Telematics and Informatics 35 (2018) 370–381

Contents lists available at ScienceDirect

Telematics and Informatics

journal homepage: www.elsevier.com/locate/tele

Beyond the numbers: The effect of 10-K tone on firms' performance predictions using text analytics

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ARTICLE INFO

Keywords:
Annual report
10-K
Firm performance
Tone
Readability
Text analytics

ABSTRACT

Investors use annual reports that companies mandatorily disclose every fiscal year-end when they make important investment-related decisions. The Securities and Exchange Commission in the United States has implemented and monitors the "Plain-English Rule" to create a transparent and readable annual report. However, only a general guideline exists for the description of annual reports (Plain English Rule), and there are no specific regulations on volume and format. As such, it is risky to interpret business managers' positive expressions because the data can include business managers' subjective opinions and viewpoints from the companies' perspectives. Additionally, the business managers' unrevealed tendencies, such as strategic reporting or cognitive bias, remain unknown. Therefore, this study focuses on the narrative sections of the annual reports that companies need to disclose after every fiscal year-end and uses text mining to determine the relationship between the assessment information of companies created by business managers and the performance of companies. The methodology of this study is grounded in text-mining. To analyze these relationships, we collected all the 10-Ks of all public firms in the United States and employed the text-mining method to identify the tones of these 10-K narratives to determine whether they changed in line with current earnings levels. Additionally, we explore factors that could give rise to tone flexibility among reports and examine companies whose tone was more positive relative to their current performance to ascertain how future performance might differ from current performance.

1. Introduction

As social interest in the disclosure transparency of corporate management has increased recently, the needs of diverse stakeholders, including investors, vis-à-vis management transparency have become clearer. All public firms in the United States are required to file an annual report (10-K) regarding overall business activities, including current performance, with the U.S. Securities and Exchange Commission (SEC); it is also suggested that they provide future performance prospects. Since the 2002 Enron scandal, there has been a refocus on transparent financial disclosure by firm managers; the tendency to use publicly disclosed information—disclosed in line with legislation such as the Sarbanes–Oxley Act in 2003—to protect investors has increased. There is a fundamental reason for why disclosure information should be transparent: to create greater information symmetry between insiders and outside traders. Schroeder (2002) argues that firms' disclosed information should be credible and appropriate for management decision-making; however, providing a high volume of information is not synonymous with being transparent, and people should understand the risks inherent in working with excessive volumes of information. Additionally, individual investors who lack expert

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https://doi.org/10.1016/j.tele.2017.12.014
Received 10 August 2017; Received in revised form 8 December 2017; Accepted 16 December 2017
Available online 21 December 2017
0736-5853/

knowledge compared with institutional or large investors (e.g. financial analysts) find that information overload can create conflict and make investment decision-making more difficult. The 10-K is an important communication instrument used to deliver corporate information clearly; in short, it provides overall information related to firm performance. The 10-K generally comprises two parts: financial statements and narrative sections that explain them. With respect to the financial market, most research has focused on the fundamentals of quantitative data in financial statements. Recently, however, the number of studies that address qualitative data—including the narrative sections, where business managers provide detailed information related to company performance—has dramatically increased (Li, 2008; Loughran and McDonald, 2011; Miller, 2010; Rennekamp, 2012).

There are three reasons why the narrative sections of financial reports have gained more attention in recent research. First, those sections can provide investors with additional and significant information. Managerial opinions or diagnoses of future performance and overall future plans (e.g., increased investment in research and development), as found in the management discussion and analysis (MD&A) section, for example, constitute important information that cannot be described in the form of numerical data. Investors are able to diagnose the future performance of companies and make decisions on whether to invest by using the additional qualitative information provided by managers; naturally, such explanations or prospects need to be objectively analyzed. Second, text-based messages are more elastic than numerical data in conveying information. Given the characteristics of language, the message as understood by the messenger can differ from that understood by the receiver; this divergence of understanding stems from differences among individuals in terms of their knowledge and cognitive features (Pang and Lee, 2008). Third, it is difficult to regulate qualitative information or even to create specific regulations regarding its provision. There is only a general guideline (i.e., the "Plain-English Rule"). No specific regulations exist with regard to the narrative sections of a 10-K; compare this to the plethora of regulations regarding the disclosure of financial statements. Nonspecific regulations are applied, and because there is the understanding that SEC oversight monitors corporate activities, the relevant employees of companies often provide as much qualitative data as they want. While it is true that objective facts cannot be distorted—especially as government authorities make efforts to enhance the transparency of financial reporting—differences in expression exist, and they often stem from business managers' personal inclinations or subjective opinions (Bloomfield, 2008; Li, 2008).

Although the narrative sections of 10-Ks include critical information on firm performance, this has not been sufficiently discussed in the literature. One reason for this dearth of research is that the narrative sections of 10-Ks include unstructured text-based data. In terms of methodology, there are limitations in extracting significant variables from hand-collected data and analyzing them; several company cases have been research targets, and it has been difficult to generalize research findings (Li, 2008; Loughran and McDonald, 2011). As technology and data analysis methodologies have greatly improved in recent years, more methods used to objectively analyze massive volumes of unstructured data objectively have become available (Jun and Park, 2017; Jun et al., 2014). Text-mining is a method used to garner useful insights, and it makes use of a defined linguistic dictionary to analyze all types of text-based data (Hsiao et al., 2017; Müller et al., 2016; Öztürk and Ayvaz, 2017). Previous studies that used text-mining largely focused on algorithm development in the field of computer science; however, recently, the sphere of text-mining has expanded to focus on diverse business topics, such as the relationship between the mood witnessed on the SNS Twitter and the stock market index (Bollen et al., 2011), as well as the relationship in e-business between the characteristics of online product reviews and consumers' purchase decisions (Lee et al., 2008, 2011; Park and Kim, 2009; Park and Lee, 2008; Park and Park, 2013; Park et al., 2007). In a few studies, text-mining was used to reveal the influence that the lexical properties of a 10-K had on market reaction (Miller, 2010; You and Zhang, 2009), but in many, the lexicon used was largely psychology-based and therefore did not align well with the financial context (Li, 2010a,b; Loughran and McDonald, 2011).

In the current study, text-mining is used to analyze the narrative sections of the 10-Ks of all public firms in the United States to examine the relationship between the narrative section and actual firm performance. Specifically, the direction of analysis taken by this study can be subjectively interpreted by investors and is related to the tone of the 10-K narrative sections—something that can be purposely manipulated by a company. The "tone of the narrative sections" refers to how positively or negatively the performance and future directions of companies are described in their 10-Ks. The 10-K itself closely relates to the past, present, and future performance of a firm, so investors might be sensitive to the tone used therein. Regarding 10-K tone, the findings thus far are that there is a correlation between the tone of narrative sections and the stock market's reaction or that it increases litigation risk (Rogers et al., 2011). In such studies, the tone of 10-K narrative sections was analyzed from an *ex post* perspective; nonetheless, this has not been studied extensively, given how interpretation can be driven or affected by current performance or business managers' cognitive inclinations. "Flexibility of tone" refers to how business managers can write narrative sections in a manner that is positive or otherwise desirable for their companies depending on their current performance or situation. That is, companies try to hide poor performance as much as possible under certain circumstances or report as conservatively as possible (Bloomfield, 2008). The research of Li (2008) reveals that many companies disclose their financial reports in a difficult-to-read form or work hard to hide negative aspects of their performance. Moreover, Lehavy et al. (2011) argue that analysts cannot accurately analyze the fundamentals of future performance when the readability of a 10-K is low and that reading such 10-Ks and analyzing the content therein requires a higher opportunity cost. The narrative sections of 10-Ks contain considerable volumes of useful information vis-à-vis a company's future performance, so it is essential that we reveal in what context business managers use a given tone within the narrative sections of 10-Ks and determine the relationship between tone and the current and future performance of firms.

This study focuses on the narrative sections of 10-Ks, which contain information that should be mandatorily disclosed in financial reporting, to reveal the relationship between company assessment information that is written directly by managers and touches on the performance of their companies. The methodology of this study is grounded in text-mining. To analyze these relationships, we collected all the 10-Ks of all public firms in the United States between 1996 and 2011 and employed the text-mining method to identify the tones of these 10-K narratives and determine whether they changed in line with current earnings levels. Additionally, we explore factors that could give rise to tone flexibility among reports and examine companies whose tone was more positive relative to their current performance to ascertain how future performance might differ from current performance.

2. Theoretical background and hypotheses development

2.1. The roles of corporate disclosure transparency

Zhu (2002) studied transparency in e-commerce and defines "information transparency" as pertaining to the level of visibility and accessibility inherent in any released information. Regarding financial reporting, "transparency" itself is rarely defined, but it has been discussed in line with increased information disclosure, the methods used to present information, and the methods that investors use to process data. Accounting and finance studies, rather than directly defining "transparency," indicate that transparency is high when investors can understand the real economic status of a company simply by assessing their accounting figures. Transparency is a precondition to the effective functioning of a market. A theoretical reason why firms' financial data should be transparent is that this creates greater information symmetry among companies, outsiders, and markets. Information is "transparent" when financial statements clearly show the nature of the economic activities fundamental to operations, together with the transactions of companies; thus, "information transparency" touches on a number of concepts, including understandability, credibility, sufficiency, and neutrality. In other words, as noted by the Financial Accounting Standards Board (FASB), financial information should be provided in such a way that it can be easily understood by those with a reasonable understanding of companies and business activities and a reasonable drive to understand such information.

Weil (2002) argues that the accuracy of information should be a necessary, but not sufficient condition in itself to the successful use of information—the proliferation of which, as a disclosure and regulation tool in resolving information-asymmetry issues, has grown substantially. Schroeder (2002) states that market regulations work when market participants have enough information, but a high volume of disclosure does not necessarily mean high transparency. He insists that information quality should be a focus, along with any quantitative expansion; the information, he claims, should also be timely, credible, appropriate for its purposes, and sufficient for linking information disclosure to transparency. Sometimes, "frequency of disclosure" does mean "transparency," but many people still have questions. Elorrieta (2002) argues that further disclosure of high-quality information should take place to increase transparency; here, "high-quality information" refers to comparable and comprehensive information that is created and sufficiently disclosed based on recognized general accepted accounting principles, where that information is credible and reflects economic realities. Maines and McDaniel (2000) state that transparency should be considered based on two aspects: the location of the information (which varies with the presentation format) and the volume of cognitive processing required to use such information properly. Their study results indicate that nonprofessional users could subconsciously consider recognized information more important than disclosed information given the location of that information; furthermore, individuals experience difficulties in linking information disclosed in notes to that in the main body and analyzing them together.

There are many reasons for the complexity of financial statements, including the proliferation of note disclosure, the use of complicated accounting standards, and diverse financing measures and corporate operations; nonetheless, there is an argument that some companies purposely make their financial statements more complex than necessary and difficult to interpret (Bloomfield, 2002). The findings of Bloomfield (2008) suggest the possibility that companies pretend that there have been good results or prospects for investors simply by using more positive expressions and selectively describing good results in detail to hide adverse information. Explanations for the necessity of such studies closely relate to the findings of Damodaran (2002), who suggests that investors underestimate the value of companies that disclose complicated and difficult-to-understand financial statements and overestimate that of companies that disclose easy-to-understand financial statements. He insists that the level of transparency inherent in financial statements is left up to the companies themselves and that the financial statements of the companies of some countries with few disclosure requirements could be more transparent than those of companies in the United States, which face many disclosure requirements. As such, business managers' decisions regarding information provision, as well as the information sources of companies, have become increasingly important; thus, the number of studies that analyze business managers' inclinations and strategic behaviors in disclosing information has increased. Tan et al. (2002) reports that financial analysts have different reactions to disclosed information depending on the ways in which that information was disclosed—that is, if bad news were disclosed multiple times, rather than on a single occasion, financial analysts' forecasts would be low. This shows that market reactions can differ depending on the ways in which information is disclosed—regardless of the actual content therein. As such, certain methods are more attractive to business managers when they select disclosure strategies in consideration of market reactions. Skinner's (1994) hypothesis—namely, that companies that report bad news are highly likely to disclose interest-related information in advance to reduce the possibility of litigation—is also supported.

Individuals can easily access financial reports, which constitute important information sources that are used to make investment-related decisions. Given such research flows, the study of business managers' subjective reportage inclinations will become an increasingly important research goal.

2.2. Research on textual analysis of corporate disclosures

In a capital market, investors can obtain financial information from various channels. For instance, they may gather information from media news, press releases, analyst reports, 10-Ks, and conference calls; they then make investment decisions based on these information resources. Moreover, these information sources contain not only numerical data, but also forms of written information.

According to Li (2010a,b), three types of data can be found in a 10-K. This typology is seen in the 2010 10-K of Dow Chemical Inc., which contains 207 pages: five pages of financial statements, 25 pages of relevant tables, and 177 pages of text-based data. The structure of a typical 10-K report relates to efforts made by the SEC to reduce data asymmetry between companies and investors. The "safe harbor" provisions of the SEC's Private Securities Litigation Reform Act of 1995 allow business managers to provide predictions of their companies' future performance and break them down in detail to facilitate investor understanding. Most investors lack specialized knowledge or experience compared with institutional investors or financial analysts, so the act pushes business managers to provide the markets with as much information as possible. In 2003, a method of writing narrative 10-K sections to facilitate reader understanding was proposed through guidelines that constitute the Plain-English Rule.

As corporate transactions become increasingly complicated and important, the text-based information offered directly by management becomes a more essential resource for individual investors, regulators, and even researchers, since it 1) explains how numerical financial data were derived (Li, 2010a,b) and 2) reveals certain managerial characteristics; thus, it has significant implications in terms of understanding corporate decisions (Lehavy et al., 2011). Therefore, earlier research on corporate disclosure has tended to investigate the text-based information released by firms. Two important measures are raised within the literature: the readability and tone of reports.

Jones and Shoemaker (1994) surveyed early studies of the readability of written narratives in financial information. Most prior studies have attempted to assess the readability of 10-Ks and their components. It is important to bear in mind, however, that the sample sizes of the early studies within the literature are very small. This fact may explain the mixed and inconclusive findings of previous studies (Li, 2008; Miller, 2010). To increase the sample size and thus garner more generalizable results, Li (2008) intensively examined the literature and used a large sample while focusing in particular on the association between 10-K readability and each firm's current and future performance. Subsequently, a growing number of studies have focused on readability while making use of a large data sample. Among them, Miller (2010) found that the complexity of 10-Ks tends to lower stock trading, since complex reports will reduce small investors' trading activities compared with those of large investors. Lehavy et al. (2011) measured the readability of corporate 10-K filings and found that the analyst following and "informative-ness" of reports are more important for firms with less-readable 10-Ks. Additionally, You and Zhang (2009) found that the market underreacts to less readable 10-Ks. Overall, previous studies on financial disclosure have mainly analyzed the influence of readability on various firm fundamentals, such as market reaction, stock price, litigation risk, and analyst forecasts (Lehavy et al., 2011; Miller, 2010; Tetlock et al., 2008; You and Zhang, 2009). However, when the report is written, business managers' unrevealed tendencies, such as strategic reporting, are still unknown.

In addition to disclosure readability, the tone of corporate disclosures constitutes another dimension of textual analysis (Davis and Tama-Sweet, 2012; Li, 2010a,b; Loughran and McDonald, 2011; Rogers et al., 2011). In particular, Davis and Tama-Sweet (2012) found a positive relationship between an increase in positive tone within earnings press releases and the short-term stock price response to firms' earnings announcements. Demers and Vega (2011) found a positive association between firms' future returns and the level of tone changes in earnings press releases. In addition, Davis and Tama-Sweet (2012) investigated whether managers adjust the tone of earnings press releases to increase the value of their stock options and found that the optimism level increased before their option exercises, assuming that the litigation risk is low.

Most studies in this line measure financial reports in terms of their qualitative characteristics using a number of methods derived from the field of computational linguistics; these methods focus on Diction, General Inquirer, Linguistic Inquiry, and Word Count characteristics (Davis and Tama-Sweet, 2012; Li, 2008; Tetlock, 2007; Tetlock et al., 2008; Kang and Park, 2016). However, many researchers argue that general-purpose dictionaries do not fit the financial context well (Li, 2010a,b; Loughran and McDonald, 2011). Li (2010a,b) suggests that the naive Bayesian machine-learning algorithm can be used to measure the tone of forward-looking statements in the MD&A section, as it captures information content better than dictionary-based measurements. There is an advantage inherent in the use of the machine-learning method: its results are more accurate than those of methods that use the bag-of-words approach, which often uses text libraries such as Diction, Linguistic Inquiry and Word Count (LIWC), and General Inquirer. These libraries consist of key words that have been transplanted from the field of social psychology into the financial context. However, when using the machine-learning method, training sets should be grouped as per a self-defined algorithm; as such, the process becomes more complicated than that seen in dictionary-based measurement. Therefore, the method also carries an inherent weakness in that researchers need considerable funds to use it and followers cannot necessarily replicate their results. Loughran and McDonald (2011) also found the prior psychology-based dictionary approach to be inappropriate for financial disclosures, since three-fourths of the negative words in the Harvard Dictionary (IV-4) do not typically have negative connotations within the context of corporate disclosures.[1] Therefore, they suggest finance-based word lists to describe positive and negative tones in financial disclosures. The current study uses the word lists suggested by Loughran and McDonald (2011) to identify positive and negative words as they appear in firms' 10-Ks; this list better reflects the financial context. Within the context of 10-K verbiage, we name the variable *TONE* as the fraction of the frequency of positive words and frequency of negative words divided by the total word counts. The literature tends to approach research questions by using small samples of hand-collected data and disclosure mediums other than 10-Ks (e.g., press releases, conference calls) *inter alia*.

[1] Loughran and McDonald (2011) found that words such as "tax," "cost," "capital," "liability," "foreign," and "vice" are classified as negative on the Harvard list. In fact, these words appear frequently in reports, albeit with a neutral tone (e.g., *board* of directors and *vice* president). Sometimes, certain words—such as "mine," "cancer," "crude" (oil), "tire," or "capital"— connote a specific industry rather than negative economic events.

2.3. 10-K tone and current firm performance

The tone of company information as disclosed by their managers (e.g., press releases, 10-K narrative sections), or that of intermediary information related to companies (e.g., analyst reports, press releases), is thought to generally correlate with market response. The results of Davis et al. (2008) prove that optimism as found in earnings press releases had a positive impact on short-term stock prices, while pessimism had a negative impact on short-term stock prices. Several studies have examined whether the tone of disclosed financial information and subsequent market reactions correlate (Loughran and McDonald, 2011; Tetlock et al., 2008). However, such information was divided into positive and negative information that had been provided by firms to identify market reaction; studies of the effects of positive and negative text-based information in documents such as 10-Ks have garnered mixed results. When investors read financial reports and make investment decisions, they consider good and bad events alike. Therefore, the current study does not separately classify the tone of reports as having a negative versus positive tone; rather, it defines tone in terms of an aggregated number. That is, we use the aggregated tone measure employed by Huang et al. (2013) and apply it to the narrative sections of various 10-Ks: for any given report, we subtract the frequency of negative words from the frequency of positive words and then divide the result by the report's total word count.

$$\textbf{\textit{Tone Measure}} = (\#\ \textbf{\textit{of Positive Words}} - \#\ \textbf{\textit{of Negative Words}})/\textbf{\textit{Total Word Count}}$$

It is suggested that all public firms explain their current situations clearly and transparently and that the narrative sections of their 10-Ks provide managerial information that is based on fact. Bens et al. (2011) show that when companies try to record their current performance in detail, the lengths of their reports' narrative sections increase. Li (2010a,b) suggests that numerical data are made available depending on the firm's current performance, because narrative sections are ultimately based on quantitative data. Consequently, firms will cite good results or favorable events in the narrative sections of their 10-Ks, but will tend not to include bad events or provide investors with reasons or excuses. Additionally, information on these events tends to closely relate to short and long-term stock prices (Davis et al., 2008). Therefore, 10-Ks closely relate to overall firm performance, so the tone will vary among them depending on the companies' current performance level. In particular, if a company's current performance is good, more positive events will have taken place than negative ones; therefore, the better a company's current performance is, the more positive the tone of its 10-K narrative section will be. In that sense, the following hypothesis is proposed:

H1:. When a firm's current performance is very strong, the proportion of positive words used in its 10-K will increase.

2.4. Abnormal tone and future performance

Under the "safe harbor" provisions of the SEC's Private Securities Litigation Reform Act of 1995, a system has been prepared that collects and describes business managers' opinions about the future prospects of their companies. The objective of this act was to enable business managers to provide investors with information they have on future company performance in as transparent a manner as possible. The tone of a 10-K narrative section reflects a firm's performance; in addition, 10-Ks deliver clear corporate images by providing overall information vis-à-vis firm performance. The narrative sections of 10-Ks serve a data-generating function vis-à-vis the numerical data found in financial statements (Li, 2010a,b). Thus, a more positive tone in a narrative section may imply that more positive events have taken place. On the one hand, Rogers et al. (2011) found that if the tone of a 10-K is overly optimistic, the tone tends to correlate positively with litigation risk. It is difficult to specifically supervise and monitor every detail of 10-K creation with respect to the law, but investors have an avenue of recourse by way of litigation. On the other hand, firm managers who prepare reports do know that writing an overly positive narrative section can lead to litigation, so they will be careful not to simply write positive things without considering actual firm performance. A 10-K is a very important information source, and the content therein closely relates to firm performance each year; most listed firms that place importance on credibility are restricted in taking misleading actions. From this viewpoint, it appears that a more positive tone implies that a company's good events have outnumbered its bad ones. Naturally, firms that have experienced predominantly good events will be more likely to maintain their current earnings in the future, and this tendency will be reflected in higher earnings persistence. Therefore, we propose the following hypothesis:

H2:. With respect to a company's current performance level, its current earnings will be more persistent as the positivity of the reporting tone increases.

However, the few studies on this topic found that there are no specific guidelines on preparing the narrative sections of a 10-K: in essence, business managers can write them somewhat flexibly. Investors use a 10-K to help predict the future performance of companies, so business managers write the narrative sections with this in mind. By and large, future performance is uncertain, so firm managers need to make decisions on the tone of the narrative sections of the 10-K. The tone can be an overtone (i.e., to make a company's investment outlook or prospects appear good), but the provision of excessively positive performance predictions can expose a company to litigation risk (Rogers et al., 2011). Otherwise, the tone can be an undertone that reduces litigation risk, but this might be detrimental to promoting the company. Additionally, companies can strategically provide reports that are difficult to read or overly long in line with firm performance to hinder investors' negative reactions (Li, 2008) or to highlight specific events further depending on their situations. Such strategies obfuscate and ultimately lead to a state where investors do not accurately recognize company performance (Bloomfield, 2008).

On the other hand, even when managers do not make strategic plans in advance, a narrative section can be upwardly or downwardly biased. For instance, two different firms can report the same sales revenue levels, but the properties of their respective reports can differ depending on the managers' ability to correctly assess their companies' current performance. In the behavioral economics field, studies have been proactively conducted on cases where companies have made decisions based on what was essentially their CEOs' cognitive bias. Additionally, the decision to disclose information plays a role in controlling the content of any disclosed information that is based on managers' cognitive biases (Kahneman, 2003). Various business managers might have different ideas with regard to future risk and differentially recognize the current performance level of their own company. For example, overconfident business managers who are comfortable with risk tend to be sure that their companies can recover losses, even within the subsequent year; as such, even when current performance levels are not as high as they had expected, they will submit reports that contain positive content to reassure investors. On the other hand, risk-averse business managers often try to preclude litigation by disclosing even small risks to investors prior to 10-K dissemination. Therefore, differences in the lexical features of the narrative sections of 10-Ks will arise depending on differences in such cognitive inclinations—even among business managers who report the same current performance level.

We define the group of companies that write narrative sections more positively than their current performance level warrants as the *Overtone* group. If the tone of a report is biased due to differences in individuals' cognition and their inclination to assess the current performance of managers, this bias will have an impact on the usefulness of the information. This phenomenon has been explained by Bloomfield (2002, 2008) and depends on the features of the content found in narrative sections. We adopt the earnings persistence model to measure the usefulness of the tone in such assessments, since it is widely used to determine how well current earnings can predict future performance. In other words, the usefulness of a report is dictated by the report tone, which users need to analyze to estimate the future profitability of companies (e.g., Dechow et al., 2010).

H3:. Companies that write reports in an overtone relative to current performance will be less able to guarantee future performance as the tone positivity increases.

In summary, we examine the differential effect of positive tone on the *Overtone* and *Overall* groups in achieving future profitability by assessing the properties of these companies' profits. On average, companies within the *Overtone* group write reports more positively relative to their current performance, indicating that their business managers interpret future potential events more positively, highlight positive events, or hide negative events. Such behavior among business managers can make the performance of their companies *appear* positive in the short term, but such an approach can have a negative impact on longer-term earnings quality, as mentioned above.

3. Research design

3.1. Current earnings as a determinant of tone

To test our first hypothesis, we test the *TONE* by using the following ordinary least square (OLS) regression model. Since the *TONE* of the 10-K of a firm is likely to be persistent over multiple years, the use of panel data can create inter-temporal correlations. Additionally, if the 10-Ks of firms within the same industry contain similar content, this may also create correlated errors cross-sectionally. To address these concerns, we use a firm cluster–robust regression model while accounting for year-fixed effects (*Year FE*).

$$TONE_{i,t} = \beta_0 + \beta_1 Earn_{i,t} + \beta_2 Size_{i,t} + \beta_3 MTB_{i,t} + \beta_4 Age_{i,t} + \beta_5 Sitem_{i,t} + \beta_6 Retvol_{i,t} + \beta_7 Earnvol_{i,t} + \beta_8 NBS_{i,t} + \beta_9 NGS_{i,t} + YearFE + \varepsilon \quad (1)$$

TONE is defined as the frequency difference in each 10-K between the numbers of positive and negative words divided by the total nonnumerical words. The determinants of tone can act as measures of current firm performance, growth opportunities, operating risks, and complexity. *Earn* is the operating earnings divided by the book value of assets. Given H1 regarding the association between current earnings and *TONE*, we expect the coefficient of *Earn* (β_1) in Eq. (1) to be positive. Regarding our control variables, we follow the lead of Li (2010a,b) and Huang et al. (2013). ***Size*** is the log of the market value of equity, ***MTB*** is the market value of assets divided by the book value of assets, ***Age*** is the number of years since the firm appeared in the Center for Research in Security Prices (CRSP), ***Sitem*** is special items divided by the book value of assets, ***Ret_vol*** is the stock return volatility over the previous 12 months, ***Earn_vol*** is the earnings volatility over the previous five years, ***NBS*** is the log number of business segments, and ***NGS*** is the log number of geographic segments.

3.2. Earnings persistence model

To test H2 and H3, we use the following OLS regression model:

$$Earn_{i,t+j} = \gamma_0 + \gamma_1 Earn_{i,t} + \gamma_2 ABTONE_{i,t} + \gamma_3 Earn_{i,t} * ABTONE_{i,t} + \gamma_4 Size_{i,t} + \gamma_5 MTB_{i,t} + \gamma_6 Age_{i,t} + \gamma_7 Sitem_{i,t} + \gamma_8 Retvol_{i,t} + \gamma_9 Earnvol_{i,t} + \gamma_{10} NBS_{i,t} + \gamma_{11} NGS_{i,t} + \gamma_{12} Acc_{i,t} + \gamma_{13} Div_{i,t} + YearFE + \varepsilon\ (j = 1,2,3). \quad (2)$$

Again, we use a firm cluster–robust regression model with year-fixed effects (*Year FE*) to minimize possible cross-sectional or inter-temporal correlations. We calculate abnormal positive tone, *ABTONE*, as the residuals from Eq. (1). From Eq. (1), we capture the firm characteristics and economic environment of firms whose 10-Ks have a positive tone; we argue that any abnormal positive tone portion that cannot be explained by a company's current situation is more likely to be related to managers' opportunistic behavior

Table 1
Sample selection.

Number of 10-K documents, excluding duplicates (1996–2010)		107,746
Less: firm-year observations with stock price less than $1	(24,377)	83,369
Less: firm-year observations lacking COMPUSTAT variables	(29,955)	53,414
Less: firm-year observations lacking CRSP variables	(3 6 3)	53,051
Number of observations used in regression analyses		53,051

rather than firm fundamentals. In Eq. (2), our variable of interest is γ_3. For H2, we run the regression to determine whether *ABTONE* captures the future profitable events of the companies. If managers intend to deliver highly probable positive news to investors by disclosing positive reports, then future earnings will be higher; in such cases, there will be higher earnings persistence vis-à-vis current earnings. Since we hypothesize regarding the usefulness of a positive tone, we expect positive γ_3 values. For H3, we run the same regression in the *Overtone* group to examine the strategic behavior of the managers therein. The control variables are identical to those of Eq. (1), except *Acc* and *Div. Acc*; the former represents accruals (calculated as (Operating income – Operating cash-flow) divided by the book value of assets), while the latter equals 1 if the firm pays dividends and 0 otherwise.

4. Data and summary statistics

4.1. Sample selection

Table 1 outlines our sample selection procedure. Following Li (2008), we collected 107,746 10-Ks from the electronic data-gathering, analysis, and retrieval (EDGAR) system for the 1996–2010 period. Firms lacking a 10-K in the EDGAR system are not included in the sample, and firms with 10-Ks that are duplicated or contain fewer than 3000 words are also excluded. We then excluded firms whose stock prices were below $1 each (i.e., so-called penny stocks). At this point, the dataset contained 83,369 observations[2] and was matched with Compustat and CRSP data to obtain company information. While matching 10-Ks with company information, we deleted any firms lacking a central index key (CIK) since company identification using the EDGAR system is only possible using CIKs. Following the merge of Compustat and CRSP data, the dataset contains 53,051 observations.

Here is the Steps to extract text data from the 10-Ks and how to analyze the tone of 10-Ks

- Download the 10-K report from Edgar system
- First, the heading information that is contained between < /SEC-HEADER > and < /SEC-HEADER > is deleted.
- All the tables that start with < TABLE > and end with < /TABLE > and the paragraphs that contain < S > or < C > are deleted.
- Tags in the form of < … > and < &… > replaced with blanks.
- All the tables, tabulated text, financial statements are excluded.
- Download the Mcdonalds' Fin-text dictionary, and I install the dictionary in the LIWC(Linguistic Inquiry and Word Count) in position ready for use.
- Then, I analyzed the text data using the LIWC (Linguistic Inquiry and Word Count). The package can calculate the general text statistics, including the document length, number of positive/negative words, number of sentences, proportion of cognitive words, number of articles, number of complex words (more than 6 letters), number of uncertainty words etc.

4.2. Descriptive statistics

Descriptive statistics on the variables used in this study are presented in Table 2.[3] We report the mean, median, standard deviation, and 1st, 25th, 75th, and 99th percentiles of the variables in our sample. The first three variables indicate the number of total words, the number of positive words, and the number of negative words. Similar to the findings of Li (2008), firms use an average total of 40,860 words. The mean (median) value of *ABTONE* is −0.82 (−0.81). Below, we present the descriptive statistics for the control variables. These are generally consistent with those of prior studies.

Table 3 shows the Pearson correlation coefficient. The bold numbers indicate correlations that are significant at the 5% significance level or higher. All correlations are small except for the correlation between *MTB* and *Earn*. Although the correlation between *MTB* and *Earn* is high, all variable inflation factors are less than 10, and this model has no multicollinearity problems.

5. Empirical results

5.1. Current earnings level and report tone

Table 4 provides the estimation results of the regression (1). As expected, we find that current earnings (*Earn*) have a positive coefficient. This fact is consistent with our hypothesis that the tone of a company's 10-K is positively affected by its current earnings;

[2] Our results are qualitatively similar when we include penny stocks.
[3] To address outlier problems, Winsorize continuous variables at the 1% and 99% levels.

Table 2
Descriptive statistics of variables (N = 53,501).

Var.	Mean	Median	Std.	P1	P25	P75	P99
Words	40,860	32,592	32,726	3042	7182	21,532	49,713
Positive	304	252	219	12	45	163	380
Negative	699	528	651	9	51	298	890
TONE	10.400	10.390	0.640	8.580	8.900	9.980	10.810
ABTONE	−0.820	−0.810	0.490	−2.460	−2.040	−1.130	−0.510
Earn	0.000	0.020	0.450	−1.600	−1.230	−0.270	0.310
Size	0.070	0.070	0.160	−1.360	−0.560	0.020	0.140
MTB	6.230	6.130	1.780	2.330	2.760	4.930	7.380
Age	1.960	1.370	1.680	0.660	0.770	1.070	2.110
Sitem	17.380	12.000	15.550	2.000	2.000	6.000	24.000
Ret_vol	−0.010	0.000	0.040	−0.400	−0.190	−0.010	0.000
Earn_vol	0.120	0.100	0.080	0.020	0.030	0.070	0.150
NBS	0.090	0.030	0.220	0.000	0.000	0.010	0.080
NGS	0.790	0.690	0.650	0.000	0.000	0.000	1.390

Table 3
Pearson Correlations (N = 53,501).

Var.	*TONE*	*ABTONE*	*Earn*	*Size*	*MTB*	*Age*	*Sitem*	*Ret_vol*	*Earn_vol*	*NBS*	*NGS*
TONE	1.000										
ABTONE	**0.930**	1.000									
Earn	**0.130**	**0.040**	1.000								
Size	**−0.090**	−0.010	**0.160**	1.000							
MTB	**0.050**	**−0.020**	**0.620**	**0.230**	1.000						
Age	**0.050**	**0.010**	**−0.010**	**0.340**	**−0.050**	1.000					
Sitem	**0.100**	**0.020**	**−0.010**	**−0.030**	**−0.040**	0.010	1.000				
Ret_vol	**−0.060**	**−0.020**	**0.170**	**−0.130**	**0.210**	**−0.160**	**−0.140**	1.000			
Earn_vol	**−0.060**	**−0.040**	**0.260**	**−0.040**	**0.310**	**−0.130**	**−0.050**	**0.250**	1.000		
NBS	**−0.030**	0.000	**0.080**	**0.230**	0.000	**0.300**	**−0.060**	**0.060**	0.000	1.000	
NGS	**0.030**	**0.020**	**0.210**	**0.260**	**0.180**	**0.200**	**−0.120**	**0.180**	**0.070**	**0.230**	1.000

Bold numbers are statistically different from zero (two-tailed), at least 0.05 levels.

Table 4
Multivariate regression of *TONE* (N = 53,051).

	Model 1 Dep. = *TONE*	
Independent variables	est.	t-stat.
Intercept	−0.9593	(−49.70)***
Earn	0.2890	(12.79)***
Size	−0.0229	(−7.89)***
MTB	0.0223	(9.64)***
Age	0.0026	(7.87)***
Sitem	1.2250	(18.21)***
Ret_vol	−0.5599	(−12.57)***
Earn_vol	−0.0885	(−5.67)***
NBS	−0.0074	(−1.11)_
NGS	0.0155	(2.39)**
Firm Cluster	Yes	
Year Dummies	Yes	
Adj. R^2	14%	

*, **, ***: statistically different from zero (two-tailed) at the < 0.10, < 0.05, and < 0.01 levels, respectively. Cross-sectional and time-series dependence are adjusted using clustered standard errors, following Petersen (2009).

when a company shows positive current earnings, the company has good news and wants to share it. Naturally, a company will not hide positive information related to current strong performance.

We also find that the 10-Ks of small, growing, and young firms tend to have a more positive tone than their larger and older counterparts. In addition, when a 10-K contains more special items or its company has more business segments and is therefore less volatile, the tone of the 10-K will again tend to be more positive. These results are generally consistent with those of prior studies. For the remainder of this study, we will use *ABTONE*, the residual values of this regression. *ABTONE* differs from the normal tone level; it

Table 5
Multivariate regression of future performance ($Earn_t \geq 0$).

	Model 1 Dep. = $Earn_{t+1}$		Model 2 Dep. = $Earn_{t+2}$		Model 3 Dep. = $Earn_{t+3}$	
var.	est.	t-stat.	est.	t-stat.	est.	t-stat.
Intercept	0.018	$(5.14)^{***}$	0.040	$(6.64)^{***}$	0.081	$(12.51)^{***}$
Tone	−0.002	(−0.96)_	−0.004	(−1.28)_	−0.007	$(-2.10)^{**}$
Earn	0.764	$(30.89)^{***}$	0.630	$(21.77)^{***}$	0.529	$(18.85)^{***}$
*Earn*Tone*	0.065	$(2.89)^{***}$	0.080	$(3.22)^{***}$	0.108	$(3.85)^{***}$
Size	−0.002	(−1.40)_	−0.001	(−0.45)_	0.000	(−0.07)_
MTB	0.014	$(5.92)^{***}$	0.010	$(4.12)^{***}$	0.009	$(3.42)^{***}$
Age	0.000	$(2.46)^{**}$	0.000	$(2.61)^{***}$	0.000	$(2.38)^{**}$
Sitem	−0.009	(−0.44)_	−0.065	$(-3.01)^{***}$	−0.056	$(-2.13)^{**}$
Ret_vol	−0.155	$(-9.80)^{***}$	−0.232	$(-11.52)^{***}$	−0.257	$(-10.26)^{***}$
Earn_vol	−0.035	$(-2.89)^{***}$	−0.050	$(-3.84)^{***}$	−0.045	$(-3.46)^{***}$
NBS	0.003	$(3.83)^{***}$	0.002	$(1.84)^{*}$	0.004	$(2.89)^{***}$
NGS	−0.001	(−0.64)_	0.002	(0.94)_	0.003	(1.49)_
Acc	−0.088	$(-3.37)^{***}$	−0.129	$(-3.81)^{***}$	−0.111	$(-3.85)^{***}$
Div	0.007	$(2.83)^{***}$	0.006	$(2.01)^{**}$	0.006	$(1.88)^{*}$
N	39,562		34,836		30,743	
Firm Cluster	Yes		Yes		Yes	
Year Dummies	Yes		Yes		Yes	
Adj. R^2	44%		28%		22%	

*, **, ***: statistically different from zero (two-tailed) at the < 0.10, < 0.05, and < 0.01 levels, respectively. Cross-sectional and time-series dependence are adjusted using clustered standard errors, following Petersen (2009).

is the predicted value of the performed regression, and by design, it is not related to firm-specific factors. Therefore, we will place focus on the positive tone while assuming that there may be a certain level of positive tone that is unrelated to the strategic decisions of managers.

5.2. Future earnings and report tone

Table 5 provides the regression results for future earnings on *ABTONE*. From this table, one may note the usefulness of positive tone in 10-Ks with regard to future earnings. A current positive tone includes not only current good news, but also positive news or profitable events pertaining to future periods. Therefore, if a company has a higher level of positive tone, its future performance is more likely to be strong (i.e., its earnings persistence will be higher). To measure earnings persistence in this model, we used only those firms with positive earnings in the current year (Li, 2008), which is why the number of observations in Table 5 is less than 53,501. Importantly, there is a positive coefficient for the interaction between *ABTONE* and *Earn*, which supports H2. We found that when the tone was abnormally positive relative to current earnings, that positive tone was related to profitable future events or future good news up to three years into the future. Additionally, we found that growing firms, older firms, firms with fewer special items, less-volatile firms, and firms with more business segments had higher future performance regardless of current earnings.

When our analyses are restricted to the *Overtone* groups, the interaction variable results of *ABTONE* and *Earn* are quite different. This stems from the fact that managers may prepare 10-Ks flexibly and at their own discretion since there are no specific guidelines for preparing the narrative sections of 10-Ks. The tone may be made to sound overly positive in order to make a company's investment outlook or prospects look good to prospective investors. Even when managers do not make such strategic plans, the narrative sections of some 10-Ks may be biased; two different firms could report the same sales revenue levels, but the properties of their reports may differ depending on their managers' recognition of the company's current performance. Table 6 shows the regression results of future earnings on *ABTONE* in the *Overtone* group (i.e., the group with *ABTONE* values exceeding 30%, 40%, or 50%).[4] The results confirm the opportunistic and misleading behavior inherent in positive tone within the *Overtone* group and with regards to their future earnings. Although we found that current positive tone includes positive news or profitable events vis-à-vis future periods (Table 5), it is interesting to note that, as shown in Table 6, positive tone has the opposite effect in the *Overtone* group. The negative coefficients on the interaction terms of *ABTONE* and *Earn* support the assertion that management exercises strategic behavior and may be directed by cognitive bias.

6. Additional analysis: 10-K Tone, and market reaction

Table 7 focuses on the market's reaction to companies in the *Overtone* group to determine whether market investors accurately recognize opportunistic and misleading behavior in the form of positive tone. If market investors penalize deceptive reporting, they

[4] Since the cutoff point of the *overtone* group is arbitrary, we analyzed the same regressions with various cutoff points; the results in Table 6 are qualitatively and statistically consistent.

Table 6
Multivariate regression of future performance in the *Overtone* Group.

	Model 1 Dep. = $Earn_{t+1}$			Model 2 Dep. = $Earn_{t+2}$			Model 3 Dep. = $Earn_{t+3}$		
var.	HIGH30 est. (t-stat.)	HIGH40 est. (t-stat.)	HIGH50 est. (t-stat.)	HIGH30 est. (t-stat.)	HIGH40 est. (t-stat.)	HIGH50 est. (t-stat.)	HIGH30 est. (t-stat.)	HIGH40 est. (t-stat.)	HIGH50 est. (t-stat.)
ABTONE	0.036	0.027	0.032	0.048	0.035	0.036	0.049	0.033	0.033
	(4.01)***	(3.56)***	(3.20)***	(4.63)***	(3.89)***	(3.34)***	(3.77)***	(3.17)***	(3.03)***
Earn	0.879	0.830	0.847	0.781	0.712	0.719	0.683	0.612	0.611
	(19.26)***	(20.60)***	(17.98)***	(16.01)***	(15.80)***	(14.02)***	(10.84)***	(12.09)***	(11.58)***
*ABTONE*Earn*	−0.213	−0.146	−0.208	−0.297	−0.193	−0.237	−0.328	−0.192	−0.211
	(−2.76)***	(−2.19)**	(−2.23)**	(−3.48)***	(−2.48)**	(−2.33)**	(−3.05)***	(−2.18)**	(−2.11)**
N	13,661	16,226	20,012	12,135	14,393	17,735	10,801	12,802	15,763
Adj. R^2	50%	50%	48%	31%	32%	31%	25%	25%	25%
Intercept and Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm Cluster	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES

*, **, ***: statistically different from zero (two-tailed) at the < 0.10, < 0.05, and < 0.01 levels, respectively. Cross-sectional and time-series dependence are adjusted using clustered standard errors, following Petersen (2009).

Table 7
Multivariate regression of market reaction in the *Overtone* group.

Dep. = *CAR (-2, 2)*		
Independent Variables	est.	t-stat.
Intercept	0.018	(2.10)**
Overtone	−0.017	(−2.01)**
Earn	0.519	(8.54)***
*Overtone*Earn*	0.221	(2.98)***
Size	0.004	(2.11)**
MTB	0.004	(1.60)
N	8852	
Firm Cluster	Yes	
Year Dummies	Yes	
Adj. R^2	15%	

*, **, ***: statistically different from zero (two-tailed) at the < 0.10, < 0.05, and < 0.01 levels, respectively. Cross-sectional and time-series dependence are adjusted using clustered standard errors, following Petersen (2009).

are less likely to overreact to the *Overtone* group. On the other hand, if the managers of these companies successfully impress investors by using a positive tone, then the market reaction to the positive tone will be significantly optimistic. In this section, we used data pertaining to firms with an *Overtone* value exceeding 30%; these firms comprise the *HIGH* group of companies, and their data is used in the following model.[5]

$$CAR(-2,2) = \gamma_0 + \gamma_1 Earn_{i,t} + \gamma_2 ABTONE_{i,t} + \gamma_3 Earn_{i,t} * ABTONE_{i,t} + \gamma_4 Size_{i,t} + \gamma_5 MTB_{i,t} + YearFE + \varepsilon(\text{ j}= 1,2,3). \tag{3}$$

Again, we used a firm cluster–robust regression model with year-fixed effects (*Year FE*) to minimize possible cross-sectional or inter-temporal correlations. We used the cumulative abnormal return (CAR) to gauge investors' immediate response to a 10-K depending on its tone. Based on the negative coefficient for *Overtone*, we believe that investors may become suspicious when *ABTONE* is high. The positive coefficient for *Earn* means that investors react positively when current earnings are higher; in addition, their evaluations are optimistic when *ABTONE* is high, given the current earnings level (coefficient of *Overtone∗Earn*). From the results in Table 7, one can see that market investors react optimistically; however, as in Table 6, the positive tone of a 10-K will have a negative effect on future earnings. By combining these two findings, we conclude that investors may be optimistic, but they are misled by companies' managers, and an overly positive 10-K tone will in fact harm future earnings.

7. Conclusion

We explored the implications of 10-K tone and 10-K reportage on current performance and earnings persistence. We collected the 10-Ks of all public firms in the United States from 1996 to 2011, extracted data pertaining to their tone, and determined whether 10-K tone levels changed along with current earnings levels. The findings may be summarized as follows. We found that the better the

[5] Again, we analyze the same regressions with various cutoff points; the results in Table 7 are qualitatively and statistically consistent.

current performance of a firm is, the more positive the tone of the company's 10-K is. In a second model, to test the persistence of firm performance, we found that the presence of a positive tone within a 10-K and earnings persistence have a negative relationship among those companies whose report tone is positively biased (i.e., overtone) relative to their current performance. Meanwhile, positive report tone and earnings persistence were found to have a positive relationship within the overall group.

This study is expected to make significant theoretical and practical contributions to the literature. In terms of theory, the tone of the narrative sections of 10-Ks was found to be related to the performance of the associated company. In previous research, positive tone and negative tone were used as independent variables to verify the one-way effects of each tone type; this study, however, provides an integrated interpretation by revealing the relationship between the relative frequency of positive and negative words in 10-Ks and the performance of the company that released it. That is, the results reveal that text-based data may align with numerical data; in this sense, the results of this study align with those of previous studies that used the text-mining method for text-based data derived from a financial reporting context. Additionally, this study reveals for the first time that the tone of the narrative sections of 10-Ks is not always positive in terms of future performance and earnings persistence; the results of additional analysis indicated that investors do not fully and accurately understand the nuances of positive tone as found in 10–Ks, and that the short-term market reaction (i.e., short-term stock price) is positively associated with positive tone among companies in the *Overtone* group. Firm managers prepare reports that are appropriate to a given situation by using narrative sections that can be flexibly worded. When analyzing the data by dividing companies into the overall and *Overtone* groups, it was found that companies in the *Overtone* group showed a proclivity to overstate their optimism about their future direction. It was also found that the more positive the tone is, the lower the possibility of strong earnings persistence in the future; nonetheless, the firms in the overall group tended to express their future direction truthfully or transparently, so the higher the positivity ratio is, the higher the possibility of strong earnings persistence. These findings indicate that firms write narrative sections in a flexible manner, and that positive, upbeat information as found in financial reports may not, in fact, be materially positive.

In terms of practice, the findings of this study have three important implications. According to Lehavy et al. (2011), even financial analysts have difficulty accurately analyzing the narrative sections of 10-Ks when they are hard to read or less readable. This study proposes the use of a methodology by which a company may self-evaluate performance by extracting and assessing the tone of their documents in relation to actual performance. Qualitative information such as readability could be used as critical variables when assessing the tone of reports. Second, report contents may be more accurately evaluated by investors if they are armed with the knowledge of business managers' reporting strategies; therefore, investors must consider tone more carefully, and they may use external sources as well as the narrative sections of 10-Ks to finalize their investment decisions. Finally, the narrative sections of 10-Ks are still elastic, and it can be challenging to determine what firm managers actually mean in those sections. Therefore, financial authorities such as the SEC need to propose standardized guidelines—beyond the Plain-English Rule—that would lead to clearer communication and thus help investors make better-educated decisions.

We can suggest more practical implications such as the system development with investment algorithms using the findings. Currently, big data solution for finance is emerging, so the research result in this paper can be utilized to develop this kind of solution. Before designing the system, we need to think about what part of the main finding of this study can be adopted in the trading system. Firstly, the tone of 10-K narrative section is related to the company's present earning level. In addition, since there is the desirable tone strength for a specific earning level throughout the industry, we can judge whether the actual tone of the 10-K narrative section of a firm is appropriate, stronger (i.e. overtone) or weaker (i.e. undertone). If the two levels are similar, the current earning will continue into the future while if there is a difference at the two levels, the current earning will not last until the future. If the system is developed using the above, first analyze the text of the narrative section at the time when 10-K is disclosed in the enterprise. It is judged whether or not the current earning level will be continued considering various text characteristics such as tone and word count of the analyzed text. The continuity can be judged as the tone strength of 10-K narrative section. If it continues, it will be valued at the current earning level, and investment decisions will be made based on this. If it is judged not to last, the current earning is discounted to predict future earning, and investment decisions are made based on this. Although more accurate verification is required, the implementation of such a system is not technically difficult, and the prominence of the system is partially supported by the results of the market reaction of this study.

Although this study provides important contributions in the theoretical and practical perspectives, there are limitations in the following two aspects. First, this study focuses on the word count and tone among the text characteristics of the narrative section in 10-K. There are a variety of linguistic and verbal characteristics other than these two factors. For example, we need to consider how confident the narrative section is written or how critically vs. friendly the narrative section expresses the performance of the company. In future studies, it is necessary to consider the various characteristics of the narrative section together.

Second, this study examines the earning persistency and market reaction of the *overtone* group in which the narrative section is written with a stronger positive tone than the current earning level. Similarly, there may also be the *undertone* group using much weaker positive tone than the earning level. In fact, to manage investor expectations, companies intentionally less emphasize performance, or even inflate risk. Focusing on the *undertone* group, the relationship between tone and earning persistency and the relationship between tone and market reaction will be a good research topic.

Acknowledgement

This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2017R1C1B5016712).

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.tele.2017.12.014.

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