Sentiment in Big Tech's Investor Relations: Does the Discourse Predict Future Stock Movements?

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Abstract

Financial disclosures are crucial for understanding a firm's status and future performance. While previous research has focused on written disclosures like press releases and reports, these documents have limitations in that they are carefully crafted one-way communication from firms to the public. Our study explores the predictive possibility of communications during investor relations calls. These calls capture unscripted narratives from between firms' senior leadership and industry analysts. By examining the interplay between the tone of public questions and senior leadership's responses, we investigate to what extent this interaction predicts a firm's future performance. We find that average question sentiment has a persistent positive association with average stock price in the successive quarter, but answer sentiment was not a significant predictor. Our study offers a fresh perspective on financial disclosures and highlights the value of oral communications and their tones in gaining insights into firms' prospects.

Keywords: text mining, sentiment analysis, investor relations, stock returns.

1. Introduction

Financial disclosures provide both academia and industry with insights into a firm's status and expected future performance. As a result, there has been great interest in the research community in using analytics techniques to derive insights from financial disclosures. Most research in this area focuses on written disclosures, such as press releases (Wang et al., 2023) and 10-Q or 10-K reports (Loughran & McDonald, 2014; Loughran et al., 2009). These disclosures are mandated by law, and they provide snapshots of each firm's view of its own enterprise and expectations for future performance.

While previous analyses have unearthed noteworthy findings, these written forms of communication have several limitations. First, these forms of communication tend to be one-way; that is, they allow a firm to express its view of its position to the public, but they do not reflect the public's view on the firm's position. While a firm's business decisions certainly impact its future performance, the public's perception is also an important consideration in understanding the firm's future prospects. Public perceptions may be a window into expected demand for a firm's products or services, and effects on a firm's stock price are driven by public perception. Second, these written forms of communication allow each firm to craft exacting language, limiting the potential for potentially insightful informal or off-the-cuff remarks. In contrast, unplanned remarks may actually provide more honest insight on senior leadership's perspective.

As an alternative angle, our work instead focuses on oral communications. Each publicly traded firm in the United States is required by the Securities and Exchange Commission to report quarterly earnings no more than 35 days after the end of each fiscal quarter. These earnings reports are accompanied by earnings conference calls (ECC) with investors and industry analysts. ECCs serve several purposes: to describe the specific earnings figures that have just been released, which may have been above or below expectation; to discuss the firm's short-term and long-term strategic direction; and to answer questions. At the beginning of each ECC, the firm's senior leadership generally offers prepared remarks explaining the previous quarter's earnings and articulating their vision for future quarters. Afterward, investors and industry analysts are permitted to ask questions about the firm's plans. We focus our analysis on the question-and-answer session of each ECC. This session is of particular interest because it captures a snapshot of unrehearsed statements on the firm's future by investors and industry analysts (questions) as well as senior leadership (answers). In fact, firms may have dedicated "investor relations officers" or "chief disclosure officers" tasked with managing such disclosures (Brown et al., 2019).

Senior leaders of major firms have made several noteworthy statements in past ECCs. For example, during the COVID-19 pandemic, Tesla CEO Elon Musk referred to stay-at-home orders as "fascist" during one

URI: https://hdl.handle.net/10125/106512
978-0-9981331-7-1

such ECC (Nyberg & Murray, 2023). In 2023, Anheuser-Busch's CEO was asked to comment on a recent controversy over a transgender influencer appearing in a Bud Light advertisement. The interplay between the tone of the public's questions and the tone of senior leadership's response is of great research interest, and in this paper we seek to investigate to what extent it may be predictive of each firm's future performance.

In this paper, we extend particular focus to technology firms listed on the S&P 500 list. Question-and-answer sessions involving technology firms may be of particular interest as these firms may need to be particularly innovative to keep up with a fast-changing industry (Desyllas & Hughes, 2010). As such, discussions with industry analysts and investors may expose the tone of industry expectations relative to firms' confidence in their technologies. Prior research has found that technology firms extend particular attention to corporate social responsibility (Okafor et al., 2021), as this may be an expectation of the marketplace. Question-and-answer sessions may also illuminate the interplay between these expectations and firms' responses.

Our research objective is to collect historical ECC transcripts for major technology firms. Using the sentiment of question and answers in these transcripts, we seek to predict effects on firm stock performance in subsequent quarters. We evaluate this performance in two ways: predicting stock price directly, and predicting directional change in stock price (positive or negative).

In the following section, we describe related work on text analyses in financial contexts. Then, we describe the data collection process used to gather ECC transcripts. Next, we describe our text analysis and regression methodologies. Then, we present our empirical findings. Finally, we discuss our findings and conclude the paper.

2. Literature review

Prior studies have used text analyses to examine financial reports, news articles, social media content, and press releases to explain financial markets' outcomes. This approach has emerged as a novel method for comprehending investors' perceptions of top management and expectations for future performance within firms. Loughran & McDonald (2016) provide a survey on the application of text analysis methods in the finance domain. These past research works are largely not methodologically novel, but rather they demonstrate the application of text analysis in a new domain. For instance, pre-existing measures of readability, document similarity, and topic modeling have been applied to financial documents.

Numerous forms of financial documentation have been analyzed in previous research. For example, Loughran & McDonald (2014) analyzed the readability of 10-K disclosures. Ridge & Ingram (2017) found that investors' perceptions of modesty can elicit positive reactions, which in turn can affect firm performance. Rennekamp et al. (2022) identified language style matching as a powerful predictor of stock returns. Pollock et al. (2023) found that disparities in language style used by celebrity and non-celebrity CEOs. Moreover, research has utilized textual analysis to uncover personality markers in CEO speeches and examine their relationship with firms' performance (Brunzel, 2023; Harrison et al., 2019), selective hedging (Bajo et al., 2022), and merger and acquisitions processes (Aktas et al., 2016).

The sentiment expressed within textual data has also been a key focus of many of these analyses. Loughran & McDonald (2011) examined tone, litigious words, uncertainty words, and modal verbs embedded in 10-K disclosures. De Amicis et al. (2021) analyzed sentiment on conference calls to find differences between female and male executives. They found that female executives tended to speak in more positive and less vague language when compared to male executives and that overall positive disclosures correlated with stock returns. Similarly, Hu et al. (2021) identified a significant relationship between the net tone of earnings and market reaction. Groß-Klußmann et al. (2019) found a relationship between global sentiment and movements of the stock market through the analysis of Twitter data. Hajek & Munk (2023) demonstrated that sentiment and emotions embedded in 10-K disclosures can serve as predictors of firms' financial distress. Furthermore, Yamamoto et al. (2022) found that the tone of communications outperformed the smart betas approach as an investment strategy.

3. Data collection

We began our data collection by collecting a list of technology firms to analyze. As our research objectives require that each firm be publicly traded to assess stock price effects, we limited our analysis to firms listed on the S&P 500. After obtaining the list of S&P 500 firms, we limited our analysis to those firms with a GICS (Global Industry Classification Standard) sector of "Information Technology." In total, 66 firms were assigned to this sector. On average (median), each firm had been a member of the S&P 500 list for 15 (11) years.

Next, we obtained ECC transcripts for each firm dating from January 2006 to March 2023. In total, we obtained 4,918 transcripts of these ECCs. Our transcript dataset disambiguated each question and answer. Consolidating these datasets, we collected a total of

121,719 questions and 144,796 answers. In some cases, multiple senior leaders contributed to answering a single question, resulting in more answers than questions. Questions contained an average (median) of 53.6 (49) words and an average (median) of 3.4 (3) sentences. Answers contained an average (median) of 125.4 (93) words and an average (median) of 6.2 (5) sentences.

Finally, in addition to these transcripts, we also collected basic historical financial details about each firm. We collected each firm's earnings per share and average stock price for each quarter covered in our dataset. In addition, we also collected each firm's market capitalization.

4. Methodology

To assess the tone of the content expressed in each question-and-answer session, we measured the sentiment of each question or answer using the VADER (Valence Aware Dictionary and sEntiment Reasoner) sentiment library (Hutto & Gilbert, 2014). VADER has been employed in many contexts as a general-purpose sentiment tool, and independent analyses have found it to perform well relative to other sentiment tools (Ribeiro et al., 2016). Using the Python implementation of VADER, sentiment values are scaled from -1 to +1, where -1 represents the most negative sentiment and +1 represents the most positive sentiment. To represent the tone of the questions as a whole, we averaged the VADER scores of all questions in a transcript. Similarly, we represented the tone of answers by averaging the VADER scores of all answers in a transcript.

We found that both questions and answers were generally positive, but answers tended to be slightly more positive than questions. The distribution of answer sentiment also exhibited less variability than the distribution of question sentiment. Table 1 shows descriptive statistics on the transcript-level average VADER scores of questions and answers.

Table 1. Descriptive analysis of transcript-level average VADER sentiment scores.

Statistic	Questions	Answers
Maximum	0.99	0.99
Median	0.58	0.64
Average	0.57	0.64
Minimum	-0.23	0.13
Std. deviation	0.16	0.14

We aim to use regression modeling to predict the average stock price in the successive quarter using these sentiment scores. Thus, in addition to sentiment scores, we also consider several control variables.

First, to control for temporal effects, we consider the year and the quarter. If there are any long-term trends over time (for instance, a relative increase in the price of technology stocks in recent years), then this can be controlled for using the year variable. Seasonal effects within a year are modeled using the quarter variable. For example, if the end of each year is systematically particularly strong, then we might expect to see a positive coefficient for the quarter variable.

Second, to control for firm size, we consider each firm's market capitalization, which is defined as the market price of outstanding shares multiplied by the quantity of outstanding shares. We employ a common transformation suggested in the finance literature, logarithmically transforming the market capitalization of each firm (Aloosh & Ouzan, 2020).

Finally, we consider two measures of the firm's historical performance. One such measure is the firm's earnings per share. We expect earnings per share to be positively associated with stock price: all other factors being equal, firms with higher earnings per share are performing well financially. Another measure is the firm's average stock price from the previous quarter. Stock performance in subsequent quarters may anchor the expectations for performance in subsequent quarters.

For a given firm f and a given quarter in time t, we can formulate an ordinary least squares linear regression model to predict stock price as follows. The average stock price for firm f at a given quarter in time t is a function of the year and quarter at time t as well as the market capitalization, average answer sentiment, average question sentiment, earnings per share, and average stock price at time $t-1$ (that is, the previous quarter's average stock price; note for quarter 1, the previous quarter is quarter 4 of the year prior). Formally, we may express this relationship as follows.

$$Average\ stock\ price_{f,t} = \beta_0 + \beta_1 Year_{f,t} + \beta_2 Quarter_{f,t} + \beta_3 Log(Market\ cap)_{f,t-1} + \beta_4 Avg.answer\ sentiment_{f,t-1} + \beta_5 Avg.question\ sentiment_{f,t-1} + \beta_6 Earnings\ per\ share_{f,t-1} + \beta_7 Average\ stock\ price_{f,t-1} + \varepsilon$$

Another modeling strategy is to predict the change in stock price rather than its expected value directly. Per the example of prior work (Parray et al., 2020), we formulate this model as a logistic regression model predicting whether the stock price increased (1) or decreased (0) between quarter $t-1$ and quarter t. Formally, we express this model as follows.

$$Log(\frac{p}{1-p}) = \beta_0 + \beta_1 Year_{f,t} + \beta_2 Quarter_{f,t} + \beta_3 Log(Market\ cap)_{f,t-1} + \beta_4 Avg.answer\ sentiment_{f,t-1} + \beta_5 Avg.question\ sentiment_{f,t-1} + \beta_6 Earnings\ per\ share_{f,t-1} + \beta_7 Average\ stock\ price_{f,t-1}$$

In addition to a regression model including all available variables, we also consider stepwise regression models optimized for Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC).

5. Results

We display the results of our first set of regression models in Table 2. Each model is an ordinary least squares linear regression model predicting the average stock price in the quarter immediately following the relevant ECC. Model 1 is a stepwise regression model optimized for BIC; Model 2 is a stepwise regression model optimized for AIC; and Model 3 is a regression model containing all available variables. Significance at the 0.10 level is indicated by †; significance at the 0.05 level is indicated by *; and significance at the 0.01 level is indicated by **.

Table 2. Linear regression results.

Model property	Model 1	Model 2	Model 3
Intercept	-3.91**	-8.18**	-98.29
Year			0.04
Quarter			0.32
Log(market cap)		0.41	0.48†
Avg. answer sentiment			-2.82
Avg. question sentiment	10.65**	10.50**	10.97**
Earnings per share	1.32**	1.31**	1.28**
Previous stock price	1.00**	1.00**	1.00**
R^2	0.97	0.97	0.97
Adjusted R^2	0.97	0.97	0.97

All three models demonstrated excellent predictive performance, with R^2 and adjusted R^2 values of 0.97. Both the stepwise models and the full model seem to suggest the conclusion that the prediction is primarily driven by a few variables. Average question sentiment, earnings per share, and previous stock price were statistically significant at the 0.01 level in all models, and they were the only three variables selected in the BIC-optimized Model 1. The regression coefficients for these variables were relatively stable across all three models.

A noteworthy finding is that the average question sentiment was positively associated with the stock price in the following quarter. Given the stability of the regression coefficients, all three models suggest that an increase in average VADER sentiment of questions by 0.1 corresponds to over +$1 in change in stock price. Interestingly, the average answer sentiment variable was not selected in either stepwise regression model, and its term was not statistically significant in Model 3 (p-value = 0.28), which utilized all available variables. This result suggests that there is little predictive utility in the tone of the answers in question-and-answer sessions. It is somewhat surprising that the sign of the coefficient is negative, implying that a more positive tone is actually associated with decreased stock price. However, the size of the effect is relatively small (a 0.1 increase in sentiment in average VADER sentiment of answers corresponds to about -$0.28 in change in stock price), and the effect did not statistically significantly differ from zero.

The control variables included in the modeling had relatively small impacts. The year and quarter variables were not selected in either stepwise regression model, and their coefficients were not statistically significant in Model 3. Thus, there did not appear to be substantial long-term (year) or seasonal (quarter) effects. There is limited evidence for a market cap-related effect as the variable was selected in the AIC-optimized Model 2 and was significant at the 0.10 level in Model 3. The positive coefficients in both models suggest that firms with larger market capitalization are associated with greater stock prices.

We display the results of our second set of regression models in Table 3. Each model is a logistic regression model predicting the change in stock price (positive or negative) in the quarter immediately following the relevant ECC. Model 4 is a stepwise regression model optimized for BIC; Model 5 is a stepwise regression model optimized for AIC; and Model 6 is a regression model containing all available variables. Significance at the 0.10 level is indicated by †; significance at the 0.05 level is indicated by *; and significance at the 0.01 level is indicated by **.

The logistic regression results offer an interesting contrast to the linear regression results. Each model had a similar accuracy score of 0.67. Like the linear regression models, the prediction appeared to be driven by a few variables. Interestingly, in stepwise models, Model 4 and Model 5, the year and quarter were statistically significant, unlike in Model 1 and 2, which did not select these variables. Also unlike Model 1 and

Model 2, the earnings per share and previous stock price variables were not selected. However, the positive effect of the average VADER sentiment of questions was again present in the logistic regression models. Moreover, like the linear regression models, there was no significant effect observed for the average VADER sentiment of answers. Finally, like the linear regression models, the market capitalization variable was not selected in BIC-optimized Model 4, but it was selected in AIC-optimized Model 5 as well as in Model 6, which contained all available variables.

Table 3. Logistic regression results.

Model property	Model 4	Model 5	Model 6
Intercept	164.19*	158.9*	146.20*
Year	-0.08**	-0.08**	-0.07**
Quarter	-0.11**	-0.11**	-0.11**
Log(market cap)		0.08**	0.07*
Avg. answer sentiment			0.27
Avg. question sentiment	2.05**	2.01**	1.96**
Earnings per share			0.02
Previous stock price			-0.01
Accuracy	0.67	0.67	0.67

6. Discussion

Applying sentiment analysis on ECC narratives to predict stock prices carries significant theoretical and practical implications. Even though stock prices already reflect all available information in the market, sentiment analysis introduces the notion that sentiment embedded within ECC narratives can offer additional insights into stock price changes. Theoretically, our study contributes to the literature by applying sentiment analysis in this context and provides valuable insights into investor behavior. By examining the relationship between sentiments in the ECC narratives and stock prices, we can understand how emotions and reactions to earnings information influence investment decision-making. It uncovers the significant role of sentiment in shaping investors' perceptions and subsequent actions.

The practical implications of sentiment analysis on ECC narratives are equally noteworthy. First, it has the potential to inform investment decision-making processes significantly. Investors can gain valuable insights into the prevailing market sentiment surrounding a firm by analyzing sentiment in ECC narratives. This information can influence investors' buy or sell decisions, allowing for more data-driven and potentially promising investment market strategies. Furthermore, sentiment analysis helps in managing investment risks. By detecting negative sentiment in ECC narratives, especially by individuals inside the organization, investors can identify potential risks or challenges a firm may face. This information enables them to adjust their portfolios and mitigate risk accordingly, resulting in more effective risk management strategies.

Sentiment analysis can be integrated into automated algorithmic trading systems to leverage sentiment-embedded signals for making buying or selling decisions based on rapid short-term market inefficiencies or sentiment-driven stock price movements. This integration improves trading outcomes by profiting from market dynamics. Additionally, sentiment analysis can be embedded in event-driven trading strategies, allowing stock traders to monitor rapid real-time sentiment shifts in response to specific events or significant announcements. Embedding sentiment analysis in trading systems and strategies allows them to effectively mitigate market volatility and gain potential benefits from sentiment-based trading decisions.

Finally, sentiment analysis on text data, such as ECCs, provides market researchers and financial analysts valuable insights into how the market changes and reacts to events and announcements. Research has just begun analyzing news articles and social media's relationships with the stock market (e.g., Lin et al., 2022; Jaggi et al., 2021; Lei et al., 2020). Some researchers have developed advanced methods to combine audio and textual information to predict financial outcomes (e.g., Qin and Yang., 2019; Hajek and Munk, 2022). Our research contributes to identifying market trends and trading patterns influencing stock prices or broader market movements by analyzing sentiment across various firms or industries. This information aids market research, enabling more accurate predictions of investors' behaviors and informed investment decisions.

However, our research is subject to several limitations. One such limitation is that our research scope pertains only to technology firms. We cannot guarantee that our findings would generalize to firms in different industries, and indeed industry-level effects are an interesting route for future research to explore in greater detail.

Lastly, stock prices vary in relation to many factors, and sentiment should not be employed to predict stock prices alone. Other firm-level data, such as press releases (Wang et al., 2023) and 10-Q or 10-K reports (Loughran & McDonald, 2014; Loughran et al., 2009), could be used to supplement information from question-and-answer sessions. Moreover, sentiment analysis models may not fully capture the complexity of human emotions, and other factors such as financial indicators, market trends, and geopolitical events can also influence stock prices. Therefore, while sentiment analysis is a valuable tool, it should be part of a comprehensive investment strategy that considers multiple factors and indicators to make well-rounded and informed investment decisions.

7. Future research

This section highlights the course for our forthcoming research, building upon insights from the current study focused on the tonal dynamics of questions and answers in ECCs.

We first aim to dive further into the substantive content of questions and answers to broaden our analysis beyond tonal attributes. By implementing methodologies such as topic modeling, we will investigate whether specific topics within questions are or corresponding answers lead to significant market effects. Furthermore, investigating the potential dissonance between market perceptions and firm stances regarding financial performance forms a core facet of our upcoming research. Through a comparative examination of semantic networks inherent in market-generated questions and the responses offered by firms, we aim to identify potential discrepancies and discern their implications for the predictive accuracy of future financial performance assessments.

We also intend to investigate whether the connection between the tonal facets of questions and future financial performance varies depending upon the questioner's identity. This exploration includes distinctions between questioners who are investors versus those who are industry analysts.

In summary, our forthcoming research endeavors will encompass an in-depth exploration of the content within questions and answers, an analysis of potential discord between market perspectives and firm viewpoints, and an inquiry into moderating effects prompted by questioner identity. These pursuits collectively aim to enrich our comprehension of ECC interactions and their role in predicting future financial performance, thereby contributing to the evolving landscape of financial analysis.

8. Acknowledgements

This research was supported by the National Science Foundation (NSF) Award 2149133.

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