Reading Between the Lines: The Immediate Stock Market Impact of Earnings Calls

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1 Introduction

Earnings calls are a vital medium through which company executives communicate financial performance, outlook, and strategic direction to investors and analysts. Beyond the quantitative figures themselves, the tone and language in these calls offer key signals about management confidence and future expectations, signals that can move markets (Loughran & McDonald, 2011, Araci, 2019). Modern advances in natural language processing, particularly finance-tailored models like PySentiment and FinBERT, now make it possible to systematically measure sentiment in corporate communications and directly relate these metrics to stock price movements (GitHub nilijing, 2021, FinBERT, 2020). Recent research suggests that capturing sentiment at a granular level, and especially segmenting it by type of corporate disclosure, can yield deeper insights into what drives immediate investor reactions (Fang & Peress, 2009, Ball & Brown, 1968).

This paper examines whether sentiment, quantified using both PySentiment and FinBERT, extracted from Microsoft Corporation's earnings call transcripts can help explain short-term abnormal returns in the company's stock price. By focusing on the first five, thirty, and sixty minutes immediately following each call, the analysis targets the exact moment when market participants react most quickly to new information, before other news or factors confound the impact (Warp Speed Price Moves, 2025, UCSD, 2025). The primary question is whether these sentiment signals, measured with financial NLP tools, are statistically and economically related to fast stock price changes, above and beyond standard quantitative market indicators.

A sharper understanding of how narrative sentiment drives rapid price jumps in this critical window can enhance strategies for risk measurement and opportunity identification, such as those used by analysts at the AlgoGators Investment Fund and beyond. More broadly, this work adds to the growing evidence that qualitative features of corporate communication are rapidly factored into market prices in today's fast-moving financial environment (Fang & Peress, 2009, Loughran & McDonald, 2011).

3 Methodology

This study is designed to test whether sentiment extracted from Microsoft Corporation's earnings call transcripts helps explain short-term abnormal returns in the company's stock price. The study will observe the 5, 30, and 60 minute time periods immediately following the end of each call, allowing us to focus on the market's fastest reaction period and minimize the influence of unrelated news.

Sample Design

The analysis focuses exclusively on Microsoft, utilizing transcripts of quarterly earnings calls drawn from the Hugging Face Microsoft earnings call dataset. The sample covers earnings calls from 2018 to 2021. Calls are filtered to ensure transcript completeness, reliable timestamps, and availability of corresponding high-frequency stock price data. After cleaning, the study includes 11 Microsoft calls and events.

Sentiment Extraction and Variable Construction

For sentiment analysis, this study employs both PySentiment and FinBERT to capture the tone and emotional intensity in Microsoft's earnings call transcripts. PySentiment uses financial-domain word lists to systematically scan the text, computing the net count of positive versus negative words and scaling this value by the total number of words in the transcript. This results in a standardized sentiment score that adjusts for transcript length, allowing for a fair comparison between different calls. In parallel, FinBERT, a transformer-based neural language model fine-tuned for financial text, classifies sentences within the transcript as positive, negative, or neutral. For each call or transcript segment, the primary FinBERT variable is calculated as the average of the probability of "positive" sentiment minus the probability of "negative" sentiment, providing a continuous score from strongly negative to strongly positive emotional content (Araci, 2019;).

Abnormal Return Calculation

For each Microsoft earnings call event, the cumulative abnormal returns (CARs) are calculated as follows:

Event definition:

Each event is defined as the start of the scheduled Microsoft earnings call (4:00 PM US/Eastern). Timestamps are converted to UTC, with minute 0 representing the first minute after the call begins, minute 5 occurring five minutes later, and so on.

Return calculation:

Minute-by-minute returns for both the stock (MSFT) and the market benchmark (SPY) are calculated from one-minute bar data. Each minute's return is computed as the simple close-to-close return:

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

Where P_t is the price at time t.

Estimation window (market model):

To estimate the expected return, a separate ordinary least squares regression is fit for each event using the 60 minutes before the call:

$$R_t = \alpha + \beta R_t^m + \varepsilon_t$$

Where R_t^m is the SPY market return at the same minute.

Abnormal returns:

For each minute in the post-call event window, the expected return is calculated using the fitted model:

$$\widehat{R}_t = \widehat{\alpha} + \widehat{\beta} R_t^m$$

The abnormal return for each minute is then:

$$AR_t = R_t - \widehat{R}_t$$

Cumulative abnormal returns (CAR):

For any window of length W minutes (such as 5, 30, or 60 minutes) starting at minute 0, the cumulative abnormal return is:

$$CAR_{0,W} = \sum_{t=0}^{W} AR_t$$

That is, summing the abnormal returns across the specified window gives the total post-call price reaction.

Regression and Analytical Framework:

To test the relationship between post-call abnormal returns and sentiment, this study uses a cross-sectional ordinary least squares (OLS) regression for each event window. The dependent variable in each regression is the cumulative abnormal return (CAR) over a given period after the earnings call. Three windows are used: 5, 30, and 60 minutes following the event.

The explanatory variables are the FinBERT mean sentiment score, calculated for each transcript, and the PySentiment polarity score derived from the pysentiment2 library. The regression specification for each window is as follows:

$$CAR_{0,W,i} = \gamma_0 + \gamma_1 FinBERT_i + \gamma_2 PySent_i + u_i$$

Where CAR0,W,i is the cumulative abnormal return for call i; FinBERTi and PySenti are the transcript's sentiment scores.

Each regression is estimated using Python's statsmodels.OLS with HC3 robust standard errors. These standard errors are well suited for small samples and address potential heteroskedasticity. Any missing sentiment values default to zero, though none occurred in the final dataset. Scores are merged from curated output files to ensure alignment.

Both sentiment measures are treated as contemporaneous with the event, as each is extracted from the same transcript that triggers the observed stock price reaction. The regression tests whether more positive language corresponds to higher (or lower) short-horizon abnormal returns.

4 Results

Overview:

This study examined whether sentiment extracted from Microsoft Corporation's earnings call transcripts predicts short-term abnormal returns in the company's stock. The main outcomes reported are cumulative abnormal returns (CARs) over 5, 30, and 60 minute windows, and their association with transcript sentiment measured using FinBERT and PySentiment scores.

Distributions of Cumulative Abnormal Returns:

For each of the 11 earnings call events studied, cumulative abnormal returns were computed for the three post-call windows. The distributions of these CARs are tightly centered around zero in each case, indicating no consistent pattern of large positive or negative price reactions immediately following the earnings calls.

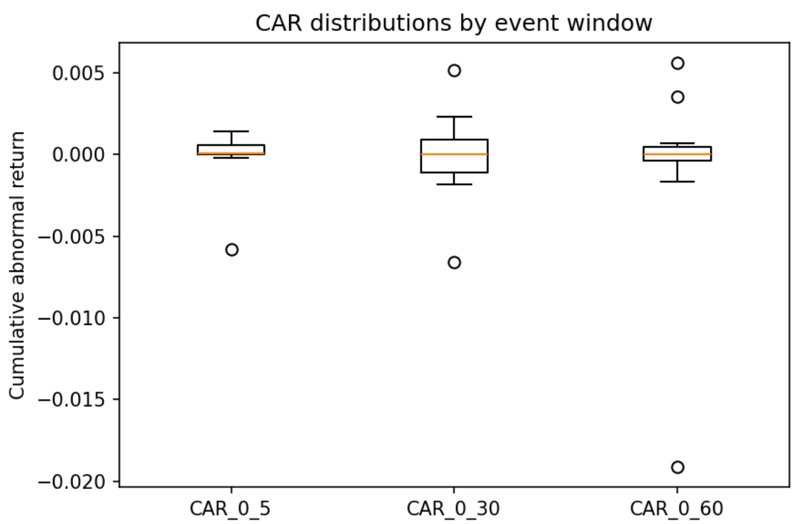

Figure 1. Distributions of cumulative abnormal returns (CARs) by event window (5, 30, 60 minutes after earnings calls).

Sentiment Score Patterns:

For all transcripts, both FinBERT and PySentiment detected generally positive or neutral language. FinBERT scores ranged from 0.25 to 0.49, with nearly all transcripts labeled "neutral" (one "positive"), and PySentiment polarity scores ranged from 0.13 to 0.50 (all labeled "positive"). This confirms that Microsoft's call language during 2018–2021 was consistently upbeat but with some quarter-to-quarter variation.

Relationship Between Sentiment and CARs:

Simple correlations between sentiment scores and CARs were generally negative and weak to moderate in strength. For the 60-minute window, the correlation between CAR and FinBERT was –0.28 and between CAR and PySentiment was –0.17. These negative values suggest that, if anything, more positive language weakly associates with marginally lower short-term returns, but the relationship is not strong or robust. To further illustrate, scatter plots show no discernable trend between sentiment and CAR:

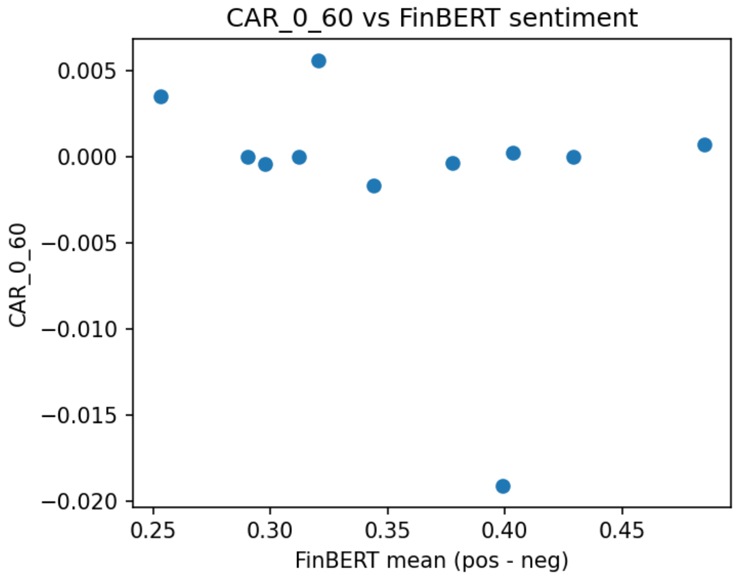

Figure 2. Scatterplot of 60-minute CAR vs. FinBERT mean sentiment score for each event.

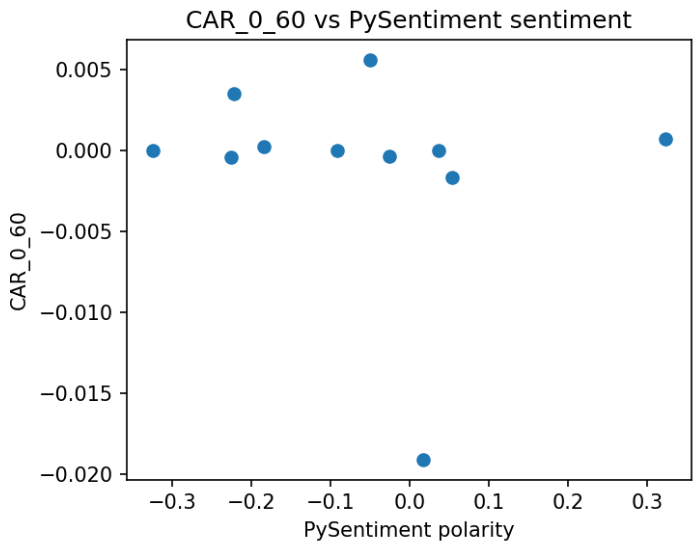

Figure 3. Scatterplot of 60-minute CAR vs. PySentiment polarity score for each event.

Both figures show the absence of a clear positive or negative pattern, with data points scattered and no obvious linear relationship.

<u>Regression Results:</u>

Ordinary least squares (OLS) regressions were estimated for each CAR window, using FinBERT and PySentiment scores as predictors. Across all three windows, R-squared values were low (maximum of 0.34 for the 30-minute window), indicating that sentiment measures explain little variance in post-call returns. No coefficient was statistically significant at conventional levels. Detailed coefficient estimates and robust t-statistics are reported in the supplementary regression tables.

<u>Summary:</u>

Overall, the findings suggest that in this sample of Microsoft earnings calls, neither FinBERT nor PySentiment sentiment scores provide meaningful explanatory power for short-term abnormal returns within an hour after the call. The lack of strong association holds across all visualization and regression results.

5 Discussion

This study found no strong link between earnings call sentiment and short-term abnormal returns in Microsoft stock. Both FinBERT and PySentiment mostly rated transcripts as positive or neutral, and cumulative abnormal returns immediately after calls were close to zero for all event windows. Regressions and scatter plots confirmed that neither sentiment measure explained a meaningful amount of the variation in returns.

These results suggest that, at least for Microsoft, measured sentiment from earnings call transcripts is not a reliable predictor of fast price reactions. This may be because Microsoft's earnings information is quickly incorporated into its stock price, and management language tends to be positive and predictable. The limited sample size also makes it hard to detect subtle effects.

It is also possible that minute-by-minute price changes reflect other market factors or that sentiment tools miss important context and details in the transcripts. This points to a bigger challenge in financial NLP: relying on single sentiment scores may be less effective than combining sentiment analysis with other data, using more complex models, or applying the method to smaller or less-followed companies.

For future research, expanding the sample, including additional firms, and testing more sophisticated sentiment features would help clarify when and where earnings call language matters. In today's fast-moving market environment, combining textual data with standard financial indicators is likely the best way to improve predictive models.

6 Conclusion

This study examined whether sentiment extracted from Microsoft's earnings call transcripts predicts short-term abnormal returns in the company's stock. Using FinBERT and PySentiment scores across eleven events, we found that transcript sentiment was largely positive or neutral and that cumulative abnormal returns after calls were generally close to zero. No statistically significant relationship emerged between sentiment measures and post-call price changes in any of the three time windows examined.

These findings suggest that, for large, widely followed firms like Microsoft, earnings call sentiment does not meaningfully influence immediate stock price reactions. While transcript-based sentiment analysis remains a promising tool in financial research, its predictive power may depend on firm characteristics, data context, and integration with other market indicators. Future studies can build on this work by including a wider range of companies, larger samples, and more nuanced sentiment features to better understand when and how executive language affects real-time market outcomes.

7 References

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