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Trading on Emotions: The Dual Regimes of Meme Stocks Driven by Social Media Sentiment

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ABSTRACT

GameStop serves as a striking example of a recent abnormal market phenomenon, where the collective actions of social media users, particularly in the WallStreetBets community on Reddit, have exerted a significant influence on stock prices, leading to phenomenon of "Meme Stocks." This paper introduces the Emotion Regime Switching-VAR methodology to explore the extent to which sentiment from WallStreetBets affects GameStop's price movements. The results reveal that while social media sentiment significantly impacts the market, this influence is not uniform. The market alternates between rational and emotional states, with social media acting as a catalyst behind these shifts. Notably, during emotional states, the market displays heightened volatility and a more substantial effect of sentiment in driving stock prices.

Introduction

The financial markets have experienced a new and unprecedented phenomenon: the growing influence of social media sentiment on stock prices. Driven by social media platforms and online forums, individual investors orchestrate drastic market movements, redefining market dynamics and challenging traditional trading paradigms. These retail investors specifically target meme stocks, stocks characterized by their high volatility and irrational price movements driven by the spread of sentiment on social media platforms [1].

A quintessential example of the influence of social media on stock prices is the short squeeze of GameStop (GME) in January 2021 by Reddit's WallStreetBets (WSB). With over 16 million members, WallStreetBets is one of the largest online investing communities in the world. Known for its high-risk and high-reward investment strategies, this community is characterized by its unconventional approach to investing, frequently ignoring market fundamentals in the pursuit of quick profits. During the short squeeze of GameStop, the intense sentiment and speculative investment advice posted within WallStreetBets drove the price of GameStop to over $500 per share—nearly 30 times its valuation of $17.25 from the previous month [2]. Similarly, other meme stocks, such as AMC Entertainment Holding (AMC) and Blackberry (BB), experienced substantial growth, with AMC and BB stock prices reaching 1,200% and 200% at their respective peaks.

This dramatic surge of meme stocks driven by WallStreetBets marks a new era of retail investing, characterized by the influence of online communities on financial markets and the power of collective action among individual investors. Research on the influence of online communities on financial markets is still in its infancy, with the underlying mechanisms of this phenomenon remaining unclear.

The objective of this research paper is to fill this gap by investigating the underlying causes that drive the influence of WallStreetBets on GameStop. Specifically, we investigate whether intense sentiment on WallStreetBets induces irrational decision-making among investors and how this behavior transitions over time to more rational decision-making influenced by market fundamentals. Our hypothesis postulates that intense sentiment on WSB triggers irrational herding behavior, leading to a price surge, and as the sentiment wanes, investors' decisions become more aligned with market fundamentals, reflecting a transition to rational behavior. By investigating our hypothesis, we shed light and provide a deeper understanding of how social media platforms can drive volatility and affect stock prices. Through this study, investors and regulators can benefit from understanding the influence of social media on investor behavior through more robust investment strategies and the creation of policies to mitigate potential market manipulations.

To analyze the impact of WSB's sentiment on GME's stock price, we first utilize the Reddit and Yahoo Application Programming Interface (API) to collect the conversations from WSB posts and the daily stock price of GME. From there, applying natural language processing techniques, we quantify the sentiment in all WSB's posts and comments. Following the data collection and sentiment analysis, we employ a Markov Regime Switching Model to identify and estimate the transition matrix between two distinct market states in the stock price behavior. After identifying the different market states, a Vector Autoregression (VAR) Model is used to illustrate the dynamic relationship between sentiment and stock prices under different market states.

In this paper, we present two major findings and offer a novel perspective using Markov Switching and VAR models to gain deeper insights into the influence of WSB on GME. Firstly, utilizing our framework with the Markov Switching model, we identified two distinct regimes with emotional and rational market behaviors: a low-volatility regime characterized by stable prices, indicative of rational investor behavior, and a high-volatility regime marked by elevated prices, reflective of emotional behaviors. Secondly, utilizing the Vector Autoregression model to investigate each regime, we find that the rational state, with lower volatility and stable prices, is primarily driven by fundamentals, while the emotional state, with higher volatility and elevated prices, is significantly driven by social media sentiment. Our findings illustrate the state-dependent predictive power of social media, bolstering the results of Birru and Young (2022) and Ur Rehman et al. (2022) [3] [4].

Below the paper proceeds as follows, Section 2 presents a literature review. Section 3 develops the hypothesis, while Section 4 presents the methodology. Section 5 illustrates the data. Section 6 presents the results. Section 7 presents the discussion and conclusions.

Literature Review

In practice, markets often deviate from theoretical expectations of rationality, influenced by irrational behaviors [5]. Nobel laureate Robert Shiller's narrative economics framework posits that economic outcomes are shaped by prevailing stories and narratives, sometimes causing irrational market dynamics [6] [7]. Building on this, our study hypothesizes that social media narratives on WallStreetBets drive irrational herding behavior, exemplified by GameStop's stock surge. We focus on three factors: social media's influence on meme stocks, sentiment's effect on investment behavior, and how market conditions shape investment reactions.

Social media significantly affects meme stocks. Costola et al. (2021) introduced "Mementum," linking social media-fueled momentum to meme stock returns [2]. Similarly, Foucault et al. (2011) showed that media attention heightens stock price volatility by attracting retail investors, reinforcing Barber and Odean's (2008) finding that media visibility drives individual investor action [8] [9]. Studies also reveal that meme stocks and cryptocurrencies experience co-explosivity due to increased internet interest, creating potential spillover effects across markets [10] [11]. However, these patterns challenge Fama's (1970) efficient market hypothesis, instead aligning with Shiller's (2020) theory of narrative-driven market fluctuations [12] [7].

Sentiment also plays a crucial role in investment behavior, often leading to irrationality. Bechara (2004) and Lerner et al. (2015) demonstrated that emotions significantly affect decision-making [13] [14]. In financial contexts, media-induced emotions can prompt irrational decisions, leading to disparities between stock prices and intrinsic value [5]. Zhang et al. (2018) and Kaplanski & Levy (2010) found that social media sentiment can influence stock indices and asset pricing, with emotions like happiness or anxiety impacting investor decisions [15] [16].

Market conditions further shape sentiment-driven investment behavior. As market uncertainty rises, the influence of sentiment on returns is amplified [3]. Under volatile conditions, noise traders exhibit stronger herding behavior, fostering market inefficiencies and price bubbles [17]. Chung and Yeh (2009) further revealed that sentiment's predictive power on returns varies by market state, underscoring how investor behavior is modulated by broader market conditions [18].

Hypothesis

Numerous empirical studies suggest that time series behaviors of economic and financial variables may exhibit distinct patterns over time, often influenced by changing market conditions. For instance, Chang and Yeh (2009) and Hamilton (2010) highlight the effectiveness of regime-switching models in accounting for disruptive events that cause breaks in economic and financial data patterns [18] [19]. The rationale for using regime-switching models in finance and economics time series analysis is rooted in the understanding that markets often transition to different states, each characterized by their own distinct characteristics.

Hamilton (1989) pioneered the use of regime-switching models to characterize economic cycles, such as expansions and contractions, providing a more accurate perspective of the non-linear behaviors in financial markets [20]. These regime-switching models offer a nuanced analysis of market dynamics, providing deeper insights into the different behaviors of economic and financial variables compared to traditional models, which assume a single constant relationship over time.

Furthermore, behavioral finance theory explains how individuals often deviate from rational decision-making due to the influence of sentiment and emotions. This effect is especially prevalent in stock prices held by noise traders, who base their investment decisions on sentiment rather than fundamental analysis. As Brown (1999) noted, the prices of these stocks exhibit increased volatility driven by an excessive amount of sentiment [21]. When arbitrage is risky and costly, stocks dominated by noise traders are vulnerable to fluctuations, as a lack of rational investors to correct mispricing allows sentiment-driven volatility [18].

However, irrational behavior triggered by sentiment on social media is unlikely to persist indefinity, as rational decision-making is prevalent in the majority of instances. Given the empirical evidence and theoretical foundations, we propose the following testable hypotheses:

Hypothesis 1: The price movement of Meme Stocks (GME) is distinct under two latent regimes, with one regime exhibiting higher volatility than the other.

Hypothesis 2: The predictive power of social media sentiment is dependent on the regime state.

Methodology

To test these hypotheses, we employ a Markov switching model, which integrates two or more dynamic models under a Markovian switching mechanism. Following Hamilton (1989) we focus on a combination between Markov switching and a Vector autoregression model (MSVAR) [20]. Integrating the Markov Switching and Vector Autoregressive models captures a more dynamic and realistic relationship between sentiment and stock prices under different market states. In this section, we first illustrate the features of Markovian switching and then discuss more general model specifications.

Numerous empirical articles in financial literature, including those of Perez-Quiros and Timmermann (2000), Gray (1996), and Chung and Yeh (2009) have demonstrated stock returns, volatility, sentiment, and other financial metrics exhibit distinct patterns under different market states [22] [23] [18]. The findings of these studies provide a rationale for using a Markov switching model, as its ability to identify distinct market states allows for a more nuanced understanding of the effects of sentiment on stock prices.

Our hypothesis states that the price movement of Meme stocks is distinct under two regimes. Therefore, we employ two equations in a Markov Switching model to illustrate the characteristics of these distinct regimes. Let y_t represent the price of GME at time t. We assume that GME's stock price dynamics are governed by a Markov switching process, with a regime variable of S_t that can alternate between two distinct states: An emotional state (State 1) and a rational state (State 2). The model is represented in the following equation:

$$y_t = \begin{cases} \alpha_{1,0} + \sum_{i=1}^{n} \alpha_{1,i} X_{t-i} + \varepsilon_{1,t}, & \text{if } S_t \text{ is in the emotional state (State 1)} \\ \alpha_{2,0} + \sum_{i=1}^{n} \alpha_{2,i} X_{t-i} + \varepsilon_{2,t}, & \text{if } S_t \text{ is in the rational state (State 2)} \end{cases} \quad (1)$$

Where X_{t-i} denotes the market fundamentals at time $t-i$, with i indicating the number of lags included in the model. The coefficients $\alpha_{1,0}$ and $\alpha_{2,0}$ are the intercepts for State 1 and State 2, respectively, while $\alpha_{1,i}$ and $\alpha_{2,i}$ measure the impact of market fundamentals on y_t in their respective states. Finally, the error terms $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are normally distributed to capture idiosyncratic shocks in each state.

The discrete regime variable S_t follow a 2-state first-order Markov chain, with the transition probability matrix P given by:

$$P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}$$

Where $p_{ij} = P(S_{t+1} = j \mid S_t = i)$ where $i, j \in \{1, 2\}$ indicating the emotional and rational states.

Within each state identified by the Markov switching model, the Vector Autoregression model (VAR) captures the dynamic interrelationships among multiple time series variables. By using the VAR model, we are able to analyze bidirectional relationships simultaneously, providing a robust framework for understanding the interdependencies among variables such as sentiment and stock prices. One of the key strengths of the VAR model lies in its ability to include lagged values of these variables, which is paramount as the influence of sentiment may not have an immediate effect on price. Instead, sentiment may have a lagged response, where the impact of sentiment manifests over time.

By incorporating these lagged relationships, the VAR model can provide a more comprehensive understanding of how past sentiment influences future prices and vice versa. VAR models have been widely used in the financial literature to study the relationship between various economic indicators, providing a strong rationale for its use in our analysis.

In the context of sentiment and price, both variables are likely to exert influence on each other over time. For example, shifts in investor sentiment may drive changes in stock prices, which may influence future sentiment. This cyclical interdependent relationship between sentiment and GameStop stock prices can be effectively modeled using a Vector Autoregressive (VAR) framework, which captures the linear interdependencies between sentiment and stock prices under two distinct market states, $s \in \{1,2\}$. In this framework, the dynamics under each state *s* are described as follows:

$$y_t = \alpha_{s,0} + \sum_{l=1}^{n} \alpha_{s,l} y_{t-l} + \sum_{l=1}^{n} \beta_{s,l} x_{t-l} + \epsilon_s \quad (2)$$

$$x_t = \gamma_{s,0} + \sum_{l=1}^{n} \gamma_{s,l} y_{t-l} + \sum_{l=1}^{n} \delta_{s,l} x_{t-l} + \upsilon_s \quad (3)$$

Here in equation 2, y_t represents the GME price at time *t*, which is influenced by both its own past values and past values of sentiment x_t over the previous *n* periods. Simultaneously in equation 3, x_t, representing the dynamics of sentiment at time *t*, is also influenced by its own past values as well as the past values of GameStop's price. The intercept term $\alpha_{s,0}$ and $\gamma_{s,0}$ represents the baseline level of GME price and sentiment specific to state *s*. While the error terms ϵ_s and υ_s capture the unexplained variance of GameStop's price and sentiment, respectively. The coefficient $\alpha_{s,l}$, $\beta_{s,l}$, $\gamma_{s,l}$, $\delta_{s,l}$ are state-dependent, meaning that the relationship between past and current values of GME prices and sentiment can vary depending on the market state. This VAR model effectively captures the feedback loop between sentiment and stock prices, providing a comprehensive view of how sentiment might drive GME prices differently under varying market states, such as periods of high or low volatility.

Data

This study analyzes the relationship between WallStreetBets sentiment and GameStop's stock price. Our data includes GameStop's daily closing prices from Yahoo Finance and sentiment scores from WallStreetBets posts/comments containing "GME" or "GameStop," collected via Reddit's API from March 23, 2021, to June 25, 2024. This period covers key events, including the GameStop short squeeze, capturing over 90,000 posts and comments. Sentiment was quantified using TextBlob, selected for its accuracy and efficiency in handling informal social media language.

Figure 1 displays average sentiment over time, highlighting peaks and troughs in optimism and pessimism that align with notable events. Figure 2 shows GameStop's closing prices, with pronounced peaks in early 2021 due to the short squeeze, followed by market correction and further fluctuations.

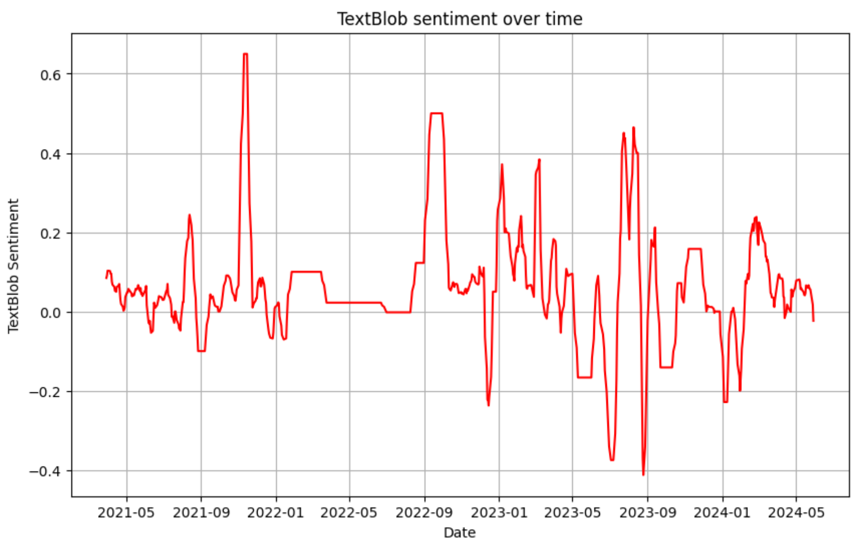

Figure 1. Average Sentiment Scores over Time

Figure 2 Close Price of GameStop over Time

A Pearson correlation test showed no significant causal relationship between sentiment and stock price, justifying our choice of the Markov Switching Vector Autoregressive model for a more nuanced analysis.

Results

This section presents our findings from our analysis of WallStreetBet's sentiment and its impact on GameStop's stock price under different states.

One of the main hypotheses of this study posits that the market behavior of GME is distinct under two distinct regimes, with one regime exhibiting higher volatility than the other. To test this hypothesis, we utilized a Markov switching model, a well-suited model designed to identify and characterize different regime shifts in series data. Below, Table 1 presents the estimated regimes, and Table 2 illustrates the transition probability between states.

Table 1. Estimated States

	Mean	Standard deviation
Regime 1	19.76***	23.88***
	-0.23	-1.62
Regime 2	41.76***	74.19***
	-0.49	-5.9

*: p<0.1;
**: p<0.05;
***: p<0.01;
The standard error is within parentheses.

Transition status	Probability

p_{s1-s1}	0.99*** （0.01）
p_{s2-s1}	0.0134** （0.01）

*: p<0.1;
**: p<0.05;
***: p<0.01;
The standard error is within parentheses.

Table 2. Transition probability

In regime 1, the mean price of GameStop is 19.76, with a standard deviation of 23.88. Our findings demonstrate that State 1 is characterized by lower volatility and lower average prices, suggesting that the market experiences more stability and prices are reflective of fundamentals. Conversely, regime 2 displays a noticeably higher average price of 41.76, with a standard deviation of 74.19. Given the higher average prices and standard deviation, our findings indicate that regime 2 is characterized by elevated prices and increased volatility, reflecting a more unstable market state driven by irrational exuberance and panic among investors. Similar to regime 1, these results are highly significant.

Furthermore, in Table 2, the transition probabilities offer insights into the frequency and likelihood of shifts between the market states. The first row, with a p_{s1-s1} value of 0.99, indicates the high probability that the market will remain in Regime 1 once it has entered it. On the other hand, the second row, with a p_{s2-s1} of 0.0134, reveals a much lower probability of the market in Regime 2 moving back to Regime 1. These probabilities highlight the persistent nature of each market state where sentiment-driven behavior may persist for an extended period of time.

Thus, from these findings we can ultimately come to our first result:

Result 1: The Markov Switching Model results align with Hypothesis 1, showing two distinct regimes consistent with emotional and rational state behaviors: a low-volatility state with stable prices, reflecting rational behavior, and a high-volatility state with elevated prices, indicative of emotional market reactions.

Our second hypothesis claims that the predictive power of social media sentiment is dependent on the regime state. In order to investigate this hypothesis, we employed a VAR specification [1]under the two states identified in the Markov Switching model. Below is the table of our results:

Table 3. VAR results of two states

Lagged Variables	Regime 1	Regime 2	Regime 1	Regime 2
	Sentiment Equation		Price Equation	
L1. Sentiment	0.72*** (0.05)	-0.74*** (0.06)	0.24 (0.40)	-0.43 (2.08)
L2. Sentiment	0.06 (0.06)	0.11 (0.07)	0.02 (0.49)	-5.06** (2.58)

[1] Stationarity test by Augmented Dickey-Fuller (ADF) test has been done before conducting VAR.

L3. Sentiment	-0.09 (0.06)	-0.00 (0.07)	-0.23 (0.49)	0.71 (2.59)
L4. Sentiment	0.08* (0.05)	-0.02 (0.06)	-0.02 (0.40)	6.08*** (2.10)
L1. Price	0.00 (0.01)	0.00 (0.00)	0.77*** (0.05)	0.85*** (0.05)
L2. Price	-0.00 (0.01)	0.00 (0.00)	0.12** (0.06)	0.01 (0.07)
L3. Price	0.01 (0.01)	-0.00 (0.00)	-0.08 (0.06)	0.14 (0.07)
L4. Price	-0.00 (0.01)	0.00 (0.00)	0.17 (0.05)	-0.05 (0.05)

*: p<0.1;
**: p<0.05;
***: p<0.01;
The standard error is within parentheses.

Table 3 presents the results from the sentiment and price equations across two distinct regimes. In order to compute the optimal number of lagged variables, we utilized the Akaike Information Criterion (AIC), which finds a balance between model complexity and how well the model fits. As shown in our results, only four lagged variables for sentiment and price are needed, as determined by AIC, which identified this as the optimum number of lags.

In regime 1, the first lagged variable of sentiment has a significant positive effect on the current sentiment, with a coefficient of 0.72 and a p-value of less than one percent, suggesting a strong autocorrelation effect. On the contrary, in regime 2, the first lagged variable of sentiment has a significantly negative effect, with a coefficient of -0.74, indicating that past positive sentiment may lead to a reduction in current sentiment, suggesting a correction mechanism in a more volatile market state. The rest of the variables in sentiment equations are not significant and show no sizable impact on the current sentiment.

On the other hand, when looking at the price equation in regime 1, the first and second lagged variables of the price were found to be significant, with a coefficient of 0.77 and 0.22, respectively. This result demonstrates an autocorrelation effect, suggesting the stock is driven by market fundamentals during this market state. More interestingly, within the price equation under Regime 2, both the second and fourth lagged variables of sentiment were found to be significant, with coefficients of -5.06 and 6.08, respectively. This finding highlights the nuanced and complex relationship between sentiment and stock market behavior.

The differing impacts of recent sentiment compared to sentiment from four days ago underline the dynamic nature of market psychology. Specifically, the negative coefficient associated with recent sentiment suggests that more immediate discussions on social media may induce a bearish reaction in the market. This could be due to heightened sensitivity or overreaction to recent information, particularly if the market perceives the sentiment as a signal of imminent risk or uncertainty. Conversely, the positive coefficient from sentiment four days ago indicates that earlier sentiment had a bullish influence on prices. This could be because market participants, having had more time to digest and reflect on earlier sentiments, may interpret them as more stable or reliable indicators, thus fostering a positive market response. This variation in the impact of sentiment across different time lags emphasizes the complexity of sentiment analysis in predicting stock movements. The results suggest that social media sentiment does indeed play a crucial role in price movements under Regime 2, but its influence is not uniform over time. Instead, it appears to fluctuate based on the timing and possibly the nature of the information being disseminated.

Our findings support the hypothesis that the effects of social media sentiment on stock prices are contingent on the regime state, further proving that understanding market sentiment requires a nuanced approach that takes into account the timing and context of the sentiment being analyzed. From these findings we can conclude with our final result:

Result 2: The VAR results confirm the state-dependent hypothesis by identifying two distinct market conditions: a rational state with lower volatility and stable prices driven by fundamentals, and an emotional state with higher volatility and elevated prices driven by social media sentiment.

Conclusion

This paper explores the market phenomenon of meme stocks, examining the interplay between social media sentiment and stock prices through both rational and emotional lenses. Our analysis reveals two distinct states: a rational state, where stock prices align with fundamentals, and an emotional state, where social media sentiment heavily influences prices. During the emotional state, social media drives significant price movements, reflecting the collective mood of investors.

Our findings align with literature suggesting that markets can shift between different behavioral states [20]. However, unlike previous studies treating sentiment as a constant, we demonstrate that its impact on stock prices intensifies under conditions of market uncertainty, mirroring observations by Birru and Young (2022) [3]. This amplification of sentiment's influence during heightened uncertainty aligns with prior studies on social media's impact on the stock market [15] [24].

The dual-state model highlights the importance of context: in volatile periods, investors may react more to collective sentiment than to fundamentals, resulting in price movements that deviate from rational expectations. While this study provides valuable insights, there are limitations. Our reliance on TextBlob for sentiment analysis may affect accuracy due to its handling of internet slang, and our focus on WallStreetBets and GameStop may limit generalizability.

Future research could broaden the dataset to include more stocks and social media platforms, as well as employ advanced sentiment analysis techniques for greater accuracy. By identifying rational and emotional states in stock price behavior, this study offers a nuanced perspective for understanding how social media sentiment influences financial markets. These insights contribute to behavioral finance and could guide investors and policymakers in managing the effects of social media on market dynamics.

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