SCHOOL OF
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From Words to Value: The Relationship between CEO Letters and Financial Performance

Master's Thesis in Accounting and Finance

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Abstract

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Five key words: CEO letters, sentiment analysis, agency theory, firm performance, Tobin's Q.

Purpose: Discern with the help of a new machine learning model whether the sentiment expressed in CEO letters can offer meaningful insights into the firm's performance.

Methodology: The new algorithm FinBERT was used to collect sentiment scores, which were used as the main independent variables in this study. OLS Regressions with fixed effects were used. The dependent variables were ROA_{t+1}, $Tobin's\ Q_{t+1}$, ΔROA_{t+1}, and $\Delta Tobin's\ Q_{t+1}$.

Theoretical perspectives: The study draws from agency theory, information asymmetry, signaling theory, and prospect theory.

Empirical foundation: The study focuses on ten years of data from the FTSE 100, 2013 to 2022. The final sample consists of around 700 observations in the different regressions. Financial firms and companies whose letters were exceedingly long were excluded.

Conclusions: Negative sentiment in the CEO letter appears to negatively affect next year's *ROA* and *Tobin's Q*. For ΔROA_{t+1} and $\Delta Tobin's\ Q_{t+1}$, the *Negative* score has a positive relationship.

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1. Introduction

1.1 Background

Annual reports are released to the company's stakeholders to mitigate information asymmetry in the market (Naranjo, Saavedra & Verdi, 2013). They are a tool for assessing the company's management team, holding them accountable, and making business decisions (Corporate Finance Institute, n.d). However, many CEOs find it time-consuming and demanding to write annual and quarterly reports (Ekonomibyrån, 2024).

The CEO letter often takes place on the first pages of the annual report. This is an unregulated section of the annual report where the CEO can express their thoughts regarding the past financial year and give forecasts (Huang, 2014). It is unregulated in the sense that there are no criteria regarding what must be included in the letter (Liu, Hong & Yook, 2022). This can make the CEO letter useful when the company, for example, is facing a crisis, since the CEO's actions and messages impact the stakeholders to a great extent (Liu et al., 2022). The CEO letter contains accounting narratives that are perceived to be highly useful for stakeholders (Clatworthy & Jones, 2003). For instance, Clatworthy and Jones (2003) write that the chairman's letter or equivalent is read by forty-eight percent of the readership and is considered the second most valuable section in the annual report by private shareholders. This is supported by Costa, Oliveira, and Rodrigues (2013), who write that although the CEO letters are unregulated, they are one of the most-read parts of the report. However, Boudt and Thewissen (2019) assert that the prevailing discourse in management and accounting literature typically views CEO letters to shareholders as impression management tools, biasing the letter's sentiment to mold the shareholders' decisions. This attempt to sway stakeholders' thoughts creates the need to understand to what extent the sentiment is associated with firm performance and market valuation. If CEOs can affect shareholders' willingness to invest, the effectiveness of a CEO's communication skills could impact investment decisions. However, the findings of Boudt and Thewissen (2019) are inconclusive with those of Patelli and Pedrini (2013) regarding how reliable the CEO letters are. Hence, we aim to investigate how CEO communication within the annual letters impacts firm performance and market valuation.

Previous research examining the rhetorical tactics of corporate executives often assesses their communication style through manual content analysis due to the letter's unstructured nature, such as

Brühl and Kury (2019), who perform the analysis by assessing the letter qualitatively. Other studies employ an analysis with the help of a tool like DICTION, such as Nel, Arendse-Fourie, and Ontong (2022), who delve into whether a company's financial performance can be linked to the level of optimism conveyed in executives' written communication with stakeholders. Nel et al. (2022) used return on assets (ROA) to measure firms' financial performance. Tobin’s Q can be used to measure firm performance (Alshorman & Shanahan, 2020), but in comparison to ROA, Tobin's Q factors in the market’s valuation (Ademi & Klungseth, 2022). DICTION can compute an optimism score based on texts by using a dictionary that says if a word is positive, neutral, or negative. However, the emerging field of machine learning also offers assistance in deciphering intricate textual and numerical data. There are methods such as natural language processing (NLP) that utilize algorithms to analyze financial texts (Huang, Wang & Yang, 2023). The advent of machine learning algorithms has shown that analysis across various dimensions can now be conducted far more rapidly than human cognitive processes. One avenue that machine learning can be of use is when it comes to the analysis of annual reports and, more specifically, unstructured information such as CEO letters. This study answers the call from Che, Zu, and Li (2020), who write that future research could explore an economic model for financial performance and point to sentiment analysis as a tool to do so. While Che et al. (2020) also used machine learning to conduct their study, they did not use the same algorithm used in this study. In other words, the combination of this study's machine learning model and using it on CEO letters has not been explored previously, to the extent of our knowledge.

1.2 Problematization

The fact that the CEO letter is mainly unregulated and unaudited (Hooghiemstra, 2010) makes it a unique part of the annual report, where the CEO can write more freely than the other sections. However, this also opens up the possibility of impression management, which refers to the attempt to manipulate the impression that the information gives to financial stakeholders (Boudt & Thewissen, 2019). In turn, this can make it more difficult to make sound investment decisions, since the annual reports become less trustworthy if the CEO predominantly highlights the successes and shies away from the challenges that a company is facing, for example. This notion is underscored by Boudt and Thewissen (2019), who find that managers tend to present the CEO letter in a way that gives the reader a more positive picture of the company's situation. For example, Boudt and Thewissen (2019) find that negative words are often used more frequently at the beginning of the letter to then use more positive words as the letter progresses. There also appears to be a link between firms doing this and practices like earnings management (Boudt & Thewissen, 2019). Acts like these being performed in the official statements provided by the companies can excavate people's faith in the companies, regulators, and auditors. In addition, Huang (2014) writes that the CEO letter is one of the most understudied framing devices researchers can access.

The accessibility of machine learning techniques presents an opportunity to conduct thorough analyses swiftly, with high accuracy and consistency. We aim to harness this potential to perform comprehensive evaluations of CEO letters to shareholders, examining whether the tone of these communications accurately mirrors the firm's performance. Previously, conducting such a study would have been challenging without machine learning techniques' rapid and consistent evaluation capabilities. It can be argued that establishing a relationship between the tone of the CEO letter and the firm's actual performance holds value since it can show to what extent the CEO letters can be relied upon by the company's stakeholders. Furthermore, from a CEO's perspective, it can be beneficial to understand the market's reaction to the sentiment expressed in the CEO letter.

1.3 Purpose and research questions

This study explores the relationship between CEO letters to shareholders and the company's financial performance. CEOs wield considerable influence in shaping narratives that may deviate from reality in an environment where these letters are primarily unregulated and unaudited. Through a machine learning model, this study endeavors to discern whether the sentiment expressed in CEO letters can offer meaningful insights into the firm's performance. However, since writing CEO letters can be time-consuming, we are also interested in seeing if the market evaluates whether CEOs express a more positive tone in their letters. Thus, the primary objective is to examine the impact of CEO communication on the firm's financial trajectory and determine if the market values the tone of the CEO. To see how the expressed sentiment relates to the future outcome, we examine the next year’s ROA and Tobin’s Q. Hence, the research questions are formulated as:

RQ1: What is the relationship between sentiment scores and next year's ROA?

RQ2: What is the relationship between sentiment scores and next year's Tobin's Q?

1.4 Outline

In the first section of the report, an introduction was presented. A presentation of the relevant theoretical and empirical literature follows the introduction. In the third section, we develop hypotheses based on the presented literature. Section four presents the methodology and how the data was collected. The fifth section presents the results from the regressions, while the sixth section discusses these findings. The conclusion is presented in the seventh section. The references are listed in the eighth section, and finally, the Appendix is presented in the ninth section. The tables in the Appendix are denoted by letters instead of numbers to differentiate from the tables in the text.

2. Literature Review

2.1 Theoretical review

2.1.1 Agency theory

Bonazzi and Islam (2007) write that the agency theory views shareholders as principals and managers as agents who work on behalf of the principals. The problem that can arise is that the agent might not always act in the interest of the principals. For instance, the CEO can lie, obfuscate information, and make decisions that do not align with the shareholders' will. One way to address this issue is with CEO letters. CEO letters allow the CEOs to explain the decisions made and the plans and risks the organization faces. By releasing these letters, the information asymmetry between principals and agents can also be reduced. This is especially true since the CEO is the most essential person in a company's daily operations and should be almost as knowledgeable as one can be about a company. At the same time, the readers might not be knowledgeable at all about the company. Hence, the letter should be able to significantly decrease the information gap since the most knowledgeable person can explain the company's surroundings in simple language to those with much less knowledge. However, this ideal scenario might not necessarily play out, for instance, due to impression management.

2.1.2 Information asymmetries

The efficient market hypothesis suggests that all available information is priced into the financial markets and that all market actors are rational (Beechey, Gruen & Vickery, 2000). This would mean that all companies are valued in a way that aligns with their fundamentals. This theory presumes that the market is rational, that information is not ignored, and that no errors are made (Beechey et al., 2000). If this theory were to hold, it would be useless for the CEO to engage in impression management since all rational market actors could see through the charade. In other words, the efficient market hypothesis presumes no market inefficiencies and market asymmetries. Akerlof (1970) wrote that market asymmetries can have detrimental consequences for the market. In Akerlof's (1970) example, he uses sellers and buyers of cars to demonstrate. The seller has better knowledge of the car and can thus sell bad cars at the same price as good cars since the buyer cannot tell the difference. Akerlof (1970) explains that this will have vast effects on the market since it can reduce the amount of good cars on the market. The same logic applies to the stock market, but the ones with more knowledge are the executives in a company, and the ones with lesser knowledge are the investors. For instance, the executives can abuse their position through insider trading or withhold information the shareholders should know. If the market actors do this, the market becomes more asymmetrical and less efficient. The consequences for society are worse resource allocation and fewer people willing to participate in the market, which means less company investment capital. In addition, He, Lepone, and Leung (2006) highlight that the cost of capital is theorized to increase when the information asymmetry increases.

2.1.3 Signaling theory in CEO communication

Connelly, Certo, Ireland, and Reutzel (2011) define signaling theory as when a messenger must choose how to signal something to another party, called a receiver, who lacks information about the company but wants to know, and the receiver must then decide how to interpret that signal. In this scenario, the CEO can be considered the messenger, and the stakeholder (who is reading the CEO letter) can be regarded as the receiver of the signal. For example, by writing about the previous year's successes, the CEO can signal that he or she is competent and the right person for the job. Connelly et al. (2011) also talk about the cost of signaling, which means that there are forms of expenses associated with certain types of signals. For instance, CEOs pay a "cost" in the form of risks to their reputation when they disclose their predictions for the forthcoming year. In other words, signaling theory suggests that, on the one hand, CEOs want to signal that they are reliable and the right person for the job and hence want to exclaim their successes and plans. Still, on the other hand, they take a cost when doing so since it can come back to haunt them if their success does not pan out in the coming year.

Impression management can be argued to be a form of signaling since it is about how the CEOs can frame the CEO letter so that the readers' perception is affected. Nel et al. (2022) claim that impression management can be done by either emphasizing the positive performance or obfuscating the negative performance. Nel et al. (2022) elaborate by writing that the fact that obfuscation can be done, relies on the market inefficiencies, since otherwise everybody would know that the company is being dishonest in their communication. The root cause for the practice of impression management can be explained by the agency theory since the CEO is utilizing the asymmetries between shareholders and managers to escape the responsibility for one's performance (Nel et al., 2022).

Alshorman and Shanahan (2020) write that there seems to be a connection between the CEO's optimism level and the firm's market value. The study analyzed how often positive words were used in CEO letters compared to negative words. Alshorman and Shanahan (2020) reason that how optimistic the CEO is can affect firm factors such as debt policy and investing policies, which by extension, affect the performance of the company. Alshorman and Shanahan (2020) conclude that CEOs who are optimistic in their CEO letters reach better market valuations and profitability and that letters provide valuable insights into the business's operations instead of being a task in impression management on the financial stakeholders that read the annual reports.

Patelli and Pedrini (2013) write that Impression Management theory predicts that firms smokescreen their failures while highlighting their successes, to maintain credibility amongst their shareholders. Patelli and Pedrini find that the optimistic tone in the CEO letters aligns with past and future performance. The authors argue that since CEO letters are routine disclosures, the company and the CEO would lose legitimacy, rather than gain it if the CEO letters were consistently incongruent with the firm performance. Furthermore, the authors argue that it would be incorrect to assume that the task of writing the CEO letters is written by somebody else. The reason for this is that the stakeholders perceive what is in the letter as the actual thoughts of the CEO, and hence, the CEO would not release a letter without being comfortable with everything that is written. Previous studies have focused on primarily two features of the text when analyzing impression management, namely text readability and the frequency of positive words. However, Patelli and Pedrini use five variables to assess impression management: certainty, optimism, activity, realism, and commonality. The authors find a significant and positive relationship between optimism in the CEO letter and future performance and that the CEO letters are honest even during economic downturns. This evidence contradicts what is indicated by Boudt and Thewissen (2019) (Patelli & Pedrini, 2013).

Aerts (2005) points to the tendency to attribute positive outcomes to oneself often and adverse consequences to external events. For instance, Aerts (2005) finds that listed companies are more defensive in their communications, using justifications and excuses more frequently. Furthermore, Aerts (2005) writes that this defensive behavior does not increase when the company's financial performance is poor. This could stem from the excessive excuses and justifications making the management team look weak instead of in control. In addition, large companies do not engage in defensive behavior as much as smaller ones, likely because the larger corporations' reputations can protect them. Examples of impression management strategies are thematic manipulation, visual effects, rhetorical manipulation, and so on. Impression management is less likely to occur if the board has a higher degree of independence. One way that impression management can manifest itself in CEO letters is by unwarranted optimism.

Tourish, Craig, and Amernic (2010) write that the CEO's viewpoint influences everything that occurs within a company and that the CEO embodies the corporation. Furthermore, the legitimacy theory suggests that companies make voluntary disclosures like the CEO letter to enhance the company's legitimacy in the eyes of the shareholders. In the same vein, impression management may be done to maintain legitimacy (Jonäll & Rimmel, 2010). Jonäll and Rimmel (2010) expand by saying that the legitimacy theory is based on the idea of a social contract between companies and society, where the information from the companies is expected to be given in a specific way and that the CEO letter is crucial for companies since it allows them to provide context to other sections of the annual report.

2.1.4 Prospect theory

Kahneman and Tversky (1979) developed the prospect theory, which says humans often take an illogical approach to risk. The authors go through several examples where the respondents in the study take the safer option, albeit the expected utility is lesser. For instance, in one of the problems, the respondents get to choose between alternative A, a sure loss of 3000 $, or alternative B, a loss of 4000 $, with a chance of 20 % of not having to pay anything at all. The expected utility in the case of A would be -3000, while in the case of B, it would be $-4000 * 0.8 = -3200$ $. Despite alternative B having the worst expected utility, the respondents considered it the better choice. However, the respondents preferred the risk-free alternative when the example was dealing with a gain. In other words, Kahneman and Tversky (1979) show that humans reason about losses differently than gains. People seem to be risk-averse when dealing with potential gains but risk-seeking when dealing with potential losses. By knowing this, CEOs can frame their letters to the shareholders to play into the stakeholders' biases.

2.2 Empirical review

2.2.1 Early studies on sentiment

Tetlock (2007) studied how the media affected investor sentiment using the content analysis program General Inquirer, which could categorize words into different categories based on the General Inquirer's Harvard IV-4 psychosocial dictionary. Tetlock (2007) found that high levels of media pessimism in a company created downward pressure on the stock. He also concluded that a spike in the trading volume happened when either pessimism or optimism in the media around the stock was high. CEO letters are also a form of media communication, albeit different from news articles. However, considering how essential the CEO letters are to the investors, as was mentioned in the previous section, it can be argued that the CEO letters can have an even more significant effect on how the investors perceive the company.

Loughran and McDonald (2011) wrote one of the pioneering papers in classifying the sentimental tone of a financial text. They created the dictionary that is often used to analyze the sentiment of financial texts such as earnings calls or CEO letters. They analyzed over 50,000 10-K reports from 1994 to 2008 to generate this dictionary. They found that regular dictionaries did not capture the correct tone of the financial text and hence developed the Loughran-McDonald dictionary as an alternative.

2.2.2 Analysis of unstructured data

An NLP method like sentiment analysis can be used to make sense of text data, which is unstructured and, hence, more difficult to manage than numerical data (Chan & Chong, 2017). Fanelli, Misangyi, and Tosi (2009), who did a thematic text analysis on CEOs in the US with 367 observations, write that market actors such as analysts and the media consider the CEO's charisma level essential for shareholder wealth. This notion pressures the CEO to deliver a letter that portrays oneself as charismatic, in control, and competent. Fanelli et al. (2009) also write that since how the vision from the CEO is presented affects external parties, the letter to shareholders can have a significant effect on how easy it is for the company to obtain resources, which is a critical part to be able to do for a company to thrive.

Many previous studies on letters to shareholders, such as those by Brühl and Kury (2019) and Hooghiemstra (2010), were written before machine learning models were well-established in this area of research. Brühl and Kury (2019) conducted a manual content analysis, and the sample consisted of 50 letters from banks in the US and Europe. The study explored how rhetorical devices like accounts were used in CEO letters in the aftermath of the financial crisis of 2007 and 2008 to influence the reader's thoughts. They found that accounts, a linguistic device to explain the actual outcome compared to the expected result, are mainly used to evade responsibility judgments and that refusals can influence the perception of the company's situation. Brühl and Kury (2019) also find that companies attempt to influence the reader's view of the stability of the company when they give a future outlook. This finding from Brühl and Kury (2019) suggests that letters to shareholders are not entirely trustworthy. Hooghiemstra's (2010) sample for the content analysis consisted of 400 CEO letters from the US and Japan, which were coded manually. Hooghiemstra's (2010) findings were that US CEOs emphasize good news more than Japanese CEOs and that US CEOs are self-serving in their explanations. These results are relevant to this study since the United Kingdom is an Anglo-Saxon market like the US, so there might be similarities between the two.

The purpose of sentiment analysis is to identify the opinions and feelings present in a large subset of texts and do so quickly. If done quantitatively, the lexicon-based and machine-learning approaches are two primary methods to conduct sentiment analysis. The lexicon approach focuses on extracting individual words and hence requires a predefined word list, often done with a tool like DICTION. The disadvantage of the lexicon approach is that words have different meanings in different contexts, and hence, the tool is likely to draw the wrong conclusions from the text. On the other hand, the machine learning method can assess the context of the words in the text since it has been trained on plenty of similar data previously. (Che, Zu & Li, 2020).

Che et al. (2020) studied the relationship between CEO letters and firm performance with the help of sentiment analysis. To the extent of our knowledge, this is the only similar study to ours. The sample consisted of 41 companies on the Hong Kong stock market, and the method utilized several different approaches, one of them being Nvivo, a qualitative software tool used to assess CEO letters. This tool was used to do a thematic analysis of the CEO letters. They then used three different machine learning models, one of which was logistic regression, achieving an accuracy of 70.46 percent when predicting financial performance. In other words, Che et al. (2020) found a strong link between the sentimental tone in the CEO letter and financial performance. This would mean that if the sentiment in the letter is positive, the financial performance is more likely to be better, according to Che et al. (2020).

Alshorman and Shanahan (2020) conducted a study on optimism and CEO letters, using three different dictionaries: one called Diction_D, one called Diction_H, and Loughran & McDonald's dictionary. The sample consisted of 180 Australian firms between the years 2010 to 2013. Alshorman and Shanahan (2020) found that CEOs who are optimistic in their CEO letters reach better market valuations and profitability. CEOs therefore have an incentive to be more optimistic than they ought to be, creating an agency problem. However, other researchers have not found this problem between agent and principal. Nel et al. (2022) studied 400 CEO letters and chairman letters from companies in South Africa between 2016 and 2019 and used DICTION as the analysis tool. While Nel et al. (2022) find a negative relationship between the chairperson's optimism in the letter and future performance, this relationship is not significant in the case of the CEO's letter. In addition, Nel et al. (2022) find that the chairpersons are more likely to be insincere in their letters regarding the future outlook of the company. This finding may seem strange since the chairperson is often a large shareholder and, hence, a principal, and therefore, should do what is in the interest of the shareholders. Hadro, Klimczak, and Pauka (2017) also found that companies in Poland with many foreign owners are more likely to write positive letters regarding future outlook despite economic difficulties and regardless of actual performance. Hadro et al. (2017) conducted a manual content analysis with a sample of 120 letters between 2008 and 2013. Hadro et al. (2017) concluded that companies with a high industry risk are likelier to engage in this behavior. In contrast, insiders such as family members of the founder are less likely to engage in such behavior, according to Hadro et al. (2017). Zhang and Wiersema (2021) also write that actions taken by the CEO, such as introducing a new policy, are considered favorable by the investors even if the action is not implemented later. This arguably incentivizes CEOs to write things in the CEO letter that nothing will come of later. Furthermore, Tailab, BenYoussef, and Al-Okaily (2023) find that firm performance can only be attributed to one-quarter of the positive words in the CEO letter, while three-quarters of the positive words can be attributed to the CEO's narcissistic traits. Tailab et al. (2023) also write that large firms tend to hire highly narcissistic leaders, and all firms on the FTSE 100 are undoubtedly large. Tailab et al. (2023) used a sample of 848 observations between 2010 and 2019, and the software used was WarpPLS.

2.2.3 Recent advancements in NLP

Mućko (2021) defines sentiment analysis as determining an author's emotions based on a given text and deciding if the text is positive, neutral, or negative. It has been commonly used to analyze press releases, news articles, and social media sentiment.

One example of a new sentiment analysis model is FinBERT, which is based on the BERT model but focuses on financial texts instead, developed by Huang et al. (2023). FinBERT has been trained on over 60,000 annual reports, over 140,000 quarterly reports, and many financial analyst reports (Huang et al., 2023). FinBERT originates from a model called Bidirectional Encoder Representations from Transformers (BERT), which Google developed (Huang et al., 2023). Models like these are publicly available on websites like Huggingface.co (Kirtac & Germano, 2024). Kirtac and Germano (2024) examined 965 375 financial news articles in the US between 2010 and 2023 and studied how machine learning models like BERT and FinBERT compare to the Loughran-McDonald dictionary (2011), and found that the machine learning models significantly outperform the Loughran-McDonald dictionary model when forecasting stock returns based on the provided news articles. Kirtac and Germano (2024) found that FinBERT created a long-short portfolio that achieved a stock return of 165 percent based on the sentiment it could perceive from the news it was given. Furthermore, Yang, Siy, and Huang (2020), who made a study on how FinBERT was made, underline that FinBERT outperforms the BERT model when it comes to scoring the sentiment of financial texts. Yang et al. (2020) also write that FinBERT can do significantly more than classifying sentiments in financial communication, such as predicting fraud and stock volatilities.

Another study that utilized sentiment analysis on annual reports was conducted by Bilinski (2024), who investigated whether ChatGPT-4 can be used to analyze annual reports. The sample consisted of companies from the FTSE 100, focusing on 2015 to 2022, amassing 304 total observations. Bilinski (2024) utilized ChatGPT-4 to conduct the sentiment analysis. The chatbot was given the entire report but was told to examine only the chairman's letter, performance highlights, and the corporate governance section. The paper uses ChatGPT to generate complexity scores and sentiment scores, which are used to predict how the stock will react to the release of the annual report. The study finds that sentiment scores generated by ChatGPT, related to the chairman's letters to shareholders, have a positive, statistically significant effect on the following year's ROA. It was also found that the sentiment score has a negative relationship with mean stock turnover and stock return volatility. Bilinski (2024) defines sentiments as the tone and depending on whether the tone is more positive or negative, it gets a higher sentiment score compared to a completely neutral text. The author suggests that future studies could examine other financial texts.

3. Hypothesis development

In this section, hypotheses for the research questions are synthesized based on the literature presented in the previous section. When reasoning about what sentiment scores can reveal about next year's ROA, one would think, from an agency theory perspective, that no relationship can be seen between the two. This is because the CEO likely has incentives to present an overly optimistic perspective of the company's position for personal gain. Hence, agency theory predicts that the sentiment score has no relationship with next year's ROA. The same goes for the information asymmetry theory. Signaling theory would predict no relationship between the sentiment scores and next year's ROA since the CEO wants to signal his or her competence and ability and hence is incentivized to exaggerate the coming year's prospects in the letter. Signaling theory would also predict that there is a relationship between the sentiment scores and next year's ROA, since while the CEO wants to signal his or her competence and ability, it would backfire if the CEO is overly optimistic for years since the signal would then be to the receives that the CEO is not predicting things correctly. Thus, signaling theory predicts no relationship between sentiment scores and ROA. Due to the reasoning around these theories, the hypotheses for ROA and ΔROA are formulated as follows:

H1: There is no relationship between sentiment scores and next year's ROA.

H2: There is no relationship between sentiment scores and growth in profitability.

Agency theory predicts a relationship between sentiment scores and *Tobin's Q* since the principals likely do not have oversight over everything that occurs within the company and, therefore, must take the agent's word. Hence they are likely to buy stocks if the CEO letter is positive. Impression management also says that *Tobin's Q* would increase for the same reason. Prospect theory predicts a strong negative relationship between negative score and firm performance since prospect theory says that people are more scared of losses than they like profit. Hence, market actors are likely to overreact to negative sentiments and react less to positive sentiments than they do to negative sentiments. Therefore, prospect theory predicts that both *Positive* and *Negative* scores have a significant relationship, albeit the *Negative* score has a stronger relationship. Hence, signaling theory predicts that there is a relationship between sentiment scores and next year's *Tobin's Q*. This leads to the following hypotheses for *RQ2*:

H3: There is a relationship between sentiment scores and next year's Tobin's Q.

H4: There is a relationship between sentiment scores and growth in market valuation.

4. Methodology and data

4.1 Research design

Investigating the relationship between sentiment and financial performance and market valuation, respectively, demands a regression analysis to be conducted. Panel data and fixed effects were chosen since we wanted to observe the relationship over time (Stathelp, n.d.). Scharkov (2017) writes that using an algorithm as a study's method can be beneficial since an algorithm does not tire, make random mistakes, or get bored. Scharkov (2017) also writes that automatic content analysis is the only option if one wants to use a large dataset. It is significantly easier to reproduce if given the same software and material to analyze compared to reproducing a manual content analysis. The FinBERT model is used to collect sentiment scores. Furthermore, we include several control and dummy variables, which are in line with prior research and are defined in section 4.6.3. We chose an OLS regression since it makes it straightforward to interpret the relationships between the dependent and independent variables, and it is consistent with previous literature, such as Kirtac and Germano (2022). In our main approach, we use fixed effects, since we are using panel data and want to control for unobservables. We implement this using the statistical software program STATA.

4.2 Regression model description

The regression models in this study are as follows:

Equation 1: ROA_{t+1}

$$\begin{aligned} ROA_{t+1} = \alpha &+ \beta_1 Positive\ score + \beta_2 Neutral\ score + \beta_3 Negative\ score + \beta_4 Sentiments \\ &+ \beta_5 Board\ Size + \beta_6 CEO\ Board\ Member + \beta_7 Chairman\ Duality \\ &+ \beta_8 \lg\ (Total\ Assets) + \beta_9 Leverage + \beta_{10} R\&D + \beta_{11} Cash\ Holdings \\ &+ \beta_{12} Negative\ score^2 + \beta_{13}(Negative * Board\ Member) + \varepsilon \end{aligned}$$

Equation 2: Tobin's Q_{t+1}

$$\begin{aligned} \lg(Tobin's\ Q_{t+1}) = \alpha &+ \beta_1 Positive\ score + \beta_2 Neutral\ score + \beta_3 Negative\ score \\ &+ \beta_4 Sentiments + \beta_5 Board\ Size + \beta_6 CEO\ Board\ Member \\ &+ \beta_7 Chairman\ Duality + \beta_8 \lg\ (Total\ Assets) + \beta_9 Leverage + \beta_{10} R\&D \\ &+ \beta_{11} Cash\ Holdings + \beta_{12} Negative\ score^2 + \beta_{13}(Negative * Board\ Member) \\ &+ \varepsilon \end{aligned}$$

Equation 3: ΔROA_{t+1}

$$\begin{aligned}\Delta ROA_{t+1} = \alpha &+ \beta_1 Positive\ score + \beta_2 Neutral\ score + \beta_3 Negative\ score + \beta_4 Sentiments \\ &+ \beta_5 Board\ Size + \beta_6 CEO\ Board\ Member + \beta_7 Chairman\ Duality \\ &+ \beta_8 \lg\,(Total\ Assets) + \beta_9 Leverage + \beta_{10} R\&D + \beta_{11} Cash\ Holdings \\ &+ \beta_{12} Negative\ score^2 + \beta_{13}(Negative * Board\ member) + \varepsilon\end{aligned}$$

Equation 4: ΔTobin's Q_{t+1}

$$\begin{aligned}\lg(\Delta Tobin's\ Q_{t+1}) = \alpha &+ \beta_1 Positive\ score + \beta_2 Neutral\ score + \beta_3 Negative\ score \\ &+ \beta_4 Sentiments + \beta_5 Board\ Size + \beta_6 CEO\ Board\ Member \\ &+ \beta_7 Chairman\ Duality + \beta_8 \lg\,(Total\ Assets) + \beta_9 Leverage + \beta_{10} R\&D \\ &+ \beta_{11} Cash\ Holdings + \beta_{12} Negative\ score^2 + \beta_{13}(Negative * Board\ Member) \\ &+ \varepsilon\end{aligned}$$

4.3 FinBERT Model

The FinBERT model developed by Huang et al. (2023) is specifically trained on financial communication texts, encompassing corporate reports (10-K & 10-Q), earnings call transcripts, and analyst reports, with a vast training set comprising 4.9 billion tokens (Huang et al., 2023). A token is a part of a text that has been broken down into smaller parts, like words or symbols, through the process of tokenization (Menzli, 2023). We utilize the transformers library to integrate the pre-trained FinBERT model into our analysis pipeline, facilitating the monitoring process of sentiment in the letters. The output displays sentiment scores categorized as *Positive*, *Neutral*, or *Negative*, accompanied by confidence scores indicating the model's certainty in its interpretation. To set up the model, we leveraged ChatGPT-3.5 to create the Python code, allowing us to run the FinBERT model locally. The code contains PyPDF2 to extract text from PDF documents, accelerating input processing within Python. However, due to the FinBERT model's token limit of 512 tokens per analysis, CEO letters must be segmented into manageable chunks. Our Python script splits the text to achieve this, ensuring chunks end at appropriate word boundaries and adhere to the token limit, inspired by ChatGPT recommendations. Notably, the FinBERT model's text-clearing process eliminates special characters, such as dots and commas, enhancing analysis efficiency and speed.

Drawing upon Bilinski's (2024) utilization of ChatGPT-4 to assess sentiment and complexity metrics within companies' annual reports, we contemplated letting ChatGPT-4 assess the sentiment in our investigation. However, besides the constraints highlighted in Bilinski's research, we observed an inherent inconsistency in ChatGPT-4's responses. Despite our efforts to provide varying instructions, ranging from concise to detailed, enabling and disabling web browsing and specifying desired output ranges, ChatGPT-4 yielded differing outcomes when tasked with replicating a previous analysis. This inconsistency undermines the reliability and validity of using ChatGPT-4 as a methodological approach. In addition, ChatGPT tends to “hallucinate”, meaning that the chatbot generates fabricated data (Alkaissi & McFarlane, 2023). Consequently, we determined that ChatGPT-4 was not a suitable choice to assess the sentiment of the letters, as its lack of consistency could significantly impact the integrity of our research findings.

4.4 Collection of data

Before conducting a linear regression analysis, we preprocess the data pertaining to the main independent variables. To gauge sentiment, we extract CEO letters from annual reports and subject them to analysis using a pre-trained FinBERT model introduced by Huang et al. (2023). Notably, their comparative study revealed that the FinBERT model surpasses earlier NLP algorithms in terms of accuracy, rendering it the optimal choice for our research.

4.5 Sample description

All data originates from the annual reports. The sentiment scores are retrieved from the CEO letters in the annual reports. At the same time, the accounting data, such as R&D expenses and ROA, are collected from Refinitiv Eikon.

Our study focuses on companies listed on the Financial Times Stock Exchange 100 index (FTSE 100), which consists of the hundred largest companies on the London Stock Exchange by market capitalization. The covered time period is a decade, from 2013 to 2022. FTSE 100 was elected since it has been researched in many previous papers, but with different methods, such as by Bilinski (2024); hence, our findings can be compared to those. In addition, the FTSE 100 is a highly influential index worldwide; thus, the CEO letters reach many stakeholders. Hence, it is of the essence for these stakeholders that the CEO letters are truthful. Observations in the study were excluded if the company did not publish a CEO letter for a specific year due to a change in the CEO role, the annual report not being available for some particular year, or the CEO letter was overtly long, such as 25 pages or over. In comparison, most others are 2-4 pages long. The sample contains 906 observations. The most prominent industry of these observations is consumer cyclicals, which comprise 21.9 percent of the sample. The second largest industry is industrials, which comprises

18.9 percent, and the third largest is consumer non-cyclicals, which comprises 16.33 percent. The chosen period covers a broad range of economic cycles. It started after the recovery from the financial crisis of 2007/2008 and includes the Brexit period and the Covid-19 pandemic. This period means that the CEOs wrote their letters in completely different macroeconomic environments during the period, which means there is likely to be a broader range of responses in their communication and that one can infer more significant trends for the companies in the FTSE 100 rather than being limited to a trend that only lasted a year or two. Following quantitative research standards within accounting and finance, we exclude the finance industry due to the inflated accounting numbers that financial companies often have compared to companies in other sectors. This also aligns with Che et al. (2020), who analyzed CEO letters and how they relate to financial performance and excluded financial firms from the sample.

4.6 Variable definition

4.6.1 Dependent variables

Our study uses ROA to measure firm performance. As defined in previous studies, ROA is an accounting-based performance measure widely used as a proxy for firm performance (Jardak & Hamad, 2023). In this case, ROA shows to what extent the CEO letter sentiment is connected to the firm's performance. To capture the effect that the sentimental tone in CEO letters has on the market, we use Tobin's Q as a measure. Tobin's Q can be defined as a market measure of profitability, and it is calculated as a ratio of the market value of assets divided by the book value (Moursli, 2020). The market value of assets is defined as the company's market capitalization and total debt. Market capitalization is the number of outstanding shares multiplied by the price per share by the end of the fiscal year. The literature supports the use of Tobin's Q as a market measure. For instance, Alshorman and Shanahan (2020) use Tobin's Q as a dependent variable to incorporate all possible aspects of firm performance. Tobin's Q is a broad measure that even incorporates intangible assets, and hence can be argued to be more comprehensive than stock returns (Alshorman & Shanahan, 2020). In addition, Tobin's Q is advantageous since it blends information from the capital market as well as accounting numbers, hence providing a holistic view of the valuation of the company (Alshorman & Shanahan, 2020). Further, the measure adjusts for risk, is not as influenced by taxes as other measures, and accounts for future profits, which makes it a forward-looking measure for performance (Alshorman & Shanahan, 2020).

By incorporating lagged effects of +1 year for ROA and Tobin's Q, we can capture the potential impact of the CEO's signaling and the market's sentiment towards the tone. Furthermore, in line with previous research (Bilinski, 2024), we use ΔROA and ΔTobin's Q to capture the growth of the company's profitability.

4.6.2 Main explanatory variables

The primary explanatory variable is the sentiment scores, which is the number of positive, neutral, and negative chunks in the CEO letters multiplied by the accuracy of the model's interpretation of the scores. The lexicon stems from the training data used by the researchers who developed FinBERT.

4.6.3 Control variables

We use control variables focusing on directors in the firms, consisting of *board size*, a dummy variable that checks whether the CEO is a board member, and a dummy variable that checks whether the CEO is the chairman as well. In our initial sample, 94% of the CEOs were also board members. When the CEO serves as a director on the board or holds the position of chairman, this may influence the tone, as the CEO may have a different perspective in that case. Additionally, if the board size is smaller, the CEO director might have more power to influence and present a more biased tone. Following McClelland (2010), we include the length of the CEO letter, defined as the sum of the number of positive, neutral, and negative chunks, to reduce the impact a long CEO letter will have on the results, since a CEO might inflate the CEO letter with positive sentiment if they can write a longer letter. Therefore, we created a dummy variable called *Sentiments*, taking the value of 1 if it is greater than 50 and 0 otherwise. Figure 1 presents a histogram of *Sentiments*' values after winsorization. By examining the histogram, we conclude that a value around 50 seems to be where outliers start to appear. We also incorporate firm-specific controls, following Moursli (2020), using *Leverage*, which is defined as the company's long-term debt, and scaling it by its total assets. *R&D* is a dummy variable, taking the value of 1 if the company has research and development costs and 0 otherwise, and we also include *Total Assets*. Alshorman & Shanahan (2021) conducted a similar study to ours, and all their models indicated that cash holdings were highly statistically significant. As a result, we decided to include *Cash Holdings* as a control variable to mitigate omitted variable bias.

4.7 Summary statistics and univariate analysis

In Table 1, summary statistics of the initial data are presented. We observe that some variables appear to have extreme values or outliers. For instance, the *Neutral* score has a maximum value of 1560.62, much higher than the *Positive* or *Negative* score, possibly indicating an observation that was included by mistake. However, as the statistics show, we note that our main explanatory variables' mean and median values are *Positive* > *Neutral* > *Negative*. This aligns with our initial hypothesis, suggesting that CEOs attempt to portray a positive image of the company to its stakeholders. Additionally, *Total Assets* have large extreme values, and some variables are slightly skewed to the right. To address this, we employ winsorization at the 1% and 99% levels for the main explanatory variables, dependent variables, and *Leverage*, a common standard procedure in the accounting and finance research field. Due to skewness, we also logarithmize *Total Assets* to get a more normally distributed variable.

Table 1 – Summary statistics of the raw data

Variables	Mean	Median	SD	Min	Max	N
ROA	.08	.05	0.22	-.23	2.37	905
Tobin's Q	2.4	1.37	5.94	.14	79.04	887
ΔROA	0	0	0.09	-1.29	.56	809
ΔTobin's Q	-.03	0	1.94	-21.62	27.31	791
Positive Score	25.11	21.35	19.28	0	360.73	906
Neutral Score	7.2	3.33	52.65	0	1560.62	906
Negative Score	2.15	1	4.49	0	84.75	906
Sentiments (dummy)	.13	0	0.33	0	1	906
Board Size	10.56	10	2.30	4	21	886
CEO Board Member (dummy)	.98	1	0.14	0	1	868
Chairman Duality (dummy)	.03	0	0.16	0	1	886
Total Assets (GBP)	1.130e+11	1.050e+10	3.44e+11	43151000	3.040e+12	906
Leverage	.35	.34	0.18	0	1.03	774
R&D (dummy)	.2	0	0.40	0	1	906
Cash Holdnings (GBP)	94055697	523.5	1.38e+09	.7	2.110e+10	860

Table 2 presents summary statistics for the winsorized and logarithmized variables. As can be seen, the main explanatory variables appear more symmetric and exhibit fewer extreme values. The median ROA_{+1} for the sample is 5 %. It can also be seen that the CEOs emphasize optimism in the letter, since the mean of the *Positive* score was 24.66, while the mean for the *Negative* score was 1.95. The initial dataset contains 906 observations for the sentiment scores. The number of observations decreased from 1000 to 906 due to CEO letters not being published or being too long in some instances. Furthermore, this number decreased to around 711 in the first regression model with

ROA_{+1} as the dependent variable, 695 in the second regression model with *Tobin's* Q_{t+1} as the dependent variable, 711 using ΔROA_{t+1} as the dependent variable, and 678 using Δ*Tobin's* Q_{t+1} as the dependent variable. The decrease in observations is primarily due to missing values in accounting data.

Table 2 – Summary statistics of the processed data

Variables	Mean	Median	SD	Min	Max	N
ROA	.07	.05	0.11	-.13	.85	905
log(Tobin's Q)	.47	.31	0.61	-.34	3.74	887
ΔROA	0	0	0.06	-.25	.26	809
Δlog(Tobin's Q)	-.01	0	0.19	-1.7	.79	791
Positive Score	24.66	21.35	14.82	1.85	94.85	906
Neutral Score	5.15	3.33	6.29	0	40.97	906
Negative Score	1.95	1	2.58	0	13.95	906
Sentiments (dummy)	.13	0	0.33	0	1	906
Board Size	10.56	10	2.30	4	21	886
CEO Board Member (dummy)	.98	1	0.14	0	1	868
Chairman Duality (dummy)	.03	0	0.16	0	1	886
log(TotalAssets)	9.63	9.26	1.89	5.08	14.68	906
Leverage	.35	.34	0.18	0	.95	774
R&D (dummy)	.2	0	0.40	0	1	906
Cash Holdnings (million GBP)	2552.7	523.5	5748.08	5.9	34900	860

Diving deeper into our first dependent variable, ROA_{t+1}, we observed from Table 2 that it has a minimum value of -23% and a maximum value of +237%. This is an extensive range, and considering our sample selection (FTSE 100), it seems relatively unusual that a top 100 company would have a 237% ROA. Looking deeper into our dataset, we see that one tech company has a ROA of this magnitude. It had a ROA between 85% and 237% for 2013-2022. The company with the highest ROA after this tech company has an ROA of 67%. In our research, we consider this sort of ROA as an outlier. We also find some outliers at the lower end and winsorize to minimize their effect.

Turning to our second dependent variable, *Tobin's* Q_{t+1}, we see in Table 1 that the mean is 2.4 and the median is 1.37, indicating a right-skewed sample. However, the standard deviation of 5.94 is extremely high, which can be due to the extensive range of values, with a minimum value of 0.14 and a maximum value of 79.04. Because of this extreme standard deviation, it is logical to logarithmize *Tobin's* Q_{t+1} to achieve a more normal distribution.

The third dependent variable, ΔROA_{t+1}, ranges from a minimum value of -129% to a maximum value of +56% in Table 2, reflecting significant year-on-year changes in *ROA*. These extremes appear quite drastic compared to the mean and median, which both are 0 %. Hence, we will employ winsorization to mitigate the influence of these extreme values. *ΔTobin's* Q_{t+1}, the fourth dependent variable, has a mean of -0.03 and a median of 0 in Table 1. The variable appears to be relatively normally distributed, with a minimum value of -21.62 and a maximum value of +27.31. However, these values may be considered extreme. A change of +27.31 implies that the market capitalization plus total debt compared to the company's total assets has increased by 27.31 times from the previous year's increase. Due to these large values combined with a significant standard deviation (1.94), we take the logarithm of $\Delta Tobin's\ Q_{t+1}$, by first taking the logarithm of both the current and next year's Tobin's Q and then subtracting the current year's Tobin's Q from next year's Tobin's Q. We follow this order to prevent a loss in the number of observations that would occur if we performed the subtraction before taking the logarithm.

4.8 Statistical tests

We conducted a series of tests to ensure the correctness of our regression models, as can be seen in Table E. We examined differences in means to assess whether our primary explanatory variables (*Positive*, *Neutral*, and *Negative* scores) exhibited significant variations in relation to firm performance. A standard T-test was deemed inadequate since we had four dependent variables and three main explanatory variables to analyze. Instead, we opted for four separate ANOVA tests, one for each dependent variable, with all primary explanatory variables included in each test. We created three dummy variables, one for each sentiment (*Positive*, *Neutral*, and *Negative*), taking the value 1 for the sentiment that appears most often in the CEO letter and 0 otherwise. Table E illustrates that the only statistically significant test for differences in means is for ΔROA_{t+1} as a dependent variable. In that case, we can reject the notion of a difference in means. However, we fail to reject that notion for the other variables.

We also conducted tests to assess non-constant variance in the error terms (heteroskedasticity), which undermines the assumption for best linear unbiased estimators in OLS regressions. White's test was initially performed for each dependent variable, as can be seen in Table E. Significant results were obtained for ROA_{t+1}, $Tobin's\ Q_{t+1}$, and ΔROA_{t+1}, with p-values <1%. However, log($\Delta Tobin's\ Q_{t+1}$) as the dependent variable showed no significance (p-value of 0.96), suggesting potential heteroskedasticity. We employ robust or clustered standard errors for the three significant cases indicating possible heteroskedasticity. Subsequently, Table E displays a Breusch-Pagan test that was conducted for $\Delta log(Tobin's\ Q_{t+1})$ to validate the absence of heteroskedasticity. Surprisingly, all dependent variables, including Δlog($Tobin's\ Q_{t+1}$), showed significant p-values (<1%), indicating heteroskedasticity. Therefore, as a precaution, robust or clustered standard errors will be utilized for all regressions, even when log($\Delta Tobin's\ Q_{t+1}$) is the dependent variable. It is worth noting that these tests were carried out after the initial regressions, implying that the first regression models will maintain normal standard errors.

4.9 Correlation analysis

In Table F, we present a correlation matrix of the dataset. The first dependent variable, ROA_{t+1}, exhibits a statistically significant correlation with one of our leading independent variables, the Positive score, at 0.078. However, neither the *Neutral* nor *Negative* score indicates a significant correlation with ROA_{t+1}. For our second dependent variable, *Tobin's* Q_{t+1}, we find that both the *Positive* and *Negative* scores demonstrate highly statistically significant correlations, with coefficients of 0.095 and -0.140, respectively. This supports our belief that the tone partially influences the future market evaluation of a company's assets in CEO letters. The Positive score correlates positively with *Tobin's* Q_{t+1}, while the *Negative* score shows a negative correlation, further reinforcing our assumption.

Regarding the third dependent variable, ΔROA_{t+1}, we observe that the *Negative* score is the only statistically significant variable, with a p-value<1% and a coefficient of 0.100 in Table F. Surprisingly, the coefficient is positive, indicating that the *Negative* score increases when the year-on-year change in ROA_{t+1} increases. None of our main explanatory variables exhibit a significant correlation for the fourth main dependent variable (Δ*Tobin's* Q_{t+1}). This lack of correlation does not support our hypothesis, suggesting that the growth in market valuation of total assets does not depend on the sentiment score in CEO letters.

It is noteworthy to see the highly statistically significant negative correlation between *Total Assets*, *Leverage*, and *R&D* with *Positive* and *Neutral* scores in Table F. This implies that as *Positive* and *Neutral* scores increase, *Total Assets*, *Leverage*, and *R&D* tend to move in the opposite direction. Interestingly, while the *Negative* score shows a negative correlation with *Leverage*, it does not exhibit a significant correlation with *Total Assets* or *R&D*. It is noteworthy that *Leverage* demonstrates a negative correlation, indicating that as the *Negative* scores increase, *Leverage* decreases, a trend that might not be immediately intuitive. However, for the *Negative* score, we observe that *CEO Board Member* (-0.131***) and *Chairman Duality* (-0.071*) become statistically significant. This finding aligns with economic logic; when the CEO also holds positions on the board or serves as chairman simultaneously, their influence and authority are likely heightened, which can amplify the impact of their letters.

4.10 Robustness

To ensure the robustness of the models, we employ clustered standard errors by firm and year. We do this to minimize the effect of external factors on specific companies in certain years. Furthermore, we observed that after winsorization, we still have one company with a Tobin's Q value of 41.955 for all ten years. This might be an outlier, considering that the second-highest Tobin's Q value is 13.267. However, we do not want to exclude these values from our dataset since we have already performed winsorization. Nonetheless, we tested to see if our results would change if we removed the company, and they did not. We also include dummy variables for the number of sentiment scores and gradually add quadratic and interaction terms. Furthermore, we are aware of the high correlation between the *Sentiments* dummy and the *Positive* score. As a test for robustness, we excluded the *Sentiments* variable, which did not result in any differences in our main results. However, since previous studies (McClelland, 2010) included a similar variable, we decided to keep the variable in our final models.

5. Empirical Results

5.1 Interpretation of the results

Section 5 presents the regression results. The focus is on the regression models considered to be the most conservative, which are found in Table 3. Tables A to D in the Appendix present all twenty-four conducted regression models. We consider coefficients with p-values under 0.1 to be weakly significant, p-values under 0.05 to be significant, and p-values under 0.01 to be strongly significant.

5.2 The models

Tables A to D have six regression models each for our four dependent variables. Table A has ROA_{t+1} as the dependent variable. Table B employs $Tobin's\ Q_{t+1}$ as the dependent variable, Table C covers the company's growth in profitability (ΔROA_{t+1}), and Table D has $\Delta Tobin's\ Q_{t+1}$ as the dependent variable.

The first regression models in Tables A to D (1, 7, 13, and 19) cover a typical model with standard errors. Robust standard errors are included for the second regression models (2, 8, 14, and 20). The third regression models (3, 9, 15, and 21) incorporate robust standard errors and utilize industry and year effects. The fourth model (4, 10, 16, and 22) introduces fixed effects, using period and ISIN as parameters. The fifth models (5, 11, 17, and 23) introduce a quadratic term of the *Negative* score, labeled *Negative* score_QT, to capture the potential curvilinear relationship between negative tone and firm performance. The sixth model (6, 12, 18, and 24) contains an interaction term (*Negative*BoardMember*) between the *Negative* score and the CEO as a Board Member. This interaction term aims to address the potential influence of negative sentiment from the CEO on financial performance if the CEO is also a board member. We argue that if the CEO is a board member, it is likely that a negative letter from the CEO will be valued more, as the CEO also indirectly represents the board's perspective and hence, the shareholders' perspective. Since we found that the quadratic term was significant in Table B, we kept the quadratic term in the sixth model, where we also included the interaction term. However, in the other regressions where we did not find the quadratic term statistically significant, we excluded it from the sixth regression and only added the interaction term. Table G presents the main models with fixed effects but excludes year effects. Table G shows that the exclusion of year effects minimally impacts the main results for ROA_{t+1}, *Tobin's* Q_{t+1}, and Δ*Tobin's* Q_{t+1}. However, it has a larger effect on Δ*Tobin's* Q_{t+1}.

5.3 Weakly significant negative impact of *Negative* score on ROA_{t+1}

The results for ROA_{t+1} are presented in Table A. Models 1-3 indicate that the *Negative* score is highly statistically significant with a p-value < 1%. As expected, the variable exhibits a negative effect on ROA_{t+1}, where for every one-unit increase in *Negative* scores, there is a corresponding decrease in ROA_{t+1} of 0.006 units (Model 1 and 2) and 0.005 units (Model 3). Models 4 reveal that when fixed effects are included, the significance of the *Negative* score diminishes, with a p-value < 10%. Notably, none of our other main explanatory variables is statistically significant. However, we conclude that there is minimal difference between these models in terms of significance and coefficients. Alshorman and Shanahan (2020) included a squared term for their optimistic score, which turned out to be significant. Our Model 5 incorporates a quadratic term of the *Negative* score because we expect that a *Negative* score might have a negative relationship with firm performance up to a certain point, where it instead is a CEO who is more pessimistic in his or her communication but not necessarily has any more negative relationship with ROA or Tobin's Q. However, this variable is not statistically significant, nor is the *Negative* score in this model. Lastly, in Model 6, we drop the quadratic term and integrate an interaction term between the *Negative* score and whether the CEO also sits on the board. This model does not turn out to be statistically significant, nor does the interaction term or the *Negative* score. Hence, we conclude that the main model for ROA_{t+1} as a dependent variable is Model 4.

5.4 Strongly significant negative impact of *Negative* score on *Tobin's* Q_{t+1}

Models 7 and 8 in Table B indicate that the *Neutral* and *Negative* variables are highly statistically significant, with negative coefficients. Moving on to Model 9, which includes industry and year effects, we observe that the *Negative* variable remains highly statistically significant with a p-value < 1%, while the significance of the *Neutral* coefficient diminishes to not being significant. The *Neutral* variable is still not statistically significant when fixed effects are included (Models 10-12). However, the *Negative* score remains highly statistically significant in all *Tobin's Q* models. This suggests that if *Negative* scores increase by one unit, *Tobin's Q*, one year from now, is expected to decrease by the coefficient of *Negative* score*100 since *Tobin's* Q_{t+1} is logarithmized. This is the case for ΔTobin's Q_{t+1} as well, since it is also logarithmized and therefore, a log-level model. As for the first testing with ROA_{t+1}, we included the quadratic term in Model 11; the results suggest that the coefficient is statistically significant, with a coefficient of 0.002 and a p-value < 5%. In Model 11, we also observe that the Negative score is highly statistically significant with a coefficient of -0.027. By employing the derivative to find the minimum value (turning point) for the U-shaped curve, we conclude that it is at 6.75. This means that when *Negative* scores surpass 6.75, the adverse effects on *Tobin's* Q_{t+1} cease and begin to increase. However, in our data sample, the number of observations with *Negative* scores over 6.75 is 43, indicating that we cannot be overly confident of the squared effect since we lack sufficient observations to be absolutely sure. The last model (12) includes an interaction term, and we also include the quadratic term since it was statistically significant in the prior model. The *Negative* variable becomes even more negative (-0.049) and remains highly statistically significant. The squared variable retains the same significance and coefficient as the previous model. An interesting finding is the interaction term's positive and highly statistically significant coefficient (0.023). The results illustrate that when the CEO writes a pessimistic letter and also sits on the board, it has a less negative effect on *Tobin's Q* in the upcoming year. If the CEO is on the board, our model shows that one *Negative* sentiment in the CEO letter will mean that *Tobin's Q* for the next year is 2.6 units lower compared to a company that did not have any negative sentiments. However, the interaction term tells us that when the CEO is not on the board and makes a *Negative* sentiment in the CEO letter, this leads to a decrease of 4.9% in the next year's *Tobin's Q*.

5.5 Significant mixed impact of *Negative* scores on ΔROA_{t+1}

Models 13-15 in Table C display that the only statistically significant explanatory variable is the *Negative* score, which shows positive coefficients in the models. However, when introducing fixed effects (Model 16), we see that the *Negative* score is insignificant and remains insignificant when adding the quadratic term in Model 17. The quadratic term is weakly statistically significant, with a coefficient of 0.000. Due to its weak statistical significance and low coefficient, it is challenging to draw any conclusions, especially since the *Negative* score is insignificant. Furthermore, since the quadratic term was weakly significant in Model 18 and the *Negative* score yielded no significance, we decided to drop the quadratic term and include an interaction term between the *Negative* score and CEO board membership in Model 18. In this case, the interaction term proved to be highly significant (p-value under 0.01), and the *Negative* score was also highly significant, with a coefficient of 0.004. In contrast to when using *Tobin's* Q_{t+1} as the dependent variable, this suggests that the *Negative* score positively impacts the change in *ROA*. However, if the CEO is also a board member, the *Negative* score's positive effect on ΔROA_{t+1} becomes negative (0.004 - 0.005).

5.6 Significant mixed impact of *Negative* scores on *ΔTobin's* Q_{t+1}

In the last table of regressions, Table D, we observe that the *Neutral* score is weakly significant for models 19-21, with a coefficient of 0.003. Model 21 also shows that the *Negative* score is statistically significant. Models 22-23 exhibit statistical significance for the *Negative* score, with coefficients of 0.009 and 0.019 for the latter model. Including the squared variable in Model 23, we find that the quadratic term shows no significance, and neither does the *Negative* score. In Model 24, we decided to drop the quadratic term and include the interaction term, which is highly significant with a coefficient of -0.034. This indicates that when the CEO makes a negative sentiment and serves on the board, it moderates the initial positive effect of *Negative* scores on *ΔTobin's* Q_{t+1}. Since the *Negative* score has a highly significant coefficient of 0.024, this suggests that a CEO who is not a board member but expresses negativity in the CEO letter leads to an increase in the year-on-year change in *Tobin's Q* by 2.4%. However, when the CEO is also on the board, the year-on-year change in *Tobin's Q* decreases by 1%. The table below presents the main models for each dependent variable.

Table 3: Main regression models

Dependents	**ROA**	**Tobin's Q**	**ΔROA**	**ΔTobin's Q**
Variables	Model_4	Model_12	Model_18	Model_24
Positive Score	0.000	-0.001	0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.001)
Neutral Score	0.000	-0.002	0.000	0.003
	(0.000)	(0.002)	(0.001)	(0.003)
Negative Score	-0.002*	-0.049***	0.004***	0.024***
	(0.001)	(0.010)	(0.001)	(0.005)
Sentiments	0.000	0.082*	-0.022*	-0.031
	(0.009)	(0.042)	(0.011)	(0.046)
Board Size	0.000	0.011*	-0.002	0.022**
	(0.002)	(0.007)	(0.002)	(0.010)
CEO Board member	-0.020*	-0.127*	-0.002	0.093
	(0.010)	(0.067)	(0.017)	(0.087)
Chairman Duality	-0.014*	0.059	0.012	-0.052
	(0.008)	(0.143)	(0.015)	(0.049)
Total Assets	-0.043***	-0.297***	0.025	-0.093**
	(0.013)	(0.060)	(0.016)	(0.037)
Leverage	-0.119**	0.085	0.062*	0.036
	(0.046)	(0.165)	(0.032)	(0.178)
R&D	0.011	0.025	0.003	0.040
	(0.011)	(0.062)	(0.022)	(0.059)
Cash Holdings	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Negative Score_QT		0.002**		
		(0.001)		
Negative*BoardMember		0.023***	-0.005***	-0.034***
		(0.005)	(0.160)	(0.007)
_cons	0.527***	3.340***	-0.330**	0.473
	(0.121)	(0.533)	(0.159)	(0.378)
Observations	711	695	711	678
R-squared	0.194	0.288	0.075	0.122
Industry effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Standard errors	Clustered	Clustered	Clustered	Clustered
Method	FE	FE	FE	FE

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

6. Discussion

6.1 Discussion of the hypotheses

The hypotheses that were made in the third section were formulated as follows:

H1: There is no relationship between sentiment scores and next year's ROA.
H2: There is no relationship between sentiment scores and growth in profitability.
H3: There is a relationship between sentiment scores and next year's Tobin's Q.
H4: There is a relationship between sentiment scores and growth in market valuation.

The main findings for each hypothesis are:
H1: There is a negative relationship between the sentiment scores and next year's ROA.
H2: There is a mixed relationship between the *Negative* score and growth in profitability.
H3: There is a negative relationship between the *Negative* score and next year's Tobin's Q.
H4: There is a mixed relationship between the *Negative* score and growth in market valuation.

6.2 CEO optimism and ROA_{t+1}

Since Model 4 in Table 3 illustrates weak significance (p-value <10%) of *Negative* scores' impact on ROA_{t+1}, we reject H1. However, we refrain from expressing too much certainty in the conclusion, given that the variable is only significant at a 10 % significance level. However, only the *Negative* scores have a significant negative effect. *Positive* and *Neutral* scores are not significant. This may be explained by the previously presented theories, such as agency and signaling theories. The CEO has the incentive to be more optimistic than they should be to secure their position in the eyes of the principals. Hence, the CEO often paints a rosier picture of the forthcoming year, even if the actual prospects are less promising. Complicating matters further, the CEO holds privileged internal information, resulting in an information asymmetry within the organization. With that in mind, it is conceivable that CEOs who convey more negative sentiments do that since they have found themselves in a situation where they must address the company's unfavorable results or poor performance. They may have little choice but to discuss such matters, which could explain why the *Negative* score emerges as the only significant factor. After all, it is relatively uncommon for a CEO to express negativity without valid reasons. Therefore, when they do, it may relate to their forthcoming financial performance, as evidenced by our case with ROA.

We also reject H2, as demonstrated by Model 18 in Table 3, which indicates that *Negative* scores have a strongly significant positive effect on growth in ROA. This outcome is unexpected, as we anticipated that a *Negative* score would have no or perhaps a negative impact on ΔROA_{t+1}. One possible explanation for these results is that the most significant changes in our dataset occur when companies experience a challenging year (potentially with negative ROA), followed by a year of positive ROA. Since the CEO letter often comments on the previous year's difficulties, CEOs might communicate more negatively in their letters. If the subsequent year shows a transformation toward positive results, this could explain the positive relationship between negative letters and ΔROA_{t+1}. Another possible reason for this result could be that firms that are transparent about their risks create a better environment to address these challenges and thus achieve more desirable outcomes. It might also be that firms receiving favorable media coverage aim to mitigate high expectations and avoid scrutiny by being more candid about the negative aspects the company has faced or might face soon. Additionally, data management issues could contribute to these findings. For instance, the training data might be flawed, the data could have been mismanaged, or the presence of many outliers could have led to misleading results. Furthermore, the results indicate that when the CEO is also a board member and writes a negative letter, it leads to negative growth in ROA. We argue that since a CEO who is also a board member has more influence and insight into the company, their view could perhaps have a stronger influence and relate better with the company's actual outcomes.

Understanding and justifying the disparity between the relationship of *Negative* scores with ROA_{t+1} and the relationship with ΔROA_{t+1} is complex, considering the outcomes from H1 and H2 and the many factors at play. It involves a nuanced interplay of various factors, including CEO incentives, organizational structure, and information asymmetry. Our findings suggest that the CEO's presence on the board moderates the positive effect of a *Negative* sentiment on ΔROA_{t+1}, turning it into a negative effect. Specifically, when the CEO is on the board, a one-unit increase in the *Negative* sentiment corresponds to a decrease of 0.004-0.005 units in ΔROA_{t+1}. In contrast, it results in a 0.004 increase in ΔROA_{t+1} if the CEO is not a board member. Furthermore, although *Negative* scores show a weakly significant negative coefficient for ROA_{t+1}, and the coefficients in both regressions are relatively small, it suggests that sentiments have a limited effect on ROA_{t+1} and growth in ROA_{t+1}. However, given that we find the *Negative* scores coefficient strongly significant in the regression with ΔROA_{t+1} as the dependent variable but not significant when using just ROA_{t+1} as the dependent variable, we place more trust in ΔROA_{t+1} regression Model 18 compared to Model 4 with next year's ROA as the dependent variable. Since there is no connection between the Positive score and

ROAt+1, our results do not support Patelli and Pedrini's (2013) findings, which found that CEO letters are a useful tool to read to understand a company's past and future performance. Instead, our findings are more in line with Boudt and Thewissen (2019), who found that the CEO letters are used for impression management since we did not find any significant relationship between positive scores and ROA_{t+1} and *Tobin's* Q_{t+1}.

6.3 CEO optimism and market valuation

We accept H3, as evidenced by the negative relationship between the *Negative* score in the CEO letter and next year's Tobin's Q in the main model (Model 12), with a significant result at the 1% level. This suggests that companies whose CEOs incorporate more negative phrases in their letters are more likely to experience negative reactions from investors. Essentially, it indicates that the market adjusts its valuation based on the CEO's pessimism, but does not respond to optimism as it is already factored into the valuation model. This could be attributed to negativity being perceived as a warning sign, while optimistic CEO letters are considered standard and therefore, do not trigger market reactions. Additionally, CEOs may have economic incentives to bolster stock performance, as their compensation often relies on it. However, given the efficiency of the London Stock Exchange (Rounaghi & Zadeh, 2016), stakeholders have access to a wide range of information. They may therefore, avoid investing in companies where the CEO's optimism seems excessive. From a broader perspective, CEOs are appointed by the board, which is elected by shareholders, implying that indirect power rests with the shareholders. Thus, if a CEO remains overly positive despite anticipating a challenging year, shareholders may question their judgment and reconsider their suitability for the role. CEOs know how their communications are perceived, recognizing that misleading shareholders could jeopardize their careers. Therefore, observing the market's negative reactions to negative letters is noteworthy. While CEO personalities vary, with some more optimistic and others more pessimistic, we generally observe a positive outlook toward the future. From this standpoint, the market expresses concerns when a CEO communicates negatively in an annual report. Furthermore, in Model 12, we observe the significance of the quadratic term at the 5% level, indicating that the *Negative* score initially impacts the market negatively, but reaches a turning point at a sentiment score of 12.25, after which it starts to trend upwards. However, with only 13 observations where the *Negative* score exceeds 12.25, it is difficult to determine whether there is a nonlinear curve or just outliers. Additionally, we note that CEOs who also serve as board members have a moderating effect on the negative impact of the *Negative* score on *Tobin's* Q_{t+1}.

We accept H4, as there is a positive relationship between the *Negative* score in the CEO letter and *ΔTobin's* Q_{t+1} in the main model in Table 3 (Model 24). This finding may seem somewhat counterintuitive. One might expect that when the CEO expresses negative sentiments in the letter, it indicates that the company has been or will go through a challenging period. However, one possible explanation for this relationship is that positive sentiments are so commonly expressed in CEO letters that the market discounts their value, recognizing the inherent bias of the CEO. Conversely, when the CEO expresses pessimism, it could signal that the company has hit rock bottom, and improvements are likely to follow. However, despite potential justifications for the results, it remains peculiar that the *Negative* score obtains a positive coefficient with strong statistical significance when *ΔTobin's* Q_{t+1} is the dependent variable. This suggests that companies whose CEO letters contain negative sentiment will likely improve their market valuation next year, if the CEO is not a board member. This finding contradicts the research of Che et al. (2020), who found that their model, which examined positive sentiment in the CEO letter, could predict financial performance with an accuracy reaching 70.46 %. This can be compared to ours, which finds that negative sentiment is the better predictor of financial performance. Model 24 also shows that the interaction term is statistically significant. This implies that if the CEO also serves as a board member, the *Negative* score has a negative effect on *ΔTobin's* Q_{t+1} compared to when the CEO is not a board member.

H3 and H4 yielded contrasting outcomes. While testing H3 resulted in a negative coefficient for the *Negative* score, indicating a decrease, H4 unexpectedly showed a positive coefficient, suggesting an increase. This contradiction is puzzling, especially considering the relationship between *Tobin's* Q_{t+1} and *ΔTobin's* Q_{t+1}, where the latter is a function of the former. One potential factor contributing to this discrepancy could be the decreasing number of observations between the models. However, another explanation could be that 94% of our initial 906 observations had a CEO sitting on the board. This means it might be more of a rule than an exception for the CEO to serve as a board member on the FTSE 100. Therefore, our results indicate that, in general, *Negative* sentiments have a negative impact on Tobin's Q and growth in Tobin's Q. However, despite this, another common thread emerges: the *Negative* score remains the only significant variable in both models, and the interaction term exerts a shifting influence on its effect on *ΔTobin's* Q_{t+1}. An interesting observation is the nonlinear pattern exhibited by the *Negative* score in the *Tobin's* Q_{t+1} regression model. Initially negative, the curve reverses direction at a turning point and begins trending upwards. This nonlinear relationship may offer insight into the disparate coefficients observed between *Tobin's* Q_{t+1} and *ΔTobin's* Q_{t+1} regressions. Since many CEOs find it time-consuming and demanding to write annual and quarterly reports (Ekonomibyrån, 2024), this finding may highlight the importance for CEOs to be aware that how they express their thoughts in the text can create a negative market reaction. Even if it might be time-consuming to write these reports, CEOs could see it as a way of preserving financial value for the firm and should not disregard the effect a negative CEO letter can have on firm value.

6.4 Comparing the results to the existing literature

We conclude that negative sentiments made by CEOs who also serve as board members have a moderating effect on the *Negative* score's negative impact on *Tobin's* Q_{t+1}, and also shifting effect from a positive impact on ΔROA_{t+1}, and Δ*Tobin's* Q_{t+1} to a negative impact. Initially, we hypothesized that CEOs with more influence (such as those also sitting on the board) who express negative sentiments would exert a more significant impact on the market due to their deeper insights into the company. However, we found that when the CEO is also a board member and gives out a negative sentiment in the CEO letter, it will impact *Tobin's* Q_{t+1}, ΔROA_{t+1}, and Δ*Tobin's* Q_{t+1} negatively, even if the effect would have been more negative for *Tobin's* Q_{t+1} if the CEO would not have been a board member. This is interesting from an agency theory perspective since CEOs who are board members should be expected to have fewer agency conflicts since they are likely shareholders and are interested in increasing or maintaining market valuation. The meaning of this should be that if the CEO writes a negative statement despite having a large vested interest, it is likely that the situation is truly concerning and should have a great negative effect on the market valuation in theory.

Alshoman and Shanahan (2020) find that optimistic CEO sentiment increases the company's market value and profitability. Furthermore, Che et al. (2020) conclude in their research that CEO sentiments strongly connect to the company's financial performance. We, however, do not find these particular relationships. We find that negative sentiments decrease market value and profitability. Still, we do not find that positive or neutral sentiment would significantly affect a company's market value or profitability.

Brühl and Kury (2019) conclude that the letter to shareholders is unreliable since it is a section where the CEO tries to influence and assure the reader that the company has a strong and stable future ahead. Therefore, they argue that the letter is biased and unreliable in making informed decisions based on its content. However, based on our results, we argue that letters to shareholders can be useful for analyzing the company's future if the reader knows how to interpret them. We find that negative sentiment impacts the company's market value and profitability. If the reader is aware of this information, they can still make informed decisions based on the content of the CEO's letter.

Regarding signaling theory, Connelly et al. (2011) discuss the importance of being aware of the costs associated with signaling, or sending a specific message to the receiver. In some sense, our study also reveals the value of negative sentiment in the CEO letters for the company and how the market reacts to the information. Since our models show that a unit increase in the *Negative* score corresponds with a 0.2% unit decrease in ROA the next year, it also leads to a 2.6-unit decrease in next year's Tobin's Q (if the CEO is also a board member). Considering the decrease in profitability compared to the decrease in the market value of the company's assets, it can seem unproportional, where the market's reaction seems far more extreme than the company's actual loss in profitability. This is also supported by prospect theory, which states that people tend to be more afraid of losing money than motivated by earning money. Therefore, the market's negative reaction is more drastic than the actual negative outcome.

Prospect theory made an incorrect prediction when we wrote in the theory section that negative sentiment would likely have a greater negative impact on the market reaction than the large positive effect on Tobin's Q when the sentiment was positive. Instead of having a large negative effect, negative sentiment had a positive effect on Tobin's Q, while the positive sentiment had no significant relationship with either dependent variable.

Since we found that negative sentiments negatively affect next year's ROA and Tobin's Q, while positive sentiment has no proven significance, we do not have evidence to support the idea that sentiments, in general, would increase next year's ROA. This can be contrasted by Bilinski (2024), who found that sentiment scores generated by ChatGPT have a positive, statistically significant effect on the following year's ROA and a negative relationship with mean stock turnover and stock return volatility. However, our study does not use the same methodology for generating sentiment scores, and we also analyze positive and negative sentiments separately, in contrast to Bilinski's (2024) research. These differences could have contributed to the discrepancy in results. However, regarding market reactions, our study indicates that negative sentiments decrease next year's Tobin's Q. Similarly, Bilinski's (2024) research shows that sentiments negatively impact market reactions. We believe the market might have already accounted for positive sentiments in the annual report, so negative sentiment would affect market reactions adversely, while positive sentiment would have no significant impact. One might argue that Bilinski's study illustrates the same point – that the market reacts negatively to sentiments (both positive and negative). However, the market may respond only to negative sentiments, which is why the study, like ours, finds a negative relationship with market reactions.

6.5 Limitations

One limitation of the study is the sample size. While the sample includes lots of years and, hence, lots of different macroeconomic situations, it is still tiny in the grand scheme of things since it is far from every macroeconomic disturbance that has occurred on the LSE that gets included. It would be beneficial to include a sample that lasted over 30 years, for example, to minimize the risk that the chosen period for this paper is merely a temporary trend for how CEO letters are written. In addition, the study is limited by FinBERT's training data. If the data is flawed in some way, the quality of the results in this study will suffer. However, previous research seems to support the notion that FinBERT is trained on a comprehensive dataset. Furthermore, when test sampling of the data was conducted, it was seen that Eikon had misinterpreted the accounting numbers in a few instances. This could stem from Eikon using data crawling on the annual reports and that the differences in design between companies' balance sheets misled the data crawler. Further along, when downloading the CEO letters, some parts that were not a part of the CEO letters were included if they were on the same page as the CEO letter since it would be too time-consuming to manually extract only the text rather than the pages that the CEO letters were on. Furthermore, it would be beneficial to add a variable that concerns the experience of the CEO, such as experience, line of study, if the CEO displays narcissistic traits, or the number of stock options that he or she possesses. However, this data is not easily accessible, so it was excluded. In addition, while we can see relationships between the dependent and independent variables, a study like this cannot show causal relationships. Furthermore, the accuracy of FinBERT on CEO letters is not yet completely known. While FinBERT has been trained on plenty of financial texts, there is a risk that words considered optimistic in the CEO letter are considered neutral in the rest of the annual report or analyst reports. In other words, it is not entirely certain that FinBERT classifies sentiment correctly in CEO letters.

Moreover, there is a possibility of potential risk for endogenous variables, meaning that it might be a reverse causality or variables that have been excluded from the model, leading to variables correlating with the error term. However, since we use fixed effects to control variation between individual companies, we address some potential endogeneity concerns, even though there are other, more effective and accurate ways to address endogeneity challenges (Roberts & Whited, 2013).

Since our main study and research question did not cover whether the CEO being on the board significantly impacted ROA or Tobin's Q, and ninety-four percent of the sample consisted of CEOs who were board members, we cannot draw any broad conclusions regarding the interaction term *Negative * Board member*. In other words, since the data is so skewed, it is difficult to say how the effect of sentiment changes when the CEO is or is not a board member.

6.6 Future research

Future studies could use a different machine learning model to see which is more efficient. In addition, future studies could try pre-training the model on more CEO letters and see what results that yield, rather than relying on the model with its pre-existing training data. In addition, it would be interesting to see how firm performance and market reactions correspond to sentiment in the auditor's report since the auditors have fewer incentives to obfuscate the company's financial standing. Furthermore, FinBERT can be utilized to compare the tone of sustainability reports that use different standards, such as GRI compared to CSRD (when companies have implemented that standard in their sustainability reports) to see which standard leads companies to become more honest in their sustainability communication. It would also be useful to analyze the notes to the financial statements with the help of a tool like FinBERT to examine if companies try to hide certain aspects of their performance.

7. Conclusion

The CEO letter is considered an essential part of the annual report. However, the CEOs have incentives to obfuscate facts and paint a rosy picture of the company's situation even if things are going poorly. Firstly, we find that *Negative* sentiment in the CEO letters has a slightly negative impact on both ROA_{t+1} and *Tobin's* Q_{t+1}. Furthermore, we also see a positive relationship between *Negative* sentiment in the CEO letter and the change in Tobin's Q and ROA from last year when the CEO was not a board member. However, the *Positive* and *Neutral* scores have no proven effect on $ROA_{t+1,}$ *Tobin´s* Q_{t+1}, ΔROA_{t+1}, or Δ*Tobin's* Q_{t+1}. Moreover, we also find that the *Negative* sentiments have a moderating effect on *Tobin's* Q_{t+1}, and a shifting effect on ΔROA_{t+1} and Δ*Tobin's* Q_{t+1} (a negative relationship) when the CEO is a board member. Furthermore, the amount of *Negative* scores has a nonlinear relationship with *Tobin's* Q_{t+1}.

Our analysis suggests that CEOs should be mindful of the impact of incorporating negative sentiments into CEO letters, as it often triggers a more negative response from the market than the actual negative outcome. Additionally, stakeholders should recognize the relationship between negative sentiments in CEO letters and a subsequent decrease in the company's ROA for the following year. The adverse effect of negative sentiments on growth in ROA and Tobin's Q is exacerbated when the CEO also holds a position on the board. Conversely, when the CEO does not serve on the board, a negative sentiment has a more pronounced negative effect on the following year's Tobin's Q. As for next year's ROA, a negative sentiment adversely affects performance, irrespective of whether the CEO holds a board position. Therefore, we conclude that the CEO’s choice of words relates to the company's performance and impacts its market value.

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9. Appendix

Table A – Regression models for the dependent variable ROA_{t+1}

Variables	Model_1	Model_2	Model_3	Model_4	Model_5	Model_6
Positive Score	-0.000	-0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Neutral Score	0.001	0.001	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Negative Score	-0.006***	-0.006***	-0.005***	-0.002*	-0.000	-0.001
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Sentiments	0.006	0.006	0.000	0.000	0.000	0.000
	(0.017)	(0.023)	(0.020)	(0.009)	(0.009)	(0.009)
Board Size	-0.000	-0.000	0.001	0.000	0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
CEO Board member	0.007	0.007	0.049***	-0.020*	-0.022**	-0.017*
	(0.024)	(0.012)	(0.018)	(0.010)	(0.010)	(0.009)
Chairman Duality	-0.044*	-0.044**	-0.018	-0.014*	-0.013	-0.015*
	(0.024)	(0.020)	(0.022)	(0.008)	(0.008)	(0.008)
Total Assets	-0.048***	-0.048***	-0.053***	-0.043***	-0.043***	-0.043***
	(0.004)	(0.007)	(0.007)	(0.013)	(0.013)	(0.013)
Leverage	-0.065***	-0.065**	-0.048**	-0.119**	-0.120**	-0.119**
	(0.024)	(0.027)	(0.022)	(0.046)	(0.047)	(0.046)
R&D	0.035***	0.035***	0.050***	0.011	0.011	0.011
	(0.010)	(0.009)	(0.010)	(0.011)	(0.011)	(0.011)
Cash Holdings	0.000***	0.000***	0.000***	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Negative Score_QT					-0.000	
					(0.000)	
Negative*BoardMember						-0.001
						(0.001)
_cons	0.527***	0.527***	0.556***	0.527***	0.526***	0.524***
	(0.039)	(0.064)	(0.056)	(0.121)	(0.122)	(0.121)
Observations	711	711	711	711	711	711
R-squared	0.302	0.302	0.440	0.194	0.196	0.194
Industry effects	No	No	Yes	Yes	Yes	Yes
Year effects	No	No	Yes	Yes	Yes	Yes
Standard errors	Standard	Robust	Robust	Clustered	Clustered	Clustered
Method	OLS	OLS	OLS	FE	FE	FE

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table B– Regression models for the dependent variable Tobin's Q_{t+1}

Variables	Model_7	Model_8	Model_9	Model_10	Model_11	Model_12
Positive Score	0.001	0.001	0.001	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Neutral Score	-0.010***	-0.010***	-0.005	-0.001	-0.002	-0.002
	(0.004)	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)
Negative Score	-0.020**	-0.020***	-0.021***	-0.011***	-0.027***	-0.049***
	(0.008)	(0.007)	(0.007)	(0.003)	(0.008)	(0.010)
Sentiments	0.069	0.069	0.069	0.083*	0.083*	0.082*
	(0.077)	(0.089)	(0.085)	(0.043)	(0.042)	(0.042)
Board Size	0.025***	0.025***	0.036***	0.013*	0.011*	0.011*
	(0.010)	(0.008)	(0.009)	(0.007)	(0.007)	(0.007)
CEO Board member	0.247**	0.247***	0.452***	-0.083	-0.063	-0.127*
	(0.111)	(0.056)	(0.081)	(0.076)	(0.072)	(0.067)
Chairman Duality	-0.096	-0.096	-0.082	0.072	0.056	0.059
	(0.109)	(0.135)	(0.148)	(0.144)	(0.143)	(0.143)
Total Assets	-0.367***	-0.367***	-0.393***	-0.298***	-0.296***	-0.297***
	(0.016)	(0.025)	(0.028)	(0.060)	(0.060)	(0.060)
Leverage	0.528***	0.528***	0.543***	0.081	0.091	0.085
	(0.108)	(0.108)	(0.092)	(0.165)	(0.165)	(0.165)
R&D	0.126***	0.126***	0.128**	0.024	0.023	0.025
	(0.047)	(0.044)	(0.050)	(0.062)	(0.062)	(0.062)
Cash Holdnings	0.000***	0.000***	0.000***	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Negative Score_QT					0.002**	0.002**
					(0.001)	(0.001)
Negative*BoardMember						0.023***
						(0.005)
_cons	3.228***	3.228***	3.023***	3.259***	3.270***	3.340***
	(0.180)	(0.230)	(0.246)	(0.542)	(0.536)	(0.533)
Observations	695	695	695	695	695	695
R-squared	0.516	0.516	0.564	0.278	0.285	0.288
Industry effects	No	No	Yes	Yes	Yes	Yes
Year effects	No	No	Yes	Yes	Yes	Yes
Standard errors	Standard	Robust	Robust	Clustered	Clustered	Clustered
Method	OLS	OLS	OLS	FE	FE	FE

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table C – Regression models for the dependent variable ΔROA_{t+1}

Variables	Model_13	Model_14	Model_15	Model_16	Model_17	Model_18
Positive Score	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Neutral Score	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Negative Score	0.005***	0.005***	0.004**	-0.000	-0.003	0.004***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Sentiments	-0.030*	-0.030	-0.021	-0.022*	-0.022*	-0.022*
	(0.017)	(0.023)	(0.020)	(0.011)	(0.011)	(0.011)
Board Size	-0.000	-0.000	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
CEO Board member	-0.014	-0.014	-0.065***	-0.017	-0.013	-0.002
	(0.025)	(0.012)	(0.017)	(0.016)	(0.015)	(0.017)
Chairman Duality	0.039	0.039*	0.016	0.013	0.010	0.012
	(0.024)	(0.020)	(0.020)	(0.014)	(0.015)	(0.015)
Total Assets	0.046***	0.046***	0.052***	0.025	0.026	0.025
	(0.004)	(0.007)	(0.007)	(0.016)	(0.016)	(0.016)
Leverage	0.061**	0.061**	0.039	0.061*	0.062*	0.062*
	(0.024)	(0.028)	(0.026)	(0.032)	(0.031)	(0.032)
R&D	-0.035***	-0.035***	-0.052***	0.003	0.003	0.003
	(0.010)	(0.009)	(0.010)	(0.022)	(0.023)	(0.022)
Cash Holdnings	-0.000***	-0.000***	-0.000**	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Negative Score_QT					0.000*	
					(0.000)	
Negative*BoardMember						-0.005***
						(0.160)
_cons	-0.501***	-0.501***	-0.497***	-0.315*	-0.313*	-0.330**
	(0.040)	(0.064)	(0.058)	(0.158)	(0.160)	(0.159)
Observations	711	711	711	711	711	711
R-squared	0.278	0.278	0.419	0.074	0.078	0.075
Industry effects	No	No	Yes	Yes	Yes	Yes
Year effects	No	No	Yes	Yes	Yes	Yes
Standard errors	Standard	Robust	Robust	Clustered	Clustered	Clustered
Method	OLS	OLS	OLS	FE	FE	FE

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table D – Regression models for the dependent variable ΔTobin's Q_{t+1}

Variables	Model_19	Model_20	Model_21	Model_22	Model_23	Model_24
Positive Score	-0.000	-0.000	-0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Neutral Score	0.003*	0.003*	0.003*	0.004	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Negative Score	-0.004	-0.004	-0.009**	-0.009*	-0.019**	0.024***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.009)	(0.005)
Sentiments	-0.038	-0.038	-0.026	-0.033	-0.033	-0.031
	(0.039)	(0.041)	(0.038)	(0.046)	(0.045)	(0.046)
Board Size	0.006	0.006	0.008	0.022**	0.020**	0.022**
	(0.005)	(0.006)	(0.006)	(0.010)	(0.010)	(0.010)
CEO Board member	-0.016	-0.016	-0.031	-0.005	0.008	0.093
	(0.056)	(0.049)	(0.056)	(0.064)	(0.062)	(0.087)
Chairman Duality	0.011	0.011	-0.008	-0.047	-0.058	-0.052
	(0.055)	(0.044)	(0.045)	(0.048)	(0.045)	(0.049)
Total Assets	-0.001	-0.001	0.011	-0.093**	-0.092**	-0.093**
	(0.008)	(0.009)	(0.012)	(0.038)	(0.037)	(0.037)
Leverage	0.078	0.078	0.063	0.026	0.032	0.036
	(0.055)	(0.058)	(0.065)	(0.177)	(0.177)	(0.178)
R&D	-0.009	-0.009	-0.049*	0.042	0.042	0.040
	(0.024)	(0.019)	(0.025)	(0.059)	(0.061)	(0.059)
Cash Holdings	0.000	0.000	0.000	0.000	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Negative Score_QT					0.001	
					(0.001)	
Negative*BoardMember						-0.034***
						(0.007)
_cons	-0.072	-0.072	0.003	0.579	0.586	0.473
	(0.092)	(0.088)	(0.105)	(0.377)	(0.372)	(0.378)
Observations	678	678	678	678	678	678
R-squared	0.016	0.016	0.114	0.119	0.121	0.122
Industry effects	No	No	Yes	Yes	Yes	Yes
Year effects	No	No	Yes	Yes	Yes	Yes
Standard errors	Standard	Robust	Robust	Clustered	Clustered	Clustered
Method	OLS	OLS	OLS	FE	FE	FE

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table E– The conducted statistical tests

Test	Dependent Variable	H_0	Chi^2	P-value	Decision	H_A
White test	ROA	Homoskedasticity	424.45	0.00	Reject	Heteroskedasticity
White test	Tobin's Q	Homoskedasticity	375.93	0.00	Reject	Heteroskedasticity
White test	ΔROA	Homoskedasticity	138.16	0.00	Reject	Heteroskedasticity
White test	ΔTobin's Q	Homoskedasticity	53.83	0.66	Accept	Heteroskedasticity
Breusch–Pagan test	ROA	Homoskedasticity	927.05	0.00	Reject	Heteroskedasticity
Breusch–Pagan test	Tobin's Q	Homoskedasticity	202.38	0.00	Reject	Heteroskedasticity
Breusch–Pagan test	ΔROA	Homoskedasticity	140.81	0.00	Reject	Heteroskedasticity
Breusch–Pagan test	ΔTobin's Q	Homoskedasticity	80.28	0.00	Reject	Heteroskedasticity
ANOVA	ROA	No differences in means	-	0.66	Accept	Differences in means
ANOVA	Tobin's Q	No differences in means	-	0.46	Accept	Differences in means
ANOVA	ΔROA	No differences in means	-	0.02	Reject	Differences in means
ANOVA	ΔTobin's Q	No differences in means	-	0.25	Accept	Differences in means

Table F – Pearson's Correlation Matrix

Variables	-1	-2	-3	-4	-5	-6	-7	-8	-9	-10	-11	-12	-13	-14	-15
ROA	1.000														
Tobin's Q	0.705***	1.000													
ΔROA	0.290***	0.025	1.000												
ΔTobin's Q	-0.021	0.134***	0.091**	1.000											
Positive Score	0.078**	0.095***	0.005	-0.017	1.000										
Neutral Score	0.045	-0.051	0.032	0.009	0.559***	1.000									
Negative Score	-0.028	-0.140***	0.100***	0.043	0.332***	0.450***	1.000								
Sentiments	0.088***	0.043	0.019	-0.019	0.715***	0.586***	0.349***	1.000							
Board Size	-0.254***	-0.230***	-0.015	0.021	-0.020	-0.036	-0.022	-0.092***	1.000						
CEO Board Member	-0.006	0.026	-0.015	-0.008	0.029	0.006	-0.131***	0.055*	-0.052	1.000					
Chairman Duality	-0.009	0.026	-0.010	0.006	-0.021	-0.047	-0.055*	-0.042	-0.012	0.024	1.000				
Total Assets	-0.453***	-0.631***	0.018	0.000	-0.134***	-0.099***	-0.031	-0.119***	0.519***	0.045	-0.063*	1.000			
Leverage	-0.233***	-0.035	0.013	0.064*	-0.107***	-0.131***	-0.071**	-0.158***	0.166***	-0.003	-0.048	0.204***	1.000		
R&D	-0.068**	-0.079**	-0.010	0.001	-0.134***	-0.118***	-0.031	-0.152***	0.248***	-0.163***	0.092***	0.194***	0.279***	1.000	
Cash Holdings	-0.166***	-0.287***	0.027	0.040	-0.135***	-0.090***	-0.063*	-0.075**	0.321***	0.051	-0.049	0.637***	0.074**	0.174***	1.000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table G – Main regression models excluding year effects

Dependents	ROA	Tobin's Q	ΔROA	ΔTobin's Q
Variables	Model_4	Model_12	Model_18	Model_24
Positive Score	0.000	-0.001	-0.000	0.000
	(0.000)	(0.001)	(0.001)	(0.000)
Neutral Score	0.000	-0.002	0.004	0.000
	(0.000)	(0.002)	(0.003)	(0.001)
Negative Score	-0.002*	-0.045***	0.014**	0.006***
	(0.001)	(0.009)	(0.006)	(0.002)
Sentiments	-0.001	0.092**	-0.024	-0.020*
	(0.009)	(0.043)	(0.052)	(0.011)
Board Size	0.000	0.010	0.019*	-0.001
	(0.002)	(0.006)	(0.010)	(0.002)
CEO Board member	-0.020**	-0.176**	0.057	0.007
	(0.009)	(0.069)	(0.091)	(0.015)
Chairman Duality	-0.014**	0.084	-0.033	0.011
	(0.007)	(0.144)	(0.047)	(0.016)
Total Assets	-0.042***	-0.263***	-0.110***	0.016
	(0.009)	(0.053)	(0.034)	(0.013)
Leverage	-0.129***	0.100	0.029	0.063**
	(0.047)	(0.163)	(0.165)	(0.031)
R&D	0.013	0.007	0.053	0.007
	(0.011)	(0.063)	(0.062)	(0.024)
Cash Holdnings	0.000	0.000	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Negative Score_QT		0.002*		
		(0.001)		
Negative*BoardMember		0.025***	-0.020***	-0.005**
		(0.005)	(0.007)	(0.002)
_cons	0.518***	3.076***	0.702*	-0.255**
	(0.081)	(0.450)	(0.359)	(0.125)
Observations	711	695	678	711
R-squared	0.171	0.233	0.043	0.043
Industry effects	Yes	Yes	Yes	Yes
Year effects	No	No	No	No
Standard errors	Clustered	Clustered	Clustered	Clustered
Method	FE	FE	FE	FE

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Figure 1 – Histogram of Sentiment score