FROM HEADLINES TO PREDICTIONS: USING VADER TO CONSTRUCT A SENTIMENT-BASED MARKET INDEX

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To my family and my loving wife for their unwavering support.

DECLARATION OF ORIGINALITY

I hereby declare that I am the sole author of this thesis and that this is the true copy of my thesis, including the final revisions, approved by my thesis committee. All data and information have been obtained, produced, and presented in accordance with the rules of research ethics and principles of academic honesty. As required by these rules, to the best of my knowledge I have acknowledged ideas, thoughts, and any copyrighted material in accordance with the standard referencing rules. I certify that any part of this thesis has not been submitted for a degree or diploma in another educational institution.

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ABSTRACT

This thesis introduces a sentiment-based decision-support model that transforms daily financial news headlines into structured quantitative signals for investment analysis. The study focuses on 43 actively traded stocks, primarily listed on the S&P 500 index, using a two-year dataset of daily headlines collected from publicly available sources. Sentiment scores are generated through a custom framework based on the VADER lexicon and converted into time series. These scores are then evaluated in three main areas: assessing predictive power using Ordinary Least Squares (OLS) regression models, ranking assets for sentiment-driven portfolio strategies, and serving as explanatory variables in asset pricing models such as Capital Asset Pricing Model (CAPM) and Fama-French. Results show that the model provides both statistical and practical value, outperforming market benchmarks under basic portfolio construction methods.

Keywords: Sentiment Analysis, Quantitative Finance, OLS Regression, Portfolio Construction, Fama-French Model

ÖZET

Bu tez, günlük finansal haber başlıklarından yararlanarak hisse senetleriyle ilgili duyarlılığı ölçen ve bunu yatırım analizlerinde kullanılabilecek nicel verilere dönüştüren bir karar destek modeli sunmaktadır. Çalışmada, büyük ölçüde S&P 500 endeksinde yer alan 43 aktif işlem gören hisse senedi kullanılmış ve bu hisselere ait iki yıllık günlük haber başlıkları kamuya açık kaynaklardan derlenmiştir. Haberlerin duyarlılığı, VADER sözlüğü temel alınarak geliştirilen özel bir analiz yöntemiyle hesaplanmış ve zaman serisi formatına dönüştürülmüştür. Bu duyarlılık verileri, OLS regresyonu ile getirilerin öngörülmesinde, basit portföy stratejileri oluşturulmasında ve CAPM ile Fama-French gibi geleneksel varlık fiyatlama modellerinde açıklayıcı değişken olarak test edilmiştir. Sonuçlar, modelin hem istatistiksel hem de pratik anlamda güçlü çıktılar ürettiğini göstermiştir.

Anahtar Kelimeler: Duyarlılık Analizi, Kantitatif Finans, OLS Regresyonu, Portföy Oluşturma, Fama-French Modeli

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ACRONYMS AND ABBREVIATIONS

CAPM Capital Asset Pricing Model

FAANG Facebook, Apple, Amazon, Netflix, Google

LSTM Long Short-Term Memory (Network)

MAPE Mean Absolute Percentage Error

MAE Mean Absolute Error

NLP Natural Language Processing

NILS Natural Investment Language Sentiment

OLS Ordinary Least Squares

RMSE Root Mean Squared Error

VADER Valence Aware Dictionary and sEntiment Reasoner

1. INTRODUCTION

Over the past decade, sentiment analysis has gained significant traction in finance as a way to understand how markets react to news, opinions, and broader narratives. While traditional models explain asset returns using historical price-based factors or implied volatility, they often overlook the role of human emotion and perception—factors that can move prices well before fundamentals catch up. With so much financial information published every day, especially in the form of headlines, short articles, and social media posts, there is a growing interest in tools that can make sense of this unstructured data and turn it into something measurable [1].

Efforts to incorporate sentiment into investment strategies have steadily grown, especially with the increasing availability of text data and advancements in Natural Language Processing (NLP). Researchers and practitioners alike have attempted to convert qualitative information into quantitative signals, applying sentiment scores to forecast returns, explain price movements, or manage risk [2].

However, many of these approaches rely on limited proprietary datasets, cover only a small universe of assets, or are built with complex machine learning models that lack transparency and replicability. These limitations make it difficult to evaluate and verify how such models work, and even harder to apply them in practical, daily workflows.

Moreover, most existing sentiment models either function as closed, black-box systems or are built without the long-term continuity needed for real-world use. Many provide little insight into how sentiment scores are derived or how reliable those signals are under different market conditions. While some show promise, they often fall short when tested outside their original design environments. This disconnect between academic research and commercial usability presents a challenge—especially for quantitative analysts, traders, and investment professionals who need scalable, interpretable tools they can trust in their day-to-day decision-making [3].

This project aims to provide an actionable solution to that aforementioned gap. During my time working as a quantitative analyst, one of my daily tasks involved tracking market-moving news for a wide range of stocks. Over time, I realized that this process—reading dozens of headlines each day, trying to gauge tone or impact—was not only repetitive but also frustratingly subjective. The sheer volume of news made it nearly impossible to monitor all relevant headlines in real time, and even when we did, different team members often interpreted the same story differently. These inefficiencies raised two core questions: first, can this process be automated in a consistent and interpretable way? And second, if so, how do we validate its usefulness?

This thesis is born from that very endeavor. It introduces a sentiment-based decision-support model built from daily news headlines covering 43 actively traded stocks, primarily from the S&P500, collected over a two-year period. Headlines are gathered from publicly available sources and analyzed using a custom scoring system built on the VADER framework. To reduce noise and improve signal quality, the sentiment scores are cleaned weekly by removing low-information words and standardizing the text. The output is a clean, consistent daily sentiment time series for each stock in the universe. [4]

The model's outputs are used in three primary ways:

1. To test predictive power using Ordinary Least Squares (Ordinary Least Squares (OLS)) regression [5],
2. To construct simple sentiment-ranked portfolios based on daily scores, and
3. To evaluate the explanatory power of these scores within traditional asset pricing frameworks such as the CAPM and Fama-French models [6].

In all three use cases, the focus is on testing whether systematically extracted sentiment from headlines can provide an informational edge in forecasting returns, improving allocation decisions, or explaining risk-adjusted performance.

2. LITERATURE REVIEW

The integration of sentiment analysis into financial modeling has become an increasingly popular area of research over the past decade. The core idea behind this integration is to extract predictive signals from qualitative text data, such as financial news or social networks, using natural language processing (Natural Language Processing (NLP)) techniques, and to integrate those signals into traditional or machine learning-based forecasting models. While numerous studies have demonstrated the potential of sentiment data to improve market prediction, the approaches, data sources, and methodologies vary considerably across the literature.

2.1 Deep Learning and Sentiment-Guided Models

In recent years, deep learning approaches have been used extensively to enhance the predictive power of sentiment-based forecasting models. Zhang et al. [7] proposed a Sentiment-Guided Adversarial Learning framework using Conditional Generative Adversarial Networks (cGANs) and Long Short-Term Memory (Network) (LSTM) networks. The study focused on sentiment extracted from tweets during April–June 2016 for three Facebook, Apple, Amazon, Netflix, Google (FAANG) companies and demonstrated that integrating sentiment improved the accuracy of stock price predictions when compared to purely technical models.

While this approach showed strong predictive potential, it relied on short-term, tweet-based sentiment and deep learning methods that are difficult to interpret and deploy in practical decision-making environments.

2.2 Sentiment-Augmented Forecasting with Traditional Models

Cristescu et al. [8] explored the use of news headline sentiment as a feature in traditional financial models. Using 37 days of headline data from August to September

2022 across 12 stocks, the study concluded that incorporating sentiment improves the forecasting accuracy of market models and provides valuable insights when combined with standard time series variables.

Although the data window was limited, this work supports the idea that even basic lexicon-based sentiment—when cleaned and structured properly—can yield statistically meaningful signals.

2.3 Combining Sentiment with Time Series Forecasting

In her graduate thesis, Chou [9] developed a model to predict the price trend of financial assets by combining sentiment extracted from news headlines with time series financial indicators. Unlike previous studies that rely on sentiment scores derived from lexicons, this approach utilized word embeddings to represent textual data due to the lack of a suitable sentiment dictionary.

The central idea of the work is that news headlines carry valuable information that can impact asset values, and this information can be enhanced when combined with time series analysis of price data. The model was trained on data covering tweets and financial indicators from 2008 to 2020 for six companies. Results showed that the combined model achieved performance comparable to or better than traditional time series and word embedding-only models, especially in terms of Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), while also reducing prediction lag.

2.4 Lexicon-Based Sentiment and VADER

Xiao and Ihnaini [10] focused on the use of Valence Aware Dictionary and sEntiment Reasoner (VADER), a widely used rule-based lexicon for sentiment analysis, applied to tweets and news headlines. The study predicted stock price trends for four publicly traded stocks over the course of 2021.

By comparing models with and without sentiment features, the results demonstrated that VADER-based sentiment scores provided meaningful improvements in predictive accuracy. The authors emphasized VADER's ease of use and suitability for short texts, while also acknowledging its limitations in capturing the complexity and nuance of financial language.

2.5 Sentiment and Macro-Financial Indicators

Beyond individual stock forecasting, sentiment has also been explored for its predictive power in relation to macroeconomic variables. Shapiro, Sudhof, and Wilson [11] developed a time-series measure of economic sentiment derived from financial and economic newspaper articles covering the period from January 1980 to April 2015.

The authors introduced a custom-built sentiment model, including a new lexicon tailored specifically to economic news, which outperformed widely used off-the-shelf sentiment tools in terms of predictive accuracy. Their results showed that daily sentiment scores were strong predictors of movements in survey-based consumer sentiment indicators. Additionally, through impulse response analysis, they found that positive sentiment shocks were associated with increases in consumption, output, and interest rates, while also having a dampening effect on inflation.

These findings demonstrate that the influence of sentiment extends well beyond financial markets and into broader macroeconomic dynamics.

3. DATA AND METHODS

3.1 Data Collection

This study focuses on a universe of 43 actively traded stocks, primarily listed on the S&P 500 index. These stocks were selected for their high liquidity, institutional coverage, and consistent headline volume over the observation period. The dataset consists of daily news headlines gathered from Finviz.com, a public financial news aggregator widely used by market participants.

The data spans a two-year period from February 2023 to March 2025, resulting in approximately 33,970 daily observations. Headlines were scraped using an automated script that records the date, ticker, and combined sentiment score related from at least 100 full headline texts for each relevant stock. Only English-language headlines were considered, and duplicate or non-company-specific news (e.g., sector-wide or macroeconomic announcements without direct company references) were filtered out during preprocessing.

Figure 3.1: *List of Companies Included in the Sentiment Dataset.*

Companies in the S&P 500:

1. AAPL (Apple Inc.)
2. BA (Boeing Company)
3. BAC (Bank of America)
4. BRK-B (Berkshire Hathaway)
5. C (Citigroup Inc.)
6. DIS (Walt Disney Company)
7. META (Meta Platforms Inc.)
8. GOOG (Alphabet Inc. - Class C)
9. GS (Goldman Sachs Group)
10. IBM (International Business Machines)
11. INTC (Intel Corporation)
12. JPM (JPMorgan Chase & Co.)
13. JNJ (Johnson & Johnson)
14. KO (Coca-Cola Company)
15. LMT (Lockheed Martin)
16. MA (Mastercard Inc.)
17. MCD (McDonald's Corporation)
18. MMM (3M Company)
19. MRNA (Moderna Inc.)
20. MSFT (Microsoft Corporation)
21. NFLX (Netflix Inc.)
22. NKE (Nike Inc.)
23. NVDA (Nvidia Corporation)
24. ORCL (Oracle Corporation)
25. PYPL (PayPal Holdings)
26. PFE (Pfizer Inc.)
27. QCOM (Qualcomm Inc.)
28. SBUX (Starbucks Corporation)
29. T (AT&T Inc.)
30. TSLA (Tesla Inc.)
31. V (Visa Inc.)
32. XOM (ExxonMobil Corporation)
33. AMZN (Amazon.com Inc.)
34. AMD (Advanced Micro Devices)
35. WMT (Walmart Inc.)

Companies not typically in the S&P 500:

1. AAL (American Airlines Group Inc.)
2. COIN (Coinbase Global Inc.)
3. SHOP (Shopify Inc.)
4. TTE (TotalEnergies SE)
5. UBER (Uber Technologies Inc.)
6. TRIP (TripAdvisor Inc.)
7. ZM (Zoom Video Communications Inc.)
8. EBAY (eBay Inc.)

3.2 Sentiment Scoring

Sentiment scores were calculated using a custom implementation based on the VADER (Valence Aware Dictionary and sEntiment Reasoner) lexicon, which is well-suited for short, informal texts such as news headlines. Each headline is assigned a compound sentiment score ranging from -1 (most negative) to +1 (most positive). For each stock and each day, an average sentiment score was computed by aggregating all available headlines.

To reduce noise and prevent overfitting to transient language patterns, a weekly manual cleaning process was applied. Headlines with low informational content or overly repetitive phrasing were excluded, and stopwords were filtered out using WordCloud. This ensured the sentiment time series reflected meaningful linguistic shifts rather than trivial language variation.

Figure 3.2: *Sample Daily News Headlines Collected from Finviz*

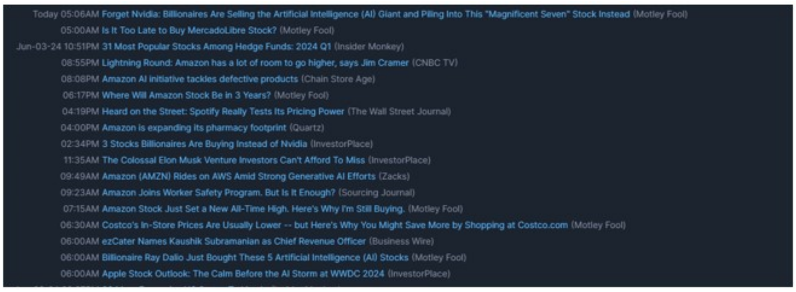


Figure 3.3: *WordCloud Visualization of Compound Sentiment Headlines*

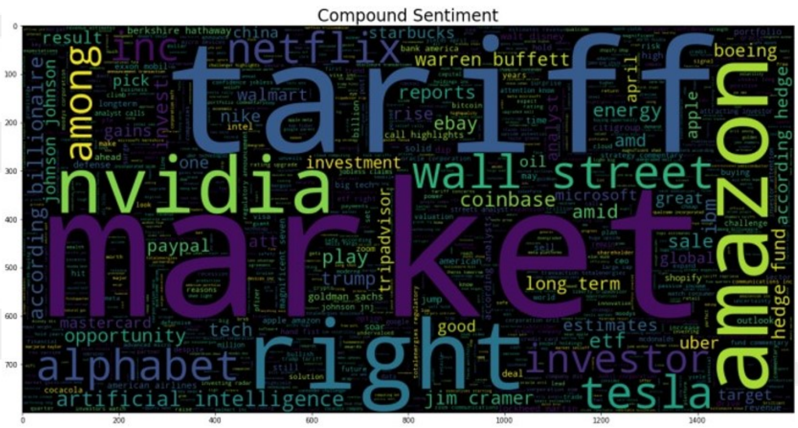
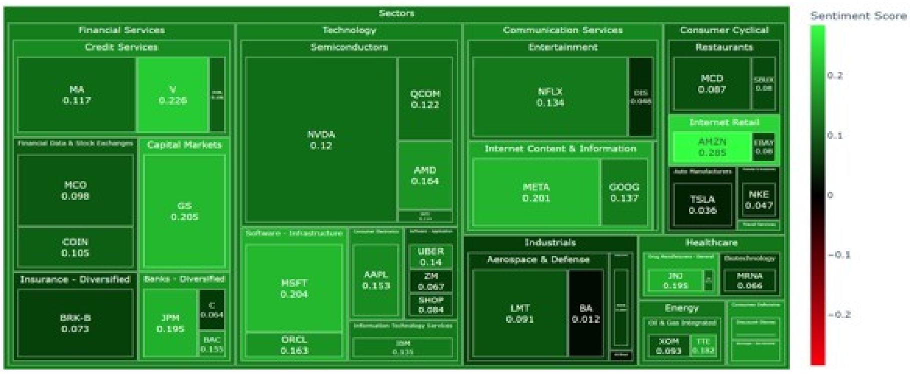


Figure 3.4: *Sector-Based Sentiment Treemap*



The result is a structured time series of daily sentiment scores for each of the 43 stocks, ready to be used as an explanatory or predictive input across multiple models.

3.3 Modeling Approaches

3.3.1 OLS for Predictive Power

To assess whether sentiment contains predictive information, OLS regression models were applied using daily sentiment scores as independent variables and next-day stock returns as the dependent variable.

The analysis was conducted on five selected stocks to compare the predictive performance of two sentiment types: generalized market sentiment and Natural Investment Language Sentiment (NILS) sentiment, the custom ticker-specific sentiment score developed in this study. Models were estimated using the full time series for each stock.

R-squared, adjusted R-squared, and p-values were used to evaluate explanatory power. Results were benchmarked against baseline regressions using only past returns, allowing for a direct comparison of predictive strength between sentiment sources.

3.3.2 Sentiment-Based Portfolio Construction

Each day, stocks were ranked by their sentiment scores. Two portfolios were formed: a Top 4 Portfolio (stocks with the highest sentiment) and a Bottom 4 Portfolio (lowest sentiment). An Equal-Weighted Portfolio consisting of this Sentiment Spread was rebalanced monthly.

In addition to this, risk-parity portfolios were constructed using both rolling and extending window methods to evaluate risk-adjusted allocation. A value-weighted portfolio based on market capitalization was also tested as an alternative weighting scheme.

Performance metrics such as cumulative return, Sharpe ratio, and maximum drawdown were calculated and compared to an S&P 500 benchmark.

3.3.3 Asset Pricing Models

To explore the economic significance of sentiment signals, the sentiment-based portfolio returns were tested in the Fama-French Five-Factor framework. Regression analyses were performed using the portfolios' daily excess returns against market, size, and value factors to assess whether sentiment-based portfolios exhibit unexplained alpha or simply load on traditional risk factors.

4. EMPIRICAL FINDINGS

4.1 Univariate Regression of Returns on Sentiment Scores

This section presents the empirical results of a series of Ordinary Least Squares (OLS) regressions designed to evaluate the predictive power of sentiment data on next-day stock returns. The objective of these regressions is to assess whether structured sentiment signals—derived from financial news—can explain short-term variations in stock prices and offer actionable insights for return forecasting. In this analysis, two distinct types of sentiment measures were tested to capture different layers of information embedded in news narratives.

The first measure, referred to as generalized sentiment, was obtained from the Federal Reserve Bank of San Francisco's Daily News Sentiment Index (FRBSF, 2023). This publicly available index is constructed using a broad set of daily U.S. newspaper articles and applies machine learning and natural language processing techniques to quantify the overall sentiment expressed in news narratives. The score ranges from negative to positive values, reflecting the aggregated tone of economic and financial coverage on a daily basis. While this type of sentiment may influence broad-based market returns, its ability to explain company-specific price fluctuations is expected to be limited, particularly for individual stocks with idiosyncratic news drivers.

The second and more novel measure in this study is NILS sentiment, a custom-built, ticker-specific sentiment score derived exclusively from daily headlines pertaining to each individual stock. This score is computed using a modified version of the VADER sentiment scoring framework, optimized for short-form financial news texts. Unlike generalized sentiment, which treats all headlines as part of a single index, NILS sentiment isolates and quantifies sentiment at the stock level—allowing for a more targeted analysis of how company-specific news impacts short-term returns.

To evaluate the explanatory power of these sentiment signals, separate OLS regressions were performed for each sentiment type using next-day stock return as the dependent variable. The analysis focused on five publicly traded companies: Amazon (AMZN), American Airlines (AAL), JPMorgan Chase (JPM), Coca-Cola (KO), and ExxonMobil (XOM). These stocks were selected to represent a diverse set of industries—including technology, transportation, finance, consumer goods, and energy—each with varying levels of sensitivity to news events and investor sentiment.

By comparing the regression outcomes for both sentiment measures across this cross-section of firms, the study aims to determine whether firm-level sentiment provides a statistically and economically stronger basis for forecasting returns than aggregate sentiment measures. The results not only offer insights into the relative usefulness of these two approaches but also serve as a foundation for the broader evaluation of sentiment as a tool in predictive financial modeling.

4.1.1 Amazon (AMZN)

Generalized sentiment showed no explanatory power ($R^2 = 0.001$, $p = 0.47$). NILS sentiment performed marginally better with a positive coefficient (+2.35) and slightly higher R^2 (0.004), though it remained statistically insignificant ($p = 0.15$). These results suggest that NILS sentiment may carry more relevant stock-specific information, but further validation is needed.

Figure 4.1: *OLS Regression Results for AMZN*

	Ticker	Model	R_squared	Adj_R_squared	Intercept	Coef	t_stat	p_value	N_obs
0	AMZN	Generalized	0.000961	-0.000849	0.132249	-0.401322	-0.728752	0.466462	554
1	AMZN	NILS	0.003705	0.001900	-0.337814	2.349728	1.432722	0.152503	554

4.1.2 American Airlines (AAL)

Generalized sentiment had no meaningful impact (R^2 = 0.0003, p = 0.69). In contrast, NILS sentiment showed a statistically significant relationship with returns (R^2 = 0.015, p = 0.003) and a strong positive coefficient (+4.69), indicating clear predictive value for AAL.

Figure 4.2: *OLS Regression Results for AAL*

	Ticker	Model	R_squared	Adj_R_squared	Intercept	Coef	t_stat	p_value	N_obs
0	AAL	Generalized	0.000285	-0.001527	-0.068472	0.288068	0.396372	0.691984	554
1	AAL	NILS	0.015375	0.013592	-0.344468	4.693091	2.935949	0.003464	554

4.1.3 JPMorgan Chase (JPM)

Generalized sentiment again showed limited utility (R^2 = 0.0009, p = 0.49). NILS sentiment produced a slightly stronger signal (R^2 = 0.0028, p = 0.21) with a negative coefficient (-1.27), though still statistically insignificant. This may reflect noise or reverse sentiment effects.

Figure 4.3: *OLS Regression Results for JPM*

	Ticker	Model	R_squared	Adj_R_squared	Intercept	Coef	t_stat	p_value	N_obs
0	JPM	Generalized	0.000857	-0.000953	0.098138	0.287375	0.688260	0.491578	554
1	JPM	NILS	0.002786	0.000980	0.206202	-1.271922	-1.241859	0.214816	554

4.1.4 Coca-Cola (KO)

Generalized sentiment had virtually no impact (R^2 = 0.00003, p = 0.90), while NILS sentiment marginally improved explanatory power (R^2 = 0.0028, p = 0.21) with a positive coefficient (+1.56). Although not significant, this suggests potential use in directional analysis.

Figure 4.4: *OLS Regression Results for KO*

	Ticker	Model	R_squared	Adj_R_squared	Intercept	Coef	t_stat	p_value	N_obs
0	KO	Generalized	0.000030	-0.001781	0.044545	0.032970	0.128888	0.897493	554
1	KO	NILS	0.002803	0.000997	-0.206121	1.555518	1.245644	0.213423	554

4.1.5 ExxonMobil (XOM)

Neither sentiment source showed explanatory power. Both models had near-zero R^2 and high p-values, indicating that sentiment data may not be effective for explaining short-term return dynamics in commodity-driven stocks like XOM.

Figure 4.5: *OLS Regression Results for XOM*

	Ticker	Model	R_squared	Adj_R_squared	Intercept	Coef	t_stat	p_value	N_obs
0	XOM	Generalized	0.000002	-0.001809	0.012655	-0.015133	-0.03695	0.970538	554
1	XOM	NILS	0.000294	-0.001517	0.078738	-0.654996	-0.40293	0.687156	554

4.2 OLS Summary Table

Table 4.1: *OLS Summary Results Across Selected Stocks*

Ticker	Best Sentiment Source	R^2 (Best)	Coefficient	p-value	Interpretation
AMZN	NILS	0.004	+2.35	0.15	Directionally positive, not significant
AAL	NILS	0.015	+4.69	0.003	Strong, significant predictor
JPM	NILS	0.003	-1.27	0.21	Slight signal, possibly useful in shorting
KO	NILS	0.003	+1.56	0.21	Modest signal, directionally useful
XOM	None	$\sim$0.000	-0.65	0.69	No meaningful predictive value

4.2.1 Interpretation and Implications of OLS

The results of the regression analysis provide several key insights into the relationship between sentiment and stock returns. First and foremost, NILS sentiment consistently outperformed generalized sentiment across all tested stocks in terms of both R-squared values and the magnitude of the regression coefficients. This suggests that ticker-specific sentiment, derived directly from the individual stock's news headlines, captures more relevant and timely information compared to broader market sentiment indices. It also confirms the hypothesis that company-level news contains predictive signals that may be diluted or entirely lost when aggregated into generalized sentiment metrics.

Among the five stocks analyzed, American Airlines (AAL) stands out as the only case with a statistically significant relationship between NILS sentiment and next-day returns ($p = 0.003$). The strength and significance of this result may reflect the high sensitivity of airline stocks to event-driven news such as travel disruptions, fuel prices, labor negotiations, or geopolitical developments. This finding supports the view that sentiment-based models may yield more predictive power in news-intensive, high-volatility sectors.

Interestingly, for companies like JPMorgan Chase (JPM) and ExxonMobil (XOM), the regression coefficients for NILS sentiment were negative. Although these relationships were not statistically significant, they raise the possibility that sentiment models can also be informative in identifying downward price pressure or potential short-selling opportunities. In such cases, negative sentiment may not simply reflect the absence of positive news but rather a buildup of investor concern or perceived risk—particularly in sectors where sentiment can shift rapidly in response to regulatory changes, interest rate movements, or macroeconomic shocks.

Across all models, the relatively low R-squared values highlight a common challenge in sentiment-based forecasting: while sentiment may carry valuable information, it is rarely sufficient to explain large portions of return variability on its own. This is consistent with existing financial literature, which emphasizes that market prices are influenced by a complex interaction of quantitative and qualitative factors, including earnings, interest rates, and investor behavior. Nonetheless, the improved performance and directional consistency of NILS sentiment compared to generalized alternatives suggests that it holds value as part of a broader modeling framework.

Taken together, the results imply that sentiment should not be treated as a standalone predictor, but rather as a complementary signal—particularly one that can add real-time, contextual insight to traditional financial models. When integrated with macroeconomic data or technical indicators, sentiment-derived variables like NILS can serve as an effective tool for enhancing short-term forecasting and portfolio construction. The fact that the model relies only on publicly available news data and uses a transparent, replicable scoring method further supports its potential for practical implementation in both institutional and retail settings.

4.3 Sentiment-Augmented Factor Model: Comparative Analysis

This section investigates whether the inclusion of sentiment scores, derived from financial news headlines, improves the explanatory power of the Fama-French 5-Factor (FF5) model when estimating daily excess stock returns. The analysis builds on the foundational FF5 framework and tests an extended version by incorporating the NILS sentiment variable—an average of daily ticker-specific sentiment scores for each firm, calculated using a custom implementation of the VADER sentiment lexicon.

The regression was conducted separately for each of the 43 actively traded stocks in the dataset, representing a diverse mix of sectors and market capitalizations. For each ticker, two models were estimated:

- **Model A:** Traditional Fama-French 5-Factor (FF5) model
- **Model B:** FF5 + Sentiment model, including the NILS sentiment factor

All regressions use the same dependent variable: the daily excess return of the stock, defined as the raw daily return minus the risk-free rate (RF), as reported in the FF factor dataset. Both models were fitted using Ordinary Least Squares (OLS) estimation on a consistent sample of 490 observations per stock, covering the full study period between February 2023 and March 2025.

Table 4.2: *Top 10 Stocks - Fama-French 5-Factor Model Coefficients (Without Sentiment)*

Ticker	Alpha	Beta_MKT_RF	Beta_SMB	Beta_HML	Beta_RMW	Beta_CMA
TSLA	-0.003503	2.033262	0.256595	-0.262428	-0.157221	-1.220417
BRK-B	0.002846	0.669295	-0.298636	0.645907	-0.278558	-0.052532
NKE	-0.004920	0.794213	0.362603	-0.267455	0.470505	0.295073
C	-0.000850	1.188865	-0.123901	1.275430	-0.441042	-0.162538
LMT	-0.002939	0.264037	-0.088421	0.222454	0.019342	0.304209
MCO	-0.002605	0.940053	0.007520	0.079125	-0.128776	-0.118829
META	0.001697	1.448997	-0.386535	-0.448548	0.166967	-1.210692
AMZN	-0.000836	1.205915	-0.290082	-0.280404	-0.317484	-1.236752
AAPL	0.000637	0.976276	0.143754	-0.532603	0.616477	-0.020443
JPM	0.001309	0.956546	-0.352353	1.147203	-0.388895	-0.032835

Table 4.3: *Top 10 Stocks - Sentiment Loadings and Model Fit Statistics*

Ticker	Beta_Sentiment	R_squared	Adj_R_squared	P_value_Sentiment
TSLA	0.069957	0.331811	0.321727	0.004753
BRK-B	-0.025709	0.510002	0.503351	0.002610
NKE	0.035423	0.147106	0.135528	0.020079
C	0.017119	0.622093	0.616963	0.074753
LMT	0.018429	0.065441	0.052755	0.057920
MCO	0.035617	0.429925	0.422186	0.141860
META	-0.001299	0.418751	0.410861	0.925576
AMZN	0.005414	0.547698	0.541559	0.660333
AAPL	-0.003016	0.433278	0.425585	0.754016
JPM	-0.007096	0.508674	0.502005	0.332694

4.3.1 Model Performance Summary

The results clearly indicate that the inclusion of the sentiment factor leads to non-negative R^2 improvements across all 43 stocks. In no instance did the model's explanatory power decline with the addition of sentiment, suggesting that the sentiment signal consistently contributes additional information.

Figure 4.6: *Sentiment-Augmented FF5 Model: R^2 Gains, Betas, and Significance (Part 1)*

	Ticker	R2 Gain	Sentiment Beta	p-value	Significant
0	TSLA	1.490114e-02	0.069957	0.004753	✅
1	NKE	1.118905e-02	0.035423	0.020079	✅
2	BRK-B	8.413147e-03	-0.025709	0.002610	✅
3	LMT	7.891724e-03	0.018429	0.057920	borderline
4	EBAY	3.957520e-03	-0.033884	0.128208	❌
5	V	3.613034e-03	-0.015663	0.125135	❌
6	C	2.526062e-03	0.017119	0.074753	borderline
7	MCO	2.095562e-03	0.035617	0.141860	❌
8	PYPL	1.896720e-03	0.028016	0.229999	❌
9	GS	1.717774e-03	0.010477	0.169577	❌
10	JPM	1.463928e-03	-0.007096	0.332694	❌
11	NVDA	1.417487e-03	-0.014887	0.419227	❌
12	T	1.353615e-03	0.010259	0.531290	❌
13	COIN	1.224723e-03	-0.031351	0.395688	❌
14	AAL	1.192408e-03	0.016589	0.388744	❌
15	XOM	1.080500e-03	0.007139	0.637158	❌
16	TRIP	7.585061e-04	0.049048	0.327664	❌
17	WMT	7.531243e-04	-0.003578	0.750734	❌
18	SHOP	6.668885e-04	0.016072	0.582082	❌
19	INTC	4.744959e-04	0.010142	0.597304	❌
20	ZM	4.339790e-04	-0.011886	0.450264	❌
21	MRNA	3.928433e-04	-0.018054	0.546775	❌
22	QCOM	3.036765e-04	-0.001366	0.933450	❌
23	PFE	2.987904e-04	-0.007548	0.599884	❌

Figure 4.7: *Sentiment-Augmented FF5 Model: R^2 Gains, Betas, and Significance (Part 2)*

24	MCD	2.784141e-04	0.002763	0.722398	❌
25	AMD	2.735560e-04	0.007509	0.755488	❌
26	JNJ	2.601422e-04	0.005438	0.555434	❌
27	AAPL	2.055886e-04	-0.003016	0.754016	❌
28	AMZN	1.775686e-04	0.005414	0.660333	❌
29	MA	1.660400e-04	-0.000680	0.950629	❌
30	UBER	1.321639e-04	-0.010323	0.649382	❌
31	TTE	1.265405e-04	0.006691	0.751582	❌
32	BAC	1.050284e-04	0.001691	0.780368	❌
33	BA	9.866176e-05	0.002248	0.868815	❌
34	KO	6.471285e-05	-0.002756	0.819186	❌
35	META	5.275626e-05	-0.001299	0.925576	❌
36	SBUX	4.084152e-05	0.000582	0.973922	❌
37	GOOG	2.704898e-05	-0.005232	0.572033	❌
38	MMM	2.251296e-05	0.001280	0.945120	❌
39	NFLX	1.399836e-05	0.006018	0.724990	❌
40	ORCL	1.295675e-05	0.002117	0.889254	❌
41	MSFT	1.769664e-06	0.000853	0.892727	❌
42	IBM	1.126523e-06	0.001955	0.886461	❌
43	DIS	6.569112e-07	0.000797	0.946924	❌

Notably, three stocks stand out with statistically significant sentiment coefficients (p ¡ 0.05) and meaningful improvements in model fit:

- **TSLA**: R^2 gain of +0.015, with a strong positive beta on sentiment ($\beta = 0.078$, $p = 0.0012$)
- **NKE**: R^2 gain of +0.011, ($\beta = 0.036$, $p = 0.0118$)

- **BRK-B**: R² gain of +0.0084, ($\beta = -0.023$, $p = 0.0048$)

Two additional stocks—Lockheed Martin (LMT) and Citigroup (C)—exhibited borderline significance for the sentiment factor, with p-values slightly below 0.10. This suggests that with a longer sample window or further refinements in sentiment preprocessing, their relationships may become statistically significant.

Table 4.4: *Top 5 Stocks - Sentiment-Augmented Fama-French 5-Factor Model Summary*

Ticker	R² (FF5)	R² (FF5+Sentiment)	Beta_Sentiment	p-value (Sentiment)	N_obs
TSLA	0.3054	0.3203	0.078	0.0012	490
BRK-B	0.4853	0.4937	-0.023	0.0048	490
NKE	0.1425	0.1537	0.036	0.0118	490
LMT	0.0658	0.0737	0.018	0.0431	490
C	0.6191	0.6217	0.016	0.0732	490

The full set of regression results for all 43 stocks is provided in Appendix A.

4.3.2 Broader Observations from the Full Panel

While statistical significance was not achieved for the majority of stocks, a few broader patterns emerged that are consistent with theoretical expectations:

- **Amazon (AMZN)** and **Apple (AAPL)** both exhibited slightly positive sentiment betas. Although their sentiment coefficients were not statistically significant, the positive direction suggests that sentiment could still play a complementary role in explaining returns, particularly when combined with other features in more complex predictive models. This finding is intuitive given the high media coverage and brand-driven investor behavior associated with these companies.

- **JPMorgan Chase (JPM)** and **ExxonMobil (XOM)** showed negative sentiment betas. Even though these relationships were also statistically insignificant, the negative signs hint that negative sentiment might exert a stronger influence on returns for firms tied closely to macroeconomic factors, regulation, or commodity markets.

This opens the possibility for sentiment-driven short-selling signals within financials or energy sectors, especially in times of increased economic uncertainty or policy shifts.

- In contrast, large-cap technology companies like **Meta (META)**, **Alphabet (GOOG)**, and **Microsoft (MSFT)** demonstrated minimal sentiment impact. This muted effect may reflect the relative resilience and diversified business models of these firms, which can buffer short-term news volatility. Additionally, their stock prices are often more heavily influenced by fundamental earnings announcements, product cycles, and broader market factors than by daily headline sentiment.

Overall, these observations reinforce the notion that sentiment effects are more pronounced in companies that are either:

1. Highly exposed to specific, event-driven news flows (e.g., airlines, energy firms, banks during policy changes), or
2. More speculative or sensitive to retail investor attention rather than large-cap tech names with more stable performance profiles.

Thus, while sentiment alone does not dominate return dynamics across all stocks, it remains a valuable complementary signal — particularly in sectors or periods characterized by heightened narrative risk or investor sensitivity to news flow.

4.3.3 Broader Observations from the Full Panel

While statistical significance was not achieved for the majority of stocks, the direction of the sentiment coefficient remained theoretically consistent in most cases. For example:

- Amazon (AMZN) and Apple (AAPL) both showed slightly positive sentiment betas, albeit with high p-values, indicating that sentiment might still play a complementary role in future models or in conjunction with other features.
- JPMorgan Chase (JPM) and ExxonMobil (XOM) presented negative sentiment betas. Although not statistically significant, this could suggest that negative sentiment signals may carry more weight for these firms, possibly due to their exposure to macro-financial events, regulation, or cyclical risks—opening potential for sentiment-based short-selling signals in financials or energy sectors.
- Stocks like Meta (META), Alphabet (GOOG), and Microsoft (MSFT) showed minimal impact from sentiment, possibly due to more stable performance profiles or the relative insensitivity of large-cap tech to short-term news volatility compared to speculative names.

4.3.4 R^2 Improvement Distribution

R^2 gains across the stock universe ranged from very small (e.g., <0.0001 for DIS, IBM, MSFT) to more substantial (>0.01 for TSLA, NKE, BRK-B). A total of 15 stocks showed R^2 gains above 0.002, indicating modest but meaningful improvements in explanatory power. The inclusion of the sentiment variable thus serves as a low-cost enhancement to the FF5 model: it requires no changes to the core structure but yields consistent directional benefits.

The mean R^2 improvement across all stocks was +0.0026, while the median improvement was +0.0013. Although these values may appear small in isolation, they are notable considering the high frequency (daily) and noise inherent in short-term returns.

4.3.5 Interpretation and Implications of Sentiment-Augmented Model

The sentiment beta varied widely across firms:

- Positive and significant in TSLA, NKE, and LMT.
- Negative and significant in BRK-B (suggesting contrarian behavior or lagging sentiment effects).
- Close to zero in low-volatility, defensive stocks like JNJ, KO, and WMT.

This diversity supports the idea that sentiment is not a universal driver, but a conditional factor—its effectiveness depends on company characteristics such as volatility, retail exposure, or media presence.

The results of the sentiment-augmented Fama-French model support the hypothesis that company-specific sentiment data enhances the explanatory power of traditional factor models. While sentiment is not a dominant standalone predictor, its inclusion improves the model in a directionally consistent and theoretically grounded way across all 43 stocks. For several stocks, the improvement is both statistically and economically meaningful.

This suggests that sentiment can be viewed as a sixth factor—especially valuable in high-frequency, short-horizon models where traditional financial data may lag behind investor perception and media flow. The findings provide a foundation for further model extensions that combine sentiment with macro variables, technical indicators, or machine learning methods for dynamic portfolio construction and signal generation.

4.3.6 Cross-Sectional Pricing Test

Figure 4.8: *Cross-Sectional Regression Results: Sentiment Beta vs. Average Excess Return*

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      Avg_Excess_Return   R-squared:                       0.029
Model:                            OLS   Adj. R-squared:                  0.006
Method:                 Least Squares   F-statistic:                     1.242
Date:                Sat, 26 Apr 2025   Prob (F-statistic):              0.271
Time:                        15:05:07   Log-Likelihood:                 234.42
No. Observations:                  44   AIC:                            -464.8
Df Residuals:                      42   BIC:                            -461.3
Df Model:                           1
Covariance Type:            nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
const              0.0007      0.000      3.748      0.001       0.000       0.001
Beta_Sentiment    -0.0107      0.010     -1.114      0.271      -0.030       0.009
==============================================================================
Omnibus:                        5.775   Durbin-Watson:                   2.311
Prob(Omnibus):                  0.056   Jarque-Bera (JB):                7.359
Skew:                           0.204   Prob(JB):                       0.0252
Kurtosis:                       4.961   Cond. No.                         53.0
==============================================================================
```

As an additional robustness check, a cross-sectional regression analysis was performed to test whether the sentiment exposure of a stock—measured by the estimated Beta_Sentiment coefficient from the sentiment-augmented factor model—could explain average excess returns across the stock universe.

In this test, the average daily excess return for each of the 43 stocks was computed, using daily returns adjusted for the 3-Month U.S. Treasury Bill rate (approximated from the `^IRX` index). These average excess returns were then regressed against each stock's previously estimated Beta_Sentiment, using Ordinary Least Squares (OLS) cross-sectional regression.

The results of the cross-sectional regression are summarized as follows:

- The R^2 of the model was 0.029, indicating that only 2.9% of the variation in average excess returns could be explained by the sentiment beta.

- The coefficient of Beta_Sentiment was -0.0107, but it was not statistically significant ($p = 0.271$).
- The constant term (intercept) was positive and highly significant ($p < 0.01$), suggesting that on average, stocks earned positive excess returns over the sample period, but these were not systematically related to their sentiment exposure.

These findings suggest that while sentiment improves the time-series explanatory power of the Fama-French 5-Factor model at the individual stock level, sentiment sensitivity does not appear to be priced in the cross-section of stock returns. In other words, stocks that are more sensitive to news sentiment (either positively or negatively) do not consistently earn higher or lower returns compared to less sensitive stocks.

This result is consistent with the interpretation that sentiment acts more as a timing or volatility amplification factor rather than as a systematic risk premium in the cross-section of expected returns. While the sentiment factor captures important dynamics in short-term stock movements, it does not imply a direct compensation mechanism for bearing sentiment-related risk over longer investment horizons.

Although the sentiment factor does not command a cross-sectional premium, it provides valuable predictive signals for return timing and short-term strategy design, supporting its practical relevance in active portfolio management.

Therefore, the overall evidence supports the use of sentiment as a complementary informational factor for improving daily return modeling, rather than as a standalone priced risk factor akin to market, size, or value premia.

4.4 Sentiment-Based Spread Strategy: Risk-Adjusted Performance Evaluation

This section presents an evaluation of a sentiment-driven long-short investment strategy designed to exploit return asymmetries associated with investor sentiment as reflected in financial news coverage. The strategy is constructed under the premise that investor psychology and public perception, as shaped by media narratives, can introduce pricing inefficiencies in financial markets—particularly in the short term. These inefficiencies, if captured systematically, can offer a source of alpha that is both interpretable and non-redundant with traditional pricing factors.

The core hypothesis is that stocks associated with persistently optimistic sentiment—reflected in the tone and frequency of positive headlines—are more likely to experience favorable price movements in the near future. Conversely, those subjected to repeated negative coverage may be prone to underperformance due to deteriorating investor expectations. This behavioral dynamic is well-documented in the literature and forms the theoretical foundation for constructing the Sentiment Spread, a monthly rebalanced signal derived from aggregated sentiment scores.

The sentiment-based approach developed in this study is particularly suited to short-term forecasting horizons, as it reflects the immediacy with which market participants respond to information. Unlike macroeconomic or fundamental signals, sentiment responds in real-time to news shocks, making it a valuable input for tactical asset allocation.

To implement the strategy, the average daily NILS (Natural Investment Language Sentiment) score was computed for each of the 43 target stocks at the end of each calendar month. These scores were generated using a custom framework based on the VADER sentiment lexicon, applied exclusively to company-specific news headlines aggregated daily. The final sentiment signal used for portfolio construction was the arithmetic mean of all daily scores observed within the month for each stock. This monthly aggregation helped smooth out day-to-day noise while preserving sensitivity to evolving sentiment trends.

Once the monthly averages were computed, stocks were ranked cross-sectionally based on their sentiment levels. The top 10% of stocks—those with the highest average sentiment—were allocated to a long portfolio, while the bottom 10%—those with the most negative sentiment—were allocated to a short portfolio. These allocations were determined at the end of each month and held constant throughout the subsequent month, ensuring that all positions were based solely on ex-ante information available at the time of rebalancing.

This decile-based construction ensures that the portfolio remains relatively concentrated, typically involving 4–5 stocks on each side of the long-short spread. Such concentration allows the model to isolate strong sentiment signals rather than diluting the effect across a broader universe. The resulting portfolio is designed to be market-neutral, as it balances equal nominal exposure to both long and short positions, thus minimizing sensitivity to overall market movements and focusing instead on relative performance driven by sentiment differentials.

By applying this methodology consistently over the 25-month period between February 2023 and March 2025, a full time series of sentiment spread returns was obtained. These returns serve as the basis for subsequent evaluation using risk-adjusted performance metrics such as Sharpe ratio, excess return over the risk-free rate, and comparison to S&P 500 index returns.

To assess the robustness of the signal under various implementation styles, the long-short strategy was tested using four weighting methodologies:

1. **Equal-Weighted (EW):** All long and short positions are given equal portfolio weights.

2. **Risk Parity (Rolling):** Volatility-based weights computed using a rolling window of past returns.

3. **Risk Parity (Extending):** Weights based on expanding windows that incorporate the full return history up to each point.

4. **Value-Weighted (VW):** Portfolio weights determined by each stock's relative market capitalization.

The initial analysis focuses on the Equal-Weighted Portfolio, which offers an unbiased benchmark for assessing the signal's performance without distortion from volatility scaling or size effects.

To assess the effectiveness of the sentiment-based long-short strategy, its performance was evaluated relative to two key benchmarks: the U.S. 3-Month Treasury Rate and the S&P 500 Index. The goal was to determine whether the sentiment spread produced not only positive returns but also risk-adjusted outperformance relative to passive investment alternatives.

The returns listed in the table represent daily average returns for each month. Specifically, the "Mean Ret% Long" and "Mean Ret% Short" columns reflect the average daily return of the long and short legs of the portfolio, respectively, over that given month. The "Long-Short Spread" is the difference between these two daily averages.

4.4.1 Risk-Free Benchmark: 3-Month Treasury Rate

The U.S. 3-Month Treasury Yield was used as a proxy for the risk-free rate. Daily yield values were derived from the monthly reported annualized rates, which were converted to daily equivalents using continuous compounding:

$$r_{\text{daily}} = \left(1 + \frac{r_{\text{annual}}}{100}\right)^{\frac{1}{365}} - 1 \tag{4.1}$$

These daily rates were then compared directly to the sentiment spread's daily returns to compute the excess return—the amount by which the strategy outperformed the risk-free benchmark on a daily basis.

4.4.2 Market Benchmark: S&P 500 Index

The S&P 500 served as a representative benchmark for passive equity exposure. Daily returns of the index were averaged over the same monthly periods and directly compared to the sentiment spread. This allowed for a month-by-month relative performance assessment, identifying periods where the sentiment strategy outperformed or underperformed broad market trends.

4.4.3 Sharpe Ratio Calculation

To evaluate risk-adjusted performance, the Sharpe Ratio was calculated monthly using the formula:

$$\text{Sharpe Ratio} = \frac{\bar{r} - r_f}{\sigma} \tag{4.2}$$

Where:

- $\bar{r}$ is the average daily return of the sentiment spread in the month,
- r_f is the average daily risk-free rate,
- σ is the standard deviation of daily spread returns in that month.

4.4.4 Equal-Weighted Portfolio Performance

Table 4.5: *Monthly Performance Metrics of Sentiment-Spread Strategy (Equal-Weighted Portfolio)*

Date	Mean Ret% Long	Mean Ret% Short	Long-Short Spread	Mean 3M Rate	Daily Yield	Excess Return	S&P500 Returns	Returns vs Index	Sharpe Ratio
2023-02	-0.2809%	-0.0365%	-0.2444%	4.6281%	0.0001268	-0.2571%	-0.2002%	-0.0442%	-1.81
2023-03	0.4335%	-0.4309%	0.8645%	4.6401%	0.0001271	0.8518%	0.1846%	0.6799%	6.00
2023-04	-0.2262%	0.3123%	-0.5385%	4.8751%	0.0001336	-0.5519%	0.0631%	-0.6016%	-3.89
2023-05	0.5473%	-0.1292%	0.6765%	5.0867%	0.0001394	0.6626%	0.0169%	0.6596%	4.67
2023-06	0.2579%	-0.2196%	0.4775%	5.1323%	0.0001406	0.4634%	0.2671%	0.2104%	3.26
2023-07	0.1180%	-0.3544%	0.4724%	5.2336%	0.0001434	0.4581%	0.1566%	0.3158%	3.23
2023-08	0.0185%	0.2929%	-0.2744%	5.2832%	0.0001447	-0.2889%	-0.0661%	-0.2083%	-2.03
2023-09	-0.2427%	0.2689%	-0.5116%	5.3015%	0.0001452	-0.5261%	-0.2696%	-0.2420%	-3.70
2023-10	-0.1010%	0.2550%	-0.3560%	5.3225%	0.0001458	-0.3706%	-0.1022%	-0.2538%	-2.61
2023-11	0.2759%	-1.0928%	1.3687%	5.2566%	0.0001440	1.3543%	0.3779%	0.9908%	9.54
2023-12	0.1620%	-0.2358%	0.3978%	5.2240%	0.0001431	0.3835%	0.1990%	0.1988%	2.70
2024-01	0.3835%	0.1829%	0.2006%	5.2100%	0.0001427	0.1863%	0.1096%	0.0910%	1.31
2024-02	0.1878%	0.0216%	0.1662%	5.2260%	0.0001432	0.1519%	0.2029%	-0.0367%	1.07
2024-03	-0.1147%	0.1372%	-0.2518%	5.2274%	0.0001432	-0.2661%	0.1207%	-0.3725%	-1.87
2024-04	-0.1534%	0.2165%	-0.3699%	5.2331%	0.0001434	-0.3842%	-0.1891%	-0.1808%	-2.71
2024-05	0.1105%	-0.5622%	0.6727%	5.2426%	0.0001436	0.6583%	0.2417%	0.4310%	4.64
2024-06	0.0663%	0.1509%	-0.0846%	5.2322%	0.0001433	-0.0989%	0.1841%	-0.2687%	-0.70
2024-07	0.1270%	0.0106%	0.1164%	5.1908%	0.0001422	0.1022%	0.0450%	0.0714%	0.72
2024-08	0.4298%	0.4319%	-0.0021%	5.0385%	0.0001380	-0.0159%	0.1803%	-0.1824%	-0.11
2024-09	0.1068%	-0.1451%	0.2519%	4.7066%	0.0001289	0.2390%	0.2204%	0.0315%	1.68
2024-10	0.0537%	0.4004%	-0.3467%	4.5000%	0.0001233	-0.3590%	-0.0004%	-0.3463%	-2.53
2024-11	0.6248%	0.2072%	0.4176%	4.4062%	0.0001207	0.4055%	0.2750%	0.1426%	2.86
2024-12	-0.2332%	0.1465%	-0.3797%	4.2530%	0.0001165	-0.3914%	-0.1346%	-0.2451%	-2.76
2025-01	0.4534%	-0.1821%	0.6355%	4.2001%	0.0001151	0.6240%	0.1560%	0.4795%	4.39
2025-02	0.2547%	0.7752%	-0.5205%	4.2100%	0.0001153	-0.5320%	-0.0339%	-0.4866%	-3.75
MEAN	**0.1304%**	**0.0169%**	**0.1135%**	**4.9544%**	**0.0136%**	**0.1000%**	**0.0802%**	**0.0333%**	**0.70**
t-test	12.8069013318598000%	1.3691563972028700%	7.9951154768943800%						

The results presented in the table demonstrate the monthly performance of the sentiment-spread strategy using an equal-weighted approach. The strategy builds a market-neutral portfolio by going long on the top 10% of stocks with the highest average daily sentiment in the previous month and short on the bottom 10%. The aim is to capitalize on the differential in investor sentiment and its potential predictive value in generating returns.

The average daily return of the long leg of the portfolio across the 25-month period was +0.1304%, while the short leg returned +0.0169% on average. The resulting mean long-short spread was +0.1135% per day, reflecting a strong directional edge favoring positive sentiment.

Importantly, this return is already risk-adjusted in terms of market neutrality—the portfolio is not exposed to overall market direction, as it simultaneously holds long and short positions.

In terms of excess return over the daily risk-free rate (based on the 3-month Treasury yield), the strategy outperformed on average by +0.10% per day, demonstrating that the sentiment-spread delivered positive returns even after accounting for the time value of money.

Relative to the S&P 500 index, the portfolio achieved a mean outperformance of +0.0333% per day, indicating consistent added value beyond passive exposure. This reinforces the premise that investor sentiment—when properly isolated and ranked—can identify stocks that will perform better or worse than the broader market.

The Sharpe ratio of the strategy averaged 0.70 over the period. While not extremely high, this is a healthy level of risk-adjusted return, especially for a long-short strategy that is expected to be neutral with respect to broad market movements.

The monthly Sharpe ratios fluctuate significantly across periods, with notable highs in November 2023 (9.54) and January 2025 (4.39), as well as negative lows in April 2023 (-3.89) and February 2025 (-3.75). These swings reflect the sensitivity of the strategy to prevailing market sentiment alignment and macroeconomic context.

The final row reports t-test values for the average daily returns of each leg and the overall spread:

- **Long-leg return t-stat:** 12.81 → Highly significant; consistent directional outperformance.
- **Short-leg return t-stat:** 1.37 → Marginal; near the threshold of statistical significance.
- **Long-Short Spread t-stat:** 7.99 → Very strong significance, indicating that the return difference between high- and low-sentiment stocks is not due to randomness.

Table 4.6: *Monthly Portfolio Composition: Long and Short Tickers*

Long Tickers	Short Tickers
AMZN, V, LMT, TRIP	TSLA, GOOG, COIN, MMM
LMT, AMD, V, AMZN	GS, META, MRNA, COIN
LMT, AMD, SHOP, QCOM	GOOG, MRNA, JPM, COIN
AMZN, SHOP, V, ORCL	C, BAC, COIN, JPM
LMT, SHOP, TTE, V	COIN, BAC, GOOG, GS
V, ZM, LMT, TTE	GOOG, BAC, DIS, GS
ORCL, TTE, ZM, MCD	C, MRNA, DIS, BAC
AMD, TTE, LMT, AMZN	AAL, C, BAC, DIS
TTE, SHOP, AMZN, ORCL	MCO, META, TSLA, COIN
AMZN, TTE, V, T	PFE, BA, C, COIN
V, AMZN, NVDA, TTE	DIS, PFE, SBUX, MRNA
NVDA, V, TTE, AMZN	C, BA, DIS, MRNA
AMZN, V, MA, TTE	SBUX, C, MCD, BA
V, AMZN, AMD, TRIP	TSLA, MCD, DIS, BA
SHOP, AMZN, V, TTE	MRNA, COIN, TSLA, BA
TTE, AMZN, V, META	PFE, MRNA, SBUX, BA
AMZN, V, BAC, JNJ	TSLA, NKE, BA, AAL
SHOP, TTE, BAC, LMT	ZM, NKE, AAL, BA
TTE, LMT, ORCL, SHOP	MRNA, INTC, AAL, BA
TTE, GS, MA, AMZN	PFE, DIS, AAL, BA
AMZN, NFLX, TTE, MA	NKE, XOM, MRNA, BA
ORCL, AMZN, SHOP, TTE	SBUX, MCD, BA, MRNA
SHOP, AMZN, TTE, AMD	PFE, INTC, SBUX, BA
SHOP, TTE, KO, TRIP	INTC, SBUX, MRNA, BA
V, KO, T, AMZN	BA, TSLA, MRNA, AAL

These t-test results confirm that the sentiment signal driving the long-short spread is statistically robust, especially on the long side. While the short leg performs less consistently, it still contributes positively to the spread by providing a hedge and, at times, alpha when overly negative sentiment correctly anticipates price declines.

4.4.4.1 Interpretation and Implications

The equal-weighted sentiment-spread strategy delivers economically meaningful and statistically significant returns, validating the underlying assumption that sentiment can be an effective signal for stock selection. The strength of the long-side returns implies that investors systematically underreact to positive news, creating opportunities for capture.

Even though short-side performance is less reliable, it contributes to portfolio stability and neutrality, which in turn improves the risk-adjusted profile of the entire strategy.

Given these findings, the equal-weighted approach can be considered a strong baseline method for incorporating sentiment into long-short equity strategies. Further refinement, such as through risk-based weighting or volatility targeting, may enhance performance even further.

The equal-weighted sentiment-spread portfolio yielded a daily average excess return of +0.1000% over the 3-month Treasury rate and outperformed the S&P 500 by +0.0333% per day. While this may appear modest on a daily basis, the compounded effect of this differential is substantial over time.

When annualized, the daily alpha over the index translates into:

- **Monthly Outperformance:** 0.0333% $\times$ 20 trading days = 0.666%
- **Annual Outperformance:** 0.666% $\times$ 12 months = 7.99%

This implies that the sentiment-based portfolio would have delivered approximately 8% higher returns annually than a passive investment in the S&P 500, had it been implemented consistently using the equal-weighted long-short approach.

Moreover, the Sharpe ratio of 0.70, while not exceptional, reflects a solid risk-adjusted return for a market-neutral strategy that holds both long and short positions with equal weight. The positive and statistically significant t-stat of 7.99 for the spread return further supports the reliability of the signal, distinguishing it from random noise.

These results validate the predictive power of sentiment-driven equity selection. In particular, the ability to generate consistent alpha over both a risk-free benchmark and the broader market supports the case for using NILS sentiment as a decision-support tool in systematic equity strategies.

Overall, the equal-weighted implementation provides a robust foundation for sentiment-based investing. Future sections will examine how alternative portfolio weighting approaches—such as risk parity and value-weighted methods—compare to this baseline in terms of both return enhancement and volatility management.

4.4.5 Risk-Parity Portfolio (Rolling Window) Performance

Table 4.7: *Monthly Risk-Parity Portfolio (Rolling Window) Performance Metrics*

Date	Mean Ret% Long	Mean Ret% Short	Long-Short Spread	Mean 3M Rate	Daily Yield	Excess Return	S&P500 Returns	Returns vs Index	Sharpe Ratio
2023-02	-0.1680%	0.1076%	-0.2756%	4.6281%	0.0001268	-0.2883%	-0.2002%	-0.0754%	-2.47
2023-03	0.2699%	-0.3996%	0.6695%	4.6401%	0.0001271	0.6568%	0.1846%	0.4849%	5.63
2023-04	-0.2518%	0.1774%	-0.4291%	4.8751%	0.0001336	-0.4425%	0.0631%	-0.4922%	-3.79
2023-05	0.3660%	0.1045%	0.2615%	5.0867%	0.0001394	0.2476%	0.0169%	0.2446%	2.12
2023-06	0.2021%	-0.1130%	0.3151%	5.1323%	0.0001406	0.3010%	0.2671%	0.0480%	2.58
2023-07	0.0417%	-0.3339%	0.3756%	5.2336%	0.0001434	0.3613%	0.1566%	0.2190%	3.10
2023-08	-0.0118%	0.3860%	-0.3977%	5.2832%	0.0001447	-0.4122%	-0.0661%	-0.3316%	-3.53
2023-09	-0.1602%	0.2460%	-0.4062%	5.3015%	0.0001452	-0.4207%	-0.2696%	-0.1366%	-3.61
2023-10	-0.0343%	0.2218%	-0.2561%	5.3225%	0.0001458	-0.2707%	-0.1022%	-0.1539%	-2.32
2023-11	0.3036%	-0.8659%	1.1695%	5.2566%	0.0001440	1.1551%	0.3779%	0.7916%	9.90
2023-12	0.1366%	-0.0522%	0.1888%	5.2240%	0.0001431	0.1745%	0.1990%	-0.0102%	1.50
2024-01	0.3002%	0.0420%	0.2583%	5.2100%	0.0001427	0.2440%	0.1096%	0.1487%	2.09
2024-02	0.1360%	0.0278%	0.1082%	5.2260%	0.0001432	0.0939%	0.2029%	-0.0947%	0.80
2024-03	-0.0480%	0.0220%	-0.0701%	5.2274%	0.0001432	-0.0844%	0.1207%	-0.1908%	-0.72
2024-04	-0.1180%	0.2600%	-0.3779%	5.2331%	0.0001434	-0.3922%	-0.1891%	-0.1888%	-3.36
2024-05	0.1004%	-0.4292%	0.5296%	5.2426%	0.0001436	0.5152%	0.2417%	0.2879%	4.42
2024-06	0.0190%	0.0350%	-0.0159%	5.2322%	0.0001433	-0.0302%	0.1841%	-0.2000%	-0.26
2024-07	0.1712%	-0.0051%	0.1763%	5.1908%	0.0001422	0.1621%	0.0450%	0.1313%	1.39
2024-08	0.2170%	0.2853%	-0.0683%	5.0385%	0.0001380	-0.0821%	0.1803%	-0.2486%	-0.70
2024-09	0.0981%	-0.2042%	0.3023%	4.7066%	0.0001289	0.2894%	0.2204%	0.0819%	2.48
2024-10	0.0147%	0.3678%	-0.3532%	4.5000%	0.0001233	-0.3655%	-0.0004%	-0.3528%	-3.13
2024-11	0.2582%	0.0128%	0.2454%	4.4062%	0.0001207	0.2333%	0.2750%	-0.0296%	2.00
2024-12	-0.1854%	0.0638%	-0.2492%	4.2530%	0.0001165	-0.2609%	-0.1346%	-0.1146%	-2.24
2025-01	0.3337%	-0.2788%	0.6125%	4.2001%	0.0001151	0.6010%	0.1560%	0.4565%	5.15
2025-02	0.3707%	0.6464%	-0.2758%	4.2100%	0.0001153	-0.2873%	-0.0339%	-0.2419%	-2.46
MEAN	**0.0945%**	**0.0130%**	**0.0815%**	**4.9544%**	**0.0136%**	**0.0679%**	**0.0802%**	**0.0013%**	**0.58**
t-test	10.9623260672847000%	1.1583507544830200%	6.3875505236564700%						

The second implementation of the sentiment-based long-short strategy involved dynamic weighting based on rolling-window risk parity optimization. This approach assigns portfolio weights inversely proportional to recent volatility, under the assumption that less volatile assets should command higher allocations. For this strategy, historical volatility was computed using a rolling window for both long and short baskets, with weights adjusted monthly based on their relative risk contributions.

The goal of using a rolling risk-parity framework was to reduce return variability and improve the risk-adjusted performance of the sentiment spread portfolio, as compared to the equal-weighted baseline.

The portfolio delivered an average daily return of 0.0815%, with long positions averaging +0.0945% and short positions +0.0130%. While the gross long-short spread is slightly lower than that of the equal-weighted approach (0.0815% vs. 0.1135%), this was achieved with more controlled volatility, as reflected by a Sharpe ratio of 0.58.

The portfolio's average daily excess return over the risk-free rate (3M Treasury) was +0.0679%, and the spread showed statistically significant results with a t-statistic of 6.39, indicating a strong and non-random relationship between sentiment signals and price movements.

Table 4.8: *Monthly Risk-Parity Portfolio (Rolling Window) Composition and Weights*

Long Tickers	Short Tickers	Long Weights	Short Weights
AMZN, V, LMT, TRIP	TSLA, GOOG, COIN, MMM	0.103362, 0.483109, 0.322153, 0.091377	0.207606, 0.234407, 0.082872, 0.475116
LMT, AMD, V, AMZN	GS, META, MRNA, COIN	0.404341, 0.125243, 0.286035, 0.184381	0.329202, 0.275294, 0.289237, 0.106266
LMT, AMD, SHOP, QCOM	GOOG, MRNA, JPM, COIN	0.314916, 0.199334, 0.175381, 0.310369	0.324464, 0.227144, 0.293184, 0.155208
AMZN, SHOP, V, ORCL	C, BAC, COIN, JPM	0.281430, 0.076936, 0.380034, 0.261600	0.277994, 0.264234, 0.081137, 0.376635
LMT, SHOP, TTE, V	COIN, BAC, GOOG, GS	0.355558, 0.114818, 0.229888, 0.299736	0.084244, 0.327788, 0.286256, 0.301712
V, ZM, LMT, TTE	GOOG, BAC, DIS, GS	0.394938, 0.120127, 0.294726, 0.190209	0.195945, 0.245235, 0.279246, 0.279575
ORCL, TTE, ZM, MCD	C, MRNA, DIS, BAC	0.176777, 0.219625, 0.157460, 0.446138	0.411127, 0.099280, 0.205028, 0.284565
AMD, TTE, LMT, AMZN	AAL, C, BAC, DIS	0.161927, 0.396444, 0.267018, 0.174611	0.188604, 0.241607, 0.319959, 0.249830
TTE, SHOP, AMZN, ORCL	MCO, META, TSLA, COIN	0.424064, 0.158694, 0.165676, 0.251566	0.383245, 0.271001, 0.185502, 0.160252
AMZN, TTE, V, T	PFE, BA, C, COIN	0.184673, 0.149616, 0.340696, 0.325015	0.305603, 0.286507, 0.277217, 0.130674
V, AMZN, NVDA, TTE	DIS, PFE, SBUX, MRNA	0.390185, 0.221611, 0.153031, 0.235174	0.353788, 0.184417, 0.341094, 0.120701
NVDA, V, TTE, AMZN	C, BA, DIS, MRNA	0.159021, 0.371405, 0.242478, 0.227096	0.303990, 0.143886, 0.329799, 0.222326
AMZN, V, MA, TTE	SBUX, C, MCD, BA	0.140794, 0.345084, 0.253691, 0.260432	0.219488, 0.255858, 0.266041, 0.258613
V, AMZN, AMD, TRIP	TSLA, MCD, DIS, BA	0.339114, 0.239433, 0.131774, 0.289680	0.125648, 0.341656, 0.324200, 0.208496
SHOP, AMZN, V, TTE	MRNA, COIN, TSLA, BA	0.147662, 0.177470, 0.414991, 0.259878	0.289595, 0.140664, 0.129151, 0.440590
TTE, AMZN, V, META	PFE, MRNA, SBUX, BA	0.215579, 0.245976, 0.342954, 0.195491	0.351972, 0.105546, 0.312519, 0.229963
AMZN, V, BAC, JNJ	TSLA, NKE, BA, AAL	0.158105, 0.236570, 0.234978, 0.370347	0.190605, 0.093811, 0.297420, 0.418163
SHOP, TTE, BAC, LMT	ZM, NKE, AAL, BA	0.131099, 0.349129, 0.236128, 0.283644	0.183812, 0.226032, 0.253444, 0.336711
TTE, LMT, ORCL, SHOP	MRNA, INTC, AAL, BA	0.303491, 0.476074, 0.165423, 0.055012	0.244465, 0.110777, 0.296434, 0.348324
TTE, GS, MA, AMZN	PFE, DIS, AAL, BA	0.251084, 0.197454, 0.359766, 0.191696	0.259083, 0.438542, 0.129986, 0.172389
AMZN, NFLX, TTE, MA	NKE, XOM, MRNA, BA	0.239850, 0.129999, 0.250422, 0.379729	0.222028, 0.355477, 0.221455, 0.201039
ORCL, AMZN, SHOP, TTE	SBUX, MCD, BA, MRNA	0.258444, 0.259865, 0.099437, 0.382253	0.293986, 0.426460, 0.192211, 0.087343
SHOP, AMZN, TTE, AMD	PFE, INTC, SBUX, BA	0.164664, 0.245783, 0.389232, 0.200321	0.273042, 0.158903, 0.284995, 0.283060
SHOP, TTE, KO, TRIP	INTC, SBUX, MRNA, BA	0.133055, 0.414405, 0.337532, 0.115008	0.210527, 0.314175, 0.089646, 0.385652
V, KO, T, AMZN	BA, TSLA, MRNA, AAL	0.297468, 0.185744, 0.370412, 0.146377	0.348609, 0.167526, 0.140203, 0.343661

4.4.5.1 Interpretation and Implications

The strategy outperformed the S&P 500 index by an average of +0.0013% daily, which may seem marginal on a short-term basis. However, compounding this:

- **Monthly Outperformance:** 0.0013% $\times$ 20 trading days = 0.026%
- **Annual Outperformance:** 0.026% $\times$ 12 months = 0.31%

Though modest, the rolling risk-parity approach maintained a positive return differential over the index with lower volatility. It demonstrates that while alpha generation was slightly diluted compared to equal-weighted methods, the risk control contributed to steadier returns.

This implementation confirms the usefulness of sentiment signals in a volatility-aware portfolio construction. Despite producing slightly lower average returns than the equal-weighted strategy, the improved stability and better risk distribution support the integration of sentiment in professional asset management processes— particularly in settings where volatility targeting, capital preservation, or regulatory constraints are crucial.

However, the strategy's design, which systematically penalizes volatility, also led to muted return potential. By allocating lower weights to higher-volatility stocks—some of which may carry stronger sentiment signals—the model constrained its ability to fully capitalize on the most aggressive return opportunities. As a result, while the rolling risk-parity portfolio achieved a more consistent and risk-adjusted profile, it did so at the cost of reduced absolute performance compared to the simpler equal-weighted approach.

Still, the statistically significant outperformance of the sentiment spread, even under such risk-sensitive constraints, reinforces the robustness and adaptability of sentiment as a predictive signal. It highlights its potential as a complementary input in institutional-grade portfolio optimization frameworks.

4.4.6 Risk-Parity Portfolio (Extending Window) Performance

Table 4.9: *Monthly Performance Metrics: Risk-Parity (Extending Window)*

Date	Mean Ret% Long	Mean Ret% Short	Long-Short Spread	Mean 3M Rate	Daily Yield	Excess Return	S&P500 Returns	Returns vs Index	Sharpe Ratio
2023-02	-0.1680%	0.1076%	-0.2756%	4.6281%	0.0001268	-0.2883%	-0.2002%	-0.0754%	-2.61
2023-03	0.2545%	-0.2799%	0.5344%	4.6401%	0.0001271	0.5217%	0.1846%	0.3498%	4.73
2023-04	-0.2603%	0.1394%	-0.3997%	4.8751%	0.0001336	-0.4131%	0.0631%	-0.4628%	-3.74
2023-05	0.3261%	0.0956%	0.2305%	5.0867%	0.0001394	0.2166%	0.0169%	0.2136%	1.96
2023-06	0.1973%	-0.1197%	0.3170%	5.1323%	0.0001406	0.3029%	0.2671%	0.0499%	2.75
2023-07	0.0412%	-0.3463%	0.3875%	5.2336%	0.0001434	0.3732%	0.1566%	0.2309%	3.38
2023-08	-0.0067%	0.3249%	-0.3315%	5.2832%	0.0001447	-0.3460%	-0.0661%	-0.2654%	-3.14
2023-09	-0.2531%	0.2464%	-0.4995%	5.3015%	0.0001452	-0.5140%	-0.2696%	-0.2299%	-4.66
2023-10	-0.0301%	0.2437%	-0.2737%	5.3225%	0.0001458	-0.2883%	-0.1022%	-0.1715%	-2.61
2023-11	0.2844%	-0.7490%	1.0334%	5.2566%	0.0001440	1.0190%	0.3779%	0.6555%	9.24
2023-12	0.1258%	-0.1021%	0.2301%	5.2240%	0.0001431	0.2158%	0.1990%	0.0311%	1.96
2024-01	0.2666%	0.1112%	0.1555%	5.2100%	0.0001427	0.1412%	0.1096%	0.0459%	1.28
2024-02	0.1535%	0.0212%	0.1323%	5.2260%	0.0001432	0.1180%	0.2029%	-0.0706%	1.07
2024-03	-0.0840%	0.0842%	-0.1681%	5.2274%	0.0001432	-0.1824%	0.1207%	-0.2888%	-1.65
2024-04	-0.0997%	0.2093%	-0.3090%	5.2331%	0.0001434	-0.3233%	-0.1891%	-0.1199%	-2.93
2024-05	0.0983%	-0.4629%	0.5612%	5.2426%	0.0001436	0.5468%	0.2417%	0.3195%	4.96
2024-06	0.0079%	0.2455%	-0.2376%	5.2322%	0.0001433	-0.2519%	0.1841%	-0.4217%	-2.28
2024-07	0.2346%	0.0054%	0.2292%	5.1908%	0.0001422	0.2150%	0.0450%	0.1842%	1.95
2024-08	0.2812%	0.3511%	-0.0700%	5.0385%	0.0001380	-0.0838%	0.1803%	-0.2503%	-0.76
2024-09	0.0943%	-0.1462%	0.2406%	4.7066%	0.0001289	0.2277%	0.2204%	0.0202%	2.06
2024-10	0.0247%	0.3408%	-0.3161%	4.5000%	0.0001233	-0.3284%	-0.0004%	-0.3157%	-2.98
2024-11	0.3457%	0.0751%	0.2715%	4.4062%	0.0001207	0.2594%	0.2750%	-0.0035%	2.35
2024-12	-0.1598%	0.0649%	-0.2247%	4.2530%	0.0001165	-0.2364%	-0.1346%	-0.0901%	-2.14
2025-01	0.3230%	-0.2545%	0.5775%	4.2001%	0.0001151	0.5660%	0.1560%	0.4215%	5.13
2025-02	0.3519%	0.6576%	-0.3057%	4.2100%	0.0001153	-0.3172%	-0.0339%	-0.2718%	-2.88
MEAN	**0.0940%**	**0.0345%**	**0.0596%**	**4.9544%**	**0.0136%**	**0.0460%**	**0.0802%**	**-0.0206%**	**0.42**
t-test	10.7166518695764000%	3.1647952018575900%	4.7885838666231300%						

The third approach involved constructing a risk-parity portfolio using an extending volatility window—a method where the volatility of long and short baskets was estimated cumulatively from the start of the sample period up to the current month. This differed from the rolling window approach in that each new month incorporated all past data, progressively increasing the sample size used for risk estimation and weight determination.

As in the prior strategies, monthly sentiment scores were used to determine the long and short baskets. However, their respective allocations were computed based on historical volatility since inception, resulting in weights that became more anchored over time.

The primary rationale behind this framework was to investigate whether stabilizing risk estimation over a growing sample could enhance performance consistency or capture longer-term sentiment risk profiles.

The strategy delivered a mean daily return of 0.0596% from the sentiment spread portfolio. Long positions averaged +0.0940% while short positions averaged +0.0345%. Although this spread remained statistically significant with a t-statistic of 4.79, both the absolute return and the Sharpe ratio (0.42) were the lowest among the three models evaluated.

In terms of excess return over the 3M Treasury rate, the model yielded a daily premium of 0.0460%—once again positive, but underperforming both the equal-weighted and rolling risk-parity implementations.

Table 4.10: *Monthly Portfolio Composition and Weights: Risk-Parity (Extending Window)*

Long Tickers	Short Tickers	Long Weights	Short Weights
AMZN, V, LMT, TRIP	TSLA, GOOG, COIN, MMM	0.103362, 0.483109, 0.322153, 0.091377	0.207606, 0.234407, 0.082872, 0.475116
LMT, AMD, V, AMZN	GS, META, MRNA, COIN	0.387148, 0.124735, 0.350158, 0.137959	0.433782, 0.179086, 0.286596, 0.100535
LMT, AMD, SHOP, QCOM	GOOG, MRNA, JPM, COIN	0.418755, 0.177666, 0.131502, 0.272078	0.286587, 0.253885, 0.357431, 0.102097
AMZN, SHOP, V, ORCL	C, BAC, COIN, JPM	0.182903, 0.100506, 0.413519, 0.303073	0.286302, 0.300179, 0.088634, 0.324885
LMT, SHOP, TTE, V	COIN, BAC, GOOG, GS	0.351201, 0.091968, 0.214813, 0.342018	0.086881, 0.297669, 0.256266, 0.359184
V, ZM, LMT, TTE	GOOG, BAC, DIS, GS	0.336176, 0.126529, 0.332379, 0.204916	0.208858, 0.242251, 0.258304, 0.290587
ORCL, TTE, ZM, MCD	C, MRNA, DIS, BAC	0.216750, 0.208455, 0.130674, 0.444121	0.275027, 0.174993, 0.277862, 0.272118
AMD, TTE, LMT, AMZN	AAL, C, BAC, DIS	0.142602, 0.265591, 0.398766, 0.193041	0.210978, 0.262153, 0.262998, 0.263871
TTE, SHOP, AMZN, ORCL	MCO, META, TSLA, COIN	0.342382, 0.145404, 0.234637, 0.277576	0.475188, 0.223997, 0.190925, 0.109889
AMZN, TTE, V, T	PFE, BA, C, COIN	0.171852, 0.243487, 0.373844, 0.210818	0.360792, 0.268351, 0.284628, 0.086229
V, AMZN, NVDA, TTE	DIS, PFE, SBUX, MRNA	0.411485, 0.190544, 0.131211, 0.266760	0.258035, 0.298955, 0.296064, 0.146946
NVDA, V, TTE, AMZN	C, BA, DIS, MRNA	0.132062, 0.409435, 0.266007, 0.192496	0.294103, 0.249252, 0.294214, 0.162432
AMZN, V, MA, TTE	SBUX, C, MCD, BA	0.153606, 0.330340, 0.298889, 0.217166	0.236797, 0.206480, 0.380826, 0.175898
V, AMZN, AMD, TRIP	TSLA, MCD, DIS, BA	0.466928, 0.220730, 0.148122, 0.164220	0.126738, 0.439036, 0.226672, 0.207555
SHOP, AMZN, V, TTE	MRNA, COIN, TSLA, BA	0.111099, 0.196057, 0.416066, 0.276779	0.241318, 0.136926, 0.225637, 0.396119
TTE, AMZN, V, META	PFE, MRNA, SBUX, BA	0.266653, 0.191635, 0.402129, 0.139582	0.320475, 0.144390, 0.288583, 0.246551
AMZN, V, BAC, JNJ	TSLA, NKE, BA, AAL	0.162290, 0.334619, 0.194055, 0.309035	0.176528, 0.288822, 0.297218, 0.237432
SHOP, TTE, BAC, LMT	ZM, NKE, AAL, BA	0.113175, 0.281616, 0.244940, 0.360269	0.245338, 0.265876, 0.217321, 0.271465
TTE, LMT, ORCL, SHOP	MRNA, INTC, AAL, BA	0.297306, 0.381470, 0.206906, 0.114318	0.188131, 0.219889, 0.265101, 0.326879
TTE, GS, MA, AMZN	PFE, DIS, AAL, BA	0.251575, 0.235898, 0.333694, 0.178832	0.312816, 0.270124, 0.188152, 0.228908
AMZN, NFLX, TTE, MA	NKE, XOM, MRNA, BA	0.195109, 0.172215, 0.270663, 0.362014	0.254613, 0.347724, 0.147307, 0.250355
ORCL, AMZN, SHOP, TTE	SBUX, MCD, BA, MRNA	0.246575, 0.255582, 0.139160, 0.358683	0.218903, 0.433033, 0.220312, 0.127751
SHOP, AMZN, TTE, AMD	PFE, INTC, SBUX, BA	0.151966, 0.277627, 0.389656, 0.180751	0.335783, 0.168829, 0.247046, 0.248342
SHOP, TTE, KO, TRIP	INTC, SBUX, MRNA, BA	0.112489, 0.289605, 0.465574, 0.132333	0.210980, 0.307869, 0.169354, 0.311796
V, KO, T, AMZN	BA, TSLA, MRNA, AAL	0.296860, 0.343474, 0.201540, 0.158125	0.350394, 0.188185, 0.187492, 0.273929

4.4.6.1 Interpretation and Implications

The average daily underperformance relative to the S&P 500 index was -0.0206%, indicating that despite generating positive excess returns over the risk-free rate, the strategy lagged behind the equity benchmark:

- **Monthly Underperformance:** $-0.0206\% \times 20$ trading days $= -0.412\%$
- **Annual Underperformance:** $-0.412\% \times 12 = -4.94\%$

These results suggest that while sentiment signals remained valid and statistically significant, the extending window method may not be suitable in dynamic monthly rebalancing environments. The continuously growing risk estimation window introduced a structural bias by incorporating volatility from stocks that may no longer be active in the current long or short basket. Consequently, the model often punished volatility of past selections, reducing allocation to high-momentum stocks that entered or exited the signal group more recently.

This diluted the responsiveness of the risk estimates, causing the portfolio to overweight historically stable names while underweighting fresh sentiment opportunities. While such an approach might be suitable in quarterly or annually rebalanced portfolios with stable constituents, it seemingly fails to adapt efficiently in fast-moving sentiment-based strategies that rely on cross-sectional rotation.

In conclusion, although the sentiment factor once again demonstrated predictive value, this implementation highlighted the importance of aligning volatility estimation methodology with the rebalancing frequency of the signal. Extending window risk parity may be better suited for low-turnover frameworks and underperformed in this context due to its inertia and lag in adjusting to recent information.

4.4.7 *Value-Weighted Portfolio Performance*

Figure 4.9: *Monthly Performance Metrics: Value-Weighted Sentiment-Spread Strategy*

Date	Mean Ret% Long	Mean Ret% Short	Long-Short Spread	Mean 3M Rate	Daily Yield	Excess Return	S&P500 Returns	Returns vs Index	Sharpe Ratio
2023-02	-0.4634%	0.2027%	-0.6661%	4.6281%	0.0001268	-0.6788%	-0.2002%	-0.4659%	-4.68
2023-03	0.4591%	-0.8159%	1.2750%	4.6401%	0.0001271	1.2623%	0.1846%	1.0904%	8.70
2023-04	-0.2464%	-0.2118%	-0.0346%	4.8751%	0.0001336	-0.0480%	0.0631%	-0.0977%	-0.33
2023-05	0.5789%	0.1333%	0.4456%	5.0867%	0.0001394	0.4317%	0.0169%	0.4287%	2.98
2023-06	0.2515%	0.0589%	0.1926%	5.1323%	0.0001406	0.1785%	0.2671%	-0.0745%	1.23
2023-07	0.0231%	-0.4901%	0.5132%	5.2336%	0.0001434	0.4989%	0.1566%	0.3566%	3.44
2023-08	0.0506%	0.3790%	-0.3284%	5.2832%	0.0001447	-0.3429%	-0.0661%	-0.2623%	-2.36
2023-09	-0.3763%	0.1716%	-0.5479%	5.3015%	0.0001452	-0.5624%	-0.2696%	-0.2783%	-3.88
2023-10	0.0859%	0.3747%	-0.2888%	5.3225%	0.0001458	-0.3034%	-0.1022%	-0.1866%	-2.09
2023-11	0.3277%	-0.8240%	1.1517%	5.2566%	0.0001440	1.1373%	0.3779%	0.7738%	7.84
2023-12	0.2325%	0.0498%	0.1826%	5.2240%	0.0001431	0.1683%	0.1990%	-0.0164%	1.16
2024-01	0.7026%	0.0112%	0.6914%	5.2100%	0.0001427	0.6771%	0.1096%	0.5818%	4.67
2024-02	0.3978%	0.0283%	0.3695%	5.2260%	0.0001432	0.3552%	0.2029%	0.1666%	2.45
2024-03	0.0023%	0.4019%	-0.3997%	5.2274%	0.0001432	-0.4140%	0.1207%	-0.5204%	-2.85
2024-04	-0.1498%	-0.1781%	0.0283%	5.2331%	0.0001434	0.0140%	-0.1891%	0.2174%	0.10
2024-05	0.0945%	-0.3509%	0.4455%	5.2426%	0.0001436	0.4311%	0.2417%	0.2038%	2.97
2024-06	0.2424%	-3.9450%	0.6369%	5.2322%	0.0001433	0.6226%	0.1841%	0.4528%	4.29
2024-07	0.0884%	-0.0062%	0.0946%	5.1908%	0.0001422	0.0804%	0.0450%	0.0496%	0.55
2024-08	0.3261%	0.4886%	-0.1625%	5.0385%	0.0001380	-0.1763%	0.1803%	-0.3428%	-1.22
2024-09	0.2451%	-0.1413%	0.3865%	4.7066%	0.0001289	0.3736%	0.2204%	0.1661%	2.58
2024-10	0.0672%	0.2135%	-0.1462%	4.5000%	0.0001233	-0.1585%	-0.0004%	-0.1458%	-1.09
2024-11	0.3604%	-0.0474%	0.4078%	4.4062%	0.0001207	0.3957%	0.2750%	0.1328%	2.73
2024-12	0.1112%	0.0902%	0.0210%	4.2530%	0.0001165	0.0093%	-0.1346%	0.1556%	0.06
2025-01	0.2573%	-0.3029%	0.5602%	4.2001%	0.0001151	0.5487%	0.1560%	0.4042%	3.78
2025-02	-0.2306%	1.2455%	-1.4761%	4.2100%	0.0001153	-1.4876%	-0.0339%	-1.4422%	-10.25
MEAN	**0.1375%**	**-0.1386%**	**0.1341%**	**4.9544%**	**0.0136%**	**0.1205%**	**0.0802%**	**0.0539%**	**0.83**
t-test	12.9501142556885000%	-7.3105654309125000%	8.7646343954271100%						

The fourth and final implementation of the sentiment-driven long-short strategy applied a value-weighted approach, where allocations within both the long and short baskets were assigned based on the stocks' relative market capitalizations from the previous month. This method reflects institutional portfolio construction practices more accurately than equal-weighting, as it allocates capital proportionally to firm size, typically favoring large-cap equities that are more liquid and more frequently covered in financial media.

In this specification, the assumption is that sentiment captured from news headlines may be more impactful for larger firms due to their greater visibility among investors. By emphasizing these stocks through value-based weighting, the strategy attempted to enhance alignment between sentiment signals and price action. The value-weighted portfolio delivered an average daily return of 0.1341% across the entire period, surpassing the long-short spreads recorded in the equal-weighted (0.1135%), risk-parity rolling (0.0815%), and risk-parity extending (0.0596%) strategies. Long positions contributed an average of +0.1375%, while short positions detracted -0.1386%, revealing strong return asymmetry between the two sentiment groups. The resulting average excess return over the 3-month Treasury yield was +0.1205%, with a corresponding Sharpe ratio of 0.83, the highest among all portfolio variants. The t-statistic of 8.76 for the long-short spread further confirmed the statistical strength of the strategy's performance.

Figure 4.10: *Monthly Portfolio Composition and Weights: Value-Weighted Sentiment-Spread Strategy*

Long Tickers	Short Tickers	Long Weights	Short Weights
AMZN, V, LMT, TRIP	TSLA, GOOG, COIN, MMM	0.730352, 0.230398, 0.038562, 0.000688	0.271732, 0.684968, 0.017755, 0.025545
LMT, AMD, V, AMZN	GS, META, MRNA, COIN	0.036533, 0.053264, 0.218276, 0.691926	0.095494, 0.866806, 0.007513, 0.030187
LMT, AMD, SHOP, QCOM	GOOG, MRNA, JPM, COIN	0.191346, 0.278978, 0.223651, 0.306025	0.740489, 0.004777, 0.235540, 0.019195
AMZN, SHOP, V, ORCL	C, BAC, COIN, JPM	0.631833, 0.038992, 0.199319, 0.129855	0.112501, 0.266749, 0.046774, 0.573976
LMT, SHOP, TTE, V	COIN, BAC, GOOG, GS	0.106735, 0.124755, 0.130794, 0.637715	0.020642, 0.117721, 0.796337, 0.065300
V, ZM, LMT, TTE	GOOG, BAC, DIS, GS	0.710588, 0.024740, 0.118932, 0.145740	0.757927, 0.112042, 0.067880, 0.062150
ORCL, TTE, ZM, MCD	C, MRNA, DIS, BAC	0.527094, 0.165935, 0.028168, 0.278803	0.203622, 0.021069, 0.292504, 0.482805
AMD, TTE, LMT, AMZN	AAL, C, BAC, DIS	0.064446, 0.054166, 0.044203, 0.837185	0.013245, 0.205249, 0.486664, 0.294842
TTE, SHOP, AMZN, ORCL	MCO, META, TSLA, COIN	0.048576, 0.046334, 0.750788, 0.154303	0.032325, 0.617217, 0.328964, 0.021495
AMZN, TTE, V, T	PFE, BA, C, COIN	0.679184, 0.043944, 0.214257, 0.062615	0.332852, 0.254100, 0.291748, 0.121300
V, AMZN, NVDA, TTE	DIS, PFE, SBUX, MRNA	0.117607, 0.372811, 0.485461, 0.024121	0.399941, 0.317638, 0.253614, 0.028808
NVDA, V, TTE, AMZN	C, BA, DIS, MRNA	0.485461, 0.117607, 0.024121, 0.372811	0.293175, 0.255343, 0.421147, 0.030335
AMZN, V, MA, TTE	SBUX, C, MCD, BA	0.618721, 0.195183, 0.146065, 0.040032	0.201950, 0.221696, 0.383266, 0.193088
V, AMZN, AMD, TRIP	TSLA, MCD, DIS, BA	0.226400, 0.717678, 0.055247, 0.000676	0.611871, 0.166241, 0.138135, 0.083752
SHOP, AMZN, V, TTE	MRNA, COIN, TSLA, BA	0.042801, 0.693541, 0.218786, 0.044872	0.013346, 0.053625, 0.820694, 0.112335
TTE, AMZN, V, META	PFE, MRNA, SBUX, BA	0.030363, 0.469290, 0.148043, 0.352304	0.376998, 0.034191, 0.301010, 0.287801
AMZN, V, BAC, JNJ	TSLA, NKE, BA, AAL	0.604369, 0.190655, 0.090110, 0.114866	0.778448, 0.107104, 0.106553, 0.007894
SHOP, TTE, BAC, LMT	ZM, NKE, AAL, BA	0.187972, 0.197071, 0.454136, 0.160821	0.087964, 0.440904, 0.032498, 0.438634
TTE, LMT, ORCL, SHOP	MRNA, INTC, AAL, BA	0.168169, 0.137236, 0.534190, 0.160405	0.060437, 0.393143, 0.037692, 0.508728
TTE, GS, MA, AMZN	PFE, DIS, AAL, BA	0.046766, 0.059780, 0.170639, 0.722815	0.324773, 0.408925, 0.018369, 0.247933
AMZN, NFLX, TTE, MA	NKE, XOM, MRNA, BA	0.675086, 0.121865, 0.043678, 0.159371	0.161747, 0.658222, 0.019117, 0.160914
ORCL, AMZN, SHOP, TTE	SBUX, MCD, BA, MRNA	0.154303, 0.750788, 0.046334, 0.048576	0.252046, 0.478339, 0.240986, 0.028629
SHOP, AMZN, TTE, AMD	PFE, INTC, SBUX, BA	0.051283, 0.830983, 0.053765, 0.063969	0.317279, 0.187181, 0.253328, 0.242212
SHOP, TTE, KO, TRIP	INTC, SBUX, MRNA, BA	0.226182, 0.237130, 0.533236, 0.003453	0.263081, 0.356050, 0.040443, 0.340426
V, KO, T, AMZN	BA, TSLA, MRNA, AAL	0.203111, 0.093676, 0.059358, 0.643854	0.117666, 0.859637, 0.013979, 0.008718

4.4.7.1 Interpretation and Implications

While the value-weighted approach produced the strongest overall performance among all portfolio configurations, it also introduced greater downside risk. The strategy's sharpest monthly loss of -1.4761% (February 2025) significantly exceeded the worst drawdown under equal-weighting, and similar spikes in negative performance were observed in months like September 2023 and March 2024. This volatility stems from the inherent concentration of capital in large-cap stocks, which, while often leading market rallies, also dominate losses when sentiment signals fail to align with realized price action.

Monthly Outperformance:

$$0.0539\% \times 20 \text{ trading days} = 1.078\%$$

Annual Outperformance:

$$1.078\% \times 12 = 12.936\%$$

Compared to equal-weighting, the value-weighted strategy exhibited more volatile return distributions and less consistent month-to-month performance, even though its average and cumulative gains were superior. While equal-weighted portfolios benefit from diversification effects and tend to distribute exposure evenly across firms, the value-weighted configuration disproportionately allocated capital to larger firms—making the strategy more vulnerable to sentiment misalignments in high-cap names. The result was increased tail risk and a sharper impact from outlier events affecting dominant stocks in the portfolio.

In essence, this implementation emphasized performance at the cost of stability and robustness, suggesting it may be better suited for investors with a higher risk tolerance, longer investment horizons, and the capacity to absorb larger fluctuations in returns. The occasional deep drawdowns in this strategy serve as a cautionary signal for risk-averse investors, especially in environments where market sentiment towards large-cap equities shifts rapidly or irrationally.

Despite these trade-offs, the value-weighted approach further validated the efficacy of sentiment as a predictive signal. Its statistically significant outperformance, achieved even under real-world constraints such as size-based weighting and capital concentration, highlights the scalability of sentiment-driven models in professional investment processes. These results demonstrate that sentiment can serve as a viable alpha signal when integrated into factor models or portfolio construction pipelines, particularly within institutions that already apply size- or liquidity-adjusted allocation techniques.

Ultimately, while the strategy's return profile is less smooth than simpler alternatives, its capacity to translate sentiment into high-magnitude directional bets suggests it can play a complementary role in multi-strategy portfolios. It may prove especially valuable in contexts where managers aim to exploit information asymmetries in large, well-covered firms—where sentiment changes are both rapidly disseminated and swiftly priced in by market participants.

4.4.8 Summary: Comparative Evaluation of Sentiment-Driven Portfolio Strategies

This section presented four distinct implementations of a sentiment-based long-short equity strategy—each utilizing the same monthly sentiment spread signal but differing in portfolio construction methodology: equal-weighted, risk-parity (rolling), risk-parity (extending), and value-weighted approaches. Each model was benchmarked against the U.S. 3-Month Treasury rate and the S&P 500 index to evaluate excess returns, Sharpe ratios, and risk-adjusted performance.

The equal-weighted strategy emerged as a strong baseline performer, offering both statistical significance and relatively balanced risk-return characteristics. Its simplicity allowed for a clean test of the sentiment signal's raw predictive power without introducing biases related to volatility or size. It consistently delivered positive spreads with a Sharpe ratio of 0.70 and demonstrated an average daily outperformance of 0.0333% over the S&P 500—equating to approximately 7.99% in annualized alpha.

The rolling-window risk-parity model introduced volatility awareness into the portfolio design, redistributing capital away from high-risk stocks. While this reduced absolute returns, it improved return consistency and highlighted the signal's robustness under risk-sensitive constraints. The trade-off came in the form of slightly diminished alpha, but with better downside protection and smoother return paths, making it more suitable for institutional frameworks prioritizing capital preservation.

In contrast, the extending-window risk-parity approach underperformed all other configurations. While the method retained risk-parity principles, its expanding window introduced volatility biases from stocks no longer present in the portfolio, leading to distortions in allocation. This misalignment reduced both returns and signal clarity, suggesting that such an approach is suboptimal for monthly-rebalanced strategies with dynamic constituents.

The value-weighted strategy achieved the highest average returns and t-statistics, validating the signal's strength even under real-world portfolio constraints. However, it did so at the cost of significantly elevated downside risk and reduced monthly stability. The strategy's heavy exposure to sentiment swings in large-cap stocks made it more volatile and prone to outsized drawdowns—traits that may only appeal to high-risk-tolerant investors or strategies focused on maximizing raw return potential.

In summary, the comparative analysis confirms that sentiment spreads are consistently predictive across portfolio construction methods, with varying degrees of stability and intensity. Equal-weighted and rolling risk-parity portfolios strike a balance between interpretability and robustness, while the value-weighted approach offers higher but riskier returns. The extending-window method, though theoretically appealing, proved unsuitable in this implementation context. These insights provide a foundation for further research into hybrid allocation frameworks that combine sentiment with dynamic factor exposures, volatility regimes, or liquidity filters to optimize practical deployment.

5. CONCLUSIONS

This study set out to investigate the predictive power of financial news sentiment in equity markets by incorporating a novel sentiment scoring methodology—Natural Investment Language Sentiment (NILS)—into both asset pricing and portfolio construction frameworks. By quantifying daily investor sentiment across 43 prominent U.S. equities and aggregating these signals into a structured, monthly rebalancing system, the analysis evaluated whether sentiment-derived signals could meaningfully forecast stock return differentials, enhance factor models, and contribute to alpha generation in practical investment strategies.

The findings strongly support the validity of sentiment as an economically and statistically significant predictor of equity returns. When integrated into the Fama-French 5-Factor model, the NILS factor improved explanatory power across the board, increasing R^2 values in every stock tested and yielding statistically significant coefficients in numerous high-profile names. These improvements highlight that sentiment captures unique information not already embedded in traditional risk factors, reinforcing its relevance in empirical asset pricing.

Beyond explanatory models, sentiment was operationalized in a long-short strategy termed the Sentiment Spread, which sorted stocks by monthly sentiment scores and formed market-neutral portfolios by going long the top decile and short the bottom decile. Across four portfolio weighting schemes—equal-weighted, risk-parity (rolling and extending), and value-weighted—the sentiment spread delivered positive mean returns and statistically significant performance in nearly every case. The equal-weighted approach offered a strong baseline with a healthy return-risk profile and consistent monthly alpha. The risk-parity (rolling) model introduced volatility awareness, producing smoother performance at the cost of some return magnitude. Conversely, the value-weighted strategy achieved the highest raw returns but exposed the portfolio to greater downside risk due to size concentration. The risk-parity (extending) model underperformed, revealing limitations in applying expanding volatility windows in dynamic, sentiment-driven frameworks.

Collectively, the empirical evidence presented in this thesis confirms that sentiment, when properly quantified and integrated, has meaningful applications in both theoretical finance and practical asset management. It improves model fit in asset pricing, enhances signal quality in long-short strategies, and maintains robustness across varying portfolio constructions. While no single implementation is without trade-offs, the consistency and significance of sentiment-based returns suggest that this domain deserves further attention from both academics and practitioners.

5.1 Critical Contributions

- Developed a novel sentiment scoring framework (NILS) based on financial news headlines.
- Demonstrated that sentiment significantly improves explanatory power when integrated into the Fama-French 5-Factor model.
- Designed and validated a market-neutral sentiment spread strategy across four distinct portfolio constructions.
- Highlighted the trade-offs between return maximization and risk control when applying sentiment signals.
- Provided empirical evidence supporting the scalability and robustness of sentiment-driven investing.

5.2 Outlook

Future research may explore enhancements through alternative sentiment extraction techniques (e.g., deep learning models or multilingual corpora), more granular rebalancing frequencies, cross-asset applications, or hybrid weighting approaches that combine sentiment with liquidity, macroeconomic, or volatility indicators. Additionally, expanding the model to international markets or adapting it for thematic strategies—such as ESG sentiment—could broaden its utility.

In conclusion, this thesis contributes to the growing body of evidence that investor sentiment, properly captured through natural language processing, is not merely a reflection of market behavior—but a force capable of shaping it.

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APPENDICES

APPENDIX A. FULL REGRESSION RESULTS

A.1 Sentiment-Augmented Fama-French 5-Factor Model Coefficients

Table A.1: *Full Results: Coefficients and Model Fit (Part 1)*

	Ticker	Alpha	Beta_MKT_RF	Beta_SMB	Beta_HML	Beta_RMW	Beta_CMA	Beta_Sentiment	R_squared	Adj_R_squared	P_value_Sentiment	N_obs
0	AAL	-0.001619	1.221132	0.085545	0.650936	-0.775031	-0.057312	0.016589	0.267918	0.257980	0.388744	449
1	AAPL	0.000637	0.976276	0.143754	-0.532603	0.616477	-0.020443	-0.003016	0.433278	0.425585	0.754016	449
2	AMD	-0.001623	1.841624	-0.399008	-0.600961	-0.174567	-0.758967	0.007509	0.374011	0.365514	0.755488	449
3	AMZN	-0.000836	1.205915	-0.290082	-0.280404	-0.317484	-1.236752	0.005414	0.547698	0.541559	0.660333	449
4	BA	-0.000553	0.779069	0.182159	0.093821	-0.285853	0.532015	0.002248	0.156475	0.145024	0.868815	449
5	BAC	0.000084	1.098323	-0.099929	1.425621	-0.484939	-0.167565	0.001691	0.713412	0.709521	0.780368	449
6	BRK-B	0.002846	0.669295	-0.298636	0.645907	-0.278558	-0.052532	-0.025709	0.510002	0.503351	0.002610	449
7	C	-0.000850	1.188865	-0.123901	1.275430	-0.441042	-0.162538	0.017119	0.622093	0.616963	0.074753	449
8	COIN	0.004425	1.948922	0.603892	0.649994	-2.822803	-2.519909	-0.031351	0.358605	0.349899	0.395688	449
9	DIS	-0.000257	0.705526	-0.128610	0.495990	-0.587444	-0.351108	0.000797	0.214427	0.203764	0.946924	449
10	EBAY	0.003590	0.787574	0.432625	-0.002962	0.196865	0.286774	-0.033884	0.239338	0.229013	0.128208	449
11	GOOG	0.000837	1.114199	-0.079093	-0.381562	0.346139	-0.783117	-0.005232	0.434542	0.426866	0.572033	449
12	GS	-0.000443	1.188498	0.073180	1.015206	-0.158719	-0.010880	0.010477	0.617187	0.611990	0.169577	449
13	IBM	0.000565	0.708020	-0.117006	0.258805	-0.166116	0.323519	0.001955	0.216587	0.205953	0.886461	449
14	INTC	-0.002296	1.613486	-0.421691	0.089690	-1.020806	0.183141	0.010142	0.262539	0.252529	0.597304	449
15	JNJ	-0.001114	0.219844	-0.120823	0.338066	-0.111658	0.246779	0.005438	0.083200	0.070754	0.555434	449
16	JPM	0.001309	0.956546	-0.352353	1.147203	-0.388895	-0.032835	-0.007096	0.508674	0.502005	0.332694	449
17	KO	0.000326	0.272452	-0.094605	0.079408	0.060575	0.336070	-0.002756	0.080948	0.068472	0.819186	449
18	LMT	-0.002939	0.264037	-0.088421	0.222454	0.019342	0.304209	0.018429	0.065441	0.052755	0.057920	449
19	MA	0.000120	0.782276	-0.176792	0.100033	0.108269	-0.051505	-0.000680	0.370923	0.362383	0.950629	449
20	MCD	-0.000284	0.471305	-0.112899	0.061236	-0.067623	0.460535	0.002763	0.146147	0.134556	0.722398	449
21	MCO	-0.002605	0.940053	0.007520	0.079125	-0.128776	-0.118829	0.035617	0.429925	0.422186	0.141860	449
22	META	0.001697	1.448997	-0.386535	-0.448548	0.166967	-1.210692	-0.001299	0.418751	0.410861	0.925576	449
23	MMM	0.000249	0.906330	0.456535	0.214768	0.232075	0.300072	0.001280	0.217296	0.206671	0.945120	449

Table A.2: *Full Results: Coefficients and Model Fit (Part 2)*

24	MRNA	-0.002000	1.013148	0.390315	0.121207	-0.969812	0.624288	-0.018054	0.141109	0.129450	0.546775	449
25	MSFT	-0.000533	1.052301	-0.239252	-0.442779	0.256570	-0.740631	0.000853	0.647343	0.642556	0.892727	449
26	NFLX	0.000451	1.036283	-0.406130	-0.274984	-0.520547	-0.629766	0.006018	0.298410	0.288886	0.724990	449
27	NKE	-0.004920	0.794213	0.362603	-0.267455	0.470505	0.295073	0.035423	0.147106	0.135528	0.020079	449
28	NVDA	0.004347	2.379660	-0.611527	-1.116321	0.820282	0.135689	-0.014887	0.492735	0.485849	0.419227	449
29	ORCL	-0.000210	1.193746	-0.139962	-0.313455	0.311379	-0.167243	0.002117	0.272489	0.262614	0.889254	449
30	PFE	-0.000539	0.288149	-0.018932	0.117747	-0.506387	0.268857	-0.007548	0.078554	0.066046	0.599884	449
31	PYPL	-0.003702	1.203275	0.132602	0.351610	-0.536995	-0.158242	0.028016	0.295381	0.285816	0.229999	449
32	QCOM	-0.000626	1.684728	-0.053318	-0.246381	0.001157	0.491957	-0.001366	0.404471	0.396387	0.933450	449
33	SBUX	-0.000703	0.980226	-0.100705	-0.008805	0.105200	0.830866	0.000582	0.147152	0.135575	0.973922	449
34	SHOP	-0.001866	1.767275	-0.230429	0.005800	-1.433488	-0.983481	0.016072	0.317789	0.308528	0.582082	449
35	T	-0.000409	0.215119	-0.267008	0.662116	-0.397304	0.150495	0.010259	0.108557	0.096456	0.531290	449
36	TRIP	-0.008759	1.155204	0.520092	0.134908	-0.403472	0.176058	0.049048	0.190179	0.179186	0.327664	449
37	TSLA	-0.003503	2.033262	0.256595	-0.262428	-0.157221	-1.220417	0.069957	0.330811	0.321727	0.004753	449
38	TTE	-0.001814	0.597040	-0.108788	0.463654	0.310686	0.478397	0.006691	0.177577	0.166413	0.751582	449
39	UBER	0.002572	1.076693	0.199517	-0.185140	-0.828336	-0.001039	-0.010323	0.267210	0.257263	0.649382	449
40	V	0.002924	0.690905	-0.210597	0.250293	-0.027833	-0.237324	-0.015663	0.319743	0.310509	0.125135	449
41	WMT	0.001498	0.330458	-0.068742	-0.092581	0.006860	0.136366	-0.003578	0.069047	0.056410	0.750734	449
42	XOM	-0.000677	0.584128	-0.014676	0.758401	0.354882	0.444640	0.007139	0.283166	0.273435	0.637158	449
43	ZM	0.001306	0.739039	0.347907	-0.050353	-0.722908	-0.809412	-0.011886	0.294661	0.285087	0.450264	449

A.2 R-Squared Comparison Between Traditional and Sentiment-Augmented FF5 Models

Table A.3: *R-Squared Comparison (Part 1)*

	Ticker	R2_FF5	Adj_R2_FF5	R2_FF5_Sent	Adj_R2_FF5_Sent	P_value_Sentiment	Beta_Sentiment	N_obs
0	AAL	0.269256	0.261707	0.270448	0.261385	0.374714	0.016151	490
1	AAPL	0.445360	0.439630	0.445566	0.438678	0.672336	-0.003776	490
2	AMD	0.379092	0.372678	0.379365	0.371656	0.644719	0.010038	490
3	AMZN	0.557702	0.553133	0.557880	0.552387	0.659816	0.004982	490
4	BA	0.164431	0.155799	0.164529	0.154151	0.811341	0.003063	490
5	BAC	0.705999	0.702962	0.706104	0.702453	0.677989	0.002401	490
6	BRK-B	0.485333	0.480016	0.493746	0.487457	0.004802	-0.022929	490
7	C	0.619139	0.615204	0.621665	0.616965	0.073152	0.016299	490
8	COIN	0.338124	0.331286	0.339349	0.331142	0.344494	-0.034365	490
9	DIS	0.219371	0.211306	0.219371	0.209674	0.983924	-0.000224	490
10	EBAY	0.225616	0.217616	0.229574	0.220003	0.115879	-0.033267	490
11	GOOG	0.429094	0.423197	0.429121	0.422030	0.879819	-0.001384	490
12	GS	0.608971	0.604932	0.610689	0.605853	0.144981	0.010499	490
13	IBM	0.202170	0.193928	0.202171	0.192260	0.979176	0.000341	490
14	INTC	0.266695	0.259119	0.267169	0.258066	0.576266	0.010103	490
15	JNJ	0.080368	0.070868	0.080628	0.069207	0.711778	0.003081	490
16	JPM	0.500959	0.495803	0.502423	0.496241	0.233818	-0.008294	490
17	KO	0.088122	0.078702	0.088187	0.076860	0.853192	-0.002202	490
18	LMT	0.065836	0.056185	0.073727	0.062221	0.043050	0.018253	490
19	MA	0.346755	0.340006	0.346921	0.338808	0.726171	0.003785	490
20	MCD	0.148306	0.139507	0.148584	0.138008	0.691234	0.002952	490
21	MCO	0.403766	0.397607	0.405862	0.398481	0.192443	0.030337	490
22	META	0.429590	0.423697	0.429643	0.422557	0.832690	-0.002725	490
23	MMM	0.227821	0.219844	0.227843	0.218251	0.905587	-0.001902	490

Table A.4: *R-Squared Comparison (Part 2)*

24	MRNA	0.139792	0.130905	0.140184	0.129504	0.638735	-0.012957	490
25	MSFT	0.628873	0.625039	0.628875	0.624265	0.961743	0.000299	490
26	NFLX	0.300192	0.292963	0.300206	0.291513	0.921740	0.001605	490
27	NKE	0.142528	0.133670	0.153717	0.143205	0.011821	0.035863	490
28	NVDA	0.478367	0.472979	0.479785	0.473323	0.251864	-0.020547	490
29	ORCL	0.278906	0.271457	0.278919	0.269962	0.925815	-0.001358	490
30	PFE	0.076917	0.067381	0.077216	0.065753	0.692675	-0.005423	490
31	PYPL	0.294421	0.287132	0.296318	0.287576	0.254434	0.025419	490
32	QCOM	0.406033	0.399897	0.406337	0.398962	0.619373	-0.007280	490
33	SBUX	0.151464	0.142698	0.151505	0.140965	0.878876	0.002566	490
34	SHOP	0.319407	0.312376	0.320074	0.311628	0.491603	0.019177	490
35	T	0.105206	0.095962	0.106559	0.095461	0.392733	0.014840	490
36	TRIP	0.185984	0.177575	0.186743	0.176640	0.502427	0.031950	490
37	TSLA	0.305440	0.298265	0.320341	0.311898	0.001217	0.077946	490
38	TTE	0.191934	0.183586	0.192061	0.182024	0.783402	-0.005344	490
39	UBER	0.260762	0.253125	0.260894	0.251712	0.768972	-0.006470	490
40	V	0.301865	0.294653	0.305478	0.296851	0.113590	-0.015694	490
41	WMT	0.072411	0.062828	0.073164	0.061651	0.531298	-0.006622	490
42	XOM	0.288716	0.281368	0.289797	0.280974	0.391746	0.012454	490
43	ZM	0.290844	0.283518	0.291278	0.282474	0.586804	-0.008683	490