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TWITTER SENTIMENT ANALYSIS FOR OPTIMAL PORTFOLIO CONSTRUCTION

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Burak Kucukaslan[1], Oktay Tas[2]
[1]Istanbul Technical University, Management Engineering, Istanbul, Turkiye.
kucukaslan16@itu.edu.tr, ORCID: 0000-0002-3245-706X
[2]Istanbul Technical University, Management Engineering, Istanbul, Turkiye.
tasokta@itu.edu.tr, ORCID:0000-0002-7570-549X

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ABSTRACT
Purpose- This research investigates the efficacy of social media sentiment analysis in constructing alpha-generating investment portfolios. Specifically, the study examines whether Twitter-derived sentiment indicators can be leveraged to develop systematic trading strategies that generate risk-adjusted returns exceeding benchmark performance. The research aims to establish quantitative criteria for position initiation and termination based on sentiment metrics, with the ultimate objective of creating a portfolio that demonstrates significant outperformance relative to the reference index.
Methodology – The study encompasses 16 companies of the Nasdaq 100 index, selected to represent diverse market sectors while controlling for liquidity and market impact considerations. The dataset comprises 708,080 Twitter posts pertaining to the selected companies throughout the 2022 calendar year, extracted via programmatic data collection methodologies. Sentiment quantification was performed utilizing the Natural Language Toolkit (NLTK) in Python, generating normalized sentiment scores within a [-1, +1] interval. The investigation employed a sophisticated aggregation methodology to compute both daily and weekly sentiment indicators for each security, deliberately excluding neutral sentiment scores (0) to enhance signal clarity. A systematic portfolio construction framework was implemented, whereby securities were hierarchically ranked based on their aggregate sentiment scores on a weekly basis. Multiple portfolio permutations were tested, incorporating various combinations of long positions in top-ranked securities and short positions in bottom-ranked securities. Position entry and exit prices were determined using weekly opening and closing prices, respectively. Portfolio performance was evaluated through the calculation of weekly returns and cumulative performance metrics over the observation period.
Findings- The empirical results reveal that portfolios constructed exclusively with short positions demonstrated superior cumulative returns compared to long-only portfolios. This observation can be contextualized within the broader market environment, specifically the Nasdaq 100's negative 33% return in 2022. The research identified statistically significant outperformance in portfolios implementing a combined long-short strategy, with these portfolios generating positive absolute returns despite the challenging market conditions.
Conclusion- The empirical evidence substantiates the hypothesis that Twitter sentiment analysis can be effectively utilized as a signal generation mechanism for systematic portfolio construction. The results demonstrate statistically significant alpha generation capabilities, particularly when implementing a long-short strategy, suggesting potential applications for institutional investors and quantitative fund managers.

Keywords: Twitter sentiment analysis, algorithmic portfolio construction, market efficiency, natural language processing, behavioral finance
JEL Codes: H30, H60, H62

1. INTRODUCTION

In contemporary financial markets, equity securities represent a cornerstone investment vehicle for market participants across the global investment landscape. A fundamental challenge confronting investment decision-makers lies in the accurate forecasting of future security prices and the subsequent formulation of optimal investment strategies predicated upon these projections. The proliferation of mobile technology and widespread internet connectivity has catalyzed an unprecedented expansion in social media engagement, transforming these platforms into vital forums for real-time dissemination of investor sentiment and market perspectives. Twitter, in particular, has emerged as a preeminent platform for investment-related discourse among market participants. Given that price discovery in equity markets is fundamentally driven by the aggregate effect of buy and sell orders—effectively representing the culmination of supply and demand dynamics—this research posits that valuable predictive signals can be extracted from social media sentiment that has not yet been fully incorporated into market prices. Specifically, we hypothesize that systematic analysis of user-generated content on Twitter pertaining to publicly traded companies can yield actionable insights into emerging investor sentiment patterns. Furthermore, this study aims to demonstrate empirically that these sentiment indicators can be effectively utilized in the construction of optimized investment portfolios capable of generating risk-adjusted returns in excess of relevant market benchmarks. The theoretical foundation and empirical methodology of this research are predicated upon the efficient market hypothesis and its various permutations, while simultaneously incorporating elements of behavioral finance theory to account for the documented impact of investor sentiment on asset prices. By synthesizing traditional financial theory with contemporary developments in natural language processing and machine learning, this study seeks to bridge the gap between theoretical frameworks and practical applications in portfolio management. The remainder of this paper is structured as follows: Section 2 presents a comprehensive review of the extant literature, examining both theoretical foundations and empirical evidence regarding the relationship between social media sentiment and equity market dynamics. Section 3 delineates the methodological framework employed in this study, including detailed descriptions of data collection procedures, sentiment analysis techniques, and portfolio construction methodologies. Section 4 presents our empirical findings and provides a thorough analysis of the results within the context of existing theoretical frameworks. Finally, Section 5 synthesizes our findings and discusses their implications for both academic research and practical applications in investment management. This research contributes to the existing body of literature by providing empirical evidence of the predictive capability of social media sentiment in equity markets and demonstrating the practical application of these insights in systematic portfolio construction. The findings have significant implications for both academic researchers investigating market efficiency and practitioners seeking to develop innovative investment strategies.

2. LITERATURE REVIEW

Mendoza-Urdiales et al. (2022) examined the asymmetric effect of Twitter sentiment on stock prices, finding that negative news has a more pronounced impact than positive news. This asymmetry was supported by analyses using Transfer Entropy and EGARCH models.Yang et al. (2017) developed a sentiment-driven trading strategy using SentiWordNet and genetic algorithms, which outperformed other strategies. Similarly, Leow et al. (2021) enhanced robo-advisor performance by employing sentiment analysis using Google's BERT model, with their proposed models outperforming traditional portfolio models. Makrehchi et al. (2013) created a successful trading system using tweet sentiment, achieving higher returns than the S&P 500 index. Ranco et al. (2015) utilized event study methodology to demonstrate the value of Twitter data in understanding and predicting financial market movements. Oliveira et al. (2017) proposed a model to predict various financial variables using Twitter data, highlighting some advantages of microblog data over traditional sentiment measures. Granholm and Gustafsson (2017) investigated the potential for generating abnormal returns using tweet sentiment, based on an analysis of 40 companies in the Nasdaq 100 index. Azar and Lo (2016) examined the impact of Federal Open Market Committee (FOMC) meetings on investors, demonstrating that Twitter sentiment during these meetings can predict market reactions. Chamberlain et al. (2023) found that sentiment from both traditional and social media sources influences stock performance, particularly for firms with high short interest ratios. Sul et al. (2017) showed that tweets from users with fewer followers play a significant role in predicting future stock returns, with their proposed strategy yielding annual returns of 11-15%. Yu et al. (2022) demonstrated the effectiveness of using investor sentiment in managing portfolio rebalancing for S&P 500 companies. Düz Tan and Taş (2021) found that social media activity and sentiment are associated with trading volume and returns across various markets, with Twitter sentiment being more pronounced for smaller and emerging market firms. Gu and Kurov (2020) showed that company-specific Twitter sentiment can be used to predict stock returns. Fan et al. (2020) proposed using social media to measure political uncertainty faced by companies, finding that disagreement among tweets impacts stock price volatility and trading volume. Kraaijeveld and De Smedt (2020) demonstrated the potential of Twitter sentiment to predict cryptocurrency price returns. Dang et al. (2020) compared the performance of different deep learning models in sentiment analysis, offering guidance for researchers. Broadstock and Zhang (2019) and Affuso and Lahtinen (2018) both found that U.S. stocks' intraday returns are sensitive to social media sentiment, with negative tweets having a stronger effect than positive ones. Hung et al. (2023) proposed using deep learning and natural language processing methods to construct views in the Black-Litterman model, achieving a high annual return rate of 46.6%. However, Behrendt and Schmidt (2018) concluded that Twitter sentiment and activity are particularly unhelpful for stock valuation, especially for high-frequency traders.

3. THE DATA AND METHODOLOGY

Tweets related to stocks of companies traded on Nasdaq 100 were accessed on Twitter by adding '$' and '#' symbols to their stock ticker symbols. A dataset was created using the tweets obtained from these search results. Table 1 presents the sectors in which the selected companies operate and the number of tweets for each company. Companies were chosen from among those with the highest market capitalization. The stock price data of the companies to be used in the study were obtained from the Yahoo Finance database using the Yfinance library of the Python programming language. The process of creating sentiment scores is a subdomain of natural language processing, and various methods and approaches exist in literature. While some studies classify texts into three categories as positive, negative, and neutral, another approach assigns a sentiment score of +1 to expressions with 100% positive meaning and -1 to those with 100% negative meaning. The method preferred in this study is to position all sentiment scores within the range of [-1, +1]. The Natural Language Toolkit library of the Python programming language was used to generate sentiment scores. Using the sentiment scores calculated for each tweet, daily and weekly average sentiment scores were computed on a company basis.

Table 1: Company and Number of Tweets

Company	Ticker	Sector	Number of Tweets	Company	Ticker	Sector	Number of Tweets
Tesla, Inc.	TSLA	Automotive and Technology	108.294	Alphabet Inc. (Class A)	GOOGL	Technology	38.265
Apple Inc.	AAPL	Technology	92.886	PayPal Holdings, Inc.	PYPL	Finance	22.714
Amazon.com, Inc.	AMZN	Retail and Technology	79.385	Costco Wholesale Corporation	COST	Retail	18.047
NVIDIA Corporation	NVDA	Technology	60.955	Intel Corporation	INTC	Technology	17.302
Advanced Micro Devices, Inc.	AMD	Technology	58.205	Starbucks Corporation	SBUX	Restaurants	14.860
Microsoft Corporation	MSFT	Technology	56.507	Pfizer Inc.	PFE	Health	14.722
Meta Platforms, Inc.	META	Technology	52.216	Micron Technology, Inc.	MU	Technology	14.282
Netflix, Inc.	NFLX	Entertainment	45.695	Salesforce.com, Inc.	CRM	Technology	13.745

The temporal aggregation of sentiment metrics followed a two-stage computational framework: first, daily sentiment indicators were computed through the arithmetic mean of tweet-level sentiment scores for each security; subsequently, weekly sentiment metrics were derived through the arithmetic averaging of daily sentiment indicators. This methodological approach ensures consistent temporal granularity in sentiment quantification while mitigating the impact of intraday volatility in social media sentiment. When constructing the portfolio, priority was given to Twitter sentiment scores. Long positions were taken for the top n companies ranked by sentiment scores, while short positions were taken for the bottom n companies. Within the scope of the study, the value of n was varied from 1 to 7, and portfolios consisting of 2, 4, 6, 8, 10, 12, and 14 companies in total were created. Table 1 presents detailed information about the companies used in the study and the number of tweets obtained. Figure 1 and Figure 2 present statistics related to the sentiments derived from tweets associated with the companies used in the scope of this study. It is observed that the number of positive tweets exceeds the number of negative tweets.

Figure 1: Distrubution of Tweets Based on Sentiment Polarity

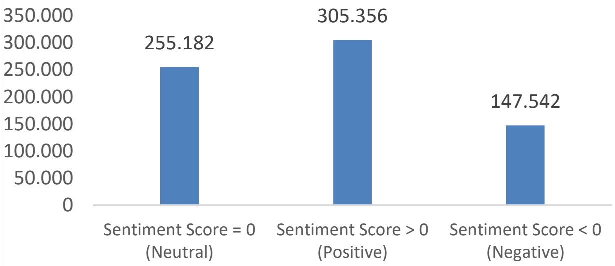
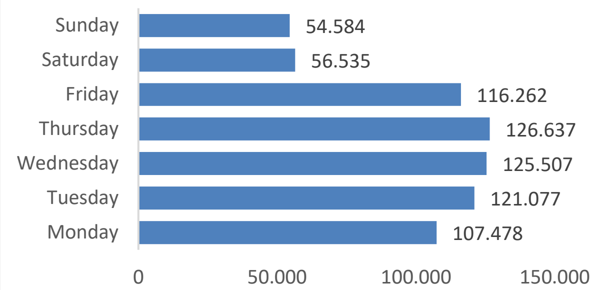


Figure 2: Distrubution of Tweets Based on Week Day



4. FINDINGS AND DISCUSSION

The empirical analysis reveals compelling evidence regarding the efficacy of sentiment-driven portfolio construction methodologies. As demonstrated in Table 2, the investigation reveals a notable non-linear relationship between portfolio size and cumulative returns, with the optimal portfolio configuration comprising six constituent securities (three long positions and three short positions), achieving a cumulative return of 1.323. This relationship is visually represented in Figure 3, which clearly illustrates the peak in portfolio performance at the six-security configuration. As evidenced by Table 2, the performance metrics exhibit diminishing marginal returns as the portfolio size increases beyond this optimal point, with cumulative returns declining to 1.314, 1.249, 1.212, and 1.217 for portfolios containing 8, 10, 12, and 14 securities respectively. This pattern strongly suggests that excessive diversification may dilute the predictive power of sentiment signals.

Table 2: Portfolio Statistics and Short & Long Portfolio Statistics

Portfolio Statistics		Short & Long Portfolio Statistics		
Number of Stocks in Portfolio	**Portfolio Cumulative Return**	**Number of Stocks in Portfolio**	**Short Portfolio Cumulative Return**	**Long Portfolio Cumulative Return**
2	0,947	1	1,771	0,423
4	1,223	2	1,955	0,677
6	1,323	3	2,003	0,785
8	1,314	4	1,963	0,796

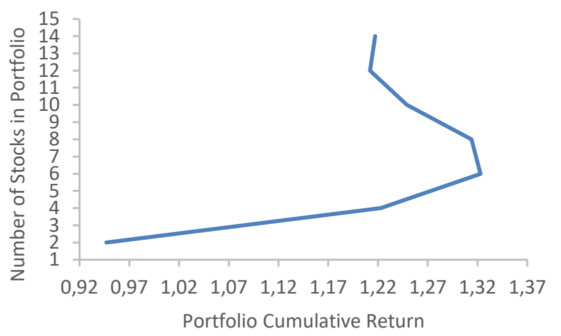
10	1,249	5	1,796	0,786
12	1,212	6	1,817	0,739
14	1,217	7	1,838	0,738
Average	**1,212**	**Average**	**1,878**	**0,706**

A particularly noteworthy finding emerges from the decomposition of portfolio returns into their constituent long and short components, as detailed in the right panel of Table 2. The short portfolios demonstrated remarkably superior performance compared to their long counterparts across all portfolio sizes, with the average cumulative return for short portfolios (1.878) substantially exceeding that of long portfolios (0.706). Figure 5 clearly illustrates this outperformance of short portfolios, showing a peak cumulative return of 2.003 for the optimal three-security configuration. In contrast, Figure 4 depicts the more modest performance of long portfolios, with even the best-performing long portfolio achieving a maximum return of only 0.796. This asymmetric performance pattern must be contextualized within the broader market environment of 2022, during which the Nasdaq 100 experienced a substantial decline of 33%.

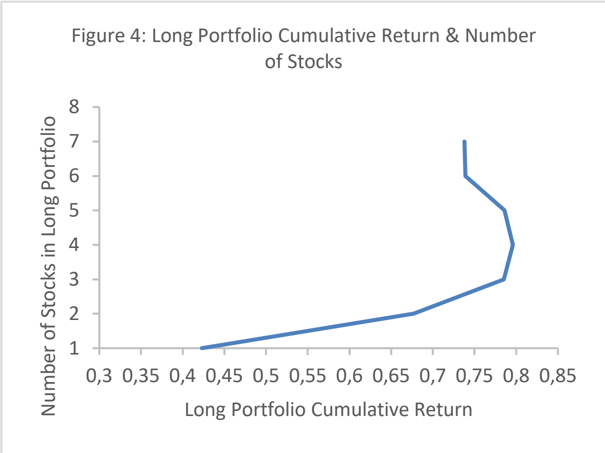
The relationship between portfolio size and performance exhibits distinct characteristics across different portfolio constructions, as evidenced by the comparative analysis presented in Table 2. In combined long-short portfolios, optimal performance was achieved with six securities, a pattern clearly visible in Figure 3's inflection point. Long-only portfolios, as shown in Figure 4, demonstrated peak performance with four securities (0.796), maintaining relatively stable performance in the three to five security range before experiencing diminishing returns. Figure 5 illustrates how short-only portfolios achieved maximum efficiency with three securities (2.003) and demonstrated robust performance across all portfolio sizes, exhibiting notably less sensitivity to portfolio size compared to long positions. These empirical findings, particularly the distinct patterns visible in Figures 3, 4, and 5, have important implications for market efficiency theory and practical portfolio management. The consistent outperformance of sentiment-driven portfolios suggests the presence of exploitable market inefficiencies, while the asymmetric performance of long and short positions indicates potential behavioral biases in market participants' reactions to negative sentiment.

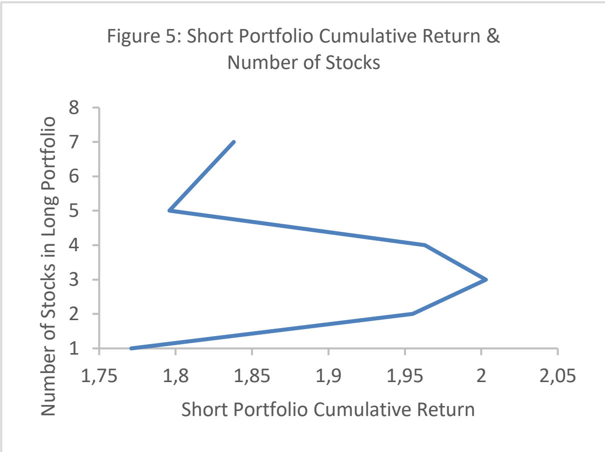
The existence of an optimal portfolio size, clearly demonstrated in Table 2 and Figure 3, suggests limits to arbitrage in sentiment-based trading strategies, a finding that aligns with contemporary behavioral finance literature. The results provide compelling empirical support for the hypothesis that social media sentiment contains valuable predictive information not fully incorporated into market prices, particularly during periods of market stress. However, the diminishing returns observed with larger portfolios, as evidenced by the rightward decline in Figure 3, suggest that this informational advantage may be limited to a subset of securities with the strongest sentiment signals. This observation has significant implications for the scalability of sentiment-based trading strategies.

Figure 3: Portfolio Cumulative Return & Number of Stocks



The findings also suggest that the integration of sentiment analysis into systematic trading strategies may be particularly valuable during periods of market turbulence, as evidenced by the superior performance of short positions during the 2022 market downturn, clearly visible in Figure 5. This temporal dimension of sentiment indicator efficacy warrants further investigation and may have important implications for dynamic portfolio management strategies. The comparative analysis of portfolio performance metrics presented in Table 2, coupled with the visual evidence in Figures 3, 4, and 5, suggests that future research might productively explore the interaction between market conditions and sentiment signal strength, potentially leading to more refined portfolio construction methodologies that account for varying market regime





4. CONCLUSIONS

This empirical investigation provides compelling evidence supporting the efficacy of Twitter-derived sentiment analysis in constructing alpha-generating investment portfolios. The findings are particularly salient given the challenging market conditions that characterized 2022, during which the Nasdaq 100 index experienced a substantial decline of 33%. The empirical results demonstrate that systematically constructed portfolios incorporating social media sentiment signals can generate statistically significant excess returns relative to conventional benchmark indices.

The methodological framework, which employed natural language processing techniques to quantify Twitter sentiment and subsequently utilized these metrics as primary portfolio allocation determinants, yielded several noteworthy insights. First, the research identifies an optimal portfolio configuration comprising six constituent securities (three long positions and three short positions), which achieved a cumulative return of 1.323. Second, the investigation revealed a marked asymmetry in the performance of long versus short positions, with short portfolios demonstrating superior risk-adjusted returns across all portfolio sizes. This asymmetric performance pattern suggests that Twitter sentiment may be particularly effective in identifying overvalued securities during periods of market stress.

However, these empirical findings must be interpreted within appropriate methodological constraints. The study's results are temporally bounded, focusing on a specific market environment characterized by substantial technological sector volatility. Furthermore, the observed relationship between portfolio size and performance exhibits diminishing marginal returns beyond the optimal six-security configuration, suggesting potential limitations to the scalability of sentiment-driven investment strategies.

Several promising avenues for future research emerge from these findings. First, subsequent investigations should examine the robustness of sentiment-based portfolio construction methodologies across varying market regimes and economic cycles. Second, the integration of technical analysis indicators with sentiment metrics warrants exploration, potentially offering enhanced signal generation capabilities. Third, the development of dynamic sentiment score thresholds, calibrated using historical performance data, may improve the precision of position initiation and termination criteria.

Additionally, future research should investigate the microstructure mechanisms through which social media sentiment influences price discovery processes. This might include examining the temporal dynamics of sentiment diffusion across market participants and analyzing the relationship between sentiment intensity and trading volume patterns. In conclusion, while this investigation provides statistically significant evidence supporting the incorporation of social media sentiment in systematic portfolio management, it simultaneously highlights the necessity for continued empirical research in this domain. The synthesis of sentiment analysis with traditional quantitative metrics and technical indicators may offer a more comprehensive framework for investment decision-making in contemporary financial markets, characterized by increasingly complex information flows and rapid digital transformation. Future research efforts should focus on developing more sophisticated methodologies for sentiment quantification and exploring the interaction between sentiment signals and other established market factors. These findings contribute to the growing body of literature examining the intersection of behavioral finance, technological innovation, and market efficiency. The results suggest that social media platforms have evolved into significant venues for price discovery, warranting their inclusion in modern portfolio management frameworks. However, the practical implementation of sentiment-based strategies requires careful consideration of transaction costs, market impact, and the potential erosion of signal strength as these methodologies gain broader adoption within the investment community.

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