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Social Media-Driven Trading and Market Outcomes: An Empirical Analysis of U.S. Meme Stocks 2020-2025

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M

2026

FACULDADE DE **ECONOMIA**

SOCIAL MEDIA-DRIVEN TRADING AND MARKET OUTCOMES: AN EMPIRICAL ANALYSIS OF U.S. MEME STOCKS 2020-2025

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Dissertation
Master in Finance

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2026

Biographical Note

Alexandra Barros was born in June 2003 in Paredes. From a very young age, she demonstrated an interest in numbers and a genuine desire to help others, a combination that would shape both her personal and professional journey.

In 2021, Alexandra enrolled in the Bachelor's Degree in Management at the School of Economics and Management (FEP) of the University of Porto. Driven by a desire to deepen her knowledge of finance and further develop her academic background, Alexandra applied to the Master in Finance at the same institution, beginning in September 2024.

Alongside her academic journey, Alexandra attended the Conservatório de Dança do Vale do Sousa, where she also volunteered as a dance instructor. This experience allowed her to develop essential competencies such as organization, time management, teamwork, and resilience, qualities that have helped shape her approach to both academic and professional challenges.

These experiences, which embrace academic rigor and artistic discipline, have allowed Alexandra to recognize that true success comes from combining technical excellence with strong interpersonal skills and that the most meaningful contributions arise where analytical thinking meets human connection.

She is beginning her professional career at Deloitte as an Audit Analyst, starting in September 2026.

Acknowledgements

This dissertation represents the culmination of one more stage in my academic trajectory. This entire journey has been marked by ups and downs; it has been a challenging and demanding process, but also an enriching one, allowing me to grow both personally and professionally. My ambition and dedication, along with the generous support of all those who, directly or indirectly, contributed to the completion of this dissertation, have made this path possible.

First of all, I would like to express my sincere gratitude to Professor Júlio Lobão for his guidance and support, his constant availability, and all the advice and suggestions that enriched this work at every stage.

I would also like to thank all the professors from whom I had the privilege of learning and who have guided me throughout this academic journey.

I would like to extend my deepest appreciation to my family for their daily love, unconditional support, and for never ceasing to believe in me. To my mother, for her constant encouragement, endless patience, and for always finding the right words when I needed them most. To my sister, for her ever-present support and for being my strength during the most difficult days. To my "family of the heart", who, amid the busyness of these days, knew how to ease every moment of discouragement with a smile and a hug.

I would also like to thank my friends, who have been by my side throughout this journey. Through countless study sessions, companionship, and mutual support, they made this path lighter, more rewarding, and truly memorable.

Finally, I would like to express my heartfelt gratitude to my boyfriend, who holds a very special place in my heart. Thank you for your kindness, encouragement, and for believing in me, even when I doubted myself. Thank you for listening to every doubt and concern, and for always finding the right words to help me recover and move forward. Thank you for being there every day and for making my days lighter and more beautiful.

To conclude, I would like to share a quote that has stayed with me my whole life: "*Those who cross our paths do not go alone; they do not leave us alone. They leave a little of themselves behind and take a little of us with them.*"

Abstract

A growing debate in financial economics concerns the extent to which social media platforms and retail investor coordination can generate persistent market distortions, challenge market efficiency, and amplify speculative dynamics. Technological innovations, including commission-free trading applications and communications, such as the Reddit forum r/WallStreetBets, have transformed the way retail investors access financial markets, exchange information, and coordinate trading strategies. These dynamics became evident during the GameStop short squeeze in January 2021, a particularly notable episode of meme stock volatility. Meme stocks are equities that have gained popularity primarily through social media, exhibiting distinct patterns in price dynamics, trading volume, and online activity (Costola et al., 2021).

Through an empirical analysis of U.S. meme stocks during 2020-2025, this dissertation investigates the relationship between social media activity and stock market dynamics, contributing to the literature on behavioral finance, investor sentiment, and retail-driven trading behavior.

The empirical analysis combines financial market data from Refinitiv with Reddit-based indicators of investor attention and sentiment to examine the impact of online discussions on stock returns, volatility, and relative trading activity. Panel regression models are employed to analyze both contemporaneous and predictive relationships between social media activity and market outcomes, as well as VAR models with Granger causality tests. Additionally, a Difference-in-Differences framework is estimated to determine the causal impact of the GameStop episode on meme stock dynamics.

The results reveal that lagged social media activity is positively associated with meme stock returns, with sentiment and post volume statistically significant. The outcomes point to a substantial increase in trading intensity and volatility during the GameStop episode compared to the control group, while the effect on returns appears transitory and is followed by a reversal pattern, in line with speculative trading dynamics and noise trader behavior. The findings have relevant implications for market efficiency, financial regulators, and investors.

Keywords: Meme Stocks, Social Media Sentiment, Retail Investors, Market Efficiency, Behavioral Finance, GameStop.

JEL-Codes: C21, C23, D83, G12, G14, G41.

Resumo

Um debate crescente na economia financeira centra-se no papel das redes sociais e na coordenação entre investidores na criação de distorções no mercado, colocando em causa a eficiência e amplificando dinâmicas especulativas. As inovações tecnológicas, i.e., aplicações de negociação sem comissões e fóruns online como o *r/WallStreetBets* do Reddit, transformaram a forma como os investidores acedem aos mercados financeiros, partilham informação e coordenam estratégias. Estas dinâmicas tornaram-se evidentes durante o *short squeeze* da *GameStop*, em janeiro de 2021, um episódio notável de volatilidade nas ações *meme*, que ganharam popularidade através das redes sociais e revelaram padrões distintos na dinâmica dos preços, volume de negociação e atividade online (Costola et al., 2021).

Através de uma análise empírica das ações *meme* dos EUA entre 2020 e 2025, esta dissertação investiga a relação entre a atividade nas redes sociais e a dinâmica do mercado bolsista, contribuindo para a investigação em finanças comportamentais ao analisar a interação entre sentimento e comportamento dos investidores.

A análise empírica combina dados financeiros do Refinitiv com indicadores do Reddit para examinar o impacto das discussões online nos retornos, volume e volatilidade. São utilizados modelos de regressão de painel e modelos VAR com testes de causalidade de *Granger* para analisar as relações contemporâneas e preditivas. Aplica-se ainda a metodologia diferenças-em-diferenças para estimar o impacto causal do episódio da *GameStop*.

Os resultados revelam que a atividade nas redes sociais, com um desfasamento temporal, está positivamente associada aos retornos, sendo o sentimento e o volume de publicações estatisticamente significativos. Observa-se um aumento no volume de negociação e na volatilidade durante o episódio da *GameStop*, face ao grupo de controlo, enquanto o efeito nos retornos é temporário e seguido de reversão, consistente com o comportamento dos investidores não informados. As conclusões têm implicações relevantes para a eficiência do mercado, reguladores e investidores.

Palavras-Chave: *Meme Stocks*, Sentimento nas Redes Sociais, Investidores de Retalho, Eficiência de Mercado, Finanças Comportamentais, *GameStop*.

JEL-Codes: C21, C23, D83, G12, G14, G41.

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1. Introduction

Recent developments in digital communication technologies have fundamentally altered how financial information is produced, disseminated, and interpreted by investors (Blankespoor et al., 2014; Shiller, 2017). Traditional frameworks assume that market prices reflect available information and rational decision-making (Fama, 1970). However, the rapid expansion of online communication platforms has created new channels through which information, opinions, and narratives spread rapidly among investors (Shiller, 2017). In this environment, social media platforms, such as Reddit, X, and Stocktwits (Tetlock, 2007), allow retail investors to exchange ideas and coordinate trading strategies in real time, influencing short-term market dynamics (Barber et al., 2022; Cookson et al., 2022) and speculative activity (Hong et al., 2004). This shift provides the central motivation for the present research on how social media-driven sentiment can challenge traditional market efficiency assumptions.

The growing importance of social media is also reflected in its global diffusion, with more than 5.44 billion users worldwide and an increasing role in shaping collective opinions (Statista Research Department, 2026). Among these platforms, Reddit stands out, with more than 500 million registered accounts and approximately 121 million daily active users across thousands of discussion communities known as subreddits (Reddit, 2025; Thuy, 2026a; Thuy, 2026b). Its community-based structure facilitates decentralized information exchange and collective decision-making, making it particularly relevant for studying investment behavior in digital environments (White, 2019). Münster et al. (2024) show that Reddit posts significantly influence investors' behavior, with stronger effects than traditional news articles.

These platforms have gained particular relevance during episodes of market turbulence, most notably the GameStop episode in 2021 (Cookson et al., 2024). The episode drew significant attention to "meme stocks," defined as stocks with unusually high levels of online attention and retail investor participation, often exhibiting price fluctuations disconnected from fundamentals (Nobanee & Ellili, 2023). During this period, coordinated retail trading, amplified by social media activity, led the stock price to increase by approximately 140% in a single trading day (Costola et al., 2021), raising crucial questions regarding potential distortions in price formation, volatility dynamics, and market efficiency (Allen et al., 2025).

Structural changes in financial markets have lowered barriers to retail participation. Declining transaction costs, technological advances (Kang et al., 2025), globalization (Haddad, 2023), and commission-free trading platforms (Ozik et al., 2021) have enabled greater retail investor participation, which now exceeds 20% of the United States (U.S.) market volume (Tabb, 2021, as cited in Münster et al., 2024). Combined with social media coordination, these changes contributed to the emergence of meme stocks. Their price dynamics are often driven more by online attention and sentiment rather than fundamentals, introducing new layers of complexity into financial markets, as online discussions amplify behavioral biases, herding, and speculative trading dynamics (Barber et al., 2022; Pandey & Guillemette, 2024).

Despite extensive research on investor sentiment and stock price dynamics, existing studies often rely on aggregate sentiment indicators while paying less attention to interaction dynamics within online discussions (Al-Badawi, 2024; Lee et al., 2025; Li et al., 2023; Lopez-Lira, 2024). In particular, the interplay among online attention, sentiment intensity, and user engagement in shaping meme stock dynamics remains underexplored. Addressing this gap is essential for understanding how digital communication influences price formation and market efficiency in contemporary financial markets.

In this context, this dissertation investigates the relationship between social media activity and stock market dynamics, using a sample of U.S. meme stocks from 2020 to 2025. The U.S. market provides a suitable empirical setting due to data availability and the prominence of recent speculative episodes (Nobanee & Ellili, 2023). The empirical analysis uses financial market data obtained from Refinitiv, while indicators of online activity and investor sentiment are constructed from Reddit discussions, particularly those originating from the r/WallStreetBets (WSB) community. The study examines whether variations in online engagement, including posts, comments, mentions, and sentiment indicators, are associated with short-term variations in returns, volatility, and trading intensity, measured by share turnover, and whether social media activity challenges traditional assumptions of market efficiency and rational investor behavior (Fama, 1970; Shiller, 2017).

To address these questions, the empirical analysis combines three complementary econometric approaches. First, fixed-effects panel regressions are employed to examine the relationship between Reddit activity and daily stock returns. Second, vector autoregressive (VAR) models and Granger causality tests are implemented to explore dynamic interactions and potential feedback effects between social media activity and market variables. Finally, the January 2021 GameStop short squeeze is treated as a quasi-natural experiment, using a difference-in-differences (DiD) methodology. By comparing meme stocks with a control sample of non-meme stocks before and after the event, this method isolates the event's impact on market outcomes, while controlling for overall market conditions and the firm-specific characteristics that remain constant over time.

The main objectives of this dissertation are the following: (i) to analyze the relationship between social media activity and short-term movements in the meme stock market; (ii) to examine whether online engagement and sentiment precede changes in returns, volatility, and trading intensity or, conversely, whether they primarily react to market movements, thereby revealing a potential feedback loop between online discussions and market outcomes; (iii) to assess whether social media influence challenges traditional assumptions about market efficiency; and (iv) to contribute to behavioral finance literature by integrating sentiment analysis with financial market data in a social media context. In pursuit of these objectives, it is anticipated that peaks in online activity will be associated with increased volatility and trading intensity. The sentiment and engagement dynamics of online discussions may contribute to temporary pricing inefficiencies and short-term reversals.

The empirical results provide evidence that social media activity is significantly associated with short-term price movements in meme stocks. Specifically, lagged indicators of engagement and sentiment on Reddit can predict returns and trading intensity. A strong increase in volatility and turnover intensity was observed during the GameStop episode, compared to the control group (non-meme stocks), consistent with the heightened speculative trading. However, the effect on stock returns proved to be temporary, with signs of subsequent reversal patterns. Overall, there is a feedback loop between online attention and market dynamics, which can potentially undermine market efficiency.

Following the introduction chapter, the remainder of the dissertation is organized as follows. Chapter 2 reviews the literature on meme stocks, investor sentiment, behavioral finance foundations, and natural language processing techniques. The following chapter presents research questions and hypotheses. Chapter 4 describes the data collection process and the methodology employed. Chapter 5 outlines the empirical results and their interpretation. Lastly, Chapter 6 summarizes the findings and conclusions, discusses limitations, and identifies avenues for future research.

2. Literature Review

This chapter provides a comprehensive review of the literature relevant to the present study, examining the relationship between social media activity, investor behavior, and meme stock dynamics. The objective is to establish a theoretical and empirical framework by bringing together prior research on investor sentiment, social media engagement, and their effects on price movements, volatility, and relative trading activity.

The chapter is organized as follows. The first section defines meme stocks and describes the criteria used to identify them. The second section reviews the behavioral finance principles underlying investor sentiment. The third section discusses investor heterogeneity and financial literacy. The fourth section explains methods for measuring social media sentiment, while the fifth section explores natural language processing (NLP) techniques applied to financial texts. Finally, the sixth section analyzes the relationship between social media activity and financial market outcomes.

2.1. Definition of Meme Stocks

Meme stocks refer to equities whose price dynamics are primarily driven by online attention, coordinated sentiment, and collective behavior on social media platforms (Li & Li, 2026). Unlike institutional investors, who evaluate stocks through formal portfolio risk frameworks, retail investors involved in meme stocks frequently base their decisions on online discussions and prevailing digital narratives to "feel the mood" of the market (Costola et al., 2021). This behavior aligns with the concept of noise traders, whose expectations are shaped by sentiment rather than fundamental information, leading them to be more reactive to market rumors and online discussions (De Long et al., 1990a).

A central feature of the meme stocks phenomenon is the role of social media as a coordination device (Nobanee & Ellili, 2023). Digital platforms, such as Reddit, have become critical spaces where retail investors share information, narratives, insights, and investment strategies in real time (Costola et al., 2021). Memes, short messages, and emotionally charged content synchronize buying signals and facilitate the rapid diffusion of investment ideas among dispersed retail traders (Shiller, 2017). In this context, Costola et al. (2021) introduce the concept of *mementum* to describe periods in which sustained, positively correlated online engagement yields abnormal returns, thereby distinguishing coordinated sentiment from general social media activity.

Beyond their online visibility, meme stocks are characterized by the social dynamics that drive broader investor participation. Financial market participation is often stimulated by social interaction, as investors are influenced by the behavior and opinions of their peers (Hong et al., 2004). Word-of-mouth communication plays a pivotal role in investment decisions, shaping expectations and stimulating new market entry (Brown et al., 2008; Hong et al., 2005). In digital environments, these dynamics are considerably amplified, enabling information and investment narratives to spread rapidly across large networks of retail investors.

Since investors consider others' opinions, herding behavior is especially relevant to explaining meme stock dynamics (Banerjee, 1992). Herding refers to investors' tendency to imitate others' actions while disregarding their own private information, particularly in environments characterized by uncertainty and limited information signals (Christie & Huang, 1995). This collective behavior can generate temporary deviations from intrinsic value and increased volatility (Kremer & Nautz, 2013). Wermers (1999) further argues that herding is more likely to occur among smaller firms, where limited information availability forces investors to make decisions in ambiguous environments, conditions that are common in meme stocks.

According to the literature, the universe of meme stocks in this study is operationalized along three main dimensions. The first concerns social attention, referring to stocks that exhibit abnormal spikes in mentions, shares, engagement, and discussion intensity in online forums such as r/WallStreetBets (WSB) (Nobanee & Ellili, 2023). The authors find that these spikes are not merely temporary popularity shocks; rather, they are systematically correlated with considerable increases in trading volume, reflecting the capacity of digital communities to mobilize investor participation.

The second dimension captures extreme deviations in price and volume that are not justified by corresponding changes in firm fundamentals (Aloosh et al., 2022; Long et al., 2022). The literature describes these atypical variations as temporary speculative bubbles, driven by herd behavior, feedback loops, and collective reinforcement among retail investors (Abreu & Brunnermeier, 2003; De Long et al., 1990b). Moreover, these deviations often persist for several days, generating abnormal momentum that is inconsistent with fundamentals-driven markets (Xiong & Yu, 2011).

Finally, the third dimension focuses on strong retail participation and collective behavior, identifying stocks whose dynamics are driven primarily by coordinated trading among online retail investors (Nobanee & Ellili, 2023). Collective action is facilitated by digital communities, where emotional narratives encourage implicit coordination and amplify the influence of retail investors on price dynamics.

These criteria are supported by prominent meme stock episodes, such as GameStop and AMC Entertainment, which illustrate that even for financially stable companies, concentrated buying pressure from online communities can produce significant and persistent deviations in both price and trading volume (Costola et al., 2021). Taken together, these three dimensions provide an operational framework for defining the meme stock universe employed in this study.

2.2. Investor Sentiment and Behavioral Finance Foundations

Traditional asset pricing frameworks assume that financial markets are informationally efficient, meaning that asset prices fully reflect available information and accurately represent fundamental value (Fama, 1970). Within this paradigm, investors are modeled as rational agents who maximize expected utility by optimally evaluating risk-return trade-offs (Ruscitti et al., 2023), and investment decisions are conceptualized as purely monetary trade-offs between profits and losses (Mathews, 2013).

However, the persistence of speculative bubbles and recurrent market anomalies challenges the assumption of full rationality, indicating that behavioral factors can generate systematic mispricing (Baker & Wurgler, 2007). As argued by Hirshleifer (2002) and Shiller (1999), investor behavior frequently deviates from purely rational decision-making. Behavioral Finance, which gained prominence in the early 1980s, addresses these limitations by incorporating psychological and emotional factors into the analysis of financial decision-making (Shiller, 2003). Bodie et al. (2021) demonstrate that investors often deviate from rationality, misled by cognitive biases, emotional reactions, and heuristic-driven judgments, so that financial decisions are influenced not only by objective information but also by cognitive, motivational, and emotional dynamics (Mathews, 2013). Jain (2012) further emphasizes the importance of studying these human behavioral processes, since cognitive distortions can lead investors to systematic errors in stock selection.

Building on this criticism, Mathews (2013) proposes the *Deficient Market Hypothesis*, which claims that asset prices do not fully reflect all available information, investors are not entirely rational, and psychological factors can cause temporary deviations from fundamentals and excessive volatility. These circumstances align with dynamics observed in meme stocks.

Baker and Wurgler (2007) identify two primary mechanisms by which investor sentiment affects asset prices. First, sentiment directly shapes the trading decisions of non-rational investors, whose expectations are influenced by emotions and biased beliefs, instead of fundamentals (Kahneman & Tversky, 2013). Second, limits to arbitrage prevent rational investors from fully correcting mispricing, since betting against sentiment-driven movements is risky, costly, and uncertain (Barberis et al., 1998). These mechanisms are particularly relevant for speculative or hard-to-value stocks, being more exposed to sentiment fluctuation (Barber & Odean, 2008; Tetlock, 2007). Baker and Wurgler (2007) further show that younger, highly volatile, growth-oriented, or financially distressed firms are disproportionately affected by aggregate sentiment waves, characteristics that align directly with those commonly observed in meme stocks.

The literature also distinguishes between bottom-up and top-down approaches to sentiment analysis (Baker & Wurgler, 2007). On the one hand, the bottom-up approach focuses on individual biases, such as overconfidence, representativeness, and conservatism, to explain investor underreaction and overreaction to past returns or fundamentals (Barberis et al., 1998; Daniel et al., 1998). On the other hand, the top-down approach examines aggregate market sentiment and identifies which types of stocks are most exposed to sentiment fluctuations (Baker & Wurgler, 2007).

Among individual cognitive biases, overconfidence plays a particularly prominent role. Gervais and Odean (2001) argue that overconfidence is not merely a fixed psychological trait but a learned behavior, as investors infer their own abilities from past trading outcomes. According to the authors, early success, even when driven by randomness, leads investors to overestimate their skill, underestimate risk, and trade more aggressively. This excessive confidence increases volatility and trading intensity, causing temporary deviations from fundamental values. Such dynamics are particularly visible in contexts where viral narratives and highly visible success stories reinforce availability bias and encourage aggressive trading behavior, as documented in meme stock communities (Gervais & Odean, 2001).

Emotional states and moods also shape investment behavior (Hirshleifer, 2002). Positive emotions tend to increase risk tolerance, while negative emotions amplify defensive and risk-averse reactions (Mathews, 2013). These dynamics are especially relevant in social media environments, where narratives and emotionally charged content can intensify collective responses that may precede market movements or merely reflect them (Mathews, 2013).

Empirical studies confirm the relevance of these behavioral mechanisms in digital contexts. Zhao et al. (2023) demonstrate that online sentiment and attention significantly influence investor reactions, particularly for assets with high information asymmetry or weak fundamental signals. In such situations, sentiment acts as a cognitive shortcut that amplifies price sensitivity and momentum-driven trading, an effect that is especially pronounced in meme stocks, where sentiment often serves as the primary trigger for investment decisions. Periods of greater uncertainty further intensify these behavioral patterns, as retail investors exhibit stronger biases and rely more on heuristics, resulting in more impulsive trading (Ahadzie et al., 2025). Under these conditions, social influence becomes particularly powerful, as investors seek peer guidance and align with the dominant sentiment in online communities (Warkulat & Pelster, 2024). Evidence from r/WallStreetBets indicates that peaks in user engagement drive higher risk-taking and larger positions in volatile stocks, often yielding negative short-term returns despite bullish market conditions (Warkulat & Pelster, 2024). Emotional expressions, such as anger and excitement, appear to exert a stronger influence on trading behavior than analytical advice, reinforcing the emotionally driven nature of meme stock dynamics (Lee et al., 2025; Wang, 2025).

All things considered, investor sentiment operates not only as a descriptive measure of investor attitude but as an active mechanism shaping price formation, volatility, and relative trading intensity, a perspective that underpins the empirical framework of this dissertation.

2.3. Investor Heterogeneity and Financial Literacy

Investor susceptibility to sentiment-driven trading is not uniform. Retail and institutional investors exhibit distinct behavioral responses, especially during periods of uncertainty, when heuristic decision-making dominates (Verma & Soydemir, 2009; Verma & Verma, 2007).

In digital environments, this asymmetry becomes more pronounced. Meme-related episodes are characterized by coordinated retail participation, in which investment decisions are driven by online discussions as opposed to formal valuation models. This behavior is consistent with the noise trader framework, in which sentiment, rather than fundamentals, drives expectations (De Long et al., 1990a).

Financial literacy further moderates these dynamics. Pandey and Guillemette (2024) find that financial knowledge moderates the impact of social-media-driven sentiment, with less financially sophisticated investors relying more heavily on online narratives, memes, and emotionally charged content. Conversely, more financially literate individuals are better equipped to filter online information and less likely to overreact to sentiment-driven signals (Cavezzali et al., 2015; Ribeiro et al., 2021). This moderation effect is particularly significant in the context of meme stocks, where the informational landscape is dominated by user-generated content, whose quality varies widely.

Baranidharan et al. (2023) highlight the dual role of social media in shaping financial literacy. On one hand, digital platforms enable financial institutions to disseminate educational content, promote financial awareness, and interact directly with users, while also allowing individuals to access expert guidance and participate in learning communities. On the other hand, the information circulating on social media is not always accurate or reliable. During periods of market uncertainty, retail investors often turn to online communities for confirmation, reinforcing collective beliefs and amplifying coordinated trading behavior (Baranidharan et al., 2023; Warkulat & Pelster, 2024).

Collectively, the literature supports the idea that investor heterogeneity moderates the effects of sentiment-driven markets and that financial knowledge acts as a buffer against social media influence, reducing susceptibility to speculative trading. These dynamics apply directly to the context of meme stock, where the retail investor base is characterized by considerable variation in financial knowledge and where online communities serve as a primary source of information. Although financial literacy is not explicitly assessed in this study due to data constraints, its moderating role provides an important theoretical framework for interpreting the heterogeneous responses to social media observed throughout the empirical analysis.

2.4. Measurement of Social Media Sentiment

Social media sentiment analysis refers to the computational study of opinions, attitudes, and emotions expressed by users in textual data generated within digital environments (Liu, 2012). In financial contexts, sentiment analysis quantifies investor attitudes derived from online discussions, enabling researchers to evaluate how digital communication influences trading behavior and market dynamics. A central component of sentiment measurement is polarity classification, which determines whether a text expresses positive, negative, or neutral sentiment and underlies most financial sentiment indicators. This distinction is consequential in financial contexts, as investors may react differently to information and emotionally charged opinions (Hatzivassiloglou & Wiebe, 2000).

Empirical research indicates that sentiment derived from social media platforms can provide meaningful insights into stock market dynamics. Broadstock and Zhang (2019) demonstrate that Twitter sentiment, both stock-specific and market-wide, is significantly related to stock price dynamics and exhibits predictive power for returns. Similarly, Bartov et al. (2018) find that social media sentiment contains valuable information that can anticipate stock returns at the firm level. These findings, however, raise a fundamental debate regarding the informational content of online discussions. While some authors argue that social media provides timely signals about investor expectations, others question whether this content reflects meaningful information or merely noise generated by large volumes of user-generated data (Broadstock & Zhang, 2019; Sprenger et al., 2014a).

In the context of meme stocks, both investor sentiment and social media attention play a critical role, as online platforms catalyze coordinated retail behavior (Di Muzio, 2023; Shiller, 2017). Investor attention reflects the degree of focus directed at specific assets and has been shown to influence trading activity and price dynamics (Da et al., 2011). In social media environments, attention is commonly measured through message volume, engagement indicators, such as likes, comments, shares, and upvotes, and the frequency of finance-related hashtags or keywords (Preis et al., 2013). These indicators transform user activity into quantitative proxies of market interest and emotional intensity.

Beyond attention, sentiment indicators aim to capture the emotional tone of online discussions. Empirical studies typically construct sentiment measures using lexicon-based approaches, such as finance-oriented dictionaries that classify words by emotional content (Loughran & McDonald, 2011), or automated content analysis techniques that identify sentiment patterns in financial texts (Tetlock, 2007). Warkulat and Pelster (2024) demonstrate that spikes in post volume and user engagement predict abnormal variations in trading volume and returns, reflecting coordinated retail reactions. More broadly, Bukovina (2016) argues that large-scale social media data capture less rational behavioral components that may influence asset prices and market volatility, and that in meme stock discussions, such indicators frequently operate as proxies for synchronized buying pressure.

The dynamics of online communities also give rise to groupthink, a concept introduced by Janis (1972), in which social pressure encourages consensus and suppresses dissent. In the context of meme stocks, groupthink reinforces homogeneous beliefs and coordinated investment behaviors, thereby amplifying sentiment-driven market dynamics (Lobão & Maio, 2021). Medvedev et al. (2019) similarly demonstrate that online forums are rich and dynamic environments in which users exchange questions, opinions, and emotional reactions, molding and reinforcing sentiment through social interaction.

2.5. NLP Techniques for Financial Text

Natural Language Processing techniques have become central to financial research, particularly for analyzing large volumes of unstructured textual data generated on digital platforms (Liu, 2020). In financial markets, NLP methods are widely used to extract investor sentiment and attention indicators from online discussions, enabling researchers to capture shifts in investor mood and assess how digital communication influences trading behavior and market outcomes (Chen et al., 2014; Sohangir et al., 2018).

One of the earliest contributions to this literature is Tetlock (2007), who demonstrates that "media pessimism predicts downward pressure on market prices" (Tetlock, 2007, p.1), followed by a reversion toward fundamentals, and is associated with high market trading volume. Tetlock (2007) establishes textual analysis as a relevant tool for measuring investor sentiment in financial markets. More recent research extends this approach to digital environments, where user-generated content provides real-time insights into investor expectations, emotions, and speculative behavior.

In practice, NLP-based sentiment analysis typically involves preprocessing textual data and assigning sentiment scores based on emotional tone. A widely used approach in financial research is lexicon-based sentiment analysis, which relies on predefined dictionaries that classify words as positive, negative, or neutral (Loughran & McDonald, 2011). These methods are particularly suitable for large-scale social media datasets due to their interpretability and computational efficiency (Bukovina, 2016).

In online financial communities, sentiment is often expressed through informal language, slang, abbreviations, and emotionally charged expressions, increasing the relevance of tools specially designed for social media text. Accordingly, this dissertation employs the VADER (Valence Aware Dictionary and sEntiment Reasoner) algorithm to measure the emotional tone of Reddit discussions. VADER is tailored for short-form text and incorporates rules that account for capitalization, punctuation, degree modifiers, and informal online communication patterns (Hutto & Gilbert, 2014). While more advanced NLP techniques, such as transformer-based models, may offer improved accuracy in detecting sarcasm and domain-specific language, VADER is preferred for its interpretability and computational efficiency. Evidence from prior studies finds that VADER performs effectively in capturing investor sentiment in digital financial environments (Bartov et al., 2018; Broadstock & Zhang, 2019).

In this dissertation, NLP techniques are applied to Reddit discussions to extract quantitative indicators of investor sentiment and online engagement. Sentiment measures are analyzed together with activity-based metrics, such as posting volume and user interaction, to examine how social media dynamics relate to returns, volatility, and trading intensity. By transforming Reddit discussions into measurable variables that can be integrated with financial market data, this approach enables a systematic assessment of the influence of online communication on financial market behavior.

2.6. The Relationship Between Social Media Activity and Market Outcomes

The relationship between social media activity and financial market dynamics has been increasingly documented in the literature. Online sentiment and attention are associated with short-term variations in returns, volatility, liquidity, and trading volume (Bollen et al., 2011b; Da et al., 2011; Selvakumar et al., 2025), with high levels of attention and bullish sentiment frequently linked to abnormal returns, particularly for speculative or hard-to-value stocks (Barber & Odean, 2008; Tetlock, 2007). This effect is especially pronounced in meme stocks, where social media discussions usually operate as catalysts for coordinated trading behavior (Costola et al., 2021).

Researchers perceive social networks as real-time measures of investor emotion and attention because of the development of digital platforms. While Sprenger et al. (2014b) discovered that tweet sentiment is linked to stock returns, message volume, and trading volume, and that user disagreement predicts more volatility, Bollen et al. (2011b) demonstrate that the aggregate mood retrieved from Twitter predicts stock market movements. Furthermore, Da et al. (2011) indicate that investor attention from online searches predicts price dynamics and trading volume, highlighting attention as a major factor influencing market behavior.

Evidence also documents that interactions among retail investors facilitate coordinated trading. Barber et al. (2022) and Cookson et al. (2022) show that such interactions generate significant price movements unrelated to fundamental values. Complementing this, Lee et al. (2025) identify a *feedback loop* between market performance and online discussion, in which price rises stimulate engagement, thereby reinforcing optimistic sentiment and increasing trading activity, particularly for meme stocks.

Additional evidence underscores the predictive role of online attention in retail trading environments. Warkulat and Pelster (2024) show that spikes in post volume, comments, and user engagement metrics can function as alternative information shocks, generating short-lived abnormal returns even in the absence of fundamental news. Causal evidence is provided by Xu et al. (2023), who examine temporary social media outages and find that platform disruptions lead to significant reductions in volatility, liquidity, and abnormal returns, particularly among retail investors who rely heavily on online communities. Consistent with behavioral finance theory, both Baker & Wurgler (2007) and Tetlock (2007) document that pessimistic sentiment and aggregate investor mood have a disproportionate impact on speculative assets, making them particularly susceptible to sentiment-driven fluctuations.

Taken together, the literature indicates that social media does not merely reflect market conditions but actively shapes them by influencing beliefs, amplifying collective sentiment, and facilitating coordination among retail traders. Although many studies link sentiment to market reactions, fewer examine the engagement dynamics and sentiment patterns of online discussions that promote this coordination. This dissertation addresses that gap by combining sentiment and engagement-based indicators derived from Reddit discussions with financial market data to investigate how online communication patterns relate to meme stock dynamics.

3. Research Questions and Hypotheses

Building on the literature reviewed in Chapter 2, this dissertation investigates the role of social media activity in shaping U.S. meme stock dynamics over the period 2020-2025. The following research questions are addressed:

RQ1: To what extent does social media activity, measured through posting volume, engagement, and sentiment metrics, predict short-term returns, volatility, and trading intensity in U.S. meme stocks?

RQ2: Does social media sentiment predict meme stock dynamics, or does it primarily respond to past market movements, indicating feedback loops between online discussions and financial markets?

RQ3: Are the market effects associated with social-media-driven speculative episodes temporary, or do they persist over time?

These research questions are directly grounded in behavioral finance theory, which emphasizes the role of psychological biases and social interaction in shaping retail investors' behavior. Overconfidence bias leads investors to trade aggressively and overreact to information signals, thereby increasing share turnover and short-term volatility (Odean, 1998; Statman et al., 2006). Similarly, biased belief updating and representativeness heuristics can produce systematic mispricing and short-lived price distortions (Daniel et al., 1998).

In online environments, these behavioral mechanisms are amplified through social interaction and public feedback. Digital platforms allow investors to observe, evaluate, and validate others' trading decisions in real time, reinforcing herd behavior and facilitating coordinated speculative activity (Banerjee, 1992; Hong et al., 2004). According to theoretical models of informational cascades developed by Banerjee (1992) and Bikhchandani et al. (1992), individuals may rationally decide to imitate previous traders in uncertain situations, leading to correlated behavior that can spread throughout markets.

In this context, online platforms such as Reddit intensify these mechanisms by increasing the speed and visibility of feedback loops between market outcomes and investor discussion (Desiderio et al., 2025). This can lead to temporary mispricing, overreaction to salient information, and deviations from fundamental values, particularly in meme stock communities where trading signals are highly visible and socially reinforced (Odean, 1998). It is important to note that, although sentiment may drive initial price movements, these effects tend to be transitory, since rational investors and arbitrageurs gradually correct the deviations caused by sentiment, causing reversals in returns in the days following the initial shock (Daniel et al., 1998; De Long et al., 1990a). Based on the theoretical framework, periods of high social media engagement and positive sentiment are expected to be associated with increased retail investor participation, which will be followed by price corrections due to elevated overconfidence, herd behavior, and collective risk-taking.

Accordingly, the following hypotheses are proposed (see **Appendix A**):

H1: Positive social media sentiment is positively associated with short-term meme stock returns.

This hypothesis is consistent with prior empirical evidence that investor sentiment derived from social media can influence short-term stock returns (Bartov et al., 2018; Bollen et al., 2011a; Tetlock, 2007). Additionally, while negative sentiment triggers selling pressure or lowers demand, an optimistic mood tends to generate buying pressure from retail investors, creating short-term price pressure.

H2: Higher levels of social media activity are positively associated with relative trading intensity in meme stocks.

Drawing on attention theory (Barber & Odean, 2008; Da et al., 2011), investors are more prone to trade stocks that attract heightened attention in information-rich environments. Increased social media engagement enhances the visibility and salience of certain stocks, thereby stimulating trading intensity through the attention channel.

H3: Higher levels of social media sentiment are associated with increased volatility in meme stocks.

Consistent with behavioral finance theory, developed by Baker & Wurgler (2007) and Shiller (2003), sentiment-driven trading gives rise to heterogeneous beliefs and disagreement among investors, which in turn amplify price fluctuations and market volatility. High-attention environments further intensify this effect, amplifying the diversity of investors' interpretations and leading to rapid price adjustments and potential overreaction effects (Barber & Odean, 2008; Da et al., 2011).

H4: The effects of social-media-driven speculative shocks on meme stock returns are transitory and followed by subsequent reversals.

Sentiment-driven price movements are expected to be short-lived, as the initial buying pressure generated by positive online sentiment gradually dissipates and rational market participants correct the resulting price distortion (Daniel et al., 1998; De Long et al., 1990a). This hypothesis directly addresses whether the influence of social media produces lasting effects on prices or merely temporary deviations from fundamental value.

4. Methodology and Sample

4.1. Empirical Strategy

This chapter outlines the empirical strategy adopted to examine the relationship between social media activity and meme stock dynamics in the U.S. equity market from 2020 to 2025. The analysis combines panel regression techniques, Vector Autoregression (VAR) models, and, lastly, a Difference-in-Differences (DiD) framework to evaluate both predictive relationships and the impact of the GameStop short squeeze. The empirical strategy is aligned with prior research that models stock market outcomes as a function of investor sentiment and attention measures (Bollen et al., 2011b; Ranco et al., 2015; Teti et al., 2019).

First, a panel regression framework is employed to assess the relationship between Reddit activity and stock market outcomes, namely, returns, volatility, and trading activity, addressing RQ1 and Hypotheses H1-H3. Second, VAR models combined with Granger causality tests are estimated to investigate the dynamic interactions among social media activity and market outcomes, examining RQ2. Third, a DiD model exploits the January 2021 GameStop short squeeze as a quasi-natural experiment to estimate the impact of an extreme social-media-driven attention shock and to evaluate whether its effects on meme stock dynamics are transitory or persistent, addressing RQ3 and testing Hypothesis H4.

This empirical approach builds on a growing literature linking investor attention and online sentiment to financial market outcomes (Barber et al., 2022; Bollen et al., 2011a; Warkulat and Pelster, 2024). Based on this literature, the present study focuses on meme stocks as a distinct asset class of speculative assets characterized by elevated retail investor participation and strong social media coordination through Reddit communities such as the r/WallStreetBets community.

4.2. Data Collection

The empirical analysis relies on two primary data sources: financial market data and social media indicators collected from Reddit.

Firstly, financial data are obtained from Refinitiv and include daily stock prices, trading volume (number of shares traded), market capitalization, and book value information. Subsequently, the daily logarithmic returns are computed as $r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$, where P_t is the daily closing price. These returns are expressed in percentage terms throughout the analysis. Daily log returns are used instead of simple returns because they are time-additive, which allows cumulative returns over multiple periods to be obtained by summing individual observations (Campbell et al., 1998). They also provide a close approximation to percentage changes for small price movements (Hull, 2018). According to Cont (2001) and Mandelbrot (1963), log returns are widely used in empirical finance due to their symmetric statistical properties and analytical convenience. Volatility is measured as the five-day rolling standard deviation of daily log returns, being therefore in the same percentage units as the returns, capturing short-term fluctuation in market risk. The five-day window is commonly used in the empirical literature as a short-horizon proxy for volatility (Andersen et al., 2003; Hansen & Lunde, 2006). This approach relies on three main considerations: the ability to reduce daily microstructure noise (Bandi and Russell, 2006), to capture short-term time fluctuations relevant to retail investor trading behavior, and, finally, to correspond to a one-week trading horizon, making it a standard and easily interpretable time aggregation in financial markets.

Trading activity is proxied by share turnover, calculated as the ratio of daily trading volume to common shares outstanding, also reported as a percentage. This measure captures the intensity of trading relative to the available share base and is particularly suitable in the context of meme stocks, where speculative trading and rapid position turnover are central features of the phenomenon.

Second, social media data are collected from a Reddit dataset sourced from Kaggle, comprising posts published on the r/WallStreetBets subreddit between 2020 and 2025. The dataset provides, for each stock discussion and each trading day, the stock ticker, publication dates, number of posts, comments, and upvotes. This online community has been widely identified as central to meme stock trading and retail investor coordination (Barber et al., 2022; Chacon et al., 2022; Lee et al., 2025).

Sentiment scores measure the average emotional tone of posts concerning each stock, indicating whether users express positive or negative opinions. Specifically, sentiment scores are computed using the VADER, commonly developed for social media text in empirical finance (Hutto & Gilbert, 2014), as discussed in Section 2.5.

All variables are aggregated at the stock-day level and merged with financial market data using stock tickers and trading dates, yielding a balanced panel covering the 2020-2025 period. This time window is chosen to include both low-activity periods and episodes of extreme social media attention, such as the GameStop short squeeze and subsequent waves of online-driven trading, ensuring sufficient variation in the key explanatory variables.

4.3. Sample Selection

The sample comprises eleven meme stocks that received considerable attention on social media during the 2020-2025 period, following the classification proposed by Aggarwal et al.

(2024) and Allen et al. (2025). This combined approach provides a comprehensive identification of meme stocks associated with the short squeeze episodes of early 2021.

Aggarwal et al. (2024) identified eight meme stocks, AMC, Bed Bath & Beyond, Blackberry, Express, GameStop, Koss, Robinhood, and Vinco Ventures, based on Factiva searches, online sources, and a review of the emerging literature. These firms experienced sharp price increases, largely driven by a substantial influx of retail investors. The authors find no evidence that these price movements reflect underlying fundamentals; instead, they are driven primarily by speculative forces. Market analysts further note that meme investors relied on Reddit to identify target firms with relatively low shares outstanding and high short interest, often aiming to penalize short sellers. This phenomenon is particularly evident among small- and mid-cap firms. In fact, each of the identified companies has a market capitalization below $10 billion, whose stock prices are more easily influenced; however, they are less likely to attract significant shareholder activities and proposals

In contrast, Allen et al. (2025) adopted a more objective perspective by selecting thirteen meme stocks based on quantitative criteria, as the stocks were subject to trading restrictions imposed by retail broker-dealers between January 28 and early February 2021. The sample includes GameStop, Bed Bath & Beyond, AMC, American Airlines, BlackBerry, Castor Maritime Inc., Express, Koss, Naked Brand Group, Nokia, Sundial Growers Inc., Tootsie Roll, and Trivago, placing them at the center of social media-driven short squeeze events.

Based on these classifications, the final sample includes GameStop Corp. (GME), AMC Entertainment Holdings Inc. (AMC), Bed Bath & Beyond Inc. (BBBY), BlackBerry Ltd. (BB), Koss Corporation (KOSS.O), American Airlines Inc. (AAL), Nokia Corporation (NOK), Sundial Growers Inc. (SNDL), Vinco Ventures Inc. (BBIG), Tootsie Roll Industries Inc. (TR), and lastly, Trivago N.V. (TRVG). All firms are listed on U.S. Exchanges, ensuring comparability across trading rules, market structure, and currency denomination. By relying on established classifications rather than arbitrary selections, this literature-based approach strengthens the validity of the sample selection, as the firms share key features of meme stocks, including a high proportion of retail investors, anomalous trading intensity, high volatility, and strong sensitivity to social media narratives.

Among these firms, GME, AMC, and KOSS stand out as the most pronounced cases and are therefore selected for the VAR analysis, a choice supported by quantitative evidence from the literature. In January 2021, coordinated retail trading drove GameStop's stock price from less than $4 to over $483 per share (Aggarwal et al., 2024), while the short position reached approximately 80% prior to the squeeze, making it the primary focus of retail coordination (Allen et al., 2025). AMC similarly capitalized on the surge, raising substantial capital at elevated prices, significantly strengthening its liquidity and solvency positions (Aggarwal et al., 2024). KOSS, by contrast, is the smallest and least liquid firm and exhibits reduced and less persistent activity on Reddit. Consequently, KOSS serves as a control case within the sample, allowing the analysis to assess whether the impact of social media on market dynamics is consistent or depends on the scale and intensity of online attention.

4.4. Variable Construction

The analysis focuses on three groups of variables: stock market outcomes, social media indicators measuring online attention and sentiment, and firm-level control variables.

4.4.1. Dependent Variables

Daily stock returns are computed as the logarithmic price difference between consecutive closing prices (Campbell et al., 1998; Jorion, 2006), a specification that facilitates temporal aggregation and exhibits more convenient statistical properties in the presence of time-varying volatility (Bollerslev, 1986; Engle, 1982). Also, volatility is measured as the rolling five-day standard deviation of returns, capturing short-term fluctuations in market risk. Lastly, trading activity is measured using share turnover.

4.4.2. Social Media Variables

Social media variables measure both investor attention and sentiment emerging from discussions on Reddit. Investor attention is proxied by the daily number of posts mentioning each stock on WSB, while additional engagement indicators, such as comments and upvotes, reflect the intensity of user interaction within the online community. Sentiment is proxied by the VADER compound score, which ranges from -1 (most negative) to +1 (most positive) and captures the overall emotional tone of posts (Hutto & Gilbert, 2014).

To account for delayed retail reactions and the predictive content of social media, all social media variables are included in the regressions with a one-period lag (Guan, 2022; Li & Li, 2026; Liew & Budavári, 2016). This approach helps reduce simultaneity bias by relying on past information, although it does not fully eliminate endogeneity concerns (Reed, 2015). A more comprehensive treatment of this issue is provided by the VAR model in Section 4.6, which models social media and market variables jointly.

4.4.3. Control Variables

Firm-level control variables are included to account for stock characteristics that may independently affect market outcomes. These include the logarithm of market capitalization, capturing firm size, and the book-to-market ratio, serving as a valuation measure. Market-wide conditions are controlled for using the daily return of the S&P 500 index, in line with standard asset pricing models that emphasize the role of common risk factors in explaining stock returns (Fama & French, 1993; Sharpe, 1964).

4.4.4. Descriptive Statistics

Table 1 presents the descriptive statistics for all variables used in the empirical analysis, computed after winsorization at the 1st and 99th percentiles. The variables in the analysis are organized into three groups: financial market variables, social media activity measures, and firm-level control. Logarithmic transformations were applied to turnover, Reddit activity, and market capitalization variables due to their highly right-skewed distributions. This transformation reduces the influence of extreme observations, improves distributional symmetry, and mitigates heteroscedasticity concerns commonly present in financial and social-media-related data.

Regarding the financial variables, daily logarithmic returns exhibit an overall mean of approximately -0.03%, close to zero, consistent with the statistical properties of high-frequency stock returns, where positive and negative price movements tend to offset each other over time. The slightly negative average return captures the sharp trend reversals experienced by several meme stocks following the speculative peaks linked to the GameStop episode. The overall standard deviation of returns is 6.08%, revealing substantial short-term variability. Importantly, the within-firm variation (6.08%) largely dominates the between-firm variation (0.13%). This pattern indicates that meme stock dynamics are predominantly driven by temporary time-series shocks as opposed to persistent cross-sectional differences across stocks, aligned with episodic speculative trading and spikes in retail attention. The observed minimum and maximum daily returns, -23.84% and 28.77%, respectively, further illustrate the extreme short-term price swings characteristic of highly speculative stocks.

Volatility presents an average value of 5.50%, which is broadly comparable to the full-sample standard deviation of returns (6.08%), as both measures capture the dispersion of daily price movements. However, while the full-sample standard deviation captures dispersion across the entire period, the rolling volatility measure reflects localized short-term fluctuations and smooths isolated extreme observations. The substantial within-firm standard deviation (8.23%), together with a maximum volatility of 73.35%, indicates pronounced volatility clustering during speculative episodes, consistent with sharp increases in uncertainty and investor disagreement. In fact, periods of extreme positive and negative returns mechanically contribute to higher realized volatility. It should be noted that the negative minimum value reported in the within-firm decomposition arises solely from the demeaning procedure used by *xtsum* and does not imply negative observed volatility.

Table 1. Descriptive Statistics

Variable	Sample	Obs.	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
Panel A - Financial Market Variables								
Return	Overall	16,571	−0.0003	0.0608	−0.2384	0.2877	0.7625	10.8498
	Between	11		0.0013	−0.0026	0.0017		
	Within			0.0608	−0.2405	0.29		
Volatility	Overall	16,514	0.055	0.096	0.0048	0.7335	5.2942	34.1534
	Between	11		0.0519	0.0151	0.2054		
	Within			0.0823	−0.1456	0.7392		
ln (Turnover)	Overall	16,581	-4.7519	2.2217	-9.4756	0.727	0.045	2.3416
	Between	11		1.8068	-7.5926	-2.5827		
	Within			1.4024	-9.7233	1.0415		
Panel B - Social Media Variables								
Sentiment	Overall	16,588	0.1038	0.1406	−0.1999	0.4997	0.6076	3.3077
	Between	11		0.0029	0.0994	0.1075		
	Within			0.1406	−0.2033	0.5023		
ln (Posts)	Overall	16,588	0.9766	0.7361	0	6.1985	0.7253	5.6620
	Between	11		0.0363	0.9419	1.0654		
	Within			0.7352	−0.0888	6.1097		
Panel C - Firm-Level Control Variables								
ln (Mkt Cap)	Overall	16,588	8.9442	1.2291	3.6972	10.512	-1.8903	8.1919
	Between	11		1.1144	6.4664	10.4013		
	Within			0.6179	6.175	11.4068		
Book-to-Market	Overall	16,586	151.3306	266.6377	1.9265	1381.006	3.3605	13.5814
	Between	11		230.2156	34.2644	818.5032		
	Within			151.3471	−533.6948	713.8335		
Market Return	Overall	16,588	0.0005	0.0133	−0.1277	0.0909	-0.6163	17.2753
	Between	11		0	0.0005	0.0005		
	Within			0.0133	−0.1277	0.0909		

The logarithm of turnover exhibits an overall mean of -4.75, corresponding to an average daily turnover ratio of approximately 0.86% per day, meaning that less than 1% of shares outstanding are traded on a typical trading day. Since turnover is defined as the ratio between daily trading volume and shares outstanding, values below one are economically expected, which mechanically results in negative logarithmic values. Nevertheless, turnover displays substantial within-firm variation, including extreme observations corresponding to turnover ratios exceeding 100% of shares outstanding in a single trading day. This reveals that trading activity fluctuates considerably over time within individual stocks. The pronounced time-series variation demonstrates that trading intensity is primarily driven by temporary retail-attention shocks rather than persistent cross-sectional differences across firms, consistent with the speculative surges seen observed during meme-stock episodes.

With respect to social media variables, sentiment has an overall mean of 0.10, indicating a slightly positive tone in WSB discussions throughout the sample period. The within-firm standard deviation of 0.14 demonstrates meaningful day-to-day variation in the emotional tone of online discussions. Nevertheless, the values observed remain far from the theoretical extremes of the VADER scale, -1 and +1. This implies that sentiment scores smooth out highly polarized individual comments and rarely represent discussions that are entirely optimistic or entirely pessimistic at the aggregate level

The logarithm of Reddit posting activity presents a mean of 0.98 and a within-firm standard deviation of 0.74, revealing relatively modest average daily discussion across the sample. Since the variable is log-transformed, the average value corresponds to approximately $e^{0.98} - 1 \sim$ 1.66 posts per stock day on average, indicating that social media attention is generally concentrated in specific episodes rather than continuously elevated. This interpretation is reinforced by the maximum observed value of 6.20, equivalent to nearly 500 posts in a single day, reflecting periods of intense speculative attention and coordinated online discussion. In contrast, the relatively limited between-firm variation indicates that the Reddit activity is largely driven by temporary shocks rather than persistence differences across stocks.

Turning to the control variables, ln (Mkt Cap) exhibits substantial cross-sectional heterogeneity within the meme-stock universe, with a between-firm standard deviation of 1.11, indicating meaningful differences in firm size across the sample. The within variation is considerably smaller, by contrast, reflecting the comparatively gradual evolution of company size over time. Finally, the book-to-market ratio displays substantial dispersion both across firms and over time, consistent with the unstable valuation dynamics commonly associated with speculative and distressed firms during periods of intense market sentiment.

Additionally, skewness and kurtosis statistics were calculated to analyze the distribution of the variables, revealing substantial heterogeneity. On the one hand, daily returns and volatility deviate significantly from a normal distribution, exhibiting positive skewness and fat tails. This evidence is consistent with excessive price fluctuations, as well as with the asymmetry and volatility concentrated in meme stocks. On the other hand, ln (Turnover), sentiment, and ln (Posts) display more moderate deviations from normality, which may be associated with the logarithmic transformation, which can enhance the asymmetry of the distribution. Among the control variables, Book-to-Market exhibits strong asymmetry and kurtosis, reflecting the presence of extreme valuation observations in the sample.

Correlation Matrix

Table 2 presents the Pearson correlation matrix for the main variables, after winsorization, providing a preliminary overview of the bivariate relationships between social media activity and stock market behavior.

Table 2. Correlation Matrix for the main variables

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Return (1)	**1**						
Volatility (2)	0.0465	**1**					
ln (Turnover) (3)	0.0332	0.0229	**1**				
Sentiment (4)	-0.0023	-0.0035	0.0614	**1**			
ln (Posts) (5)	0.0244	-0.0022	0.1708	0.1373	**1**		
ln (Mkt Cap) (6)	-0.0052	0.5546	0.1553	0.0271	0.0551	**1**	
Book-to-Market (7)	-0.0029	-0.0459	-0.1399	0.0239	0.0539	-0.1025	**1**

The correlation between sentiment and return is negligible and slightly negative (-0.002), indicating that aggregate sentiment does not linearly track daily price movements. This result, however, should not be interpreted as evidence against the relevance of investor sentiment in meme stock dynamics, as its effects are likely nonlinear, lagged, and concentrated during periods of heightened retail attention. Consequently, these dynamics are more appropriately captured by panel regression, VAR models, and event-based analyses than through a simple pairwise contemporaneous correlation.

Similarly, the correlation between sentiment and volatility is also negligible and slightly negative (-0.004). While prior research often associates investor disagreement and speculative sentiment with higher volatility, the weak relationships may reflect the noisy nature of online discussions and the limitations of aggregate sentiment measures, which may fail to capture investor uncertainty or disagreement within meme-stock communities.

Sentiment exhibits a moderate positive correlation with ln (Turnover) (0.061), indicating that more optimistic online discussions may encourage retail participation and speculative trading even without directly affecting contemporaneous price movements. Likewise, sentiment and ln (Posts) are positively correlated (0.137), indicating that emotionally charged or optimistic discussions tend to occur during periods of elevated posting activity. However, the moderate strength of this link indicates that posting volume and sentiment capture distinct dimensions of retail investor behavior, while sentiment reflects the tone of discussions, and posting activity mainly measures investor attention and user involvement.

By contrast, ln (Posts) presents a small positive correlation with returns (0.024), implying that the attention intensity appears to be more closely related to short-term price movements than sentiment polarity alone. This aligns with the attention channel described by Barber and Odean (2008) and Da et al. (2011), where visibility triggers retail investor participation and buying pressure, regardless of the emotional tone of discussions.

The correlation between ln (Posts) and ln (Turnover) is positive (0.171), meaning that increased Reddit activity is typically associated with higher trading intensity. This is consistent with the attention channel hypothesis, i.e., increased online visibility stimulates trading activity even when posts contain limited fundamental information. Conversely, the near-zero correlation between ln (Posts) and volatility (-0.002) implies that day-to-day fluctuations in online activity are not systematically associated with contemporaneous volatility. Instead, volatility effects may emerge during extraordinary periods of speculation marked by synchronized retail trading.

Among control variables, ln (Mkt Cap) exhibits a moderate positive correlation with volatility (0.555), indicating that larger meme stocks, such as GME and AMC, experienced the most speculative price fluctuations during the sample period, contrasting with the traditional firms. Also, there is a slight positive correlation between ln (Mkt Cap) and ln (Turnover) (0.155), indicating that larger meme stocks typically attract greater liquidity and trading intensity. Finally, the book-to-market ratio shows weak correlations with most variables, consistent with the view that firms with lower relative valuation ratios tend to attract greater retail trading activity and investor attention. Subsequent VIF tests reported in Section 5.3.3 confirm the absence of severe multicollinearity issues in the final regression models.

4.5. Baseline Panel Regression

The baseline analysis adopts a panel regression framework to evaluate whether lagged social media activity predicts stock market outcomes across the sample of eleven meme stocks over the period 2020-2025. The general form of the specification is defined as:

$$Y_{i,t} = \alpha + \beta_1 Sentiment_{i,t-1} + \beta_2 \ln{(Posts)}_{i,t-1} + \beta_3 Y_{i,t-1} + \gamma' X_{i,t} + \mu_i + \tau_t + \varepsilon_{i,t} \quad \textbf{(4.5.1)}$$

Where $Y_{i,t}$ represents the outcome of interest for the stock i on day t, specifically, daily returns, volatility, or the log turnover. The variables $Sentiment_{i,t-1}$, and $Posts_{i,t-1}$ capture lagged Reddit sentiment and investor attention. The vector $X_{i,t}$ includes firm-level controls, i.e, the logarithm of market capitalization and the book-to-market ratio. Stock fixed effects (μ_i) absorb time-invariant firm-specific characteristics, while date fixed effects (τ_t) capture common shocks affecting all firms on a given trading day.

Lagged dependent variables are included to account for persistence identified by the Wooldridge test for first-order autocorrelation, which strongly rejects the null hypothesis of no serial correlation (Wooldridge, 2010). This persistence, if unaddressed, could bias inference and overstate the precision of the estimates. Including lagged outcomes allows for a more accurate estimation of the effect of social media activity by controlling for past values of the dependent variable. Standard errors are clustered at the stock level to account for potential serial correlation and heteroscedasticity within firms over time.

Reddit activity is captured through posts, comments, and upvotes, which were initially considered separate engagement measures. However, due to high multicollinearity with the post volume, yielding VIF values greater than 9, comments and upvotes are excluded from the main specification. The final model retains only the logarithm of post volume as the primary proxy for investor attention. Alternative engagement specification as reported in robustness checks.

The daily return of the S&P 500 was initially included to control for market-wide movements. However, when date fixed effects are included, it becomes perfectly collinear and is therefore omitted, as these effects already capture common shocks affecting all stocks.

To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles. This approach is preferred over trimming, where all observations are preserved while reducing the influence of extreme values on regression estimates, which are economically meaningful in the context of meme stocks (Lusk et al., 2011). As noted by Petersen (2009), winsorization is a widely used procedure in empirical finance.

These specifications directly test H1 (positive sentiment predicts returns), H2 (social media activity predicts trading volume), and H3 (higher sentiment predicts volatility), and are grounded in the literature linking investor attention and sentiment to market outcomes (Barber et al., 2022; Da et al., 2011). The models are estimated using the $reghdfe$ estimator developed by Correia (2016), which is specifically designed for linear regression with high-dimensional multiple fixed effects (Frisch & Waugh, 1933; Guimarães & Portugal, 2010).

4.6. VAR Model and Granger Causality Tests

The main regression framework focuses on determining whether lagged social media variables can predict market outcomes, but it does not address the question of whether prior market movements drive subsequent social media activity. RQ2 examines how sentiment and engagement on social media function as leading indicators of price dynamics, whether they respond to past market performance, or whether both mechanisms operate simultaneously, forming a feedback loop between online attention and market behavior.

To address these questions, a Vector Autoregression (VAR) model is estimated separately for GME, AMC, and KOSS, allowing for the joint modeling of dynamic interactions between daily returns, WSB sentiment, and discussion intensity. These firms are selected to provide variation in meme stock intensity, retail investor engagement, size, and liquidity. GME, as the epicenter of the January 2021 short squeeze episode, offers the most data-rich environment to analyze these dynamics (Kim et al., 2023; Lucchini et al., 2022), while AMC captures sustained online attention and KOSS serves as a smaller benchmark.

The VAR structure treats all variables as endogenous, modeling each as a function of its own lags and those of the other variables. The trivariate system includes daily returns, VADER sentiment indices, and the natural logarithm of WSB post volume, with the logarithmic transformation addressing right-skewness and mitigating the influence of extreme observations during periods of heightened social activity.

Before estimation, stationarity is assessed using the Augmented Dickey-Fuller (ADF) test, which tests the null hypothesis of a unit root against the alternative of stationarity (Said & Dickey, 1984). The optimal lag length is determined using the Akaike Information Criterion (AIC) (Akaike, 1974), considering up to five lags, with a two-lag specification retained for parsimony and consistency with evidence that social media effects typically materialize within the first two trading days following a given post (Da et al., 2011; Lütkepohl, 2005; Warkulat & Pelster, 2024).

Granger causality tests are conducted to evaluate the direction of predictability between social media activity and market outcomes, allowing for the identification of unidirectional or bidirectional relationships, including potential feedback effects. The analysis is complemented by Orthogonalized Impulse Response Functions (OIRFs), which trace the dynamic response of each variable to a one-standard-deviation shock over a ten-day trading horizon. Following Sims (1980), these functions trace the propagation of shocks, while Cholesky decomposition accounts for contemporaneous interactions (Hamilton, 1994;

Lütkepohl, 2005). Together, these functions provide insights into the timing, persistence, and propagation of social media-induced market dynamics, supporting the evaluation of H4.

4.7. Difference-in-Differences (DiD)

In a subsequent stage, a Difference-in-Differences (DiD) framework was implemented to assess the impact of the January 2021 GameStop short squeeze on meme stock dynamics. This strategy aims to determine whether meme stocks exhibited abnormal behavior in returns, volatility, and trading activity relative to non-meme stocks following the event. The empirical strategy combines a DiD specification with an event study framework and multiple robustness checks.

4.7.1. Data Preparation and Sample Construction

The full panel sample contains 78,416 daily observations covering meme stocks and non-meme stocks over the 2020-2025 period. Given the highly skewed distributions typically observed in financial variables, turnover, post volume, and stock price were log-transformed to reduce excessive dispersion and heteroscedasticity (Campbell et al., 1998). Additionally, the winsorization method was applied to the 1st and 99th percentiles for the main variables to limit the influence of extreme observations, while preserving economically significant variation. This procedure follows standard practice in empirical finance research (Adams et al., 2019; Leone et al., 2019) and is particularly relevant in the context of meme stocks, which exhibit unusually sharp price swings, trading volume spikes, and sudden surges in online attention (Costola et al., 2021).

The treatment group consists of eleven meme stocks identified in Section 4.2: GME, AMC, BBBY, BB, KOSS, AAL, NOK, SNDL, BBIG, TR, and TRVG. An indicator variable takes the value 1 for meme stocks and 0 for all other cases. The analytical window was restricted to ±130 trading days around the event date, yielding a final DiD sample of 9,256 observations, of which 1,958 correspond to the treated group (21.15%) and 7,298 to the control group (78.85%). It should be noted that the event window was deliberately chosen to capture both the immediate speculative surge and the subsequent adjustment period, while limiting contamination from unrelated macroeconomic shocks.

4.7.2. Propensity Score Matching

One of the principal empirical challenges lies in the identification of an appropriate control group, since meme stocks differ structurally from conventional firms. Consequently, a simple comparison between meme stocks and the broader market could introduce substantial biases. To overcome this limitation, the Propensity Score Matching (PSM) methodology was initially implemented as a preliminary balancing procedure following Rosenbaum and Rubin (1983). The propensity scores were estimated using pre-event firm characteristics observed before January 13, 2021, including market capitalization, turnover, historical volatility, logarithmic price level, and return volatility.

However, the results indicate an almost complete separation between treated and control firms. The logit model yields a high Pseudo-R^2 of 0.845, indicating that pre-treatment characteristics strongly predict treatment assignment. Moreover, treated firms have an average propensity score of approximately 0.87, compared to only 0.03 for control groups. As shown in **Appendix B**, the distributions of propensity scores reveal limited overlap, with treated firms concentrated at high propensity values and control firms clustered close to zero.

The absence of meaningful common support implies that only a very limited number of control firms could be successfully matched to treated firms. Under this condition, estimated treatment effects would depend on extrapolation rather than genuinely comparable observations, which weakens the validity of the matching procedure.

These findings indicate that meme stocks possess unique characteristics and are structurally distinct from other firms even in the pre-treatment period, exhibiting lower market capitalization, higher volatility, and stronger retail participation. For this reason, the uniqueness of meme stocks should be understood as an intrinsic economic characteristic of the phenomenon and not merely as a methodological limitation. As a result, the quality of the matches is inherently limited, making PSM unsuitable as the primary identification strategy. Instead, the analysis relies on a DiD framework with stock fixed effects, which allows the estimation to account for unobserved time-invariant heterogeneity across firms.

4.7.3. Empirical Specification

Following PSM, the baseline DiD specification is defined as follows:

$$Y_{it} = \alpha + \beta_1 Treated_i + \beta_2 Post_t + \beta_3 (Treated_i \times Post_t) + Controls_{it} + FE + \varepsilon_{it} \quad \textbf{(4.7.3.1)}$$

Where Y_{it} is the outcome variable for the firm i on day t, namely, daily returns, volatility, or log turnover. $Post_t$ is a post-event indicator equal to one after January 13, 2021, while the interaction term $(Treated_i \times Post_t)$ represents the ATT (Average Treatment Effect on the Treated), that is, the differential effect of the GameStop episode on meme stocks relative to the control group.

All specifications include stock fixed effects and firm-level controls, especially the logarithm of market capitalization and book-to-market ratio. Standard errors are clustered at the firm level to account for heteroscedasticity and serial correlation. A centered quadratic time trend is also included to capture non-linear market dynamics during the event period. The interaction term $(Treated_i \times Post_t)$ was constructed manually to prevent Stata from eliminating it through automatic collinearity detection, which is a known problem in two-way fixed-effects models with a small number of treated units (Correia, 2016).

4.7.4. Parallel Trends and Event Study

The validity of the DiD approach relies on the parallel trends assumption, which requires that treated and control firms would have exhibited similar pre-treatment dynamics in the absence of the GameStop shock. This assumption is assessed by estimating the interactions between a time-to-event variable and the treatment indicator in the pre-event period ($post = 0$). A non-significant coefficient in this interaction provides evidence in favor of parallel trends (Angrist & Pischke, 2009). However, because the treated indicator is absorbed by stock fixed effects, the interaction term becomes partially collinear, reducing the statistical power of the test, a common limitation of DiD frameworks with a limited number of treated units under two-way fixed effects (Callaway & Sant'Anna, 2021).

To complement this analysis, an event study specification is estimated to characterize the dynamic evolution of treatment. Weekly interaction dummies were constructed as $ewt^w = 1(event_{week} = w) \times Treated_i$, over a $\pm$10-week window around the event, using week -1 as the reference period. Pre-event coefficients provide a visual assessment of the parallel trends assumption, while post-event coefficients capture the timing, magnitude, and persistence of any treatment effect (Callaway & Sant'Anna, 2021).

4.7.5. Robustness Tests

The baseline DiD findings are complemented by various robustness analyses to assess the sensitivity of the results.

First, the event window is progressively narrowed to $\pm$ 30 and $\pm$ 60 trading days to verify that the benchmark results are not influenced by the specific choice of time horizon, thereby mitigating contamination from unrelated market events. Second, a first-difference specification was estimated to overcome the potential nonstationarity and unobserved persistent heterogeneity. Although this approach reduces statistical power, the similarity of the estimates across specifications provides additional support for the interpretation of ATT estimates. Following that, a placebo test was conducted by assigning a fictitious January 2020 event to assess whether the estimated effects incorrectly reflected pre-existing trends.

Given the limited number of clusters (k = 11), inference is complemented using the Wild Cluster Bootstrap (WCB) procedure. In settings with few clusters, conventional cluster-robust standard errors may lead to biased inference and excessive rejection of the null hypothesis. To mitigate this concern, the WCB (Cameron et al., 2008) is employed, using the Webb weights with 999 bootstrap replicates (MacKinnon & Webb, 2019), which provides more reliable inference in small samples (MacKinnon & Webb, 2018).

Coarsened Exact Matching (CEM) was implemented as a nonparametric alternative to PSM, as it does not rely on propensity score estimates and is therefore less sensitive to the separation issues observed in the logit model (Iacus et al., 2012). Firms are then matched on pre-treatment characteristics, including market capitalization, trading volume, volatility, and price level, after grouping the variables into discrete intervals. The WCB procedure is also applied to the CEM-weighted DiD specification to ensure reliable inference with a limited number of clusters. The consistency of the estimated treatment effects across the baseline and CEM specifications reinforces the robustness of the main results.

4.7.6. Spike vs. Reversal Analysis

In order to be able to distinguish between temporary and persistent effects, the post-event period was divided into two distinct phases: a spike phase, covering the first two weeks after the event ($event\_time \in [0, 14]$), and a reversal phase, comprising the remainder of the post-event period ($event\_time \in [15, 130]$). Furthermore, two distinct interaction terms, $treat_{spike}$ and $treat_{reversal}$, were estimated for each phase, making it possible to assess whether the anomalies in meme stocks were driven by a short-lived speculative episode, rather than a structural change in corporate behavior.

4.7.7. Within-Treated Analysis: Reddit Sentiment and Activity

Finally, as a supplementary analysis, the sample was restricted to the eleven meme stocks to examine whether lagged Reddit sentiment and posting activity predict subsequent market outcomes within the treated group. This specification is grounded in the literature on transmission mechanisms discussed in Section 2.6. The model includes one-day lags of the sentiment and posts volume, alongside stock-specific fixed effects, a quadratic time trend, and the posting dummy variable, with standard errors clustered at the stock level. Lagged regressors are used to mitigate concerns of reverse causality, as contemporaneous Reddit activity could respond to market movements.

Unlike the main DiD framework, this specification does not estimate a causal treatment effect relative to a control group. Instead, it tests whether Reddit activity acts as a transmission mechanism within meme stocks, capturing the extent to which online coordination contributes to the persistence of speculative dynamics after the initial shock.

5. Results

5.1. Baseline Panel Regression Results

This chapter presents the baseline panel regression results, examining the relationship between lagged social media activity and three stock market outcomes: daily returns, realized volatility, and share turnover, across a panel of eleven meme stocks over the 2020-2025 period. The analysis addresses Research Question 1 and tests Hypotheses H1, H2, and H3.

All specifications are estimated using the *reghdfe* estimator with fixed effects at firm and time levels. Standard errors are clustered at the firm level (k = 11). Additionally, each model includes a lagged dependent variable to account for strong persistence detected by the Wooldridge autocorrelation test. The market return variable is excluded from the final specifications, as date fixed effects already capture aggregate shocks common to all firms.

5.1.1. Main Results

Table 3 reports the results for the three baseline panel regression specifications.

Table 3. Baseline Panel Regression Results

Variable	Return	Volatility	ln (Turnover)
Return (t-1)	-0.118* (0.056)		
Volatility (t-1)		0.877*** (0.008)	
ln (Turnover) (t-1)			0.814*** (0.033)
Sentiment (t-1)	0.010** (0.004)	0.001 (0.001)	0.013 (0.047)
ln (Posts) (t-1)	0.001* (0.001)	0.001 (0.000)	0.007 (0.010)
ln (Mkt Cap)	-0.001 (0.002)	-0.007**(0.002)	0.235*** (0.071)
Book-to-Market	0.000 (0.000)	-0.000 (0.000)	0.000** (0.000)
N	12,963	12,920	12,973
Within R^2	0.016	0.848	0.779
Adj. R^2	0.161	0.892	0.932

Notes: *p<0.10, **p<0.05, ***p<0.01. Standard errors, in parentheses, clustered at the firm level (k = 11).

The return specification provides support for Hypothesis 1. Both lagged Reddit sentiment and posting intensity are positively associated with next-day return. In particular, lagged sentiment remains statistically significant ($\beta = 0.010$; $p = 0.039$), indicating that more optimistic online discussions are followed by higher subsequent returns. Economically, a one-unit increase in the VADER sentiment score is associated with approximately a one percentage point increase in next-day stock returns. Also, lagged post volume exhibits a positive but weaker effect ($\beta = 0.001$; $p = 0.076$), in a way that Reddit attention is followed by modest positive movements. The coefficient's sign is still in line with the literature on investor attention, although the coefficient is only marginally significant.

It is important to note that both effects remain significant after controlling for lagged returns, which display a negative coefficient ($\beta = -0.118$), consistent with short-term reversals. This result reinforces the interpretation that Reddit activity contains incremental predictive information beyond simple return persistence and aligns with the investor-attention mechanism proposed by Barber and Odean (2008) and Da et al. (2011). Although the within R^2 of return regression is relatively low (1.59%), this result is expected in daily returns models, where a substantial portion of variation is driven by idiosyncratic shocks, new arrivals, and short-lived speculative fluctuations. In this context, even modest explanatory power may still be economically meaningful.

By contrast, the volatility specification does not support H3. After controlling for strong volatility persistence through the inclusion of lagged volatility ($\beta = 0.877$; $p = 0.000$), neither lagged sentiment nor lagged post volume remains statistically significant. This result indicates that daily activity on Reddit does not systematically predict next-day volatility throughout the entire sample period. Two complementary factors could explain this evidence. First, the relationship between social media activity and volatility tends to be episodic rather than continuous, with effects concentrated during extreme speculative episodes, such as short squeezes and coordinated retail trading. Second, the winsorization procedure attenuates extreme observations, precisely where the impact of social media on volatility may be strongest. These considerations indicate that the volatility may be better captured through event-specific methods than with a linear panel model estimated over the full sample period.

Finally, the turnover regression provides no support for Hypothesis 2. Neither lagged sentiment nor lagged posting activity significantly predicts next-day turnover once persistence and firm characteristics are controlled for. Importantly, turnover is defined as the ratio of trading volume to shares outstanding, so the dependent variable captures the relative intensity of trading, rather than the absolute volume. The results indicate that turnover is primarily driven by strong temporal persistence and firm-specific structural characteristics, as reflected in the highly significant lagged dependent variable ($\beta = 0.814$; $p = 0.000$). Interestingly, firm size remains positively associated with turnover ($\beta = 0.235$; $p = 0.008$) even after normalizing trading activity by shares outstanding, indicating that larger meme stocks exhibit systematically higher relative trading intensity, likely due to greater liquidity, wider retail participation, and increased market-maker activity. Similarly, the positive coefficient on the book-to-market ratio indicates that firms with more distressed or speculative profiles experience higher trading intensity, consistent with the characterization of meme stocks as "lottery-like" assets (Barberis & Huang, 2008).

Taken together, the baseline regressions indicate that Reddit activity is more closely linked to the predictability of short-term returns than to persistent changes in volatility or trading intensity. Therefore, rather than long-term shifts in market risk or liquidity conditions, the evidence implies that an attention channel predominantly affects transient price creation.

5.1.2. Robustness Checks

To assess the stability of the baseline findings (see **Appendix C** and **D**), two robustness checks were conducted.

The first robustness check extends the baseline model by incorporating an alternative engagement measure combining comments and upvotes into a single logarithmic index alongside lagged posting activity: $L1\_\ln_{\mathbf{engagement}} = \ln(comments + Upvotes + 1)$.

The results remain broadly stable. Lagged sentiment continues to exhibit a positive and statistically significant relationship with returns, while the engagement measure itself is not statistically significant. Moreover, once the engagement measure is included, the coefficient on post volume loses individual significance, reflecting the substantial overlap among Reddit attention proxies. Overall, the inclusion of the engagement index does not improve the model's explanatory power, which supports the parsimonious baseline specification based exclusively on post volume.

The second robustness check replaces raw returns with abnormal returns as the dependent variable, defined as the stock return net of contemporaneous market returns. Under this specification, lagged sentiment becomes more strongly significant ($\beta = 0.018$, $p = 0.014$), while post volume remains statistically insignificant. The findings indicate that Reddit sentiment is particularly relevant in explaining excess price movements beyond those associated with general market-wide dynamics.

Overall, the robustness checks reinforce the baseline conclusion that Reddit sentiment mainly affects short-term returns formation, rather than volatility or relative trading activity.

5.1.3. Diagnostic Tests

The diagnostic tests were conducted to evaluate the adequacy of the econometric specification (see **Appendix E**).

First, the Wooldridge test strongly rejects the null hypothesis of no first-order autocorrelation in the residuals ($F(1,10) = 27.861$, $p = 0.0004$), confirming the presence of serial correlation in the panel structure. This result justifies both the inclusion of lagged dependent variables and the use of clustered standard errors at the firm level.

Second, Pesaran's test for cross-sectional dependence yields a negative CD statistic (CD = -15.52, p = 0.000), rejecting the null hypothesis of weak cross-sectional dependence. Instead of indicating a strong positive correlation across firms, the negative sign of the CD statistic points to negative residual cross-sectional dependence after controlling for firm and date fixed effects (Pesaran, 2021). This outcome is not surprising in a sample of meme stocks, where coordinated retail trading and shared social media narratives drive common dynamics. The inclusion of two-way fixed effects helps address these concerns by absorbing market-wide shocks, leaving only idiosyncratic variation and implying a slight negative dependence on the residuals, rather than a problematic structure of common factors.

Third, multicollinearity does not appear to represent a concern. All variance inflation factors (VIF) remain very close to unity, with a mean VIF of 1.02, indicating very limited linear dependence among the explanatory variables retained in the final specification.

A key limitation concerns the relatively small number of clusters (k = 11). Because of this, inference based on clustered standard errors should be evaluated cautiously, especially for coefficients significantly only at the 10% significance level. Despite this, the panel framework should be interpreted primarily as identifying conditional associations rather than definitive causal relationships, since simultaneity and reverse causality between social media activity and market outcomes cannot be fully excluded. Nevertheless, the diagnostic tests provide overall support for the econometric validity of the estimation strategy.

5.1.4. Summary

The baseline panel results indicate that Reddit activity exhibits a statistically significant association with short-term meme stock returns. Both sentiment and posting intensity positively predict next-day returns, providing support for Hypothesis 1 and emphasizing the importance of investor attention and online sentiment in speculative trading environments.

By contrast, once persistence and firm characteristics are controlled for, Reddit activity does not robustly explain realized volatility or relative trading intensity, providing no support for Hypotheses 2 and 3 within the daily panel framework.

In general, these results imply that social media is not a continuous determinant of day-to-day market dynamics. Instead, its influence appears concentrated during periods of heightened attention and retail coordination, a conclusion further explored in the DiD analysis.

5.2. VAR Model and Granger Causality Tests Results

5.2.1. Preliminary Tests

Prior to estimating the VAR models, the stationarity of all variables was evaluated through the Augmented Dickey-Fuller (ADF) test with five lags. **Table 4** reports the test statistics for Return, Sentiment, and ln (Posts) across GME, AMC, and KOSS.

Table 4. Augmented Dickey-Fuller (ADF) Test Statistics

Variable	GME	AMC	KOSS
Return	-17.036	-15.922	-17.173
Sentiment	-13.024	-12.559	-14.647
ln (Posts)	-6.258	-6.621	-7.900

Notes: All tests are estimated with five lags. The 1% critical value is −3.430. All p-values are below 0.001. The null hypothesis (H0) corresponds to the presence of a unit root.

As reported in **Table 4**, the null hypothesis of a unit root is rejected for all variables across three stocks, indicating that the series are stationary in levels and therefore can be estimated within a VAR framework without differencing.

Although the Akaike Information Criterion initially indicates a five-lag specification, a two-lag VAR was retained throughout the analysis. The choice preserves degrees of freedom, focuses on the most relevant short-run dynamics, and reduces the risk of overfitting in a sample with 1,505 daily observations per stock. Given the highly short-term and attention-driven nature of meme stock dynamics, longer lag structures are unlikely to provide significant economic information.

5.2.2. VAR Estimation

The trivariate VAR model, comprising Returns, Sentiment, and ln (Posts), was estimated separately for each stock using two lags. **Table 5** summarizes the main goodness-of-fit statistics for each equation in the system across the three stocks. In this context, estimating stock-specific VAR systems is essential, as combining all firms could hide significant heterogeneity in the relationship between online attention and market dynamics. Therefore, variations in liquidity, visibility, retail participation, and speculative intensity justify allowing these relations to vary across stocks rather than imposing homogeneity.

Table 5. Summary of key fit statistics for the trivariate VAR models

	GME	AMC	KOSS
R^2 Return	2.72%	2.06%	2.22%
R^2 Sentiment	2.47%	3.33%	1.45%
R^2 ln (Posts)	46.00%	39.71%	16.47%
N (observations)	1,505	1,505	1,493
Stability Condition	✓	✓	✓

Note: Model stability is confirmed through eigenvalue analysis, with all eigenvalues lying strictly inside the unit circle, confirming that the models are dynamically stable and suitable for impulse response analysis.

Across the three equations, the results reveal significant heterogeneity among the stocks. The ln (Posts) equation consistently exhibits the greatest explanatory power, particularly for GME and AMC, with R^2 values of 46.00% and 39.71%, respectively, indicating strong persistence in Reddit posting activity. By contrast, the Return and Sentiment equations display considerably lower R^2 values (ranging from 1% to 3%), which is expected in daily financial data characterized by considerable idiosyncratic noise and short-term volatility.

The relatively low R^2 values are consistent with the broader literature on attention and social media in financial markets. Roll (1988) demonstrated that U.S. firms' stock returns exhibit low R^2 values in common asset pricing models, implying that idiosyncratic volatility is indicative of informed trading or temporary frenzy unrelated to concrete information, an interpretation particularly applicable to meme stocks. Kelly (2014) further argues that a low R^2 reflects a poor information environment with greater obstacles to informed trading, making stocks more susceptible to noise trading, in line with Chang and Luo (2010). Similarly, Da et al. (2011) demonstrated that attention-based measures significantly predict stock returns, but with limited explanatory power at the daily frequency due to the elevated level of noise present in return series. Taken together, these findings indicate that the low R^2 values obtained are a structural feature of the data, consistent with the speculative and attention-driven nature of meme stocks. It is important to emphasize that the relatively low explanatory power of the return equations indicates that Reddit activity should not be interpreted as the primary determinant of meme stock returns. Instead, social media variables appear to provide small but statistically detectable, short-term predictive information, primarily during periods of greater retail investor attention.

Table 6 reports the key coefficients from the Return, Sentiment, and ln (Posts) equations.

Table 6. Selected VAR Coefficients – Return, Sentiment, and ln (Posts) Equations

Regressor	Lag	GME	AMC	KOSS
Dependent: Return				
Return	L1	-0.001 (0.026)	-0.074*** (0.026)	0.044* (0.026)
Return	L2	0.024 (0.026)	0.027 (0.026)	0.129*** (0.026)
Sentiment	L1	0.043*** (0.015)	-0.012 (0.016)	0.010 (0.016)
Sentiment	L2	0.004 (0.015)	0.042*** (0.016)	0.011 (0.016)
ln (Posts)	L1	0.013*** (0.003)	0.008** (0.003)	0.005 (0.003)
ln (Posts)	L2	-0.002 (0.003)	0.003 (0.003)	0.002 (0.003)
Dependent: Sentiment				
Return	L1	-0.099** (0.044)	-0.043 (0.042)	0.033 (0.042)
Return	L2	0.043 (0.044)	0.017 (0.042)	-0.017 (0.042)
Sentiment	L1	0.055** (0.026)	0.070*** (0.026)	0.024 (0.026)
Sentiment	L2	0.024 (0.026)	-0.014 (0.026)	0.013 (0.026)
ln (Posts)	L1	0.007 (0.005)	0.004 (0.005)	0.005 (0.006)
ln (Posts)	L2	0.015*** (0.005)	0.024*** (0.005)	0.020*** (0.006)
Dependent: ln (Posts)				
Return	L1	0.076 (0.214)	0.342 (0.201)	0.028 (0.190)
Return	L2	0.562*** (0.213)	0.377* (0.201)	-0.317* (0.19)
Sentiment	L1	0.163 (0.124)	0.128 (0.122)	0.365*** (0.117)
Sentiment	L2	0.153 (0.124)	0.104 (0.122)	0.053 (0.118)
ln (Posts)	L1	0.376*** (0.024)	0.359*** (0.024)	0.235*** (0.025)
ln (Posts)	L2	0.363*** (0.024)	0.338*** (0.024)	0.242*** (0.025)

Notes: Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

The estimated coefficients show significant differences across firms in the link between Reddit activity and stock performance.

For GME, both lagged sentiment and posting activity positively predict next-day returns. The first lag of sentiment is positive and statistically significant ($p = 0.004$), as is the first lag of posting activity ($p = 0.000$), indicating that heightened online optimism and visibility generate short-term retail buying pressure and temporary price increases, in line with investor-attention and noise-trading theories. AMC displays a similar pattern, although the sentiment effect emerges with a two-day lag, while lagged post volume remains positively associated with returns at the first lag. The transmission mechanism appears to be weaker and less immediate, indicating that retail attention is translated into market activity more gradually, relative to GME. In contrast, no statistically significant relationship was found between the Reddit variables and KOSS returns. Neither sentiment nor posting activity shows predictive power for future returns (all $p>0.17$), meaning that online discussions surrounding KOSS did not consistently translate into price movements during the sample period. These results demonstrate that social media's market impact depends not only on the presence of discussion but also on its scale, persistence, and visibility. The economic magnitude of these coefficients should nevertheless be interpreted cautiously, as realistic daily changes in VADER sentiment tend to imply moderate effects on returns.

Concerning short-term return dynamics, AMC exhibits moderate mean reversion at the first lag ($p = 0.004$), consistent with a short-term correction after overreaction. For KOSS, it exhibits a positive second lag ($p = 0.000$), which indicates short-term momentum. However, for GME, no autoregressive coefficient was found to be significant. These findings are aligned with the speculative and retail-driven nature of meme stocks.

In the sentiment equation, past returns negatively predict sentiment for GME ($\beta = -0.099$; $p = 0.026$), indicating that negative price movements reduce the tone of Reddit discussions on the following day. Sentiment also proves to be slightly persistent for GME and AMC, with the first lag being statistically significant for both stocks. This effect is absent for KOSS. Notably, the second lag of ln (Posts) is positively and significantly associated with sentiment for all three stocks, showing that continuous posting activity tends to be accompanied by improvements in the tone of the discussion, reflecting the reinforcing community engagement.

The ln (Posts) equations further indicate a high degree of persistence in online activity, namely for GME and AMC, with both lags of posting activity remaining strongly significant across all specifications. This indicates that Reddit discussions develop progressively over time rather than emerging as isolated daily shocks, consistent with attention-based mechanisms. According to the results, for KOSS, the first lag of sentiment is significant, implying that more positive discussions are followed by higher post volume, a pattern that is not observed in GME or AMC. Finally, past returns influence subsequent posting activity on GME and AMC at the second lag, reflecting a reflexive dynamic in which rising prices attract online attention and amplify speculative engagement.

5.2.3. Granger Causality Tests

Table 7 presents the Granger Causality Wald Test Results for the three VAR systems, allowing a comparison of the directional relationships between social media activity and market outcomes.

Table 7. Granger Causality Wald test results for Returns, Sentiment, and ln (Posts) across GME, AMC, and KOSS

Equation	Excluded	GME	AMC	KOSS
Return	Sentiment	8.554**	7.460**	0.940
Return	ln (Posts)	27.830***	12.958***	3.043
Return	All	39.817***	22.356***	4.861
Sentiment	Return	5.934*	1.261	0.794
Sentiment	ln (Posts)	23.895***	38.665***	17.780***
Sentiment	All	29.950***	39.945***	18.865***
ln (Posts)	Return	7.053**	5.963*	2.842
ln (Posts)	Sentiment	3.486	1.958	9.998***
ln (Posts)	All	10.126**	7.865	12.641**

Notes: All tests are based on two degrees of freedom corresponding to a VAR with two lags. ***$p < 0.01$, **$p < 0.05$, * $p < 0.10$.

The results indicate a substantial heterogeneity across the three stocks in the dynamic relationship between social media activity and stock market behavior.

First, for GME, past sentiment and posting activity Granger-cause returns ($p = 0.014$ and $p = 0.000$, respectively), confirming that past Reddit activity contains statistically significant predictive information about future price movements, beyond what is captured by the stock's own historical returns. At the same time, returns also predict future posting activity, providing evidence consistent with a bidirectional feedback mechanism between market performance and online attention. Economically, this result aligns with the notion that price appreciation reinforces coordinated behavior among retail investors (Lee et al., 2025; Costola et al., 2021). The reverse channel from returns to sentiment is relatively weaker and only marginally significant at the 10% level ($p = 0.051$), indicating a present but limited reverse channel. Nevertheless, GME displays the clearest evidence of a self-reinforcing interaction between Reddit activity and market behavior.

Second, AMC exhibits a similar but weaker structure compared to GME. Returns are Granger-caused by both sentiment and posting activity, indicating that Reddit activity stores predictive information about future price movements; however, the reverse direction is considerably less pronounced. This evidence may indicate that, for AMC, the flow of information is predominantly unidirectional, flowing from social media activity to stock returns, rather than a fully bidirectional feedback loop process.

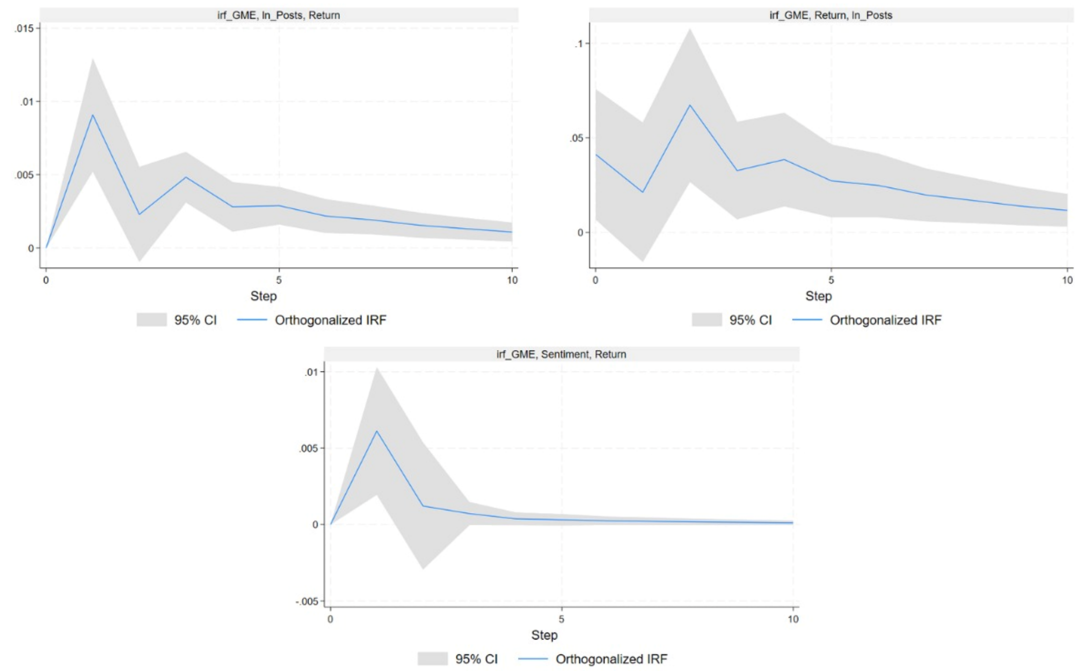
Lastly, KOSS displays no significant causal predictive relationship between social media variables and returns in either direction. The only statistically significant interactions occur between sentiment and posting activity itself, which indicates that online discussions surrounding KOSS remained largely internal to the WSB community without generating measurable spillovers into market prices. This conclusion is economically interpretable, as KOSS's substantially smaller market presence and lower liquidity relative to GME and AMC. Even when online attention increased, the stock may not have attracted sufficient coordinated retail participation to produce consistent price responses.

Overall, the Granger Causality analysis reveals that social media's predictive effect is concentrated on the most well-known and liquid traded meme stocks rather than being a consistent phenomenon across all firms connected to the meme stocks episode.

5.2.4. Impulse Response Functions

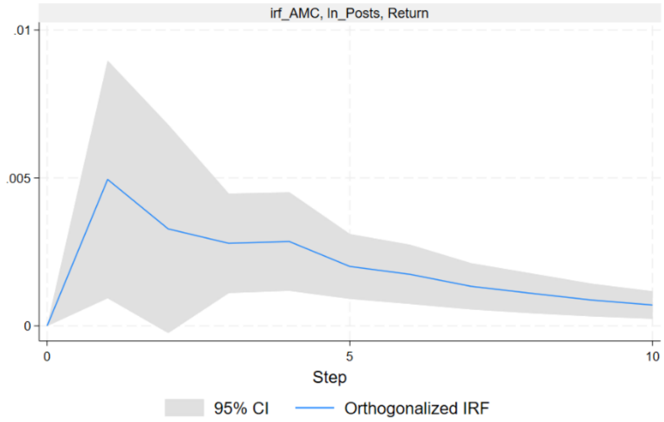
By displaying the time and durability of the predicted dynamic relationships across a ten-day trading horizon, the Orthogonalized Impulse Response Functions (OIRFs) enhance the Granger Causality study. Given the absence of meaningful causal links for Koss, the IRF discussion concentrates on GME and AMC.

Figure 1. Dynamic Feedback Effects Between Reddit Activity and Returns for GME



For GME, a positive shock to Reddit post volume results in an immediate increase in returns, peaking within the first trading day before gradually dissipating within five to six days. This indicates that heightened online visibility translates into short-term buying. Conversely, positive return shocks lead to increased posting volume, reinforcing the feedback loop, with effects peaking around day two and gradually declining. Similarly, positive sentiment shocks produce a temporary increase in returns, concentrated in the initial trading days. The impulse responses gradually dissipate toward zero within several trading days, indicating that the effects are temporary rather than permanent. However, the absence of a statistically significant negative overshooting pattern provides only partial support for H4, implying limited evidence of strong overreaction and correction dynamics.

Figure 2. Dynamic Response of AMC Returns to Reddit Attention Shock



AMC exhibits broadly similar dynamics, although the magnitude of the responses is weaker and dissipates more rapidly. Positive shocks to trading volume and sentiment generate temporary increases in returns, whereas the reverse effect, from returns to online activity, is more limited, consistent with the weaker feedback loop identified in the Granger causality tests. Importantly, the absence of a negative reversal within the ten-day horizon does not imply the rejection of H4, as the VAR model captures short-term dynamics, and potential corrections may occur over a longer horizon, as analyzed in greater detail in Section 5.5.

5.2.5. Summary

The VAR analysis reveals substantial heterogeneity in the relationship between social media activity and meme stock dynamics across GME, AMC, and KOSS.

For GME, when bidirectional predictive correlations between online discussions and returns emerge, the feedback loop over WSB engagement and market outcomes is particularly noticeable. While KOSS shows no meaningful evidence that Reddit discussions systematically translate into measurable market effects, AMC displays a weaker and primarily unidirectional relationship between social media and pricing. The impulse response functions verify that these effects are concentrated during the first few trading days following a social media shock and dissipate relatively quickly thereafter.

Overall, the findings imply that, especially for the most visible and liquid meme stocks, social media engagement functions mainly as a short-term amplification mechanism during times of increased retail attention.

5.3. Difference-in-Differences (DiD) Results

This chapter presents the results of the DiD analysis, as outlined in Section 4.5. The discussion is structured in five stages: first, the assessment of the parallel trends; second, the baseline ATT estimates; third, the dynamic event study; fourth, the robustness analyses; and finally, the spike versus reversal decomposition. A complementary within-treatment analysis based on Reddit activity is presented separately. The DiD analysis is relevant for addressing RQ 3 and Hypothesis 4, as it allows the examination of whether the market effects associated with the GameStop episode were temporary or persistent over time.

5.3.1. Parallel Trends Test

Before assessing the treatment effects, the parallel trends assumption was tested by interacting the treatment indicator with pre-event dummies (post = 0), while controlling for stock fixed effects, market capitalization, and the book-to-market ratio.

Since the treatment indicator is time-invariant and largely absorbed by the stock fixed effects, some interaction terms are omitted due to collinearity, reducing the test's statistical power and the informative capacity of a regression-based pre-trend coefficient in isolation. Nevertheless, before the GME episode, there is no indication that meme stocks and the control group have systematically different pre-treatment dynamics.

Additional support for the parallel trends assumption is provided later by the dynamic event-study analysis, which shows that pre-event coefficients remain economically small and statistically insignificant, thereby corroborating the parallel trends assumption required for causal identification in the DiD framework.

5.3.2. Main DiD Estimates

Table 8 below presents the baseline ATT estimates for daily returns, volatility, and turnover over the ±130 trading days window around January 13, 2021.

Table 8. Main DiD Results

Variable	ATT	Standard Error	Adjusted R^2
Return	-0.0002	0.0029	0.003
Volatility	0.0457***	0.0098	0.397
ln (Turnover)	0.740***	0.2466	0.806

Note: Stock fixed effects and quadratic time trend included. Standard errors clustered at the firm level (k =11). ***p<0.01.

The data analysis shows that the GameStop episode generated economically meaningful increases in both volatility and trading intensity among meme stocks, while no statistically significant average treatment effect is detected for returns over the full event window.

The strongest and most persistent effect concerns turnover. The ATT estimator for ln (Turnover) is positive and highly significant ($\beta = 0.740$; $p = 0.013$), indicating a differential increase of approximately 0.740 logarithmic points. This corresponds to about a 110% increase in trading intensity relative to shares outstanding following the GME episode, compared to the control firms ($e^{0.740} - 1 \sim 1.10$). Economically, this result is consistent with the speculative trading dynamics of meme stocks. Higher turnover reflects increased investor participation and more frequent trading, typical of retail-driven speculation and short squeeze episodes. The magnitude of the estimate also supports the attention-based trading hypothesis in a way that coordinated retail activity amplified trading intensity even without corresponding changes in returns or volatility.

Similarly, volatility increases significantly following the shock ($\beta = 0.0457$; $p < 0.001$), indicating that meme stocks experienced persistently higher daily price fluctuations relative to the control group. This finding is economically plausible given the heightened uncertainty, disagreement among investors, and speculative trading pressure commonly observed during short squeeze episodes.

By contrast, the ATT effect on returns is statistically insignificant over the full sample window ($\beta = -0.0002$; $p = 0.944$), demonstrating that although meme stocks experienced sharp temporary price increases during the event, these gains were not sustained in the post-event period. This result is consistent with the spike-reversal decomposition in Section 5.5.5, which shows that positive abnormal returns were largely offset by subsequent corrections.

Taken together, the DiD estimates demonstrate that the GameStop episode was primarily characterized by persistent increases in speculative trading activity and market instability, rather than permanently high returns.

5.3.3. Event study

The event study offers a dynamic overview of the treatment effects throughout a ±10-week timeframe surrounding the event (see **Appendix F**).

Regarding returns and volatility, pre-treatment coefficients remain close to zero across the pre-event period, further supporting the absence of anticipation effects and reinforcing the credibility of the DiD identification strategy. The confidence intervals remain relatively wide across the entire dataset, reflecting the limited number of treated clusters and the resulting reduction in statistical power.

When it comes to turnover, the event study reveals a more economically informative dynamic pattern. Prior to the event, coefficients fluctuated around zero and remained statistically insignificant, while after the GME stock, turnover rose sharply and remained strongly positive for several subsequent weeks. The largest effects occur around three to four weeks after the event, revealing a substantial and persistent increase in speculative trading intensity. It is important to note that, since turnover measures volume relative to shares outstanding, the increase reflects more intensive trading of the same shares rather than firm-size effects, being in line with higher retail participation and short-term speculative trading during the meme stock episode. Subsequently, the turnover effects gradually decline but remain positive over the remaining post-event window.

5.3.4. Robustness Tests

Table 9 summarizes the robustness analyses, confirming the baseline findings across alternative specifications and event windows.

Table 9. Robustness Checks

Variable	Baseline (±130 days)	±60 days	±30 days	First Differences
Return ATT	-0.0002	0.009*	0.015	-0.0004
Volatility ATT	0.0457***	0.048***	0.030**	0.0003
ln (Turnover) ATT	0.740***	0.611**	0.508*	0.039**

Note: Clustered standard errors at the firm level. * $p<0.10$; ** $p < 0.05$; *** $p < 0.01$.

The turnover effect remains positive and statistically significant across alternative window lengths, with magnitudes in alignment with the baseline, indicating that the results are not driven by a specific horizon choice. Similarly, volatility remains consistently positive and significant across all specifications, reinforcing the evidence that the elevated volatility among meme stocks was a persistent feature of the post-shock period.

In contrast, return effects become more pronounced within a narrower timeframe, implying that abnormal price appreciation was primarily concentrated immediately after the occurrence and then dissipated relatively quickly thereafter. This pattern predicted the spike versus reversal analysis, which will be examined further in Section 5.5.5.

The first differences specification further supports the robustness of the turnover results. While the return and volatility coefficients lose statistical significance after differencing, turnover remains positive and statistically significant. The reduction is expected, as first-differencing lowers the number of observations and increases standard errors, especially in small samples (Wooldridge, 2010), thereby diminishing statistical power. This outcome is economically intuitive, since the intensity of speculative trading persisted beyond the initial price spike, while the abnormal returns were comparatively short-lived.

Following that, a placebo test was performed, using January 2020 as a fictional treatment date, which failed to yield noticeable results, lending validity to the identification technique. The interaction terms were partially excluded due to multicollinearity with the fixed effects, reflecting modest within-stock variation in the placebo period and preventing their direction from being interpreted. However, no systematic placebo effect was identified, and no evidence was presented that would bring the design's credibility into question.

Wild Cluster Bootstrap

The dataset employed in this study contains a small number of clusters (k = 11), so conventional cluster-robust standard errors may generate inaccurate results in finite samples. To overcome this issue, the Wild Cluster Bootstrap approach with Webb weights and 999 replicates was implemented. The bootstrap p-values support the statistical significance of the baseline estimates for both volatility and turnover effects. These findings confirm that the observed significance is not triggered by small-sample distortions.

Coarsened Exact Matching (CEM) DiD

As a robustness exercise, the Coarsened Exact Matching (CEM) procedure was applied to the pre-treatment covariate. The procedure achieves perfect balance across strata (L1 = 0), but only a very small subset of control firms could be matched to the treated firms, confirming the same structural limitation identified in the PSM analysis. Since the matched sample becomes extremely small, the resulting estimates are determined almost exclusively by the treated units and, therefore, cannot be interpreted as a standard matched comparison.

Notwithstanding this limitation, the CEM-weighted DiD estimates are quantitatively identical to the baseline results, namely for volatility and turnover, and the Wild Cluster Bootstrap supports the statistical significance of these findings. The consistency across specifications allows one to conclude that the key results are not sensitive to the exact definition of the control group. Accordingly, CEM should be understood as a sensitivity test of the main estimator rather than an alternative identification strategy.

5.3.5. Spike versus Reversal Analysis

This section is intended to analyze whether the treatment effects were temporary or persistent. To this end, the post-event period is divided into two phases: a spike phase, covering the first two weeks after the event, and a reversal phase, covering the remaining post-event window.

Table 10. Spike versus Reversal Analysis

Variable	Spike ATT	Reversal ATT	Difference (p-value)
Return	+0.024**	-0.019**	+0.043** (p = 0.006)
Volatility	+0.038**	+0.052***	-0.014 (p = 0.377)
ln (Turnover)	+0.804***	+0.689**	+0.115 (p = 0.615)

Note: Stock fixed effects and quadratic time trend included. Standard errors were clustered at the firm level. **p<0.05, ***p<0.01.

The return results reveal a clear reversal dynamic. During the first two weeks after the event, meme stocks experienced strongly positive abnormal returns, followed by significantly negative returns in the subsequent period. The difference between the two phases is statistically significant (p = 0.006), indicating that the initial price increase was temporary and subsequently corrected. This pattern is consistent with short-lived price inflation and a later reversal, characteristic of short squeeze dynamics (Barber et al., 2022). It also explains why the average ATT over the entire ±130-day window is relatively small, as the two effects partially offset each other.

In contrast, volatility remains positive and elevated throughout both phases, while the difference between them is not statistically significant (0 = 0.377). This evidence indicates that significant uncertainty persisted beyond the initial peak, although the difference between the two periods is not strong enough to be statistically distinguished.

The trading volume follows a similar pattern. Turnover remains significantly positive during both phases, with the difference between them not being statistically significant (p = 0.615), indicating that elevated investor participation continued throughout the post-event period, with no meaningful decline recorded between the peak and reversal phases.

In general, these results indicate a clear distinction between channels. While the return effect is temporary and consistent with short squeeze dynamics, followed by a price correction, the liquidity and attention channel appears more persistent and extends beyond the price peak.

5.3.6. Within-Treated Analysis: Reddit Sentiment and Activity

In this complementary analysis, the sample is restricted to the eleven meme stocks used in the baseline panel regression to examine whether lagged Reddit sentiment and posting activity predict subsequent market outcomes within the treatment group (N = 1,540 after accounting for lagged variables). This analysis is conceptually distinct from the main DiD framework, as it assesses whether Reddit activity functions as an amplification mechanism within the meme stocks rather than estimating a causal ATT relative to a control group.

Neither lagged sentiment nor lagged posting activity is statistically significant for the next-day stock returns. Regarding share turnover, both variables proved insignificant, indicating that Reddit activity has little daily predictive power over trading intensity within the group analyzed. However, both lagged sentiment and lagged posting activity are positively and significantly associated with the following day's volatility ($\beta = 0.010$, $p = 0.048$ and $\beta = 0.003$, $p = 0.034$, respectively), allowing one to conclude that periods of higher engagement on Reddit predict greater price dispersion the following day.

Overall, the evidence indicates that Reddit activity has limited explanatory power as a day-to-day predictor of meme stock returns and relative trading intensity but appears to amplify short-term volatility. Moreover, the results support the interpretation that Reddit primarily operates as a coordination device during extreme speculative episodes, instead of being a continuous driver of daily price formation. The evidence should therefore be understood as indicative of attention and feedback effects, not as definitive proof of a causal social media influence on market outcomes. The absence of stronger effects may also reflect the limitations of lexicon-based sentiment measures in capturing the slang, irony, and meme-coded language characteristic of r/WallStreetBets discussions.

5.3.7. Overall Interpretation and Conclusions

Taken together, the DiD results lead to a clear and consistent conclusion. The GameStop episode was primarily a temporary speculative shock characterized by elevated trading intensity and persistent market instability, instead of permanently higher stock valuations.

The estimated increase in intense trading activity relative to shares outstanding is consistent with coordinated retail participation, speculative recycling of shares, and heightened investor attention. Volatility also increased sharply and remained elevated throughout both the spike and reversal phases. At the same time, the absence of a persistent return effect indicates that the initial price increases were ultimately temporary and subject to subsequent reversal.

Overall, these findings align with the broader narrative emerging from VAR/IRF: social media and retail coordination behave as short-term amplification mechanisms during a speculative episode rather than as drivers of sustained fundamental revaluation.

6. Conclusion

Technology has been evolving at an unprecedented pace, transforming economic and social activity. Over the past decades, social media has become an integral part of modern life, lowering participation costs in financial markets and increasing investor synchronization, causing these platforms to function as mechanisms for transmitting speculative dynamics. This is particularly concerning, as it calls into question traditional assumptions of market efficiency, given the ability of retail investor coordination to significantly amplify trading intensity and volatility. These considerations raise a fundamental question: can the coordination of retail investors through social media generate temporary distortions in market prices and challenge traditional assumptions of market efficiency?

In pursuit of an answer, this study aims to analyze how Reddit activity influences meme stock price movements, focusing on a sample of eleven meme stocks that have gained popularity among retail investors through social media. To this end, three complementary methodological approaches were employed: panel regression models, VAR models with Granger causality tests, and a DiD model that exploits the GameStop episode of January 2021 as a quasi-natural experiment.

The panel regression demonstrates that lagged Reddit sentiment and the posting volume are statistically significant predictors of short-term meme stock returns, supporting Hypothesis 1. However, Reddit activity did not allow for a robust prediction of volatility or trading intensity, providing no support for Hypotheses 2 and 3 within the panel framework. These findings lead to the conclusion that these effects, instead of operating as continuous market drivers, are episodic and concentrated during periods of heightened attention.

Concerning the VAR model, there is evidence of heterogeneity among the stocks analyzed. GME exhibits the strongest feedback mechanism between Reddit and the market, revealing a bidirectional relationship between online discussions and returns. The effects are weaker and less persistent, with a predominantly unidirectional relationship for AMC, while KOSS showed little evidence of meaningful transmission. Furthermore, IRF confirms that these effects are primarily short-term, concentrated in the first 2–3 days, and dissipate rapidly thereafter. In addition, social media effects are concentrated on the most visible meme stocks, where online attention is more likely to translate into coordinated trading behavior.

The DiD results reveal that the GameStop episode was associated with a substantial increase in trading activity, approximately 110% higher relative to the control group, and a significant rise in volatility among meme stocks. However, no significant effect was found on average returns over the full period. This pattern is explained by the initial spike in positive returns during the first two weeks, followed by a statistically significant reversal, supporting Hypothesis 4, indicating that social-media-driven price effects were largely temporary.

This study also contributes to the literature on social media and financial markets. First, it combines panel regressions, VAR models, and a Difference-in-Differences framework to simultaneously examine the relationship between Reddit activity and meme stock behavior from predictive, dynamic, and quasi-causal perspectives. While a large part of the existing literature focuses primarily on sentiment measures, this dissertation extends the analysis by jointly examining sentiment, posting activity, and their dynamic interactions over time. The results revealed that social media functions primarily as an amplification mechanism during periods of heightened investor attention, rather than acting as a continuous driver of market outcomes. Second, whereas literature has often treated meme stocks as a relatively homogeneous group, the evidence reveals substantial cross-stock heterogeneity. GME exhibits considerably stronger and more persistent feedback effects than AMC and KOSS, which means that meme stocks cannot be fully understood without accounting for firm-specific differences in investor attention and market dynamics. Finally, the evidence indicates that social-media-driven shocks generate temporary price distortions that are subsequently corrected, providing only limited support for persistent deviations from market efficiency.

Overall, the findings are broadly consistent with behavioral finance literature, investor attention theory, and prior evidence on sentiment-driven trading and herding in financial markets. The results indicate that social media influences markets through sentiment, attention, and coordinated trading behavior.

From a policy perspective, the findings highlight the growing need for regulators to monitor investor coordination through social media, incorporating sentiment and activity metrics as complementary risk indicators. The GameStop episode raises relevant questions regarding market transparency and the balance between investor protection and market efficiency. The evidence points to several policy implications. First, financial literacy among retail investors should be promoted, given the speculative dynamics observed, aligned with the behavior of noise traders rather than fundamentals-based decision-making. Second, regulators could implement adequacy mechanisms to assess whether retail investors have sufficient knowledge of the risks inherent in highly speculative assets before trading them. Third, regulators should strengthen the monitoring of digital platforms and require greater transparency, especially during periods of abnormal spikes in sentiment and trading volume.

From an investor's perspective, short-term meme stock movements may reflect speculation rather than fundamentals. As a result, any abnormal returns are uncertain, temporary, and risky, limiting their practical relevance. Retail investors are also disadvantaged compared to institutional investors, as they lack access to real-time social media monitoring tools, face slower execution speeds, and wider bid-ask spreads on illiquid and speculative stocks, even on commission-free platforms, and tend to act after the peak of attention has already passed, leaving them exposed to the reversal patterns documented in this study.

In terms of market efficiency, the evidence reveals limited short-term market efficiency. The semi-strong form of the Efficient Market Hypothesis (EMH) states that prices should fully reflect all available information. However, social media signals predict future returns, which contrasts with the EMH. Social media activity and noise trader behavior appear to lead to temporary deviations in prices from their fundamental value. The temporary effects and reversion patterns reveal that markets eventually partially self-correct, which is not entirely inconsistent with long-term efficiency.

Notwithstanding the contributions made, this study presents several limitations. Panel and VAR results should be approached with caution, as social media attention and stock market behavior may be jointly determined, creating endogeneity. Although DiD is more robust, the relationship remains largely associative. Furthermore, the distinct nature of meme stocks limits the availability of comparable control units and constrains the sample size. Finally, VADER may not fully capture the informal language and sarcasm typical of online discussions.

While these limitations are important to recognize, they do allow for future research aimed at deepening the understanding of the topic. First, the adoption of more sophisticated sentiment analysis tools, such as finance-specific language models (FinBERT or FinGPT) or domain-specific lexicons such as the Loughran-McDonald dictionary, could improve the accuracy of sentiment measurement in informal online communities, potentially revealing effects not captured by lexicon-based techniques. Second, extending the analysis to platforms such as X and Stocktwits would allow for the identification of cross-platform trends. Third, it would be relevant to assess whether these results generalize to stock markets outside the U.S., given differences in terms of retail investor participation, market structure, and regulatory environments. Finally, assessing the effectiveness of regulatory interventions, such as temporary trading restrictions and stricter disclosure requirements, in moderating the speculative dynamics identified in this study constitutes a relevant line of research.

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Appendix

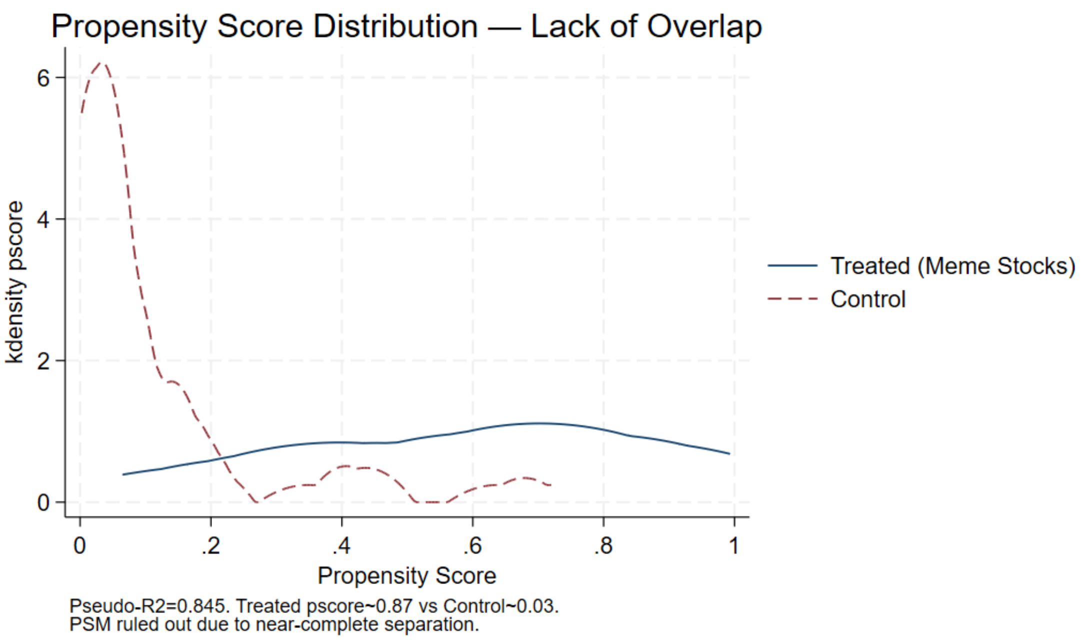
Appendix A - Research Questions and Associated Hypotheses

Table 11. Research Questions and Associated Hypotheses

Research Questions	Focus	Associated Hypotheses
RQ1	Social media activity and meme stock dynamics.	H1, H2, H3
RQ2	Feedback loops between sentiment and market outcomes.	H1, H3
RQ3	Persistence versus reversals of sentiment effects.	H4

Appendix B - Propensity Score Distribution

Figure 3. Propensity Score Distribution: Treated and Control Groups



Appendix C - Robustness Checks Results I – Engagement Specification

Table 12. Return Specification: Main vs Engagement Specification

Variable	Main	With Engagement
Return (t-1)	-0.118* (0.056)	-0.118* (0.056)
Sentiment (t-1)	0.010** (0.004)	0.010** (0.004)
ln (Posts) (t-1)	0.001** (0.001)	0.004 (0.002)
ln (Engagement) (t-1)		-0.001 (0.002)
ln (Mkt Cap)	-0.001 (0.002)	-0.001 (0.002)
Book-to-Market	0.000 (0.000)	0.000 (0.000)
N	12,963	12,963
Within R^2	0.016	0.016
Adj. R^2	0.161	0.161

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All specifications include firm and time fixed effects. ln (Engagement) is a composite logarithmic index of comments and upvotes.

Appendix D - Robustness Checks II – Abnormal Returns

Table 13. Robustness: Raw Returns vs Abnormal Returns

Variable	Raw Returns	Abnormal Returns
Return (t-1)	-0.118* (0.056)	-0.427* (0.242)
Sentiment (t-1)	0.010** (0.004)	0.018** (0.006)
ln (Posts) (t-1)	0.001** (0.001)	0.002 (0.001)
ln (Mkt Cap)	-0.001 (0.002)	0.017*** (0.001)
Book-to-Market	0.000 (0.000)	0.000 (0.000)
N	12,963	12,963
Within R^2	0.016	0.032
Adj. R^2	0.161	0.064

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All specifications include firm and time fixed effects. Abnormal returns are defined as stock returns net of contemporaneous market returns.

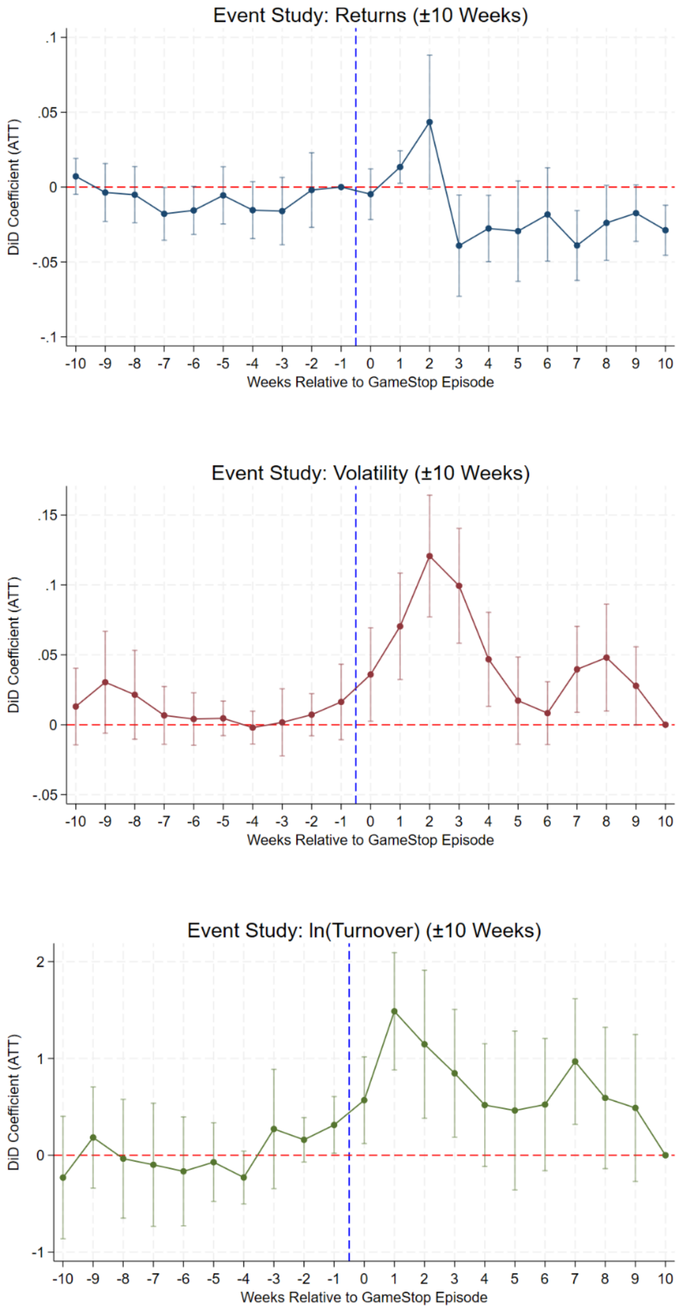
Appendix E - Diagnostic Tests

Table 14. Diagnostic Tests for the Baseline Panel Regression Model

Test	Statistic	p-value	Conclusion
Wooldridge (autocorrelation)	$F_{(1,10)} = 27.861$	0.0004	Serial Correlation Present □ lag of dependent variable included.
Pesaran's CD (cross-sect. Dependence)	CD = - 15.52	0.000	Negative CSD detected.
Mean VIF (multicollinearity)	1.02	-	No concern.

Appendix F - Event Study Plots

Figure 4. Event Study Estimates for Returns, Volatility, and Turnover Around the GameStop Episode



Appendix G – Variable description

Table 15. Description of the Variables Extracted from the Databases

Variable Acronym	Description	Source
Date	Trading date	
Stock	Stock ticker Symbol	
Volume	Daily trading volume (number of shares)	Refinitiv
Price	Daily closing price (USD)	Refinitiv
LogMarketCapitalization	Natural Log of total market capitalization (USD)	Refinitiv
Return	Daily stock return (%)	Refinitiv
Volatility	5-day rolling standard deviation of daily returns	Refinitiv
Turnover	Daily Turnover Ratio (Volume/Shares Outstanding)	Refinitiv
BookValuePercentageofMarket	Book-to-market ratio proxy (%)	
ReturnMarket	Daily market return (S&P 500) (%)	
Abnormal_Return	Daily abnormal stock return (%)	
Posts	Daily Number of Reddit posts	Reddit
Sentiment	Daily Reddit sentiment score (VADER: -1 to +1)	Reddit
Comments	Daily Number of Reddit comments	Reddit
Upvotes	Daily Number of Reddit upvotes	Reddit
Sentiment_Lag1	Lagged Reddit sentiment score (t-1)	
Posts_Lag1	Lagged number of Reddit posts (t-1)	