Earnings Expectations and Interactive Discussions with Corporate Insiders

Abstract

This paper aims to empirically clarify the informational role of interactive discussions with corporate insiders by analyzing how participants' expectations are affected by each participant comment during analyst/investor days. To this end, I analyze the influence of the linguistic tone of management (corporate insiders) presentation, comments from peers, and management responses to each analyst's earnings forecast. The results indicate that the tone of management presentation, as well as responses to participants' comments, have no impact on analysts' expectations of the company's performance. In contrast, analysts' earnings forecasts significantly react to comments from their peers (especially star analysts). Furthermore, analysts whose earnings forecasts diverge positively (negatively) from the consensus are influenced by the negative (positive) opinions of their peers. The results also suggest that interactive meeting plays a role in acquiring information and opinions from other participants (especially informed participants) rather than from corporate insiders.

Keywords: interactive discussion; linguistic tone; peer's opinion; herding behavior

JEL classification: G11, G14, G15, G24

1. Introduction

Interactive discussions with corporate insiders have recently gained importance as a source of information (Valentine 2011; Brown et al. 2015). Although providing interaction opportunities is costly for firms (Porter 2012), they do so to reduce information asymmetry between firms and investors. Despite the increasing importance of interactive discussions, the question of how the information provided by the discussions is shared has largely remained underexamined.

Specifically, prior studies analyze the informational role of voluntary disclosure in light of exchanging information between corporate insiders and event (outside) participants. However, the informational role of the discussion could be further explored; since each participant can listen to their peers' comments, voluntary disclosure could facilitate exchanging of information and ideas among event participants. Hence, in this study, the contents of the discussion are divided based on specific details. For each participant (participant *i*), the comments in the discussion are first divided into three categories: comments made by themselves (participant *i*), comments made by corporate insiders, and comments made by peers (outside event participants except for participant *i*). In terms of comments by corporate insiders, I decompose them into management's presentation and replies to participants' comments. Further replies to participants' comments are decomposed into replies to participant *i*'s comments and replies to peers' comments.

This study analyzes the influence of comments on earnings expectations of financial (sell-side) analysts because sell-side analysts play a major role during the Q&A sessions, and their expectations are observable. Specifically, this study clarifies the underlying mechanism of information sharing through discussions by analyzing how ex-post revisions in each analyst's (analyst *i*'s) earnings forecasts are associated with the tone (positiveness and negativeness) of these five categories of comments, that is, management presentation, their (analyst *i*'s) own comments, the manager's response to analyst *i*'s questions, comments from analyst *i*'s peers, and the manager's response to peers' comments. In this study, the rationality of the influence is analyzed if any influence of the tone is observed.

The study focuses on the interactive discussions that take place on analyst/investor days (hereafter, AI days) since AI days provide a greater opportunity to interact with corporate insiders (through the Q&A session) than other disclosure mediums (e.g., earnings conference call). In this sample, the length (number of words) of each participant's comment on AI days is more than three times as large as that in earnings calls. Thus, the discussions on AI days can be regarded as a suitable sample for testing the hypotheses (especially testing the information sharing between event participants).

First, the results indicate that the linguistic tone of management comments and presentations is not associated with ex-post revisions of analysts' earnings forecasts. In contrast, an ex-post revision of earnings forecasts is significantly associated with comments from peers (other event participants): a positive (negative) tone of other participants' comments (especially star analysts) induces an ex-post upward (downward) revision of analyst's earnings forecast. Furthermore, analysts whose earnings forecasts diverge positively (negatively) from consensus forecasts are more significantly affected by their peers' negative (positive) opinions. In addition, analysts are more influenced by other participants' discussions, especially when star analysts, representatives of informed participants, join the discussion. This finding supports the view that analysts' expectations are significantly affected by other participants' (especially informed ones) comments rather than management comments. Finally, the analysis shows that a positive (negative) tone of other participants does not result in the overestimation (underestimation) of analysts' earnings forecasts, supporting the rationality of analysts' reactions to comments from peers. The results support the view that interactive discussions provide an opportunity to acquire opinions and information from other event participants (especially informed participants) rather than corporate insiders. The influence of peers' opinions is substantial for participants whose earnings expectations diverge due to their peers' opinions.

The findings contribute to the literature on corporate disclosure by providing direct evidence of information sharing between outside participants through interactive discussions. Furthermore, the findings give an essential implication regarding herding behavior in analysts' earnings forecasts. Trueman (1994) argues that analysts' earnings forecasts are significantly influenced by their peers' forecasts. However, it is not well explored how opinions are shared by analysts. This study shows that interactive discussions provide opportunities for analysts to follow (mimic) their peers' opinions.

The remainder of this paper is organized as follows. Section 2 reviews the related literature and formulates the hypotheses. Section 3 presents the methodology. Section 4 discusses the findings and results, and Section 5 discusses the additional analyses. Finally, Section 6 summarizes the findings.

2. Related Literature and Hypothesis Development

2.1. Interactive discussions

Since conference calls about earnings (earnings calls) are regarded as a traditional communication medium that represents a valuable source of information to investors and analysts (Frankel et al. 1999, Bowen et al. 2002, Brown et al. 2004), prior studies have focused on analyzing these calls.[1] The earnings calls typically take place within one day of the earnings announcement and organize brief Q&A sessions to provide an opportunity for investors and analysts to interact with corporate insiders. Usually, sell-side analysts play a major role during the Q&A sessions, and they often receive preferential treatment during the sessions and are often the first to question corporate insiders (Huang and Wermers 2021).

Bowen et al. (2002) report that earnings calls reduce informational asymmetry between market participants. Matsumoto et al. (2011) and Price et al. (2012) show the informational value of tones in short discussions on quarterly earnings calls. Specifically, Matsumoto et al. (2011) find that the Q&A sessions of the earnings calls are relatively more informative than the management presentations. Chen et al. (2018) show that stock prices react to analysts' tones rather than management tones raising the possibility that analysts' comments have more informational value. [2]

Although these studies mainly analyze whether interactive discussions provide additional information, they rarely focus on how the information is shared. Specifically, few studies provide direct evidence of information sharing between (outside) event participants. The hurdle to analyzing such information sharing is that traditional disclosure channels provide only limited opportunities to interact with financial analysts and investors (Kirk and Markov 2016). However, reflecting an increasing demand for face-to-face interactions (Kary 2005; Wagner 2005; Brinkley 2012), firms have been increasing interaction opportunities through new disclosure channels, that is, AI days.

[1] In terms of mandatory disclosure, considerable studies perform a textual analysis of 10-K and show that this textual information has informational value for predicting the firm's stock return, volatility, liquidity, firm earnings, and risk factors, among others (Jegadeesh and Wu 2013; Cohen et al. 2020; Goodell et al. 2021; Mushtaq et al. 2022).

[2] They show that a subsequent revision of analysts' earnings forecast is weakly associated with the tone of their comments during the Q&A session, indicating that analysts' tone conveys a noisy signal for subsequent revisions in their earnings forecast. This association could be attributed to the information sharing between participants as well as their forecast-revising comments (comment on positive (negative) issues before they upgrade (downgrade) their earnings expectations).

Nowadays, practitioners view this channel as a major corporate disclosure and investor relations activity (Rossi 2010; Buckley 2011). Valentine (2011) argues that it is a valuable source of information for sell-side and buy-side analysts. AI days provide a longer period to interact with corporate insiders than earnings calls. Analysis of long-duration interactive discussions is crucial for understanding the influence of other participants' comments (opinions). In this sample, the length (number of words) of each participant's comment on AI days is more than three times as large as that in earnings calls. Thus, the discussion on AI days can be regarded as a suitable sample to test this study's hypotheses regarding information sharing between event participants. Furthermore, unlike earnings calls, AI days are rarely held in conjunction with earnings announcements (the most important mandatory disclosure events). While the influence of the discussion on earnings calls could contain the impact of earnings announcements, such confronting effects could be less relevant for the discussion on AI days.

Kirk and Markov (2016) argue that investigating AI days is critical to acquiring a complete understanding of interactions between corporate insiders and participants as an element of a firm's disclosure policy. Accordingly, academic researchers have begun to analyze the effect of AI days. Prior studies (e.g., Kirk and Markov 2016; Wu and Yaron 2018; Park 2019) analyze the effect of holding an AI day on analysts' actions, trading volume, and stock prices. Specifically, Kirk and Markov (2016) demonstrate that the choice to hold AI days relates positively to information demand from analysts and institutional investors. They show that the frequency of their forecast updates increases after AI days. However, the mechanism of information sharing via AI days is not examined thoroughly. My analysis extends these studies by further clarifying information sharing through interactive discussions.

2.2. Hypothesis development

2.2.1 Management comments

Interactive discussions can be divided into management (corporate insiders) comments and participants' (analysts and investors) comments. The management comments could have a significant informational value since managers spend time discussing detailed topics regarding the company's performance (Park 2019). Thus, the management comments have a substantial impact on participants' expectations regarding company performance. Specifically, the positive (negative) linguistic tones of management comments, which represent the positive (negative) view or sentiment of corporate insiders, could induce upward (downward) revisions in participants' expectations. This argument leads to the first hypothesis:

H1a: The tones of management comments have an impact on analysts' forecasts of the company's performance.

In contrast, corporate insiders comment and respond to questions for the sake of the company's benefit, which could lead to strategic biases in the management. If participants realize this bias, they will disregard corporate insiders' comments on the subject. Consistent with this view, Davis et al. (2015) show that management comments are strategically optimistic. Furthermore, Chen et al. (2018) show that investors do not react to the tone of management comments in earnings calls. Thus, the participants' expectations might not be significantly influenced by the tone of management comments during AI days. Therefore, the following alternative hypothesis is posited:

H1b: Management comments have little impact on analysts' forecasts of company performance.

2.2.2. Peers' opinions

The role of interactive discussions with corporate insiders could be to know other participants' (peers') opinions. Trueman (1994) argues that analysts' earnings forecasts are significantly influenced by their peers' forecasts. Hence, if an analyst's opinion is found to be different from other participants' (peers') views, the analyst will assess if the difference is reasonable. This assessment could influence their expectations regarding the company's performance. Therefore, their expectations about the company's performance are likely influenced by peers' opinions through interactive discussions. Specifically, the positive (negative) comments by other participants could induce upward (downward) revisions in analysts' expectations. Thus, the following hypothesis is posited:

H2: Analysts' forecasts of the company's performance are influenced by their peers' comments.

If interactive discussions play a role in exchanging information and opinions among participants, the influence of peers' opinions could be substantial when ex-ante bullishness of the analyst's opinion is inconsistent with the direction of peers' opinions. In other words, an analyst whose ex-ante expectation diverges positively (negatively) from the consensus is likely to be influenced by negative (positive) opinions from peers. This argument leads to the following hypothesis:

H3: The influence of peers' comments on analysts' forecasts is substantial when the direction of peers' opinions is opposite to analysts' ex-ante bullishness regarding the company's performance.

2.2.3. Reasonability of the influence

If peers faithfully and straightforwardly provide and distribute information on the company's performance, the positive (negative) tone of these comments would not result in the overestimation (underestimation) of analysts' earnings forecasts. Thus, there should be no positive association between the tones and ex-post optimism in those earnings forecasts. Therefore, the following hypothesis is posited:

H4a: The positive (negative) tones of peers' comments do not induce the overestimation (underestimation) of analysts' earnings forecasts.

In contrast, since analysts might overreact to peers' opinions (Trueman 1994), their comments could worsen analysts' forecast accuracy. Specifically, the positive (negative) tone of peers' comments might induce the overestimation (underestimation) of analysts' forecasts regarding the company's performance. Hence, an overestimation (underestimation) of earnings forecasts would be observed after an AI day for stocks with a positive (negative) tone in their comments. Hence, the following alternative hypothesis is proposed:

H4b: The positive (negative) linguistic tone of peers' comments induces the overestimation (underestimation) of analysts' earnings forecasts.

3. Methodology

3.1. Linguistic tone of comments

For this study, I form a sample of AI days of U.S. firms using company-level events calendar data from Factset. When an AI day is a multiple-day event, only the first day is included in the sample. Following Kirk and Markov (2016), this study excludes AI days on which the firm announced earnings within two trading days. For each observation, transcripts of the discussions are collected from the Factset transcript database. Using this database, I divide comments based on a speaker and then identify management comments and each participant's comments. I collect earnings forecasts of each analyst from Factset.

I obtain the tones of the comments following the methodologies of Loughran and McDonald (2011). Each comment j (and management presentation) is processed to identify each word, and then the word is categorized based on its inclusion in the positive or negative word list. This process generates raw word counts of positive ($Positive_j$) and negative words ($Negative_j$) for each management and participant's comment j. Subsequently, I take the difference in the opposing categories and divide it by the total number of words to construct a measure for the linguistic tone ($TONE_j$) of each comment j. This ratio, bounded between –1 and +1, provides a metric for a relative tone.

3.2. Research design

3.2.1. Analysts' response to comments

To test H1a, H1b, and H2, I analyze how the linguistic tones of comments from management and peers induce revisions in analysts' forecasts regarding the company's performance.

In terms of the management comments' tone, I separately analyze the tone of management's presentation from the AI day s ($Tone\_MPT_s$) and the tone of management responses to participants' comments. For each analyst (analyst i), I further decompose management responses into responses to their own (analyst i's) comments and responses to other participants' comments. Then, I calculate the linguistic tones of management responses to analyst i's comments ($Tone\_MS_{i,s}$), and those of responses to the other participants' comments ($Tone\_MO_{i,s}$).[3] In terms of the participants' comments, I decompose them into analyst i's comments and comments from analyst i's peers (outside participants excluding analyst *i*). Then, I calculate the linguistic tones of analyst *i*'s comments ($Tone\_PS_{i,s}$) and the corresponding peers' comments ($Tone\_PO_{i,s}$).[4]

According to Jung et al. (2019), most analysts issue earnings per share (EPS) estimates for the current fiscal year (FY1 = Fiscal Year 1) and next fiscal year (FY2 = Fiscal Year 2). Thus, I analyze the association of the tones with the forecast revisions of EPS for the current and next fiscal years. Specifically, I analyze whether the subsequent 10-day revisions of each analyst's earnings forecasts are positively associated with the linguistic tone of the management's presentation ($Tone\_MPT_s$), management's responses to their own (analyst $i's$) comments ($Tone\_MS_{i,s}$), and management's responses to the corresponding peers' comments ($Tone\_MO_{i,s}$).[5] To test H2, I analyze how the subsequent 10-day revisions are associated with the linguistic tones of the peers' comments ($Tone\_PO_{i,s}$). Specifically, the following regression is estimated to determine the extent to which revisions of each analyst's earnings forecasts are associated with the tones[6]:

$$Rev\_EPS_{i,s} = \alpha_0 + \beta_1\, Tone\_PO_{i,s} + \beta_2\, Tone\_PS_{i,s} + \beta_3\, Tone\_MPT_s + \beta_4\, Tone\_MS_{i,s} + \beta_5\, Tone\_MO_{i,s} + (Controls) + \varepsilon_{i,s}. \quad (1)$$

The dependent variable ($Rev\_EPS_{i,s}$) is the change in analyst *i*'s EPS forecasts for the current and next fiscal years for days *t* (the day of the event) through t+9 deflated by the closing price on the AI day (*t*).[7] The standard errors in all the empirical tests are estimated with a cluster control at the event level.

I include the following control variables (lists of the variables used in this study are provided in Table A1). First, I include the 10-day lagged revisions of analyst *i*'s EPS forecasts ($PRev\_EPS_{i,s}$) to control for a gradual update of earnings forecasts. When $Rev\_EPS_{i,s}$ is based on EPS for the

[3] $Tone\_MS_{i,s}$ and $Tone\_MO_{i,s}$ are different between analysts.
[4] $Tone\_PS_{i,s}$ and $Tone\_PO_{i,s}$ are different between analysts.
[5] I find that the result holds when I analyze the subsequent five-day and 20-day revisions.
[6] The regression model does not have any fixed effect. However, I find that the result holds even if I consider analyst, company, or event fixed effects (the results are available upon request).
[7] The bottom and top 1% of the revision variables (i.e., Rev_EPS and $PRev\_EPS$) are winsorized to reduce the effect of outliers.

current (next) fiscal year, $PRev\_EPS_{i,s}$ is also based on EPS for the current (next) fiscal year. Since analysts may piggyback on recent news and events, I control any gradual response to the event by including 10-day lagged abnormal stock returns ($PCAR_s$), where abnormal returns are calculated based on the Fama–French three-factor model.

Since a revision in an analyst's earnings forecast is associated with lagged consensus recommendations (Eames 2002), the consensus recommendation (REC_s) is also included.[8] Moreover, to control analysts' gradual reaction to earnings surprises, I include the most recent earnings surprise based on the difference between actual earnings and analysts' consensus forecast (SUE_s). Next, I include the firm size (MV_s), and the book-to-market ratio (BM_s). I also include (fiscal) year dummies in Equation (1).

Furthermore, following Jung et al. (2019), who investigated the predictivity of REV_EPS, I employ the following accounting-based control variables. First, I control for working capital accruals (ACC_s) since firms with higher accruals are more likely to experience lower future earnings (Sloan 1996), and analysts do not incorporate this information into their initial forecasts (Bradshaw et al. 2001). I also include two measures of past firm performance: return on assets (ROA_s) and a loss indicator variable ($LOSS_s$) because past firm performance could be associated with the subsequent revisions of earnings forecasts due to analysts' underreaction to prior losses (Klein 1990; Dowen 1996; Sedor 2002).

A negative association could be expected between guidance and subsequent revisions as firms often provide earnings forecasts to guide analysts' estimates down to beatable targets (Matsumoto 2002; Richardson et al. 2004; Cotter et al. 2006; Ke and Yu 2006). Thus, I include D_GUI_s, an indicator variable that equals 1 if a firm provides any earnings guidance during the current fiscal year and 0 otherwise. Furthermore, Matsumoto (2002) finds that firms with higher institutional ownership are more likely to issue guidance to lower analysts' expectations and avoid negative earnings surprises. Thus, institutional ownership ($INST_s$), which is the percentage of shares owned by institutions, is included. Next, I include the change in external financing ($CHXFIN_s$). Analysts

[8] Even if analyst *i*'s stock recommendation is included instead of the consensus recommendation, the results still hold.

tend to provide overly optimistic estimates for firms that issue new securities to win investment banking business and generate brokerage business (Bradshaw et al. 2006).

Stock splits also convey positive information about future earnings (Grinblatt et al. 1984; Asquith et al. 1989). Analysts are less likely to reduce their initial estimates for firms that recently had stock splits. I include the stock splits indicator, denoted as $SPLIT_s$, which takes 1 (-1) if a firm conducts a stock split (a reverse stock split) over 12 months and 0 otherwise.

Finally, the disparity between analysts' long- and short-term earnings growth forecasts ($DISPARITY_s$) is considered. Da and Warachka (2011) define $DISPARITY_s$ as the within-industry decile rank of the consensus long-term growth forecast minus the decile rank of the implied short-term growth forecast. $DISPARITY_s$ captures the slow incorporation of analysts' information into their long-term forecasts relative to their short-term forecasts. This disparity is negatively related to subsequent revisions of analysts' earnings forecasts.

If the coefficient of $Tone\_MPT$, $Tone\_MS$, or $Tone\_MO$ is significantly positive, the positive (negative) tones of management's comments induce upward (downward) revisions in participants' expectations regarding the company's performance (H1a is supported). In contrast, neither of these coefficients is significant; the analysts' expectations are not influenced by the tone of management's comments (H1b is supported). A positive coefficient of $Tone\_PO$ means that the positive (negative) tone of the peers' comments induces upward (downward) revision in analysts' forecasts, supporting H2.

3.2.2. Information sharing among participants

To test H3, which is the hypothesis regarding information sharing among the participants, I test whether analysts whose ex-ante earnings forecasts diverge positively (negatively) from consensus forecast are more likely to respond to negative (positive) comments from peers. In other words, I test whether analysts' responses to peers' comments are substantial when their ex-ante forecast bullishness (relative to consensus forecast) is inconsistent (opposite to) with peers' opinions. To this end, I estimate the following regression model.

$Rev\_EPS_{i,s} = \alpha_0 + \beta_1 Inconsistency_{i,s} \cdot Tone\_PO_{i,s} + \beta_2 Tone\_PO_{i,s} + \beta_3\, Tone\_PS_{i,s} +$

$$\beta_4\, Tone\_MPT_s + \beta_5\, Tone\_MS_{i,s} + \beta_6\, Tone\_MO_{i,s} + (Controls) + \varepsilon_{i,s}. \qquad (2)$$

$$Inconsistency_{i,s} = \begin{cases} 1 & if\ sign(Tone\_PO_{i,s}) \neq sign(Bullishness_{i,s}) \\ -1 & if\ sign(Tone\_PO_{i,s}) = sign(Bullishness_{i,s}) \end{cases}$$

Where $Bullishness_{i,s}$ is defined as an analyst's earnings forecast subtracted from the consensus forecast at day t-1. Thus, positive (negative) $Bullishness_{i,s}$ means an analyst's earnings forecast is more bullish (conservative) than the consensus forecast. $Inconsistency_{i,s}$ takes 1 when the direction of the bullishness of analyst i's ex-ante forecast is opposite to the direction of peers' tones and -1 otherwise.[9] For example, when the ex-ante forecasts are more optimistic (pessimistic) than their peers' opinions but the peer's tone is negative (positive), $Inconsistency_{i,s}$ takes 1. Thus, positive β_1 (positive coefficient of $Inconsistency_{i,s} \cdot Tone\_PO_{i,s}$) indicates that analysts significantly react to peers' comments when their tones are opposite to their ex-ante bullishness, supporting H3.

3.2.3. Rationality of the reaction

To test H4a and H4b, I analyze whether the positive and negative $Tone\_PO$ (positive and negative peers' comments) induce an overestimation and underestimation in earnings forecasts, respectively, when these tones are found to affect the analysts' forecasts. Thus, I analyze whether the optimism in earnings forecasts after analysts' responses to AI days (the ex-post optimism in their earnings forecasts) is associated with the tones. We observe the analysts' responses to the comments using the revisions of their earnings forecasts for days t through t+9. Thus, to test the rationality of the reaction, I observe $OPT\_EPS_{i,s}$ (i.e., ex-post optimism in earnings forecasts of analysts *i* after an AI day *s*) defined as analysts *i*'s EPS forecast on day t+9 minus the actual EPS deflated by the closing price on day t+9.[10] Then, I estimate Equation (1) for OPT_EPS. If the coefficient of $Tone\_PO$ is insignificant, the positive (negative) tones are unlikely to induce overestimation (underestimation) of analysts' earnings forecasts, thereby supporting H4a. In contrast, a positive coefficient of $Tone\_PO$ indicates that analysts' earnings forecasts with positive (negative) $Tone\_PO$ are upwardly

[9] I perform the analysis after excluding the case that the bullishness or conservativeness is marginal. Specifically, I exclude the case that an absolute value of bullishness is less than one standard deviation of analysts' EPS forecasts (forecast dispersion). I find that the result still holds in such a case.
[10] The bottom and top 1% of OPT_EPS are winsorized to reduce the effect of outliers.

(downwardly) biased, supporting a possibility that analysts' forecasts are misguided by the tones of the comments.[11]

4. Results

4.1. Descriptive statistics and correlations

This study's sample includes 27,466 participants' comments and corresponding management responses for 3,276 AI days hosted by 1,095 firms over the 2010–2019 period. I start the sample in 2010, because sufficient transcript data for the AI days is available only from 2010. Moreover, to evaluate forecast errors (ex-post forecast optimism), the study requires the realized EPS of two subsequent years. Thus, the final year of the sample is 2019. Consistent with the argument of Kirk and Markov (2016), Figure 1 confirms that few AI days overlap with earnings announcement days.[12] Additionally, it shows that there is some tendency for the AI day to be hosted after an earnings announcement rather than before it, consistent with the quiet period policy.

According to the descriptive statistics in Table 1, the optimism of EPS forecasts for the next fiscal year ($OPT\_EPS(FY2)$) tends to be positive, consistent with the optimism in analysts' earnings forecasts (DeBondt and Thaler 1990; Abarbanell 1991; Easterwood and Nutt 1999). Furthermore, the table shows that the linguistic tone of the management presentation ($Tone\_MPT$) tends to be positive, consistent with the study of Brockman et al. (2015), depicting strong optimism in the management's presentation of earnings conference calls. In contrast, such tendency is not observed for the tone of participants' comments ($Tone\_PO$ and $Tone\_PS$), consistent with the view that analysts and investors are less positively biased.

According to the correlations between the variables in Table 2, the tone of participants' comments ($Tone\_PO$, $Tone\_PS$) is associated with the tone of the management's comments

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[11] To support H4b, further testing is needed to examine whether the overestimation and underestimation have worsened after AI days.

[12] Although AI days are rarely held around earnings announcement days, the possibility that analysts' revisions are attributed to the earnings announcements cannot be denied. Thus, for checking the robustness of the results, I perform the same analyses after excluding the AI days held within 10 days before the earnings announcement. I find that the results hold.

($Tone\_MPT$, $Tone\_MS$, and $Tone\_MO$). Specifically, $Tone\_MO$ and $Tone\_MS$ are associated with $Tone\_PO$ and $Tone\_PS$, respectively. This association is consistent with the view that management discusses (responses to) the topics mentioned (questioned) by event participants. However, the level of these correlations is not significantly high, indicating that the participants' comments contain independent opinions (information) beyond those contained in the management's comments.

Next, the tones of management's comments have a positive association with MV, ROA, and D_GUI, indicating that the tones are higher for firms with larger market capitalization, higher profitability, and earnings guidance. In addition, they are negatively associated with $LOSS$ and $CHXFIN$, indicating that the tones are higher for firms with positive earnings and a decrease in external financing. The association of these variables is weaker with the tones of participants' comments than the tones of management comments, suggesting that the participants' comments are less biased than management's comments.

[Table 1]

[Table 2]

4.2. Impact of management and participants' comments

Table 3 presents the results of estimating Equation (1) with t-statistics (in parentheses) based on robust standard errors clustered by an event (an AI day). The study reports the results of the revisions of the earnings forecasts for the current and next fiscal year separately. The results indicate that none of the control variables has a consistent association with the dependent variable.

In terms of the association with tones, the coefficients of $Tone\_MPT$, $Tone\_MO$, and $Tone\_MS$ are insignificant. These insignificant coefficients indicate that the tone of management's comments has no impact on analysts' earnings forecasts, supporting H1b. This result supports the view that the management's presentation and responses to (outside) participants' questions have a small informational role as a disclosure medium.

Table 3 also shows the association between tones of other participants' comments and subsequent revisions in analysts' earnings forecasts (Rev_EPS). The result suggests that analysts' earnings expectations are significantly influenced by the tones of comments from their peers. The coefficients of $Tone\_PO$ (0.0086, 0.0172) are significantly positive (at the 0.01 level), indicating that positive (negative) tones of comments from peers induce upward (downward) revisions in their earnings forecasts of current and next fiscal years. The results indicate that analysts' forecast errors in FY1 and FY2 forecasts are expected to be reduced (or at least changed) by 12.1% and 5.2% with one sigma change in peer's tone, respectively.[13] The results suggest that AI days play a role in exchanging information and ideas between outside participants rather than between the participants and corporate insiders, thereby supporting H2.

[Table 3]

Table 4 reveals the estimated coefficients of the regression model (2), showing whether the reaction to peers' opinions is influenced by the inconsistency between the analyst's ex-ante bullishness and peers' tones. The results reveal that the coefficient of $Inconsistency_{i,s} \cdot Tone\_PO_{i,s}$ is significantly positive, indicating that analysts whose ex-ante earnings forecasts diverge positively (negatively) from their peers are more influenced by peers' negative (positive) comments (H3 is supported). In other words, these results also support the view that analysts exchange their opinions and information on AI days.

[Table 4]

4.3. Rationality of analysts' reactions

Table 5 presents the association between the tones and ex-post optimism in earnings forecasts (OPT_EPS). The results indicate that the coefficient of $Tone\_PO$ is not positive, rejecting the possibility that a positive (negative) tone of other participants' comments induces an overestimation (underestimation) of earnings forecasts. Considering that analysts' forecasts are significantly influenced by the tones of peers' comments, the results indicate that this influence does not deteriorate the forecast accuracy. Thus, this result rejects H4b, positing that other participants'

[13] To assess the impact of one sigma change in peer's tone (TONE_PO) on REV_EPS (FY1 and FY2 earnings revisions), I multiply the coefficients of TONE_PO (0.0086 and 0.0172) by one sigma of TONE_PO (0.016). Then, the impact is scaled by ex-ante forecast errors (the difference between analysts' forecast and the actual one) as of an AI day. Since the analysis shown in Section 4.3. reveals that peers' opinions are expected to reduce the forecast errors, the values can be regarded as how much analysts' forecast errors are reduced by peers' opinions.

comments during AI days misguide analysts' expectations. In turn, the findings support H4a; other participants' comments could mitigate analysts' forecast errors.

[Table 5]

5. Additional Tests and Discussions

5.1 Association with own comments

Table 3 shows that the coefficients of $Tone\_PS$ (0.0011, 0.0027), which represent the association of revisions in analysts' earnings forecasts with tones of their own comments, are statistically positive at 0.05 and 0.01 levels, respectively. Positive (negative) tones of analysts' comments indicate subsequent upward (downward) revisions in their earnings forecasts. Although the statistical significance of the association is weaker than the association with tones of peers' comments ($Tone\_PO$), analysts seem to have a certain tendency to comment on (question) positive (negative) issues in AI days before upgrading (downgrading) their earnings expectations. In other words, the tones partly capture their forecast-revising comments. This result provides additional empirical evidence to the findings of Chen et al. (2018), which shows the weak influence of the tones of analysts' comments on their own earnings forecasts. Considering that their revisions in earnings forecasts are not affected by $Tone\_MS$, which represents management responses to analysts' questions, the results could indicate that management (corporate insiders) fails to answer the hard questions (the questions regarding negative issues). Hence, analysts became more convinced about their ex-ante negative views, resulting in a subsequent downward revision of their forecasts.[14]

5.2. Alternative tone measures

This study evaluates the tones of the participants' comments and management's comments using the dictionary-based methodology of Loughran and McDonald (2011) because theirs is the most common financial dictionary. However, although Henry's dictionary has a drawback in that it picks up a negative tone document (due to the limited number of negative words), the financial dictionary of Henry (2008) was commonly used previously. Hence, it is necessary to check the robustness of

[14] Consistent with this view, I find that the influence is stronger for negative $Tone\_PS$ than for positive $Tone\_PS$.

this study's key results, that is, the significant reaction to peers' opinions, by analyzing whether these results hold while using Henry's dictionary. Thus, I evaluate the tones of comments ($Tone\_MPT$, $Tone\_MS$, $Tone\_MO$, $Tone\_PS$, and $Tone\_PO$) using Henry's dictionary.

The results shown in Table 6 reveal that the coefficients of tones of the management's comments ($Tone\_MPT$, $Tone\_MS$, and $Tone\_MO$) remain insignificant, indicating that revisions in analysts' earnings forecasts have little association with tones of managements comments (H1b is supported). In addition, the results show that the coefficients of $Tone\_PO$ remain significantly positive, indicating that revisions in the analysts' forecasts have a positive association with the tones of other participants' comments, supporting H2. In sum, I find that the results hold even if the tones are evaluated using a different financial dictionary.[15]

[Table 6]

5.3. Denominator of the earnings revision

This study evaluates forecast revisions by deflating them by stock prices. However, the level of the EPS estimate (the absolute value of the original EPS estimate) is also a common denominator. In this section, to check the robustness of the key results, I analyze whether the association of analysts' earnings revisions with the tones remains significant while using the absolute value of EPS as the denominator.

Table 7 shows the results of the regression model (1) for Rev_EPS when the denominator is replaced by the absolute value of reported EPS. It reveals that the coefficients of the tones of management's comments ($Tone\_MPT$, $Tone\_MS$, and $Tone\_MO$) remain insignificant. Furthermore, the coefficient of the tones of other participants' comments ($Tone\_PO$) remain significantly positive, indicating that a positive (negative) tone of peers' comments induces upward (downward) forecast revisions. In sum, H1b and H2 are supported even if I use the absolute value of EPS as the denominator.[16]

[Table 7]

[15] It was also found that other hypotheses (H3 and H4a) hold when I use Henry's dictionary.
[16] I also find that other hypotheses (H3 and H4a) hold, even if I use the absolute value of EPS as the denominator.

5.4. Long-term EPS forecasts

This study observes the forecasts for the current and the next fiscal year since most analysts issue these forecasts. However, recently an increasing number of analysts have started to issue longer-term EPS estimates (especially three-year-ahead EPS). In addition, AI days tend to address long-term company performance more than other disclosure mediums (Park 2019). Thus, the significant association with tones of other participants' comments ($Tone\_PO$) would be observed for analysts' long-term forecasts (especially forecasts for three-year-ahead EPS). Although a considerable number of analysts (half of the analysts in my sample) do not issue three-year-ahead EPS estimates, an analysis of these estimates is necessary for checking the robustness of this study's results.

Hence, I calculate Rev_EPS and $PRev\_EPS$ using three-year-ahead EPS forecasts and run the Regression Model (1) for Rev_EPS. Although the number in the sample is almost halved (reduced from 10,997 to 5,398), the coefficients of the tones of other participants' comments ($Tone\_PO$), shown in Table 8, remain significantly positive, indicating that a positive (negative) tone of the other participants' comments induces upward (downward) forecast revisions of the three-year-ahead EPS. The results support H2.

[Table 8]

5.5. Informed Participants

The results show that each analyst's earnings expectations are influenced by each peer's opinions (tones) rather than the corporate insiders' opinions, possibly because some informed peers provide incremental information regarding the company's performance. To further test the prediction, I analyze whether each analyst is differently influenced by the opinions of star (prestigious) analysts and those of non-star analysts.

Stickel (1995) and Leone and Wu (2007) find that recommendation changes of star analysts have more impact on prices; Fang and Yasuda (2013) show that top-ranked All-American (AA) analysts provide more profitable information, that is, following the advice of these analysts increases returns for investors; star analysts' earnings forecasts outperform their peers' forecasts (Kerl et al., 2015). These findings suggest that star analysts are more informed about company performance and stock valuation. Furthermore, Mayew (2008) shows that star analysts are more involved in the discussion during the Q&A sessions than non-stars. Additionally, Rennekamp et al. (2020) show greater levels of engagement in conversations with star analysts. These findings support the view that star analysts play a key role in an interactive discussion on AI day.

These findings lead to the following two predictions regarding the influence of peers' opinions. First, since star analysts are expected to provide more useful information than non-stars, star analysts' comments have a stronger influence on other participants' earnings expectations. Second, since star analysts take the initiative with information sharing during Q&A sessions, overall peers' comments could be more influential when star analysts are involved in the discussion. In other words, when peers' comments include star analysts' ones, the overall peers' comments (all opinions from peers) could be more influential. In such cases, the influence of peers' opinions on each analyst's earnings expectation could be more substantial.

To test the first prediction, I additionally calculate the linguistic tones of star analysts' comments ($Tone\_SO_{i,s}$). As a metric for analysts' star status, I use the AA title awarded by the influential Institutional Investor magazine. Following Fang and Yasuda (2013), we specifically focus on top-rank AAs that are first and second-place winners.[17] Then, I analyze whether the subsequent 10-day revisions in each earnings forecast are positively associated with the linguistic tones of star analysts' opinions ($Tone\_SO_{i,s}$) even after controlling for tones of peers' comments ($Tone\_PO_{i,s}$). Specifically, the following regression is estimated to determine the extent to which revisions of each analyst's earnings forecasts are associated with tones:

$$Rev\_EPS_{i,s} = \alpha_0 + \beta_1\, Tone\_SO_{i,s} + \beta_2\, Tone\_PO_{i,s} + \beta_3\, Tone\_PS_{i,s} + \beta_4\, Tone\_MPT_s + \beta_5\, Tone\_MS_{i,s} + \beta_6\, Tone\_MO_{i,s} + (Controls) + \varepsilon_{i,s}. \quad (3)$$

To test the second prediction, I estimate the following regression model:

$$Rev\_EPS_{i,s} = \alpha_0 + \beta_1\, STAR_{i,s} * Tone\_PO_{i,s} + \beta_2\, Tone\_PO_{i,s} + \beta_3\, Tone\_PS_{i,s} +$$

[17] If bottom-rank AAs (third and runners-up) are included, the statistical significance becomes weaker. These results are consistent with the prediction that opinions of top rank analysts are heavily influenced by other analysts.

$\beta_4\, Tone\_MPT_s + \beta_5\, Tone\_MS_{i,s} + \beta_6\, Tone\_MO_{i,s} + (Controls) + \varepsilon_{i,s}$. (4)

where $STAR_{i,s}$ is a dummy variable that takes 1 if participants (except for analysts i) include AA analysts with either the 1st- or 2nd-place titles.[18] The other control variables are the same as in Equation (1). I analyze the sign of interaction of $STAR_{i,s}$ with $Tone\_PO_{i,s}$ ($Tone\_PO_{i,s} * STAR_{i,s}$). The positive coefficient indicates that the influence of other participants' (peers') opinions is more substantial when star analysts are involved in the discussion.

The estimated coefficients for Equation (3) are shown in Table 9(a). The coefficient of the tones of star analysts' comments ($Tone\_SO$) for revisions in the next fiscal year's forecasts is positive (significant at the level of 5%); revisions in analyst's forecast regarding the next fiscal year's earnings have a positive association with linguistic tones of star analysts' comments, even if I control for an association of $Tone\_PO$ with the revisions. The results support the view that star analysts' comments have an additional influence on each analyst's forecasts.

Furthermore, the estimated coefficients for Equation (4), shown in Table 9(b), reveal that the coefficients of the interaction ($STAR_{i,s} * Tone\_PO_{i,s}$) for revisions in the next fiscal year's forecasts are significantly positive (at the level of 1%). The results support the view that analysts are more influenced by peers' comments, especially when star analysts join the discussion.

Considering that star analysts are categorized as informed participants, these results indicate that participants' opinions are particularly influenced by some informed participants. In other words, the purpose of interactive discussions is to acquire information from other informed participants rather than from corporate insiders.

[Table 9]

6. Conclusions

Several academic studies investigate the informational role of the interactive discussion between event participants and corporate insiders, reflecting the increased importance of these

[18] Approximately, 53% of $STAR$ in this sample take 1.

discussions. However, few studies have examined how information is shared among corporate insiders and (outside) event participants. Moreover, no studies provide direct evidence of information sharing between event participants. This study helps to fill this gap in the literature.

Several conclusions can be drawn from the results. First, the results indicate that the positive (negative) tone of comments from peers, especially from star analysts, induces upward (downward) revisions of analysts' earnings forecasts without resulting in any overestimation (underestimation) of their earnings forecasts. Specifically, analysts whose ex-ante forecasts diverge from peers' opinions are significantly influenced by peers' comments. Furthermore, the influence of peers' comments is substantial, especially when star analysts are involved in the discussion. In contrast, the tones of management's comments have little association with analysts' forecast revisions. These findings suggest that interactive discussions facilitate the exchange of information and ideas among event participants (between informed and uninformed participants) rather than between corporate insiders and participants.

This study contributes to the literature in several ways. First, it is the first to provide direct evidence that interactive discussion plays a role in the information sharing between event participants. Specifically, I show that information sharing is substantial between star analysts (informed analysts) and other participants. Second, these findings give an essential implication regarding herding behavior in analysts' earnings forecasts; the results indicate that interactive discussion opportunities could be one of the drivers of herding behavior in analysts' forecasts. Finally, the results highlight the current problem in interactive discussions. Despite the high cost of providing an opportunity for interactive discussions, the results show that not only management's presentations but also management's explanations (answers) for participants' questions have little impact on participants' expectations. Hence, interactive discussions (at least, those on AI days) fail to play a role in exchanging information and opinions between a hosting firm and participants.

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Table 1

Descriptive statistics

This table reports the descriptive statistics. "Mean," "Std. Dev.," and "Median" show the average value, standard deviation, and median value, respectively; "5th," "25th," "75th," and "95th" show the 5th, 25th, 75th, and 95th percentiles, respectively. Rev_EPS(FY1) and Rev_EPS(FY2) denote the changes in the current fiscal year and next fiscal year EPS forecasts, respectively. Opt_EPS(FY1) and Opt_EPS(FY2) denote optimism in the current fiscal year and next fiscal year EPS forecasts, respectively. $RPev\_EPS$(FY1) and $PRev\_EPS$(FY2) denote $PRev\_EPS$ based on the EPS for the current and next fiscal years, respectively.

	Mean	Std. Dev	Median	5^{th}	25^{th}	75th	95th
Rev_EPS(FY1)	0.000	0.002	0.000	-0.002	0.000	0.000	0.001
Rev_EPS(FY2)	0.000	0.004	0.000	-0.005	0.000	0.000	0.003
Opt_EPS(FY1)	0.001	0.024	-0.001	-0.013	-0.002	0.001	0.017
Opt_EPS(FY2)	0.005	0.028	0.001	-0.028	-0.005	0.011	0.054
Tone_PS	-0.012	0.038	-0.012	-0.073	-0.034	0.011	0.049
Tone_PO	-0.012	0.016	-0.012	-0.036	-0.021	-0.003	0.011
Tone_MA	-0.002	0.047	0.000	-0.062	-0.024	0.021	0.061
Tone_MO	0.003	0.013	0.003	-0.018	-0.005	0.011	0.024
Tone_MPT	0.016	0.014	0.017	-0.007	0.007	0.025	0.038
PRev_EPS(FY1)	0.000	0.002	0.000	-0.002	0.000	0.000	0.002
PRev_EPS(FY2)	0.000	0.002	0.000	-0.003	0.000	0.000	0.002
REC	1.484	0.255	1.500	1.037	1.318	1.675	1.875
MV	4.117	0.657	4.102	3.075	3.659	4.556	5.272
PB	0.376	0.560	0.291	0.012	0.149	0.479	1.022
SUE	0.001	0.009	0.001	-0.003	0.000	0.001	0.005
ACC	0.003	0.013	0.000	-0.007	0.000	0.003	0.022
LOSS	0.151	0.358	0.000	0.000	0.000	0.000	1.000
ROA	0.037	0.166	0.052	-0.190	0.014	0.094	0.181
D_GUI	0.531	0.499	1.000	0.000	0.000	1.000	1.000
CHXFIN	0.005	0.211	-0.029	-0.183	-0.075	0.018	0.353
INST	87.860	15.304	89.330	62.079	79.168	97.031	110.980
SPLIT	0.020	0.139	0.000	0.000	0.000	0.000	0.000
DISPARITY	-0.216	3.169	0.000	-6.000	-2.000	2.000	5.000

Table 2

Correlations

This table shows the Pearson correlations between the explanatory variables of Equation (1)

	Tone_PS	Tone_MO	Tone_MS	Tone_MPT	PRev_EPS (FY1)	PRev_EPS (FY2)	REC	MV	PB	SUE	ACC	LOSS	ROA	D_GUI	CHXFIN	INST	SPLIT	DISPARITY
Tone_PO	0.076	0.27	0.062	0.183	0.018	0.04	0.019	0.022	-0.106	0.039	0.02	-0.051	0.072	0.064	-0.049	0.105	-0.003	-0.022
Tone_PS		0.087	0.127	0.061	0.01	0.038	0.007	-0.004	-0.041	0.004	0.005	-0.013	0.017	0.025	-0.011	0.042	0.007	-0.008
Tone_MO			0.188	0.552	0.02	0.032	-0.026	0.148	-0.101	0.044	-0.019	-0.111	0.151	0.146	-0.141	0.021	0.006	-0.025
Tone_MS				0.15	-0.003	-0.005	-0.003	0.041	-0.037	0.018	-0.015	-0.03	0.052	0.055	-0.048	0.011	0.009	-0.02
Tone_MPT					0.013	0.03	-0.113	0.222	-0.068	0.046	-0.092	-0.254	0.255	0.22	-0.236	-0.034	0.008	-0.046
PRev_EPS(FY1)						0.636	0.059	0.018	-0.025	0.092	0.034	0.02	-0.03	0.025	0.026	-0.009	0.015	-0.036
PRev_EPS(FY2)							0.051	0.036	-0.009	0.061	0.018	0.016	-0.015	0.011	0.009	-0.012	0.021	-0.016
REC								-0.004	-0.02	0.032	0.11	0.204	-0.189	-0.065	0.265	0.114	0.019	0.076
MV									-0.038	0.05	-0.116	-0.314	0.322	0.085	-0.273	-0.461	0.002	-0.018
PB										-0.002	-0.066	-0.033	-0.05	-0.09	0.016	-0.112	-0.023	0.001
SUE											0.036	-0.067	0.134	0.013	-0.055	0.056	-0.012	0.002
ACC												0.177	-0.178	-0.066	0.19	0.052	0.021	0.059
LOSS													-0.568	-0.133	0.427	0.152	-0.031	-0.092
ROA														0.144	-0.677	0.006	0.03	0.091
D_GUI															-0.114	0.039	0.021	-0.112
CHXFIN																0.074	-0.006	0.019
INST																	-0.019	0.032
SPLIT																		0.026

Table 3

Influence of peers' and management's comments

This table shows the results of estimating Equation (1) for Rev_EPS (results for the year dummies are not reported). The columns "EPS for the current fiscal year" and "EPS for the next fiscal year" indicate the regression results when the dependent variables are the forecast revisions in the EPS forecasts of the current and next fiscal years, respectively. The values reported in parentheses are t-statistics estimated using cluster-robust standard errors. ** and *** indicate statistical significance at the 0.05 and 0.01 levels, respectively.

	Dependent Variables					
	EPS for the current fiscal year			EPS for the next fiscal year		
$Tone\_PO$	0.0086	***	(3.24)	0.0172	***	(3.70)
$Tone\_PS$	0.0011	**	(2.17)	0.0027	***	(2.76)
$Tone\_MO$	-0.0024		(0.76)	-0.0036		(0.63)
$Tone\_MS$	0.0000		(0.08)	0.0009		(1.42)
$Tone\_MPT$	0.0047		(1.29)	0.0021		(0.41)
PRev_EPS	-0.0067		(0.51)	0.0115		(0.68)
REC	0.0004	**	(2.52)	0.0004		(1.26)
MV	0.0000		(0.35)	0.0000		(0.08)
PB	-0.0001		(1.17)	-0.0001		(0.69)
SUE	0.0169	***	(2.66)	0.0119		(1.61)
ACC	0.0034		(1.68)	-0.0035		(0.91)
LOSS	0.0000		(0.24)	-0.0001		(0.51)
ROA	-0.0001		(0.43)	-0.0002		(0.29)
D_GUI	0.0000		(0.10)	-0.0003	**	(2.48)
CHXFIN	-0.0002		(0.74)	-0.0006		(1.11)
INST	0.0000		(0.58)	0.0000		(0.99)
SPLIT	0.0001		(1.06)	0.0004		(1.85)
DISPARITY	0.0000		(1.30)	0.0000	**	(2.46)
Controls for Year Effects	Yes			Yes		
Intercept	-0.0010		(1.58)	0.0005		(0.55)
Adjusted R2	1.88%			1.36%		
N	10997			10997		

Table 4

Inconsistency with analyst's ex-ante bullishness

This table shows the results of estimating Equation (2) for Rev_EPS (results for the year dummies are not reported). The columns "EPS for the current fiscal year" and "EPS for the next fiscal year" indicate the regression results when the dependent variables are the forecast revisions in the EPS forecasts of the current and next fiscal years, respectively. The values reported in parentheses are t-statistics estimated using cluster-robust standard errors. ** and *** indicate statistical significance at the 0.05 and 0.01 levels, respectively.

	EPS for the current fiscal year			EPS for the next fiscal year		
$Inconsistency \cdot Tone\_PO$	0.0069	***	(3.03)	0.0170	***	(3.82)
$Tone\_PO$	0.0005		(0.14)	-0.0019		(0.33)
$Tone\_PS$	0.0003		(0.72)	0.0013		(1.43)
$Tone\_MO$	-0.0012		(0.42)	-0.0008		(0.15)
$Tone\_MS$	0.0001		(0.26)	0.0008		(1.28)
$Tone\_MPT$	0.0030		(0.89)	0.0004		(0.09)
PRev_EPS	0.0006		(0.05)	0.0360	**	(2.17)
REC	0.0001		(1.66)	0.0001		(1.62)
MV	0.0000		(0.70)	0.0000		(0.08)
PB	-0.0001		(1.10)	-0.0001		(0.73)
SUE	0.0185	***	(2.88)	0.0130		(1.77)
ACC	0.0040	**	(2.02)	-0.0027		(0.70)
LOSS	0.0000		(0.18)	-0.0001		(0.50)
ROA	0.0000		(0.11)	-0.0001		(0.16)
D_GUI	0.0000		(0.38)	-0.0003	**	(2.33)
CHXFIN	0.0000		(0.20)	-0.0005		(0.99)
INST	0.0000		(0.32)	0.0000		(0.90)
SPLIT	0.0001		(1.13)	0.0004		(1.81)
DISPARITY	0.0000		(1.01)	0.0000	**	(2.44)
$Inconsistency$	-0.0003	***	(4.95)	-0.0008	***	(5.85)
Controls for Year Effects	Yes			Yes		
Intercept	-0.0010		(1.58)	0.0341	***	(3.82)
Adjusted R2	3.56%			4.65%		
N	10997			10997		

Table 5

Association with optimism

This table shows the results of estimating Equation (1) for Opt_EPS (results for the year dummies are not reported). The columns "EPS for the current fiscal year" and "EPS for the next fiscal year" indicate the regression results when the dependent variables are the optimism in the EPS forecasts of the current and next fiscal years, respectively. The values reported in parentheses are t-statistics estimated using cluster-robust standard errors. ** and *** indicate statistical significance at the 0.05 and 0.01 levels, respectively.

	Optimism in analysts' forecasts					
	EPS for the current fiscal year			EPS for the next fiscal year		
$Tone\_PO$	-0.0626		(1.35)	-0.0603		(1.58)
$Tone\_PS$	-0.0150	**	(2.00)	-0.0104		(1.34)
$Tone\_MO$	-0.0144		(0.34)	0.0519		(0.94)
$Tone\_MS$	-0.0044		(0.98)	-0.0013		(0.27)
$Tone\_MPT$	0.0738		(1.19)	0.0215		(0.36)
PRev_EPS	-0.7010	**	(2.40)	-0.0861		(0.44)
REC	0.0025		(1.03)	0.0060	**	(2.40)
MV	-0.0007		(0.46)	-0.0032	**	(2.40)
PB	0.0007		(0.74)	0.0012		(1.18)
SUE	0.1816		(0.63)	0.1437	**	(2.13)
ACC	-0.0291		(1.33)	-0.1339	**	(2.33)
LOSS	0.0013		(0.69)	-0.0042		(1.90)
ROA	0.0113		(1.35)	0.0024		(0.37)
D_GUI	-0.0023		(1.83)	-0.0040	***	(3.26)
CHXFIN	0.0033		(0.71)	0.0020		(0.43)
INST	0.0001		(0.94)	0.0000		(0.14)
SPLIT	-0.0005		(0.18)	-0.0043		(1.92)
Disparity	0.0001		(0.62)	-0.0001		(0.33)
Controls for Year Effects	Yes			Yes		
Intercept	-0.0242		(1.00)	0.0092		(1.01)
Adjusted R2	2.63%			2.19%		
N	10992			10992		

Table 6

Alternative tone measures

The table shows the results of estimating Equation (1) for Rev_EPS when I use Henry's dictionary to calculate tones. Results for the year dummies are not reported. The values reported in parentheses are t-statistics estimated using cluster-robust standard errors. ** and *** indicate statistical significance at the 0.05 and 0.01 levels, respectively.

	Dependent Variables					
	EPS for the current fiscal year			EPS for the next fiscal year		
$Tone\_PO$	0.0087	***	(3.02)	0.0170	***	(3.06)
$Tone\_PS$	0.0006		(0.97)	0.0024	**	(2.17)
$Tone\_MO$	0.0006		(0.24)	-0.0002		(0.03)
$Tone\_MS$	0.0003		(0.80)	0.0007		(0.91)
$Tone\_MPT$	0.0022		(0.78)	0.0011		(0.27)
PRev_EPS	-0.0065		(0.50)	0.0133		(0.77)
REC	0.0004	**	(2.51)	0.0004		(1.31)
MV	0.0000		(0.52)	0.0000		(0.03)
PB	-0.0001		(1.21)	-0.0001		(0.81)
SUE	0.0173	***	(2.65)	0.0126		(1.66)
ACC	0.0037		(1.78)	-0.0028		(0.73)
LOSS	0.0000		(0.33)	-0.0001		(0.34)
ROA	-0.0002		(0.52)	-0.0002		(0.36)
D_GUI	0.0000		(0.11)	-0.0003	**	(2.55)
CHXFIN	-0.0002		(0.80)	-0.0006		(1.12)
INST	0.0000		(0.32)	0.0000		(0.75)
SPLIT	0.0001		(1.01)	0.0004		(1.81)
DISPARITY	0.0000		(1.35)	0.0000	**	(2.49)
Controls for Year Effects	Yes			Yes		
Intercept	-0.0014	**	(2.26)	-0.0003		(0.38)
Adjusted R2	1.55%			0.98%		
N	10997			10997		

Table 7

Alternative denominator

This table shows the results when I use the absolute value of EPS as the denominator (results for the year dummies are not reported). The table shows the results of estimating Equation (1) for Rev_EPS. The values reported in parentheses are t-statistics estimated using cluster-robust standard errors. ** and *** indicate statistical significance at the 0.05 and 0.01 levels, respectively.

	Dependent Variables					
	EPS for the current fiscal year			EPS for the next fiscal year		
$Tone\_PO$	0.0086	***	(3.24)	0.1988	***	(3.39)
$Tone\_PS$	0.0011	**	(2.17)	0.0419	***	(2.93)
$Tone\_MO$	-0.0024		(0.76)	-0.0843		(0.99)
$Tone\_MS$	0.0000		(0.08)	0.0114		(1.17)
$Tone\_MPT$	0.0047		(1.29)	0.0722		(0.91)
PRev_EPS	-0.0067		(0.51)	0.0285		(1.41)
REC	0.0004	**	(2.52)	0.0047		(1.10)
MV	0.0000		(0.35)	-0.0004		(0.23)
PB	-0.0001		(1.17)	0.0001		(0.10)
SUE	0.0169	***	(2.66)	0.1127		(0.88)
ACC	0.0034		(1.68)	-0.0229		(0.37)
LOSS	0.0000		(0.24)	-0.0067		(1.51)
ROA	-0.0001		(0.43)	-0.0071		(0.64)
D_GUI	0.0000		(0.10)	-0.0034		(1.83)
CHXFIN	-0.0002		(0.74)	-0.0122		(1.24)
INST	0.0000		(0.58)	-0.0001		(1.30)
SPLIT	0.0001		(1.06)	0.0066		(1.89)
DISPARITY	0.0000		(1.30)	-0.0010	***	(3.43)
Controls for Year Effects	Yes			Yes		
Intercept	-0.0010		(1.58)	0.0081		(0.60)
Adjusted R2	1.88%			1.51%		
N	10997			10997		

Table 8

Forecasts of three-year-ahead earnings

This table shows the results of estimating Equation (1) for Rev_EPS (results for the year dummies are not reported). The columns "EPS for the three-year-ahead fiscal year" indicate the regression results when the dependent variables are the revisions in the EPS forecasts of the three-year-ahead fiscal year. The values reported in parentheses are t-statistics estimated using cluster-robust standard errors. ** and *** indicate statistical significance at the 0.05 and 0.01 levels, respectively.

	EPS for the three-year-ahead fiscal year		
$Tone\_PO$	0.0195	***	(3.71)
$Tone\_PS$	0.0018		(1.23)
$Tone\_MO$	0.0000		(0.01)
$Tone\_MS$	0.0003		(0.37)
$Tone\_MPT$	0.0086		(1.50)
PRev_EPS	-0.0157		(0.55)
REC	0.0003		(0.98)
MV	0.0001		(1.00)
PB	-0.0001		(0.65)
SUE	0.0007		(0.05)
ACC	0.0035		(0.54)
LOSS	-0.0001		(0.23)
ROA	-0.0003		(0.56)
D_GUI	-0.0004	**	(2.49)
CHXFIN	-0.0007		(1.52)
INST	0.0000		(0.33)
SPLIT	0.0003		(1.38)
DISPARITY	-0.0001	**	(2.43)
Controls for Year Effects	Yes		
Intercept	-0.0002		(0.22)
Adjusted R2	1.40%		
N	5398		

Table 9

Star Analyst

Panel (a) and (b) show the results of estimating Equation (3) and (4) for Rev_EPS (results for the year dummies are not reported), respectively. The values reported in parentheses are t-statistics estimated using cluster-robust standard errors. ** and *** indicate statistical significance at the 0.05 and 0.01 levels, respectively.

(a) Tones of Star Analysts

	EPS for the current fiscal year			EPS for the next fiscal year		
TONE_SO	0.0028		(1.89)	0.0081	**	(2.36)
TONE_PO	0.0060	***	(2.62)	0.0117	***	(2.98)
TONE_PS	0.0005		(1.14)	0.0016		(1.79)
TONE_MO	-0.0010		(0.37)	-0.0020		(0.35)
TONE_MS	0.0000		(0.06)	0.0008		(1.38)
TONE_MPT	0.0035		(1.02)	0.0012		(0.24)
PRev_EPS	-0.0134		(1.10)	0.0120		(0.70)
REC	0.0000		(1.06)	0.0000		(0.06)
MV	0.0000		(0.73)	0.0001		(0.48)
PB	-0.0001		(1.16)	-0.0001		(0.56)
SUE	0.0179	***	(2.79)	0.0130		(1.76)
ACC	0.0035		(1.76)	-0.0027		(0.68)
LOSS	0.0000		(0.21)	-0.0001		(0.50)
ROA	-0.0001		(0.22)	-0.0002		(0.32)
D_GUI	0.0000		(0.28)	-0.0003	**	(2.32)
CHXFIN	0.0000		(0.21)	-0.0006		(1.01)
INST	0.0000		(0.34)	0.0000		(0.67)
SPLIT	0.0001		(1.02)	0.0004		(1.72)
DISPARITY	0.0000		(1.19)	0.0000	**	(2.38)
Controls for Year Effects	Yes			Yes		
Intercept	-0.0004		(0.66)	0.0002		(0.18)
Adjusted R2	1.71%			1.36%		
N	10776			10776		

(b) Existence of Star Analysts

	EPS for the current fiscal year			EPS for the next fiscal year		
TONE_PO * STAR	0.0028		(0.63)	0.0214	***	(2.74)
TONE_PO	0.0058	**	(2.11)	0.0074		(1.74)
TONE_PS	0.0006		(1.19)	0.0017	**	(1.98)
TONE_MO	-0.0009		(0.31)	-0.0028		(0.50)
TONE_MS	0.0000		(0.14)	0.0008		(1.38)
TONE_MPT	0.0033		(0.97)	0.0008		(0.16)
STAR	0.0001		(0.85)	0.0002		(1.45)
REC	0.0000		(1.14)	0.0000		(0.08)
PRev_EPS	-0.0127		(1.05)	0.0121		(0.71)
MV	0.0000		(0.50)	0.0001		(0.51)
PB	-0.0001		(1.17)	-0.0001		(0.62)
SUE	0.0179	***	(2.79)	0.0131		(1.77)
ACC	0.0036		(1.81)	-0.0027		(0.69)
LOSS	0.0000		(0.29)	-0.0001		(0.34)
ROA	0.0000		(0.17)	-0.0002		(0.25)
D_GUI	0.0000		(0.22)	-0.0003	**	(2.37)
CHXFIN	0.0000		(0.18)	-0.0006		(1.03)
INST	0.0000		(0.41)	0.0000		(0.80)
SPLIT	0.0001		(1.23)	0.0004		(1.83)
DISPARITY	0.0000		(1.17)	0.0000	**	(2.34)
Controls for Year Effects	Yes			Yes		
Intercept	-0.0002		(0.29)	0.0001		(0.15)
Adjusted R2	1.71%			1.36%		
N	10997			10997		

Table A1

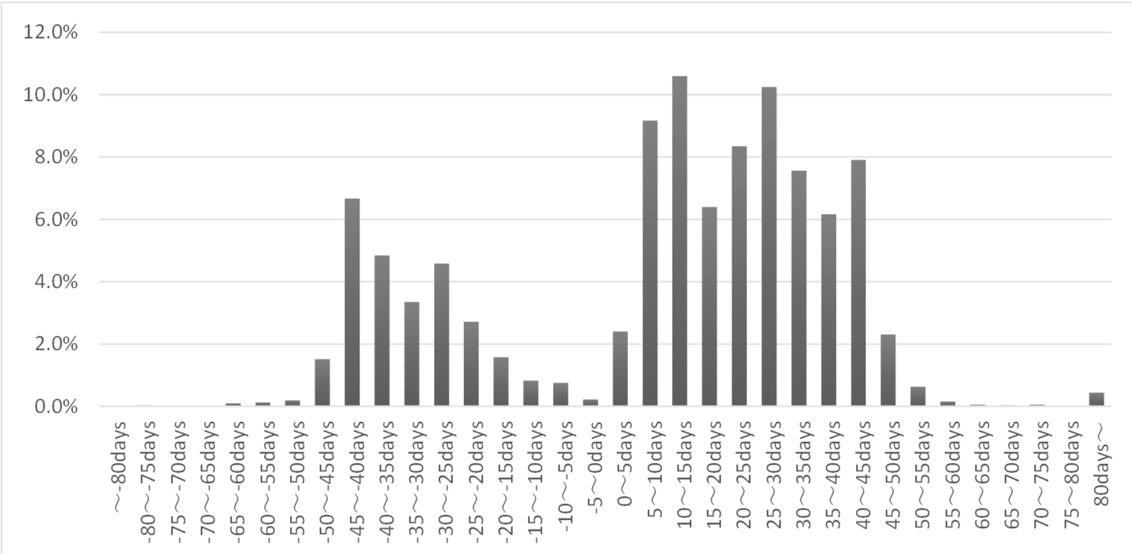
List of variables

Variables	Definition
$Rev\_EPS_{i,s}$	A revision in earnings forecast defined as the change in analyst *i*'s EPS forecasts for the current and next fiscal years for days *t* (the day of the event) through t+9 deflated by the closing price on AI day (*t*)
$Tone\_MPT_s$	A linguistic tone of management presentation of AI day *s*
$Tone\_MS_{i,s}$	A linguistic tone of management responses to analyst *i*'s comments on AI day *s*
$Tone\_MO_{i,s}$	A linguistic tone of management responses to other participants' comments for analyst *i*'s on AI day *s*
$Tone\_PS_{i,s}$	A linguistic tone of analyst *i*'s comments on AI day *s*
$Tone\_PO_{i,s}$	A linguistic tone of other participants' comments for analyst *i*'s on AI day *s*
$Tone\_SO_{i,s}$	A linguistic tone of star analysts' comments (except for analyst *i*'s ones) on AI day *s*
$PRev\_EPS_{i,s}$	A 10-day lagged revision of EPS forecast defined as the change in analyst *i*'s EPS forecasts for days t-10 through t-1 deflated by the closing price on day t-10
$PCAR_s$	A 10-day lagged abnormal return defined as cumulative abnormal returns for days t-10 through t-1, where abnormal returns are calculated based on the Fama–French three-factor model.
REC_s	A consensus recommendation, coded as strong buy = 1, buy = 0.5, hold = 0, sell = -0.5, and strong sell= -1
SUE_s	The most recent earnings surprise measured as actual earnings minus consensus (mean) EPS forecasts deflated by the stock price on the most recent earnings announcement day
MV_s	A logarithm of the market value of equity in the most recent June
ACC_s	A working capital accrual measured as the sum of 1) increases in accounts receivable, 2) increases in inventory, 3) decreases in accounts payable and accrued liabilities, 4) decreases in accrued income taxes, and 5) increases (decreases) in other assets (liabilities). ACC_s is deflated by average total assets.
ROA_s	return on assets measured as income before extraordinary items scaled by total assets
$LOSS_s$	A loss indicator variable that equals 1 if income is negative and 0 otherwise
D_GUI_s	An indicator variable that equals 1 if a firm provides earnings guidance during the current fiscal year and 0 otherwise
$INST_s$	Institutional ownership defined as the percentage of shares owned by institutions at the end of the most recent fiscal year
$CHXFIN_s$	A change in external financing defined as the sum of $\Delta EQUITY_s$ and $\Delta DEBT_s$ deflated by average total assets, where $\Delta EQUITY_s$ is the cash received from the sale of common and preferred stock less the cash used to repurchase common and preferred stock less the cash dividends paid; $\Delta DEBT_s$ is the cash received from the issuance of short- and long-term debt less the cash used to retire short- and long-term debt
$SPLIT_s$	A stock split indicator, which takes 1 (-1) if a firm conducts a stock split

	(reverse stock split) over the 12 months, and 0 otherwise
$DISPARITY_s$	The within-industry decile rank of the consensus long-term growth minus the decile rank of the implied short-term growth, where the implied short-term growth forecast is defined as the consensus EPS estimate for the current fiscal year minus the previous fiscal year's actual EPS, scaled by the absolute value of the prior fiscal year's (the most recent reported) EPS.
$Inconsistency_{i,s}$	$\begin{cases} 1 & if\ sign(Tone\_PO_{i,s}) \neq sign(Bullishness_{i,s}) \\ -1 & if\ sign(Tone\_PO_{i,s}) = sign(Bullishness_{i,s}) \end{cases}$ where $Bullishness_{i,s}$ is defined as an analyst's earnings forecast subtracted by consensus forecast at day t-1
$OPT\_EPS_{i,s}$	Ex-post optimism in earnings forecasts of analysts *i* after an AI day *s* defined as the EPS forecast on day t+9 minus the actual EPS deflated by the closing price on day t+9
$STAR_{i,s}$	A dummy variable that takes 1 if other participants of AI day *s* (for analysts *i*) includes All-American analysts with either the 1st- or 2nd-place titles

Figure 1

AI Days Relative to Earnings Announcements



This figure shows AI days relative to the closest earnings announcement date. The histogram graphs the distance between the AI day and the closest earnings announcement date, with the distance defined as the date of the AI day minus the closest earnings announcement date.