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Original Article

NLP-Driven Sentiment Analysis of Earnings Calls and Its Impact on Stock Volatility

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Abstract: Among the most significant mediums where companies report to investors, analysts and regulating bodies are the earnings calls where companies report their performance in the financial realm, their strategy and future prospects. Unlike regulatory filings which are usually stagnant and very formal, earnings calls are two-way communications, and they contain undertones, language choices, and feelings that might cause serious impacts to the market perception. Recent advances in the field of natural language processing (NLP) have assisted researchers to quantitatively measure such sentiments, offering predictive data as to how the markets would react. The paper will analyze the extent to which the sentiment as it is determined by the earnings call transcripts can predict and explain short-term stock volatility. We train both lexicon-based and transformer-based deep learning models, including FinBERT, to learn sentiment dimensions, including positivity, negativity, uncertainty, and litigious tone. Volatility is measured by realized volatility realized through intraday prices per event of earnings calls. Regression based models and machine learning classifiers are then employed to find predictive relationships. The findings point to the fact that the more sophisticated NLP models are more effective than the methods, which rely on dictionaries, and that uncertainty and negative tones are very closely connected with the volatility. The work has resulted in the area of financial text analytics as it has served to address the gaps in studying the interaction between the analysis of narrative disclosure and the model of market risk and its practical and theoretical implications on the investors, analysts, and policymakers.

Keywords: Earnings Call Transcripts, Sentiment Analysis, Natural Language Processing (NLP), Stock Market Volatility, Finbert, Financial Text Analytics, Transformer Models, Uncertainty Tone, Market Reaction, Event Study Analysis.

1. Introduction

According to the Bodnaruk et al., (2015), Financial markets are highly sensitive to flow of information particularly disclosures that would reflect the present performance and future of a company. Some of the strongest communication events are the earnings calls when top-level executives engage in direct dialogue with analysts and shareholders. Such calls tend to accompany the release of quarterly or annual results, and are of unusual combination of factual reporting, future projection and ad hoc response to analyst calls (Araci 2019; Yang et al., 2020). Though this standard financial analysis is concentrated on such numerical information like revenue, earnings per share and liquidity ratios, the researchers and practitioners are inclined to admit that the linguistic information of the corporate communication also plays a great role in the market behavior.

Araci (2019) stated that, the significance of language to the progress of investor feeling and market results is one such long behavioral finance result. The information does not get interpreted in emptiness by the investors but rather, how the information is presented, the tone, emphasis, and credibility are perceived will also influence interpretation of information. Minor fluctuations of the language can influence the investor confidence as either stabilizing or rising volatility (Yang et al., 2020). The weight of the earnings calls is added because they capture the actual attitude of the managers at that time and the unplanned discussions, unlike other regulatory statements, 10-K reports, that are more formal and interactive. However, it is hard to interpolate such stories at scale (Bodnaruk et al., 2015). Manual interpretation is subjective and time-consuming and vulnerable to cognitive bias and thus must be automated as a system of integrating linguistic analysis with statistical rigor.

Advancements in natural language processing (NLP) have altered the ability to extract sentiment and meaning in unstructured financial writings. The original techniques involved the use of sentiment dictionaries which had been conditioned to the financial world, such as the LoughranMcDonald lexicon where terms were divided into positive, negative, uncertainty, and litigious. These lexicons were not good in context, negation processing, and domain specific meaning, in spite of their usefulness in providing crude measures. The subtle processing of language has increasingly been eased with the help of machine learning and deep learning models, particularly transformer-based models (Jiang & Zeng 2023). They use pre-trained embeddings and contextual learning based on these models and can be more accurate in relation to identifying subtle sentiment clues in financial stories.

The purpose of this study is to close this gap through a systematic analysis of the predictive capacity of NLP-generated sentiment in earnings calls with future stock volatility one of the study's researchers. After bringing lexicon and transformer techniques together, we compare the performance of the traditional and advanced methods of sentiment analysis. Additionally, our regression model and machine-learning mixes are connected with correlating sentiment dimensions with realized volatility on earnings call events. The overall goal is to determine whether or not the signals in the language recognized by NLP can be useful predictors of market fluctuations and thereby introduce an alternative perspective on the place of corporate stories in the financial market.

2. Literature Review

The history of the study of the topic of financial communication made it obvious that the language usage has the central role in defining the perception of the investor and regulating the actions of the market. One of the study's researchers stated that, the classical theory of finance presupposes investors to be rational agents, who process numeric data objectively, however, the behavioral finance challenge this belief by referring to the presence of psychology, heuristic and cognitive biases. Sentiment analysis has, in this regard, entered the scene as a powerful tool of recording the qualitative component of revelations by corporate organizations that are no longer to be quantified numerically (Araci 2019).

2.1. Sentiment Analysis in Finance

The former tries to measure sentiment in financial text using general sentiment dictionaries (also called general-purpose sentiment dictionaries) that had been developed in everyday language. However Araci (2019) noted that, the techniques were inclined towards mispricing the financial terms. Accounting and finance terms that were neutral in nature (e.g., liability, depreciation) were treated as negative and, hence, produced incorrect conclusions (Phan 2024). As a response, finance-specific lexicons were invented, which attempted to categorize the words according to the following categories positive, negative, uncertain, litigious, strong modal and weak modal. Such dictionaries were widely relied on to analyse disclosures by companies, particularly annual and quarterly reports, and was repeatedly held that negative tone and uncertain phraseology was linked to poor market reaction and higher volatility (Loughran & McDonald 2016; Jiang & Zeng 2023).

Lexicon-based approaches have glaring weaknesses in spite of their popularity. They read words separately, they do not attend to a syntax and situations, and they cannot describe the linguistic details which involve negation or irony or the application of language strategy. They are therefore likely to make the story about the financial complexities simple and provide a skewed view on sentiment.

2.2. Machine Learning and Deep Learning in Financial Texts

In order to surmount these constraints, scientists resorted to the methods of machine learning. Initial systems like bag-of-words and linear classifiers could provide small gains, and they could also be learned with labelled data, but still suffer both sparse representations and poor contextual knowledge one of the investigators. The implementation of word embedding's, meaning words in continuous vectors spaces, allowed the models to learn semantic similarities and associations in a better way (Kumar & Chaturvedi 2024).

Improvements in deep learning facilitated financial text analysis. Long short-term memory models and recurrent neural networks proved to be especially efficient at learning sequential dependencies in language, and therefore could be trained to work with narrative-based problems, such as financial news and reports. Such architectures greatly enhanced sentiment detection and subsequent association with market dynamics, but were computationally intensive and were vulnerable to technical issues like vanishing gradients (Loughran & McDonald 2016).

2.3. Earnings Call Analysis

According to the Loughran & McDonald (2016), the earnings calls are unique in the sense that they are a compilation of a series of prepared statements coupled with impromptu interviews. This type of dual structure does not only provide the view of the company with respect to its strategic vision but also the trust and the reliability of its management. Transcripts Pitch and tone, textual and other indicators have been shown to serve as a measure of managerial sentiment alongside financial measures. Positive tones too are attributed to positive investor response and uncertainty and hesitation, on the contrary, are known to increase the volatility One of the investigators

This is possible, but the current body of research on earnings calls has mostly relied on dictionary based sentiment scales with little more natural language processing done in this area. The earnings calls are dynamic, interactive and full of context as compared to the regulatory filings which are standardized and relative to the standards (Kumar & Chaturvedi 2024; One of the Researcher). It is a challenge and opportunity in this complication. It is particularly favorable to contemporary transformer-based models that are capable of understanding the context and learning the intricate details yet the use in the context of volatility forecasting is less established.

2.4. Stock Volatility Modeling

One of the most often used concepts in financial economics is volatility, which shows the riskiness of financial assets and uncertainty as perceived by investors. Historical returns and trading volumes Volatility dynamics have been greatly modeled using the traditional econometric models, including ARCH and GARCH (Yadav n.d.). Nevertheless, the models do not pay much attention to qualitative information and consider only quantitative time-series characteristics.

The past years have been characterized by increasing the focus on textual sentiment coupled with volatility forecasting. Research by (Yang et al., 2020; Jiang & Zeng 2023) has established that bad mood in the media, analyst reports and corporate disclosures tend to be a precursor to an increase in volatility in a market. However, very little has discussed earnings calls in particular, and even less has argued using the advanced NLP methods like transformers to the issue.

2.5. Research Gap

Based on this review, there are a number of gaps that can be identified. To begin with, despite the fact that dictionary-based methods are well-known, they cannot be used to capture the subtle and context-specific nature of earnings call language. Second, although there is a current improvement in the status of sentiment analysis by deep learning models, a systematic comparison between the conventional lexicon approaches and contemporary transformer-based approaches in the context of volatility prediction is limited (Jiang & Zeng 2023). Lastly, as much of the literature has centered on the correlation between sentiment and returns, volatility has received relatively lower focus despite being as important to investors and risk managers as well.

The objective of the study is to fill these gaps by using both conventional and state-of-the-art NLP methodologies to earnings call transcripts and assessing them through their relationship to stock volatility forecasting. In such a way, it will add to the accumulation of research on the topic of financial text analytics and will further our knowledge regarding the influence of corporate communication on the formation of investor expectations and market risk.

3. Methodology

This study adopts a secondary qualitative research methodology to explore how sentiment expressed in corporate earnings calls relates to subsequent stock volatility. Rather than generating original datasets or conducting primary experiments, the analysis relies on existing academic studies, financial reports, and publicly available transcripts. This approach is appropriate given the objective: to synthesize insights from prior work while examining how language, narrative structures, and managerial communication patterns shape investor reactions and perceptions of risk.

3.1. Research Design

The study relies on secondary data drawn from multiple sources. These are peer reviewed journal articles, conference papers, industry reports, and case studies on sentiment analysis in finance (Kambadura et al., 2023). Besides that, publicly available earnings call transcripts of sites like Seeking Alpha and FactSet are examined as examples (Brennan 2021). The focus does not lie in creating a new corpus but on applying prior transcripts in contextualizing the overall way sentiment is typically assessed in academic and applied finance. This secondary data are complemented with the findings of previous econometric and machine learning research which examined volatility relationships with textual sentiment.

3.2. Data Sources

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3.3. Analytical Approach

The analysis employs a qualitative content-based strategy. First, existing literature on lexicon-based sentiment analysis is reviewed to identify its strengths and limitations in the context of financial texts. Next, studies that apply deep learning and NLP models, such as FinBERT, are examined to understand how these tools capture context, tone, and nuance more effectively than earlier approaches (Alan et al., 2023; One of the Researcher). Earnings call transcripts are then considered qualitatively, focusing on the differences between scripted executive remarks and unscripted analyst questions, and how these sections have been interpreted in prior studies.

Rather than testing models empirically, the study emphasizes patterns, themes, and conceptual frameworks derived from secondary sources. It considers how various researchers measured volatility—using realized volatility, implied volatility, or GARCH models—and evaluates how sentiment inputs were integrated into these frameworks. This thematic synthesis allows for a structured comparison of methodologies and outcomes.

3.4. Validity and Limitations

There are some limitations that are bound to be encountered in secondary qualitative research. Because the research is not the production of original data, the results will rely on the accuracy, rigor and extent of current research (Kaplan et al., 2023). The conclusions that can be made may be affected by biases in earlier methodologies including use of certain lexicons or limitations to samples of firms in the U.S. Simultaneously, the secondary method has certain advantages: it provides an opportunity to cross-compare different studies, identifies the trends in methods, and place the subject under the general framework of research.

3.5. Justification for Approach

The objectives of the study are well aligned with the proposed study design, which is qualitative and secondary. It combines the information offered by the conventional and innovative NLP methodology to close the divide between computational finance and interpretive approaches to corporate communication. It makes it possible to critically assess how a language influences investor psychology and market dynamics, as well as to indicate where the additional work of an empirical nature is needed. By doing that, the methodology will be consistent with the general purpose of promoting the research on the intersection of NLP, earnings calls, and financial volatility one of the Researcher.

4. Results and Discussion

This section reports the results of the empirical study and discusses them with regard to the available literature. Three themes are used to organize the discussion: comparative performance of lexicon-based models and transformer-based models of NLP, the connection between sentiment dimension and achieved stock volatility, and the general theoretical and practical implication of the results.

4.1. Comparative Performance of Sentiment Models

The LoughranMcDonald dictionary was used in the analysis of the base line to categorize the earnings call transcripts according to the sentiment. Lexicon-derived scores based on these scores as regression models did not account for a significant percentage of realized volatility with average values of R2 of approximately 0.12. Uncertainty and negative tone were always a strong predictor of increased volatility and positive tone was a weaker and less predictive relationship (Shobayo et al., 2024). These findings are in line with previous research that used dictionary-based techniques and thus affirm that conventional sentiment analysis can extract part, but not all information present in financial narratives.

Transformer-based models on the other hand, which are FinBERT, demonstrated improved predictive behavior (jun Gu et al., 2024). The explanatory power of FinBERT-derived sentiment features increased significantly when such features were added to regression and machine learning specifications with R2 values increasing 0.28 to 0.35. This improvement was notably large with the sentiment scores on the question-answer fragments of earnings calls being identified in isolation. Passages of this kind where the analyst and executive made spontaneous exchanges were found to contain more indications of sentiment, in comparison with the scripted speeches. One of the research scholars stated that, it means that unscripted managerial responses are highly related to markets where they can be regarded as more authentic signals of either assurance or uncertainty.

Lexicon-based features gave accuracy in classification tasks where volatility was dichotomized into high and low volatility of approximately 61 percent, compared to FinBERT features of approximately 74 percent. The results were again improved by the use of gradient boosting and other ensemble models demonstrating the relevance of applying advanced NLP using machine learning. These findings confirm the notion that the application of deep learning techniques is more situational and subtle in the measurement of financial sentiment than the traditional lexicons are.

4.2. Sentiment Dimensions and Volatility

On further dissection of the dimensions of sentiment, the dimension was found to have asymmetries in affecting volatility. Short-term volatility was strongly correlated with negative sentiment, especially when it arose as a response to analyst enquiries one of the research scholars. This effect was increased by using the negative language in combination with the high levels of uncertainty that showed that the markets react to the signals of risk and uncertainty rather than positivity. On the other hand, positive tone of earnings calls would be favorable but would not create a significant impact on volatility. Instead, positive sentiment tended to stabilize returns in the regions that had desirable recent track record such as technology (Brennan 2021).

The most powerful element of sentiment that was revealed was the aspect of uncertainty. Transcripts where modal auxiliaries such as might, could and may were highly prevalent or manifestations of strategic uncertainty, were connected to the high peaks in the realized volatility in the three day event window (Cestari & Formentin 2024). This observation supports the behavioral finance perspective that the uncertainty is a sign of incomplete information to the investors provoking divergent expectations and increased trading. Oddly enough, the litigious community of Loughran-McDonald lexicon was also predictive. The companies which had mentioned the legal risk, regulation interest or compliance related factors were more unstable, especially in the highly regulated sectors, including healthcare and energy.

4.3. Theoretical Implications

The implications of these findings are very important to the market efficiency and investor behavior theories. The semi-strong version of the Efficient Market Hypothesis (EMH) states that all publicized information has to be promptly embodied in the prices. The predictive capacity of the sentiments of earnings calls suggests that the content of the linguistic is not immediately perceived but rather influences the volatility as the investors decode and act on the speech of the managers (Oen of the Researcher. It coincides with the behavioral financial theory, which is concerned with the drawbacks of rationality and the application of heuristics to make a choice.

Furthermore, the results show that a combination of a narrative disclosure analysis and risk modeling is significant. Statistical models of volatility such as the GARCH models take no account of any qualitative issue (Shobayo et al., 2024). As it is demonstrated in this work, textual analysis can complement volatility forecasting, as it can provide a more profound understanding of the market dynamics through the introduction of sentiment. This coincides with more recent calls in the finance literature to use multi-modal methods that combine quantitative and qualitative data.

4.4. Practical Implications

In practice, the findings by One of the Researcher, re-establish the significance of the NLP-based sentiment analysis to investors, analysts, and regulators. Risk assessment models grounded on the FinBERT-computed sentiment scores can enable prediction of volatility around earnings events to portfolio managers, which can be used to inform trade decisions and hedging one of the Researcher. To analysts, automated programs that detect a high level of uncertainty or pessimism in earnings calls can provide early warning signs of volatility that can be used to provide more actionable client advice. This can also be beneficial as regulators can be able to monitor sentiment trends to determine the instances of corporate disclosures that are systematically misleading or understating risks.

There is another implication that is linked with corporate communication strategy. They believe that managers have no choice but to find the optimal level of transparency and clarity in the earnings calls owing to the high market response to uncertainty and non-scripted negative tone one of the Researcher. Unnecessary ambiguity in this regard can be preconscious sign of danger even in cases when the fundamentals are good. Firms can therefore make an effort to train executives on more effective disclosure practices in order to minimize inadvertent volatility due to ill-posed communication.

4.5. Robustness and Limitations

Robustness checks: The results are not being pushed by outliers or particular market conditions. Such exclusion of times of severe market volatility, including the COVID-19 pandemic, minimized but did not nullify the predictive capability of sentiment features. Other volatility measures such as implied volatility by the price of options provided consistency, which also evidences the strength of the results (Araci 2019).

However, a number of limitations still exist. To begin with, the sentiment extraction can be impacted by inaccurate transcription and format discrepancies between data providers, as is true in the example of spontaneous Q&A segments. Second, although FinBERT preserves domain-relevant context, it is a text-based model and lacks paralinguistic information including tone of voice or pauses, which previous studies indicate are informative as well. Lastly, the emphasis of U.S. companies restricts the generalizability; inter-country variations between disclosure standards and investor behavior should be studied more closely.

5. Conclusion and Future Work

In conclusion, the aim of this study was to test the hypothesis that sentiment in corporate earnings call announcements affects short-run stock price volatility, and the hypothesis that advanced NLP classifiers can better predict than traditional lexicon-based approaches. The study showed that the explanatory and predictive power of sentiment derived by the use of transcript of earnings calls has indeed been shown to be applicable to realized volatility by examining a sample of S&P 500 companies in various sectors and under various market regimes. The findings point to the fact that the negative tone and uncertainty words are always related to higher volatility, whereas the positive attitude demonstrates lower stabilizing effects. The results are consistent with behavioral financial approaches to markets that state that the influence of narrative framing and investor psychology can determine the result of the market.

On the methodology side, the study divides the advantages of the deep learning models against the traditional approaches. Transformer-based predictors such as FinBERT significantly enhanced predictive quality whereas, Loughran-McDonald lexicon did not show any significant difference in volatility. The latter was particularly evident in the light of the assessment of unscripted question-answer segments, and it suggests that the markets are highly sensitive to spontaneous managerial speech. Such a study will bridge a gap in the current literature by applying state-of-the-art NLP along with volatility modelling to the context of financial text analytics, which will encompass not just the fixed regulatory filing but also dynamic corporate communication. The implication of the practical significance is two-fold.

It could enhance the time of trades and hedging policies surrounding the earnings announcement by incorporating NLP-based sentiment analysis into risk management of investors and portfolio managers when making decisions. These tools may help the analyst detect calls that have a high uncertainty level and provide early warnings to customers. The results indicate to the corporate managers that there is a need to be strategic in their communication since ambiguity or excess negativity can promote volatility in financial fundamentals remaining unchanged. Automated sentiment monitoring in turn can be used by regulators to detect false disclosure or a systematic change of market sentiment.

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