Investor Sentiment as a Priced Factor and Stock Returns: Evidence from the Magnificent Seven

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Abstract

This study investigates whether investor sentiment exhibits characteristics similar to a priced factor in stock returns. Using data from the Magnificent Seven stocks over the period 2020–2024, the study conducts firm-level regressions to examine each firm's sensitivity to sentiment, proxied by Bloomberg's NLP-based sentiment scores derived from news and Twitter data. The resulting time-varying sentiment betas, estimated using rolling regressions, are then used to sort stocks and construct sentiment-based portfolios. Portfolio performance is evaluated against an equal-weighted benchmark. The results show that both news-based and Twitter-based sentiment portfolios outperform the equal-weighted benchmark in terms of returns, with Twitter-based strategies also achieve the highest risk-adjusted performance, as measured by the Sharpe ratio. Overall, the findings suggest that investor sentiment contains economically meaningful information and exhibit strong predictive power within the technology sector.

Keywords: News and Twitter Sentiment; Sentiment Beta; Priced Factor; Magnificent Seven

Introduction

Although the S&P 500 consists of 500 companies, a select few significantly influence its performance. Among these are referred by the press as the Magnificent Seven, the group of seven U.S. mega-cap technology firms (Apple, Microsoft, Alphabet, Amazon, Nvidia, Meta, and Tesla). As of 2025, the Magnificent Seven account for over 30% of the S&P 500 (Brock, 2025). The Magnificent Seven have a significant impact on the S&P 500 and demonstrate superior growth in stock prices, earnings per share, and return on equity (Nenkov, 2024). Strong historical stock price growth among the Magnificent Seven reflects investors' confidence in their ability to generate sustained

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earnings in the future. Also, the Magnificent Seven represent some of the most influential drivers of innovation and account for a large share of market capitalization in major U.S. equity indices. Their strong performance is largely supported by investment in research and development, which promotes technological leadership and long-term growth. One notable example is the rapid advancement in artificial intelligence (AI) over the past decade, which these firms play an important role through both innovation and technology adoption. Because information about large technological progress is frequently conveyed through official announcements and social media, the stock prices of the Magnificent Seven are highly sensitive to information flows and changes in investor sentiment.

Early studies of investor sentiment relied primarily on indirect market-based proxies, such as trading volume, IPO activity and survey-based indicators to capture investor moods. While these measures provide useful aggregate signals, they are slow to reflect new information and provide only limited insight into firm-level sentiment. With advances in artificial intelligence and data analytics, recent research has increasingly adopted text-based approaches to extract sentiment from news, corporate disclosures, and social media using natural language processing (NLP) techniques. These methods allow a comprehensive and systematic assessment of market sentiment.

Traditional asset pricing theory explains expected stock returns through exposure to systematic risk factors. The theories have achieved empirical success in the past, but they are grounded in rational expectations and do not account for behavioral factors that could influence investor decision making. Studies have found that investor sentiment could also influence price movement (Wu et al., 2014; Wurgler & Baker, 2007) and many existing studies on investor sentiment focus on predictive power for future returns and volatility (Ang et al., 2009; Girard & Biswas, 2007; Liu et al., 2025), treating sentiments as a forecasting variable, rather than a systemic factor. While this approach provides valuable insights to the influence of investor sentiment, it does not directly address whether assets with greater exposure to sentiment earn different expected returns as compensation for sentiment-related risk.

This study seeks to bridge this gap by examining whether exposure to investor sentiment is priced in the cross-section of stock returns. This study focuses on the Magnificent Seven firms and estimates firm-level sentiment betas calculated from Bloomberg news sentiment and Twitter sentiment indicators. The estimated betas are then used to sort stocks into portfolios. By evaluating the performance of these sentiment-sorted portfolios, the study assesses whether sentiment contains economically meaningful factor within a factor investing framework.

Literature Review

1. Asset Pricing Models and Multi-Factor Models

Fama and French (1996) proposed a three-factor model that add additional factors capturing firm size and value characteristics. Empirical results show that this model substantially improves explanatory power relative to CAPM by significantly improving the model's ability to explain cross-sectional variations in returns. Furthermore, the framework is further extended to five-factor model that adds profitability (Robust Minus Weak) and risk (Conservative Minus Aggressive) factors (Fama & French, 2015). These models show that there is more than a single market factor that affect systematic risk. The progression from the CAPM to multifactor models highlights the flexibility of asset pricing framework in the inclusions of new factors and provide a theoretical justification for examining alternative factors derived from non-traditional sources.

However, for the factor to be considered economically meaningful within asset pricing theory, it must capture exposure to risks that are systematic and not easily diversify away. Behavioral finance literatures suggest that investor sentiment may influence returns through noise trader risk and limits to arbitrage. Under this condition, sentiment exposure may reflect market dynamics that are difficult to diversify, especially on high-growth technology firms whose valuations rely heavily on future expectations such as the Magnificent Seven.

2. Factor Loadings, Beta and Factor Investing

Betas are commonly estimated using time-series regressions of asset returns on factors and measure the degree of comovement between an asset and an underlying factor. Black et al. (1972) provide an empirical framework by grouping portfolios sorted by beta and reducing exposure to idiosyncratic noise. This portfolio sorting methodology has become a standard approach in asset pricing as it isolates systematic risk by diversifying away specific firm variations. The use of beta-sorted portfolios later become the foundation to factor investing studies. While some studies provided evidence that these betas could capture systematic risks (Ai et al., 2025; Frazzini & Pedersen, 2014; Kogan & Papanikolaou, 2014) others state these factors show little risk premium (Chen et al., 2025; Hou et al., 2020). These mixed findings motivate further examination of whether sentiment-related beta exposure contains economically meaningful information for return variation.

3. Investor Sentiment in Financial Markets

Measuring investor sentiment is complex, as not all investors are rational, and their decisions are often driven by emotions and incomplete information. These relationships make sentiments difficult to quantify and use. Early work on market-wide sentiment are based on proxies such as investor surveys, retail investor trades, mutual fund flows, trading volumes, or IPO volume. Wurgler and Baker (2007) develop a behavioral framework on how investor sentiment can be empirically measured and modeled, explaining why sentiment-driven effects can influence asset prices in a systematic manner.

Twitter posts are one of the largest sources of public social media data. This real-time and unfiltered nature of Twitter makes it a valuable source of public mood. By using textual analysis from natural language processing (NLP) models and artificial intelligence (AI), posts can be categorized into positive or negative sentiment based on the presence of specific keywords. While many studies show a strong predictive relationship between sentiment and stock market movements (Bollen et al., 2011; Li et al., 2014; Pagolu et al., 2016), some suggest that social media sentiment may have little to no effect on stock returns and trading volume (Tumarkin & Whitelaw, 2001).

Both social media and news information have become increasingly more reliable and important data source in financial market. With the recent advancement of AI, particularly in NLP, researchers are now able to extract unstructured textual data and measure investor sentiment using such information more accurately. As a result, AI-driven sentiment analysis has become a valuable tool for examining how information could influence stock returns and market behavior.

Objective

This study aims to examine whether exposure to investor sentiment constitutes a priced risk factor in equity markets. Specifically, the study estimates firm-level sentiment factor loadings of the Magnificent Seven and evaluates whether stocks with different levels of sentiment exposure earn systematically different returns.

Scope

This study focuses on the analysis of seven prominent publicly traded companies collectively known as the Magnificent Seven, including Apple, Microsoft, Amazon, Alphabet (Google), Meta (Facebook), Tesla, and Nvidia. Investor sentiment is measured using aggregated news and Twitter sentiment scores generated through Bloomberg's NLP model. The period of study is from 2020-2024.

Methodology

1. Data

1.1. Financial Market Data

Weekly stock price data are collected from the seven firms over the study period from 2020 to 2024. The weekly return of the stock is calculated using the following formula:

$$r_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

where P_t is the closing price at time t . These returns are used for subsequent regression analysis and portfolio construction.

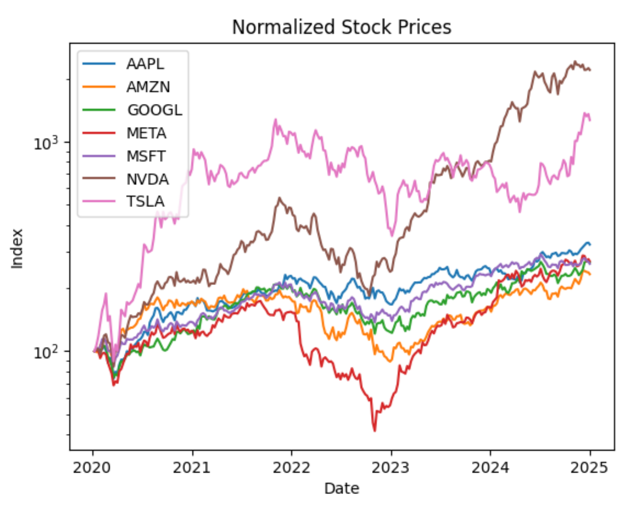

Figure 1: Normalized stock prices of the Magnificent Seven Stocks

Figure 1 presents the normalized stock price of the Magnificent Seven stocks, where each stock is normalized to start at 100 at the beginning of the sample period. The figures show a sharp decline during the early 2020 due to COVID-19 market crash. Another notable period of sharp decline can be observed towards the end of 2022, which coincides with the interest rate increase by the Federal Reserve to combat inflation. There is also a strong upward trend, especially for Nvidia and Tesla, during the beginning of 2023 which reflects an increase in investors' expectation from AI technology development.

1.2. Twitter and News Sentiment Data

Bloomberg uses NLP models and AI to determine posts that are relevant to the company and the models are trained to classify data as positive, negative, and neutral. Each post is tagged with relevant company identifiers such as ticker symbols and filtered to include only relevant, non-spam content. This ensures that the sentiment data reflects financially significant views. In this study, the sentiments used include news sentiment and Twitter sentiment on stock return to estimate sentiment factor loadings. These estimated exposures are then used to form sentiment-sorted portfolio. For each sentiment score, two categories of information are obtained, positive and negative sentiment counts. These counts represent the number of posts classified under each sentiment category for firm $\boldsymbol{i}$ at time $\boldsymbol{t}$. The sentiment measures are incorporated into the equation to examine whether sentiment provides incremental explanatory power beyond standard asset-pricing factors.

$$\boldsymbol{Sent_{i,t}^{TW}} = \frac{Pos_{i,t}^{TW} - Neg_{i,t}^{TW}}{Pos_{i,t}^{TW} + Neg_{i,t}^{TW}} \qquad \boldsymbol{Sent_{i,t}^{NEWS}} = \frac{Pos_{i,t}^{NEWS} - Neg_{i,t}^{NEWS}}{Pos_{i,t}^{NEWS} + Neg_{i,t}^{NEWS}}$$

Where $Pos_{i,t}^{TW}$ and $Neg_{i,t}^{TW}$ denote the number of positive and negative Twitter posts, respectively for firm $\boldsymbol{i}$ at time $\boldsymbol{t}$. The index is bounded between -1 and 1, with higher values indicating more optimistic investor sentiment. Similarly, $Pos_{i,t}^{NEWS}$ and $Neg_{i,t}^{NEWS}$ denote the number of positive and negative News-based posts, respectively for firm $\boldsymbol{i}$ at time $\boldsymbol{t}$.

Table 1 *Summary Statistics of Bloomberg Sentiment Measures (News and Twitter)*

	AAPL		AMZN		GOOGL		META	
	News	Twitter	News	Twitter	News	Twitter	News	Twitter
Mean	-0.2027	-0.2048	-0.0743	-0.1966	-0.2794	-0.5919	-0.3038	-0.5531
Std Dev	0.3948	0.5158	0.351	0.5427	0.3181	0.3902	0.392	0.4456

Median	-0.2583	-0.244	-0.0774	-0.25	-0.3132	-0.7019	-0.3206	-0.691
Min	-0.9646	-1	-0.9373	-1	-0.9004	-1	-1	-1
Max	0.7355	1	0.8643	1	0.8389	0.8639	1	0.8671
	MSFT		NVDA		TSLA			
	News	Twitter	News	Twitter	News	Twitter		
Mean	0.0169	-0.054	0.2303	0.2597	-0.134	-0.2013		
Std Dev	0.3518	0.6131	0.33	0.6412	0.2889	0.5517		
Median	0.0496	-0.0556	0.2803	0.3976	-0.1546	-0.3333		
Min	-0.9638	-1	-0.6784	-1	-0.8229	-1		
Max	0.8539	1	0.8441	1	0.7287	1		

Table 1 presents summary statistics for sentiment scores calculated on both News and Twitter. Overall, sentiment appears to be mostly negative, represented by both negative mean and median of the data. This suggests a pessimistic tone in both news coverage and social media coverage across the sample period. A key observation is that Twitter sentiment shows greater standard deviation, suggesting a more dispersed data compared to news sentiment across all firms.

1.3. Fama-French Factors

Market and factor return data are obtained from the Kenneth R. French Data Library. The study employs the Fama-French three-factor model, which includes the market excess return, the size factor, and the value factor. The market excess return is defined as the return on the value-weighted market portfolio minus the risk-free rate. The size factor, SMB, captures the return differential between portfolio of small and large capitalization firms, while the value factor, HML captures the return differential between high book-to-market and low book-to-market firms.

2. Model

This study examines the impact of firm-level sentiment on stock returns using sentiment-augmented Fama-French three-factor model. For each stock i, the following time-series regression is estimated:

$$R_{i,t} - RF_t = \alpha_i + \beta^s_{sent,i} Sent^s_{i,t} + \beta_m (Mkt - RF)_t + \beta_s SMB_t + \beta_h HML_t + \varepsilon_{i,t}, s \in \{TW, NEWS\}$$

Where $R_{i,t} - RF_t$ represents the return of stock i at time t minus risk-free rate. the term α_i represents the stock-specific intercept, $Sent^s_{i,t}$ captures firm-level sentiment at time t. The coefficient $\beta^{TW}_{sent,i}$ and $\beta^{NEWS}_{sent,i}$ denote Twitter-based and news-based firm-level sentiment respectively.

The variables $(Mkt - RF)_t$, SMB_t and HML_t represent the market excess return, the size factor (small minus big), and the value factor (high minus low), respectively. Their associated β_m , β_s , β_h represent the factor loadings. The error term $\varepsilon_{i,t}$ captures idiosyncratic shocks.

3. Result

Table 2 *Regression of individual stock sentiment measures with News sentiment score (full sample)*

Variable	MSFT	AAPL	TSLA	GOOGL	AMZN	NVDA	META
Sent Score	0.0090***	0.0140***	0.0573***	0.0232***	0.0173***	0.0254***	0.0397***
Mkt-RF	1.0005***	1.0670***	1.7827***	0.9729***	0.9156***	1.5021***	1.1153***
SMB	-0.5473***	-0.4674***	-0.0221	-0.2957**	-0.1396	-0.1755	-0.2876
HML	-0.5145***	-0.3979***	-0.8017***	-0.3841***	-0.7876***	-0.9137***	-0.5671***
Constant	0.0028**	0.0063***	0.0242***	0.0167***	0.0060***	0.0051*	0.0254***
R^2	0.733	0.651	0.437	0.516	0.557	0.643	0.424
N	251	251	251	251	251	251	251

Notes: **** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$*

Table 3 *Regression of individual stock sentiment measures with Twitter sentiment score (full sample)*

Variable	MSFT	AAPL	TSLA	GOOGL	AMZN	NVDA	META
Sent Score	0.0099***	0.0103**	0.1374***	0.0361***	0.0292***	0.0510***	0.0291***
Mkt-RF	1.0101***	1.1051***	1.6981***	1.0141***	0.9381***	1.4917***	1.1124***
SMB	-0.5469***	-0.4999***	0.0175	-0.3902***	-0.134	-0.2049	-0.3492*
HML	-0.5370***	-0.4216***	-0.7964***	-0.4089***	-0.8122***	-0.8723***	-0.5930***
Constant	0.0022*	0.0054***	0.0317***	0.0132***	0.0049**	0	0.0125***
R^2	0.721	0.633	0.485	0.542	0.564	0.645	0.371
N	251	251	251	251	251	251	251

Table 2 and Table 3 report regression of individual stock of sentiment-augmented Fama-French three factor regressions estimated separately for each stock using news and Twitter sentiment score, respectively. The adjusted R^2 values range from 0.42 to 0.73 for News and 0.37 to 0.72 for Twitter. The sentiment coefficient is positive and statistically significant at the 1% level for all firms, indicating that higher investor sentiment is associated with higher stock returns, controlling for systematic risk factors. The magnitude of the coefficients suggests a meaningful economic relationship between sentiment and returns, with TSLA exhibiting the highest sensitivity to sentiment among all firms. Furthermore, the estimated coefficients are generally larger in the Twitter-based model compared to the news-based model, indicating that social media sentiment has a stronger influence on stock returns. META is the only exception, where the sensitivity to sentiment is not higher in the Twitter-based specification.

2. Portfolio Sorting

The sentiment betas are then estimated using a 52-week rolling window regression framework, which corresponds to approximately one year of weekly observations. The regression is estimated repeatedly by rolling the window forward one period at a time, generating a time series of sentiment beta estimates for each stock. The use of rolling regression is motivated by evidence that factor loadings may vary over time due to changes in firm characteristics, investor behavior, and market conditions. By allowing sentiment beta to change accordingly, the rolling framework provides a more realistic representation of how stock responds to shock.

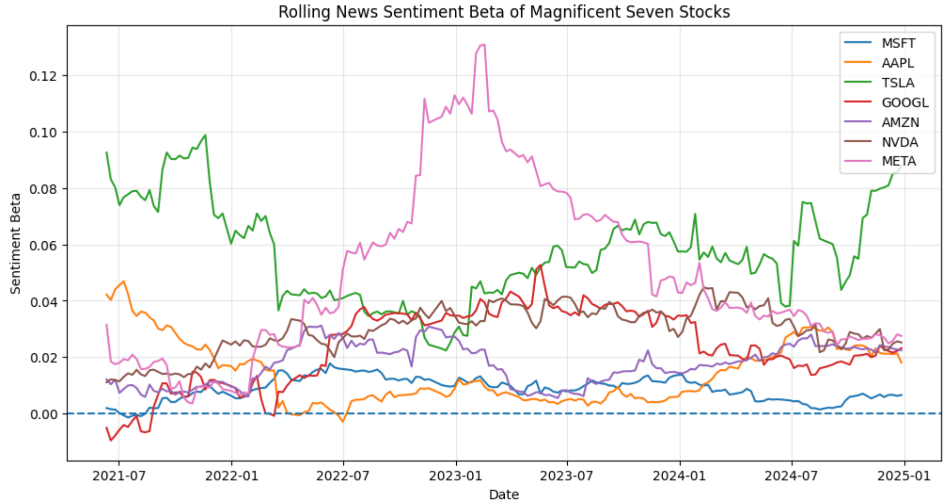

Figure 2: 52-Week Rolling News Sentiment Beta of Magnificent Seven Stocks

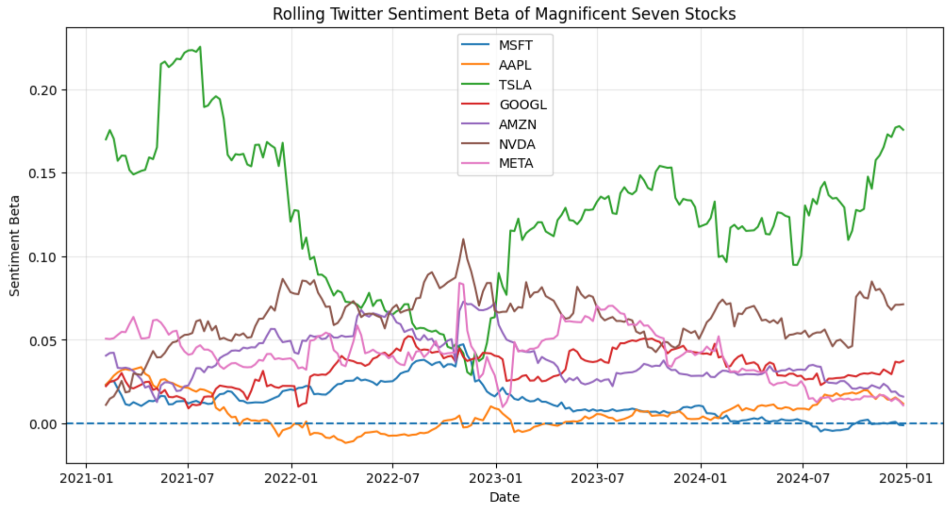

Figure 3: 52-Week Rolling Twitter Sentiment Beta of Magnificent Seven Stocks

Figure 2 and Figure 3 illustrate the changes in rolling sentiment beta for each firm based on news and Twitter sentiment, respectively. The results show that sentiment fluctuates over time. The rolling sentiment beta is the variable used to sort stocks by rank for portfolio construction. At each rebalancing date, stocks are ranked based on their estimated sentiment betas from the most recent rolling windows. Portfolios are then formed according to these rankings and cumulative returns are used to evaluate the result of each strategy.

3. Factor Investing

The sentiment beta-sorted portfolios are then used to conduct a backtest to evaluate the performance of the constructed factor. Specifically, stocks are ranked based on their estimated sentiment betas, and portfolios are formed accordingly. These include a portfolio that takes a long position in the top 3 stocks with the highest sentiment betas and a portfolio that takes a long position in the bottom 3 stocks with the lowest sentiment betas. Portfolio returns are computed as the average return of the selected stocks within each portfolio. The portfolios are rebalanced on a 4-week period based on updated sentiment beta estimates. Finally, the performance of the sentiment-based strategies is compared to an equal-weighted benchmark portfolio consisting of all stocks in the sample.

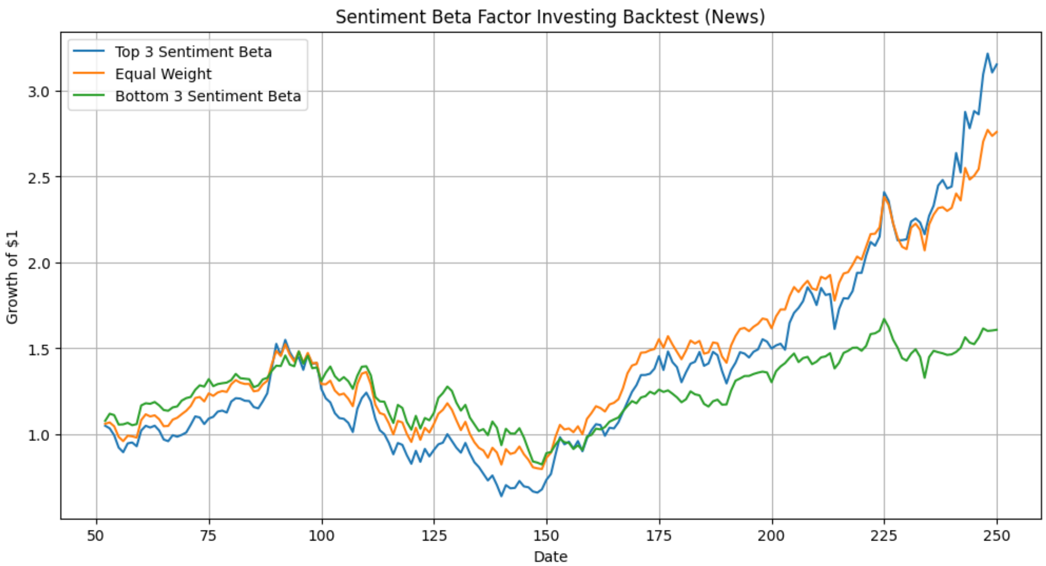

Figure 4: Cumulative Returns of Sentiment Beta–Based Portfolios Using News Data

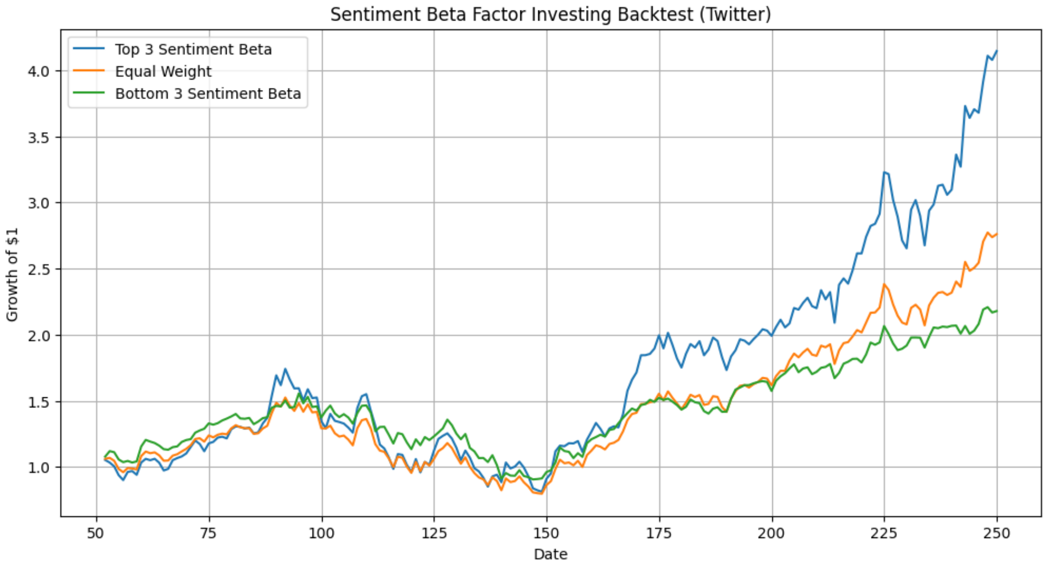

Figure 5: Cumulative Returns of Sentiment Beta–Based Portfolios Using Twitter Data

Table 4: Performance of News-Based and Twitter Based Sentiment Investment Strategies

	News			*Twitter*		
Strategy	Sharpe	Volatility	Return	Sharpe	Volatility	Return
Equal-Weight	**0.95**	0.29	1.76	0.95	0.29	1.76
Long Top 3	0.93	0.36	**2.15**	**1.04**	0.40	**3.14**
Long Bottom 3	0.48	**0.26**	0.60	0.82	**0.24**	1.17

Table 4 reports the Sharpe ratio, volatility, and final return of sentiment-based investment strategies constructed using both news and Twitter sentiment indicators. For news-based portfolio, the equal-weight portfolio achieves the highest Sharpe ratio (0.95), slightly outperforming the long top 3 strategy (0.93), despite the latter generating higher cumulative return (2.15). This suggests that while selecting stocks with high news sentiment beta can result in a better return at the cost of increased volatility (0.36). In contrast, the long bottom 3 portfolio performs considerably worse, with lower Sharpe ratio (0.48) and lower return (0.60).

For Twitter-based portfolio, the long top 3 strategy delivers the strongest performance, achieving the highest Sharpe ratio (1.04) and the highest cumulative return (3.14), outperforming the equal-weight benchmark (0.95). This suggests that Twitter-based sentiment signals may be more effective in identifying high-return opportunities, although they are associated with higher volatility (0.40).

Discussion

This study examines whether investor sentiment may behave similarly to a priced factor by analyzing firm-specific sentiment sensitivity and evaluates the performance using the beta-sorted portfolio. The empirical results provide several important insights.

First, the firm-level full sample regression results show that sentiment beta is positive and statistically significant across all firms, indicating that higher investor sentiment is consistently associated with higher stock returns. Moreover, this effect is stronger on Twitter-based sentiment compared to news-based sentiment, suggesting that the real-time and high frequency information from social media may have a more significant effect on influencing investor behavior.

Furthermore, the portfolio formed using rolling sentiment beta shows that sorting stocks based on their sentiment beta and taking a long position in the highest beta stocks generate higher return than the equal-weighted benchmark, while taking long position on low-sentiment beta stocks consistently underperform. This pattern is broadly consistent with asset pricing intuition, where assets with greater exposure to common risk-related characteristics may exhibit higher expected returns. One possible explanation is that large technology firms characterized by high growth expectations and valuation uncertainty may be more susceptible to sentiment-driven pricing effects, particularly when limits to arbitrage prevent rational investors from fully correcting temporary mispricing.

Overall, the findings provide evidence that sentiment-based portfolio sorting remains economically meaningful, particularly for identifying high-performing stocks. However, the effectiveness of sentiment scores varies across sources, with Twitter sentiment showing stronger performance for the Magnificent Seven sample. This provides evidence that social media sentiment, such as Twitter, holds valuable information that could be used in portfolio management.

Conclusion and Limitations

This study provides empirical evidence that investor sentiment may contain economically meaningful information related to excess returns on the Magnificent Seven stocks. The findings demonstrate that portfolios sorted by firm-level sentiment beta outperformed equal weighted benchmarks during the 2020-2024 period. However, the observed predictive performance within a limited sample period does not yet fully confirm that sentiment functions as a persistent, priced risk factor across the broader market.

While the findings suggest that sentiment exposure may contain characteristics similar to a priced factor, several limitations must be acknowledged. First, the current study does not account for implementation costs, such as transaction fees or taxes, which may impact the practical feasibility of the investment strategies. Secondly, the sample size is limited to the Magnificent Seven. While these firms represent a significant portion of the S&P 500's market capitalization, focusing exclusively on mega-cap technology stocks limits the generalizability of the results. It remains unclear if these sentiment-driven effects persist in other sectors, smaller market capitalizations, or different equity indices. Furthermore, the five-year study period (2020-2024) is relatively short for establishing the existence of a persistent systematic risk factor. Future research should seek to broaden the cross-sectional evidence and improve the robustness of the results by expanding the sample to include more diverse set of firms across various industries.

References

Ai, H., Li, J. E., & Tong, J. (2025). Equilibrium Value and Profitability Premiums [Working Paper]. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.5267354

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2009). High idiosyncratic volatility and low returns: International and further U.S. evidence. *Journal of Financial Economics*, *91*(1), 1-23. https://doi.org/10.1016/j.jfineco.2007.12.005

Black, F., Jensen, M. C., & Scholes, M. S. (1972). The Capital Asset Pricing Model: Some Empirical Tests. In M. C. Jensen (Ed.), *Studies in the Theory of Capital Markets* (pp. 79-121). Praeger.

Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science*, *2*(1), 1-8. https://doi.org/10.1016/j.jocs.2010.12.007

Brock, C. (2025). S&P 500's Weight in Mag 7 Stocks Passes 30%. Is This A Diversification Risk? *Forbes*. https://www.forbes.com/sites/investor-hub/article/sp-500-weight-mag-7-stocks-diversification-risk/

Chen, Z., Liu, B., Wang, H., Wang, Z., & Yu, J. (2025). Investor Sentiment and the Pricing of Characteristics-Based Factors. (12), 3580-3625. https://ideas.repec.org/a/oup/rfinst/v38y2025i12p3580-3625..html

Fama, E. F., & French, K. R. (1996). Multifactor Explanations of Asset Pricing Anomalies. *The Journal of Finance*, *51*(1), 55-84. https://doi.org/10.2307/2329302

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1-22. https://doi.org/10.1016/j.jfineco.2014.10.010

Frazzini, A., & Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics*, *111*(1), 1-25. https://doi.org/10.1016/j.jfineco.2013.10.005

Girard, E., & Biswas, R. (2007). Trading Volume and Market Volatility: Developed versus Emerging Stock Markets. *Financial Review*, *42*(3), 429-459. https://doi.org/10.1111/j.1540-6288.2007.00178.x

Hou, K., Xue, C., & Zhang, L. (2020). Replicating Anomalies. *The Review of Financial Studies*, *33*(5), 2019-2133. https://doi.org/10.1093/rfs/hhy131

Kogan, L., & Papanikolaou, D. (2014). Growth Opportunities, Technology Shocks, and Asset Prices. *The Journal of Finance*, *69*(2), 675-718. https://doi.org/10.1111/jofi.12136

Li, X., Xie, H., Chen, L., Wang, J., & Deng, X. (2014). News impact on stock price return via sentiment analysis. *Knowledge-Based Systems*, *69*, 14-23. https://doi.org/10.1016/j.knosys.2014.04.022

Liu, Q., Huang, C., Liu, Y., & Son, H. (2025). Purely Sentiment-Driven Stock Index Trend Forecast: A Probability Model Based on Social Media Sentiment Space. *Knowledge-Based Systems*, 113985. https://doi.org/10.1016/j.knosys.2025.113985

Nenkov, D. N. (2024). "The Magnificent Seven" Technology Stocks and Their Impact on the S&P 500: A Review 4 Years Later. *Finance, Accounting and Business Analysis (FABA)*, *6*(2), 180-195. https://doi.org/10.37075/FABA.2024.2.07

Pagolu, V. S., Reddy, K. N., Panda, G., & Majhi, B. (2016, 3-5 Oct. 2016). Sentiment analysis of Twitter data for predicting stock market movements. 2016 International Conference on Signal Processing, Communication, Power and Embedded System (SCOPES),

Tumarkin, R., & Whitelaw, R. F. (2001). News or Noise? Internet Postings and Stock Prices. *Financial Analysts Journal*, *57*(3), 41-51. https://doi.org/10.2469/faj.v57.n3.2449

Wu, D., Zheng, L., & Olson, D. (2014). A Decision Support Approach for Online Stock Forum Sentiment Analysis. *Systems, Man, and Cybernetics: Systems, IEEE Transactions on*, *44*, 1077-1087. https://doi.org/10.1109/TSMC.2013.2295353

Wurgler, J., & Baker, M. (2007). Investor Sentiment in the Stock Market. *Journal of Economic Perspectives*, *21*, 129-152. https://doi.org/10.2139/ssrn.962706