The Informational Role of Analysts' Qualitative Research Outputs

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Abstract

This study explores the reasons why textual tones in analysts' reports, a representative qualitative output of analysts' reports, possess informational value. As a driver of the informational value, I focus on non-synchronous updates of analyst's outputs. I predict that analysts' quantitative outputs are updated more slowly than qualitative outputs due to their incentive structures. As a consequence, their textual tone could contain incremental information that is not yet reflected in their quantitative outputs. Consistent with my prediction, I find that the tones predict subsequent revisions in their earnings and sales forecasts. Specifically, negative tones of sell-side analysts, who are reluctant to incorporate negative information into quantitative outputs, have stronger predictive power than positive tones; in contrast, positive tones of media analysts, who have a weak incentive to incorporate positive information, have stronger predictive power. Also, prices underreact to sell-side analysts' negative tone and media analysts' positive tone, suggesting that the lead-lag relationship between qualitative and quantitative outputs induces gradual price adjustment to the information contained in the tone.

Keywords: analyst report; textual information; report tone; earnings forecasts; sales forecasts

JEL classification: G10, G14, G20

1. Introduction

Academics and practitioners have long been interested in analyst research reports as one of the most important sources of information in stock markets. Analysts' reports provide not only quantitative

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outputs, e.g., stock recommendations, earnings and sales forecasts, and target prices, but also qualitative verbal outputs (textual information), e.g., comments regarding company performance, business strategy, and business risk. However, while many studies focus on the quantitative outputs, extant studies largely overlook the importance of textual information (Ramnath et al., 2008; Bradshaw, 2009). Specifically, although some studies show the informational value of analysts' textual tone, few studies empirically clarify the underlying reason why their textual tone has informational value beyond their quantitative outputs.

In this study, as a driver of the informational value, I focus on analysts' incentive structures that induce non-synchronous updates of each report's research outputs. While their incentive structures prevent them from incorporating information into their quantitative outputs, the text itself in analyst reports could be subject to fewer restrictions. Therefore, I predict that analysts' research outputs are not synchronously updated. Specifically, their forecasts about a company's performance, a representative quantitative output of analysts' reports, could be updated more slowly than qualitative outputs. As a result, analysts' textual tone could be informative to predict subsequent revisions in their forecasts regarding company performance. In other words, there would be the transition (propagation) of information from the report tone to their quantitative outputs, e.g., their earnings and sales forecasts.

To test my prediction, I first analyze the association of analysts' report tones with subsequent changes (revisions) in their earnings and sales forecasts. Second, I test whether the informational value (the association) is driven by analysts' incentives regarding the incorporation of the obtained information into their quantitative outputs. Analysts might utilize the report text to express uncertain information. To deny the possibility and test the plausibility of the incentive-based explanation, I compare reports from two categories of security analysts with different incentives: sell-side analysts and media analysts.

Sell-side analysts work for brokerages. They evaluate firms' prospects and recommend stocks or other securities on which their employers earn underwriting fees or retail commissions. Media analysts earn revenues by selling their services, which include financial reports, commentary, and database information.

Libby et al. (2008) and Mayew (2008) argue that sell-side analysts have less incentive to incorporate negative information into their quantitative outputs. Therefore, it is likely that quantitative outputs incorporate negative information more slowly than qualitative verbal outputs. As a consequence, information propagation from analyst's quantitative outputs to their qualitative verbal outputs is observed especially for the negative information. Since the negative information could be implied by their negative textual tone, negative tones of sell-side analysts' reports would have stronger predictive power for subsequent revisions of their earnings and sales forecasts than positive tones.

Conversely, Ahmad et al. (2016) and Garcia (2018) suggest that the general media is likely to pick up and run with negative news stories than positive. Media analysts are prone to emphasize negative information rather than positive information in their quantitative conclusions. Therefore, quantitative outputs of media analysts could incorporate positive information more slowly than qualitative verbal outputs. As a consequence, information propagation from media analyst's quantitative outputs to their qualitative verbal outputs is observed especially for the positive information. Since the positive information could be implied by their positive textual tone, positive tones of their reports would be more informative to predict subsequent forecasts revisions than negative ones.

My empirical results support the predictions. The result, first, reveals that report tones of both analysts have significant predictive power for revisions in their earnings and sales forecasts, supporting the view that the report tone reflects information that is not yet incorporated into its quantitative output. In other words, some fundamental information is firstly reflected in the qualitative verbal outputs, then their quantitative outputs reflect it with lag.

Besides, the result specifies the asymmetric features in the predictive power between the sell-side and media analysts. Negative report tones of sell-side analysts have higher predictive power for subsequent forecast revisions than positive ones. In contrast, positive tones of media analysts have higher predictive power than negative ones. Therefore, report tones of sell-side analysts contain incremental negative information that is not yet incorporated into their quantitative forecasts, while report tones of media analysts contain incremental positive information. These asymmetric features support the view that the informational value of the report tone is driven by analysts' incentive structures.

To provide further evidence for my hypothesis, I analyze the predictive power of sell-side analysts' tone for subsequent revisions in their target prices and recommendations. The result reveals that report tones of sell-side analysts have predictive power for those final outputs, and negative report tones have stronger predictive power than positive ones do. The result also supports the view that the report tones contain information that is subsequently incorporated into their quantitative outputs, and the informational value is driven by analysts' incentive structures.

Finally, I analyze whether information propagation from analyst's quantitative outputs to their qualitative verbal outputs affect stock prices. The result reveals that negative tones of sell-side analysts' reports and positive tones of media analysts' reports have predictive power for subsequent returns, suggesting that the information propagation affects prices by inducing a gradual price adjustment to the information.

Overall, my findings provide a much clearer picture regarding the information content and role of quantitative verbal outputs of financial analysts' reports.

This paper proceeds as follows. Section 2 explains our research motivation and cites related literature. Section 3 develops hypotheses. Section 4 discusses our sample and method. Section 5 describes the findings. As supplementary evidence, section 6 shows the association of the report tones with subsequent target prices and recommendations. In addition, Section 7 shows the influence on stock prices. Section 8 summarizes the paper.

2. Motivation and Related Literatures

The informational value of analyst research reports has been analyzed mainly on the basis of quantitative outputs, e.g., recommendations, earnings and sales forecasts, and target prices (Stickel, 1995; Womack, 1996; Francis and Soffer, 1997; Asquith et al., 2005). Recently, the studies of Twedt and Lee (2012) and Huang et al. (2014) show that stock prices react to the textual tone of analyst reports, and therefore, it has informational value. Despite evidence on the informational value of the textual tone, few studies empirically clarify the reason why the report tone has informational value beyond quantitative outputs.

As a driver of the informational value, I focus on non-synchronous updates of each report's research outputs. Several studies (e.g., Hwang and Lou, 2011; Miwa and Ueda, 2014) show a lead-lag relationship between quantitative outputs which could be resulted from the non-synchronous updates; levels and changes of stock recommendations are associated with subsequent earnings forecast revisions[1]. I predict that such lead-lag relationship also exists between quantitative and qualitative outputs. Specifically, since analyst's incentive structure could delay updates in quantitative outputs rather than those in qualitative verbal outputs, the report tones could signal subsequent revisions of earnings and sales forecasts. Thus, I test an association between report tones and subsequent forecast revisions.

In addition, to test whether the lead-lag relationship (the informational value of the report tones) is attributed to analysts' incentive structure, I analyze the lead-lag relation observed in not only sell-side analysts' reports but also media analysts' ones.

Prior studies show that sell-side analysts are reluctant to incorporate negative information into quantitative outputs (Das et al., 1998; Libby et al., 2008, Mayew, 2008), due to their incentives to generate underwriting business (Lin and McNichols, 1998) and trading commissions (Jackson, 2005; Irvine et al., 2007), as well as for information and access to management (Francis et al., 1997; Lim, 2001; and Libby et al., 2008). These conflicts of interest adversely affect the quality of sell-side analysts' quantitative outputs, since these conflicts disturb the reflection of information in their quantitative outputs (Michaely and Womack, 1999; Barber et al., 2007). Thus, tones of sell-side analysts could mainly contain incremental negative information that is not yet incorporated into their earnings and sales forecasts.

In contrast, the general media is more interested in negative news stories than positive ones (Ahmad et al., 2016; Garcia, 2018). Media analysts likely have a lower incentive to incorporate

[1] They argue that the relationship could be attributed to analysts' incentive to enhance their stock recommendation performance or counter the negative effects unfavorable recommendations have on analyst-management relationships.

positive information into their quantitative outputs than negative information, and thus, their quantitative outputs, e.g., earnings and sales forecasts, are more conservative than those of sell-side analysts. In fact, Toyo Keizai analysts who are highly respected media analysts in Japan (Mande, 1996) issue much more conservative earnings forecasts than sell-side analysts do. Specifically, although management earnings forecasts are quite influential in the Japanese stock market, their forecasts are more conservative than the management's, while sell-side analysts' forecasts are more optimistic than the management's (Kondo & Ota, 2010). Thus, tones of media analysts could mainly contain incremental positive information that is not yet incorporated into their earnings and sales forecasts.

A detailed analysis of the informational value of analysts' textual opinions contributes not only to existing studies with regard to the informational role of financial analysts but also to studies regarding the value of textual information in financial markets. Recently, an increasing number of financial studies have been performing textual analysis on a wide variety of texts such as: corporate disclosures (e.g., Henry, 2008; Li, 2010; Loughran and McDonald, 2011; Rogers et al., 2011; Price et al., 2012; Ferris et al., 2013; Jegadeesh and Wu, 2013; Arslan-Ayaydin et al., 2016), media articles (e.g., Tetlock, 2007; Tetlock et al., 2008; Engelberg et al., 2012; Garcia, 2012), and internet postings (e.g., Antweiler and Frank, 2004; Das and Chen, 2007; Bollen et al., 2011; Curtis et al., 2016; Bartov et al., 2018). The analysis on the report text is expected to provide further robust evidence regarding the value of qualitative (textual) information in financial markets for the following reasons. First, financial research reports are expected to contain far more essential information about a company's performance because financial analysts are considered as important professional information providers to investors. Second, since both quantitative and textual outputs are available for analysts' research reports (while only textual outputs are available for most textual information sources), the analysis on the report text has the advantage of clarifying the incremental role of qualitative outputs relative to quantitative outputs.

3. Hypotheses Development

3.1. Incremental Information in Textual Tones

As discussed in Section 1, analysts' incentive structures prevent analysts from incorporating fundamental information, including earnings and sales information, into their quantitative outputs (e.g., their earnings and sales forecasts), while qualitative verbal outputs of analyst reports could be subject to fewer restrictions. Thus, some information is firstly reflected in the qualitative verbal outputs, then their quantitative outputs reflect it with lag. In other word, the report tone, a representative qualitative output of analysts' reports, is likely to contain information which is not yet reflected in its quantitative output. In this case, the positive (negative) report tones are accompanied by subsequent positive (negative) forecast revisions. Thus, I state the following hypothesis:

H1: Tones of analysts' research reports have predictive power for revisions of their forecasts about a company's performance.

3.2. Asymmetric Informational Content

Sell-side analysts have a weak incentive to incorporate negative information, including negative earnings and sales information, into their quantitative outputs. The incorporation of negative information could be slower for their earnings and sales forecasts than for their qualitative verbal outputs. Since negative report tones of sell-side analysts could reflect such negative information, the negative report tones would signal subsequent downward revisions of their forecasts. In contrast, there are far fewer constraints and stronger incentives for sell-side analysts to incorporate positive information into their forecasts. Thus, the positive report tone is unlikely to reflect incremental positive information that is not yet reflected in their forecasts. In other words, the positive report tone is unlikely to be accompanied by subsequent upward revisions of their forecasts. Therefore, I state the following hypothesis:

H2: Negative report tones of sell-side analysts have higher predictive power when it comes to detecting revisions of their forecasts about a company's performance than positive report tones do.

Meanwhile, media analysts have a weak incentive to incorporate positive information. The incorporation of positive information could be slower for their earnings and sales forecasts than for their qualitative verbal outputs. While some positive information is likely to remain unincorporated into their forecasts, report tones of media analysts could incorporate such positive information. In this case, the positive report tones would signal subsequent upward revisions of their forecasts. In contrast, since they have a strong incentive to incorporate negative information into their forecasts, the negative tones are unlikely to reflect additional negative information beyond their forecasts. In other words, the negative report tone is unlikely to be accompanied by subsequent downward revisions of their forecasts. Thus, I state the following hypothesis:

H3: Positive report tones of media analysts have higher predictive power when it comes to detecting revisions of their forecasts about a company's performance than negative report tones do.

4. Data and Methodology

4.1. Samples

In this study, to clarify the influence of analyst’s incentives on informational value of the report tones, I compare report tones of sell-side analysts with those of media analysts. To analyze whether textual tones of media analysts contain information that is not yet reflected in their quantitative outputs, we should analyze media reports or articles that contain not only textual comments but also its quantitative outputs (specifically, its forecasts regarding a company’s performance). Thus, although several prior studies (e.g., Tetlock, 2007; Tetlock et al., 2008; Engelberg et al., 2012; Garcia, 2012) perform textual analysis on news articles (e.g., news stories of Wall Street Journal and Dow Jones News Service), news articles are not suitable samples for my analysis, because they do not contain any quantitative output.

Hence, in this study, I focus on Toyo Keizai analyst reports, as a comprehensive sample of media analysts’ reports. Toyo Keizai, Inc. is a highly respected news media publishing company in Japan, and the company’s analysts cover most of Japan’s listed firms. The analysts provide earnings and sales forecasts along with their perspective regarding company performance through brief comments. Forecasts provided by Toyo Keizai analysts are generally accepted by the Japanese securities industry as the standard publication source for media analysts’ forecasts (Mande, 1996). Therefore, to test the hypothesis, I analyze tones of their brief comments as the indicative textual tones found in media analyst reports.

I compare tones of the brief comment of Toyo Keizai reports with those of sell-side analyst reports. As Miwa (2018) argued, the brief comment of sell-side analysts for Japanese stocks mainly outlines their view and has sufficient informational value.

Brief comments and earnings and sales forecasts for media analysts' reports are garnered from Toyo Keizai fundamental database. Brief comments of sell-side analysts' reports are obtained from the Factset database. Factset manually collects the comments or requests sell-side analysts to provide the comments to augment to the database. Stock prices and accounting data are acquired from the Factset database. Stock returns are calculated based on the Japanese Yen. The review period ranges from January 2013 to December 2017 (five years), as sufficient historical data for the brief comments are available only from 2013.

I include reports for companies listed on the first section of the Tokyo Stock Exchange and covered by at least one sell-side analyst[2]. Further, I exclude those where sell-side analysts' earnings and sales forecasts for current and next fiscal years are unavailable. Additionally, in terms of sell-side reports, I exclude sell-side analysts' reports with a change in recommendation, since, as explained in the following section, upgraded and downgraded reports are used to identify positive and negative words that are utilized in calculating the report tones; I further exclude sell-side reports provided in language other than Japanese, as well as ones whose comments only give the company name or the purpose of issuing the report. When a sell-side analyst issues more than two reports for a stock within a day, only the first report is included in the sample.

4.2. Tone Measure

In terms of evaluating the report tone, I utilize the dictionary-based methodology by word lists (i.e., dictionaries). While several finance-specific dictionaries (e.g., Loughran-McDonald financial dictionary and Henry's dictionary) are available for English text analysis, there is no suitable finance-

[2] Toyo Keizai reports cover all the stocks listed on Japanese stock exchanges, while sell-side analysts mainly cover large or mid-cap stocks. To mitigate the difference in firm's size between the two samples, we limit our analysis to the stocks covered by sell-side analysts.

specific dictionary for Japanese text analysis. Thus, following the study of Kobayashi et al. (2017), which developed tone measures for analyst reports written in Japanese, the word list is originally generated from upgraded and downgraded reports of sell-side analysts[3]. Specifically, words (nouns, verbs, and adjectives) that are frequently used in upgraded (downgraded) analyst reports are considered to be positive (negative) words.

To identify positive and negative words, I extract 1,389 upgraded reports and 1,178 downgraded reports from 39,562 ones. I calculate the frequency of word *t* appearing in the brief comments of upgraded (S_U) and downgraded reports (S_D), and denote it as TF(t, S_U) and TF(t, S_D), respectively. Higher TF(t, S_U) and TF(t, S_D) implies that word *t* more frequently appeared in upgraded and downgraded reports, respectively. Next, I calculate the information entropy of word *t* for upgraded (H(t, S_U)) and downgraded reports (H(t, S_D)). Information entropy is defined as:

$$\mathrm{H}(\mathrm{t}, S_U) = -\sum_{s \in S_u} P_U(t,s) log_2 P_U(t,s)$$

$$\mathrm{H}(\mathrm{t}, S_D) = -\sum_{s \in S_d} P_D(t,s) log_2 P_D(t,s)$$

$P_U(t,s) = \frac{tf(t,s)}{\sum_{s \in S_U} tf(t,s)}$, $P_D(t,s) = \frac{tf(t,s)}{\sum_{s \in S_D} tf(t,s)}$, where $tf(t,s)$ is the frequency that word *t* appeared in comment *s*.

High H(t, S_U) (H(t, S_D)) implies that word *t* is widely and equally observed in upgraded (downgraded) reports. I calculate the degree of positiveness and negativeness of each word, and denote it as W_P(t) and W_N(t), thereby obtaining the following:

$$W_P(\mathrm{t}) = \mathrm{TF}(\mathrm{t}, S_U)\mathrm{H}(\mathrm{t}, S_U)$$

$$W_N(\mathrm{t}) = \mathrm{TF}(\mathrm{t}, S_D)\mathrm{H}(\mathrm{t}, S_D)$$

Analysts prefer to use positive words more than negative ones in their reports, therefore $W_P(\mathrm{t})$ tends to be higher than $W_N(\mathrm{t})$; in fact, $\sum W_P(\mathrm{t})$ is approximately 1.5 times higher than $\sum W_N(\mathrm{t})$. To

[3] Since Toyo Keizai analysts do not issue stock recommendations, I also utilize the word list generated by sell-side analysts' reports for calculating report tones of media analysts. However, the result reveals that report tones of media analysts have enough informational value, indicating that the word list is also useful for calculating report tones of media analysts.

adjust for this bias, I calculate adjusted $W_N(t)$ (denoted as $W_N^*(t)$) as:

$$W_N^*(\mathrm{t}) = \left(\frac{\sum \mathrm{W}_P(\mathrm{t})}{\sum \mathrm{W}_N(\mathrm{t})}\right) * \mathrm{W}_N(\mathrm{t})$$

Positive (negative) words can be defined by whether $W_P(\mathrm{t})$ ($W_N^*(\mathrm{t})$) is significantly higher than $W_N^*(\mathrm{t})$ ($W_P(\mathrm{t})$). Specifically, following the methodology of Kobayashi et al. (2017), I define positive and negative words as:

Word *t* is included in the positive words list, if $W_P(\mathrm{t}) > 2W_N^*(\mathrm{t})$

Word *t* is included in the negative words list, if $W_N^*(\mathrm{t}) > 2W_P(\mathrm{t})$

For convenience, I define the tone of individual word *t*, denoted as IT(t), as the following:

$$\mathrm{IT}(\mathrm{t}) = \begin{cases} W_P(\mathrm{t}) - W_N^*(\mathrm{t}) & W_P(\mathrm{t}) > 2W_N^*(\mathrm{t}) \; or \; W_N^*(\mathrm{t}) > 2\mathrm{W}_P(\mathrm{t}) \\ 0 & elsewhere \end{cases}$$

Positive (negative) IT(*t*) implies that word *t* is categorized into positive (negative) words. *s* denotes the sentences found in the report summary (the brief comments of sell-side analysts' reports and Toyo Keizai reports). A report's tone (denoted as TONE) is defined as follows.[4]

$$\mathrm{TONE}(s) = \sum_{t \in s} \mathrm{IT}(\mathrm{t})$$

where $t \in s$ represents the wordlist that appears in comment *s*.[5]

More positive (negative) value of $\mathrm{TONE}(s)$ indicates that the report tone is more positive (negative). In addition, I decompose $\mathrm{TONE}(s)$ into the positive (negative) report tones, denoted as TONE_P and TONE_N, respectively, as:[6]

$$\mathrm{TONE}_P(s) = \max(\mathrm{TONE}(s), 0)$$

$$\mathrm{TONE}_N(s) = \min(\mathrm{TONE}(s), 0)$$

4.3. Research Design

I focus on earnings and sales information, and analyze whether the report tone predicts subsequent revision in analyst's earnings and sales forecasts. To test the hypotheses, I run different regression

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[4] Since brief comments are highly standardized with little redundancy, TONE measure is not scaled by the number of total words. However, additional analysis reveals that the result still holds, even if TONE is scaled (the detail is available upon request).

[5] In this study, the tone measure is calculated on the basis of how many kinds of positive and negative words appear in the brief comments, aiming to mitigate the effects of redundant expressions in the brief comments. However, in untabulated analysis, I find that the result still holds, even if the measure is based on the number of positive and negative words appeared in the brief comments.

[6] $\mathrm{TONE}(s) = \mathrm{TONE}_P(s) + \mathrm{TONE}_N(s)$

models for the sell-side analysts' and media analysts' reports, since their quantitative outputs differ.

4.3.1. Sell-Side Analyst Reports

To test the hypotheses regarding sell-side analysts, I evaluate the association of the report tones with subsequent forecast revisions. Since most (approximately 70%) of analysts' forecasts are updated within 2 months, I first analyze the association between the report tone and subsequent 2-month (40-day) revisions of earnings forecasts by estimating the following regression[7]:

$$y = \alpha_0 + \beta_0 TONE + \gamma_1 EPS1\_REV + \gamma_2 EPS2\_REV + \gamma_3 TP\_REV + \gamma_4 REC + (Controls) + \varepsilon \quad (1)$$

where:

$EPS1\_REV$ = a change in EPS forecast for the current fiscal year scaled by the firm's stock price as of the publication date.

$EPS2\_REV$ = a change in EPS forecast for the next fiscal year scaled by the firm's stock price as of the publication date).

TP_REV = a change in a target price scaled by the firm's stock price as of the publication date.

REC = stock recommendation coded as: Buy=1, Hold=0, Sell=-1[8]

In addition, I include the following control variables:

PCAR = a prior nine trading days market-adjusted return (a market-adjusted return from t-10 to t-1).

SIZE = the logarithm of the market value of equity.

BM = book-to-market ratio.

The dependent variable is a change in analyst's EPS (earnings per share) forecast from t+1 to t+40 scaled by the firm's stock price as of *t* (the publication date). Specifically, we regress revisions of unreported current fiscal year's forecasts (denoted as $EPS1\_REV[2,40]$[9]) and next fiscal year's ones ($EPS2\_REV[2,40]$), separately.

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[7] In untabulated analysis, I find that the result still holds, even if I analyze the predictive power for 1-month and 3-month revisions.

[8] Due to constraints of analyst detail data provided by Factset, I used three broad categories of recommendation (buy, hold, and sell).

[9] If there is an earnings announcement from t+2 to t+40, $EPS1\_REV[2,40]$ equals EPS forecast error, defined by actual EPS minus analyst's EPS forecast (for the current fiscal year) scaled by the firm's stock price as of the publication date.

In Equation (1), I include quantitative outputs, i.e., the level of recommendation (REC)[10], revisions of earnings forecasts (EPS1_REV and EPS2_REV[11]), and a revision of target price (TP_REV), as control variables. The regression also includes several control variables. Since analysts may piggyback on recent news or events, I, therefore, include market-adjusted returns from nine trading days prior to the report date (PCAR). To control for forecast accuracy, stemming from firm characteristics, I include firm size (SIZE), measured as the logarithm of the market value of equity, and book-to-market ratio (BM). Multiple analysts could possibly follow the same firm, and multiple reports for the firm could be issued on the same date. Therefore, standard errors in all empirical tests are estimated with two-way cluster control for the firm and publication date.

To analyze the difference in informational content between positive and negative tones, I run the following regression model.

$$y = \alpha_0 + \beta_P TONE_P + \beta_N TONE_N + \gamma_1 EPS1\_REV + \gamma_2 EPS2\_REV + \gamma_3 TP\_REV + \gamma_4 REC + (Controls) + \varepsilon \qquad (2)$$

The dependent variable is $EPS1\_REV[2,40]$ or $EPS2\_REV[2,40]$. As argued in Section 3.2., since a strong negative report tone (negative $TONE_N$) could signal subsequent negative revision in earnings forecasts (negative $\mathrm{EPS\_REV1}[2,40]$ or negative $\mathrm{EPS\_REV2}[2,40]$), the report tone, specifically, a negative tone ($\mathrm{TONE_N}$), could be positively associated with subsequent earnings forecast revisions. Thus, a coefficient of $\mathrm{TONE_N}$ would be significantly positive. In contrast, since the positive tones are less likely to contain additional positive information beyond their forecast, a coefficient of $\mathrm{TONE_P}$ would be statistically insignificant or would have less statistical significance than a coefficient of $\mathrm{TONE_N}$.

In addition to earning-related information in the report tone, I analyze sales-related information in the tone. To this end, I analyze whether the report tones have predictive power for detecting revisions in analysts' sales forecasts, by analyzing the association between sell-side analysts' report tones and subsequent two-month revisions of their sales forecasts. I estimate the following regressions:

[10] As mentioned in Section 4.1., I exclude sell-side analysts' reports with a change in recommendation from the sample. As such, I do not include a change in stock recommendation as a control variable.
[11] $EPS1\_REV$ and $EPS2\_REV$ are equivalent to $EPS1\_REV[0,0]$ and $EPS2\_REV[0,0]$, respectively.

$$y = \alpha_0 + \beta_0 TONE + \gamma_1 SALES1\_REV + \gamma_2 SALES2\_REV + \gamma_3 TP\_REV + \gamma_4 REC + (Controls) + \varepsilon \quad (3)$$

$$y = \alpha_0 + \beta_P TONE_P + \beta_N TONE_N + \gamma_1 SALES1\_REV + \gamma_2 SALES2\_REV + \gamma_3 TP_{REV} + \gamma_4 REC + (Controls) + \varepsilon \quad (4)$$

The dependent variable is $SALES1\_REV[2,40]$ or $SALES2\_REV[2,40]$, where $SALES1\_REV[2,40]$ and $SALES2\_REV[2,40]$ are changes in sales forecast for the current fiscal year and next fiscal year from t+1 to t+40 scaled by market capitalization, respectively. I separately analyze the predictive power of the tone measures for $SALES1\_REV[2,40]$ and $SALES2\_REV[2,40]$. If there is an earnings announcement from t+2 to t+40, $SALES1\_REV[2,40]$ equals the sales forecast error, defined by actual sales minus the analyst's sales forecast (for the current fiscal year) scaled by market capitalization.

Similar to Equation (1), I include REC, TP_REV, PCAR, SIZE, and BM as control variables. Additionally, to consider the serial correlation of forecast revisions, I include SALES1_REV and SALES2_REV, defined by changes in an analyst's sales forecast for both the current and next fiscal years scaled by market capitalization as of the publication date[12].

By estimating Equation (4), I analyze the difference in predictive power for subsequent revision in analyst's sales forecast between positive and negative tones. If the report tone of sell-side contains negative information that is not yet incorporated into sales forecasts, a negative report tone (negative $\mathrm{TONE_N}$) would signal subsequent negative revisions in sales forecasts; the coefficient of $\mathrm{TONE_N}$ would be significantly positive. In contrast, the coefficient of $\mathrm{TONE_P}$ would be statistically insignificant or have less statistical significance than the coefficient of $\mathrm{TONE_N}$.

4.3.2. Media Analyst Reports

To test the hypothesis regarding media analysts, I analyze the predictive power of media analysts' report tones for subsequent forecast revisions. I first analyze the association between report tones of media analysts and corresponding earnings forecast revisions by estimating the following regression:

$$y = \alpha_0 + \beta_0 TONE + \gamma_1 EPS1\_REV + \gamma_2 EPS2\_REV + (Controls) + \varepsilon \quad (5)$$

[12] SALES1_REV and SALES2_REV are equivalent to SALES1_REV[0,0] and SALES2_REV[0,0], respectively.

The dependent variable is $EPS1\_REV[2,40]$ or $EPS2\_REV[2,40]$; I separately analyze the predictive power of the tone measures for $EPS1\_REV[2,40]$ and $EPS2\_REV[2,40]$. I include EPS1_REV, EPS2_REV, PCAR, SIZE, and BM as control variables. Media (Toyo Keizai) analysts do not issue stock recommendations and target prices; therefore, I do not include stock recommendations (REC) and revisions of target prices (TP_REV), as control variables. To analyze the differences in informational content between positive and negative tones, I run the following regression model for $EPS1\_REV[2,40]$ and $EPS2\_REV[2,40]$:

$$y = \alpha_0 + \beta_P TONE_P + \beta_N TONE_N + \gamma_1 EPS1\_REV + \gamma_2 EPS2\_REV + (Controls) + \varepsilon \qquad (6)$$

As argued in Section 3.2., since report tones of media analysts could contain positive information that will be gradually incorporated into their earnings forecast, the positive tones would signal subsequent positive revision of their earnings forecasts. Thus, a stronger positive tone (higher $\mathrm{TONE_P}$) would be accompanied by higher subsequent earnings forecast revisions; a coefficient of $\mathrm{TONE_P}$ would be significantly positive. In contrast, since the negative tones are less likely to reflect additional negative information, a negative report tone ($\mathrm{TONE_N}$) would have a weaker association with subsequent forecast revisions. Consequently, a coefficient of $\mathrm{TONE_N}$ would be statistically insignificant or have less statistical significance than the coefficient of $\mathrm{TONE_P}$.

I then analyze the association between media analysts' report tones and subsequent sales forecast revisions by estimating the following regressions:

$$y = \alpha_0 + \beta_0 TONE + \gamma_1 SALES1\_REV + \gamma_2 SALES2\_REV + (Controls) + \varepsilon \qquad (7)$$

$$y = \alpha_0 + \beta_P TONE_P + \beta_N TONE_N + \gamma_1 SALES1\_REV + \gamma_2 SALES2\_REV + (Controls) + \varepsilon \qquad (8)$$

The dependent variable is $SALES1\_REV[2,40]$ or $SALES2\_REV[2,40]$. Similar to equations (5) and (6), I include PCAR, SIZE, and BM as control variables. To account for the serial correlation of forecast revisions, I include SALES1_REV and SALES2_REV.

Since positive report tones of media analysts could signal subsequent upward revisions in their sales forecasts, a positive tone ($\mathrm{TONE_P}$) would be associated with subsequent forecast revisions. Conversely, a negative report tone ($\mathrm{TONE_N}$) would have a weaker association with subsequent sales forecast revisions. Therefore, the coefficient of $\mathrm{TONE_P}$ would be significantly positive, whereas the coefficient of $\mathrm{TONE_N}$ would be statistically insignificant or have less statistical significance than the coefficient of $\mathrm{TONE_P}$

5. Empirical Results

5.1 Descriptive Statistics and Correlations

As described in Section 4.2., positive and negative words are selected by utilizing sell-side analyst reports for which recommendations are upgraded or downgraded. As a result, 28 positive words and 33 negative ones are selected to calculate the report tones.

My sample consists of 36,991 sell-side analyst's reports. As indicated in Table 1(a), within the sample, 14,026 reports (37.9%) recommend buying and 3,339 reports (9.0%) recommend selling; the number of buy-recommendations exceeds that of sell-recommendations. In terms of revisions of quantitative outputs, the number of upward revisions is larger than that of downward revisions; the number of positively revised earnings forecasts for the current fiscal year (9,532) exceeds that of negatively revised ones (8,269); the number of positively revised earnings forecasts for the next fiscal year (9,806) also exceeds those of negatively revised ones (8,042). The target prices of 9,787 reports (26.5%) are revised upward, and those of 4,869 reports (13.2%) are revised downward. In terms of TONE measures, the number of reports with a positive TONE (i.e., positive-tone reports) is 14,317 (38.7%), which is greater than those with a negative one (4,705; 12.7%).

As evident from Table 1(b), my sample consists of 16,585 media analyst's reports; within the sample, the number of upward revisions is also greater than that of downward revisions. In terms of TONE measures, there are 12,239 positive-tone reports (73.8%) and 3,375 negative-tone ones (20.3%).

Tables 2(a) and (b) indicate the correlation of TONE measures with other variables. Report tones of both sell-side analysts and media analysts have no strong association with their quantitative outputs (recommendation, revisions in earnings and sales forecasts and target prices). In addition, since there is no significant association with returns during the nine trading days immediately prior to the report date (PCAR), it is unlikely that the tone simply reflects recent events and news. Thus, these results might indicate that the report tone contains independent information.

[Table 1]

[Table 2]

5.2. Results of Sell-Side Analyst Reports

Table 3 marks the association of the sell-side analysts' report tones with subsequent earnings forecast revision. The table presents the results from estimating regressions for equations (1) and (2).

In terms of association of quantitative outputs with earnings forecast revisions, the result reveals that subsequent revisions of earnings forecasts for current and next fiscal years (EPS1_REV[2,40] and EPS2_REV[2,40]) have a positive association with TP_REV (i.e., a change in the target price), indicating that a change in the target price might contain incremental information.

The table (i.e., the first column in Table 3) reveals that the report tones (TONE) have additional predictive power for EPS1_REV [2,40] (subsequent revisions of earnings forecast for the current fiscal year) and EPS2_REV [2,40] (subsequent revisions of earnings forecast for the next fiscal year). The estimated coefficient of 0.0027 for TONE related to EPS1_REV [2,40] and that of 0.0016 related to EPS2_REV [2,40] are statistically significant, indicating that higher (lower) report tone of sell-side analysts is accompanied by a subsequent positive (negative) revision of their earnings forecasts for the current and next fiscal years. These results support H1.

The table (i.e., the second and third columns in Table 3) reveals that the negative tones, rather than the positive ones, have predictive power for EPS1_REV [2,40] and EPS2_REV [2,40]. In terms of predictive power for EPS1_REV [2,40], although both estimated coefficients on $TONE_P$ and $TONE_N$ are statistically significant, the statistical significance is higher for $TONE_N$ than $TONE_P$. In addition, an association with EPS2_REV [2,40] is only statistically significant for $TONE_N$. On an average, a one-standard-deviation decrease in $TONE_N$ (i.e., indicating a stronger negative tone) lowers EPS2_REV[2,40] by 2.4 basis points, while the increase in $TONE_P$ (i.e., a stronger positive tone) heightens EPS2_REV[2,40] by only 0.7 basis points. This result indicates that negative tones have higher predictive power for subsequent revisions in their earnings forecasts than positive tones do, suggesting that report tones of sell-side analysts contain incremental negative information. This finding is consistent with sell-side analysts' weak incentives to incorporate negative information into their quantitative output, supporting H2.

Table 4 matches the association of the sell-side analysts' report tones with subsequent sales forecast revisions. The tables present the results from estimating regressions for equations (3) and (4).

In terms of association of quantitative outputs with sales forecast revisions, the result reveals that subsequent revisions of sales forecast for the current fiscal year ($\mathrm{SALES1\_REV}[2,40]$) has a negative association with a stock recommendation (REC) , thereby indicating the sales forecast is more optimistic for a report with a more favorable recommendation (i.e., higher REC). This is consistent with the findings of previous studies (e.g., Eames et al., 2002).

The estimated coefficient of TONE for $\mathrm{SALES1\_REV}[2,40]$ (0.0043) is statistically significant. In terms of predictive power for $\mathrm{SALES2\_REV}[2,40]$, although the estimated coefficient of TONE (0.0041) is insignificant, the estimated coefficient of the negative tone ($TONE_N$) for $\mathrm{SALES2\_REV}[2,40]$ (0.0187) are statistically significant. Thus, regarding the predictive power for detecting sales forecast revisions, the result also supports H1. In addition, the statistical significance of the estimated coefficients for $\mathrm{SALES1\_REV}[2,40]$ is higher for $TONE_N$ than $TONE_P$, and an association with $\mathrm{SALES2\_REV}[2,40]$ is only statistically significant for $TONE_N$. Consequently, the results support H2 and the view that the negative report tones generated by sell-side analysts, in contrast to positive ones, contain incremental information that is not yet incorporated in their sales forecasts.

[Table 3]

[Table 4]

5.3. Result of Media Analyst Reports

Table 5 denotes an association between media analysts' report tones and subsequent earnings forecast revisions, summarizing the results from estimating the regression of equations (5) and (6).

The result reveals that a report tone has predictive power for EPS2_REV[2,40]. The first column in Table 5 reveals that the estimated coefficients for TONE related to EPS2_REV[2,40] are statistically significant, supporting H1.

The table (the second and third columns in Table 5) reveals that the estimated coefficients for

$TONE_P$ related to EPS2_REV[2,40] is statistically significant. Meanwhile, those for $TONE_N$ related to EPS1_REV[2,40] and EPS2_REV[2,40] are insignificant. These results indicate that positive report tones of media analysts have higher predictive power for subsequent forecast revisions than negative tones do, supporting H3.

Table 6 indicates associations of media analysts' report tones with subsequent revisions of their sales forecasts, summarizing the results rendered from estimating regressions based on equations (7) and (8). The estimated coefficients of TONE for SALES1_REV[2,40] is statistically significant. This outcome indicates that the report tones have predictive power pertaining to subsequent forecast revisions (SALES_REV1[2,40]), supporting H1.

The second and fourth columns reveal that SALES1_REV[2,40] and SALES2_REV[2,40] have no significant association with $TONE_N$, but SALES1_REV[2,40] does have a significant association with $TONE_P$. Thus, positive report tones, rather than negative ones, have predictive power for sales forecast revisions. These results support H3 and suggest that the positive report tones of media analysts, rather than negative ones, contain incremental information which is not yet reflected in their sales forecasts.

The evidence suggests that report tones of media analysts mainly contain incremental positive earnings and sales information, while those of sell-side analysts contain incremental negative earnings and sales information.

Overall, the asymmetric features in the informational content between sell-side analysts and media analysts are consistent with a difference in their incentive structure regarding the incorporation of obtained information into their quantitative outputs. The results support the view that informational value of the textual opinion is driven by the analysts' incentive structure.

[Table 5]

[Table 6]

6. Predictive Power for Other Quantitative Measures

To provide additional robust evidence for the hypotheses, I analyze the predictive power of the report tones for subsequent revisions in analysts' target prices and their stock recommendations. Changes in target prices and stock recommendations reflect not only fundamental information but also changes in the discount rate.[13] In addition, stock recommendations and target prices are not available for media (*Toyo Keizai*) analysts' reports. However, the analysis is expected to provide further evidence regarding the informational value of the report tones of sell-side analysts when testing H1 and H2.

Analysts' recommendations and target prices could be updated more slowly than their textual opinion due to their incentive structures. In this case, there would be a lead-lag relationship between the textual tone and stock recommendation and that between the tone and target price. In other words, the report tone would predict subsequent revisions of their stock recommendations and target prices. Specifically, it is likely that the report tones of sell-side analysts contain incremental negative information that is not yet reflected in their stock recommendation and target price, due to their weak incentive to incorporate negative information into these quantitative outputs. Therefore, the negative tones would be associated with subsequent revisions within their recommendations and those within their target prices, while the positive tones would not.

To test the predictions, I first analyze the association between the report tones of sell-side analysts and subsequent two-month revisions of their stock recommendations $REC\_REV[2,40]$, defined by a change in REC from t+1 to t+40, by estimating the following regressions for $REC\_REV[2,40]$:

$$y = \alpha_0 + \beta_0 TONE + \gamma_1 EPS1\_REV + \gamma_2 EPS2\_REV + \gamma_3 SALES1\_REV + \gamma_4 SALES2\_REV + \gamma_5 TP\_REV + \gamma_6 REC + (Controls) + \varepsilon \quad (9)$$

I include PCAR, SIZE, and BM as control variables. I also include EPS1_REV, EPS2_REV, SALES1_REV, SALES2_REV, REC, and TP_REV, since these measures can be considered as supplemental information pertinent to future stock recommendation revisions. To analyze the differences in informational content between positive and negative tones, I run the following regression model for $REC\_REV[2,40]$.

$$y = \alpha_0 + \beta_P TONE_P + \beta_N TONE_N + \gamma_1 EPS1\_REV + \gamma_2 EPS2\_REV + \gamma_3 SALES1\_REV +$$

[13] In addition, changes on stock recommendation might be induced by stock price movements.

$\gamma_4 SALES2\_REV + \gamma_5 TP\_REV + \gamma_6 REC + (Controls) + \varepsilon$ (10)

I finally analyze the association between sell-side analysts' report tones and subsequent two-month revisions of their target prices (denoted as $TP\_REV[2{,}40]$, defined by a change in the target price from t+1 to t+40, scaled by the stock price) by applying the regression model on equations (9) and (10) for $TP\_REV[2{,}40]$.

Table 7 denotes an association between sell-side analysts' report tones and the subsequent revisions of their target prices and recommendations, respectively. In terms of the association of quantitative outputs with subsequent recommendation and target revisions, the result reveals that they have a negative association with REC (i.e., the level or degree of stock recommendation), thereby indicating some mean reversion in stock recommendations and excessive optimism for a report with a favorable recommendation.

The estimated coefficients on TONE for $TP\_REV[2{,}40]$ and $REC\_REV[2{,}40]$ (0.0337 and 0.0446, respectively) are statistically significant. That outcome indicates that the report tones have predictive power for subsequent revisions in stock recommendations and target prices, supporting the view that the report tone contains information not reflected in their quantitative outputs.

Although both estimated coefficients on $TONE_P$ and $TONE_N$ for $REC\_REV[2{,}40]$ (0.0325 and 0.0983, respectively) are statistically significant, the statistical significance is higher for $TONE_N$ than $TONE_P$. In addition, an association with $TP\_REV[2{,}40]$ is only statistically significant for $TONE_N$. Thus, the results support the view that negative report tones of sell-side analysts, rather than positive report tones, contain additional information that is not yet reflected in their stock recommendations and target prices.

Overall, similar to the results pertaining to earnings and sales information in the report tone, these results reveal that report tones of sell-side analysts contain incremental negative information. This finding is consistent with the weak incentive of sell-side analysts to incorporate negative information into their quantitative outputs. Thus, the results also support the view that the informational value of the report tones is driven by analysts' incentive structures.

[Table 7]

7. Gradual Price Adjustment

The results shown in previous sections suggest that some information is first incorporated into qualitative verbal outputs, and then quantitative outputs reflect the information with a lag. Since quantitative information is much more easily processed than qualitative verbal information, investors (prices) might react to the information contained in the report tone, after quantitative outputs reflect it. Thus, the gradual transition (propagation) of the information from qualitative outputs to quantitative outputs might result in a gradual price adjustment (underreaction) to the information contained in the report tone.

To test this prediction, I analyze the association between the report tones and subsequent returns. Specifically, since I analyzed the association of the report tone with subsequent 2-month (40-day) revisions of earnings and sales forecasts, I analyze the association with subsequent two-month market-adjusted returns $CAR[2,40]$, defined by a cumulative stock return relative to the value-weighted return from t+1 to t+40[14]. Since negative tones of sell-side analysts' reports and positive tones of media analysts' ones contain incremental earnings and sales information, a gradual price adjustment could be observed for these tones. In other words, in terms of sell-side analysts, $CAR[2,40]$ is significantly associated with their negative tones rather than their positive tones; in terms of media analysts, $CAR[2,40]$ is significantly associated with their positive tones rather than their negative tones.

To test the predictions regarding sell-side analysts, I estimate the regressions (9) and (10) for $CAR[2,40]$. To test the predictions regarding media analysts, I estimate the following regressions for $CAR[2,40]$.

$$y = \alpha_0 + \beta_0 TONE + \gamma_1 EPS1\_REV + \gamma_2 EPS2\_REV + \gamma_3 SALES1\_REV + \gamma_4 SALES2\_REV + (Controls) + \varepsilon \quad (11)$$

$$y = \alpha_0 + \beta_P TONE_P + \beta_N TONE_N + \gamma_1 EPS1\_REV + \gamma_2 EPS2\_REV + \gamma_3 SALES1\_REV + \gamma_4 SALES2\_REV + (Controls) + \varepsilon \quad (12)$$

[14] I also analyze the association with $CAR[2,10]$ and $CAR[2,20]$. I find that the result still holds.

Table 8 denotes an association between sell-side analysts' report tones and subsequent returns. The result reveals that the coefficient of $TONE_N$ is significantly positive, while the coefficient of $TONE_P$ is insignificant. On average, a one standard deviation decrease in $TONE_N$ decreases the return by 13 basis points. Meanwhile, that of positive report tones ($TONE_P$) have no significant association with CAR[2,40]. The results indicates that prices underreact only to the negative report tones. The negative tones of sell-side analysts' reports are accompanied with not only subsequent downward revisions in earnings and sales forecasts but also subsequent negative market-adjusted returns.

Table 9 denotes an association between media analysts' report tones and subsequent returns. The result reveals that the coefficient of $TONE_P$ is significantly positive indicating that the positive report tones (positive $TONE_P$) are accompanied with subsequent positive returns. On average, a one standard deviation increase in $TONE_p$ increases the return by 31 basis points. On the other hand, that of negative report tones ($TONE_N$) have no significant association with CAR[2,40].

The results support the view that the gradual transition of the information from qualitative verbal outputs to quantitative output affects stock prices by inducing a gradual price adjustment to the information contained in the report tone.

[Table 8]

[Table 9]

8. Conclusion

Analysts' incentives and constraints could delay reflecting information in their quantitative outputs, e.g., earnings and sales forecasts. There might be fewer obstacles to express the information in text; therefore, their opinion in the report text itself, i.e., textual report tone, could contain incremental information that is not yet incorporated into their quantitative outputs.

In this paper, I test the given prediction by clarifying informational contents regarding report tones of sell-side and media analysts. First, I examine whether the textual tones of both analysts predict subsequent revisions in their earnings and sales forecasts. Second, I analyze a difference in informational value of report tones between sell-side analysts and media analysts, examining whether the difference is consistent with their different incentive structures. This analysis clarifies whether the predictive power (the informational value) is induced by analysts' incentive structure.

The empirical results reveal that report tones of both the sell-side and media analysts have predictive power for subsequent revisions of their earnings and sales forecasts, suggesting that the report tone contains incremental earnings and sales information. In addition, report tones of sell-side analysts contain incremental negative information that is not yet reflected in their earnings and sales forecasts. In contrast, those of media analysts contain incremental positive information not reflected in their forecasts. This finding is consistent with a weak incentive of sell-side analysts to incorporate negative information into their quantitative outputs and a weak incentive of media analysts to incorporate positive information. Thus, the finding supports the view that the informational value of the report tone is driven by analysts' incentive structures. Additional analysis reveals that stock prices underreact specifically to the negative tones of sell-side analysts and the positive tones of media analysts. The results support the view that the gradual transition (propagation) of the information from qualitative verbal outputs to quantitative outputs affect stock prices by inducing gradual price adjustment to the information.

Although previous studies empirically show that the report tone has informational value, few studies empirically clarify the underlying reason. First, my study contribute to the studies by exhibiting that the report tones contain sales and earnings information that is not yet reflected in their forecasts. Second, the study raises the possibility that the incremental information is induced by analysts' incentive structures. Although previous studies argue that such incentives might affect informational value in report text, no study provides such evidence, and mine is the first to do so, by showing the asymmetric features in informational content seen in the report tones between sell-side and media analysts.

Overall, the analyses provide a much clearer picture regarding the informational content of textual opinion. The analyses contribute to not only existing studies regarding the informational role of financial analysts but also studies regarding the value of textual information in financial markets.

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Table 1

Descriptive Statistics

Panels (a) and (b) report the descriptive statistics for the sell-side reports and media analysts, respectively. The "Mean" row shows the average value. "Median" shows the median value. "Std" shows the standard deviation. "#(>0)," "#(<0)," and "#(=0)" show the number of values greater than zero, the number of the negative value, and the number of zero values, respectively. "Ratio(>0)," "Ratio(<0)," and "Ratio(=0)" show the probability that the value is greater than zero, or negative, or that it is zero, respectively.

a) Sell-side analyst's reports

	Mean	Median	Std	# (>0)	Ratio(>0)	#(<0)	Ratio(<0)	# (=0)	Ratio(=0)
TONE	0.0398	0.0000	0.1052	14317	38.7%	4705	12.7%	17969	48.6%
$TONE_P$	0.0511	0.0000	0.0919	14317	38.7%	0	0.0%	22674	61.3%
$TONE_N$	-0.0113	0.0000	0.0384	0	0.0%	4705	12.7%	32286	87.3%
REC	0.2889	0.0000	0.6213	14026	37.9%	3339	9.0%	19626	53.1%
EPS1_REV	-0.0011	0.0000	0.0285	9532	25.8%	8269	22.4%	19190	51.9%
EPS2_REV	-0.0001	0.0000	0.0114	9806	26.5%	8042	21.7%	19143	51.8%
SALES1_REV	-0.0008	0.0000	0.0828	8532	23.1%	7339	19.8%	21120	57.1%
SALES2_REV	-0.0007	0.0000	0.1242	8609	23.3%	7124	19.3%	21258	57.5%
TP_REV	0.0140	0.0000	0.0985	9787	26.5%	4869	13.2%	22335	60.4%
PCAR	0.14%	-0.08%	5.03%	18177	49.1%	18811	50.9%	0	0.0%
MV	5.7436	5.7316	0.5586	-	-	-	-	-	-
BM	0.7569	0.6824	0.4217	-	-	-	-	-	-
EPS1_REV[2,40]	-0.09%	0.00%	0.83%	8032	21.7%	7588	20.5%	21371	57.8%
EPS2_REV[2,40]	0.08%	0.00%	0.60%	9279	25.1%	5872	15.9%	21840	59.0%
SALES1_REV[2,40]	0.05%	0.00%	2.45%	7427	20.1%	6036	16.3%	23528	63.6%
SALES2_REV[2,40]	0.55%	0.00%	4.13%	8449	22.8%	5004	13.5%	23538	63.6%

b) Media analyst's reports

	Mean	Median	Std	# (>0)	Ratio(>0)	#(<0)	Ratio(<0)	# (=0)	Ratio(=0)
TONE	0.1240	0.0857	0.1765	12239	73.8%	3375	20.3%	971	5.9%
$TONE_P$	0.1433	0.0857	0.1515	12239	73.8%	0	0.0%	4346	26.2%
$TONE_N$	-0.0193	0.0000	0.0516	0	0.0%	3375	20.3%	13210	79.7%
EPS1_REV	-0.0009	0.0000	0.0284	6246	39.1%	4307	27.0%	5428	34.0%
EPS2_REV	0.0001	0.0000	0.0106	4134	25.9%	2815	17.6%	9032	56.5%
SALES1_REV	-0.0035	0.0000	0.1760	4908	30.7%	3963	24.8%	7110	44.5%
SALES2_REV	-0.0049	0.0000	0.1677	3036	19.0%	2572	16.1%	10373	64.9%
PCAR	0.13%	-0.20%	6.46%	7705	48.2%	8274	51.8%	0	0.0%
MV	5.2088	5.1591	0.6295	-	-	-	-	-	-
BM	0.8609	0.7778	0.5578	-	-	-	-	-	-
EPS1_REV[2,40]	-0.0001	0.0000	0.0039	1091	6.6%	1119	6.7%	14375	86.7%
EPS2_REV[2,40]	0.0000	0.0000	0.0022	803	4.8%	1045	6.3%	14737	88.9%
SALES1_REV[2,40]	-0.0003	0.0000	0.0089	743	4.5%	719	4.3%	15123	91.2%
SALES2_REV[2,40]	-0.0001	0.0000	0.0117	558	3.4%	508	3.1%	15519	93.6%

Table 2

Correlations

Panels (a) and (b) show Pearson’s correlations between the variables for the sell-side analysts’ sample and media analysts’ reports, respectively.

a) Sell-side analyst’s reports

	TONE	REC	EPS1_REV	EPS2_REV	SALES1_REV	SALES2_REV	TP_REV	PCAR	MV	BM
TONE		0.099	0.012	0.050	0.005	0.010	0.091	0.037	-0.034	-0.008
REC			0.018	0.001	0.005	0.011	0.039	0.010	0.088	-0.098
EPS1_REV				0.126	0.225	0.210	0.143	0.028	0.051	-0.097
EPS2_REV					0.171	0.167	0.390	0.101	0.040	-0.056
SALES1_REV						0.756	0.157	0.026	0.025	-0.055
SALES2_REV							0.155	0.015	0.022	-0.051
TP_REV								0.180	0.022	-0.095
PCAR									0.012	-0.021
MV										-0.220

b) Media analyst’s reports

	TONE	EPS1_REV	EPS2_REV	SALES1_REV	SALES2_REV	PCAR	MV	BM
TONE		0.027	0.049	0.035	0.030	0.037	0.010	-0.143
EPS1_REV			0.299	0.214	0.136	0.010	0.039	-0.068
EPS2_REV				0.117	0.131	0.012	0.052	-0.042
SALES1_REV					0.610	0.016	0.025	-0.059
SALES2_REV						0.018	0.018	-0.053
PCAR							-0.050	-0.125
MV								-0.186

Table 3

Sell-Side Analysts' Report Tones and Earnings Forecast Revisions

Table 3 presents the association of sell-side analysts' report tones with earnings forecast revisions, presenting the results from estimating the regressions on equations (1) and (2) for $EPS1\_REV[2,40]$ and $EPS2\_REV[2,40]$, respectively. The columns of "Eq. (1)" and "Eq. (2)" signify estimation results of equations (1) and (2), respectively. Standard errors are estimated with two-way cluster control at the firm and on the date of publication. **, *** indicate statistical significance at the 0.05 and 0.01 levels, respectively.

	EPS1_REV[2,40]		EPS2_REV[2,40]	
	Eq.(1)	Eq.(2)	Eq.(1)	Eq.(2)
TONE	0.0027 ***		0.0016 ***	
	(4.73)		(4.70)	
$TONE_P$		0.0017 ***		0.0004
		(2.99)		(1.25)
$TONE_N$		0.0072 ***		0.0066 ***
		(4.87)		(7.04)
REC	-0.0002	-0.0002	0.0000	-0.0001
	(0.94)	(1.03)	(0.61)	(0.82)
EPS1_REV	0.0022	0.0023	-0.0016	-0.0015
	(1.26)	(1.27)	(0.56)	(0.56)
EPS2_REV	0.0053	0.0052	-0.0051	-0.0052
	(0.82)	(0.79)	(1.07)	(1.10)
TP_REV	0.0015 ***	0.0014 ***	0.0014 ***	0.0014 ***
	(3.03)	(2.94)	(3.02)	(2.92)
SIZE	-0.0003	-0.0003	0.0002 ***	0.0002 **
	(0.62)	(0.65)	(2.63)	(2.46)
BM	0.0000	0.0000	0.0003 **	0.0004 **
	(0.10)	(0.09)	(2.51)	(2.55)
PCAR	0.0055 ***	0.0054 ***	0.0056 ***	0.0056 ***
	(4.72)	(4.71)	(5.05)	(5.03)
Intercept	0.0009	0.0010	-0.0008	-0.0006
	(0.33)	(0.40)	(1.54)	(1.15)
Adj. R2	0.37%	0.41%	0.44%	0.55%

Table 4

Sell-Side Analysts' Reports Tone and Sales Forecast Revisions

Table 4 marks the association of sell-side analysts' report tones with sales forecast revisions, presenting the results from estimating the regression on equations (3) and (4) for $SALES1\_REV[2{,}40]$ and $SALES2\_REV[2{,}40]$. The columns of "Eq. (3)" and "Eq. (4)" show estimation results of equations (3) and (4), respectively. Standard errors are estimated with two-way cluster control at the firm and on the date of publication. **, *** indicate statistical significance at the 0.05 and 0.01 levels, respectively.

	SALES1_REV[2,40]		SALES2_REV[2,40]	
	Eq.(3)	Eq.(4)	Eq.(3)	Eq.(4)
TONE	0.0043 ***		0.0041	
	(3.74)		(1.85)	
$TONE_P$		0.0030 **		0.0008
		(2.19)		(0.33)
$TONE_N$		0.0101 **		0.0187 ***
		(2.49)		(2.78)
REC	-0.0012 ***	-0.0012 ***	0.0004	0.0004
	(3.92)	(4.01)	(0.83)	(0.74)
SALES1_REV	-0.0002	-0.0002	0.0145 **	0.0145 **
	(0.06)	(0.07)	(2.26)	(2.25)
SALES2_REV	0.0003	0.0003	-0.0055	-0.0055
	(0.27)	(0.28)	(1.47)	(1.46)
TP_REV	0.0035 ***	0.0034 **	0.0033	0.0032
	(2.58)	(2.53)	(1.20)	(1.14)
SIZE	0.0006	0.0006	-0.0009	-0.0009
	(1.77)	(1.73)	(1.51)	(1.58)
BM	-0.0014 **	-0.0014 **	0.0017	0.0017
	(2.34)	(2.33)	(1.59)	(1.60)
PCAR	0.0076 **	0.0076 **	0.0078	0.0077
	(2.33)	(2.32)	(1.25)	(1.24)
Intercept	-0.0018	-0.0016	0.0090 **	0.0096 ***
	(0.87)	(0.77)	(2.48)	(2.66)
Adj. R2	0.22%	0.23%	0.10%	0.12%

Table 5

Media Analyst's Report Tones and Earnings Forecast Revisions

Table 5 marks the association of media analysts' report tones with earnings forecast revisions, summarizing the results from estimating the regression of equations (5) and (6) for $EPS1\_REV[2,40]$ and $EPS2\_REV[2,40]$, respectively. The columns of "Eq. (5)" and "Eq. (6)" determine the estimation results of equations (5) and (6), respectively. Standard errors are estimated with two-way cluster control at the firm and on the date of publication. **, *** indicate statistical significance at the 0.05 and 0.01 levels, respectively.

	EPS1_REV[2,40]				EPS2_REV[2,40]			
	Eq.(5)		Eq.(6)		Eq.(5)		Eq.(6)	
TONE	0.0002				0.0002	**		
	(1.13)				(2.01)			
$TONE_P$			0.0003				0.0004	***
			(1.40)				(2.75)	
$TONE_N$			-0.0003				-0.0006	
			(0.39)				(1.59)	
EPS1_REV	0.0005		0.0005		-0.0001		-0.0001	
	(0.23)		(0.23)		(0.11)		(0.10)	
EPS2_REV	0.0200	***	0.0200	***	0.0077		0.0077	
	(3.05)		(3.05)		(1.44)		(1.44)	
SIZE	0.0000		0.0000		0.0000		0.0000	
	(0.33)		(0.34)		(1.39)		(1.33)	
BM	-0.0001		-0.0001		0.0000		0.0000	
	(1.29)		(1.34)		(0.66)		(0.94)	
PCAR	0.0012	**	0.0012	**	0.0009	***	0.0009	***
	(2.53)		(2.54)		(3.40)		(3.43)	
Intercept	0.0002		0.0002		-0.0002		-0.0002	
	(0.32)		(0.30)		(1.37)		(1.52)	
Adj. R2	0.38%		0.37%		0.10%		0.13%	

Table 6

Media Analyst's Report Tones and Sales Forecast Revisions

Table 6 determines the association of media analysts' report tones with sales forecast revisions, presenting the results from estimating the regression on equations (7) and (8) for $SALES1\_REV[2,40]$ and $SALES2\_REV[2,40]$,. The columns of "Eq. (7)" and "Eq. (8)" show estimation results of equations (7) and (8), respectively. Standard errors are estimated with two-way cluster control at the firm and on the date of publication. **, *** indicate statistical significance at the 0.05 and 0.01 levels, respectively.

	SALES1_REV[2,40]		SALES2_REV[2,40]	
	Eq.(7)	Eq.(8)	Eq.(7)	Eq.(8)
TONE	0.0010 **		0.0003	
	(2.50)		(0.60)	
$TONE_P$		0.0017 ***		0.0010
		(3.38)		(1.57)
$TONE_N$		-0.0023		-0.0032
		(1.42)		(1.67)
SALES1_REV	-0.0003	-0.0003	-0.0007	-0.0007
	(0.64)	(0.63)	(0.94)	(0.93)
SALES2_REV	0.0005	0.0005	0.0017	0.0017
	(0.60)	(0.60)	(1.18)	(1.17)
SIZE	0.0002	0.0002	0.0001	0.0001
	(1.12)	(1.08)	(0.33)	(0.29)
BM	-0.0003 **	-0.0004 **	-0.0004 **	-0.0004 **
	(2.06)	(2.19)	(2.22)	(2.33)
PCAR	0.0018	0.0019	0.0035 ***	0.0035 ***
	(1.86)	(1.88)	(2.78)	(2.79)
Intercept	-0.0010	-0.0011	-0.0001	-0.0002
	(1.25)	(1.36)	(0.13)	(0.23)
Adj. R2	0.24%	0.27%	0.08%	0.10%

Table 7

Recommendation Revisions Tone and Target Price Revisions

A column ”Change in Target price” determines the association of sell-side analysts’ report tones with target price revisions, presenting the results from estimating the regression on equations (9) and (10) for $TP\_REV[2,40]$. A column ”Change in Recommendation” determines the association of sell-side analysts’ report tones with recommendation revisions, presenting the results from estimating the regression on equations (9) and (10) for $REC\_REV[2,40]$. The columns of “Eq. (9)” and “Eq. (10)” show estimation results of equations (9) and (10), respectively. Standard errors are estimated with two-way cluster control at the firm and on the date of publication. **, *** indicate statistical significance at the 0.05 and 0.01 levels, respectively.

	Change in Target Price		Change in Recommendation	
	Eq.(9)	Eq.(10)	Eq.(9)	Eq.(10)
TONE	0.0337 ***		0.0446 ***	
	(3.49)		(3.51)	
$TONE_P$		0.0131		0.0325 **
		(1.25)		(2.31)
$TONE_N$		0.1255 ***		0.0983 ***
		(7.26)		(2.62)
REC	-0.0039 **	-0.0042 **	-0.0896 ***	-0.0898 ***
	(2.29)	(2.47)	(24.87)	(24.89)
EPS1_REV	0.0113	0.0117	0.0196	0.0198
	(0.47)	(0.49)	(0.52)	(0.53)
EPS2_REV	0.0580	0.0553	-0.0389	-0.0405
	(0.65)	(0.62)	(0.31)	(0.32)
SALES1_REV	0.0071	0.0068	-0.0123	-0.0125
	(0.95)	(0.90)	(1.01)	(1.03)
SALES2_REV	0.0011	0.0013	0.0085	0.0087
	(0.25)	(0.31)	(1.03)	(1.04)
TP_REV	0.0094	0.0086	0.0570 ***	0.0565 ***
	(1.08)	(0.97)	(4.68)	(4.63)
SIZE	0.0032	0.0030	0.0066 **	0.0064 **
	(1.95)	(1.80)	(2.28)	(2.24)
BM	0.0016	0.0017	-0.0045	-0.0044
	(0.58)	(0.61)	(1.09)	(1.08)
PCAR	0.1803 ***	0.1797 ***	-0.0028	-0.0032
	(7.11)	(7.10)	(0.10)	(0.11)
Intercept	-0.0056	-0.0020	-0.0165	-0.0144
	(0.58)	(0.21)	(0.96)	(0.84)
Adj. R2	0.64%	0.72%	4.87%	4.87%

Table 8

Sell-Side Analysts' Reports Tone and Subsequent Returns

The table determines the association of sell-side analysts' report tones with target price revisions, presenting the results from estimating the regression on equations (9) and (10) for $CAR[2,40]$. The columns of "Eq. (9)" and "Eq. (10)" show estimation results of equations (9) and (10), respectively. Standard errors are estimated with two-way cluster control at the firm and on the date of publication. **, *** indicate statistical significance at the 0.05 and 0.01 levels, respectively.

	CAR[2,40]	
	Eq.(9)	Eq.(10)
TONE	-0.0005	
	(0.09)	
$TONE_P$		-0.0084
		(1.43)
$TONE_N$		0.0349 **
		(2.44)
REC	-0.0006	-0.0007
	(0.47)	(0.56)
EPS1_REV	-0.0394	-0.0392
	(0.91)	(0.91)
EPS2_REV	0.0880	0.0870
	(1.31)	(1.29)
SALES1_REV	-0.0096	-0.0097
	(0.66)	(0.67)
SALES2_REV	-0.0059	-0.0059
	(0.48)	(0.48)
TP_REV	-0.0081	-0.0085
	(0.99)	(1.03)
SIZE	-0.0103 ***	-0.0104 ***
	(5.08)	(5.11)
BM	-0.0017	-0.0016
	(0.67)	(0.65)
PCAR	-0.0062	-0.0064
	(0.34)	(0.35)
Intercept	0.0659 ***	0.0673 ***
	(5.40)	(5.48)
Adj. R2	0.34%	0.35%

Table 9

Media Analysts' Reports Tone and Subsequent Returns

The table determines the association of media analysts' report tones with target price revisions, presenting the results from estimating the regression on equations (9) and (10) for $CAR[2,40]$. The columns of "Eq. (9)" and "Eq. (10)" show estimation results of equations (9) and (10), respectively. Standard errors are estimated with two-way cluster control at the firm and on the date of publication. **, *** indicate statistical significance at the 0.05 and 0.01 levels, respectively.

	CAR[2,40]	
	Eq.(9)	Eq.(10)
TONE	0.0181 ***	
	(3.10)	
$TONE_P$		0.0206 ***
		(3.20)
$TONE_N$		0.0065
		(0.29)
EPS1_REV	0.0161	0.0162
	(0.33)	(0.33)
EPS2_REV	0.3687 **	0.3687 **
	(2.19)	(2.19)
SALES1_REV	0.0068	0.0068
	(0.96)	(0.96)
SALES2_REV	-0.0065	-0.0065
	(0.88)	(0.88)
SIZE	-0.0163 ***	-0.0163 ***
	(7.61)	(7.60)
BM	-0.0067 ***	-0.0068 ***
	(2.82)	(2.86)
PCAR	-0.0410	-0.0409
	(1.30)	(1.30)
Intercept	0.0977 ***	0.0973 ***
	(7.70)	(7.73)
Adj. R2	1.04%	1.04%