Can Earnings Call Sentiment Predict Stock Price Movement?

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ABSTRACT
The quarterly earnings conference call is a popular avenue for corporate disclosure. The extent to which the market incorporates information contained in the sentiment (linguistic tone) of the conference call is still an active area of research. Using a Natural Language Processing technique called Sentiment Analysis, we extract the sentiment contained in earnings conference calls. We then build machine learning models using the extracted sentiment as features, to predict the direction of movement of stock prices post earnings announcement. We find that earnings call sentiment can predict the direction of stock price movement with a high degree of accuracy (73%). We also find that the predictive power of the earnings call sentiment is about the same as the predictive power of the actual EPS and revenue surprise numbers, used as proxies for earnings call content. The predictive power of earnings call sentiment was found to be robust to methodology, as an OLS regression also confirmed our finding that earnings call sentiment is a strong predictor of the percent change in stock price post earnings announcement.

Keywords
Earnings conference calls, sentiment analysis, content analysis

1 INTRODUCTION

Earnings conference calls have increasingly become a medium for dissemination of important relevant information to the market (Frankel, Mayew & Sun, 2010; Kimbrough, 2005). Typical earnings conference calls begin with prepared remarks by the management which is followed by a question answer session with analysts. The conversation between analysts and management is potentially full of rich information that can have an impact on subsequent stock price movement. Core (2001) suggests that it is possible to use techniques such as Natural Language Processing (NLP) to better understand how the linguistic content of the earnings call will impact stock price movement.

Content analysis and textual tone analysis have become increasingly used in corporate disclosure research in recent years. Many studies (e.g. Davis et al., 2008; Demers & Vega, 2008; Henry, 2008) have extracted the tone of the quarterly earnings press releases and related it to stock returns, stock volatility and other firm performance measures. Most of these textual analysis studies find that the linguistic tone of the disclosure is statistically significant, suggesting that relevant information is conveyed by managers in how they use language in their disclosures.

However, very few studies have examined the disclosures embedded in the language of the earnings conference calls. Managers face more constraints when communicating with investors through formal reports such as annual reports, earnings announcements, etc. (Li, 2008). Conference calls may be less subject to these types of restrictions and hence may provide a better setting in which to investigate the relationship between linguistic content and firm performance. In other words, quarterly earnings conference calls, by means of the unscripted question and answer dialogue between management and analysts, provide a richer setting in which one can more fully examine corporate disclosure and its relationship to stock price movement.

Most studies that examine corporate disclosures such as 10-Ks, earnings calls etc. use content analysis to extract tone, and other linguistic features from the disclosures and proceed to determine if there is a statistically significant relationship between the extracted linguistic information and some measure of market performance such as abnormal stock returns. We take a slightly different approach in our study and focus purely on how accurately we can predict stock price movement based on the sentiment extracted from earnings calls, rather than the statistical significance of the relationship between earnings call sentiment and stock price movement after controlling for numerous variables that may have an impact on stock price movement. This is more in line with a pure machine learning approach where prediction and accuracy of prediction are the primary concerns rather than statistical significance. We contend that a machine learning approach is more suited to practice. If one can accurately predict the post earnings call stock price movement based on the sentiment in the earnings call, irrespective of statistical significance, then trading strategies can be constructed to profit from the accurate prediction. An accurate prediction model would be more desirable from an industry and practical application standpoint. Thus, we choose to focus on accuracy of prediction rather than statistical significance. This is not to say that statistical significance of the relationship is not important; we have just chosen to look at the problem from a different angle than which is common in the literature. In fact, we do perform robustness checks to test the statistical significance of the earnings call sentiment as a predictor of stock price change post earnings announcement by running an ordinary least Squares regression.

To the best of our knowledge ours is among the first studies to take a machine learning based prediction approach to investigating whether earnings call sentiment can predict stock price movement. Thus, we contribute to the meagre literature on earnings call sentiment and its ability to predict stock price movement.

2 METHODS

Data

We obtained earnings call transcripts from Seeking Alpha for 1200 companies traded on the NASDAQ for the period 1/1/2017 to 9/6/2018. Since sentiment analysis is a resource intensive time consuming process, we chose the most recent 18 months of data to keep the size of the data, processing time and computing resources manageable. We had on an average about six quarterly earnings call transcripts per ticker in our data. We had 7520 quarterly earnings call transcripts in our sample with a mean of 304 sentences per transcript. We ended up with a large dataset of over 2 million sentences that we analyzed for sentiment. We also obtained the EPS surprise, revenue surprise, closing price on earnings announcement date, opening price on the next trading day for the 1200 companies from Bloomberg.

Data Preprocessing

The first step in our analysis was to preprocess and prepare the earnings call transcript data for sentiment analysis. We tokenized the earnings call transcript into sentences using the Natural Language Tool Kit (NLTK) library in Python. We then removed punctuations, numbers, stop words, and numerous other words such as welcome, participants, earnings call, etc. that have no impact on sentiment. After this data preprocessing step we were left with just over 2 million sentences.

Sentiment Analysis

We used the lexicon based approach to sentiment analysis, which uses dictionaries of words to identify sentiment in text. The Loughran-McDonald sentiment word lists are curated specifically for the finance domain and have been used extensively in prior literature and hence we have chosen to use the Loughran & McDonald (2011) dictionary in our study. We computed the sum and mean of the positive, negative and uncertain words by ticker and date. This resulted in six independent variables or four features in machine learning parlance.

Variables/Features

The dependent variable in our study is the direction of stock price movement post earnings announcement – a binary variable that denotes a negative price change as a 0 and a positive change as a 1. The main independent variables or the features that were used in our machine learning prediction models were the six sentiment measures described above in the sentiment analysis section. Since stock price movement post earnings announcement is impacted by the earnings call sentiment and the earnings call content we use the EPS surprise and revenue surprise variables as proxies to capture the effect of the call content and control for it in our statistical models.

Prediction Models

The goal of our prediction model was to accurately predict the direction of movement in the stock price based on the sentiment measures extracted from the earnings conference call transcripts. We used three popular classification models – random forest, support vector machines, logistic regression – that have been shown to have good performance. We trained the models using 75% percent of our data and tested them for out of sample accuracy on the remaining 25% of the data. We used a 10 fold cross validation to avoid overfitting.

Robustness Checks

We conducted robustness checks to assess whether our results are robust to change in methodology. The first test we performed was by fitting a simple Ordinary Least Squares (OLS) regression model using the mean sentiment variables as independent variables and EPS, revenue surprise as control variables in the regression. The dependent variable in the regression was the actual price change and not the binary direction variable we used in the classification models.

3 RESULTS

Table 1 shows the results of training various classification models to predict the direction of stock price movement using the earnings call sentiment features. We report the precision, recall and F1 score measures of accuracy. The F1 score is the harmonic mean of precision and recall and reaches its best value at 1 and worst value at 0 and provides a good balanced measure of accuracy taking into account both precision and recall.

Table 1 Classifier performance using sentiment features

Algorithm	Movement	Precision	Recall	F1-Score
Random Forest	Negative	0.75	0.71	0.73
	Positive	0.71	0.75	0.73
	Average	0.73	0.73	0.73
Support Vector Machine	Negative	0.66	0.67	0.67
	Positive	0.65	0.64	0.65
	Average	0.66	0.66	0.66
Logistic Regression	Negative	0.55	0.52	0.55
	Positive	0.54	0.59	0.55
	Average	0.55	0.55	0.55

The Logistic Regression provides a baseline model with an accuracy of around 55%. The Support Vector Machine model with a radial kernel improves on this baseline to achieve an accuracy of 66%. The Random Forest model is the best performing and reaches an accuracy of 73%. Thus, we are able to predict the direction of stock price movement (positive or negative) based on earnings call sentiment with a reasonably high accuracy of 73%.

We investigated what level of prediction accuracy we could attain if we just used the EPS/revenue surprise features in our machine learning models. We found that the prediction accuracy was roughly about the same at 73%. Thus we find that the predictive power of the earnings call sentiment is about the same as the predictive power of the actual EPS and revenue surprise numbers typically used as proxies for earnings call content. We then combined both the earnings call sentiment features and the EPS/revenue surprise features and found the accuracy to increase by 5% to 78%. Thus, using both sets of features does improve the predictive power, but, only marginally.

Table 2 shows the feature importance from the random forest model incorporating both sentiment and market surprise features. The EPS and revenue surprise were the top two and mean sentiments are next. But the weights of the sentiment features are not too far off from the surprise features, indicating that the sentiment features have nearly as much predictive power as the market surprise features.

Table 2 Feature Importance

Variable	Importance
Earnings surprise	0.173
Revenue surprise	0.156
Mean positive sentiment	0.128
Mean uncertain sentiment	0.119
Mean negative sentiment	0.116
Sum positive sentiment	0.106
Sum uncertain sentiment	0.092
Sum negative sentiment	0.090

We now describe the results of our robustness checks. Table 3 shows the results of the OLS regression. We find all the sentiment variables to be statistically significant ($p < 0.01$). The sign of the coefficients of the sentiment variables are also directionally correct with positive sentiment being associated with a positive price change and vice versa. The earnings surprise variable was not significant, while the revenue surprise variable was weakly significant ($p < 0.1$). Thus we find that earnings call sentiment is strongly associated with stock price change post earnings announcement.

Table 3 Robustness Check: OLS Regression

Mean positive sentiment	0.091 (0.0047)***
Mean negative sentiment	-0.123 (0.05)***
Mean uncertain sentiment	-0.007 (0.04)**
Earnings surprise	0.0006 (0.0004)
Revenue surprise	0.0012 (0.0002)*

4 DISCUSSION

The results presented above show that the sentiment extracted from earning calls have significant predictive power in predicting stock price movement post earnings announcement. The earnings call sentiment has similar predictive power as the market surprise (call content) measures. We were surprised by this finding as we were expecting the explicit market surprise measures to have greater predictive power in forecasting the direction of stock price movement. As we expected, combining both the sentiment features and the surprise features did increase our prediction accuracy. The findings were also robust to a change in methodology to a traditional regression analysis. Thus, our findings underscore the importance of the "soft" information contained in earnings conference calls. Our findings are in line with prior research that show that earnings call linguistic tone is a significant predictor of stock performance (Price, Doran, Peterson & Bliss, 2012; Doran, Peterson & Price, 2012; Jiang, Lee, Martin & Zhou, 2019). Thus, we contribute to the meagre literature on the predictive power of sentiment in earnings conference calls by confirming results found in prior literature using a different methodology and more recent data.

Our findings have practical implications. We have demonstrated that just sentiment alone can predict stock price movement with fairly high accuracy. Thus, stock traders and other market participants such as risk managers could utilize the rich sentiment information contained in earnings calls in their stock price forecasts. Trading strategies can also be constructed based on predictions from sentiment models such as ours.

5 CONCLUSION

This study extends the empirical corporate disclosure literature by examining the sentiment (tone) contained in quarterly earnings conference calls and the subsequent market reaction. In particular, we add to the meagre literature analyzing earnings calls sentiment. We employ the widely used Loughran-McDonald dictionary to quantify the sentiment in the earnings calls. We then build machine learning models to predict the direction of stock price movement based on the sentiment in the earnings calls. We find that the sentiment (linguistic tone) in the earnings call can predict stock price movement with a high level of accuracy (73%). We find that earnings call sentiment has the same predictive power as the actual earnings (EPS, revenue) surprise data. Our findings are robust to change in methodology. Thus, we conclude that the rich sentiment information in earnings calls should be exploited in stock price forecasts that are routinely used in trading and risk management.

6 REFERENCES

Core, J.E. (2001). A review of the empirical disclosure literature: discussion. *Journal of Accounting and Economics* 31, 441–456.

Davis, A.K., Piger, J.M., & Sedor, L.M. (2008). Beyond the numbers: managers' use of optimistic and pessimistic tone in earnings press releases. AAA 2008 Financial Accounting and Reporting Section (FARS) Paper.

Demers, E., & Vega, C. (2008). Soft information in earnings announcements: news or noise? Working paper, Federal Reserve Board.

Doran, J.S., Peterson, D.R., & Price, S.M. (2012). Earnings conference call content and stock price: the case of REITs. The *Journal of Real Estate Finance and Economics*, 45(2), pp.402-434

Frankel, R.M., Mayew, W.J., & Sun, Y. (2010). Do pennies matter? Investor relations consequences of small negative earnings surprises. *Review of Accounting Studies* 15, 220–242.

Henry, E. (2008). Are investors influenced by how earnings press releases are written? *The Journal of Business Communication* 45 (4), 363–407.

Jiang, F., Lee, J., Martin, X., & Zhou, G. (2019). Manager sentiment and stock returns. *Journal of Financial Economics*, 132(1), 126-149

Kimbrough, M.D. (2005). The effect of conference calls on analyst and market underreaction to earnings announcements. *The Accounting Review* 80, 189–219.

Li, F. (2008). Annual report readability, current earnings, and earnings persistence. *Journal of Accounting and Economics* 45, 221–247

Loughran, T., & McDonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *Journal of Finance* 66 (1), 35–65

Price, S.M., Doran, J.S., Peterson, D.R. & Bliss, B.A. (2012). Earnings conference calls and stock returns: The incremental informativeness of textual tone. *Journal of Banking & Finance*, 36(4), pp.992-1011