**Do financial performance indicators predict 10-K text sentiments? An application of artificial intelligence**

**Abstract**

In this study, we employ Natural Language Processing (NLP), a subdomain of artificial intelligence (AI), to predict the sentiments while analyzing 3729 annual 10-k financial reports of S&P 500 companies over the 2002–2019 time period. Our findings suggest that the firm’s financial performance indicators help reduce negativity in the textual part of 10-ks. In contrast, we do not observe any significant association between the firm’s financial performance indicators and 10-ks positivity. Our findings are robust to alternative econometric specifications and alternative measures of key variables. Our results contribute to the accounting and financial disclosure literature by indicating that corporate financial performance indicators can predict the tone of 10-k filings.

**Keywords**

Natural Language Processing (NLP); Financial reports sentiments ; Artificial intelligence (AI)

**1. Introduction**

A firm’s annual reports help various stakeholders in their decisions regarding transactions with the company. For instance, investors analyze financial data to predict stock prices and future returns. [Bankers](https://www.sciencedirect.com/topics/economics-econometrics-and-finance/bank-managers) and other creditors analyze financial statements to determine the repayment capacity of the firm. Suppliers and competitors also evaluate financial performance to expand or reduce the ties with their corporate partners. This information also permits financial markets to efficiently allocate resources based on the investor’s prudent decisions because of [financial statements analysis](https://www.sciencedirect.com/topics/economics-econometrics-and-finance/financial-statement-analysis). However, despite its significance, empirical research has largely concentrated on the quantifiable information from the financial statement (as it is readily available). On the other hand, very few studies have analyzed the textual data from the financial statements to predict the financial performance of the firms due to its complex structure and lack of standardized analysis techniques. Textual analysis of 10-k, such as sentiment inference and complexity, could be useful to predict the firm’s [stock return](https://www.sciencedirect.com/topics/economics-econometrics-and-finance/capital-market-returns), volatility, liquidity, firm earnings, and risk factors, among others ([Huang and Li, 2011](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib33), [Jegadeesh and Wu, 2013](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib34), [Boubaker et al., 2019](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib7), [Cohen et al., 2020](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib17), [Goodell et al., 2021](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib29)).[2](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "fn2)

Corporate disclosure helps in a number of ways to assess and predict the firm’s performance, particularly the firm’s stock performance. [Huang et al. (2014)](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib32) report that the stock market reaction to the 10-Q and 10-k negativity is more important than positivity, as the markets and investors react more keenly to the negative disclosures. Moreover, [Feldman et al. (2010)](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib23) argue that the stock market reaction around SEC filings is significantly associated with the tone of the firm’s financial disclosure and such reaction is stronger than that to other financial performance indicators. [Tetlock et al. (2008)](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib51) conclude that adverse words in the financial press are negatively associated with the firm’s earnings and stock prices. Similarly, [Jegadeesh and Wu (2013)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib34) also examine the tone of the 10-k documents by investigating the firm’s market-related financial indicators such as volatility, turnover, and [accruals](https://www.sciencedirect.com/topics/economics-econometrics-and-finance/accrual), among others.

Noticeably, the application of artificial intelligence (AI) algorithms to predict textual analysis is still at the embroynic stage, despite its importance for financial market efficiency and investor performance ([Ren et al., 2013](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib46)). The nature of the textual analysis is time-consuming and complex, and the results may depend on the choice of the applied algorithm. Despite the importance of firm’s textual information, the prior literature has largely overlooked it and focused mainly on the quantitative analysis of the firm. As a result, this gap between qualitative and quantitative research may inhibit the understanding of the informativeness of corporate disclosure ([Bradshaw, 2011](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib11)).

This study addresses this void in current research and focuses on the textual analysis of the financial statements, which could be aligned with the latter strands of literature that examines the impact of the textual description on financial indicators. However, this research departs from the previous studies ([Jegadeesh and Wu, 2013](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib34), [Krishnamoorthy, 2018](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib37), [Boubaker et al., 2019](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib7), [Cohen et al., 2020](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib17), [Mousa et al., 2022](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib42); Rijba et al., 2021) that examine the impact of corporate disclosure on a range of financial performance indicators. Contrary, we examine which quantifiable factors determine the non-quantifiable information, such as positivity and negativity of the financial reports of the listed firms.

Based on these conjectures, we hypothesize that quantitative financial performance indicators may impact the tone of the text of the company’s 10-k report. However, extracting sentiments from each annual document is a cumbersome and time-consuming job. We, therefore, proceed to extract the sentiments with the help of NLP algorithms. While following [Cohen et al. (2020)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib17), we extract and analyze the 10-k sentiments. The focus of [Cohen et al. (2020)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib17) was to examine the impact of 10-k sentiments on firm performance in financial markets. [Jegadeesh and Wu (2013)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib34) also examine the tone of the 10-k documents by investigating the firm’s market-related financial indicators such as volatility, turnover, and accruals, among others.

Consequently, we contribute to the literature on the application of artificial intelligence in finance by utilizing the NLP approach in a number of ways. First, extracting and using sentiments of the 10-k report enables investors and stakeholders to understand the tone of management at a glance, which is helpful in making critical financial decisions regarding their investments. Second, this study contributes to the limited literature on the determinants of 10-k report sentiments. The results highlight the importance of financial performance for 10-k sentiments. Finally, this is a premier study that comprehensively and exclusively examines the relationship between the firm’s financial performance and 10-k report sentiments.

We test our arguments by analyzing 3729 annual 10-k filings for a sample of S&P 500 companies over the 2002–2019 time period. We find that firm’s financial performance indicators (e.g., ROA, Tobin’s Q, ROE and ROIC): (a) facilitate in decreasing the *Negativity*, and (b) does not affect the *Positivity* in the textual/descriptives of 10-k filings. Further, the results of different firm-level features such as [corporate governance](https://www.sciencedirect.com/topics/economics-econometrics-and-finance/corporate-governance), cash holding and R&D expenditures show mixed results in relevance to the above nexuses. [Bassyouny and Abdelfattah, 2022](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib10) find that corporate narrative tone can predict future financial performance. They examine the impact of 10-k sentiments/disclosure tone on the stock market/financial performance of the company. Contrary to these studies, we mainly focus on the inverse relation, i.e., the impact of key financial performance indicators on the tone, i.e., positivity and negativity of the 10-k text.

The remainder of the paper is structured as follows: [Section 2](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "sec0010) discusses the literature review and develops hypotheses of the study; [Section 3](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "sec0015) describes data sources, measurement of variables and methodology. Empirical findings are presented and discussed in [Section 4](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "sec0045); and finally, [Section 5](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "sec0080) concludes the paper.

**2. Literature review and hypotheses development**

Agency theory posits that the transparency between agent and principal is crucial to evade agency problems. The executives (agents) of the profitable corporations disclose more information to amplify their success and to gain the shareholder’s confidence. In contrast, the executives show hesitancy or hide the negative performance to avert the risk of a decrease in their compensation or cessation of responsibilities. Therefore, they disclose positive financial performance predominantly and use a more positive tone to escape the potential influx of agency problems (e.g., [Aly et al., 2018](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib1); [Wang et al., 2008](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib52)). The disclosure and corporate financial performance relation could also be explained under the purview of the signaling theory, which states that corporate executives attempt to portray a positive image of the company and disclose more information when financial performance is positive. Prior literature ([Schleicher, 2012](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib48), [Clatworthy and Jones, 2006](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib18)) suggests that the companies reveal a more positive tone in the disclosure when financial performance is positive and disclose less when they suffer from loss. Corporate executives manipulate disclosure to maintain their reputation and position in the company, and this manipulation depends on their ability. For instance, [Hasan (2020)](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib31) analyzes the impact of [managerial ability](https://www.sciencedirect.com/topics/economics-econometrics-and-finance/managerial-ability) on the readability and narrative disclosures in 10-k reports for a sample of US companies. He concludes that managerial ability is positively related to the 10-k readability.

Firms’ financial performance boosts the managerial confidence/optimism that ultimately translates into managerial decisions and public communications, as managerial ability is positively related to the readability of narrative disclosure of 10-k reports ([Hasan, 2020](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib31)). [González et al. (2021)](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib28) suggest that powerful CEOs can influence the tone of information disclosure to the market by avoiding negative tones and disseminating positive words. In addition, powerful managers can also reduce the readability of financial reports by making them more complex. Under the managerial obfuscation hypothesis, [De Souza et al. (2019)](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib19) find that in order to hide information about poor financial performance, managers intentionally add more complexity to the narrative disclosures.

Moreover, managerial communications usually reflect the general sentiments about the financial performance of the company ([Batra and Daudpota, 2018](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib3), [García-Meca and García-Sánchez, 2018](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib27), [Sohangir et al., 2018](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib50)). The 10-k filing is one of the managerial communications regarding business overview, risks, and market-related indicators that exhibit ample information about the firm’s operations, performance, risks and future estimates ([Lawrence, 2013](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib38), [Boubaker et al., 2019](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib7), [Cheng et al., 2020](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib16)). For instance, [Jegadeesh and Wu (2013)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib34) analyze the 10-k filings of US companies between 1995 and 2010 and extracted the score of positive and negative sentiments based on the number of positive/negative words in the respective document. They concentrate on the firm-specific indicators such as firm risk, [return volatility](https://www.sciencedirect.com/topics/economics-econometrics-and-finance/returns-volatility), [accruals](https://www.sciencedirect.com/topics/economics-econometrics-and-finance/accrual) and turnover measured as the number of shares traded. They conclude that filing date returns are related to the tone of the 10-k document after controlling for firm-specific indicators such as earning announcement date, volatility, and accruals.

In a seminal study, [Cohen et al. (2020)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib17) examine the tone of the company’s filings and market-related indicators. They analyze a comprehensive dataset of quarterly 10-Q and annual 10-k filings of the US corporations from 1995 to 2014. They report that 10-ks are relevant for the firm’s financial indicators such as future earnings, profitability, future news announcements, and predict firm-level bankruptcies. They also find that the investors do not consider the changes and valuable information given in 10-k that could help improve the returns on their portfolios. The groundbreaking studies in this area ([Jegadeesh and Wu, 2013](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib34), [Loughran and McDonald, 2017](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib40), [Boubaker et al., 2019](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib7), [Cohen et al., 2020](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib17), [Rjiba et al., 2021](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib47)) focused on the extracted sentiments from the financial reports of the companies and associated those sentiments to several firm’s market-related indicators such as [stock returns](https://www.sciencedirect.com/topics/economics-econometrics-and-finance/capital-market-returns), stock liquidity, risks, and portfolios among others.[3](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "fn3) Furthermore, these studies examine the implications and complexity of the financial report’s disclosure on market performance indicators of the firms. However, less is known about the firms’ book (income statement, balance sheet, cash flow statement) level indicators and their role in 10-k sentiments.

Our study extends the work of [Jegadeesh and Wu (2013)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib34) and [Kang et al. (2018)](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib35), who investigated the impact of financial indicators on the tone (positive/negative) of the 10-k filings.[4](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "fn4) In particular, we hypothesize that firm-specific indicators such as return on assets and Tobin’s Q, among others, influence the tone of 10-k texts. [Jegadeesh and Wu (2013)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib34) argue that the firm-specific indicators could be the predictors of the tone of 10-k filings. They state that risky firms could translate more risky terms in the filings than relatively safe firms. Similarly, the recent poor performance by the firms is likely to be pronounced in their reporting. Moreover, turnover firms that have higher trading volume in the market will also be more cautious in their reflections in the text of 10-k. They follow the approach of [Sloan (1996)](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib49), to measure the firm’s accruals because large amounts of accruals are taken as bad news by the investors since large amounts of accruals indicate an increase in working capital that could be due to poor business conditions or earnings manipulations.[5](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "fn5) Their results indicate that the book to market (BM) ratio and volatility are significantly related to the positivity and negativity of the 10-ks, suggesting that firm size is significantly related to the negative score but not to the positive score of the 10-k report. In addition, they do not report any significant impact of accruals and stock price response on the 10-k negativity/positivity.

Although our study takes inspiration from the seminal work of [Jegadeesh and Wu (2013)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib34), our adopted approach is different from theirs. In particular, the predictors they used to predict the tone were around the date of the filing except for accruals. We, therefore, argue that other financial performance indicators such as the return of equity, Tobin’s Q and return on invested capital could also be used to predict the tone of the 10-k filings.

Noticeably, there is a lack of research examining the impact of firm-level indicators on the tone of 10-ks except that of [Kang et al. (2018)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib35). However, emerging literature discusses the impact of firm-level performance indicators on 10-k report readability ([Bonsall and Miller, 2017](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib5), [Hasan, 2020](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib31), [Nadeem, 2021](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib43)). Consistent with this assertion, we attempt to fill this gap by undertaking the firm-level financial performance and other related indicators as potential predictors of the annual 10-k sentiments.[6](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "fn6) Consequently, drawing from the agency and signaling theories and from the pertinent literature, we propose our hypotheses as follows:

***H1a:*** *Ceteris paribus, the firm’s financial performance increases/decreases the positivity of the 10-k textual disclosure.*

***H1b:*** *Ceteris paribus, the firm’s financial performance increases/decreases negativity of the 10-k textual disclosure.*

**3. Methodology**

**3.1. Data and sample**

We extract our data mainly from two sources. As our main variable comes from the 10-k financial document, we download these from the SEC official website.[7](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "fn7) The data on firms’ fundamentals come from the Worldscope database. In particular, the SEC is a government body that legally abides the companies to disclose accurate information in their financial statements. In general, annual reports filed by the companies are called 10-ks and reports filed quarterly are called 10-Qs. Both financial reports are a regulatory obligation for companies, where 10-k is a more detailed and comprehensive document as compared to the 10-Q. A standard 10-k document has four major parts, i.e., (i) business overview, (ii) markets and finance, (iii) governance, and (iv) complete financial statements. The first three components include information about general business, threats, legal proceedings, business and market-related information and governance-related indicators. The fourth part contains complete financial information about the company. It is evident that the first three indicators contain textual/descriptive data, and the fourth part is composed of quantitative data such as sales, the value of assets, [retained earnings](https://www.sciencedirect.com/topics/economics-econometrics-and-finance/reserves-for-contingencies) etc.

Moreover, we collect the quantitative data from the Worldscope database and textual/descriptive information from SEC’s EDGAR (Electronic Data gathering Analysis Retrieval) database. The EDGAR is an open-source, publicly available data repository that contains all financial reports of US companies. The information provided in the first three sections of the 10-k report is quite useful and can be accessed conveniently by the investors to analyze the company’s security market return and risks ([Campbell et al., 2014](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib12)).

We download 10-k documents from EDGAR, clean them using NLP technique, and extract sentiments for each annual 10-k for the period between 2002 and 2019, in sequence. Our sample of companies comes from the S&P 500, however, we drop the financial and utility firms due to their different nature of operations. After eliminating the financial and utility firms and merging data from both sources, we are left with the 3729 firm-years and 10-k financial reports.[8](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "fn8)

**3.2. Measurement of main variables (sentiments)**

Although both types of information are publicly available (for US companies) in the financial statements, still analyzing textual data is challenging because of its non-standadized interpratation as compared to standard definitions of quantitative ratios/data. Consequently, misinterpretation may cause loss to investors and other stakeholders ([Cheng et al., 2020](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib16), [Lawrence, 2013](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib38)). However, the advent of advanced AI and machine learning techniques has improved the analysis of a large amount of text as well as extraction of the sentiment which was previously challenging and time-consuming.

This study focuses on the determinants of 10-k sentiments instead of the impact of readability on financial indicators. In particular, readability and sentiments should be treated as different concepts, where the former deals with document complexity and the latter refers to the positivity/negativity of the document.[9](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "fn9) In this study, we follow the approach of [Cohen et al. (2020)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib17) and develop our own measure of 10-k positivity and negativity. The processing of text involves some important steps as the unstructured text is quite complex (e.g., composed of alphabets, numbers, punctuations, stop words, language-specific special characters etc.). In its original form, it is difficult for a machine to analyze the text. Therefore, the text must be cleaned before the final analysis. As mentioned above, we extract the annual 10-ks from EDGAR, which is an electronic database. The underlying text format that we must clean is written in the HTML and CSS languages.[10](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "fn10) The web page is prepared in HTML and CSS (there will be HTML tags and CSS rules). The cleaning of text for analysis largely depends on the structure of the document.[11](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "fn11) In this case, we first remove the HTML tags and normalize the text, i.e., convert the text to lowercase and remove the punctuations. The next step includes stemming and lemmatization of the words to their roots. For instance, financials, financed, financing will be brought to their root, that is finance. Lemmatization is preferred over stemming because it follows some rules and the final output of the lemmatized words is a meaningful word, but it depends on the type of the text.

We then remove the stop words,[12](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "fn12) these words are common and less important and could be removed in the text preprocessing steps. One can get the same sense of the sentence even after removing the unnecessary words. The list of stop words varies from language to language. As, the 10-ks are drafted in English, we, therefore, adopt the list of English stop words.[13](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "fn13) We repeat the same text preprocessing steps for all our 10-ks (n = 3729) and avail the cleaned text for further analysis.

Once the unstructured and uncleaned text is properly cleaned, we proceed to the next phase, i.e., extracting sentiments. There exist several techniques to predict the sentiments from the cleaned text. We matched 10-ks cleaned text with the word sentiment list of [Loughran and McDonald (2011)](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib39). The Master dictionary compiled by [Loughran and McDonald (2011)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib39) is considered more appropriate and related to finance that has been built on the same concept as the Harvard IV-4 Psychosociological Dictionaries.[14](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "fn14) We make the sentiment bag of words for each document by matching the cleaned 10-ks text with the [Loughran and McDonald (2011)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib39) Master dictionary and move the words to their corresponding categories. The bag of words sentiment now provides the sentiments for our text. We rely on TF-IDF (Term Frequency- Inverse Document Frequency) instead of matching words with the sentiments because a given word may be overrepresented in the document and could affect the sentiment. For a given word, the inverse document frequency can be defined as the inverse of the fraction of the documents containing that document.[15](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "fn15)

By using TF-IDF, we may reduce the overrepresentation of the most frequent words. The sentiment extracted are “Positive”, “Negative”, “Interesting”, “Litigious”, “uncertainty” and “constraining”. To use these sentiments for further analysis, we calculate cosine similarities following [Cohen et al. (2020)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib17). Since the text of 10-ks documents does not differ drastically; therefore it is more appropriate to consider a time-varying indicator that represents the true sentiment of the document and compares it to the others. The formula to calculate the cosine similarity metrics is as follows:

Where

represents cosine similarity, v and u are two vectors derived from the TF-IDF. The cosine similarity compares the two documents; as it appears in the formula, it is the dot product of two vectors divided by the product of their corresponding absolute length. With the help of these metrics, we compute cosine similarities for each of our 10-k documents. These similarities measured from the extracted sentiments were then used for further analysis.

**3.2.1. Financial performance indicators**

After extracting the sentiments from 10-ks between 2002 and 2019, we collect quantitative data from Worldscope. We argue that the firm’s key financial performance indicators such as return on assets (*ROA*), return on equity (*ROE*), Tobin’s Q (*TQ*) and return on invested capital (*ROIC*) help to increase/decrease the positivity and negativity of the textual part of annual 10-ks, which is consistent with the previous related studies (see, e.g., [Hasan, 2020](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib31); [Jegadeesh and Wu, 2013](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib34); Kang and Han, 2018).

**3.2.2. Firm-specific controls**

Firm-specific controls represent indicators that are based on related prior literature (Hasan, 2021; Kang and Han, 2018; [Jegadeesh and Wu, (2013)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib34). Firm-level control variables such as firm size (*SIZE*), the tangibility of firm’s assets (*TANG*), liquidity (*LIQ*), firm’s financing needs or deficit (*DEF*), and financial leverage (*LEV*). Furthermore, we consider that firm’s cash holdings (*CASH*) could also play an important role in establishing the tone of 10-ks. As excess cash reserves may be a source of managerial anxiety that the firm is failing to utilize its reserves in an efficient manner. The prior literature presents contradictory arguments about excess cash reserves and firm performance. [Harford et al. (2008)](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib30) document that excess cash reserves and low shareholders rights are negatively associated with the firm’s profitability and valuation. [Dittmar and Mahrt-Smith (2007)](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib20) examine the impact of [corporate governance](https://www.sciencedirect.com/topics/economics-econometrics-and-finance/corporate-governance) and the effective use of cash reserves. They establish that well-governed firms utilize their reserves better than poorly governed firms.

The firm’s ability to develop innovative capabilities is also considered a vital determinant of performance. A decrease in R&D spending might negatively influence the tone of 10-k because the firm has not taken initiatives to expand its innovative capabilities. For instance, [Artz et al. (2010)](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib36) found that R&D spending is positively associated with the patents and negatively associated with ROA and sales growth for a sample of 274 firms from 1996 to 2004. Similarly, [Cardinal and Hatfield (2000)](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib15) report that higher R&D spending firms have more patents than firms with lower R&D spending. All variables are defined in [Table 1](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "tbl0005).

**Table 1. Description of the variables.**

| **Variable** | **Symbol** | **Measurement** |
| --- | --- | --- |
| ***Dependent variables:*** |  |  |
| **10-k Positivity** | *Positivity* | Cosine similarities of extracted sentiments from 10-k based on positive words (explained in[Section 3.2](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "sec0025)). |
| **10-k Negativity** | *Negativity* | Cosine similarities of extracted sentiments from 10-k based on negative words (explained in[Section 3.2](https://www.sciencedirect.com/science/article/pii/S0275531922000678#sec0025)). |
| ***Independent variables:*** |  |  |
| **Return on Assets** | *ROA* | Net income divided by total assets. |
| **Tobin’s Q** | *TQ* | Firm’s market value plus assets minus total equity divided by assets. |
| **Return on Equity** | *ROE* | Net income divided by shareholder’s equity. |
| **Return on Invested Capital** | *ROIC* | Operating profit or EBIT multiplied by (1 - effective tax rate) divided by value of debt plus value of equity. |
| ***Control variables:*** |  |  |
| **Liquidity** | *LIQ* | Current assets divided by current liabilities. |
| **Financing Needs/Deficit** | *DEF* | Dividend plus Capital Expenditure plus the change in net working capital plus short-term debt & current portion of long-term debt minus Net Cash flow. |
| **Research & Development** | *RD* | Research and development expenses scaled by total assets. |
| **Tangibility** | *TANG* | Net property, plant, and equipment divided by total assets. |
| **Cash Holdings** | *CASH* | Cash & Equivalents divided by total assets. |
| **Leverage** | *LEV* | Ratio of total debt divided by the total asset. |
| **Size** | *SIZE* | Natural logarithm of total assets in US dollars at the end of the fiscal year. |
| ***Corporate governance variables:*** | | |
| **Board Size** | *B\_SIZE* | Natural log of the total number of board members. |
| **Female Proportion** | *F\_PRO* | The proportion of female directors on the board. |
| **Board Independence** | *B\_IND* | The proportion of independent directors on the board. |
| **CEO-Chairman Separation** | *SEP* | Dummy variable equals 1 the CEO and board chairman roles are separated and 0 otherwise. |

**Note:** All financial variables are winsorized at 1% and 99% levels.

**3.3. Estimation techniques**

We now have both sets of transformed variables for further analysis. We matched firm-year financial indicators (quantitative variables) with the extracted sentiment (time-varying cosine similarities) along with their ticker identifications. Although, we extracted six sentiments discussed previously from the financial statements, yet in this study, we focus on only two “positive” and “negative” due to their greater importance and acceptance ([Azimi and Agrawal, 2021](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib2); Kang and Han, 2018).[16](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "fn16) To empirically test our arguments, we employ OLS (Ordinary Least Square) regression followed by advanced [panel data analysis](https://www.sciencedirect.com/topics/economics-econometrics-and-finance/panel-data-analysis) techniques such as Fixed Effects techniques for robustness check. Following prior studies (Kang and Han, 2018; [García-Meca and García-Sánchez, 2018](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib27)), we use all independent and control variables at their first lags to avoid reverse causality between quantitative and textual data in the same year.[17](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "fn17) The use of lagged variables helps eliminate the issue of reverse causality and correct for endogeneity. The baseline regression model is as follows:(1)

(2) Where, in [(1)](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "eqn0010), [(2)](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "eqn0015), *Positivity/Negativity* refers to the increase/decrease in positive/negative sentiments of 10-k. A positive/negative variation in the firm’s financial performance could be considered a good/bad indicator for the management, which ultimately is reflected in their disclosure that we estimated from the 10-k texts. *Financials* represent the firm’s financial

performance indicators, and *Controls* shows firm-level control variables as described above.

**4. Results and discussion**

**4.1. Descriptive statistics and correlations**

[Table 2](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "tbl0010) reports the descriptive statistics of the key variables and control variables. The mean scores of *Positivity* and *Negativity* are 0.925 and 0.889, respectively. We observe that *Positivity* has a relatively higher mean score as compared to *Negativity*. Similarly, mean scores for *ROA* and *TQ* are 0.083 and 0.582, respectively.

Table 2. Summary statistics.

| **Variable** | **N** | **Mean** | **SD** | **Min** | **Quartile 1** | **Quartile 2** | **Quartile 3** | **Max** |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| ***Positivity*** | 3729 | 0.925 | 0.187 | 0.000 | 0.956 | 0.980 | 0.990 | 1.000 |
| ***Negativity*** | 3729 | 0.889 | 0.193 | 0.000 | 0.905 | 0.953 | 0.975 | 0.997 |
| ***ROA*** | 3729 | 0.083 | 0.088 | -0.840 | 0.052 | 0.084 | 0.123 | 0.336 |
| ***TQ*** | 3729 | 0.583 | 0.219 | 0.057 | 0.446 | 0.579 | 0.710 | 1.362 |
| ***LIQ*** | 3729 | 1.991 | 1.408 | 0.330 | 1.142 | 1.615 | 2.370 | 15.289 |
| ***DEF*** | 3729 | 6.21 | 6.46 | 0.000 | 5.03 | 5.81 | 6.30 | 7.05 |
| ***RD*** | 3729 | 0.035 | 0.061 | 0.000 | 0.000 | 0.009 | 0.046 | 0.589 |
| ***TANG*** | 3729 | 0.257 | 0.218 | 0.000 | 0.094 | 0.179 | 0.366 | 0.935 |
| ***CASH*** | 3729 | 0.159 | 0.163 | 0.001 | 0.041 | 0.102 | 0.218 | 0.930 |
| ***LEV*** | 3729 | 0.268 | 0.189 | 0.000 | 0.140 | 0.248 | 0.366 | 1.048 |
| ***SIZE*** | 3729 | 16.014 | 1.428 | 10.700 | 15.098 | 15.970 | 16.993 | 19.228 |

Note: This table reports summary statistics for all variables used in the main analysis. All variables are as defined in Table 1.

[Table 3](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "tbl0015) provides the correlations among all variables used in the analysis. Correlation among all variables is within the acceptable limit, and the unreported results of Variance Inflation Factors (VIF) show that all VIF values are below 4, which is less than the threshold value of 10. Hence, these values suggest that our sample does not suffer from multicollinearity issues.

Table 3. Correlation matrix.

| **Variables** | ***1*** | ***2*** | ***3*** | ***4*** | ***5*** | ***6*** | ***7*** | ***8*** | ***9*** | ***10*** | ***11*** |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **1. *Positivity*** | 1.000 |  |  |  |  |  |  |  |  |  |  |
| **2. *Negativity*** | 0.931 \* | 1.000 |  |  |  |  |  |  |  |  |  |
| **3. *ROA*** | -0.024 | -0.035 \* | 1.000 |  |  |  |  |  |  |  |  |
| **4. *TQ*** | 0.067 \* | 0.083 \* | -0.133 \* | 1.000 |  |  |  |  |  |  |  |
| **5. *LIQ*** | 0.004 | 0.013 | 0.022 | -0.469 \* | 1.000 |  |  |  |  |  |  |
| **6. *DEF*** | 0.005 | 0.011 | -0.010 | -0.054 \* | 0.215 \* | 1.000 |  |  |  |  |  |
| **7. *RD*** | 0.051 \* | 0.070 \* | -0.202 \* | -0.193 \* | 0.295 \* | 0.055 \* | 1.000 |  |  |  |  |
| **8. *TANG*** | -0.111 \* | -0.105 \* | -0.067 \* | 0.128 \* | -0.258 \* | -0.119 \* | -0.279 \* | 1.000 |  |  |  |
| **9. *CASH*** | 0.004 | 0.035 \* | 0.006 | -0.231 \* | 0.455 \* | 0.184 \* | 0.437 \* | -0.353 \* | 1.000 |  |  |
| **10. *LEV*** | 0.021 | 0.056 \* | -0.139 \* | 0.466 \* | -0.205 \* | 0.018 | -0.186 \* | 0.158 \* | -0.231 \* | 1.000 |  |
| **11. *SIZE*** | -0.026 | -0.006 | 0.018 | 0.237 \* | -0.325 \* | 0.449 \* | -0.265 \* | 0.217 \* | -0.293 \* | 0.136 \* | 1.000 |

**Note:** This table reports the results of correlation analysis among the variables used in main analysis.

\* shows significance at the 5% level.

All variables are as defined in [Table 1](https://www.sciencedirect.com/science/article/pii/S0275531922000678#tbl0005).

**4.2. Main analysis**

[Table 4](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "tbl0020) presents the results of the OLS model for the impact of performance indicators, i.e., return on assets (*ROA*) and Tobin’s Q (*TQ*) on time-varying *Positivity* and *Negativity* of the 10-ks, after controlling for a set of control variables. We estimate [Eq. (1)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#eqn0010) using a pooled cross-section time-series regression by including industry and time-fixed effects along with robust [standard errors](https://www.sciencedirect.com/topics/economics-econometrics-and-finance/measure-of-dispersion) clustered at the firm level. Columns 1 and 3 of [Table 4](https://www.sciencedirect.com/science/article/pii/S0275531922000678#tbl0020) show that the coefficients of *ROA* and *TQ* are statistically insignificant, suggesting that firms’ financial performance does not influence the positive tone of the 10-k report. Columns 2 and 4 of [Table 4](https://www.sciencedirect.com/science/article/pii/S0275531922000678#tbl0020) report the results of [Eq. (2)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#eqn0015), where the coefficients of both these indicators show a negative and statistically significant impact on *Negativity* at a 1% significance level, suggesting that firm’s financial performance helps reduce negative sentiment in the 10-k report. It implies that an increase in *ROA* and *TQ* enhances the confidence of the management, which eventually translates into the disclosure. Eventually, it reduces the *Negativity* in the 10-k reports. Overall, these findings imply that the firms experiencing an increase in the *ROA* and *TQ* use fewer negative words in their 10-k reports (e.g., [Aly et al., 2018](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib1); [Wang et al., 2008](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib52)).[18](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "fn18)

Table 4. Financial performance and 10-k sentiments.

|  | **(1)** | **(2)** | **(3)** | **(4)** |
| --- | --- | --- | --- | --- |
| **Variables** | **Positivity** | **Negativity** | **Positivity** | **Negativity** |
| ***ROA*** | -0.000 | -0.001 \* \*\* |  |  |
|  | (−1.43) | (−2.59) |  |  |
| ***TQ*** |  |  | -0.983 | -0.183 \* \*\* |
|  |  |  | (−0.67) | (−4.00) |
| ***LIQ*** | -0.005 \* | -0.005 \* | -0.005 \* | -0.002 |
|  | (−1.86) | (−1.91) | (−1.91) | (−0.67) |
| ***DEF*** | -0.000 \* \* | -0.000 \* | -0.000 \* \* | -0.000 |
|  | (−1.98) | (−1.92) | (−1.98) | (−0.00) |
| ***RD*** | -0.034 | -0.003 | -0.004 | 0.237 \* \*\* |
|  | (−0.52) | (−0.05) | (−0.06) | (3.59) |
| ***TANG*** | -0.017 | 0.007 | -0.016 | -0.080 \* \*\* |
|  | (−0.75) | (0.29) | (−0.67) | (−4.47) |
| ***CASH*** | -0.022 | 0.016 | -0.018 | -0.026 |
|  | (−0.82) | (0.60) | (−0.65) | (−0.89) |
| ***LEV*** | -0.004 | 0.015 | -0.002 | 0.030 \* |
|  | (−0.22) | (0.84) | (−0.13) | (1.68) |
| ***SIZE*** | -0.007 \* \* | -0.007 \* \* | -0.007 \* \* | -0.009 \* \*\* |
|  | (−2.43) | (−2.45) | (−2.42) | (−2.80) |
| ***Constant*** | 0.983 \* \*\* | 0.923 \* \*\* | 0.987 \* \*\* | 1.010 \* \*\* |
|  | (16.02) | (14.89) | (15.55) | (18.64) |
| ***Observations*** | 3595 | 3595 | 3595 | 3595 |
| ***Industry*** | Yes | Yes | Yes | Yes |
| ***Year*** | Yes | Yes | Yes | Yes |
| ***Adj. R2*** | 0.216 | 0.226 | 0.217 | 0.0740 |
| ***F-stat*** | 14.39 | 15.15 | 14.15 | 10.36 |

**Note:** This table presents the results from regressing financial performance indicators (i.e., *ROA* & *TQ*) on 10-k sentiments (i.e., *Positivity* & *Negativity*) and several control variables using OLS estimations.

T-statistics are reported in parenthesis.

\*\*\*, \*\* and \* shows significance level at 1%, 5% and 10% respectively.

All variables are as defined in [Table 1](https://www.sciencedirect.com/science/article/pii/S0275531922000678#tbl0005).

These results are consistent with those of [Jegadeesh and Wu (2013)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib34), who report that firm-specific indicators such as size and volatility do not contribute significantly to the positive tone of 10-ks.[19](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "fn19) They also report that risky firms adopt more negative words and less positive words in their 10-k disclosure. Several empirical studies ([Tetlock et al., 2008](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib51), [Epstein and Schneider, 2008](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib22); Rijba et al., 2021) have shown that the negative sentiment is more powerful than the positive. The negative words are more relevant to the low firm earnings and stock price under-reaction ([Tetlock et al., 2008](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib51)). Similarly, Rijba et al. (2021) argue that a more negative or ambiguous tone of the 10-k increases the magnitude of the relationship between annual report complexity and firm’s cost of capital. In particular, investors react differently to good and bad news, i.e., strong reaction to the bad news and dampened reaction to the good news ([Epstein and Schneider, 2008](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib22)) because investors and the other stakeholders give more importance to the negative or ambiguous sentiments/news than positive. Our results are partially aligned with the theory, i.e., positive financial performance leads to the reduction in the negative sentiments in the 10-k filings.

**4.2.1. Controlling for board-level corporate governance mechanisms**

In the main analysis, we incorporate a diverse set of potential determinants of *Positivity* and *Negativity* of 10-ks as control variables. However, possibly omitted variable bias may affect our main results. In a recent study, [Nadeem (2021)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib43) finds a positive association between board gender diversity and 10-k readability, suggesting that board-level corporate governance mechanisms may also influence the tone of 10-k.[20](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "fn20) Therefore, it is important to examine the influence of board-level corporate governance mechanisms on the relationship between the firm’s financial performance indicators and 10-k sentiments. Prior studies ([Aly et al., 2018](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib1), [Wang et al., 2008](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib52), [Clatworthy and Jones, 2006](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib18)) have explained that corporate managers manipulate disclosure information to magnify their performance and to avoid agency conflict. The managers disclose more positive information and hide negative. Therefore, the corporate governance characteristics such as board size, independence, diversity, and CEO separation may influence the company’s disclosure in the 10-ks. To do so, we focus on widely used proxies of board-level of corporate governance mechanisms, i.e., board size (*B\_SIZE*), board independence (*B\_IND*), the level of board gender diversity (*F\_PRO*) and the CEO-Chairman separation (*SEP*) and re-estimate [(1)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#eqn0010), [(2)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#eqn0015) after including these corporate governance variables along with other control variables.[21](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "fn21) The results of this analysis, presented in [Table 5](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "tbl0025), also show that financial performance indicators (*ROA* & *TQ*) have no significant influence on *Positivity* but are negatively and significantly associated with *Negativity*. Hence, reaffirming that our results are consistent even after controlling for the effect of board-level corporate governance mechanisms and are not subject to omitted variables bias.

Table 5. Financial performance and 10-k sentiments: the role CG characteristics.

|  | **(1)** | **(2)** | **(3)** | **(4)** |
| --- | --- | --- | --- | --- |
| **Variables** | **Positivity** | **Negativity** | **Positivity** | **Negativity** |
| ***ROA*** | -0.000 | -0.002 \* \*\* |  |  |
|  | (−0.53) | (−3.49) |  |  |
| ***TQ*** |  |  | 0.764 | -0.133 \* \*\* |
|  |  |  | (0.22) | (−2.93) |
| ***B\_SIZE*** | -0.009 | -0.024 | -0.008 | -0.023 |
|  | (−0.49) | (−1.25) | (−0.43) | (−1.13) |
| ***B\_IND*** | -0.023 | 0.075 \* \*\* | -0.017 | 0.079 \* \*\* |
|  | (−0.82) | (2.59) | (−0.59) | (2.62) |
| ***F\_PRO*** | 0.037 | -0.051 | 0.038 | -0.042 |
|  | (0.94) | (−1.26) | (0.94) | (−1.03) |
| ***SEP*** | -0.002 | -0.004 | -0.002 | -0.002 |
|  | (−0.23) | (−0.50) | (−0.28) | (−0.26) |
| ***LIQ*** | -0.008 \* \* | -0.002 | -0.008 \* \* | -0.002 |
|  | (−2.38) | (−0.68) | (−2.49) | (−0.66) |
| ***DEF*** | -0.000 \* | -0.000 | -0.000 \* | -0.000 |
|  | (−1.77) | (−0.06) | (−1.75) | (−0.01) |
| ***RD*** | -0.008 | 0.178 \* \* | -0.002 | 0.274 \* \*\* |
|  | (−0.11) | (2.29) | (−0.03) | (3.55) |
| ***TANG*** | -0.029 | -0.093 \* \*\* | -0.028 | -0.090 \* \*\* |
|  | (−1.12) | (−4.83) | (−1.07) | (−4.66) |
| ***CASH*** | -0.018 | -0.070 \* \* | -0.019 | -0.063 \* |
|  | (−0.57) | (−2.15) | (−0.60) | (−1.90) |
| ***LEV*** | -0.025 | 0.007 | -0.025 | 0.003 |
|  | (−1.18) | (0.33) | (−1.16) | (0.16) |
| ***SIZE*** | -0.007 \* | -0.002 | -0.007 | -0.004 |
|  | (−1.69) | (−0.48) | (−1.64) | (−1.05) |
| ***Constant*** | 1.013 \* \*\* | 0.915 \* \*\* | 1.008 \* \*\* | 0.948 \* \*\* |
|  | (12.61) | (12.83) | (12.25) | (12.86) |
| ***Observations*** | 3102 | 3102 | 3102 | 3102 |
| ***Industry*** | Yes | Yes | Yes | Yes |
| ***Year*** | Yes | Yes | Yes | Yes |
| ***Adj. R2*** | 0.222 | 0.0675 | 0.222 | 0.0667 |
| ***F-stat*** | 12.32 | 7.597 | 12.24 | 7.466 |

**Note:** This table presents the results from regressing financial performance indicators (i.e., *ROA* & *TQ*) on 10-k sentiments (i.e., *Positivity* & *Negativity*) after controlling for the effect of board-level corporate governance mechanisms such as board size (*B\_SIZE*), board independence (*B\_SIND*), board gender diversity (*F\_PRO*) and CEO-Chairman separation (*SEP*) using OLS estimations.

T-statistics are reported in parenthesis.

\*\*\*, \*\* and \* shows significance level at 1%, 5% and 10% respectively.

All variables are as defined in [Table 1](https://www.sciencedirect.com/science/article/pii/S0275531922000678#tbl0005).

**4.3. Alternative econometric specification**

Although, we address the issue of endogeneity using all independent and control variables at their first lag under the main analysis. To further address this issue, we employ the firm-fixed effect estimations to examine the association between financial performance indicators and 10-k sentiments. We report the results of this analysis in [Table 6](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "tbl0030), which are qualitatively similar to those reported under the main analysis (i.e., [Table 4](https://www.sciencedirect.com/science/article/pii/S0275531922000678#tbl0020)). Hence, providing further evidence that our main findings are not subject to any potential endogeneity issues.

Table 6. Firm fixed-effect regressions.

|  | **(1)** | **(2)** | **(3)** | **(4)** |
| --- | --- | --- | --- | --- |
| **Variables** | **Positivity** | **Negativity** | **Positivity** | **Negativity** |
| ***ROA*** | -0.000 | -0.001 \* \* |  |  |
|  | (−0.86) | (−2.32) |  |  |
| ***TQ*** |  |  | -0.733 | -0.713 \* \* |
|  |  |  | (−0.92) | (−1.97) |
| ***LIQ*** | 0.008 \* \*\* | 0.009 \* \*\* | 0.008 \* \*\* | 0.009 \* \*\* |
|  | (2.64) | (2.89) | (2.63) | (2.85) |
| ***DEF*** | -0.000 | -0.000 | -0.000 | -0.000 |
|  | (−0.66) | (−1.18) | (−0.69) | (−1.09) |
| ***RD*** | -0.059 | -0.034 | -0.042 | -0.011 |
|  | (−0.65) | (−0.36) | (−0.45) | (−0.11) |
| ***TANG*** | -0.010 | -0.014 | -0.006 | -0.005 |
|  | (−0.24) | (−0.31) | (−0.15) | (−0.11) |
| ***CASH*** | -0.081 \* \* | -0.053 | -0.081 \* \* | -0.051 |
|  | (−2.57) | (−1.59) | (−2.52) | (−1.50) |
| ***LEV*** | 0.040 \* | 0.065 \* \*\* | 0.047 \* \* | 0.081 \* \*\* |
|  | (1.86) | (2.84) | (2.09) | (3.37) |
| ***SIZE*** | 0.001 | 0.000 | 0.001 | 0.001 |
|  | (0.09) | (0.07) | (0.17) | (0.09) |
| ***Constant*** | 0.847 \* \*\* | 0.781 \* \*\* | 0.836 \* \*\* | 0.768 \* \*\* |
|  | (9.07) | (7.91) | (8.56) | (7.45) |
| ***Observations*** | 3595 | 3595 | 3595 | 3595 |
| ***Industry*** | No | No | No | No |
| ***Year*** | Yes | Yes | Yes | Yes |
| ***R2*** | 0.050 | 0.099 | 0.051 | 0.098 |
| ***F-stat*** | 7.448 | 15.45 | 7.342 | 14.98 |

**Note:** This table presents the results from regressing financial performance indicators (i.e., *ROA* & *TQ*) on 10-k sentiments (i.e., *Positivity* & *Negativity*) and several control variables using fixed-effect estimations.

T-statistics are reported in parenthesis.

\*\*\*, \*\* and \* shows significance level at 1%, 5% and 10% respectively.

All variables are as defined in [Table 1](https://www.sciencedirect.com/science/article/pii/S0275531922000678#tbl0005).

**4.4. Alternative measures of main variables**

Under the main analysis, we measured financial performance using *ROA* and *TQ*, and 10-k sentiments were measured using the NLP technique. It might be possible that our main findings are subject to the use of these measures of financial performance or 10-k sentiments. We, therefore, use return on equity (*ROE*) and return on invested capital (*ROIC*) as alternative measures of financial performance and measure *Positive* and *Negative* sentiments by dividing the number of positive and negative words by the total number of words in each 10-k, as suggested by [Tetlock et al. (2008)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib51). We then re-estimate [(1)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#eqn0010), [(2)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#eqn0015) using alternate measures of firm performance and 10-k sentiments to ensure that our results are not subject to the measurement issues (i.e., the measurement of the key variables). The results of these analyses are presented in [Table 7](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "tbl0035), [Table 8](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "tbl0040) which also show that financial performance indicators do not have any significant influence on *Positivity* (*Positive*) while negatively and significantly associated with the *Negativity* (*Negative*), implying that our main findings are not subject to measurement issues or the use of alternative measures of financial performance and 10-k sentiments.

Table 7. Alternative measures of financial performance.

|  | **(1)** | **(2)** | **(3)** | **(4)** |
| --- | --- | --- | --- | --- |
| **Variables** | ***Positivity*** | ***Negativity*** | ***Positivity*** | ***Negativity*** |
| ***ROE*** | -0.001 | -0.001 \* |  |  |
|  | (−1.62) | (−1.69) |  |  |
| ***ROIC*** |  |  | -0.001 | -0.002 \* \* |
|  |  |  | (−1.28) | (−2.18) |
| ***LIQ*** | -0.005 \* | -0.003 | -0.007 \* \* | -0.004 |
|  | (−1.90) | (−1.11) | (−2.11) | (−1.28) |
| ***DEF*** | -0.000 \* | -0.000 | -0.000 | 0.000 |
|  | (−1.89) | (−0.15) | (−1.38) | (0.22) |
| ***RD*** | -0.018 | 0.116 \* | -0.065 | 0.147 |
|  | (−0.30) | (1.83) | (−0.71) | (1.61) |
| ***TANG*** | -0.021 | -0.076 \* \*\* | -0.026 | -0.099 \* \*\* |
|  | (−0.94) | (−4.46) | (−0.98) | (−4.98) |
| ***CASH*** | -0.023 | -0.025 | -0.037 | -0.060 \* |
|  | (−0.86) | (−0.93) | (−1.16) | (−1.86) |
| ***LEV*** | -0.007 | 0.028 \* | -0.029 | 0.007 |
|  | (−0.38) | (1.68) | (−1.40) | (0.35) |
| ***SIZE*** | -0.008 \* \*\* | -0.008 \* \*\* | -0.009 \* \* | -0.007 \* \* |
|  | (−2.75) | (−2.65) | (−2.50) | (−2.22) |
| ***Constant*** | 1.005 \* \*\* | 0.991 \* \*\* | 0.984 \* \*\* | 0.975 \* \*\* |
|  | (16.33) | (19.49) | (13.57) | (16.59) |
| ***Observations*** | 3556 | 3556 | 3098 | 3098 |
| ***Industry*** | Yes | Yes | Yes | Yes |
| ***Year*** | Yes | Yes | Yes | Yes |
| ***Adj. R2*** | 0.176 | 0.071 | 0.184 | 0.075 |
| ***F-stat*** | 11.23 | 10.18 | 10.56 | 9.388 |

**Note:** This table presents the results from regressing alternative measures of financial performance (i.e., *ROE* & *ROIC*) on 10-k sentiments (i.e., *Positivity* & *Negativity*) and several control variables using OLS estimations.

T-statistics are reported in parenthesis.

\*\*\*, \*\* and \* shows significance level at 1%, 5% and 10% respectively.

All variables are as defined in [Table 1](https://www.sciencedirect.com/science/article/pii/S0275531922000678#tbl0005).

Table 8. Alternative measures of 10-k sentiments.

|  | **(1)** | **(2)** | **(3)** | **(4)** |
| --- | --- | --- | --- | --- |
| **Variables** | **Positive** | **Negative** | **Positive** | **Negative** |
|  | [Loughran and McDonald (2017)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib40) | | | |
| ***ROA*** | 0.000 | -0.001 \* \*\* |  |  |
|  | (1.09) | (−8.03) |  |  |
| ***TQ*** |  |  | 0.047 | -0.262 \* \*\* |
|  |  |  | (1.60) | (−4.18) |
| ***LIQ*** | 0.000 \* | -0.000 | 0.000 \* \*\* | 0.000 |
|  | (1.85) | (−0.27) | (3.35) | (0.45) |
| ***DEF*** | -0.000 \* | -0.000 | -0.000 | -0.000 |
|  | (−1.73) | (−1.13) | (−1.33) | (−0.71) |
| ***RD*** | 0.004 \* \*\* | 0.001 | 0.002 \* \*\* | 0.005 \* \*\* |
|  | (5.76) | (0.88) | (3.46) | (3.83) |
| ***TANG*** | -0.001 \* \*\* | -0.001 | 0.000 | -0.001 |
|  | (−2.92) | (−1.09) | (0.28) | (−1.08) |
| ***CASH*** | -0.000 | 0.005 \* \*\* | 0.000 | 0.005 \* \*\* |
|  | (−1.36) | (9.59) | (0.02) | (9.40) |
| ***LEV*** | -0.000 \* \* | -0.000 | -0.000 \* \* | -0.000 |
|  | (−1.96) | (−1.17) | (−2.35) | (−0.87) |
| ***SIZE*** | 0.000 \* \*\* | 0.000 \* \* | 0.000 \* \*\* | 0.000 |
|  | (6.35) | (1.96) | (6.25) | (0.66) |
| ***Constant*** | 0.003 \* \*\* | 0.012 \* \*\* | 0.002 \* \*\* | 0.013 \* \*\* |
|  | (4.38) | (9.56) | (2.76) | (10.19) |
| ***Observations*** | 3202 | 3202 | 3202 | 3202 |
| ***Industry*** | Yes | Yes | Yes | Yes |
| ***Year*** | Yes | Yes | Yes | Yes |
| ***Adj. R2*** | 0.183 | 0.293 | 0.340 | 0.293 |
| ***F-stat*** | 10.82 | 19.13 | 9.829 | 18.75 |

**Note:** This table presents the results from regressing financial performance indicators (i.e., *ROA* & *TQ*) on alternative measures of 10-k sentiments (i.e., *Positive* & *Negative*) and several control variables using OLS estimations.

T-statistics are reported in parenthesis.

\*\*\*, \*\* and \* shows significance level at 1%, 5% and 10% respectively.

All variables are as defined in [Table 1](https://www.sciencedirect.com/science/article/pii/S0275531922000678#tbl0005).

**4.5. Additional analysis**

Notably, our sample period is 2002–2019, which also includes the global financial crisis period (i.e., 2007–2009). Arguably, the global financial crisis had an adverse effect on the financial performance of companies which may also affect the 10-k sentiments. [Campello et al. (2010)](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib13) report that financially constrained firms paid less or no dividends to their shareholders during the financial crisis period. The slumped profitability and other performance indicators can also affect the tone of financial disclosure. For example, [Bodnaruk et al. (2015)](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib6) highlight that the 10-k of “*The New York Times*” on February 26, 2008, contains 1.5% constraining words that is the highest percentage of constraining words firm has ever reported.

We, therefore, perform additional analysis after splitting our sample into (i) the pre-crisis (2002–2006) and (ii) the post-crisis period (2010–2019) to examine whether our results remain consistent under both time periods.[22](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "fn22) We report the results of the analysis based on the pre- and post-crisis samples in [Table 9](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "tbl0045), [Table 10](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "tbl0050), respectively. The results reported under both sub-samples show that financial performance indicators are negatively associated with *Negativity* but do not have any significant impact on *Positivity*. Therefore, reaffirming that our results remain consistent in the pre- as well as post-crisis periods.

Table 9. Pre-crisis period.

|  | **(1)** | **(2)** | **(3)** | **(4)** |
| --- | --- | --- | --- | --- |
| **Variables** | **Positivity** | **Negativity** | **Positivity** | **Negativity** |
| ***ROA*** | -0.002 | -0.003 \* \*\* |  |  |
|  | (−1.47) | (−2.81) |  |  |
| ***TQ*** |  |  | -0.785 | -0.850 \* |
|  |  |  | (−0.51) | (−1.88) |
| ***LIQ*** | -0.005 | -0.011 | -0.003 | -0.007 |
|  | (−0.66) | (−1.43) | (−0.37) | (−0.86) |
| ***DEF*** | 0.000 | 0.000 | 0.000 | 0.000 |
|  | (0.30) | (1.28) | (0.19) | (1.23) |
| ***RD*** | -0.019 | -0.016 | 0.096 | 0.215 |
|  | (−0.08) | (−0.07) | (0.41) | (0.95) |
| ***TANG*** | -0.082 | -0.087 | -0.079 | -0.078 |
|  | (−1.13) | (−1.60) | (−1.05) | (−1.37) |
| ***CASH*** | -0.045 | 0.105 | -0.044 | 0.121 |
|  | (−0.51) | (1.28) | (−0.47) | (1.40) |
| ***LEV*** | 0.113 \* \* | 0.127 \* \* | 0.140 \* \* | 0.146 \* \*\* |
|  | (2.13) | (2.46) | (2.46) | (2.62) |
| ***SIZE*** | -0.005 | -0.005 | -0.002 | -0.004 |
|  | (−0.64) | (−0.59) | (−0.30) | (−0.46) |
| ***Constant*** | 1.039 \* \*\* | 0.986 \* \*\* | 0.983 \* \*\* | 0.937 \* \*\* |
|  | (6.46) | (7.66) | (5.94) | (7.10) |
| ***Observations*** | 610 | 610 | 610 | 610 |
| ***Industry*** | Yes | Yes | Yes | Yes |
| ***Year*** | Yes | Yes | Yes | Yes |
| ***Adj. R2*** | 0.163 | 0.154 | 0.164 | 0.153 |
| ***F-stat*** | 3.046 | 3.070 | 3.018 | 2.943 |

**Note:** This table presents the results from regressing financial performance indicators (i.e., *ROA* & *TQ*) on 10-k sentiments (i.e., *Positivity* & *Negativity*) and several control variables using OLS estimations based on pre-crisis period sub-sample.

T-statistics are reported in parenthesis.

\*\*\*, \*\* and \* shows significance level at 1%, 5% and 10% respectively.

All variables are as defined in [Table 1](https://www.sciencedirect.com/science/article/pii/S0275531922000678#tbl0005).

Table 10. Post-crisis period.

|  | **(1)** | **(2)** | **(3)** | **(4)** |
| --- | --- | --- | --- | --- |
| **Variables** | **Positivity** | **Negativity** | **Positivity** | **Negativity** |
| ***ROA*** | -0.000 | -0.001 \* \*\* |  |  |
|  | (−0.11) | (−2.64) |  |  |
| ***TQ*** |  |  | -0.853 | -0.758 \* \* |
|  |  |  | (−0.26) | (−2.54) |
| ***LIQ*** | -0.003 | 0.002 | -0.004 | 0.001 |
|  | (−1.08) | (0.61) | (−1.23) | (0.40) |
| ***DEF*** | -0.000 | -0.000 | -0.000 | -0.000 |
|  | (−1.25) | (−0.21) | (−1.19) | (−0.07) |
| ***RD*** | -0.033 | 0.098 | -0.030 | 0.185 \* \*\* |
|  | (−0.49) | (1.36) | (−0.45) | (2.64) |
| ***TANG*** | 0.001 | -0.079 \* \*\* | 0.003 | -0.076 \* \*\* |
|  | (0.04) | (−4.02) | (0.13) | (−3.84) |
| ***CASH*** | -0.019 | -0.078 \* \* | -0.016 | -0.070 \* \* |
|  | (−0.66) | (−2.51) | (−0.54) | (−2.19) |
| ***LEV*** | -0.046 \* \* | -0.004 | -0.051 \* \* | -0.012 |
|  | (−2.42) | (−0.23) | (−2.53) | (−0.60) |
| ***SIZE*** | -0.011 \* \*\* | -0.008 \* \* | -0.012 \* \*\* | -0.011 \* \*\* |
|  | (−3.03) | (−2.14) | (−3.05) | (−2.73) |
| ***Constant*** | 1.071 \* \*\* | 1.071 \* \*\* | 1.081 \* \*\* | 1.116 \* \*\* |
|  | (14.67) | (16.87) | (14.26) | (16.63) |
| ***Observations*** | 2341 | 2341 | 2341 | 2341 |
| ***Industry*** | Yes | Yes | Yes | Yes |
| ***Year*** | Yes | Yes | Yes | Yes |
| ***Adj. R2*** | 0.249 | 0.134 | 0.250 | 0.133 |
| ***F-stat*** | 12.40 | 4.440 | 12.27 | 4.361 |

**Note:** This table presents the results from regressing financial performance indicators (i.e., *ROA* & *TQ*) on 10-k sentiments (i.e., *Positivity* & *Negativity*) and several control variables using OLS estimations based on post-crisis period sub-sample.

T-statistics are reported in parenthesis.

\*\*\*, \*\* and \* shows significance level at 1%, 5% and 10% respectively.

All variables are as defined in [Table 1](https://www.sciencedirect.com/science/article/pii/S0275531922000678#tbl0005).

**5. Conclusion**

In this study, we attempt to predict 10-k report sentiments based on the firm’s financial performance. We hypothesize that the level of the firm’s financial performance is likely to be pronounced in the 10-k disclosure. To investigate this hypothesis, we analyzed 3729 annual 10-k filings for a sample of S&P 500 companies over the years 2002–2019. We employ a battery of econometrics techniques and robustness tests to examine this hypothesis.

Our analyses suggest that the firm’s financial performance indicators, such as *ROA*, *Tobin’s Q*, *ROE* and *ROIC* fall short of influencing the *Positivity* of 10-ks. However, we observe that firm’s financial performance indicators help reduce *Negativity* in the textual/descriptive part of 10-k filings. Moreover, other firm characteristics such as corporate governance, cash holding, and R&D expenditure exhibit mixed trends in terms of their impact on *Positivity* and *Negativity*. Due to the ambiguous impact of these indicators, we are unable to confirm their association with the 10-k sentiments.

To further validate our results, we apply alternative estimations and proxies for financial performance and sentiments. Our findings hold across all estimations and with alternative proxies of main variables. Our research contributes to the rapidly growing literature on the firm’s disclosure, sentiment analysis and firm’s financial performance. These findings are valuable for investors, suppliers, and other stakeholders to evaluate and assess the tone of 10-k filings. Our results contribute to the accounting and financial disclosure literature by showing that corporate financial performance can predict the tone of 10-k filings. This study has practical implications for corporations and external users of the corporate’s financial reports. However, the scope of this research is limited to the positive and negative sentiments only; future research could be conducted to predict the other sentiments suggested by Loughran and McDonald (2016).

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[2](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bfn2)The adoption of AI and Machine learning is not only limited to the analysis of firms, it is being widely employed in macroeconomic indicator’s forecasting as well (e.g., [Duan et al., 2021](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib21)).

[3](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bfn3)[Gandhi et al. (2019)](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib25) find that sentiments of quantitative indicators are associated with large delisting probabilities, lower payment of dividend, reduced return on assets and higher loan loss provisions. [Cannon et al. (2020)](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib14) extract the corporate social responsibility (CSR) related disclosure from the annual 10-k reports. Their results show that 10-k disclosure intensity negatively impacts the gross margin while positively affects firm’s selling, general, and administrative (SG&A) margins.

[4](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bfn4)Similarly, the focus of Tang et al., (2018) also remained on firm’s market related indicators such as stock return volatility, earning volatility, they also examine the impact of some firm performance indicators such as operating earnings, market to book value of assets etc. However, their measure of 10-k report tone was slightly different from the one we developed, they computed frequency difference of positive and negative tone of current year and previous year’s positivity and negativity. In addition, they ignored other firm’s financial performance indicators such as return of equity, tobin’s Q and return on invested capital.

[5](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bfn5)They measure accruals as “one-year change in current assets excluding cash minus change in current liabilities excluding long-term debt in current liabilities and taxes payables minus depreciation divided by average total assets.”

[6](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bfn6)We utilize modern NLP techniques to extract the sentiments and use the Loughran and McDonald (2016) master dictionary that is highly appropriate for financial documents as compared to the general word list dictionary by the Harvard IV-Psycho-sociological Dictionaries.

[7](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bfn7)Securities and Exchange Commission USA

[8](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bfn8)Following [Jegadeesh and Wu, (2013)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib34), we exclude financial firms because of the different meaning of the words such as risks and causality in this sector.

[9](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bfn9)There are some other categories of the sentiments suggested by Loughran and McDonald (2016) such as litigious, uncertainty, interesting and constraining. Bonsall et al. (2017) introduce the Bog index that measures the word complexity of 10-k documents, higher value of Bog index implies that the document is less readable and more complex. On the other hand, a large number of studies adopts the Gunning-Fog index to assess the 10-k readability, see for instance ([Merkley, 2014](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib41), [Frankel et al., 2016](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib24), [Garel et al., 2019](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib26)) is based on the syllable count. The Bog index is now being preffered among the researchers because it overcomes the issues of the application of Fog index for financial statements see for example Loughran and McDonald (2016). Loughran and McDonald (2016) also propose the use of file size to measure the readability. However, Bonsall et al. (2017) raise concerns on the use of this measure over time, since file size may change drastically, and the measure would become noisy.

[10](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bfn10)HTML stands for Hyper Text Markup Language and CSS stands for Cascading Styling Sheets. These are web development languages where the former deals with markup and latter is used to style and design a web page.

[11](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bfn11)Since, it is a general practice to convert text to lower case for generalization purposes. Otherwise, the words Deficit and deficit convey the same meaning.

[12](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bfn12)Stop words are the words like is, am, are, the, an, to, at, in etc. that do not add meaning to the main text.

[13](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bfn13)For more information of stop word, see official website of NLTK- Natural Language Toolkit

https://www.nltk.org/book/ch02.html

[14](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bfn14)Harvard sentiment dictionary can be accessed here http://www.wjh.harvard.edu/~inquirer/homecat.htm

[15](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bfn15)The term frequency is useful when we have only one document. However, in case of multiple documents it is preferred to use TF-IDF, term frequency inverse document frequency. To read further on TF-IDF and similarities and the steps used in this study see https://www.udacity.com/course/natural-language-processing-nanodegree--nd892

[16](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bfn16)Kang and Han (2018) suggest that positive and negative sentiments are informative when measured accurately. Both these sentiments have been preferred and used in the literature, see also ([Jegadeesh and Wu, 2013](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib34)).

[17](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bfn17)The intuition of taking previous years values also come from the fact that companies aggregate their fundamentals at the end of fiscal year, while financial report (the textual part) may be drafted before that aggregation. The results were not significantly different when tested the models with variables at time (t) and (t-1) the previous year’s financial performance may predict current sentiments in the 10-ks. More detailed discussion on the use of lagged variables to address endogeneity from econometrics aspect can be found in ([Bellemare et al., 2017](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib4), [Reed, 2015](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib45)).

[18](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bfn18)Although the impact is statistically significant, the coefficients are not economically sizeable, this could be due to the reason that all variables are at the]\ir first lag that may affect the magnitude of coefficients. We observe that previous studies also report relatively lower values of coefficients as well as adjusted R-square when they measure the impact on 10-k positivity/negativity. The coefficients from the other direction i.e., from sentiments or readability to financial performance are also quite low, see for instance Rijba et al. (2021) where they examine the impact of financial readability (Bog index) on implied cost of equity. [Bodnaruk et al. (2015)](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bib6) also reports very low correlations between constraining sentiment of 10-k and firm’s financial constraints.

[19](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bfn19)It is important to note here that decrease in negativity does not necessarily imply increase in positivity. Since, both these measures are based on word count from 10-k, where *Positivity* and *Negativity* are represented based on the (TF-IDF defined above) for each of positive and negative wordcount.

[20](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bfn20)For more details on how board level corporate governance mechanism influence firms’ policies (See [Boubaker et al., 2012](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib8); [Boubaker and Nguyen, Boubaker and Nguyen, 2012](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib9)), and [Neifar and Jarboui, (2018)](https://www.sciencedirect.com/science/article/pii/S0275531922000678" \l "bib44) for mechanisms of corporate governance on the informational content of operational risk disclosure.

[21](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bfn21)The board level corporate governance variables are also defined in [Table 1](https://www.sciencedirect.com/science/article/pii/S0275531922000678#tbl0005).

[22](https://www.sciencedirect.com/science/article/pii/S0275531922000678#bfn22)To avoid the impact of any distortions in the financial reporting due to financial crisis, we exclude the year 2007–2009 (i.e., financial crisis period) to perform sub-sample analysis.