of positive sentiment: stock’s cumulative average abnormal return exhibits upward trend before WSB users attention peaks in the forum. Meanwhile, on Robinhood (it was hypothesized by authors that a lot of WSB users trade on Robinhood) the number of investors holding the stock consistently increases. This pattern can be interpreted as social network spillover effect significant enough it influences the prices. In line with Long et al. (2023), any specific abnormal return pattern was not spotted in the case of negative sentiment. However, it is important to note that this pattern can partially be explained by the fact that there is no short selling feature on Robinhood. Also, the general sentiment among WSB users that short sellers are “bad” actors should not be overruled.

Huang and Shum Nolan (2023) have tested the role of influencers on WSB forum through micro attention event study. The results suggest that that influencers tend to write about stocks that have been gaining in excess returns, and their posts actually correlate with an increase in the number of Robinhood users purchasing the stocks. Most notably, the sentiment classification of posts made by influencers reveals that influencers either have some predictive powers to determine if the stock will experience quick correction (negative sentiment posts) or they may have a hand in affecting subsequent price movements through their opinions.

Cruz et al (2023) have employed machine learning models to predict the stock price movements of GameStop and AMC Entertainment. Two sentiment metrics generated based on discussions on Reddit were combined with 85 fundamental and technical indicators as a feature set for machine learning models. The findings imply that a mix of fundamental indicators, technical indicators, and Reddit sentiment it is possible to predict next day closing prices. Moreover, combination of anomaly detection model with Reddit discussions can assist in identification of potential market manipulators. Furthermore, it was observed that fundamental stock metrics, such as the price-to-book ratio, have an extremely negative association with the closing price.

Methodology

This section contains the methodology applied in this thesis: introduction of the selected model, data collection and data processing algorithm. As it was previously discussed in the meme stock specific investor sentiment and asset performance literature there are various methodologies to perform sentiment analysis as well as several models for regression analysis.

Valence Aware Dictionary for Sentiment Reasoning

VADER (Valence Aware Dictionary for Sentiment Reasoning) is a model within Natural Language Toolkit (NLTK) of python library that is often used in analyzing social media sentiment. The VADER weighs words in a text from -1 (negative) to 1 (positive) with the use of dictionary of words and assigns compound sentiment intensity. The most advantageous feature of the VADER is that it considers intensity and polarity of the emotions expressed. Moreover, compared to other language processing models like Google's BERT or Recurrent Neural Network, VADER is more accessible and easier in use as it can be installed as library in RStudio.

Fama-French five-factor model

The Fama-French five-factor model supplemented with momentum factor was chosen as the model for this thesis regression analysis as it is recognized to be effective in cross-sectional average returns of stocks. There are several other models that were used in existent literature. For instance, Gianstefani et al (2022) have applied contemporaneous regression estimated via ordinary least square regression with HAC estimator for the variance by Newey and West (1987) for each stock, while Hu et al (2021) utilized bid-ask average closing prices to run multiple regressions. The Fama-French five-factor model supplemented with momentum was also used by Nakstad and Hasle (2022) mentioned in Literature Review section on meme stocks case; in their research the model was used to analyze the performance of the portfolio containing 41 most mentioned stocks in WSB community, whereas this thesis is focused on individual approach to each stock in the sample, by separately analyzing correlation between sentiment and performance of a specific stock – namely excess return and trading volume. This model proves to be efficient as it has six additional market and company related factors to predict excess returns and trading volumes which minimizes statistical error.

The three-factor asset pricing model was first presented by Fama and French (1993), who added two market related factors as size of the firm and its book-to-market ratio to classic Capital Asset Pricing Model in order to further explain excess returns of the stocks. Three-factor model was also applicable for the returns of portfolios created on the basis of Earnings/Price ratio, Cash Flow/Price ratio, and Sales Growth. However, it was extended by Carhart (1997) who added momentum element into the equation, as this approach was providing greater explanation of average stock returns variation. Furthermore, Titman, Wei, and Xie (2004) have presented evidence that firm's stock performance is impacted by the amount of investment it makes, specifically abnormal capital investment and stock returns are negatively correlated. In 2013 Novy-Marx argues that profitability if an important factor in asset pricing based on the evidence that stocks of profitable companies generate significantly higher returns than of their unprofitable counterparts. He also finds that, controlling for profitability, value strategies perform better. As a result of the evidence presented regarding these aspects, Fama and French (2015) have extended their original three-factor model to include two more factors as profitability and investment activity of the firm.

The model equation is the following for an asset s:

$$Excess(Rst) - rft = ai + bi(E(RMt) - RFt) + ssSMBt + hsHMLt + rsRMWt + csCMAt + eit + Sentimentscorest + Mentionsst$$

$$Volumet = Mkt.rft + SMBt + HMLt + RMWt + CMAt + MOMt + Sentimentscorest + Mentionsst$$

	Variable Definition
ExcessReturn st	The logarithm of 1 the daily excess return. Daily excess return is on a close-to-close basis where the risk free rate is subtracted from the daily % return.
E(Rst)	Expected return of asset s at time t
rft	The daily % risk free rate.
Mkt.rft	The daily % excess return on the Fama-French market portfolio. Can also be expressed as $Rm - Rf$.
SMBt	The daily return on the Small-Minus-Big Fama-French(FF) portfolio.
HMLt	The daily % return on the High-Minus-Low FF portfolio.
RMWt	The daily % return on the Robust-Minus-Weak FF portfolio.
CMAt	The daily % return on the Conservative-Minus-Aggressive FF portfolio.
MOMt	The daily % return on the Momentum FF portfolio.
Sentimentscorest	The first-difference of the compound sentiment score on a daily aggregated basis for each stock
Mentionsst	Mentions on an aggregated daily basis for each stock.

Data Collection

Three data sources were utilized for research purposes of this thesis and based on availability of data the sample period from July 1, 2022 to June 30, 2023 has been set. The sample of stocks was determined by selecting the most mentioned stocks on WSB subreddit during the sample period. (AAPL, AMC, AMD, GME, NVDA, META, TSLA) Data collection:

- Daily data for Fama-French factors and momentum were downloaded from the Darthmouth University database
- Daily performance of each stock in the sample was retrieved from Yahoo! Finance (daily adjusted close prices, volumes, market capitalization)
- WSB content: Reddit API became unavailable for scraping the data, so it was not possible to get the data directly from Reddit. Therefore, the database collected starting from Q2 2022 using automated WSB scraper was used.

Data Processing Algorithm

As Fama-French factors and Yahoo! Finance data only required basic calculations, this section is mostly focused on processing WSB content and performing sentiment analysis.

1. Cleaning the dataset: unnecessary columns like post URL, score, user_id were removed. For the sample period July 1, 2022 – June 30, 2023, the dataset accounted 382 670 rows of user generated content both posts and comments.
2. Searching and grouping by stock mentions: using NASDAQ Stock Screener ticker list each post and comment was searched for stock mentions. If the stock ticker was mentioned in subreddit submission, the program would assign it respective stock ticker from NASDAQ Stock Screener list.
3. Counting stock mentions: top 7 most mentioned stocks were filtered out – 6284 rows of user generated content. Mentions count was the following TSLA – 1753, GME – 1695, NVDA - 965, AMC - 650, AAPL – 455, AMD - 429, META – 337.
4. Adjusting the date of WSB content: 7 csv files that contain all WSB content mentioning the ticker were exported from RStudio and merged together. As users can post or comment on WSB at any day of the week, it is important to reassign the date of the posts that were done on weekends and holidays for the next trading day using Excel with the help of Fame-French date span.
5. Reprogramming VADER library: VADER library had to be reprogrammed by adding WSB specific words, since WSB community is known for its unique style of communication that includes slang and specific emojis, as well as using foul language that actually does not represent negative sentiment.
6. Calculating daily compound sentiment for each stock: by running VADER library functions daily mentions and compound sentiment is obtained for each stock
7. Regression analysis: After merging stock data, Fama-French factors, daily compound sentiment and mentions data two sets regression analyses for each stock with dependent variables as daily excess returns and trading volumes are carried out.

Results

WSB user generated content analysis and companies' overview

Data regarding the mentions and compound sentiment as well as a brief overview of the seven companies constituting research sample is presented in this section. This will provide a detailed context for better understanding the regression analysis results and discussion. I would like to start with short introduction of each company in the sample, then general trends in WSB user generated content are presented. Subsequently, deep dive in mentions and sentiment patterns associated with each stock will follow.

AAPL - Apple Inc. is a global technology company founded and based in the USA. The company engages in designing, manufacturing, and marketing personal computers, tablets, smartphone as well as other tech products and services. As of 2022 Apple was the most profitable technology business and in March 2023 it has become the largest company by market capitalization in the world. (Apple Inc, AAPL:NSQ Profile - FT.com)

AMC - AMC Entertainment Holdings, Inc. is an American movie exhibition company. AMC movie theaters chain is considered to be the largest in the world. The company's main activity is the theatrical exhibition of film, it owns and has interest in theaters primarily located in the USA and Europe. AMC operates 10 500 screens and 940 theaters worldwide. (AMC Entertainment Holdings Inc, AMC:NYQ Profile - FT.com)

AMD - Advanced Micro Devices, Inc. (AMD) is a global semiconductor firm based in Santa Clara, California producing computer processors and related technologies for the commercial and consumer markets. The processors produced by AMD can be grouped as: server central processing units (CPUs), graphics processing units (GPUs), data processing units (DPUs), field programmable gate arrays (FPGAs), and adaptive system-on-a-chip (SoC). (Advanced Micro Devices Inc, AMD:NSQ Profile - FT.com)

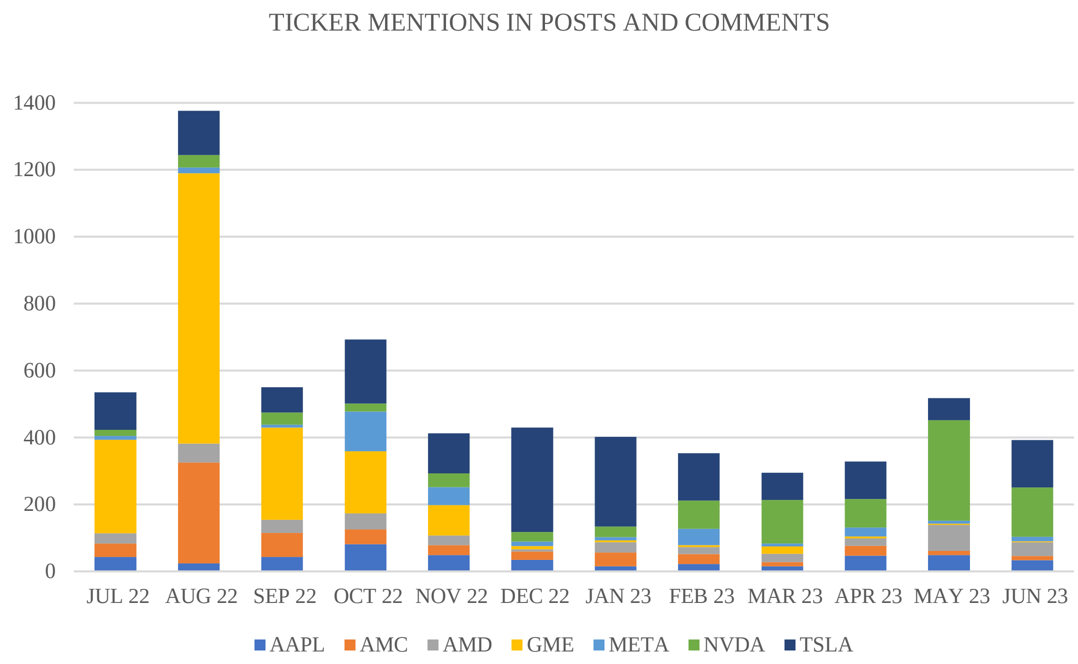
GME - GameStop Corp. is an American retailer of video games, consumer electronics, and gaming accessories. Through its storefronts and e-commerce channels, GameStop Corp. focuses on providing games, entertainment items, and technology. (GameStop Corp, GME:NYQ Profile - FT.com)

META - Meta Platforms, Inc., formerly known as Facebook, Inc., is a global American technology company. The firm owns and manages social media platforms as Facebook, Instagram, Threads, and WhatsApp. Primary profit source of Meta Platforms is advertising on its social media platforms, but CEO of the company Mark Zuckerberg has an alternative vision for the company future in Meta's metaverse and augmented reality projects. (Meta Platforms Inc, META:NSQ Profile - FT.com)

NVDA - Nvidia Corporation is multinational tech company, its primary activity is designing graphics processing units, application programming interface for high-performance computing and developing chip units for the mobile computing and automotive market incorporated. Nvidia is the market leader in artificial intelligence hardware and software. (NVIDIA Corp, NVDA:NSQ Profile - FT.com)

TSLA - Tesla, Inc. is an American multinational automotive and clean energy company. Tesla designs and manufactures electric vehicles specifically cars and trucks, stationary battery energy storage devices from home to grid-scale, solar panels and solar shingles, and related products and services. (Tesla Inc, TSLA:NSQ Profile - FT.com,)

	AAPL	**AMC**	**AMD**	**GME**	**META**	**NVDA**	**TSLA**
Market Capitalization USD	2.88 trillion	1.73 billion	171.13 billion	5.56 billion	766.78 billion	1.20 trillion	805.87 billion
Net Profit Margin	24.68%	-17.40%	-0.18%	-3.56%	19.96%	31.59%	12.97%
Return on equity	160.09%	--	-0.05%	-15.11%	18.52%	40.21%	27.96%
Price/Cash flow per share	27.03	--	40.97	--	22.7	101.21	50.07
Total debt/total capital	0.6445	2.13	0.0428	0.0284	0.1288	0.2609	0.0428



Source: Personal elaboration

During the sample period 6284 posts and comments mentioning one or more of the tickers were posted in WSB community. (Mentions count was the following TSLA – 1753, GME – 1695, NVDA - 965, AMC - 650, AAPL – 455, AMD - 429, META – 337) As it can be seen from Figure 1, except the peak of discussion mainly attributed to GME and AMC in August 2022, the average number of posts and comments fluctuates around 400 per month. Discussion regarding GME is significant in the beginning of the sample period, however towards the end of the period NVDA gains more popularity in WSB community. It is interesting to note that AMC mentions co-move with GME mentions during its explosivity period July – November 2022. During meme stock episodes AMC was the second most popular stock after GME, this illustrates that the relation between these two stocks still remains in the second half of 2022. However, in 2023 AMC is discussed more than GME.

The most mentioned stock TSLA occurs in posts and comments quite consistently throughout all months, with major peaks in December 2022 and January 2023. Additionally, AAPL and AMD also get consistent attention as TSLA, even though these stocks are mentioned only 455 and 429 times a year respectively. AAPL has two peaking discussion periods in autumn of 2022 and spring of 2023, while AMC gets highest attention in May 2023.

Month	AAPL	AMC	AMD	GME	META	NVDA	TSLA	Monthly avg. total sample
JUL 22	0.10	0.14	0.18	0.10	0.24	-0.01	0.20	0.14
AUG 22	0.04	0.23	0.18	0.18	0.16	0.08	0.16	0.15
SEP 22	0.05	0.19	0.12	0.15	0.09	0.02	0.14	0.11
OCT 22	-0.11	0.22	0.10	0.13	0.17	-0.02	0.16	0.09
NOV 22	0.08	0.17	0.05	0.12	0.05	0.03	0.25	0.11
DEC 22	0.20	-0.01	0.10	-0.17	0.11	0.15	0.10	0.07
JAN 23	-0.03	0.19	0.14	0.01	-0.09	-0.05	0.11	0.04
FEB 23	0.11	0.09	0.21	-0.11	0.14	0.12	0.08	0.09
MAR 23	0.03	0.09	0.10	-0.08	-0.02	0.03	0.14	0.04
APR 23	0.18	0.15	0.15	-0.22	0.01	0.03	0.12	0.06
MAY 23	0.10	0.03	0.22	-0.16	0.04	0.00	0.08	0.05
JUN 23	0.06	0.15	0.23	-0.08	0.01	0.17	0.14	0.10
Avg. yearly sentiment	0.07	0.14	0.15	-0.01	0.08	0.05	0.14	

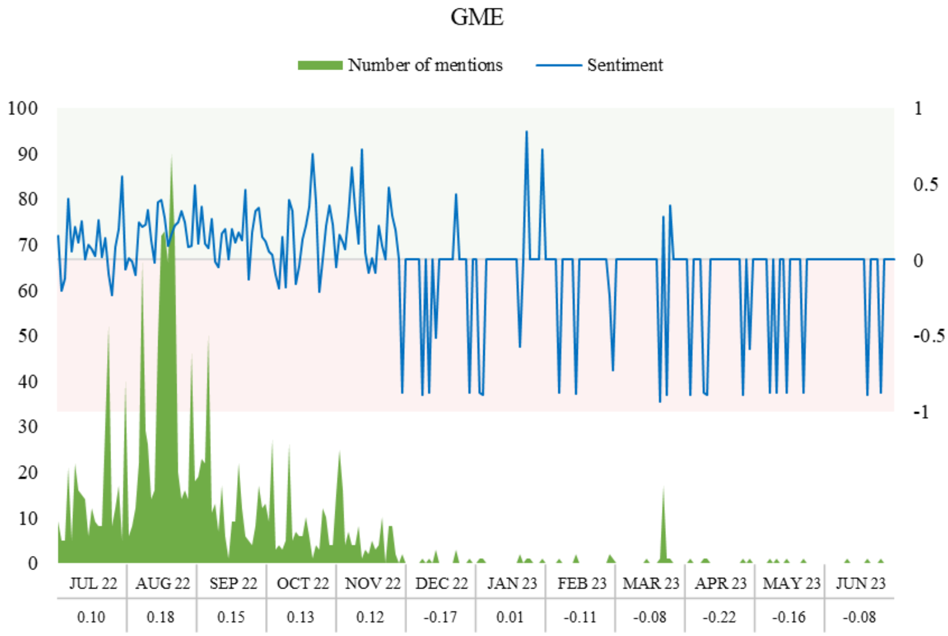
** Please note that conditional formatting of cells in the table is based on the greatest and the least value, Monthly avg of total sample column and Avg. yearly sentiment row were formatted separately. This was done to better illustrate the contrast. If cells were conditionally formatted based on values from -1 to 1 there would be no contrast as sentiment fluctuates closely to zero.*

Source: Personal elaboration

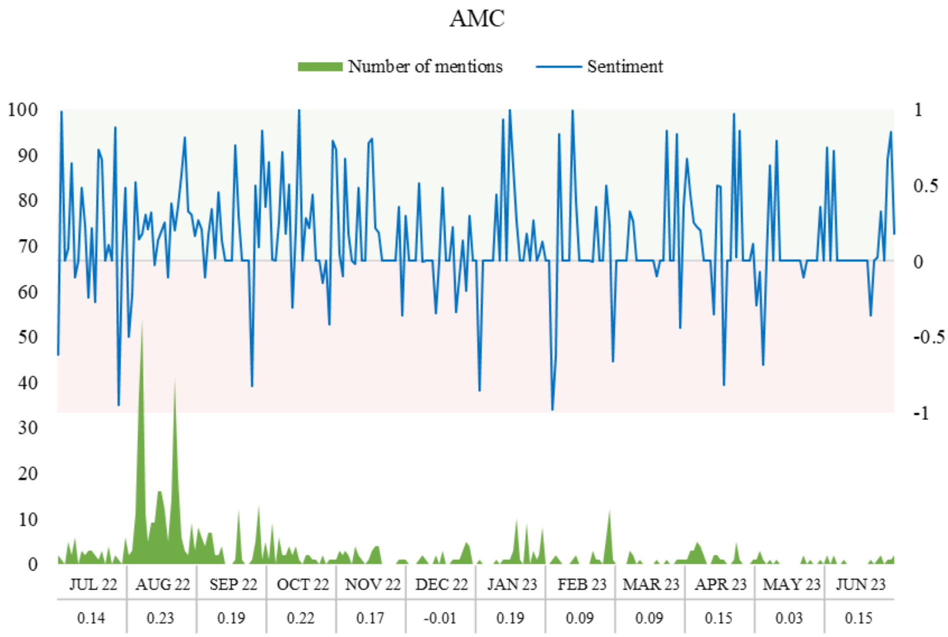
The analysis performed with Valence Aware Dictionary for Sentiment Reasoning model yields daily compound sentiment for each stock in the range from -1 (negative) to 1 (positive). In the course of the sample period analyzed WSB content demonstrates neutrally positive average sentiment fluctuating between 0.04 and 0.14. It can be seen that in second half of 2022 WSB community was more positive regarding the sample stocks, while this year the sentiment is less positive.

On average discussions regarding AMC, AMD and TSLA had more positive tone. Average yearly sentiment towards AAPL, META and NVDA was close to neutral, while GME generated slightly negative discussions in WSB community. The most mentioned TSLA, also had the most consistent positive sentiment in comparison with other stocks in the sample with more positive discussions in the beginning of the sample period. NVDA is also quite consistent in its sentiment but remains in more neutral range than TSLA. In its peak months of mentions GME has received positive sentiment, however with less mentions in the rest of the sample period discussions regarding this stock demonstrate negative sentiment which is the lowest among all stocks in the sample. Interestingly, AAPL that was consistently mentioned throughout the sample period has the most fluctuating average sentiment, let's deep dive in each stock's individual pattern and try to find out what was the reason for sentiment change.

GME and AMC

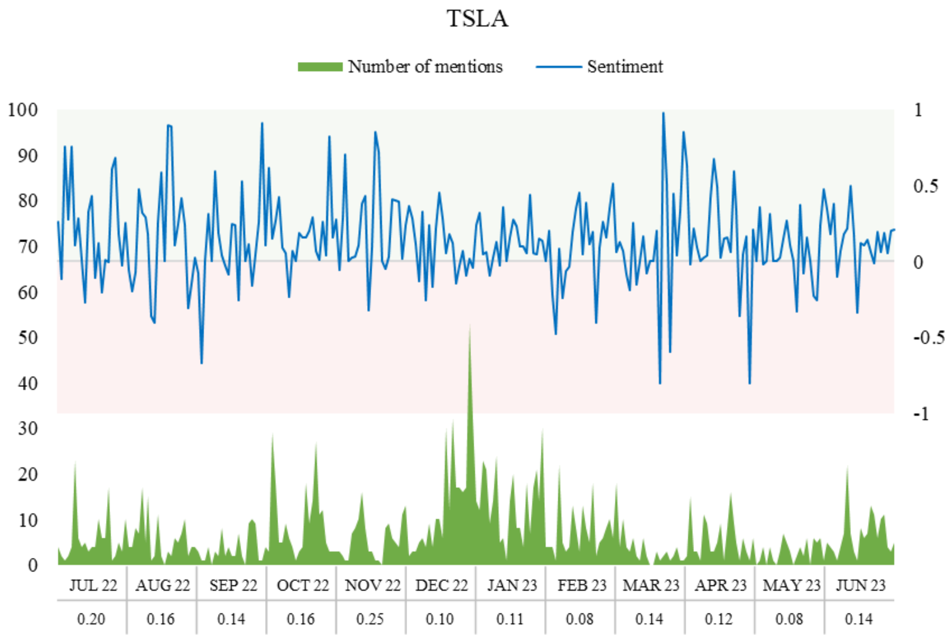


Source: Personal elaboration



Mentions for GME and AMC tickers follow quite similar pattern. Both of the stocks being labelled as meme stocks, the peak of discussion in summer 2022 can be attributed to the aftermath of meme stock events as there were no particular reasons for discussion in financial media environment about these companies. It can be clearly seen that the buzz around meme stocks has diminished significantly since the beginning of 2023.

TSLA

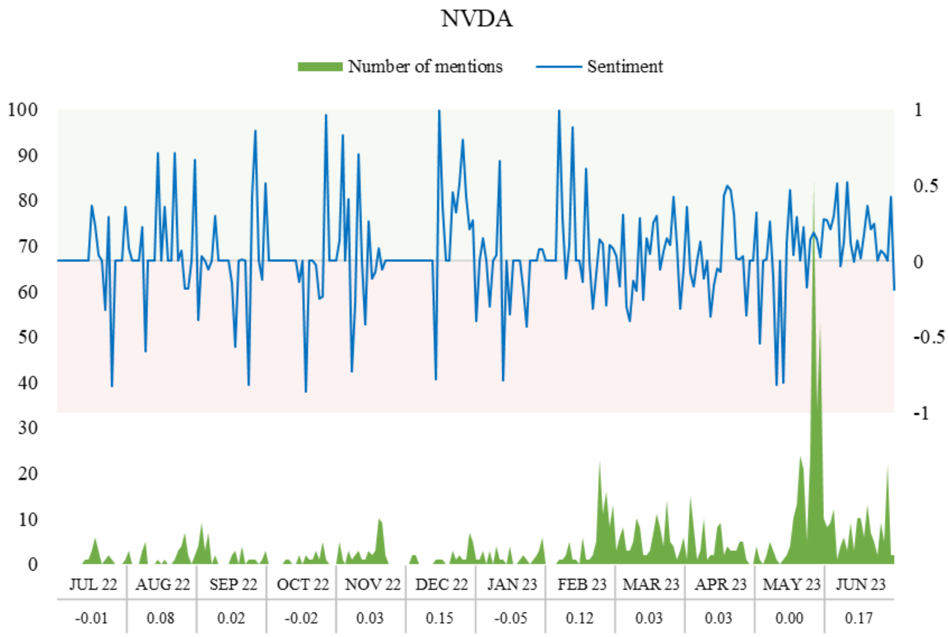


Source: Personal elaboration

As the most mentioned ticker on the platform TSLA has a constant significant discussion throughout the sample period. One of the highest peaks in mentions corresponds with Tesla delivering less vehicles than forecast on 2nd October 2022. This might have implied that Tesla earnings, scheduled for October 19, would also come in below forecasts. However, this anxious forecast did not come to life, the balance sheet of Tesla came to be far more robust than it used to be few years ago, free cash flow hit a record with over 21 billion dollars of marketable securities and cash.

The highest number of mentions was registered in the end of December. The worst week was registered for Tesla since the pandemic, the company has lost $85bn in market value as investors had doubts about Elon Musk's reputation and him running Twitter and Tesla at the same time. Downward pressure on Tesla's stock has intensified in recent months due to increasing concerns about Tesla's upcoming sales. The share price dropped further with 9 per cent decrease after the company announced offering price discounts of $7,500 to US consumers on two of its best-selling models, which further sparked worries over consumer demand on the market.

NVDA



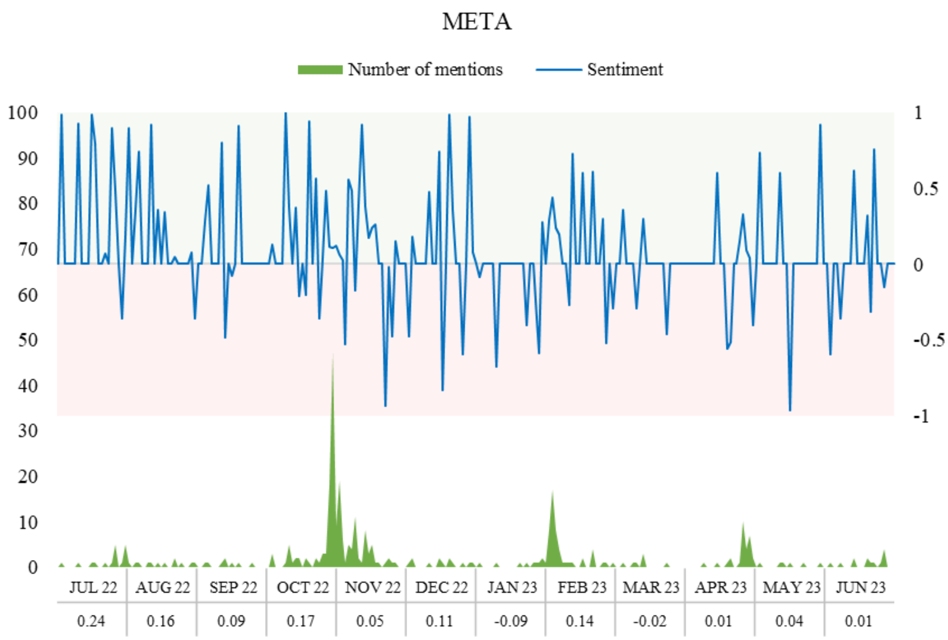
Source: Personal elaboration

In the case of Nvidia Corp. it is interesting to take a look at period from February to June this year as the amount of discussion regarding the company rapidly increases. Mentions first peak on February 23 (23 mentions) and then gain momentum from May 17, reaching the sample period maximum on May 25th (84 mentions).

This increased attention to the company can be attributed to the unfolding battle for AI dominance in the tech industry. As leading manufacturer of graphical processing units (GPUs) used in the training of large AI models Nvidia is a prominent player in the field. Due to increased investor focus in February 2023 the company's share price was already up 55% in 2023 and had been growing since then. ("It's All About the Chips in the AI War," 2023) The first peak in mentions on February 23rd can be explained by the announcement that Nvidia is going to change its business model by directly offering AI services to large corporations and governments, putting it in direct competition with its current clients, major tech companies. ("Nvidia Extends Its AI Ambitions to the Cloud," 2023)

Then on 23rd of May Nvidia has announced a sales forecast of $11 billion for the next three month, triggering 24% increase in its share prices and $184 billion surge in market capitalization. A week later Nvidia became the first chipmaker to reach valuation of $1tn and joined tech titans as Amazon, Alphabet, Apple, Microsoft in the "Trillion-dollar club". ("Nvidia Hits $1tn Market Cap as Chipmaker Rides AI Wave," 2023)

META



Source: Personal elaboration

The amount of discussion regarding META has three key peak periods: late October-November 2022, beginning of February and end of April 2023.

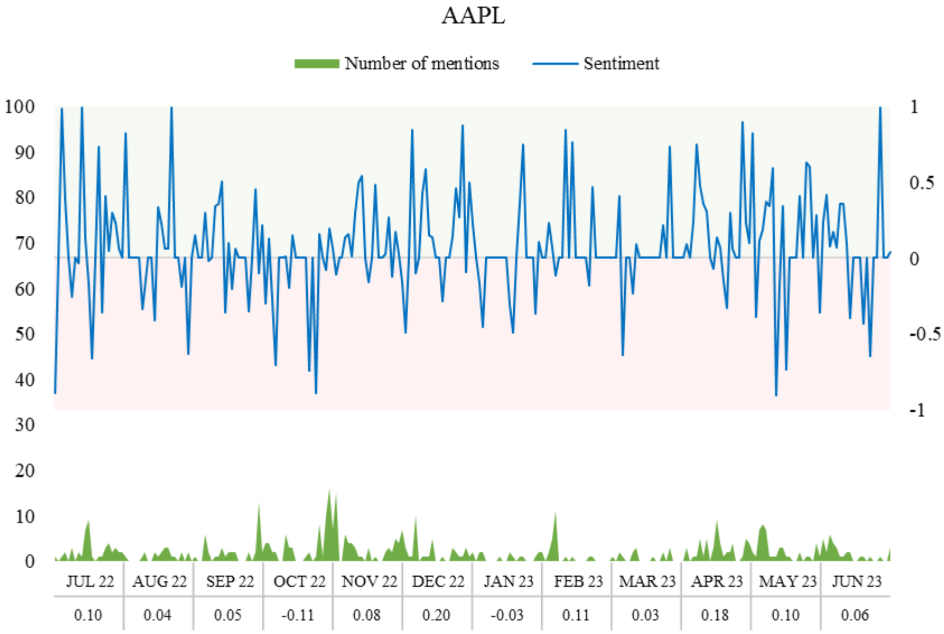
On October 27, 2022, the company experienced a significant setback as its market capitalization plummeted by over $89 billion following a disappointing financial quarter. The company reported declining revenues, which led to a 25% drop in its stock price. Meta attributed these woes to an economic slowdown affecting its advertising business, exacerbated by competition from platforms like TikTok and Apple's privacy policy changes. Investors were concerned about Meta's aggressive spending and its heavy investments in metaverse which is not expected to generate returns in upcoming years in particular. Expenses were projected to remain high, and analysts were raising questions whether Meta can keep the healthy balance between experimental and core business decisions. ("Meta's Value Plunges by $89bn Amid Falling Sales and Rising Costs," 2022)

On the 2nd of February Mark Zuckerberg has declared 2023 the "Year of Efficiency" by announcing Meta's plans to reduce capital expenditures as well as to control operating expenses. This cost-conscious approach was well-received by investors, consequently Meta's stock price has surged by 20% during after-hours trading. Meta could recover $88 billion in market value. (Meta: Taking Spending Back to Reality, 2023)

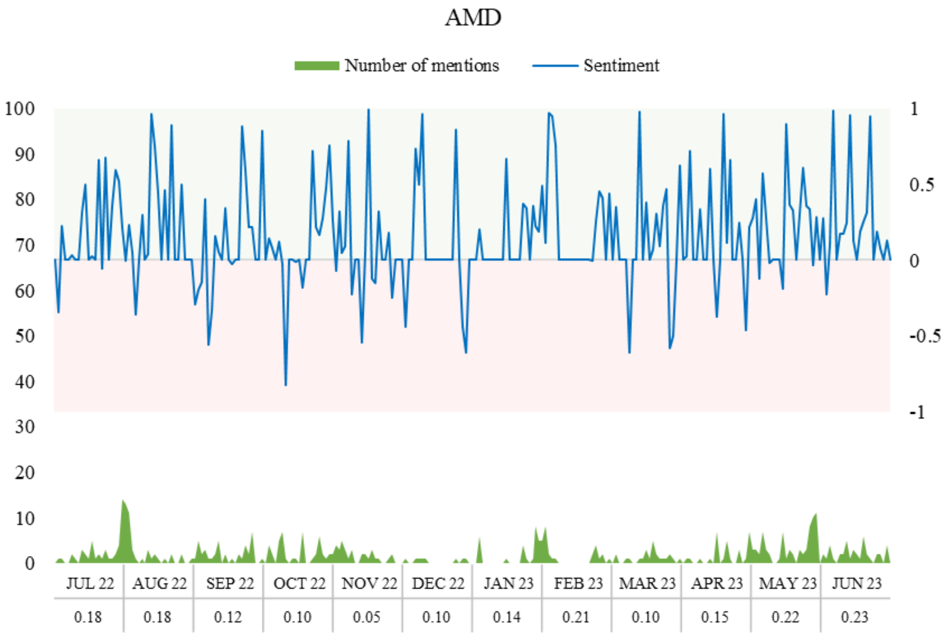
In the end of April Meta Platforms has reported sales growth in the first quarter of 2023, with revenues up 3% to $28.6 billion, beating analyst expectations. The positive performance after three quarters of declining sales boosted META share price by 14%. Mark Zuckerberg mentioned that the success of the quarter can be attributed to new AI-driven recommendations system which increased time spent on Instagram by 24% since launching Reels, a short-form video content that was created to compete with TikTok. (Meta's Revenue Growth Boosts Shares as It Touts AI Progress, 2023)

AAPL and AMD

As it can be seen from the graphs below, the mentions for AAPL and AMD were consistent with no significant peaks throughout sample period. Apple constantly receives attention in mainstream media as the market where it competes is very dynamic, however the attention from WSB community does not fluctuate dramatically. Whereas AMD has less attention in mainstream media and this dynamic is corresponding to WSB activity.



Source: Personal elaboration



Regression results

	AAPL	AMC	AMD	GME	META	NVDA	TSLA
Model Summary							
Multiple R	0.878	0.511	0.782	0.501	0.719	0.810	0.706
R Square	0.771	0.261	0.612	0.251	0.517	0.657	0.498
Adjusted R Square	0.764	0.237	0.599	0.226	0.501	0.645	0.481
Standard Error	0.009	0.060	0.021	0.045	0.025	0.022	0.027
Observations	250	250	250	250	250	250	250
Significance F	8.4E-73	8.3E-13	2.1E-45	4.2E-12	3.6E-34	9.9E-52	3.6E-32
Coefficients							
Intercept	0.0014	-0.0018	-0.0009	-0.0013	0.0035	-0.0010	0.0068
Mkt-RF	1.2269	1.2294	1.1111	0.6878	1.0523	1.3793	0.7237
SMB	-0.1740	0.9925	0.0693	1.5975	0.1337	-0.1387	-0.8068
HML	-0.5567	0.5075	-0.3295	0.3329	-0.9014	-0.2348	1.0919
RMW	0.5364	-2.4661	1.2789	0.0130	1.0915	0.7920	-0.8046
CMA	0.1032	0.8461	-2.4429	-1.5220	0.4096	-2.1828	-3.1249
MOM	0.0026	-1.0106	-0.0014	-0.4454	-0.9630	0.0085	-0.2494
Compound Sentiment	-0.0007	0.0166	-0.0001	0.0050	0.0111	-0.0017	-0.0047
Mentions	-0.0006	-0.0010	0.0008	0.0001	-0.0023	0.0011	-0.0008
Standard Error							
Intercept	0.0007	0.0045	0.0018	0.0033	0.0017	0.0016	0.0027
Mkt-RF	0.0653	0.4316	0.1537	0.3236	0.1781	0.1578	0.1980
SMB	0.1264	0.8447	0.2985	0.6321	0.3474	0.3063	0.3833
HML	0.1097	0.7303	0.2597	0.5468	0.3003	0.2652	0.3318
RMW	0.1296	0.8618	0.3087	0.6448	0.3538	0.3149	0.3965
CMA	0.1811	1.2015	0.4356	0.9004	0.4967	0.4531	0.5512
MOM	0.0818	0.5387	0.1913	0.4052	0.2221	0.1987	0.2466
Compound Sentiment	0.0018	0.0111	0.0043	0.0094	0.0048	0.0047	0.0063
Mentions	0.0002	0.0007	0.0006	0.0002	0.0004	0.0002	0.0003
t Stat							
Intercept	1.9051	-0.3995	-0.4911	-0.3896	2.0665	-0.6232	2.5192
Mkt-RF	18.7749	2.8481	7.2303	2.1255	5.9091	8.7403	3.6543
SMB	-1.3774	1.1749	0.2321	2.5271	0.3848	-0.4527	-2.1047
HML	-5.0771	0.6949	-1.2687	0.6089	-3.0012	-0.8854	3.2904
RMW	4.1402	-2.8617	4.1430	0.0202	3.0847	2.5153	-2.0293
CMA	0.5700	0.7042	-5.6084	-1.6902	0.8247	-4.8173	-5.6695
MOM	0.0318	-1.8759	-0.0074	-1.0992	-4.3367	0.0428	-1.0114
Compound Sentiment	-0.3585	1.4981	-0.0348	0.5305	2.3380	-0.3620	-0.7447
Mentions	-2.6650	-1.5023	1.2759	0.5695	-5.6173	5.5285	-3.1305
P-value							
Intercept	0.0580	0.6899	0.6238	0.6972	0.0399	0.5338	0.0124
Mkt-RF	0.0000	0.0048	0.0000	0.0346	0.0000	0.0000	0.0003
SMB	0.1697	0.2412	0.8167	0.0121	0.7007	0.6512	0.0363
HML	0.0000	0.4878	0.2058	0.5432	0.0030	0.3768	0.0012
RMW	0.0000	0.0046	0.0000	0.9839	0.0023	0.0125	0.0435
CMA	0.5692	0.4820	0.0000	0.0923	0.4104	0.0000	0.0000
MOM	0.9747	0.0619	0.9941	0.2728	0.0000	0.9659	0.3128
Compound Sentiment	0.7203	0.1354	0.9723	0.5963	0.0202	0.7177	0.4572
Mentions	0.0082	0.1343	0.2032	0.5696	0.0000	0.0000	0.0020

Source: Personal elaboration

In this section the results of regression analyses for each stock with excess return being dependent variable are presented.

Significance F values are extremely small in all of the cases which indicates that all seven models are statistically significant. However, the goodness of fit of the models varies in the sample. AAPL – 77%, NVDA – 65% and AMD – 61% have the highest R-squared measure. GME – 25% and AMC – 26% have the lowest R-squared measures, which can be explained by high volatility of the stock, so the regression models explain less significant portion of excess returns, it is interesting to note that specifically these two stocks are considered as most popular meme stocks. The Standard Error measures follow alike pattern as R-squared. AAPL model demonstrated the lowest standard error – 0.009, followed by AMD, NVDA, META and TSLA with Standard Error values fluctuating between 0.021 and 0.027. Standard Error measures for AMC and GME accounted 0.060 and 0.045 respectively.

For AAPL excess returns the amount of discussion is statistically significant and negatively related, meaning that increased number of mentions correspond to decreased returns for Apple. It is also interesting to note that AAPL was mentioned for 455 times, which is almost two times less than average count of mentions on the sample, but the mentions are still significant. TSLA as the most mentioned stock also follows the same pattern as AAPL the number of mentions is negatively correlated with excess returns. The peculiarity in the case of these two stocks is that TSLA has one of the most positive sentiments, while AAPL sentiment was mostly neutral and even negative sometimes. On the other hand, NVDA experiences positive social media impact NVDA: mentions are statistically significant and positively associated with excess returns for NVDA.

The AMC and GME models suggest less robust relationship between excess returns and model factors. Surprisingly neither number of mentions nor the compound sentiment have statistical significance over these stock’s excess returns. This suggests that there might be other factors that are more prominent in AMC and GME performance, most probably it is because of stocks’ high volatility. Through these results we can say that the number of mentions does not correspond to the significance of daily mentions over excess returns.

Alternatively, social media has mixed impact on META excess returns. Both mentions and sentiment are statistically significant, but they have opposite effects. Mentions are negatively related to excess returns, meaning increased discussion on WSB community corresponds with decreasing excess return. On the other hand, positive daily sentiment corresponds with positive excess returns on the same day and visa versa. It is a very peculiar observation as it is expected that mentions usually amplify the effects of compound sentiment, however here we can see that they have two different effects on the performance.

The significance of other market factors also varied for each stockThe daily % return on the Robust-Minus-Weak FF portfolio was the most consistent factor in significance, it was significant for all the stocks in the sample except GME. AAPL, AMD, META, NVDA models exhibited positive coefficients, while AMC and TSLA demonstrated negative correlation with RMW. The daily % return on the Conservative-Minus-Aggressive FF portfolio had a negative correlation with AMD, NVDA and TSLA excess daily returns. The daily % return on the High-Minus-Low FF portfolio effects were mixed, HML demonstrated negative correlation for AAPL and META models, but was positive for TSLA model. The daily return on the Small-Minus-Big Fama-French(FF) portfolio was positively correlated with GME returns, but negatively correlated with TSLA returns. The momentum was only statistically significant for META and had negative coefficient.

In conclusion results show that the impact of social media factors on excess daily returns vary significantly across these stocks, which indicates nuanced and stock-specific effects of social media on asset performance. Even though some stocks like NVDA and META exhibit a notable relationship with WSB activity, others like AMC and GME appear less influenced by it. It was a surprising observation; however, it might further highlight the fact that social media factors require momentum previously uncovered by Costola et al. (2021). These results highlight significance of market factors, compound sentiment, and mentions influence stock returns as the relationship among them is multifaceted and unique for each stock and time period.

Regression results with volume as dependent variable

	AAPL	AMC	AMD	GME	META	NVDA	TSLA
Model Summary							
Multiple R	0.335	0.671	0.410	0.327	0.829	0.481	0.457
R Square	0.112	0.450	0.168	0.107	0.687	0.232	0.209
Adjusted R Square	0.083	0.431	0.141	0.077	0.677	0.206	0.183
Standard Error	2E+07	2E+07	2E+07	5E+06	1E+07	1E+07	5E+07
Observations	251	251	251	251	251	251	251
Significance F	3E-04	1E-27	3E-07	5E-04	9E-57	6E-11	1E-09
Coefficients							
Intercept	7E+07	2E+07	7E+07	5E+06	3E+07	5E+07	1E+08
Mkt-RF	-4E+07	-1E+08	-3E+08	-6E+07	-1E+08	-1E+08	-5E+08
SMB	-2E+08	-4E+07	4E+07	4E+07	-1E+08	-2E+08	5E+08
HML	-3E+07	-1E+07	-4E+07	-1E+07	-6E+07	5E+07	-9E+08
RMW	5E+08	-2E+08	4E+08	8E+07	4E+08	3E+08	1E+09
CMA	5E+08	4E+07	-3E+08	-7E+07	1E+08	-2E+08	1E+08
MOM	-6E+08	-2E+08	-3E+08	-6E+07	-3E+08	-2E+08	-9E+08
Compound Sentiment	-5E+06	4E+06	-1E+06	1E+06	6E+05	-6E+04	-1E+07
Mentions	2E+06	3E+06	4E+06	1E+05	5E+06	9E+05	3E+06
t Stat							
Intercept	39.66	20.22	38.66	12.22	29.87	47.56	23.52
Mkt-RF	-0.23	-1.13	-1.83	-1.47	-1.08	-1.17	-1.39
SMB	-0.68	-0.16	0.15	0.55	-0.71	-0.95	0.78
HML	-0.12	-0.06	-0.15	-0.20	-0.42	0.28	-1.62
RMW	1.55	-0.77	1.47	1.07	2.20	1.46	2.29
CMA	1.13	0.13	-0.83	-0.70	0.45	-0.59	0.16
MOM	-3.09	-1.62	-1.59	-1.32	-2.70	-1.76	-2.30
Compound Sentiment	-1.17	1.17	-0.23	0.87	0.26	-0.02	-1.12
Mentions	4.41	13.34	6.15	4.50	22.19	7.48	6.88
P-value							
Intercept	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Mkt-RF	0.820	0.261	0.068	0.143	0.279	0.243	0.167
SMB	0.495	0.871	0.882	0.586	0.476	0.343	0.436
HML	0.908	0.953	0.881	0.840	0.677	0.781	0.107
RMW	0.122	0.444	0.142	0.287	0.029	0.145	0.023
CMA	0.259	0.900	0.408	0.483	0.655	0.558	0.875
MOM	0.002	0.107	0.113	0.188	0.007	0.080	0.022
Compound Sentiment	0.244	0.241	0.818	0.383	0.797	0.984	0.265
Mentions	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Source: Personal elaboration

In this section the results of regression analyses for each stock with daily trading volume being dependent variable are presented.

Statistical significance of all seven models is closely approaching zero which affirms that all models are robust and meaningful. However, even though adjusted R square measures demonstrate that these regression models are quite efficient in explaining the variability of trading volumes, the measures fluctuate among the stocks with an average of 26% percent which is much lower result compared to regression models for excess returns. This finding shows that the ability of the model to capture trading volume dynamics is less apt than for excess returns dynamics. The model for META has the highest goodness of fit 67% followed by AMC 43%. NVDA and TSLA models explain 20% and 18% of daily volumes respectively, while the models for AMD, AAPL, and GME were the least efficient (14%, 8% and 8%).

As the first set of regressions the trading volumes regression results demonstrate various degrees of statistical significance of the independent variables for each stock. Interestingly, the effects of stock mentions were positively significant for each stock trading volumes, whereas compound sentiment did not exhibit any significance.

META stock mentions exhibited the highest positive coefficient among all models, meaning that more rigorous discussions correlated with higher trading volumes of the stock, it is interesting to note that mentions were negatively correlated with daily excess returns in the first regression. AAPL and TSLA demonstrate similar pattern, but the coefficients are a bit lower for mentions than for META. NVDA model also shows positive relation between mentions and daily trading volumes, which is the same as in the excess return regression.

AMC, AMD and GME models demonstrate positive significant relationship between mentions and trading volumes, even though in the first set of regressions mentions were not statistically significant in explaining excess returns dynamic.

To conclude, similar to the previous analysis, number of stock mentions is more statistically significant in explaining performance of the stocks than compound sentiment, which had no significance in the second set of regressions. Also, it is important to note that overall fit of the chosen model to explain trading volumes is not effective, it can be seen that most of the factors were not statistically significant. Only two Fama-French factors were significant for some of the stocks. The daily % return on the Robust-Minus-Weak FF portfolio is positively correlated with META and TSLA daily volumes, while the daily % return on the Momentum FF portfolio was negatively correlated with APPL, META and TESLA.

Discussion and Conclusion

The results of this thesis work reveal varying effects of WSB community sentiment and mentions on daily excess returns and trading volume of stocks: AAPL, AMC, AMD, GME, META, NVDA and TSLA. The influence of social media factors appears to be multifaceted and unique for specific time periods and each stock in the sample. All of the regression models were statistically significant and had good fit in predicting excess returns and trading volume of the sample. Stocks like NVDA and META, exhibit notable relationship with the dynamics on WSB community, while others, like GME and AMC appear less influenced which was very surprising given their involvement in meme stock frenzy.

The influence of mentions on stock performance is stronger compared to the compound sentiment for both excess returns and trading volumes. This result is in line with Nakstad and Hasle (2022) and Long et al. (2023), but less prominent than in the study of Hu et al (2021) and Cuvelier (2022) which can be attributed to the different sample periods of the studies.

Notably, the number yearly of mentions did not consistently correspond to the significance of daily mentions on excess returns. This suggests that mentions of the stock ticker should be consistent throughout the whole period (previously discussed “mementum” in Costola et al. (2021)) and that other factors like the fundamentals of the stock may amplify the effects of social media factors. For instance, even though GME was second topmost mentioned stock on WSB community, the mentions were concentrated in the end of 2022 with no further momentum leading to no statistical significance of social media factors on asset performance. (AMC follows similar pattern with fewer mentions)

Additionally, this indicates a clear difference between the results of “classical” meme stocks like AMC and GME and other non-meme, but popular stocks in the sample, corresponding with the findings of Gianstefani et al (2022). From this finding it can be derived that the GameStop frenzy had fully come to its end by the beginning of 2023, but the potential of investor sentiment to affect financial markets is still prominent on the example of the other stocks like META, NVDA and TSLA.

Taking all the points into consideration it can concluded that, the results demonstrate an ever changing and intricate nature of financial markets and how behavioral factors such as investor sentiment play out significantly on asset performance. However, one should be always aware of the research limitations, there are several assumption and technical limitations faced by this thesis work:

- The reverse causality issue is the most significant limitation as it is almost impossible to avoid it since closed environment cannot be created in this research field. Therefore, in the attempt to decrease the bias of reverse causality I have included major events in the market linked to particular stocks which can give impulse for the dynamic change among WSB community members.
- From May 2022 direct data scraping with Reddit API became unavailable. Therefore, WSB content database was collected starting from Q2 2022 using automated scraper. This limitation affected the sample period as it was not possible to obtain earlier data from 2021 to compare it with last year. Moreover, the quality of database is high as it was obtained with automated process, but since it is retrieved from the open source it might have some errors.
- Data processing included reprogramming VADER library in RStudio to ensure better fit of the library to the specific language used in WSB community. Since the reprogramming was done manually, I could have omitted some additional important words that I was not aware of. This might be a reason of less significance of the compound sentiment.
- Moreover, the study was focused on the WSB content that included stock tickers of the sample companies, however it was not possible to link comments which do not include the stock ticker but were posted as replies to a post or a comment that mentions the stock ticker. Unfortunately, there is no such process that makes including additional comments possible except manual data processing that has time and human factor limitations.

Taking into consideration the limitations there is a vast potential for the future research: extending the sample period might reveal deeper insights into the relationship between social media sentiment and asset performance and its evolution over time. Moreover, a greater study that encompasses all of the social platforms that are popular among retail investors would reveal even more groundbreaking results for understanding the human factor in the functioning of financial markets. Even though a completely closed environment cannot be created for behavioral finance studies, adding generalist social media platforms would significantly improve the accuracy of the results. Additionally, it would be interesting to include Robinhood application into the research as this app is the most popular among retail investors and studying user behavior on this app could bring additional layer of significance to the study.

This study contributes to behavioral finance underlining growing effects of social media platforms on retail investing and broader markets' performance and efficiency. From the practitioners-investors' point of view, I believe the results of this study are cautionary. Even though findings demonstrate significant statistical relation between social media factors and asset performance, varying results across the stocks highlight the fact that financial decision making should be backed up with knowledge of the markets, rigorous analysis, and critical thinking. Individual investors can get support and sense of belonging as well as learn more about investing in communities like WSB, but they should always do their own due diligence research and think critically as retail investing involves high levels of risk. Alongside with investors, policy makers should also stay alert regarding meme stocks due to their structural uniqueness in price formation and potential to destabilize financial markets, as accelerating segment of retail investing already requires regulations on emerging financial technologies and social aspects of trading.

So, meme stocks are here to stay? GameStop meme stock frenzy is an example of a perfect storm. Perhaps, there will not be an exact event like that anymore, but it has changed the landscape of financial markets once and for all. Meme stocks will remain a relevant phenomenon until humans seize taking investment decisions.

Appendix

R-studio algorythm:

1. Downloading WSB content from the dataset: https://www.kaggle.com/datasets/gpreda/wallstreetbets-2022

Cleaning the data in excel removing unnecessary columns (score, URL, user_id), selecting the sample period July 1, 2022 – June 30, 2023. * All excel calculations are available on request

2. Using RStudio to find and assign the stock tickers to the posts/comments using NASDAQ Stock Screener ticker list, count the mentions of the stocks and find the top 7 mentioned stocks, filter out the sample with the WSB content. Shortened code below:

```
library(tidyverse)
library(tidyquant)

#wsb contents
wsb <- read.csv("~/datasets/dataset1.csv")

#stock tickers from NASDAQ
stocks <- read.csv("~/datasets/nasdaq.csv")

#unting datasets
reg_expression <- regex(paste0("\\b(?:",
                               paste(stocks$Symbol, collapse = "|"),
                               ")\\b"))

wsb_mentions <- wsb %>%
  mutate(stock_mention = str_extract(text, reg_expression)) %>%
  unnest()

#removing false positives
fp <- c("RH", "DD", "CEO", "IMO", "EV", "PM", "TD", "ALL", "USA",
        "IT", "NA", LETTERS )

Top7 <- wsb_mentions_count %>%
  group_by(stock_mention) %>%
  summarise(n = sum(n)) %>%
  ungroup() %>%
  arrange(-n) %>%
  filter(!(stock_mention %in% fp)) %>%
  head(7) %>%
  pull(stock_mention)
```

```
#saving the processed data for each top 7 ticker
STOCK EXAMPLE  <- wsb_mentions %>%
  filter(stock_mention == "STOCK EXAMPLE") ( AAPL, AMC, AMD,
GME, NVDA, META, TSLA)
```

3. 7 csv files that contain all WSB content mentioning the ticker are obtained and merged together. As users can post or comment on WSB at any day of the week, it is important to reassign the date of the posts that were done on weekends and holidays for the next trading day using Excel with the help of Fame-French dataset.
4. Using RStudio Vader library sentiment analysis is performed (shortened code):

```
library(tidyverse)
library(vader)

# reprogramming Vader for WSB specific lexicon
load("~/Vader files/vader/R/sysdata.rda")

# reprogramming Vader for WSB specific lexicon
wsbLexicon <- bind_rows(tibble(V1 = c("retard", "retarded", "fuck",
"fucking", "autist", "fag", "gay", "stonk"), V2 = 0, V3 = 0.5),
                        tibble(V1 = c("bull", "bullish", "tendie", "tendies", "call",
"long", "buy", "moon", "hold",
                                      "diamond", "hands", "yolo", "yoloed", "free", "btfd",
"rocket", "elon", "gain",
                                      "420", "calls", "longs", "sky", "space", "roof",
"squeeze", "balls"), V2 = 1.5, V3 = 0.5),
                        tibble(V1 = c("bear", "sell", "put", "short", "shorts", "puts",
"bagholder", "wife", "boyfriend",
                                      "shorting", "citron", "hedge", "fake"), V2 = -1.5, V3 =
0.5))

# add back to lexicon
vaderLexiconWSB <- vaderLexicon %>%
  as_tibble() %>%
  # anti_join(wsbLexicon, by = "V1") %>%
  filter(!(V1 %in% wsbLexicon$V1)) %>%
  bind_rows(wsbLexicon) %>%
  as.data.frame()

vaderLexicon <- vaderLexiconWSB
save(vaderLexicon, file = "~/Vader files/vader/R/sysdata.rda")

# remove the vader package and reinstall
detach("package:vader", unload = T)
```

```
remove.packages("vader")
install.packages("~/Vader files/vader", repos = NULL, type = "source")
library(vader)

# sentiment analysis

totalsample <- read.csv("~/datasets/totalsample.csv")
totalsample_sentiment <- totalsample %>%
  select(text) %>%
  distinct() %>%
  mutate(text_clean = str_replace_all(text, "\\\\", " ")) %>%
  mutate(sentiment = vader_df(text_clean)$compound)

final_sentiment <- totalsample %>%
  left_join(totalsample_sentiment %>% select(-text_clean),
            by = "text")

final_sentiment_count <- final_sentiment %>%
  group_by(date, stock_mention) %>%
  summarise(sentiment = mean(sentiment),
            n = n())

write.csv(final_sentiment_count, file = "final_sentiment_count.csv")
```

The obtained file contains the date, number of mentions and compound sentiment for the day for the specific stock

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