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Mining the emotional information in the audio of earnings conference calls : A deep learning approach for sentiment analysis of securities analysts' follow-up behavior[☆]

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ABSTRACT

In this paper, we propose a deep learning approach to extract emotional information from the audio of earnings conference calls and empirically examine the influences of these emotional variables on securities analysts' follow-up behavior. Our findings suggest that, in the statement section, positive emotional information tended to positively influence the analysts' willingness to issue rating reports, while the inverse was true for negative emotional information; non-negative emotional information in the question section had a positive influence, while negative emotional information in the response section had a negative influence. Secondly, for the specific rating of the issued reports, negative emotional information in the response section tended to result in a lower rating, and neutral emotional information might also have caused a lower rating. Thirdly, in terms of rating adjustments, non-negative emotional information in the question section tended to cause an upgrade revision, while the inverse was true for the negative emotional information in this section. Positive emotional information in the response section also caused an upgrade revision. The approach we proposed provides new insight for understanding analysts' follow-up behavior and offers practical implications for analysts, management, investors, and regulators.

1. Introduction

Because securities analysts have more access to different channels of information than ordinary investors, they play a key role in the market as information intermediaries, who aims at eliminating the information asymmetry among market participants (Brown, Hagerman, Griffin, & Zmijewski, 1987; O'Brien, 1988). They are important investigators and interpreters of internal company information and are an important medium for communicating internal company information to the market (Chen, 2010). As the upward or downward target price revisions in the rating reports issued by securities analysts may affect the institutional investors to buy or sell the same stocks (Gu, Guo, & Zhang, 2022) and leading to a lot of capital to move between stocks, the factors that influence the behavior of analysts are widely studied by researchers.

Earlier studies have found that traditional financial indicators like ownership structure, firm size, return volatility, firm business complexity, and stock price synchronization were all key factors influencing on the forecasting accuracy of analysts (Bhushan, 1989). Nowadays, analysts receive and deal with enormous amounts of information from various channels, and non-numeric information sources, especially earnings conference calls, have been widely studied by scholars. The earnings conference call is an important channel that enables analysts and corporate management to communicate with each other in public. Previous research has confirmed that earnings conference call transcripts are informative and can provide valid information to the market and analysts (Kimbrough, 2005). Researchers have shown that the higher the complexity of management's language, the greater the information asymmetry (Brochet, Miller, Naranjo, & Yu, 2019;

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Bushee, Gow, & Taylor, 2018; Davis, Ge, Matsumoto, & Zhang, 2015), and that high linguistic complexity tends to make investors' less willing to trade and thus reduce the liquidity of the stock (Boubaker, Gounopoulos, & Rjiba, 2019).

In recent years, emerging literature has focused more on emotional information, aspect of which can be measured in various ways. A line of research has focused on the sentiment index calculated by news media articles, twitter tweets, Google trends and so on (e.g., Al-Nasseri, Ali, & Tucker, 2021; Zhang, Hardle, Chen, & Bommes, 2016; Cookson & Niessner, 2020; Da, Engelberg, & Gao, 2015; Anastasiou, Ballis, & Drakos, 2022; Fang & Peress, 2009; Garcia, 2013; Gong, Liu, Xiong, & Zhang, 2022; Gong, Zhang, Wang, & Wang, 2022; Yousaf, Youssef, & Goodell, 2022; Islam, 2021; Sapkota, 2022; Song & Yu, 2022; Sprenger, Tumasjan, Sandner, & Welpe, 2014; Tetlock, 2007; Yuan, 2015;).While another line of research has focused on tone, a variable that captures the emotional information of textual data. Fruitful research has been conducted on tone (Loughran & McDonald, 2011), abnormal tone (Blau, DeLisle, & Price, 2015), tone dispersion (Allee & DeAngelis, 2015), tone volatility (Campbell, Lee, Lu, & Steele, 2020), etc.

However, most of the research put the emphasis on the emotional information and their relationships with the stock return (volatility), there has been few research exploring the emotional information and its impact on the securities analysts' follow-up behavior. Another research gap is that almost all research focus on the numeric or textual data and then conduct sentiment analysis by constructing sentiment index or extracting emotional information, audio data is ignored by scholars.

On the basis of previous literature, we set out to explore the relationship between the emotional information contained in the audio of earnings conference calls and the behavior of securities analysts. It has been shown that traditional financial indicators are closely correlated with the behavior of securities analysts (Bhushan, 1989) and that the emotional information in earnings conference calls represented by tone is explanatory for the behavior of the stock market (Loughran & McDonald, 2011), the listed firms themselves (Allee & DeAngelis, 2015), and management (Ma, 2021). Nevertheless, scholars have not investigated whether emotional information contained in audio is related to the behavior of securities analysts. Our research not only addresses this question but explores the emotional information contained in audio in comparison with textual transcript. Due to the difficulties of dealing with audio, we suggest a deep learning approach to extract emotional information from the audio, ultimately constructing variables similar to those extracted from textual sources.

We than seek to answer the following question by conducting empirical analysis:

RQ. How the emotional information in the audio of earnings conference calls influence the behavior of securities analysts?

In our research, we first segmented the raw audio into small pieces according to who was speaking, grouping them according to their distinct roles. Then, we utilized a deep learning approach to identify the specific emotions of each speaker, and thus we constructed emotional variables to explore their influence on the behavior of the analysts.

Our empirical results showed that the emotional information in the audio is closely related to the behavior of the analysts. First, positive information of the from a company's management in the statement section of the call positively affected the analysts' willingness to issue a rating report, while negative information had a negative influence. In the question section, non-negative information of peer analysts means worth issuing (a positive influence), while in the response section, negative information of management still matters (a negative influence). Secondly, in terms of the specific rating, the negative information revealed by management in the response section is still a key factor. What's more, due to the potential mechanism of the expectation gap, objective and neutral information tended to have significant influence on the specific ratings themselves in the issued reports. Thirdly, with regard to the rating adjustment, the question section is particularly informative. Both positive and neutral content from peer analysts caused upward revision, while negative information had the inverse effect. Furthermore, we found the conclusions did not change with different time windows or based on the prestige of analysts. We further explored the information content across different sections of the earnings conference calls, and we compared content differences in the audio and its textual transcripts. Our results showed that the Q&A section is more informative than the statement section and that audio is more informative than the corresponding textual transcripts.

Our work makes several contributions. First, we studied an under-researched data source, audio data, and its impact on the behavior of securities analysts. Although emotional information extracted from textual data has been widely researched, a research gap persists concerning audio data, especially emotional information extracted from such data. In addition, we contributed to the related literature, as our research showed that securities analysts are influenced differently by emotional information in different sections of the conference and by different specific emotion. We also confirmed that the Q&A section is richer in information content than the statement section in the audio and that the audio is richer in information content than its transcripts. Finally, there are practical implications. For securities analysts, our findings suggest that the information conveyed by peers in the earnings conference calls is worth focusing on. For management, our findings showed that analysts still detect management's attempts to withhold information, and thus it is wise for management to properly reveal information. For investors, our results revealed that the conference calls are informationally rich, so making good use of such information is of vital importance. For regulators, we highlighted that the earnings conference calls contain important information, and are worth regulating so they are not reduced to a tool for the profit of a few.

The remainder of this paper is structured as follows: Section 2 provides an overview of the related literatures; Section 3 contains our research hypotheses; Section 4 introduces the data and the approach we propose; Section 5 gives our results and findings; and Section 6 has the conclusion and limitation.

2. Literature review

In this section, referring the research of tone, one of the lines of research of sentiment analysis, we review three relevant streams of literature: voluntary information disclosure, emotional information in earnings conference calls and speech sentiment recognition.

2.1. Voluntary information disclosure

Voluntary information disclosure refers to information released by listed companies that goes beyond the information that regulators require companies to disclosure. Unlike the information required by stock regulators, which is largely numeric, most of the voluntarily disclosed information is in non-numeric form. Among the many data sources, the textual content of financial reports, management discussion and analysis(MD&A), and the transcripts of earnings conference calls have been widely investigated by researchers.

Henry (2008), Demers and Vega (2008, 2011) have found that the market provides feedback on the textual information in financial reports. Davis, Piger, and Sedor (2012) found that management uses optimistic and pessimistic words in financial reports to describe the future performance of companies and the market reacts to this. Loughran and McDonald (2011), looking at 10-Q and 10-K documents, also found that market performance is positively correlated with the optimism of the textual information.

MD&A generally contains the management's summary of the current state of the listed company's operations and the outlook on the company's future development together with the analysis of industry changes, making it a very important type of information released by listed companies. Knutson and Napolitano (1998), Tavcar (1998), Rogers and Grant (1997), etc., showed that MD&A had gradually become the most widely read part of a company's annual report and was recognized by investors as the most important component. Li (2010) further found that MD&A contains useful information about the company's outlook by examining the forward-looking statements in MD&A. Brown and Tucker (2011) used a new approach to measure the usefulness of information in MD&A and showed that market response was positively related to the degree of variance between MD&A and 10-K filings. Davis and Tama-Sweet (2012) found that managers choose to disclose more information in order to positively influence reporting performance. Kravet and Muslu (2013) found evidence that management discloses more forward-looking information in MD&A when the company's stock price does not reflect information about the company's future earnings. In light of the recent shift towards ESG for corporate evaluation, Ben-Amar and Belgacem (2018) found that corporate social performance correlates with the textual information in MD&A.

Besides financial reports and MD&A, the informative content of earnings conference calls has gradually become a focus of research over the past two decades. Bradshaw (2004) found that earnings conference call transcripts can significantly reduce analysts' forecast errors. Kimbrough (2005) confirmed that earnings conference call transcripts are informative and can provide valid information to the market and analysts. Chen, Matsumoto, and Rajgopal (2011) concluded that both the narrative and question-and-answer sections of earnings conference call transcripts have incremental information content, with the question-and-answer section containing more information than the narrative section. Larcker and Zakolyukina (2012) found that CEOs of companies that falsified their financial reports generally use more language that expresses extreme positive emotions and less language that expresses negative emotions and indecision in the narrative section of conference call transcripts. Studies by Bushee et al. (2018), Davis et al. (2015), and Brochet, Naranjo, and Yu (2016) all found that the higher the complexity of management language, the greater the information asymmetry and the lower the market response. The findings of Boubaker et al. (2019) corroborate this finding, as annual reports with high linguistic complexity that are difficult to read can hinder investors' ability to process and analyze the information contained in the company's annual report, thus making them less willing to trade and so reducing the liquidity of the stock.

Abundant research has focused on the relationship between such information and the listed companies themselves, or the relationship between such information and stock market performance. However, relatively less research has focused on analysts, a non-negligible participants group of participants in the market.

Some of the scholars who have studied analysts include Mayew, Sharp, and Venkatachalam (2013), who used earnings conference calls to identify analysts with superior private information. Jung, Kang, Lim, and Yoo (2017) found that the participation of buyside analysts in earnings conference calls was associated with the future stock performance of the listed company. Cen, Chang, and Dasgupta (2020) found that the access of an analyst invited to be among the first to ask questions in the Q&A section of an earnings conference call was valued by analysts and their employers.

Nevertheless, among the few studies focused on analysts, hardly any research has focused on the behavior of analysts. In this paper, we want to further reveal how analysts' behavior, specifically, their decisions about whether to issue rating reports, what rating to issue or whether to make adjustments is influenced by the information hidden in earnings conference calls.

2.2. Emotional information in earnings conference calls

In the abundant research on voluntary information disclosure, tone, a variable that captures the emotional information in textual sources, is widely used by researchers. However, most of these papers merely study the tone itself and/or its correlation with firm performance or stock market returns, like Loughran and McDonald (2011). In recent years, some studies have examined the statistical variation in tone. Allee and DeAngelis (2015) found a correlation between tone dispersion and firm performance, and Campbell et al. (2020) revealed that tone volatility correlated strongly with firms' operating risks. Furthermore, the tone of speakers in different roles (e.g., managers' tone in Price, Doran, Peterson, & Bliss, 2012, analysts' tone in Milian & Smith, 2017 and Chen, Nagar, & Schoenfeld, 2018), abnormal tone (Blau et al., 2015), and extreme language (Bochkay, Hales, & Chava, 2020) has been studied by researchers as well. Meanwhile, some researchers have begun researching tone across different parts of the earnings conference call: Cheng, Roulstone, and Van Buskirk (2021) found that investors show more interest in the early parts rather than the later parts of the earnings conference calls, and Ma (2021) found the evidence that a positive tone near the end of earnings conference calls suggests managers intend to conceal negative information.

However, few studies have been conducted on raw audio files rather than textual records. Mayew and Venkatachalam (2012) is one of the few studies of earnings conference calls using raw audio data instead of its transcripts, which they analyzed the with LVA software to measure the emotional state of management during the conference calls. They confirmed that the speech sentiments of management were largely correlated with the company's financial outlook.

In this paper, we collected raw audio records of earnings conference calls made by companies listed in China. Using this data sources enriches the literature by extracting emotional information hidden in the audio that might influence analysts' follow-up behavior.

2.3. Speech sentiment recognition

Thanks to the fruitful research on speech sentiment recognition and the development of GPU computing, dealing with audio data and extracting emotional information from it has become more practical. Huang, Gong, Fu, and Feng (2014) combined a deep belief network (DBN) with support vector machine (SVM) and achieved 86.5% accuracy with the Buaa Emotional Speech Database, a 7% improvement over the original method. Lim, Jang, and Lee (2016) combined a convolutional neural network (CNN) and long-short-term memory network (LSTM) to create the Time Distributed Convolutional Neural Network (TDCNN), which achieved 88.01% accuracy with the Berlin dataset (EMODB), compared to the 87.74% accuracy of CNN and 79.87% accuracy of LSTM. Zhang, Zha, Tashpolat, Xu, and Zhao (2019) optimized the SVM algorithm using an improved hybrid frog-jumping algorithm, which improved the accuracy of the SVM algorithm from 73.4% to 84.2% with the Berlin dataset (EMODB). Zhao, Mao, and Chen (2019) achieved a high accuracy of over 90% with the Berlin dataset (EMODB) by using deep 1D & 2D CNN LSTM networks.

However, current literatures in this field mainly focus on improving prediction accuracy rather than actual cross application with other fields. In this paper, we trained a deep learning model on the CASIA dataset, a Chinese corpus, to capture emotional information across the audio data from earnings conference calls segmented according to the different sections of the calls and tried to find how such emotional information influenced analysts' behavior. Details of the audio segmentation and the synthesis of the emotional variables will be set forth in the following sections.

3. Development of hypotheses

In this study, we aim at exploring how the emotional information in the audio influences the analysts' follow-up behavior, so we refer to the former literatures that focus on that of emotional information extracted from text to construct our hypotheses.

Kimbrough (2005) has demonstrated that earnings conference call transcripts provide valid information to the market and analysts, and Bradshaw (2004) also found that earnings conference call transcripts can significantly reduce analysts' forecast errors. Chen et al. (2011) further concluded that both the statement and question-and-answer sections of earnings conference call transcripts have incremental informational content. As speech information is more "high-dimensional" than textual information, the audio of company's earnings conference call is likely a rich source of information. According to previous studies, the emotional information of corporate management, like tone in earnings conference calls, is often correlated with the future stock performance and the firm's outlook. That is, in general, the more positive the sentiment expressed, the better the future stock performance and the firm's outlook, while the more negative the sentiment, the worse the future stock performance and the firm's outlook. So, it is reasonable to predict that analysts' willingness to issue their rating reports would change similarly on the basis of tone.

H1a. Positive emotional information conveyed by management during the statement section of earnings conference calls will positively influence analysts' behavior of issuing rating reports.

H1b. Negative emotional information conveyed by management during the statement section of earnings conference calls will negatively influence analysts' behavior of issuing rating reports.

The Q&A section of the earnings conference calls is usually conducted in a high-stress environment. Analysts, who are the questioners, often ask questions that challenge what the management previously presented in the statement section. In their questions, if the analysts convey more non-negative emotional information, the willingness of other analysts on the conference call to issue rating reports may be influenced positively. Of course, not everything we say carries either positive emotion or negative emotion, so in this study we extracted the emotionally neutral information from the audio to see if such objective information is valuable.

H2a. The positive emotional information conveyed by analysts during the question section of the earnings conference calls will positively influence analysts' behavior of issuing rating reports.

H2b. The neutral emotional information conveyed by analysts during the question section of the earnings conference calls will positively influence analysts' behavior of issuing rating reports.

During the response section, if corporate management face this high-stress situation (when analysts ask some questions management may have been unprepared for) yet still stays composed, analysts might assume management has truthfully conveyed the important information to investors. However, if the management conveys any negative emotional information here, analysts might consider management to have concealed some important information, thus reducing their willingness to issue rating reports.

H3. Negative emotional information conveyed by management during the response section of the earnings conference calls will negatively influence analysts' behavior of issuing rating reports.

Previous studies such as Brown et al. (1987), O'Brien (1988) and Affleck-Graves, Davis, and Mendenhall (1990) have found that analysts generally tend to issue high ratings. A study by Francis and Philbrick (1993) suggests that this phenomenon can be attributed to analysts' maintaining relationships with listed companies through optimistic investment ratings. Das, Levine, and Sivaramakrishnan (1998) provides a more in-depth interpretation of this phenomenon through empirical studies, suggesting that analysts are motivated by the desire to please the management of listed companies and thus gain access to private information. Studies by Lim (2001), Bowen, Davis, and Matsumoto (2002), Richardson, Teoh, and Wysocki (2004), Mayew (2008), and Mayew and Venkatachalam (2012), among others, also provide evidence to support this view. Others like Libby, Hunton, Tan, and Seybert (2008) have also attributed this phenomenon to analysts' access to commissions.

Analysts have limited attentional resources such as energy and time. McNichols and O'Brien (1997) have found that, constrained by this "limited attention", analysts are more willing to shift their attention resources from companies with uncertain or unpromising growth prospects to companies that they believe have better growth prospects.

This phenomenon may be related to the characteristics and background of China's securities market itself. Since China's securities market is more concerned about protecting the interests of small- and medium-sized investors, the market lacks effective shorting tools. Also, due to conflicts of interest, China's securities analysts rarely issue reports with "sell" or "decreasingly hold" ratings. Instead, more reports carry "increasingly hold" and "buy" ratings in the market, which causes analysts to award high ratings in their reports in general.

All these findings support the idea that analysts often issue high-rating reports. However, with the development of China's securities market in recent years, the securities analyst industry has been gradually regulated, and behaviors such as colluding with executives of listed companies to issue high-rating reports to attract investment are cracked down on severely by the regulatory authorities. Industry feedback mechanisms such as the New Fortune Analyst Awards, which require analysts to have high prediction accuracy and strong information processing ability, inhibit analysts' optimism. Accordingly, we estimate that analysts will be rational when rating listed companies. That is, the emotional information may not have influence on the specific ratings in general.

However, we still believe that negative emotional information revealed by management in such a high-stress situation could negatively affect the rating given by analysts.

H4. Negative emotional information conveyed by management during the response section of earnings conference calls will negatively influence analysts' ratings of listed companies.

Because of some restrictions on specific ratings given by analysts, we further focus on the rating adjustments. Although previous studies have shown that analysts tend to give reports with high ratings for various reasons related to their own interests, contrary to the specific ratings, emotional information in earnings conference calls might still influence their rating adjustments. Studies such as Mayew and Venkatachalam (2012), McNichols and O'Brien (1997) and D'Amico, Whitley, Tesone, O'Brien, and Roth (2005) have found that when faced with "soft information" such as tone, analysts have "inertia" motivating them to maintain their current rating levels and so are reluctant to revise their forecasts. However, if the emotional information in a call is rich in information content, the analysts might make rating adjustments. Research by Mayew and Venkatachalam (2012) has confirmed this inference that analysts' rating adjustments are influenced by the emotional fluctuation extracted from earnings conference calls by LVA software.

In line with the above hypotheses, we suggest that analysts' rating adjustments will be closely related to the emotional information in the audio from the conference calls.

H5a. Negative emotional information conveyed by analysts during the question section of the earnings conference calls will negatively influence analysts' rating adjustments.

H5b. Positive emotional information conveyed by analysts during the question section of the earnings conference calls will positively influence analysts' rating adjustments.

H5c. Neutral emotional information conveyed by analysts during the question section of the earnings conference calls will positively influence analysts' rating adjustments.

As we have estimated that the negative emotional information revealed by management in the response section of calls could negatively affect the rating given by analysts, when it comes to making rating adjustments, the negative emotional information should already have been reflected in the initial ratings. On the contrary, when management remains confident and composed under such a high-stress situation, the positive emotional information might encourage the analysts to adjust their ratings upward.

H6. Positive emotional information conveyed by analysts during the response section of the earnings conference calls will positively influence analysts' rating adjustments.

Previous research has confirmed that textual information from earnings conference calls is a significant incremental information resource. Kimbrough (2005) found that corporate management's textual tone can also offer incremental information relevant to predicting future company performance.

This raises a question: Is the information content in audio is richer than that in text? Audio is a "higher dimensional" data source than text, and the current research on earnings conference calls is mainly based on transcripts of audio (i.e., text is the information left after audio compression and dimensionality reduction). Thus, the same sentence may convey completely different meanings depending on the speaker's sentiment, but compression into text makes it difficult for others to obtain the original, lossless information.

What's more, Chen et al. (2011) showed that both the statement and Q&A sections of earnings conference call transcripts have incremental information content, and that the Q&A section is richer in information than the statement section. This raises another question that we are interested in: Is this finding corroborated when researchers use the information from the audio?

4. Methodology

In this section, we firstly introduce the data and the variables involved in our study in subsection 4.1. Then we detailly show how we extract emotional information directly form audio files and how the emotional variables are finally composed.

4.1. Data collection and variables

4.1.1. Data sources

The data involved in this paper could be divided into two main categories. One is the unstructured data, such as the original audio files of listed companies' earnings conference calls and the corresponding transcripts. The other category is the structured data, including the listed company's financial information and information from analysts' research reports.

The data terminal most widely used by industry professionals and researchers in China is the WIND financial terminal, and the audio data in this paper comes from the WIND3C China Financial Conference Platform. The platform contains data such as audio, video, and text collected from various conference calls. We collected information from all meeting records on this platform before December 31st, 2019.

After filtering, a total of 848 audio files concerned with a single company were selected, of which a total of 789 samples contained management statements (presentation section), while 59 samples did not contain management statements (presentation section) due to the setting or arrangement of the meeting session. The time span during which the audio was recorded from March 30, 2012, to December 2, 2019.

In addition to the audio data, the text transcripts of the audio files were required for comparison. The audio-to-text interface of XunFei Open Platform was used. Since the recognition accuracy using speech algorithms cannot be 100% completely error-free, audio was converted to text using this coarse method and then supplemented with manual proofreading to ensure the integrity of the information.

The Listed Company Profit Forecast Database of Suntime Company[1] is one of the most extensive databases focusing on analysts in China's securities market at present.

It contains data on analysts' rating reports and related data, all of high quality with wide coverage. All the variables in this paper related to analysts come from this database.

Other data variables such as financial data as control variables, were retrieved from the WIND database, the GilData database, the CSMAR database or through the TUSHARE financial data package.

4.1.2. Dependent variables

In order to investigate the relationship between speech sentiment and analysts' behavior during earnings conference call, this study used the ratio of the number of analysts who renewed their rating reports after the conference call to the number of analysts who issued reports before the calls. The larger the ratio, the greater the attention received from analysts; the smaller the ratio, the less the attention. The specific formula is as follows.

$$REC\_PCT(T) = \frac{NReport(0,T)}{NReport(-T,0)} \tag{1}$$

where *NReport(s,t)* represents the number of research reports issued by all analysts during the period from *s* day before the base date (the day when the listed company held the earnings conference call) until *t* day after that day. Based on this definition, the following four variables are generated for the purpose of the study and for robustness testing.

$$REC\_PCT\_WEEK = REC\_PCT(7) \tag{2.1}$$

$$REC\_PCT\_MONTH = REC\_PCT(30) \tag{2.2}$$

$$REC\_PCT\_QUARTER = REC\_PCT(90) \tag{2.3}$$

$$REC\_PCT\_HALFYEAR = REC\_PCT(180) \tag{2.4}$$

In order to investigate the speech sentiment and analysts' rating content, this study used the mean value of the rating levels of all analysts' rating reports issued on the listed company within the time window. That is

$$RECLEVEL(s,t) = MEAN(ReportRating(s,t)) \tag{3}$$

As different analysts might use different expressions in their rating reports, ratings of a company were measured by scoring; see Table 1.[2]

Generally, RECLEVEL in this paper refers to

$$RECLEVEL = RECLEVEL(0,90) = MEAN(ReportRating(0,90)) \tag{4}$$

which reflects the average ratings issued by analysts within a certain time window. In order to examine analysts' rating adjustments before and after the event, variables indicating rating adjustments were also defined as follows.

$$RECLEVE\_CHG = RECLEVEL(0,90) - RECLEVEL(-90,0) \tag{5}$$

Table 1
Correspondence between analyst ratings and scores.

Meaning	Score
Selling	1
Reducing holding	2
Neutral	3
Increasing holding	5
Buying	7

[1] https://www.go-goal.com/product/forecast
[2] The rating scales we use are consistent with the rating system of the dataset.

In addition, in the robustness test, we will also discuss the similarities and differences between star analysts and non-star analysts, and the variables will therefore be separated into a star group and non-star group.

4.1.3. Control variables

We controlled a bundle of variables, as presented in Table 2. Bhushan (1989) has confirmed that analysts' follow-up behavior can be influenced by many factors, including company shareholding structure, company size, company performance, and stock price synchronization. To eliminate the influence of these variables that have been found to impact analysts' behavior, we controlled several variables following Lin and Xie (2017) and Zhao, Li, and Liu (2013).

In addition, we have added DURATION as another control variable to capture the potential effects of conference duration.

$$DURATION = \frac{LENGTH}{SUM} \tag{6}$$

DURATION is defined as the proportion of time occupied by the section containing the emotional variable, i.e., LENGTH, to the total duration of the conference SUM. For example, if the emotional variable is S_positive, then the control variable DURATION represents the proportion of statement section duration to the total duration of the conference.

It is noteworthy that, due to the division of the entire conference into different sections, there exist three specific variables for DURATION. Specifically, S_DURATION denotes the proportion of length occupied by the statement section in the entire conference, while Q_DURATION and A_DURATION correspond to the proportions taken up by the questioning and answering sections, respectively.

4.2. Deep learning approach for speech sentiment extraction

Capturing sentiment information from the audio is vitally important. This section details how we deal the audio data and how the emotional variables were constructed.

4.2.1. Segmentation and transcoding of raw audio

Chen et al. (2011) showed that different sections of earnings conference calls are different from each other, and that the Q&A section is richer in information than the statement section. Thus, it was necessary to deal with the audio in sections.

The first step of data processing was to split the audio into presentation section (Statement section), question section and answer section (Response section) so that the different sentiments in different sections voiced by speakers with different roles could be measured separately.

Kaldi is a toolkit for speech recognition written in C++, which contains tools for speech recognition that we could easily use, including speaker recognition.

In this paper, we first applied the speech recognition tools to 848 speech samples collected from the WIND3C Chinese financial conference platform to locate them on the time axis of the raw audio so that we could obtain the starting and ending time coordinates for the different speakers. Since there was no readily available technical means to automatically obtain the roles of different speakers during the call, we manually determine the speaker's role from the information processed with Kaldi and also manually calibrated the timeline obtained in the previous step.

After obtaining the calibrated timeline and the respective roles of the speakers, the audio was segmented using the open-source toolkit FFMPEG and transcoded into the same form as training sources; thus, the 848 long audios were segmented into 28,915 short audio files according to the different roles of the speakers and different sections of the call.

A simple schematic of the segmentation and transcoding is shown below in Fig. 1.

4.2.2. A speech sentiment recognition model

After acquiring the short audio files segmented by the different sections of the conference call and the different roles of speakers, the next step was to identify the sentiments in the audio. Considering the Chinese context of our materials, the CASIA Chinese emotion database was selected as the training dataset with which to train a prediction model with excellent performance, accurate classification, and good robustness to measure the sentiment of each speaker during the conference.

4.2.2.1. Training set. Although the Berlin Dataset (EMODB) is widely used in research involving speech sentiment recognition, CASIA Chinese emotion database was adopted by us because it, like our data resource, was in Chinese. CASIA is one of the most complete speech emotion data in Chinese today. It divides human emotions into six categories: joy, panic, anger, surprise, sadness, and neutrality. The speech database was manually screened to get 9600 utterances, which were recited by four professional announcers, two men and two women, on 500 sentences of text under different emotions. The data was collected in a pure recording environment with a signal-to-noise ratio of about 35 dB. We used a subset of the database available for free on the Internet, which contain 50 sentences for each of the 6 emotions expressed by each of the 4 speakers, totaling 1200 sentiments with annotation.

4.2.2.2. Feature engineering. MFCC Mel inverse spectral coefficients is one of the most widely used speech features in the field of speech recognition, which simulates the human ear's mechanism of nonlinear perception and therefore has better robustness. The extraction of MFCC coefficients was mainly divided into the following steps.

Step1. Boosting the high-frequency portion through a high-pass filter flattened the spectrum of the signal.

Step2. Framing by different window functions made the signal smooth and again highlights the high frequency part.

Step3. Converting the frequency domain energy distribution into a spectral energy distribution by fast Fourier transform, after which the power spectrum was obtained by taking the square of its mode.

Step4. Applying the DFT transform on the results of the previous step to obtain the discrete spectrum, then passing it through a Mel delta filter

Table 2
List of control variables.

Variable	Explanation
DURATION	A variable to capture the potential effects of conference duration.
SUE	Year-over-year change in net income for the prior quarter of the earnings conference call.
INSTOWN	The percentage of shares held by institutional investors for the prior quarter of the earnings conference call.
NAL	The number of analysts whose rating reports covered the company for the prior quarter of the earnings conference call.
BIG10	A dummy variable for whether the auditor of a listed company's prior year's annual report was from a top 10 accounting firm.
EPSG	The growth rate of the earnings per share of the listed company for the prior quarter of the earnings conference call.
LNMV	Logarithm of the total market capitalization of the listed company at the end of the previous year.
DIVIDENDS	A dummy variable for whether the listed company paid dividends in the previous year.
ROEG	The growth rate of the ROE (return on equity) for the prior quarter of the earnings conference call.
MTB	The book-to-market ratio of a listed company for the previous year, i.e. the total market capitalization of the company divided by the owner's equity.
CA	A dummy variable for whether the listed company had refinancing (additional issue, share placement, convertible bonds) and M&A in the previous year.
TURNOVER	The average turnover rate of the listed company for the prior quarter of the earnings conference call.

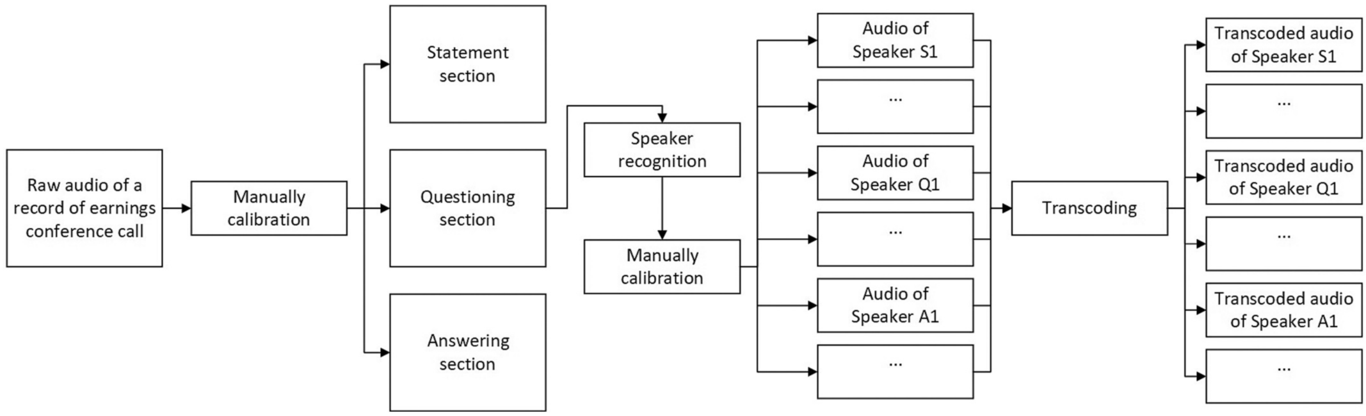

Fig. 1. The Process of Segmentation and Transcoding.

set to smooth and eliminate harmonics so that the resonant peaks in the original speech were highlighted and the number of operations was reduced.

Step5. After that, the MFCC coefficients were obtained by applying discrete cosine transformation on the log energy spectrum obtained in the last step.

In this paper, we used Librosa, a speech processing package to complete the extraction of MFCC features.

Since the average length of 1200 speech items in the training dataset was 1.98 s, 2 s was selected as the input length of the audio for the training model. Parts that were less than 2 s were replaced by 0.

4.2.2.3. Model selection. Deep learning has a comparative advantage in processing complex data, and in recent years, the improvement of computing power has led to deep learning being widely used in fields such as speech recognition and image processing.

Recurrent neural networks (RNN) including two derivatives, long short-term memory networks (LSTM) and gated recurrent units (GRU) and convolutional neural networks (CNN) are the two major classes of widely adopted basic model structures. A study by Lim et al. (2016) shows that CNNs are superior in accuracy when dealing with speech emotions because MFCC features mainly represent the underlying features of human vocal organs and are less related to sequence-dependent speech content, in which RNNs are specialized. Zhao et al. (2019) achieves a high accuracy of 95.33% with the Berlin dataset (EMODB) by using deep 1D & 2D CNN LSTM networks. CNN plays an important role in image processing, and the processed MFCC features can be regarded in sense as “images” when used as input; that is, the dimensionality of MFCC features is analogous to the RGB color channels in an image, and the Conv1D one-dimensional convolution operation of MFCC features is analogous to the Conv2D two-dimensional convolution for images.

Therefore, a CNN-based model was adopted in this study.

Using the above settings, we trained a model that performed well on both the training set and the validation set. Fig. 2 and Fig. 3 show the structure of the network and the variation of accuracy and loss function in each round during the training process.

4.2.3. Construction of emotional variables

The output of the model is the probability value under twelve sentiment labels of the single segment of audio inputted; these labels contain six predefined sentiment dimensions for each of the two genders.

In this paper, referring to the current construction for the emotional variables proxied by the tone, which is established using textual data, we aggregate these probability values over different speakers and different sections of the conference to finally get the variables that represent the different sentiments for different sections.

For example, a single sample, Audio A, which lasted for 10 s, is inputted; then, using 2-s-long pieces of it as the input for the model, we could get 12 probability values as output for each piece. According to the predefined labels, 3 values representing positive sentiment, negative sentiment, and neutral sentiment are summed for the 2-s piece. Then, for the whole Audio A, the 3 mean values from each tiny piece represent the sentiments of the longer audio. A given piece of raw audio consists of many segments, and also belongs to one of the three sections of the conference, allowing us to further aggregate the sentiment values for each of the three sections of a single conference.

The specific emotional variables are shown in Table 3, and the entire flow of the variable construction is shown in Fig. 4.

4.3. Empirical models

To test the research hypothesis 1a,1b,2a,2b,3, by referring the previous literatures focusing on tone, such as Lin and Xie (2017) and Zhao et al. (2013), the following regression model was developed.

$$REC\_PCT\_QUARTER = \alpha + \beta \times EmotionalVariable + \sum_i \beta_i \times ControlVariable_i + \varepsilon \quad (7)$$

Here, Emotional Variable is one of the nine emotional variables extracted from the audio. According to Mayew and Venkatachalam (2012), analysts tend not to merge information when making forecasts, so the relationship between each emotional variable and analysts’ behavior will be examined separately. Control Variable refers to the control variables introduced in the previous section 4.1.3. Since analysts’ behavior is related to various factors, these factors are controlled.

To test Research Hypothesis 4, the following regression model was developed.

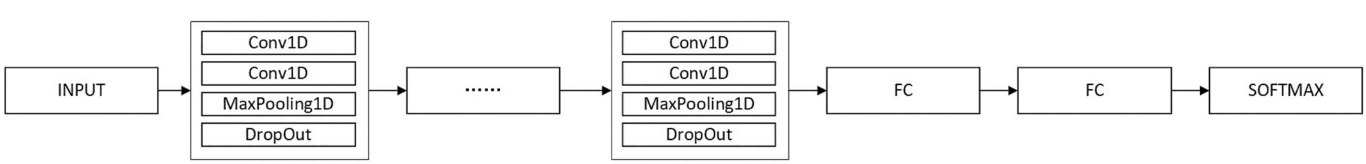

Fig. 2. The network structure.

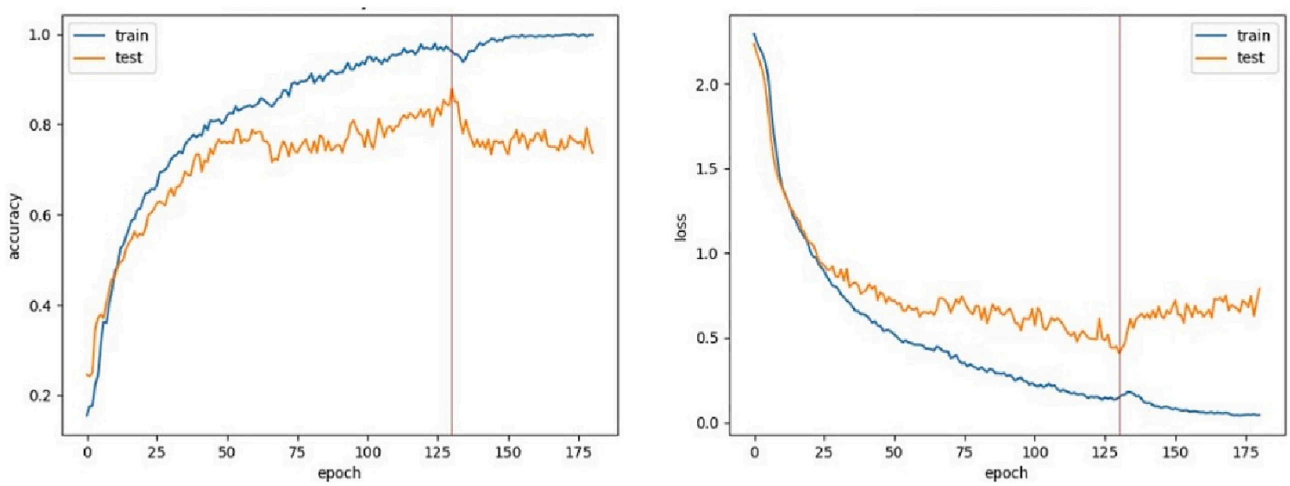

Fig. 3. The variation of accuracy and loss.

Table 3
List of emotional variables.

Variable	Explanation
S_negative	speaker's negative sentiment level during statement section
S_positive	speaker's positive sentiment level during statement section
S_neutral	speaker's neutral sentiment level during statement section
Q_negative	speaker's negative sentiment level during questioning section
Q_positive	speaker's positive sentiment level during questioning section
Q_neutral	speaker's neutral sentiment level during questioning section
A_negative	speaker's negative sentiment level during answering section
A_positive	speaker's positive sentiment level during answering section
A_neutral	speaker's neutral sentiment level during answering section

$$RECLEVEL = \alpha + \beta \times EmotionalVariable + \sum_i \beta_i \times ControlVariable_i + \varepsilon \tag{8}$$

To test research hypothesis 5a,5b,5c,6, the following regression model was developed.

$$RECLEVEL\_CHG = \alpha + \beta \times EmotionalVariable + \sum_i \beta_i \times ControlVariable_i + \varepsilon \tag{9}$$

5. Results and findings

5.1. Main results

The descriptive statistics of the variables are presented in Table 4 and Table 5. Table 4 displays the results for the statement section, and Table 5 presents the results for the questioning section and the answering section.

To exclude the potential mutual influence among emotional variables, we have conducted a correlation test for the emotional variables. As shown in Table 6, the coefficients do not appear high correlation between the variables whose threshold is below 0.8 as suggested by Kline (2023).

The main results are presented in Table 7, and a complete version is shown in **Appendix A**.

5.1.1. Results of issuing rating reports

Row(1) of Table 7 reports the regression results of **Model 1** regarding the relationship of speech sentiments to whether analysts issue their rating reports.

It can be seen that if a company's management conveys more positive sentiments during the statement section of the earnings conference call, the analysts tend to be more willing to issue rating reports for the company. Conversely, if management shows more negative sentiments during the statement section, the analysts' willingness to recommend stocks is greatly reduced. This is also consistent with the findings of previous studies.

When it comes to the questioners' sentiments in the question section, we found that both positive and neutral sentiments positively affected analysts' willingness to issuing rating reports. This indicates that the open question section facilitates the transfer and exchange of information with investors and analysts, who are relatively weaker than the companies in terms of information; the Q&A section thus reduces

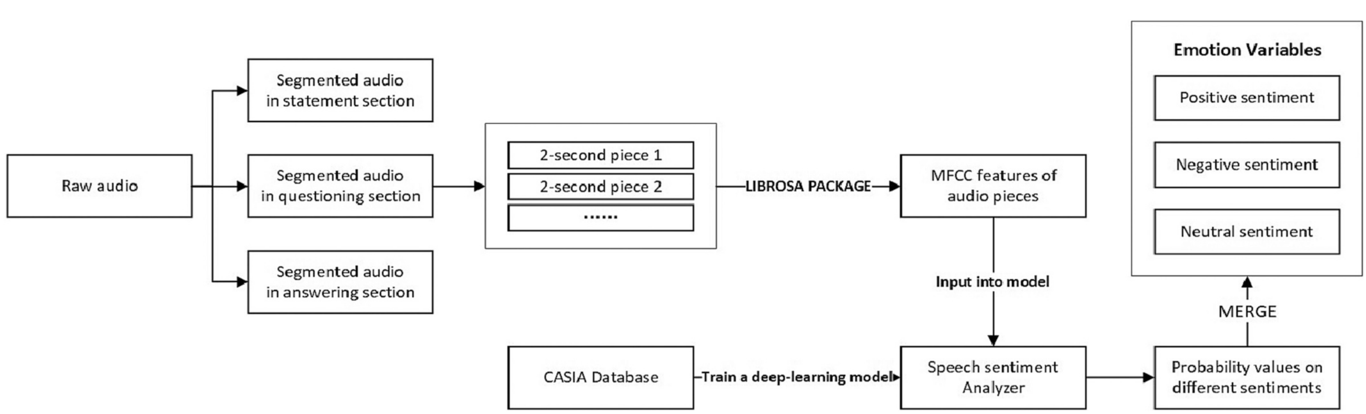

Fig. 4. The entire flow of the variable construction.

Table 4
Description of statement section.

	count	mean	std	min	25%	50%	75%	max
REC_PCT_WEEK	789	1.2475	1.6499	0	0.2857	1	1.2408	18
REC_PCT_MONTH	789	1.4193	2.0745	0	0.5	1	1.5	40
REC_PCT_QUARTER	789	1.3546	1.3143	0	0.6667	1.0588	1.6	19
REC_PCT_HALFYEAR	789	1.2616	1.1946	0	0.697	1.0164	1.4167	14
RECLEVEL	789	6.196	0.6367	2.7143	5.8889	6.28	6.6522	7
RECLEVEL_STAR	789	6.2813	0.8031	2.7143	5.8182	6.5	7	7
RECLEVEL_NONSTAR	789	6.175	0.6466	2.7143	5.8485	6.25	6.6364	7
RECLEVEL_CHG	789	−0.0212	0.6515	−4	−0.3117	−0.0055	0.2782	4.1385
RECLEVEL_CHG_STAR	789	0.0083	0.7551	−4	−0.25	0	0.3	3.2007
RECLEVEL_CHG_NONSTAR	789	−0.0231	0.6828	−4	−0.3333	0	0.2857	4.4444
S_negative	789	0.438	0.1983	0.0004	0.3054	0.4659	0.5818	0.9134
S_positive	789	0.1757	0.1731	0.0005	0.0438	0.1157	0.2592	0.9951
S_neutral	789	0.307	0.2043	0.0041	0.1537	0.2556	0.4092	0.9802
Q_negative	789	0.4415	0.1712	0.0015	0.3286	0.455	0.5729	0.8271
Q_positive	789	0.1572	0.1202	0.0008	0.0705	0.1237	0.2075	0.7434
Q_neutral	789	0.3462	0.1679	0.029	0.2214	0.3283	0.4429	0.9538
A_negative	789	0.4401	0.1845	0	0.3221	0.4744	0.568	0.8323
A_positive	789	0.1791	0.1627	0	0.0545	0.1241	0.254	0.9816
A_neutral	789	0.2989	0.1839	0	0.1672	0.256	0.387	0.9514
SUE	789	1.3529	11.1756	−121.2208	−0.0009	0.3113	0.8645	225.2187
INSTOWN	789	0.2996	0.224	0	0.0989	0.2531	0.4754	0.907
NAL	789	15.2573	14.0141	0	5	11	22	119
BIG10	789	0.583	0.4934	0	0	1	1	1
EPSG	789	0.9679	6.9115	−41.2632	−0.2652	0.0868	0.5589	101.625
LNMV	789	22.6586	3.4904	0	22.4977	22.9783	23.6863	26.6092
DIVIDENDS	789	0.8885	0.315	0	1	1	1	1
ROEG	789	−0.0012	0.0331	−0.2884	−0.011	−0.0002	0.0091	0.1983
MTB	789	4.0549	2.7092	0	2.2314	3.4015	5.3503	22.5537
CA	789	0.4385	0.4965	0	0	0	1	1
TURNOVER	789	1.4501	1.3338	0	0.5705	1.0284	1.9209	10.1436
S_DURATION	789	0.2506	0.1826	0.013	0.1135	0.2019	0.3459	0.949
Q_ DURATION	789	0.1592	0.0836	0.0112	0.0971	0.1498	0.2055	0.6538
A_ DURATION	789	0.5902	0.155	0	0.506	0.6137	0.6982	0.9409

Table 5
Description of questioning section and answering section.

	count	mean	std	min	25%	50%	75%	max
REC_PCT_WEEK	848	1.2392	1.6416	0	0.2857	1	1.2408	18
REC_PCT_MONTH	848	1.4332	2.0635	0	0.5	1	1.5139	40
REC_PCT_QUARTER	848	1.3589	1.3075	0	0.6667	1.062	1.6	19
REC_PCT_HALFYEAR	848	1.2663	1.1815	0	0.6975	1.0247	1.4314	14
RECLEVEL	848	6.2008	0.6263	2.7143	5.8919	6.28	6.6473	7
RECLEVEL_STAR	848	6.2888	0.7915	2.7143	5.8571	6.5	7	7
RECLEVEL_NONSTAR	848	6.1793	0.6356	2.7143	5.8571	6.25	6.6313	7
RECLEVEL_CHG	848	−0.0233	0.6432	−4	−0.3299	−0.009	0.2808	4.1385
RECLEVEL_CHG_STAR	848	0.0058	0.7496	−4	−0.25	0	0.2893	3.2007
RECLEVEL_CHG_NONSTAR	848	−0.0257	0.6733	−4	−0.3351	−0.0051	0.2857	4.4444
S_negative	848	0.4075	0.2214	0	0.2505	0.4492	0.5696	0.9134
S_positive	848	0.1635	0.1728	0	0.0349	0.1031	0.2452	0.9951
S_neutral	848	0.2856	0.212	0	0.1335	0.2399	0.3916	0.9802
Q_negative	848	0.4412	0.1696	0.0015	0.3302	0.4561	0.5703	0.8271
Q_positive	848	0.1576	0.1209	0.0008	0.0707	0.1233	0.2075	0.7434
Q_neutral	848	0.3462	0.1668	0.029	0.2225	0.328	0.4397	0.9538
A_negative	848	0.4395	0.1838	0	0.3217	0.4734	0.5667	0.8323
A_positive	848	0.179	0.1623	0	0.0543	0.1245	0.2541	0.9816
A_neutral	848	0.2994	0.1835	0	0.1672	0.2576	0.3939	0.9514
SUE	848	1.2918	10.787	−121.2208	0.0054	0.31	0.8468	225.2187
INSTOWN	848	0.2969	0.2223	0	0.1	0.2441	0.4734	0.907
NAL	848	15.3679	13.7594	0	6	11	22	119
BIG10	848	0.5861	0.4928	0	0	1	1	1
EPSG	848	0.9279	6.6787	−41.2632	−0.2625	0.0851	0.5598	101.625
LNMV	848	22.5967	3.7185	0	22.5081	23.0199	23.6879	26.6092
DIVIDENDS	848	0.8939	0.3082	0	1	1	1	1
ROEG	848	−0.0011	0.0339	−0.2884	−0.011	−0.0002	0.0099	0.1983
MTB	848	4.0768	2.7405	0	2.2603	3.449	5.3666	22.5537
CA	848	0.4363	0.4962	0	0	0	1	1
TURNOVER	848	1.457	1.3492	0	0.5852	1.0389	1.9236	10.1436
S_DURATION	848	0.2332	0.1873	0	0.0932	0.1907	0.3335	0.949
Q_DURATION	848	0.1624	0.0847	0.0112	0.0986	0.1518	0.2094	0.6538
A_DURATION	848	0.6044	0.1601	0	0.5138	0.6242	0.7131	0.957

Table 6
Correlation test.

	S_negative	S_positive	S_neutral	Q_negative	Q_positive	Q_neutral	A_negative	A_positive	A_neutral
S_negative	1.000	−0.291	−0.362	0.255	−0.196	−0.174	0.679	−0.366	−0.476
S_positive	−0.291	1.000	−0.017	−0.180	0.301	0.020	−0.367	0.752	−0.100
S_neutral	−0.362	−0.017	1.000	−0.198	0.046	0.235	−0.499	−0.033	0.732
Q_negative	0.255	−0.180	−0.198	1.000	−0.534	−0.584	0.369	−0.260	−0.270
Q_positive	−0.196	0.301	0.046	−0.534	1.000	−0.035	−0.264	0.409	0.038
Q_neutral	−0.174	0.020	0.235	−0.584	−0.035	1.000	−0.267	0.051	0.332
A_negative	0.679	−0.367	−0.499	0.369	−0.264	−0.267	1.000	−0.532	−0.659
A_positive	−0.366	0.752	−0.033	−0.260	0.409	0.051	−0.532	1.000	−0.085
A_neutral	−0.476	−0.100	0.732	−0.270	0.038	0.332	−0.659	−0.085	1.000

Table 7
Main results.

	S_negative	S_positive	S_neutral	Q_negative	Q_positive	Q_neutral	A_negative	A_positive	A_neutral
REC_PCT_QUARTER	−0.4917**	0.7222***	0.1637	−0.0979	0.6797*	0.5015*	−0.5685**	0.2024	0.379
	(−2.158)	(2.748)	(0.736)	(−0.381)	(1.888)	(1.918)	(−2.408)	(0.748)	(1.592)
REC_PCT_WEEK	−0.5883**	0.6093*	−0.4840*	0.1113	0.8686*	0.4864	−0.5678*	−0.2947	−0.2881
	(−1.987)	(1.782)	(−1.677)	(0.333)	(1.856)	(1.426)	(−1.842)	(−0.836)	(−0.927)
REC_PCT_MONTH	−0.6721*	0.8128*	0.0675	0.0483	1.4652**	0.8308*	−0.5779*	−0.5464	0.4374
	(−1.791)	(1.879)	(0.185)	(0.114)	(2.483)	(1.934)	(−1.482)	(−1.228)	(1.116)
REC_PCT_HALFYEAR	−0.3525*	0.4200*	−0.0890	0.0948	0.5884*	0.6743***	−0.5216**	−0.2898	−0.1083
	(−1.746)	(1.805)	(−0.453)	(0.422)	(1.865)	(2.953)	(−2.506)	(−1.22)	(−0.517)
RECLEVEL	0.1139	0.0277	−0.1793*	0.027	−0.1936	0.0658	−0.2337**	0.1601	−0.113
	(1.022)	(0.216)	(−1.654)	(0.217)	(−1.113)	(0.521)	(−2.043)	(1.226)	(−0.981)
RECLEVEL_STAR	0.2181	0.0142	−0.2644*	−0.3445**	−0.1885	0.0188	−0.4299***	0.1915	−0.2082
	(1.542)	(0.087)	(−1.92)	(−2.179)	(−0.852)	(0.117)	(−2.959)	(1.153)	(−1.423)
RECLEVEL_NONSTAR	0.1049	0.0483	−0.1888*	0.1193	−0.1869	0.0798	−0.2141*	0.1466	−0.1101
	(0.927)	(0.37)	(−1.715)	(0.944)	(−1.058)	(0.621)	(−1.842)	(1.105)	(−0.941)
RECLEVEL_CHG	−0.1389	0.1394	0.0633	−0.3270**	0.3933**	0.2653**	−0.0715	0.2335*	0.1827
	(−1.19)	(1.036)	(0.556)	(−2.506)	(2.149)	(1.996)	(−0.593)	(1.698)	(1.508)
RECLEVEL_CHG_STAR	−0.0318	0.0365	−0.0271	−0.2114	0.3797*	0.1331	0.0363	0.2924*	0.0514
	(−0.234)	(0.233)	(−0.205)	(−1.386)	(1.779)	(0.858)	(0.258)	(1.822)	(0.363)
RECLEVEL_CHG_NONSTAR	−0.1381	0.1381	0.0640	−0.3294**	0.3319*	0.2896**	−0.0731	0.2655*	0.1973
	(−1.127)	(0.978)	(0.536)	(−2.408)	(1.729)	(2.079)	(−0.579)	(1.842)	(1.554)
Observations	789	789	789	848	848	848	848	848	848

Note: This table only reports the coefficient β of each emotional variable, with its t-statistics in parentheses and *, **, *** representing statistical significance at 10%, 5%, and 1%, respectively.

information asymmetry. Moreover, through this process analysts could not only attain positive information (the optimistic sentiments expressed by a questioner) and reflect it in their own rating behavior but could also use the objective and neutral information of a questioner's sentiments in the question section and reflect it in their own behavior. This shows that the question section facilitates the exchange of information, not only from the information-advantaged side to the information-disadvantaged side, but also from one information-disadvantaged party to another.

The management's sentiment in the response section is also noteworthy. Though management might be able to hide its negative sentiment during the statement section, it could be "triggered" in the Q&A section due to surprising questions from investors, for which management often could not prepare in advance. In this section, as compared to the statement section, management's optimism was no longer a major influence on analysts' rating decisions, but negative sentiment was still a consideration as it better reflected management's true feelings. That is, in the response section, a high level of negative sentiment from management significantly reduced the willingness of analysts to issue reports.

In summary, Hypotheses 1a, 1b, 2a, 2b, 3 were tested, and the results showed that analysts could use the emotional information in the audio of companies' earnings conference calls, which had explanatory power for analysts considering whether to issue rating reports for the companies. In terms of specific emotional variables, the positive and negative sentiments of management in the statement section, the positive and neutral sentiments of questioners in the question section, and the negative sentiments of management in the response section were some of the influential emotional variables.

5.1.2. Results of ratings of listed companies

It was mentioned previously that analysts might give higher ratings to listed companies for the purpose of pleasing the management of those companies and thus obtaining private information. From the perspective of self-interest (e.g., getting commissions), analysts also were motivated to give high ratings. Finally, issuing reports to cooperate with the capital operation of major shareholders could also explain the optimism of analysts found in earlier studies. However, with the development of China's securities market and the regulatory crackdown on "stock market black mouths" (online voices manipulating prices) and other chaos, as well as the rise of institutions such as the New Fortune Analyst Awards, the accuracy of analysts' own ratings is the basis for their presence in the market. As the massive amount of information in the market could already reflect and explain analysts' ratings and forecasts, from the perspective of incremental information content it is only when the information content of expressed sentiment is sufficient that it will affect analysts' forecast content.

Row(5) of Table 7 reports the regression results of Model 2 regarding the speech sentiments and specific analysts' ratings.

As is shown in the table, negative emotion in the response section is a significant variable. Since the Q&A section is a good way to "elicit" the true (negative) emotions of management, and there is less access to this information, this information is more "valuable". Thus, Hypothesis 4 was tested.

However, to our surprise, neutral sentimental content in the statement section significantly reduced the final rating issued by the analysts. This might because analysts and other investors participating in the call would expect management to disclose positive information and put an optimistic "spin" on things, so if management displays more neutral and objective sentiments rather than positive ones, it would likely lead to a psychological gap and thus affect the rating of the company.

5.1.3. Results of rating adjustments

Early research found that when faced with "soft information" such as tone or mood, analysts tend to maintain their current rating levels and are reluctant to revise their forecasts. This suggests that only if the emotional information is rich in information content would analysts be motivated to adjust their ratings. If analysts' rating adjustments are related to speech sentiment information, this could be shown if sentiments in audio proved to be very rich in information content.

Row(8) of Table 7 reports the regression results for speech sentiments and the adjustments in analysts' rating levels of Model 3.

In the question section, analysts' rating changes were significantly associated with negative sentiment, positive sentiment, and neutral sentiment. The results indicate that when peers show negative sentiments, for instance by questioning management during question sections, analysts reflect this information in their downgrades. Conversely, when fellow analysts show positive or neutral sentiments and convey private information to peers who are at an information disadvantage, other analysts also use this private information and then promptly "price in", which is reflected in an upward revision of the rating.

Positive management sentiment in the response section is also a significant influence variable. This suggests that if management can maintain positive sentiment in a "high stress" situation like the Q&A section, analysts interpret this information as confidence on the part of management, which is in turn reflected in upward rating changes. Therefore, Hypotheses 5a, 5b,5c, 6 were tested.

5.1.4. Robustness check

The previous subsection discussed speech sentiment and analyst behavior over a quarterly time window. In order to investigate whether those findings were generalizable, time windows of half a year and one month were also tried, to explore the impact on longer or shorter time windows. A very short time window of one week was also considered.

Rows (2,3,4) of Table 7 report the regression results, which demonstrate that there is no significant difference when using different time windows, and thus the conclusions drawn in the previous subsection are generalizable. That is, speech sentiment variables are generally well captured and utilized by analysts, as reflected in their willingness to issue rating reports.

To explore whether the correlations identified above hold true for analysts of different qualification levels, we further classified analysts into star and non-star analysts, and the results of the experiment are reported in **Rows (6,7,9,10)** in Table 7.

As can be seen in **Rows (6,7)** of Table 7, there was no significant difference in the ratings of the star analysts as compared to the ratings of the non-star analysts. However, the star analyst group was more sensitive to negative information of the question section. This suggests that celebrity analysts are more adept than non-celebrity analysts at exploiting "soft information" such as negative sentiments conveyed by peers during questioning, which in turn is reflected in the research reports they produce.

Rows (9,10) of Table 7 present the regression results regarding rating adjustments and speech sentiment information for the two categories of star analysts and non-star analysts. The results show the relationship between rating changes and speech sentiment information does not differ significantly between star analysts and non-star analysts.

Note that for the star analysts, negative peer sentiment in the question section was not statistically significant, but as stated above, the star analysts were able to identify negative peer sentiment information more accurately than non-star analysts, as reflected in their ratings. It is reasonable to believe that this subtle difference is due to the star analysts' ability to detect and extract information earlier than non-star analysts and react in a timely manner. This could be the characteristic that distinguishes star analysts from non-star analysts.

5.2. Additional analysis

To compare the audio information content with the textual information from the earnings conference calls, we used the self-trained speech emotion prediction model and the pre-trained BERT-wmm model with weights based on Chinese text from HIT as the feature extractor. We extracted the same number of features through the fully connected layer to represent the respective features of the audio and text information. The information content of the model was compared with the benchmark model BASE, which does not incorporate audio information or textual information, by observing the increase in the predictive power of the model before and after incorporating these two parts of information (audio and textual information). Since the sample size and the number of sample features affect the model's prediction, we chose the correction coefficient of determination $\overline{R}^2$ as the evaluation criterion of the model. The relationship of $\overline{R}^2$ and R^2 is shown as follows:

$$\overline{R}^2 = 1 - \frac{\left(1 - R^2\right)(n-1)}{n-p-1} \tag{10}$$

In the above equation, n is the number of samples, and p is the number of features. Thus, the effect of sample size and number of features on the results may decrease to some extent.

Table 8 documents the results based on linear regression models for the real EPS before and after incorporating information extracted from textual sources and audio sources, as well as using both kinds. The variables used in the benchmark model BASE are the control variables mentioned in the previous sections.

The results show that both text and audio information improved the predictions, so both text and audio information are effective incremental information. Furthermore, since the prediction improvement was greater for information extracted from audio than for information from text. (32% improvement vs. 9%, respectively), it seems audio information contains more incremental information than textual information. The results also show that the combination of these two types of information could further improve predictive power.

To test whether the above results were influenced by the choice of prediction algorithm, the gradient boosting regression tree algorithm was also used to predict the results in this study. The results are recorded in Table 9. For the purpose of testing whether the above results were affected by the choice of financial indicators (i.e., the explanatory variables), the prediction of ROE was also selected for the experiment. The results are recorded in Table 10. In addition, to test whether the above results were affected by the different sections of the earnings conference calls, we also conducted experiments in the statement section, question

Table 8
Predicting power before and after adding different types of information for EPS prediction.

	Base	Base + Text	Base + Audio	Base + Text + Audio
$\overline{R}^2$	7.130%	7.774%	9.445%	9.920%
Number of Features	11	26	26	41
Lift over Base Model	/	0.644%	2.315%	2.790%
Relative Lift over Base Model	/	9.032%	32.648%	39.130%
Lift over Base Model + Text	/	/	1.671%	2.146%
Relative Lift over Base Model + Text	/	/	21.498%	27.605%

Table 9
Predicting power of GBRT model before and after adding different types of information for EPS prediction.

	Base	Base + Text	Base + Audio	Base + Text + Audio
$\overline{R}^2$	8.339%	8.668%	16.757%	18.616%
Number of Features	11	26	26	41
Lift over Base Model	/	0.329%	8.418%	10.277%
Relative Lift over Base Model	/	3.945%	100.947%	123.240%
Lift over Base Model + Text	/	/	8.089%	9.948%
Relative Lift over Base Model + Text	/	/	93.320%	114.767%

Table 10
Predicting power before and after adding different types of information for ROE prediction.

	Base	Base + Text	Base + Audio	Base + Text + Audio
$\overline{R}^2$	10.410%	11.507%	16.773%	17.899%
Number of Features	11	26	26	41
Lift over Base Model	/	1.097%	6.363%	7.489%
Relative Lift over Base Model	/	10.538%	61.124%	71.940%
Lift over Base Model + Text	/	/	5.266%	6.392%
Relative Lift over Base Model + Text	/	/	45.763%	55.549%

section, and response section. The results are recorded in Table 11.

All the results indicate that the audio information contains more incremental information than the textual information. The results are robust. Therefore, it seems to be true that the audio of the earnings conference calls of listed companies contains more information content than the textual version, and the Q&A section contains more information than the statement section.

Table 11
Predicting power before and after adding different types of information for each section for EPS prediction.

	Base	Base + SText	Base + SAudio	Base + SText + SAudio
$\overline{R}^2$	7.130%	7.858%	9.628%	10.319%
Number of Features	11	16	16	21
Lift over Base Model	/	0.728%	2.498%	3.189%
Relative Lift over Base Model	/	10.210%	35.035%	44.727%
	Base	Base + QText	Base + QAudio	Base + QText + QAudio
$\overline{R}^2$	7.130%	7.503%	9.044%	9.053%
Number of Features	11	16	16	21
Lift over Base Model	/	0.373%	1.914%	1.923%
Relative Lift over Base Model	/	5.231%	26.844%	26.971%
	Base	Base + AText	Base + AAudio	Base + AText + AAudio
$\overline{R}^2$	7.130%	7.724%	9.945%	10.446%
Number of Features	11	16	16	21
Lift over Base Model	/	0.594%	2.815%	3.316%
Relative Lift over Base Model	/	8.331%	39.481%	46.508%

6. Conclusion

Most previous researchers focused on extracting emotional information only from the textual transcript of earnings conference calls to conduct their studies. Therefore, we investigated whether the information in the audio of earnings conference calls of listed companies, especially the speech sentiment information, has an impact on the follow-up behavior of analysts in the Chinese securities market, specifically their intention to publish rating reports, the content of their ratings, and rating adjustments.

In this paper, we proposed a deep learning approach to identify the specific emotions of speakers in these calls, and thus we composed the emotional variables in this study to their influence on the behavior of analysts. Our results showed that the emotional information in the audio was closely related with the behavior of the analysts in the following three ways.

When deciding whether to issue a rating report, positive information from the management in the statement section positively affected the analysts' willingness, while negative information had a negative influence. In the question section, non-negative information from peer analysts made analysts likelier to issue a report, while in the response section, negative information was influential.

Regarding the content of the rating itself, negative information revealed by managements in the response section was still a key factor. What's more, perhaps due to the mechanism of expectation gap, objective neutral information had a significant influence on the rating.

In terms of rating adjustments, the question section was greatly informative. Positive and neutral content conveyed by peer analysts caused upward revision of ratings, while negative information caused downward revision.

In addition, we found that the above conclusion did not change when we used different time windows or separated the analysts into prestigious and ordinary categories. We also found that the Q&A section was more informative than the statement section and that the audio was also more informative than the textual transcripts.

This research makes several new contributions to the literature.

Firstly, our paper enriches the research related to voluntary information disclosure, especially the research on the emotional information in earnings conference calls. Contrary to the previous research, which extracted emotional information from textual data, we proposed a deep learning approach that extracted the emotional information directly from the audio, providing new insight for researchers.

Secondly, from the perspective of professional securities analysts, our conclusions suggest that the Q&A section is rich in information, especially information from peer analysts. Thus, making good use of the Q&A sections of earnings conference calls should broaden the information channels to the benefit of analysts.

Thirdly, from the perspective of management, our paper has found that since management's true emotion are inevitably triggered by analysts' questions, disclosing information rather than concealing it would be a wise choice for management.

Fourthly, from the perspective of stock market participants, it is advisable to obtain information from the earnings conference call (which is open to the public) and thus to revise investment strategies.

Finally, from the perspective of regulators, our findings could provide important insights for better regulating such a channel of information disclosure not letting it become the domain of a small group of people who can profit from their information advantage and harm the interests of other investors by exchanging private information.

In closing, our paper still has some limitations that could be investigated in subsequent research. First, we studied the behavior of analysts as a whole, aggregated group, but more fine-grained research is possible, such as the behavior of analysts with different personal characters. Second, given the data limitations, we only collected 847 qualified pieces of audio and only investigated the Chinese securities market (using a training set for the deep learning in Chinese); whether these findings hold true in other markets still requires further study. Third, our approach is not the only method for extracting emotional information from audio, so other approaches could be proposed and compared with ours. Despite these limitations, we hope our study enriches the literature and gives practitioners and regulators valuable new insights.

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Appendix A

A.1. The complete results

The complete content of main results is shown in Table A1-A10.

Table A1
REC_PCT_QUARTER.

S_negative	−0.4917								
	(−2.158)								
S_positive		0.7222							
		(2.748)							
S_neutral			0.1637						
			(0.736)						
S_DURATION	0.1193	0.1250	0.1120						
	(0.477)	(0.499)	(0.447)						
Q_negative				−0.0979					
				(−0.381)					
Q_positive					0.6797				
					(1.888)				
Q_neutral						0.5015			
						(1.918)			
Q_DURATION				0.0678	0.0420	0.0725			
				(0.129)	(0.080)	(0.138)			
A_negative							−0.5685		
							(−2.408)		
A_positive								0.2024	
								(0.748)	
A_neutral									0.3790
									(1.592)
A_DURATION							−0.0928	−0.0809	−0.0889
							(−0.341)	(−0.296)	(−0.326)
SUE	0.0157	0.0153	0.0157	0.0157	0.0156	0.0157	0.0153	0.0153	0.0155
	(3.286)	(3.187)	(3.272)	(3.296)	(3.280)	(3.296)	(3.238)	(3.220)	(3.261)
INSTOWN	−0.0140	−0.0457	−0.0265	−0.0512	−0.0551	−0.0423	−0.0266	−0.0560	−0.0339
	(−0.060)	(−0.196)	(−0.114)	(−0.228)	(−0.245)	(−0.188)	(−0.118)	(−0.249)	(−0.150)
NAL	−0.0264	−0.0261	−0.0264	−0.0271	−0.0272	−0.0270	−0.0275	−0.0272	−0.0272
	(−7.701)	(−7.598)	(−7.679)	(−7.999)	(−8.047)	(−7.975)	(−8.263)	(−8.150)	(−8.175)
BIG10	0.0378	0.0348	0.0398	0.0170	0.0136	0.0170	0.0158	0.0129	0.0223
	(0.408)	(0.375)	(0.429)	(0.191)	(0.153)	(0.191)	(0.179)	(0.145)	(0.251)
EPSG	−0.0129	−0.0121	−0.0121	−0.0119	−0.0113	−0.0119	−0.0126	−0.0116	−0.0120
	(−1.656)	(−1.552)	(−1.554)	(−1.533)	(−1.471)	(−1.546)	(−1.631)	(−1.508)	(−1.560)
LNMV	0.0083	0.0091	0.0073	0.0102	0.0098	0.0098	0.0102	0.0110	0.0087
	(0.550)	(0.601)	(0.482)	(0.763)	(0.727)	(0.731)	(0.769)	(0.820)	(0.650)
DIVIDENDS	0.2599	0.2556	0.2642	0.2690	0.2732	0.2645	0.2609	0.2758	0.262
	(1.782)	(1.749)	(1.807)	(1.877)	(1.906)	(1.843)	(1.828)	(1.928)	(1.830)
ROEG	−0.7781	−0.7727	−0.8177	−1.1719	−1.2563	−1.2253	−1.1422	−1.1698	−1.2141
	(−0.565)	(−0.561)	(−0.592)	(−0.909)	(−0.973)	(−0.952)	(−0.886)	(−0.905)	(−0.941)
MTB	−0.0073	−0.0115	−0.0077	−0.0056	−0.0052	−0.0049	−0.0028	−0.0065	−0.0021
	(−0.412)	(−0.646)	(−0.434)	(−0.331)	(−0.304)	(−0.288)	(−0.167)	(−0.383)	(−0.122)
CA	0.0240	0.0190	0.0268	0.0308	0.0275	0.0327	0.0317	0.0253	0.0305
	(0.261)	(0.207)	(0.290)	(0.349)	(0.312)	(0.370)	(0.361)	(0.286)	(0.346)
TURNOVER	−0.0305	−0.0329	−0.0303	−0.023	−0.0228	−0.0211	−0.0233	−0.0235	−0.0227
	(−0.771)	(−0.832)	(−0.763)	(−0.628)	(−0.622)	(−0.576)	(−0.639)	(−0.640)	(−0.621)
Const	1.5593	1.2306	1.3167	1.3732	1.2379	1.1593	1.6437	1.3418	1.3025
	(3.962)	(3.283)	(3.337)	(3.894)	(3.802)	(3.413)	(4.131)	(3.414)	(3.340)
R^2	9.56%	9.36%	9.08%	9.32%	9.27%	9.38%	9.89%	9.33%	9.54%
R^2 adj.	8.04%	7.84%	7.56%	7.91%	7.85%	7.97%	8.49%	7.92%	8.13%
Observations	789	789	789	848	848	848	848	848	848

Table A2
REC_PCT_WEEK.

S_negative	−0.5883 (−1.987)								
S_positive		0.6093 (1.782)							
S_neutral			−0.4840 (−1.677)						
S_DURATION	−0.1627 (−0.501)	−0.1636 (−0.502)	−0.1498 (−0.461)						
Q_negative				0.1113 (0.333)					
Q_positive					0.8686 (1.856)				
Q_neutral						0.4864 (1.426)			
Q_DURATION				0.6551 (0.956)	0.7036 (1.029)	0.7113 (1.037)			
A_negative							−0.5678 (−1.842)		
A_positive								−0.2947 (−0.836)	
A_neutral									−0.2881 (−0.927)
A_DURATION							−0.0676 (−0.190)	−0.0781 (−0.219)	−0.0741 (−0.208)
SUE	0.0027 (0.437)	0.0030 (0.485)	0.0027 (0.436)	0.0026 (0.415)	0.0028 (0.458)	0.0028 (0.447)	0.0028 (0.454)	0.0029 (0.471)	0.0027 (0.430)
INSTOWN	−0.0522 (−0.173)	−0.0181 (−0.060)	−0.0588 (−0.194)	−0.0708 (−0.242)	−0.0546 (−0.187)	−0.0636 (−0.217)	−0.0902 (−0.307)	−0.0626 (−0.213)	−0.0767 (−0.260)
NAL	0.0112 (2.513)	0.0110 (2.458)	0.0112 (2.524)	0.0086 (1.947)	0.0088 (1.996)	0.0088 (2.006)	0.0100 (2.312)	0.0098 (2.244)	0.0098 (2.243)
BIG10	0.0532 (0.442)	0.0546 (0.452)	0.0491 (0.407)	0.0182 (0.157)	0.0223 (0.192)	0.0254 (0.219)	0.0227 (0.196)	0.0260 (0.224)	0.0183 (0.158)
EPSG	−0.0050 (−0.499)	−0.0061 (−0.606)	−0.0055 (−0.548)	−0.0054 (−0.533)	−0.0061 (−0.611)	−0.0064 (−0.637)	−0.0057 (−0.566)	−0.0066 (−0.651)	−0.0063 (−0.630)
LNMV	−0.0052 (−0.265)	−0.0051 (−0.258)	−0.0042 (−0.213)	0.0032 (0.186)	0.0012 (0.070)	0.0038 (0.220)	0.0020 (0.114)	0.0006 (0.036)	0.0033 (0.187)
DIVIDENDS	0.2612 (1.378)	0.2603 (1.369)	0.2601 (1.371)	0.2804 (1.503)	0.2733 (1.466)	0.2729 (1.459)	0.2991 (1.605)	0.284 (1.523)	0.2949 (1.579)
ROEG	−1.0912 (−0.610)	−1.0804 (−0.602)	−1.0197 (−0.569)	−0.8652 (−0.515)	−0.8998 (−0.536)	−0.6948 (−0.414)	−0.7699 (−0.458)	−0.7569 (−0.449)	−0.7011 (−0.416)
MTB	−0.0156 (−0.678)	−0.0119 (−0.516)	−0.0174 (−0.753)	−0.0209 (−0.942)	−0.0182 (−0.817)	−0.0214 (−0.964)	−0.0203 (−0.921)	−0.0161 (−0.726)	−0.0202 (−0.914)
CA	0.1471 (1.232)	0.1500 (1.254)	0.1395 (1.167)	0.1459 (1.270)	0.1553 (1.354)	0.1532 (1.331)	0.1421 (1.237)	0.1488 (1.295)	0.1444 (1.256)
TURNOVER	−0.1059 (−2.061)	−0.1038 (−2.016)	−0.1082 (−2.102)	−0.091 (−1.908)	−0.0902 (−1.893)	−0.0919 (−1.923)	−0.0907 (−1.899)	−0.0904 (−1.892)	−0.0911 (−1.906)
Const	1.3975 (1.724)	1.0050 (2.296)	1.2812 (2.503)	0.7932 (1.261)	0.7236 (2.143)	0.6487 (1.807)	1.2300 (1.407)	1.0581 (2.065)	1.0488 (2.061)
R^2	3.04%	2.64%	2.90%	2.59%	2.67%	2.28%	2.54%	2.23%	2.25%
R^2 adj.	1.42%	1.01%	1.27%	1.07%	1.15%	0.76%	1.02%	0.70%	0.72%
Observations	789	789	789	848	848	848	848	848	848

Table A3
REC_PCT_MONTH.

S_negative	−0.6721 (−1.791)								
S_positive		0.8128 (1.879)							
S_neutral			0.0675 (0.185)						
S_DURATION	−0.1899 (−0.461)	−0.1945 (−0.472)	−0.1878 (−0.456)						
Q_negative				0.0483 (0.114)					
Q_positive					1.4652 (2.483)				
Q_neutral						0.8308 (1.934)			
Q_DURATION				0.8006 (0.924)	0.7747 (0.899)	0.8927 (1.033)			
A_negative							−0.5779 (−1.482)		

(*continued on next page*)

Table A3 (*continued*)

A_positive								−0.5464 (−1.228)	
A_neutral									0.4374 (1.116)
A_DURATION							0.1487 (0.331)	0.1573 (0.35)	0.1367 (0.304)
SUE	0.0056 (0.708)	0.0059 (0.746)	0.0056 (0.712)	0.0053 (0.682)	0.0054 (0.695)	0.0056 (0.714)	0.0053 (0.674)	0.0058 (0.746)	0.0052 (0.667)
INSTOWN	0.7127 (1.860)	0.733 (1.915)	0.7331 (1.910)	0.6076 (1.643)	0.615 (1.670)	0.6489 (1.756)	0.6261 (1.686)	0.6143 (1.658)	0.6547 (1.763)
NAL	−0.0113 (−1.996)	−0.0115 (−2.031)	−0.0113 (−2.002)	−0.0128 (−2.308)	−0.0131 (−2.361)	−0.0122 (−2.195)	−0.0120 (−2.186)	−0.0118 (−2.158)	−0.0121 (−2.21)
BIG10	0.0100 (0.065)	0.0122 (0.080)	0.0097 (0.063)	0.0180 (0.123)	0.0115 (0.079)	0.0276 (0.189)	0.0179 (0.122)	0.0199 (0.136)	0.0277 (0.189)
EPSG	−0.0111 (−0.866)	−0.0116 (−0.905)	−0.0118 (−0.923)	−0.0114 (−0.897)	−0.0107 (−0.845)	−0.0131 (−1.036)	−0.0114 (−0.896)	−0.0110 (−0.865)	−0.0120 (−0.942)
LNMV	−0.0159 (−0.642)	−0.0166 (−0.668)	−0.0152 (−0.612)	−0.0063 (−0.284)	−0.0105 (−0.476)	−0.0070 (−0.319)	−0.0072 (−0.329)	−0.0105 (−0.476)	−0.0086 (−0.390)
DIVIDENDS	0.1443 (0.601)	0.1480 (0.616)	0.1392 (0.579)	0.1768 (0.750)	0.1820 (0.775)	0.1506 (0.639)	0.1871 (0.794)	0.1862 (0.791)	0.1723 (0.731)
ROEG	0.6943 (0.306)	0.6878 (0.303)	0.7046 (0.311)	0.9973 (0.470)	0.6614 (0.313)	1.0358 (0.490)	0.8859 (0.416)	0.7977 (0.375)	0.8691 (0.409)
MTB	0.0270 (0.927)	0.0298 (1.022)	0.0286 (0.979)	0.0197 (0.702)	0.0247 (0.883)	0.0216 (0.770)	0.0235 (0.844)	0.0266 (0.954)	0.0271 (0.970)
CA	0.1398 (0.924)	0.1434 (0.947)	0.1405 (0.928)	0.1139 (0.784)	0.1148 (0.794)	0.1304 (0.899)	0.1105 (0.761)	0.1120 (0.772)	0.1155 (0.795)
TURNOVER	−0.0859 (−1.319)	−0.0842 (−1.293)	−0.0849 (−1.302)	−0.0817 (−1.355)	−0.0800 (−1.331)	−0.0763 (−1.267)	−0.0798 (−1.322)	−0.0793 (−1.315)	−0.0792 (−1.313)
Const	1.9038 (2.276)	1.4603 (2.591)	1.5625 (2.409)	1.2656 (2.114)	1.1314 (2.717)	0.9757 (1.638)	1.5592 (2.002)	1.4572 (2.254)	1.1950 (1.861)
R^2	1.52%	1.51%	1.44%	1.41%	2.13%	1.85%	1.32%	1.5%	1.47%
R^2 adj.	−0.13%	−0.14%	−0.21%	−0.13%	0.61%	0.32%	−0.22%	−0.04%	−0.07%
Observations	789	789	789	848	848	848	848	848	848

Table A4
REC_PCT_HALFYEAR.

S_negative	−0.3525 (−1.746)								
S_positive		0.4200 (1.805)							
S_neutral			−0.0890 (−0.453)						
S_DURATION	0.1241 (0.560)	0.1264 (0.570)	0.1252 (0.565)						
Q_negative				0.0948 (0.422)					
Q_positive					0.5884 (1.865)				
Q_neutral						0.6743 (2.953)			
Q_DURATION				−1.0888 (−2.369)	−1.0186 (−2.21)	−1.0822 (−2.357)			
A_negative							−0.5216 (−2.506)		
A_positive								−0.2898 (−1.22)	
A_neutral									−0.1083 (−0.517)
A_DURATION							0.2073 (0.864)	0.2071 (0.863)	0.2060 (0.858)
SUE	0.0372 (8.786)	0.0371 (8.755)	0.0372 (8.784)	0.0367 (8.846)	0.0370 (8.876)	0.0368 (8.871)	0.0373 (8.931)	0.0376 (8.979)	0.0373 (8.920)
INSTOWN	0.2772 (1.344)	0.2745 (1.333)	0.2695 (1.305)	0.2765 (1.409)	0.2919 (1.482)	0.2579 (1.314)	0.2839 (1.432)	0.2883 (1.457)	0.2865 (1.443)
NAL	−0.0142 (−4.677)	−0.0141 (−4.653)	−0.0142 (−4.671)	−0.0141 (−4.771)	−0.0137 (−4.636)	−0.0142 (−4.803)	−0.0146 (−4.981)	−0.0146 (−4.996)	−0.0147 (−5.012)
BIG10	−0.0639 (−0.778)	−0.0648 (−0.789)	−0.0644 (−0.784)	−0.1083 (−1.394)	−0.1003 (−1.286)	−0.1060 (−1.365)	−0.0968 (−1.238)	−0.0950 (−1.216)	−0.0986 (−1.259)
EPSG	−0.0229 (−3.322)	−0.0229 (−3.328)	−0.0227 (−3.300)	−0.0212 (−3.147)	−0.0225 (−3.329)	−0.0214 (−3.169)	−0.0221 (−3.248)	−0.0222 (−3.272)	−0.0222 (−3.274)
LNMV	−0.0228 (−1.709)	−0.0224 (−1.676)	−0.0229 (−1.718)	−0.0144 (−1.231)	−0.0147 (−1.247)	−0.0132 (−1.128)	−0.0119 (−1.014)	−0.0135 (−1.143)	−0.0115 (−0.974)
DIVIDENDS	−0.0541	−0.0563	−0.0525	−0.0315	−0.0425	−0.0231	−0.0625	−0.0676	−0.0630

(*continued on next page*)

Table A4 (*continued*)

	(−0.418)	(−0.436)	(−0.407)	(−0.251)	(−0.338)	(−0.185)	(−0.497)	(−0.538)	(−0.500)
ROEG	2.3557	2.3618	2.362	1.9866	2.1132	2.1646	2.1532	2.1255	2.1746
	(1.931)	(1.936)	(1.936)	(1.764)	(1.868)	(1.927)	(1.895)	(1.871)	(1.914)
MTB	0.0090	0.0084	0.0082	0.0137	0.0144	0.0118	0.0078	0.0103	0.0076
	(0.575)	(0.534)	(0.522)	(0.920)	(0.960)	(0.794)	(0.527)	(0.690)	(0.512)
CA	−0.0933	−0.0945	−0.0946	−0.1094	−0.0987	−0.1115	−0.0888	−0.0861	−0.0883
	(−1.147)	(−1.162)	(−1.162)	(−1.419)	(−1.277)	(−1.447)	(−1.145)	(−1.111)	(−1.139)
TURNOVER	0.0567	0.0563	0.0560	0.0888	0.0888	0.0841	0.0883	0.0885	0.0881
	(1.618)	(1.606)	(1.598)	(2.775)	(2.765)	(2.629)	(2.738)	(2.747)	(2.732)
Const	2.0169	1.7853	1.8975	1.7895	1.7224	1.5833	1.7453	1.5953	1.5421
	(5.367)	(5.341)	(5.442)	(4.889)	(5.936)	(6.475)	(4.108)	(4.620)	(4.492)
R^2	14.04%	14.06%	14.06%	15.37%	14.65%	15.45%	14.21%	14.29%	14.17%
R^2 adj.	12.60%	12.62%	12.62%	14.05%	13.32%	14.13%	12.87%	12.96%	12.83%
Observations	789	789	789	848	848	848	848	848	848

Table A5
RECLEVEL.

S_negative	0.1139								
	(1.022)								
S_positive		0.0277							
		(0.216)							
S_neutral			−0.1793						
			(−1.654)						
S_DURATION	−0.0725	−0.0707	−0.0687						
	(−0.592)	(−0.577)	(−0.563)						
Q_negative				0.0270					
				(0.217)					
Q_positive					−0.1936				
					(−1.113)				
Q_neutral						0.0658			
						(0.521)			
Q_DURATION				0.0994	0.0941	0.1051			
				(0.390)	(0.371)	(0.413)			
A_negative							−0.2337		
							(−2.043)		
A_positive								0.1601	
								(1.226)	
A_neutral									−0.1130
									(−0.981)
A_DURATION							0.0941	0.0932	0.0941
							(0.713)	(0.706)	(0.713)
SUE	−0.0002	−0.0002	−0.0002	−0.0002	−0.0002	−0.0002	−0.0001	0.0000	−0.0002
	(−0.086)	(−0.092)	(−0.091)	(−0.094)	(−0.093)	(−0.088)	(−0.065)	(−0.012)	(−0.076)
INSTOWN	−0.0301	−0.0247	−0.0377	−0.0381	−0.0375	−0.0351	−0.0393	−0.035	−0.0397
	(−0.264)	(−0.217)	(−0.331)	(−0.351)	(−0.345)	(−0.323)	(−0.360)	(−0.322)	(−0.364)
NAL	0.0087	0.0087	0.0087	0.0084	0.0084	0.0085	0.0086	0.0086	0.0086
	(5.179)	(5.175)	(5.202)	(5.162)	(5.146)	(5.187)	(5.338)	(5.322)	(5.311)
BIG10	−0.0819	−0.0824	−0.0832	−0.0711	−0.0722	−0.0705	−0.0715	−0.0704	−0.0736
	(−1.807)	(−1.817)	(−1.838)	(−1.651)	(−1.679)	(−1.639)	(−1.665)	(−1.640)	(−1.710)
EPSG	−0.0050	−0.0052	−0.0050	−0.0052	−0.0050	−0.0053	−0.0048	−0.0049	−0.0049
	(−1.315)	(−1.381)	(−1.310)	(−1.383)	(−1.353)	(−1.413)	(−1.287)	(−1.323)	(−1.308)
LNMV	0.0078	0.0082	0.0079	0.0076	0.0070	0.0075	0.0075	0.0066	0.0079
	(1.056)	(1.104)	(1.076)	(1.174)	(1.083)	(1.163)	(1.163)	(1.021)	(1.228)
DIVIDENDS	0.2033	0.2010	0.2043	0.2109	0.2119	0.2090	0.2141	0.2105	0.2149
	(2.849)	(2.814)	(2.866)	(3.042)	(3.060)	(3.013)	(3.095)	(3.047)	(3.104)
ROEG	2.1700	2.1779	2.1911	2.0897	2.0406	2.0888	2.0258	2.0137	2.0425
	(3.222)	(3.231)	(3.256)	(3.351)	(3.273)	(3.356)	(3.244)	(3.224)	(3.271)
MTB	−0.0003	0.0000	−0.0014	−0.0006	0.0001	−0.0004	−0.0007	0.0008	−0.0011
	(−0.035)	(−0.005)	(−0.156)	(−0.073)	(0.009)	(−0.054)	(−0.087)	(0.094)	(−0.138)
CA	0.0197	0.0193	0.0170	0.0215	0.0214	0.0226	0.0207	0.0225	0.0206
	(0.439)	(0.429)	(0.379)	(0.504)	(0.502)	(0.530)	(0.486)	(0.528)	(0.484)
TURNOVER	−0.0023	−0.0022	−0.0033	−0.0110	−0.0107	−0.0105	−0.0103	−0.0102	−0.0105
	(−0.118)	(−0.111)	(−0.171)	(−0.618)	(−0.605)	(−0.593)	(−0.582)	(−0.574)	(−0.591)
Const	5.7356	5.7713	5.8451	5.7521	5.8052	5.7400	5.8225	5.7061	5.7474
	(29.79)	(30.313)	(30.393)	(32.795)	(33.589)	(32.721)	(29.382)	(30.359)	(30.467)
R^2	7.77%	7.66%	7.97%	7.59%	7.72%	7.61%	7.75%	7.79%	7.73%
R^2 adj.	6.23%	6.11%	6.43%	6.14%	6.28%	6.17%	6.31%	6.35%	6.29%
Observations	789	789	789	848	848	848	848	848	848

Table A6
RECLEVEL_STAR.

S_negative	0.2181 (1.542)								
S_positive		0.0142 (0.087)							
S_neutral			−0.2644 (−1.920)						
S_DURATION	−0.082 (−0.528)	−0.0795 (−0.511)	−0.076 (−0.490)						
Q_negative				−0.3445 (−2.179)					
Q_positive					−0.1885 (−0.852)				
Q_neutral						0.0188 (0.117)			
Q_DURATION				−0.1039 (−0.321)	−0.0941 (−0.291)	−0.0881 (−0.272)			
A_negative							−0.4299 (−2.959)		
A_positive								0.1915 (1.153)	
A_neutral									−0.2082 (−1.423)
A_DURATION							0.1788 (1.067)	0.1757 (1.048)	0.1789 (1.067)
SUE	0.0002 (0.056)	0.0002 (0.057)	0.0002 (0.052)	0.0001 (0.033)	0.0002 (0.052)	0.0001 (0.051)	0.0003 (0.112)	0.0004 (0.152)	0.0003 (0.096)
INSTOWN	−0.1595 (−1.104)	−0.1487 (−1.029)	−0.1683 (−1.164)	−0.1388 (−1.005)	−0.1354 (−0.981)	−0.1353 (−0.978)	−0.1400 (−1.011)	−0.1303 (−0.942)	−0.1408 (−1.016)
NAL	0.0085 (4.006)	0.0085 (3.992)	0.0086 (4.027)	0.0084 (4.052)	0.0085 (4.076)	0.0085 (4.091)	0.0085 (4.169)	0.0084 (4.124)	0.0085 (4.128)
BIG10	−0.0550 (−0.955)	−0.0556 (−0.964)	−0.0570 (−0.991)	−0.0574 (−1.049)	−0.0566 (−1.036)	−0.0555 (−1.014)	−0.0557 (−1.021)	−0.0541 (−0.991)	−0.0596 (−1.090)
EPSG	−0.0055 (−1.136)	−0.0059 (−1.231)	−0.0055 (−1.150)	−0.0058 (−1.222)	−0.0060 (−1.258)	−0.0061 (−1.285)	−0.0054 (−1.142)	−0.0057 (−1.206)	−0.0056 (−1.171)
LNMV	0.0240 (2.566)	0.0246 (2.617)	0.0243 (2.604)	0.0206 (2.499)	0.0201 (2.438)	0.0207 (2.508)	0.0210 (2.556)	0.0200 (2.418)	0.0218 (2.649)
DIVIDENDS	0.2372 (2.619)	0.2339 (2.577)	0.2380 (2.630)	0.2524 (2.864)	0.2510 (2.850)	0.2496 (2.829)	0.2506 (2.853)	0.2444 (2.782)	0.2522 (2.867)
ROEG	1.8724 (2.189)	1.8848 (2.200)	1.9060 (2.231)	2.0024 (2.526)	1.9927 (2.513)	2.0384 (2.575)	1.9437 (2.450)	1.9375 (2.440)	1.9745 (2.489)
MTB	0.0077 (0.706)	0.0085 (0.768)	0.0064 (0.58)	0.0093 (0.884)	0.0099 (0.939)	0.0093 (0.882)	0.0077 (0.745)	0.0099 (0.947)	0.007 (0.667)
CA	0.0612 (1.073)	0.0608 (1.065)	0.0571 (1.002)	0.0636 (1.172)	0.0655 (1.209)	0.0659 (1.213)	0.0666 (1.231)	0.0696 (1.285)	0.0665 (1.227)
TURNOVER	−0.0048 (−0.195)	−0.0044 (−0.180)	−0.0062 (−0.254)	−0.0129 (−0.571)	−0.0127 (−0.564)	−0.0128 (−0.567)	−0.0121 (−0.536)	−0.0119 (−0.529)	−0.0124 (−0.550)
Const	5.3578 (21.919)	5.4349 (22.464)	5.5378 (22.675)	5.6732 (24.469)	5.5552 (25.269)	5.5085 (24.69)	5.5783 (21.596)	5.3723 (22.545)	5.4401 (22.701)
R^2	6.57%	6.29%	6.73%	6.51%	6.53%	6.45%	6.84%	6.71%	6.79%
R^2 adj.	5.00%	4.71%	5.16%	5.05%	5.08%	5.00%	5.39%	5.26%	5.34%
Observations	789	789	789	848	848	848	848	848	848

Table A7
RECLEVEL_NONSTAR.

S_negative	0.1049 (0.927)								
S_positive		0.0483 (0.370)							
S_neutral			−0.1888 (−1.715)						
S_DURATION	−0.1004 (−0.808)	−0.0982 (−0.790)	−0.0966 (−0.779)						
Q_negative				0.1193 (0.944)					
Q_positive					−0.1869 (−1.058)				
Q_neutral						0.0798 (0.621)			
Q_DURATION				0.1560 (0.603)	0.1472 (0.571)	0.1595 (0.617)			
A_negative							−0.2141 (−1.842)		

(continued on next page)

Table A7 (*continued*)

A_positive								0.1466	
								(1.105)	
A_neutral									−0.1101
									(−0.941)
A_DURATION							0.1097	0.1089	0.1100
							(0.819)	(0.813)	(0.820)
SUE	−0.0006	−0.0006	−0.0006	−0.0006	−0.0006	−0.0006	−0.0006	−0.0005	−0.0006
	(−0.255)	(−0.269)	(−0.261)	(−0.268)	(−0.272)	(−0.266)	(−0.247)	(−0.199)	(−0.257)
INSTOWN	−0.0119	−0.0073	−0.0207	−0.0292	−0.0293	−0.0263	−0.0290	−0.0252	−0.0299
	(−0.103)	(−0.063)	(−0.179)	(−0.265)	(−0.266)	(−0.238)	(−0.262)	(−0.228)	(−0.270)
NAL	0.0085	0.0086	0.0086	0.0083	0.0082	0.0083	0.0085	0.0085	0.0084
	(5.018)	(5.022)	(5.043)	(4.989)	(4.962)	(5.008)	(5.176)	(5.162)	(5.154)
BIG10	−0.0787	−0.0794	−0.0801	−0.0675	−0.0690	−0.0672	−0.0684	−0.0674	−0.0704
	(−1.71)	(−1.723)	(−1.741)	(−1.543)	(−1.58)	(−1.538)	(−1.566)	(−1.544)	(−1.611)
EPSG	−0.0033	−0.0035	−0.0032	−0.0035	−0.0033	−0.0035	−0.0030	−0.0032	−0.0031
	(−0.846)	(−0.908)	(−0.831)	(−0.917)	(−0.868)	(−0.935)	(−0.803)	(−0.834)	(−0.819)
LNMV	0.0045	0.0049	0.0046	0.0050	0.0044	0.0049	0.0048	0.0040	0.0052
	(0.602)	(0.66)	(0.618)	(0.755)	(0.665)	(0.738)	(0.731)	(0.606)	(0.793)
DIVIDENDS	0.2110	0.2084	0.2122	0.2175	0.2191	0.2158	0.2217	0.2184	0.2227
	(2.911)	(2.872)	(2.932)	(3.089)	(3.115)	(3.063)	(3.155)	(3.111)	(3.166)
ROEG	2.5242	2.5330	2.5455	2.3751	2.3180	2.3650	2.2915	2.2804	2.3071
	(3.690)	(3.701)	(3.726)	(3.750)	(3.661)	(3.741)	(3.612)	(3.594)	(3.637)
MTB	0.0002	0.0003	−0.0010	−0.0006	0.0001	−0.0004	−0.0004	0.0010	−0.0008
	(0.021)	(0.035)	(−0.111)	(−0.071)	(0.009)	(−0.047)	(−0.049)	(0.115)	(−0.101)
CA	0.0057	0.0051	0.0029	0.0088	0.0082	0.0097	0.0074	0.0090	0.0072
	(0.126)	(0.111)	(0.063)	(0.204)	(0.189)	(0.223)	(0.171)	(0.209)	(0.167)
TURNOVER	−0.0023	−0.0023	−0.0035	−0.0116	−0.0114	−0.0111	−0.0108	−0.0107	−0.0110
	(−0.119)	(−0.118)	(−0.176)	(−0.647)	(−0.634)	(−0.617)	(−0.602)	(−0.595)	(−0.611)
Const	5.7911	5.8189	5.9009	5.7378	5.8318	5.7628	5.8391	5.7324	5.7719
	(29.617)	(30.099)	(30.220)	(32.513)	(33.219)	(32.346)	(29.075)	(29.996)	(30.122)
R^2	7.77%	7.69%	8.02%	7.46%	7.57%	7.49%	7.59%	7.62%	7.58%
R^2 adj.	6.23%	6.14%	6.48%	6.02%	6.13%	6.05%	6.15%	6.18%	6.14%
Observations	789	789	789	848	848	848	848	848	848

Table A8
RECLEVEL_CHG.

S_negative	−0.1389								
	(−1.190)								
S_positive		0.1394							
		(1.036)							
S_neutral			0.0633						
			(0.556)						
S_DURATION	0.1255	0.1274	0.1232						
	(0.980)	(0.994)	(0.961)						
Q_negative				−0.3270					
				(−2.506)					
Q_positive					0.3933				
					(2.149)				
Q_neutral						0.2653			
						(1.996)			
Q_DURATION				0.0211	−0.0129	0.0090			
				(0.079)	(−0.048)	(0.034)			
A_negative							−0.0715		
							(−0.593)		
A_positive								0.2335	
								(1.698)	
A_neutral									0.1827
									(1.508)
A_DURATION							−0.1688	−0.1650	−0.1722
							(−1.215)	(−1.188)	(−1.241)
SUE	−0.0020	−0.0022	−0.0020	−0.0018	−0.0020	−0.0019	−0.0021	−0.0019	−0.0021
	(−0.834)	(−0.887)	(−0.835)	(−0.765)	(−0.824)	(−0.791)	(−0.864)	(−0.795)	(−0.866)
INSTOWN	−0.1982	−0.2074	−0.2005	−0.1962	−0.2047	−0.1907	−0.2096	−0.2164	−0.2013
	(−1.663)	(−1.741)	(−1.678)	(−1.721)	(−1.791)	(−1.668)	(−1.826)	(−1.889)	(−1.754)
NAL	0.0025	0.0026	0.0025	0.0027	0.0025	0.0027	0.0024	0.0025	0.0024
	(1.405)	(1.455)	(1.402)	(1.572)	(1.474)	(1.561)	(1.433)	(1.487)	(1.433)
BIG10	0.0256	0.0247	0.0263	0.0156	0.0120	0.0135	0.0104	0.0107	0.0143
	(0.540)	(0.520)	(0.554)	(0.346)	(0.266)	(0.299)	(0.23)	(0.236)	(0.315)
EPSG	0.0052	0.0054	0.0053	0.0049	0.0055	0.0052	0.0053	0.0055	0.0052
	(1.293)	(1.351)	(1.341)	(1.255)	(1.407)	(1.312)	(1.354)	(1.414)	(1.325)
LNMV	−0.0126	−0.0123	−0.0129	−0.0066	−0.0062	−0.0072	−0.0072	−0.0080	−0.0078
	(−1.634)	(−1.595)	(−1.670)	(−0.978)	(−0.904)	(−1.057)	(−1.053)	(−1.174)	(−1.142)
DIVIDENDS	−0.1209	−0.1224	−0.1199	−0.1155	−0.1103	−0.1172	−0.1078	−0.1063	−0.1124

(*continued on next page*)

Table A8 (*continued*)

	(−1.618)	(−1.637)	(−1.604)	(−1.588)	(−1.513)	(−1.608)	(−1.479)	(−1.461)	(−1.543)
ROEG	1.0867	1.0890	1.0741	1.2105	1.1713	1.1160	1.1920	1.1630	1.1785
	(1.540)	(1.543)	(1.521)	(1.850)	(1.785)	(1.706)	(1.813)	(1.768)	(1.794)
MTB	−0.0153	−0.0166	−0.0153	−0.0165	−0.0172	−0.0157	−0.0160	−0.0156	−0.0148
	(−1.694)	(−1.827)	(−1.685)	(−1.907)	(−1.983)	(−1.814)	(−1.866)	(−1.804)	(−1.714)
CA	−0.0838	−0.0854	−0.0828	−0.0789	−0.0844	−0.0794	−0.0861	−0.0864	−0.0846
	(−1.782)	(−1.813)	(−1.758)	(−1.761)	(−1.882)	(−1.769)	(−1.918)	(−1.926)	(−1.888)
TURNOVER	−0.0522	−0.0529	−0.0520	−0.0414	−0.0415	−0.0395	−0.0422	−0.0420	−0.0419
	(−2.576)	(−2.611)	(−2.564)	(−2.224)	(−2.227)	(−2.119)	(−2.260)	(−2.254)	(−2.248)
Const	0.5818	0.4998	0.5068	0.5396	0.3359	0.3132	0.5505	0.4915	0.4736
	(2.885)	(2.507)	(2.512)	(2.924)	(1.960)	(1.699)	(2.711)	(2.791)	(2.387)
R^2	3.38%	3.33%	3.24%	3.53%	3.04%	3.26%	3.01%	3.08%	3.23%
R^2 adj.	1.76%	1.71%	1.61%	2.02%	1.53%	1.76%	1.50%	1.57%	1.72%
Observations	789	789	789	848	848	848	848	848	848

Table A9
RECLEVEL_CHG_STAR.

S_negative	−0.0318								
	(−0.234)								
S_positive		0.0365							
		(0.233)							
S_neutral			−0.0271						
			(−0.205)						
S_DURATION	0.0012	0.0017	0.0012						
	(0.008)	(0.011)	(0.008)						
Q_negative				−0.2114					
				(−1.386)					
Q_positive					0.3797				
					(1.779)				
Q_neutral						0.1331			
						(0.858)			
Q_DURATION				−0.1871	−0.2072	−0.1989			
				(−0.599)	(−0.664)	(−0.637)			
A_negative							0.0363		
							(0.258)		
A_positive								0.2924	
								(1.822)	
A_neutral									0.0514
									(0.363)
A_DURATION							0.0275	0.0290	0.0250
							(0.169)	(0.179)	(0.154)
SUE	−0.0036	−0.0037	−0.0036	−0.0036	−0.0037	−0.0036	−0.0036	−0.0034	−0.0036
	(−1.280)	(−1.291)	(−1.282)	(−1.269)	(−1.304)	(−1.287)	(−1.275)	(−1.216)	(−1.282)
INSTOWN	−0.3786	−0.3807	−0.3822	−0.3781	−0.3839	−0.3764	−0.3852	−0.3864	−0.3796
	(−2.730)	(−2.748)	(−2.752)	(−2.837)	(−2.881)	(−2.818)	(−2.875)	(−2.89)	(−2.831)
NAL	0.0012	0.0013	0.0013	0.0019	0.0018	0.0018	0.0016	0.0016	0.0015
	(0.611)	(0.622)	(0.615)	(0.941)	(0.896)	(0.921)	(0.784)	(0.799)	(0.765)
BIG10	0.0572	0.0569	0.0571	0.0278	0.0259	0.0260	0.0250	0.0258	0.0263
	(1.036)	(1.031)	(1.034)	(0.526)	(0.490)	(0.493)	(0.473)	(0.489)	(0.497)
EPSG	0.0107	0.0108	0.0108	0.0103	0.0106	0.0105	0.0108	0.0109	0.0107
	(2.309)	(2.323)	(2.334)	(2.236)	(2.314)	(2.284)	(2.362)	(2.377)	(2.333)
LNMV	0.0024	0.0025	0.0023	0.0045	0.005	0.0042	0.0047	0.0037	0.0045
	(0.271)	(0.279)	(0.261)	(0.563)	(0.630)	(0.523)	(0.586)	(0.457)	(0.569)
DIVIDENDS	−0.0473	−0.0477	−0.0464	−0.0458	−0.0428	−0.0458	−0.0454	−0.0467	−0.0481
	(−0.544)	(−0.548)	(−0.534)	(−0.539)	(−0.504)	(−0.538)	(−0.533)	(−0.550)	(−0.565)
ROEG	1.0407	1.0416	1.0413	1.1839	1.1787	1.1218	1.1188	1.0956	1.1209
	(1.268)	(1.269)	(1.269)	(1.548)	(1.540)	(1.468)	(1.457)	(1.427)	(1.46)
MTB	−0.0156	−0.0159	−0.0159	−0.0147	−0.0155	−0.0143	−0.0157	−0.0146	−0.0151
	(−1.480)	(−1.506)	(−1.505)	(−1.452)	(−1.524)	(−1.410)	(−1.568)	(−1.449)	(−1.501)
CA	−0.0913	−0.0917	−0.0917	−0.0928	−0.0963	−0.0938	−0.0945	−0.0935	−0.0935
	(−1.668)	(−1.675)	(−1.674)	(−1.771)	(−1.841)	(−1.789)	(−1.803)	(−1.787)	(−1.784)
TURNOVER	−0.0478	−0.0479	−0.0480	−0.0447	−0.0449	−0.0438	−0.0448	−0.0446	−0.0447
	(−2.027)	(−2.034)	(−2.036)	(−2.058)	(−2.067)	(−2.011)	(−2.056)	(−2.051)	(−2.053)
Const	0.2383	0.2185	0.2368	0.2983	0.1423	0.1661	0.1508	0.1312	0.1535
	(1.016)	(0.942)	(1.009)	(1.383)	(0.765)	(0.771)	(0.636)	(0.919)	(0.662)
R^2	2.68%	2.68%	2.68%	2.95%	2.89%	2.81%	2.68%	2.81%	2.69%
R^2 adj.	1.05%	1.05%	1.04%	1.44%	1.38%	1.30%	1.17%	1.29%	1.17%
Observations	789	789	789	848	848	848	848	848	848

Table A10
RECLEVEL_CHG_NONSTAR.

S_negative	0.1049								
	(0.927)								
S_positive		0.0483							
		(0.370)							
S_neutral			−0.1888						
			(−1.715)						
S_DURATION	−0.1004	−0.0982	−0.0966						
	(−0.808)	(−0.79)	(−0.779)						
Q_negative				0.1193					
				(0.944)					
Q_positive					−0.1869				
					(−1.058)				
Q_neutral						0.0798			
						(0.621)			
Q_DURATION				0.1560	0.1472	0.1595			
				(0.603)	(0.571)	(0.617)			
A_negative							−0.2141		
							(−1.842)		
A_positive								0.1466	
								(1.105)	
A_neutral									−0.1101
									(−0.941)
A_DURATION							0.1097	0.1089	0.1100
							(0.819)	(0.813)	(0.820)
SUE	−0.0006	−0.0006	−0.0006	−0.0006	−0.0006	−0.0006	−0.0006	−0.0005	−0.0006
	(−0.255)	(−0.269)	(−0.261)	(−0.268)	(−0.272)	(−0.266)	(−0.247)	(−0.199)	(−0.257)
INSTOWN	−0.0119	−0.0073	−0.0207	−0.0292	−0.0293	−0.0263	−0.0290	−0.0252	−0.0299
	(−0.103)	(−0.063)	(−0.179)	(−0.265)	(−0.266)	(−0.238)	(−0.262)	(−0.228)	(−0.270)
NAL	0.0085	0.0086	0.0086	0.0083	0.0082	0.0083	0.0085	0.0085	0.0084
	(5.018)	(5.022)	(5.043)	(4.989)	(4.962)	(5.008)	(5.176)	(5.162)	(5.154)
BIG10	−0.0787	−0.0794	−0.0801	−0.0675	−0.0690	−0.0672	−0.0684	−0.0674	−0.0704
	(−1.71)	(−1.723)	(−1.741)	(−1.543)	(−1.580)	(−1.538)	(−1.566)	(−1.544)	(−1.611)
EPSG	−0.0033	−0.0035	−0.0032	−0.0035	−0.0033	−0.0035	−0.0030	−0.0032	−0.0031
	(−0.846)	(−0.908)	(−0.831)	(−0.917)	(−0.868)	(−0.935)	(−0.803)	(−0.834)	(−0.819)
LNMV	0.0045	0.0049	0.0046	0.0050	0.0044	0.0049	0.0048	0.0040	0.0052
	(0.602)	(0.660)	(0.618)	(0.755)	(0.665)	(0.738)	(0.731)	(0.606)	(0.793)
DIVIDENDS	0.2110	0.2084	0.2122	0.2175	0.2191	0.2158	0.2217	0.2184	0.2227
	(2.911)	(2.872)	(2.932)	(3.089)	(3.115)	(3.063)	(3.155)	(3.111)	(3.166)
ROEG	2.5242	2.5330	2.5455	2.3751	2.3180	2.3650	2.2915	2.2804	2.3071
	(3.69)	(3.701)	(3.726)	(3.75)	(3.661)	(3.741)	(3.612)	(3.594)	(3.637)
MTB	0.0002	0.0003	−0.0010	−0.0006	0.0001	−0.0004	−0.0004	0.0010	−0.0008
	(0.021)	(0.035)	(−0.111)	(−0.071)	(0.009)	(−0.047)	(−0.049)	(0.115)	(−0.101)
CA	0.0057	0.0051	0.0029	0.0088	0.0082	0.0097	0.0074	0.0090	0.0072
	(0.126)	(0.111)	(0.063)	(0.204)	(0.189)	(0.223)	(0.171)	(0.209)	(0.167)
TURNOVER	−0.0023	−0.0023	−0.0035	−0.0116	−0.0114	−0.0111	−0.0108	−0.0107	−0.0110
	(−0.119)	(−0.118)	(−0.176)	(−0.647)	(−0.634)	(−0.617)	(−0.602)	(−0.595)	(−0.611)
Const	5.7911	5.8189	5.9009	5.7378	5.8318	5.7628	5.8391	5.7324	5.7719
	(29.617)	(30.099)	(30.220)	(32.513)	(33.219)	(32.346)	(29.075)	(29.996)	(30.122)
R^2	7.77%	7.69%	8.02%	7.46%	7.57%	7.49%	7.59%	7.62%	7.58%
R^2 adj.	6.23%	6.14%	6.48%	6.02%	6.13%	6.05%	6.15%	6.18%	6.14%
Observations	789	789	789	848	848	848	848	848	848

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