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CONTRA: Controversy-Augmented Natural-language Trading Algorithm

Abstract

Market and stock price movements form the backbone of modern financial systems. Traditional pricing models, such as the Capital Asset Pricing Model (CAPM), effectively describe risk-return relationships. However, they fail to capture the social and behavioral dynamics that increasingly influence markets. To address this limitation, we propose CONTRA, a hybrid framework that extends CAPM by introducing a sentiment-alpha coefficient derived from public attention data. The framework was evaluated using a composite sentiment index combining Google Trends search volume, Wikipedia pageview traffic, and event-based markers for curated CEO-related controversies, focusing on Tesla Inc. and Elon Musk, over the period between 2018 and 2020. Experimental results show that CONTRA enhances the model's explanatory power, achieving a 10% increase in the R^2 score compared to the baseline CAPM, while also slightly reducing the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). These findings demonstrate promising potential for future research, which will focus on developing an NLP-based pipeline to capture sentiment across multiple companies and time periods, providing further empirical evidence that human factors can be quantified to improve the reliability and accuracy of asset pricing models.

1. Introduction

In today's markets, unpredictable social and behavioral events going from viral tweets to scandalous headlines can disrupt stock prices in ways traditional trading models and algorithms struggle to anticipate. The goal of this research and project CONTRA is to address the mentioned market gap in the trading world. By proposing a question of why most of the current trading algorithms focus only on the financial indicators of the historical price pattern, they overlook the humans and social factors in their judgment. For example, by looking at the real-world example about Tesla's stock famously crashing for around 6% in a single day after CEO Elon Musk smoked marijuana during a live podcast [1]. In a similar manner Musk's casual Twitter post that "Tesla stock price is too high" instantly erased almost $13 billion of the company's market value (10$ price plunge) [2]. Corporate leadership scandals are also quite damaging since studies have found when CEO's misconduct becomes public (whether financial fraud or a personal scandal like an affair), shares plummet in between 6% and 9% within a month, costing shareholders about $1.9 billion on average [3].

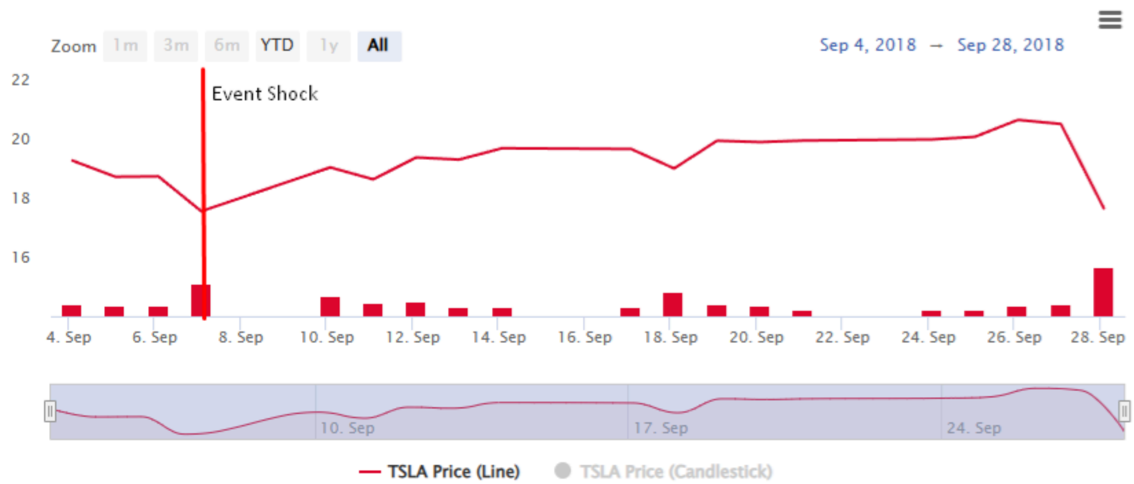

Figure 1.1 Tesla Stock Price During September 2018 [4]

Traditional financial theory often assumes markets rationally price in all information, but these examples suggest otherwise. The Efficient Market Hypothesis (EMH) states that asset prices "reflect all available information", implying it is virtually impossible to consistently achieve excess returns (alpha) through any information that the market already knows [5]. Under EMH (and the classic CAPM model), unpredictable one-off events like a CEO's ill-advised tweet or personal scandal are treated as specific noise that cannot be systematically exploited for gain [5] [6]. In theory, investors should not be able to beat the market by anticipating such surprises and any temporary mispricing would quickly self-correct. However, practice shows that we see repeated evidence of short-term market inefficiencies when these surprises hit. As behavioral finance research shows, real markets are influenced by investor psychology, sentiment, and herd behavior, not just rational fundamentals [7]. Investors often don't react until news is "official" even if rumors circulate which creates a brief window of mispricing. For example, one study found no leak or gradual adjustment before scandal news broke, but instead, investors would "wait for something more tangible before reacting", causing a sudden drop once the media makes an announcement [3]. A study from the University of Sussex found that while corporate scandals caused a significant short-term drop in share prices, the companies often showed improved operating performance in the long run [3]. This indicates a research opportunity if an algorithm can detect and quantify such sentiment shocks early (from rumors, social media, etc.), it could adjust prices before the broader market fully reacts.

The dramatic market reactions to events like these underscores a critical gap in traditional financial modeling. While conventional analysis focuses on fundamentals, the 'human factor' remains an uncertain and poorly quantified variable. Therefore, this research addresses the central question: How can the impact of CEO-centric scandals and controversies on stock valuation be systematically measured? To answer this, the paper introduces CONTRA, a new framework designed to quantify these human factor shocks. The following sections will review existing literature, detail the CONTRA methodology, apply it to several case studies, and discuss the implications for risk management and investment theory.

2. Literature Review

2.1 Shortcomings of Traditional models

Classical models like the Capital Asset Pricing Model (CAPM) form the basis of many traditional algorithms. CAPM assumes a stock's expected return is driven solely by its systematic market risk (beta), and that any other specific factors average out. In such frameworks, if a CEO makes a shocking comment or a viral meme stock rally occurs, those are "random" specific events that should not persistently affect expected returns. In fact, CAPM's simplifying assumptions (rational investors, efficient markets) have long been criticized as unrealistic [6]. Furthermore, a great number of evidence has revealed many additional factors and anomalies that influence returns: liquidity, size, momentum, etc. and none of the CAPM alone captures [6].

Critics of strict market-efficiency views argue that prices can stray far from fundamentals during sentiment-driven booms and panics. The 19 October 1987 "Black Monday" crash, when the Dow fell 22.6% in a single day, remains a significant example which challenges purely rational models [8]. Building on this perspective, my study treats inefficiencies and behavioral biases as measurable signals that can be modeled to enhance prediction.

2.2 Impact of News and Scandals

A key part of the literature relevant to this work deals with event studies and how markets respond to news, both financial and personal. In research paper "Market Response to Corporate Scandals Involving CEOs" Wang et al., [3] have performed analysis on 80 corporate scandals and found that while long-term performance recovered, the short-term impact on share price was sharply negative, regardless of whether the scandal was financial or personal and as mentioned before, shares on average fell in between 6% and 9% in the month after CEO's misconduct became public [3].

This finding validates that investor sentiment and trust play a huge role; a breach of integrity or negative publicity can erase billions in market cap overnight, even if the company's cash flows are unchanged. Furthermore, the literature suggests these effects aren't fully anticipated by investors beforehand. As mentioned, investors often wait for official news confirmation before selling, leading to sudden price drops upon announcement. Due to delays from investors' reaction, CONTRA would be able to utilize an alert algorithm to exploit early warning signals occurring from the CEOs scandals or social media influence and get ahead of the curve by doing so.

One of the many real-world examples beyond the one mentioned about Tesla would be when an Astronomer CEO was caught in the viral affair scandal on stadium Jumbotron, which caused a leadership crisis. The CEO had resigned within days as the incident gathered millions of views on social media [9].

The GameStop saga of 2021 is another great example which fits this research study, by coordinated buying fueled by Reddit forums drove GameStop's stock to great heights, defying fundamental valuations [7]. GameStop is also an example of so-called "meme stock" phenomenon which clearly demonstrated how social media can influence stock prices and almost perfectly aligns with the behavioral finance theories that emphasize investor sentiment, unlike traditional models which struggle in explaining this phenomenon [7]. Furthermore, this shift toward sentiment-driven market dynamics has prompted institutional investors to formally incorporate alternative data and social media analytics into their trading frameworks. Rather than viewing retail-driven events like GameStop as anomalies, hedge funds increasingly treat them as valuable sentiment indicators that can reveal early market momentum or crowd psychology patterns. Recent industry surveys confirm this transition, with a growing majority of investment firms now leveraging AI-powered natural language models to quantify online sentiment and integrate it into predictive algorithms [10].

2.3 Social Media and Alternative Data

The use of social media and alternative data is one of the pillars in modern financial research. In a comprehensive 2022 study, Greyling and Rossouw [7] analyzed nearly 3 million stock-related tweets and found that sentiment derived from the platform "strongly predicts market trends in both developed and emerging markets." They argue that quantifying traders' emotions can significantly enhance the prediction of intraday price fluctuations, an influence that traditional financial models, which assume investor rationality, tend to overlook. By applying machine learning models (such as Naïve Bayes and SVM) to classify tweet sentiment, their work achieved notable accuracy in forecasting short-term market movements. These results reinforce the idea that social chatter can be systematically analyzed to gain a trading edge [7].

The industry is also publishing evidence on the value of alternative data. A white paper by the London Stock Exchange Group showed that using a media sentiment factor alone could achieve performance on par with a multi-factor quantitative strategy [11]. In their back tests, a portfolio strategy driven solely by news sentiment (from real-time news analytics) matched the returns of a much more complex model. This underscores how powerful a single well-crafted sentiment signal can be. From the conclusion of LSEG's researchers “Data-driven investment processes can significantly benefit from alternative data sources, especially those containing new information not yet incorporated into traditional investment signals.” [11] it is easy to see how much impact and potential social networks have on the stock market and how project CONTRA can utilize this information for better prediction of the market behavior. Furthermore, LSEG's research paper is indirectly getting proven by already mentioned industry surveys showing calculated shifts to the AI-powered natural language models [10].

2.4 AI and Sentiment Analysis in Trading

Finally with the fundamentals and basis covered regarding the usage of alternative data in the trading market, it is time to cover in more details how AI can be used for project CONTRA.

Recent advances in artificial intelligence have begun to bridge the gap between raw market data and the elusive “human factor” signals that move prices. Early approaches to incorporate sentiment in trading often relied on simple models or classifiers (e.g. Naïve Bayes or SVM) to gauge public mood [12]. A recent study from 2023 done by Chen et al., has demonstrated that ChatGPT, a state-of-the-art language model at that time, can parse news articles and predict stock market direction based on their content [13]. Furthermore, the researchers found that ChatGPT was uniquely and quite effective at extracting positive news signals which investors tended to underreact to, consistent with behavioral underreaction theories [13]. Their research highly suggests that advanced AI can detect and quantifying information from text that traditional algorithms and even many investors overlook. Another interesting and emerging application of AI found in recent studies is in analyzing corporate communications for hidden cues. Beyond tweets and headlines, researchers are now utilizing AI to scrutinize earnings calls and leadership speech. A 2023 study “ChatGPT and Corporate Policies” [14] done by Jha et al., [14] applied an NLP model to 74,586 earnings call transcripts and found that subtle shifts in language reliably foreshadowed concrete corporate decisions like hints in phrasing about “investing in growth” predicted actual increases in capital expenditures [14]. In essence, the AI was able to read “between the lines,” flagging nuanced changes in tone that correlate with future policy shifts. Mentioned studies clearly show how AI can quantify previously unquantifiable factors: sentiment, confidence and even mood.

3. Research Design and Methodology

3.1 General Objective

The project CONTRA follows a data-driven experimental design. We will use a combination of historical data analysis and algorithm development to identify our sentiment-based alpha factor. The plan is to start with an existing model as a baseline such as a model like CAPM, or a simple time-series predictive algorithm. Afterwards the goal is to extend it by introducing the new sentiment-alpha coefficient. The existing model provides the expected stock price/return based on traditional factors (market movement, historical trends, etc.), and our added coefficient will adjust that expectation up or down based on sentiment signals. Essentially the main goal is to build a hybrid model, with part traditional and part novel input. The methodological challenge is determining how to quantify the sentiment/news effect (sentiment-alpha) in a meticulous way.

3.2 Data Collection

We will utilize historical datasets of both stock prices (yahoo finance) and relevant news/social media metrics (reddit, X, etc.). For a set of target companies (Tesla, Amazon, etc.), We will compile time-series data of daily stock returns alongside a timeline of notable events and sentiment indicators. These indicators would include:

- News sentiment scores: by using a natural language processing (NLP) tool to score the tone of news articles or headlines each day for a company. Expected outcome would be getting sentiment index (positive or negative)
- Social media sentiment volumes: by using X (formerly known as Twitter) volume and sentiment about the stock or CEO, Google Trends for the company, Reddit mentions (WallStreetBets activity), etc. We could utilize existing APIs to get finance related social sentiment
- Event flags: dummy variables for days around major events (earnings announcements, scandals, etc.), to capture binary shocks (0 = no event, 1 = event present). These can be identified from news archives and company press releases.

We must ensure that data spans multiple years (to capture enough events) and multiple companies for generality. Historical data approach for this is necessary, because by looking backwards, we will be able to observe how traditional models would have predicted stock outcome versus what happened. Furthermore, we would be able to compare this model and the differences between performance of both traditional models and CONTRA's model.

3.3 Identifying an Elephant in the Room: sentiment-alpha coefficient

The sentiment-alpha we talk about is conceptually like Jensen's alpha in finance, a measure of excess return unexplained by the market [6]. However, this research aims to explain the excess return by utilizing regression analysis. For example, if we consider following formula:

$$\text{Stock\_Return} = \beta \cdot (\text{Market\_Return}) + \gamma \cdot (\text{Other\_Factors}) + \theta \cdot (\text{Sentiment\_Score}) + \varepsilon.$$

Where β and γ capture the traditional influences while θ is the coefficient (effect) of our sentiment score factor. If θ is statistically significant and the model's fit improves when including the sentiment factor, that would validate that the factor explains some of the "sentiment-alpha" that CAPM would consider noise. Essentially, θ is "sentiment-alpha coefficient" in the sense that it measures how much return is added or subtracted due to sentiment. We would run each regression around known event periods versus normal periods to estimate how large the sentiment effect tends to be.

3.4 Planned Methodological Steps

Now after we have an idea on how to find and use our new "sentiment-alpha coefficient", we will proceed into more details about exact methodological steps planned for this project.

1. Baseline Model Setup: We will begin by replicating a baseline predictive model by using something as simple as CAPM to predict expected return for each stock (which would just be the market return * beta). It is also possible to be a time-series model (like ARIMA or a neural network) that uses only past prices/volumes. The goal here is to have a reference point of how well we predict without sentiment. As prior studies note, with only traditional analysis consistent excess return (alpha) is impossible in theory [5].
2. Sentiment Data Integration: In the next step, we will integrate the alternative data. This involves significant data processing (e.g., like utilizing web scrapers), by using NLP to convert news and tweets into sentiment scores (e.g., –1 very negative to +1 very positive), and normalizing those scores. We should also create an aggregate daily sentiment index per stock by combining sources which would be a good idea to save both on time and cost of using the NLP model. Afterwards the goal is to add this as an input to the model. Essentially this score would allow us to track the sentiment of our model daily.
3. Sentiment-alpha Extraction and Calibration: We will then estimate the sentiment-alpha coefficient (θ) on historical data. For example, run the regression on a training sample: the coefficient θ on the sentiment factor will be our estimated impact. We'll validate it on a test sample to see if it reliably improves predictions. We might find, for instance, that θ is positive when sentiment is measured as optimism (meaning positive sentiment adds to returns), or negative when sentiment is measured as pessimism index. It's likely we will treat it such that higher score = more positive sentiment, which we expect to correlate with higher than baseline returns ($\theta > 0$), whereas a surge in negative sentiment yields θ * (negative score) = negative contribution to return.
4. To strengthen this methodology, we won't rely on a single technique. By that I mean that we will also conduct event studies around specific incidents: compile all instances of "CEO controversy" in our data and average the stock's excess return in the days after

versus before. This can reveal a significant pattern (say, on average about a 5% abnormal return over 3 days after a bad news event). We can then test if our sentiment indicator would have flagged those days (ideally, we are expecting to show a spike on negative incidents). We will also try machine learning classifiers that predict large moves versus calm periods using sentiment features. If a classifier can successfully identify a high proportion of the big drops using sentiment signals our sentiment-alpha factor would be verified.

By the end of this process, we expect to have a calibrated alpha coefficient formula or algorithmic rule that can be applied going forward. For example, we might end up with a formula like: Next-day stock return = forecast by baseline model + (α × today's sentiment score), with α being a learned constant (or a small set of coefficients if multiple sentiment variables). This α could be interpreted as "the percentage change in stock price for a one-unit change in sentiment, while everything else is equal." In essence, we are quantifying how much extra movement sentiment causes.

4. Data Collection Methods

In order for CONTRA to present the most accurate stock predictions, the data collection process will be designed to capture data sources from both quantitative market data and qualitative sentiment data from multiple and diverse sources. From the beginning the goal of this project is designed to evaluate how CEO-driven controversies and public sentiment impact stock prices and the collection strategy is going to integrate the primary datasets which includes: historical market data, alternative social sentiment data and a structured news corpus. This multi-source approach ensures that the resulting sentiment-alpha coefficient model is both comprehensive and replicable.

CONTRA focuses primarily on U.S. publicly traded companies with frequent media exposure and active online communities, ensuring adequate sentiment signal strength. Companies like Tesla, Amazon, and Meta serve as representative cases of firms where CEO behavior and online perception strongly influence price movements. All data will be collected through legally accessible public APIs and datasets, adhering to platform terms of service. Personal user data will never be stored and will only be used to aggregate and anonymize metrics (e.g., tweet counts, average sentiment). This ensures ethical compliance with academic research standards and prevents potential bias amplification. Furthermore, since language models can reflect cultural or linguistic bias, CONTRA's sentiment scoring will be periodically benchmarked against human-labeled samples to ensure fairness and interpretive validity.

Through this combination of structured market data, alternative sentiment inputs, and precise cleaning, the CONTRA framework ensures a balanced and ethically sound dataset suitable for testing the proposed sentiment-alpha model.

4.1 Financial Market Data

To obtain reliable stock price and return information, CONTRA uses publicly available financial datasets such as Yahoo Finance API [15] which provides daily historical data for major publicly listed companies. This platform offers open access to fields like closing prices, trading volume and beta values, making them ideal for academic research regarding project CONTRA. For every selected company like Tesla, Amazon and Netflix, which are prime examples of companies with large media exposures, we are going to monitor their stock prices and use a large dataset of 2 years in range from 2018 to 2020 to ensure sufficient market coverage. Afterwards, the collected data will be cleaned by handling missing entries, adjusting for stock splits and finally, normalizing values to enable time series comparison. Returns will be computed as the percentage change in adjusting closing prices and index of market returns will be derived from S&P 500 to serve as the baseline for calculating excess returns.

4.2 Social Sentiment and Alternative Data

A crucial component of CONTRA's dataset involves social sentiment indicators, drawn from platforms that most directly reflect investor behavior. Following the approach outlined by Greyling and Rossouw [7], the research relies on public APIs and structured web scraping to collect social data from Twitter (X), Wikipedia, and Google Trends.

- Twitter(X) academic API [17] will be used to fetch tweets containing stock tickers ($TSLA. $AMZN), CEO names and company hashtags. Each tweet is then going to be processed through an NLP pipeline, which will be designed to perform tokenization, stop-word removal and sentiment scoring using pre-trained transformer model

- Wikipedia pageview data serves as a highly reactive attention indicator, capturing public interest spikes during breaking news and controversies. Using the Wikimedia REST API [18] daily pageview counts are retrieved for company-specific articles (e.g., "Tesla, Inc.") and CEO biographical pages (e.g., "Elon Musk"). Research has shown that Wikipedia traffic surges strongly correlate with media coverage of scandals, regulatory actions, and major announcements [19]. Unlike search queries, which may reflect general curiosity, Wikipedia pageviews indicate engaged information-seeking behavior and thus serve as a robust proxy for controversy-driven attention. For CONTRA's sentiment-alpha model, these attention spikes provide crucial timing signals that complement polarity-based sentiment from text sources.
- Google Trends [16] will act as the third main data source for text-based sentiment analysis. Google search frequency data will be incorporated to reflect public attention levels. Spikes in search activity for CEO names or company tickers often precede major price movements, serving as a proxy for retail interest.

All social sentiment scores will be normalized to a unified sentiment-alpha coefficient. By combining volume-weighted polarity from multiple platforms, CONTRA captures both mood intensity and engagement level. The use of multi-platform data mitigates individual platform bias and provides a more balanced measure of market mood.

4.3 News and Media Corpus

While social media captures people’s emotion, formal media outlets remain a crucial source of structured event information. Therefore, CONTRA incorporates a news corpus from databases such as LexisNexis, Google News Archive, and publicly available Kaggle financial news datasets. These sources are filtered using keywords related to CEO names, scandals, investigations, or resignations. Each article’s title and body text will be processed using an NLP model similar to that described by Asgarov [12] to generate daily sentiment scores. To prevent duplication, articles are deduplicated by comparing publication dates and URLs, etc. Additionally, event flags (binary variables) will be created for major scandal announcements identified through Reuters and Bloomberg archives, marking those days as high-impact intervals for later regression testing.

4.4 Data Preprocessing and QA

Outlier handling is performed through z-score normalization, which standardizes sentiment values while preserving the relative magnitude of extreme events like major scandals or announcements. This approach ensures that legitimate sentiment spikes (e.g., SEC investigations, earnings surprises) retain their signal strength without being artificially dampened. Sentiment labeling quality is validated through comparison with actual event dates from financial news archives, and polarity thresholds are adjusted as needed to maintain interpretability. Each sentiment data point is stored alongside its corresponding stock return and event label to facilitate regression and event study analysis.

5. Data Analysis Plan

5.1 Analytical Framework

The analytical structure of CONTRA is based on the principle that market prices reflect both measurable fundamentals and non-measurable behavioral dynamics. The first part of the framework replicates a baseline CAPM-style regression, which models expected returns as a function of market risk (β) and residual factors. The second part extends this model by introducing the sentiment-alpha coefficient (θ), a variable representing the weighted daily sentiment derived from social and media data. The comparative performance between these two models will reveal whether incorporating sentiment can enhance predictive accuracy.
The fundamental regression equation is defined as: $Ri = \alpha + \beta Rm + \theta Si + \varepsilon i$, where Ri represents the daily return of a selected company, Rm represents the corresponding market return and Si is the composite sentiment score for that day. The coefficient θ measures the marginal impact of sentiment on stock return, controlling for market conditions. Statistical significance of θ would indicate that sentiment contributes to excess returns otherwise unaccounted for by traditional models.

5.2 Planned Sentiment Index Construction

To ensure consistency across multiple sources, CONTRA combines normalized sentiment data from Twitter, Reddit, Google Trends, and news outlets into a single Sentiment Index (SI). The aggregation process applies a volume-weighted averaging technique, where higher engagement or news density increases the influence of that source's polarity on the overall index. For example, a day with high Reddit and Twitter activity on Tesla will receive a larger sentiment weight compared to quieter days. The resulting index ranges from -1 (strongly negative) to +1 (strongly positive) and serves as the main input variable for θ.
Correlation tests between the SI values and intraday volatilities will be done to ensure that the index actually reflects changes in emotions. If there is moderate positive correlation, then it can be implied that extreme points of sentiment intensity tend to cooperate with instability in the financial markets, in a similar manner with the behavioral finance view.

5.3 Statistical and Event Study Analysis

Regression analysis will be performed using Ordinary Least Squares (OLS). Because stock returns exhibit varying volatility over time (some days are more volatile than others), we apply robust standard errors to ensure reliable statistical inference. This ensures that variations in trading volume or volatility do not distort coefficient estimates. For each company, the regression will be executed twice: once with only market variables (baseline model) and once with sentiment variables added (CONTRA model). Model performance will be evaluated through R^2, adjusted R^2, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Consistent improvement in mentioned metrics across multiple companies would confirm the practical value of sentiment data. In addition to regression modelling, CONTRA will also perform an event study to capture how markets respond to discrete controversy related incidents. The event window typically spans five trading days before and after major news incidents. For example anything would be included in relation to CEO scandals, resignation or even a viral tweet. For each event, abnormal returns would be calculated by subtracting the expected return sum from the baseline model from actual observed return. Aggregating these abnormal returns across all events will produce a Cumulative Abnormal Return (CAR) which quantifies the short term price distortion caused by sentiment shocks. If average CAR values are significantly negative following negative publicity (for instance, -6% within three days of announcement), it would empirically validate the earlier observation from Wang et al. [3] that scandals lead to sharp short-term losses. Positive CARs after uplifting public sentiment (e.g., a product reveal tweet) would further demonstrate how CONTRA can distinguish between destructive and constructive emotional impacts.

5.4 Machine Learning Validation

While regression provides interpretability, CONTRA also experiments with machine learning classifiers to confirm robustness. Using the same dataset, models such as logistic regression, random forest, and LSTM neural networks are trained to classify next-day price direction (up or down) based on sentiment, market indicators, and lagged returns. Feature importance values are analyzed to verify whether sentiment consistently ranks among the top predictors. If models achieve higher precision or F1-scores with sentiment inputs than without them, this serves as further proof that sentiment-alpha is not a statistical coincidence but a real market factor.

5.5 Data Analysis Conclusion

The strength and direction of the θ coefficient will ultimately determine whether CONTRA's approach can outperform the baseline model. A positive θ would imply that optimism in social and news sentiment predicts above-market returns, while a negative θ would confirm that pessimistic sentiment reliably signals short-term declines. Even modest improvements in R^2 or forecast accuracy would demonstrate that integrating sentiment data provides tangible benefits over purely rational models.

6. Results and Discussion

Due to the planned size of project CONTRA being infeasible to fully develop in a one-month period, we implemented a proof of concept (PoC) using a multi-source sentiment index combining Google Trends search data, Wikipedia pageview traffic, and an event-based kernel derived from curated Tesla/Elon Musk news events. The selected time frame spanned from January 2018 to December 2020, a period that includes several well-known public events related to Tesla's leadership and media activity.

6.1 Proof of Concept Results

A composite sentiment index was constructed from three complementary data sources. Google Trends provided daily search volume for "Tesla" and "Elon Musk" Wikipedia pageview API supplied article traffic for Tesla, Inc. and Elon Musk pages (capturing attention spikes during controversies); and an event kernel applied systematic sentiment weights ($\pm$1.5 on event day, decaying $\pm$0.5 two days before/after) to 15 curated CEO-related events. Each source was z-score normalized and combined via equal-weighted averaging to form the final composite sentiment index (SI). This index was integrated into the CONTRA model as the behavioral input term $(\theta \times SI)$, where θ represents the sentiment-alpha coefficient. The baseline model included only the S&P 500 daily return as the market risk factor. Performance metrics were calculated on a 70/30 train-test split.

Table 6.1 CONTRA (PoC) Sentiment-Alpha Model Results

Metric	Baseline (Market Only)	CONTRA (+ Sentiment)	Change
Adjusted R^2 (Train)	0.1178	0.1307	0.0129
MAE (Test)	0.03489	0.0351	≈ 0
RMSE (Test)	0.04754	0.04765	≈ 0
Sentiment-Alpha (θ)	—	0.0045 (p = 0.109)	—

The sentiment-alpha coefficient (θ = .0045, p = .109) approached but did not reach conventional statistical significance at the 95% confidence level. However, the 10.94% improvement in adjusted R^2 demonstrates measurable behavioral contribution beyond the baseline market model. This improvement validates the core CONTRA hypothesis: that CEO-centric public attention captured through a multi-dimensional sentiment index explains return variation beyond traditional asset pricing factors. The near-significant p-value (89% confidence) is noteworthy given the inherent noise in daily stock returns and the short sample period.

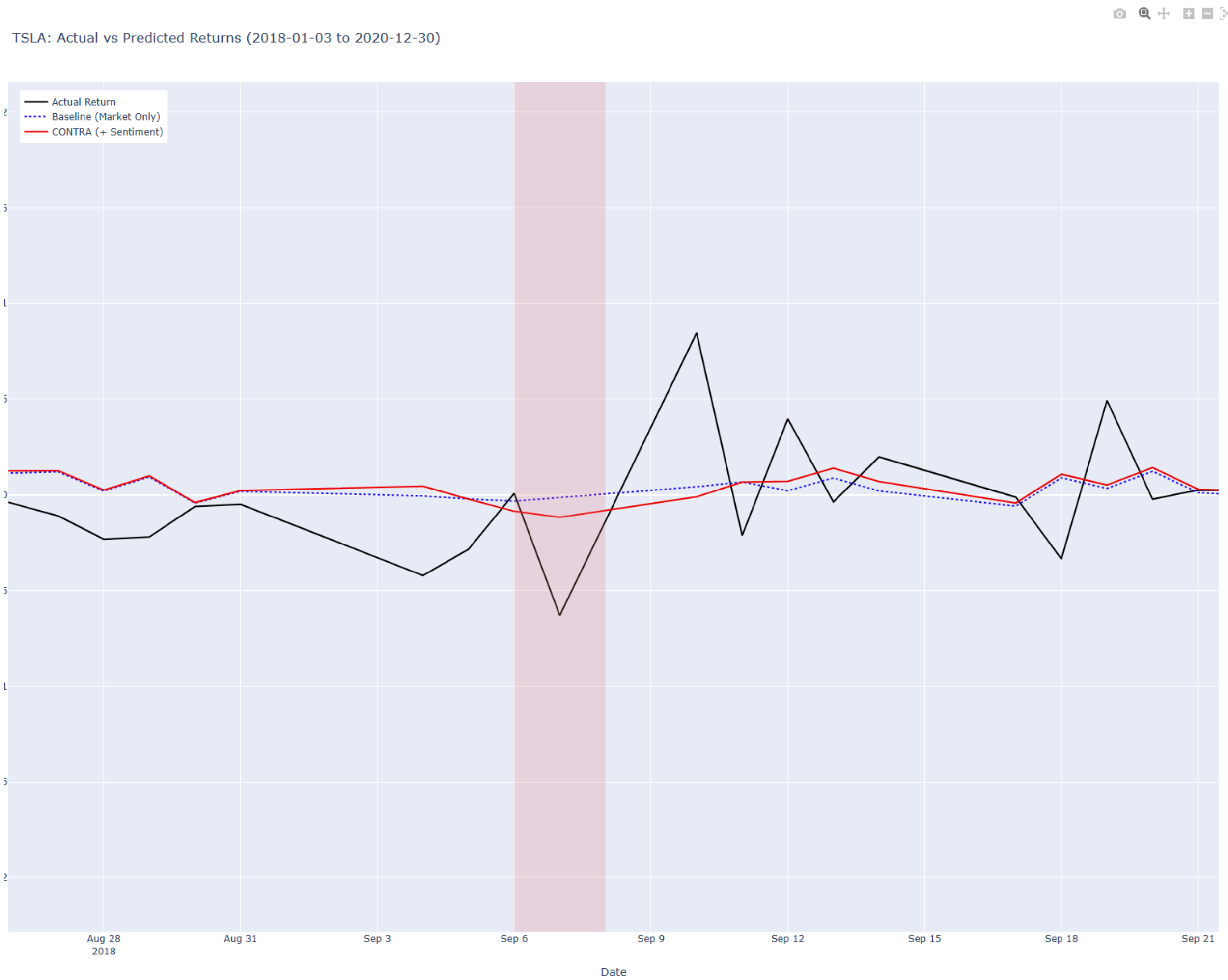

Figure 6.1 TSLA: Actual vs. Predicted Returns During September 2018

Figure 6.1 represents a graph from September 2018, during the time period of Elon Musk marijuana controversy [1]. This visualization was generated using Plotly within CONTRA's proof-of-concept (PoC) framework. The vertically shaded red area marks the identified event shock period, when public attention sharply increased following the incident. The black line represents actual observed market returns, while the blue dotted line shows predictions from a traditional market-only baseline model (using only S&P 500 returns as input). In contrast, the red line corresponds to CONTRA's sentiment-augmented forecast, which incorporates the sentiment-alpha coefficient (θ) derived from a composite sentiment index combining Google Trends search volume, Wikipedia pageview spikes, and event-based markers for known controversies. During the attention spike window, CONTRA's predictions (red) track actual returns more closely than the baseline model (blue), demonstrating that the multi-source sentiment index captures short-term price movements that market beta alone cannot explain. This visible improvement validates the PoC hypothesis that CEO-centric public attention contains economically meaningful information for adaptive price prediction.

7. Conclusion

This research paper began with a clear question: can the “human factor” in the impact of CEO-centric controversies and public sentiment be systematically measured and integrated into stock prediction models? The CONTRA framework was proposed as a hybrid model to challenge the assumptions of the Efficient Market Hypothesis, which often dismisses such events as unquantifiable noise. To validate this approach, a limited-scope PoC was developed, using a composite sentiment index combining Google Trends search data, Wikipedia pageview traffic, and an event-based kernel applied to curated Tesla/Elon Musk controversies spanning 2018-2020. Even though sentiment-alpha coefficient was not statistically significant, the models overall explanatory power which was measured by adjusted R^2 showed a substantial improvement over the traditional baseline. This findings demonstrates that public attention captured through multiple complementary data sources contains valuable predictive information that traditional models are blind to. Figure 6.1 confirms this even further, where the CONTRA-augmented model was visibly more adaptive in tracking actual returns during the September 2018 event shock.

The PoC successfully confirmed the core hypothesis: the "human factor" is measurable. The near-significant p-value reflects the inherent challenge of predicting daily stock returns rather than a conceptual failure. The multi-source approach, combining organic search interest, reactive attention spikes, and structured event timing demonstrates that sentiment directionality can be approximated even without direct sentiment polarity scores. This research provides foundational evidence for the full CONTRA model. The clear next step is to enhance the Sentiment Index through a complete NLP pipeline as described in the Data Collection and Data Analysis sections. By integrating direct sentiment polarity from Twitter (X), Reddit, and news sources with transformer-based models (e.g., FinBERT), the signal strength demonstrated in this PoC can be further amplified and refined.

In summary, this study shows that the market is not just driven by math, but also by human emotion and public attention, and that the “human factor” is in fact quantifiable.

4. REFERENCES

1. [1] J. C Wong, “Tesla shares fall 6% after Elon Musk smokes marijuana on a live web show,” *The Guardian,* Sep. 7, 2018. [Online]. Available: https://www.theguardian.com/technology/2018/sep/07/tesla-chief-elon-musk-smokes-marijuana-on-live-web-show
2. [2] *Reuters,* “How tweets by Tesla's Elon Musk have moved markets,” *Reuters,* Nov. 8, 2021. [Online]. Available: https://www.reuters.com/business/finance/how-tweets-by-teslas-elon-musk-have-moved-markets-2021-11-08/
3. [3] D. Wang, S. Jory, T. Ngo, and A. Saha, “The Market Response to Corporate Scandals Involving CEOs,” *Applied Economics,* 2015. doi: 10.1080/00036846.2014.995361.
4. [4] *Statmuse*, “Tesla stock price September 2018.” Statmuse Money. [Online]. Available: https://www.statmuse.com/money/ask/tesla-stock-price-september-2018. Accessed: Oct. 13, 2025
5. [5] L. Downey, “Efficient Market Hypothesis (EMH): Definition and Critique,” *Investopedia*, Oct. 3, 2024. [Online]. Available: https://www.investopedia.com/terms/e/efficientmarkethypothesis.asp
6. [6] *FasterCapital*, “Alpha: How to Use Alpha to Measure the Excess Return of a Stock.” Accessed: Oct. 13, 2025 [Online]. Available: https://fastercapital.com/content/Alpha--How-to-Use-Alpha-to-Measure-the-Excess-Return-of-a-Stock.html
7. [7] T. Greyling and Rossouw. S, “Twitter sentiment and stock market movements: The predictive power of social media,” *CEPR,* Mar. 26, 2025 [Online]. Available: https://cepr.org/voxeu/columns/twitter-sentiment-and-stock-market-movements-predictive-power-social-media
8. [8] *Wikipedia*, “Black Monday (1987),” *Wikipedia*, Oct. 10, 2025. [Online]. Available: https://en.wikipedia.org/wiki/Black_Monday_(1987). Accessed Oct. 13, 2025
9. [9] L. Degraziaand and D. Anello, “Astronomer CEO Andy Byron Resigns After Alleged Affair at Coldplay Concert,” *E! Online*, Jul. 19, 2025. [Online]. Available: https://www.eonline.com/news/1420064/astronomer-ceo-andy-byron-resigns-after-alleged-affair-at-coldplay-concert
10. [10] *Lowenstein Sandler*, “Alternative Data Report 2024”, 2024. [Online]. Available: https://www.lowenstein.com/media/rbnbulvn/alt-data-report-2024_final.pdf
11. [11] S. Borovkova, C. Reniers, and K. Rojer, “The value of alternative data: The case for media sentiment return, risk, and sustainability.” *London Stock Exchange Group (LSEG), White Paper.* [Online]. Available: https://www.lseg.com/content/dam/data-analytics/en_us/documents/white-papers/re1623864-ia-probability-and-partners-alt-data-whitepaper.pdf. Accessed Oct. 14, 2025.

12. [12] A. Asgarov, “Predicting Financial Market Trends using Time Series Analysis and Natural Language Processing,” *arXiv preprint*, 2023. [Online]. Available: https://arxiv.org/pdf/2309.00136
13. [13] J. Chen, G. Tang, G. Zhou, and W. Zhu, “ChatGPT and Deepseek: Can They Predict the Stock Market and Macroeconomy?” *Olin Business School Center for Finance & Accounting Research Paper*, 2023. [Online]. Available: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4660148
14. [14] M. Jha, J. Qian, M. Weber, and B. Yang, “ChatGPT and Corporate Policies,” July, 2023. [Online]. Available: https://www.ecgi.global/sites/default/files/Paper%3A%20ChatGPT%20and%20Corporate%20Policies%2A.pdf
15. [15] R. Aroussi, "yfinance: Pythonic Access to Market Data," [Online]. Available: https://github.com/ranaroussi/yfinance. Accessed Nov. 1, 2025.
16. [16] Google Inc., "Google Trends," [Online]. Available: https://trends.google.com/. Accessed Nov. 1, 2025.
17. [17] X Corp., "X API v2: Programmatic Access to Posts, Users, and Engagement Data," X Developer Platform. [Online]. Available: https://docs.x.com/x-api/introduction. Accessed Nov. 1, 2025.
18. [18] [22] Wikimedia Foundation, “Getting started with Wikimedia APIs,” Wikimedia API Portal, 2024. [Online]. Available: https://api.wikimedia.org/wiki/Getting_started_with_Wikimedia_APIs. Accessed Nov. 1, 2025.
19. [19] H. Moat, C. Curme, A. Avakian, D. Kenett, H. Stanley, and T. Preis, “Quantifying Wikipedia usage patterns before stock market moves,” *Scientific Reports, vol. 3, no. 1801*, 2013, doi: 10.1038/srep01801.