Active Verbal Communication with Corporate Insiders

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Abstract

This study empirically examines the impact of verbal communication with corporate insiders on market participants' discount rates and its subsequent effect on stock prices. The analyses reveal that active analysts who have verbal communication with corporate insiders on analyst and investor days (AI days) tend to make more positive revisions to their price targets and stock recommendations, which are potentially induced by the reduction of their discount rates, compared to non-active analysts; however, such a tendency is not observed in analysts' earnings forecasts, which are irrelevant to their discount rates. These finding support the view that the verbal communication can primally reduce communicators' discount rates for the company. Furthermore, the abnormal returns of the hosting firm are positively associated with revisions in active analysts' price targets and stock recommendations. This indicates that verbal communication could ultimately positively influence stock prices. My prediction is further supported by the finding that the effects of verbal communication persisted even during virtual AI days, where interactions primarily consist of verbal exchanges without additional components like factory tours or meals with corporate insiders. Overall, the study demonstrates that verbal communication with corporate insiders plays a key role in elevating participants' fair value estimations by reducing their discount rates.

Keywords: verbal communication; financial analyst; voluntary disclosure; virtual meeting; COVID-19

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1. Introduction

As an increasing number of analysts and investors emphasize the importance of access to management (Kary 2005; Wagner 2005; Brinkley 2012), companies are increasingly offering opportunities for these market participants to communicate with corporate insiders (Valentine 2011; Brown et al. 2014). Prior studies (e.g., Bowen et al., 2002; Kimbrough, 2005; Kirk and Markov, 2016; Park, 2019; Miwa, 2023a) have primarily focused on the influence of verbal communication on participants' short-term earnings expectations.

This study empirically investigates the impact on communicators' discount rates and the subsequent influence on stock prices. Specifically, I analyze the influence of long verbal communication that occurs on analyst and investor days (commonly referred to as AI days) on sell-side analysts' estimates, given their significant role on AI days and the observability of their estimates.

Companies offer opportunities for market participants to communicate with corporate insiders, as they believe such interactions can reduce the cost of capital by raising stock prices. Consistently, Wu and Yaron (2018) report that a host company's stock price tends to rise following AI days, which provide ample opportunities for communication with corporate insiders (Kirk and Markov, 2016). Although AI days provide earnings-related information to investors (Park, 2019), both positive and negative information is shared equally in interactive discussions (Miwa, 2023a). Thus, the positive price impact of verbal communication cannot be attributed solely to the earnings-related information conveyed during these interactions.

Since stock prices can be affected not only by changes in earnings forecasts but also by changes in discount rates, I focus on the influence of verbal communication on communicators' discount rates. Investors' discount rates for a firm may be influenced by their perception of information uncertainty regarding the company. Communication with corporate insiders, even when it includes both positive and negative information, may reduce communicators' concerns about the firm's performance. This, in turn, could lower the discount rates applied to future cash flows, ultimately positively influencing stock prices.

To test this prediction, I compare two groups of analysts: those who communicate verbally with corporate insiders (hereinafter referred to as active analysts) and those who do not (non-active analysts). I analyze whether active analysts revise their estimates differently from non-active analysts. Specifically, since analysts' discount rates influence their price targets and stock recommendations, I examine whether price targets and stock recommendations of active analysts are revised more upwardly than those of nonactive analysts on AI days. Additionally, as analysts' discount rates do not impact earnings forecasts, I verify whether such differences in revisions between active and non-active analysts are not observed in earnings forecasts.

Next, I investigate whether responses to AI days by active analysts affect stock prices. The analysis specifically focuses on price reactions to disparities in the revisions of price targets and stock recommendations between active and non-active analysts on AI days. Furthermore, to eliminate the possibility that stock prices merely react to revisions by active analysts unrelated to verbal communication, I verify whether price responses to active analysts' adjustments in price targets and stock recommendations are not weaker on AI days compared to non-AI days.

Finally, I analyze the influence of verbal communication on virtual AI days. Before the COVID-19 pandemic, nearly all AI days were held face-to-face. Such AI days provide several additional face-to-face events (e.g., factory tours and meals with corporate insiders), and these events could affect analysts' estimates (Brown et al. 2014). Therefore, I also analyze whether the impact of verbal communication remains consistent on virtual AI days because such additional events are limited in virtual settings.

First, the analysis confirms that analysts who actively engage in verbal communication with corporate insiders more significantly revise their earnings forecasts and price targets on AI days, supporting the significant influence of verbal communication on communicators' expectations. In terms of the difference in the (average) response to AI days between active and non-active analysts, I find that the price targets and stock recommendations of active analysts undergo more upward revisions than those of non-active analysts. Meanwhile, active analysts do not revise earnings forecasts more positively than non-active analysts. Even after controlling for differences in analyst characteristics between active and non-active analysts, or accounting for analyst fixed effects, the results hold. These outcomes support the perspective that verbal communication with corporate insiders reduces communicators' discount rates, resulting in an upward revision of price targets and stock recommendations.

Second, the analysis demonstrates that stock prices react significantly to revisions in price targets and recommendations made by active analysts. Specifically, when active analysts revise their price targets and stock recommendations more upwardly than non-active analysts, the host firm experiences higher abnormal stock returns. These abnormal returns are irrelevant to differences in earnings forecast revisions between active and non-active analysts. Additionally, I confirm that reactions to revisions in analysts' fair value estimates are not weaker on AI days compared to non-AI days. This supports the view that stock prices react to revisions induced by verbal communication, suggesting that the information conveyed by active analysts' revisions on AI days is not fully incorporated into stock prices.

Finally, the results show no significant difference in the impact of verbal communication on analysts' price targets and stock recommendations on virtual and face-to-face AI days. This outcome supports the inference that the reaction of active analysts to AI days is not solely due to their responses to additional face-to-face events (attributable to verbal communication).

This study contributes to the existing literature in three ways. First, it enhances the understanding of the effects of corporate insiders' verbal communication. While prior studies have primarily focused on the impact of verbal communication on participants' short-term earnings expectations, my findings show that verbal communication can influence communicators' discount rates, ultimately affecting their fair value estimates for the hosting firms.

Second, this study contributes to corporate disclosure research by providing evidence that events that interact with corporate insiders (categorized as voluntary disclosure channels) are beneficial for hosting firms. The analysis reveals that the increased fair value estimate of analysts who actively communicate with corporate insiders leads to an increase in the host firm's stock price potentially implying a decrease in the cost of capital for the host firm.

Finally, I clarify the influence of virtual investor meetings. Ever since the COVID-19 pandemic, virtual investor meetings have become increasingly common. However, few studies have analyzed the differences in participants' reactions to virtual and face-to-face meetings. My study reveals that the responses of active analysts to AI days do not differ between virtual and face-to-face formats. These results suggest that verbal communication with corporate insiders, available in both virtual and face-to-face formats, is essential for meeting participants.

The remainder of this paper is organized as follows: Section 2 reviews related literature and formulates the hypotheses. Section 3 presents preliminary tests on the determinants of verbal communication. Section 4 analyzes the impacts on communicators' estimates. Section 5 examines the effects on hosting firms' share prices. Section 6 discusses additional analyses, and finally, Section 7 summarizes the findings.

2. Related Literature and Hypothesis Development

2.1. Interactive discussion between investors and corporate insiders

Interactive discussions with corporate insiders have recently gained importance as a source of information (Valentine 2011; Brown et al. 2014). Traditionally, short-term interactions occur at the end of earnings calls and usually occur immediately after earnings announcements. Therefore, a considerable number of studies have focused on analyzing these calls.

Bowen et al. (2002) report that earnings calls reduce information asymmetry among market participants. Matsumoto et al. (2011) find that the Q&A sessions of earnings calls are relatively more informative than management presentations. Price et al. (2012) analyze investor reactions to the textual tone of quarterly earnings conference calls and find that linguistic tone dominates earnings surprises. Brockman et al. (2015) demonstrate that both manager and analyst tones significantly affect cumulative abnormal returns.

However, such traditional disclosure channels provide limited opportunities for interaction with financial analysts and investors. Additionally, because earnings calls are made in conjunction with earnings announcements, price reactions to earnings calls likely include those to earnings announcements (Kirk and Markov 2016).

Meanwhile, owing to the growing demand for intense interactions with corporate insiders (Kary 2005; Wagner 2005; Brinkley 2012), firms have been offering more opportunities for interaction through a new disclosure channel, AI days. Today, practitioners view this channel as a significant corporate disclosure and investor relations activity (Rossi 2010; Buckley 2011). Valentine (2011) argues that it is a valuable source of information for institutional investors and sell-side analysts.

AI days offer a more extended period of interaction with corporate insiders than earnings calls. Analyzing prolonged interactive discussions is crucial for understanding the influence of verbal communication with corporate insiders (Kirk and Markov, 2016). Furthermore, unlike earnings calls, AI days are rarely held in conjunction with earnings announcements, which are the most important mandatory disclosure events. Furthermore, in line with the quiet-period policy, AI days are rarely scheduled before earnings announcements (Miwa, 2023a). While participants' reactions to earnings calls can be attributed to reactions to earnings announcements, such contaminating effect of earnings announcements may be less relevant for the reactions to AI days. Therefore, the discussion of AI days serves as a suitable sample to test this study's hypotheses regarding the impact of verbal communication with corporate insiders on discount rates and stock prices.

Recently, an increasing number of academic researchers have analyzed the effects of AI days. Kirk and Markov (2016) argue that AI days play a critical informational role for investors. They consistently demonstrate dramatic increases in price variability, turnover, and analyst activity around AI days, supporting the informational role of these events. Park (2019) shows that hosting AI days complements the information content of the subsequent quarter's earnings announcements. Wu and Yaron (2018) show a positive price reaction to the event, supporting the view that verbal communication positively influences stock prices. Miwa (2023a) shows that the positive (negative) tone of the Q&A session significantly induces positive (negative) revisions in analysts' earnings forecasts. However, these tones do not affect stock prices.

These studies mainly focus on earnings-related information provided on AI days and its influence on participants' earnings estimates. However, they cannot explain why such communication has an impact on stock prices. This study clarifies the reason by analyzing the influence of verbal communication on participants' discount rates. My analysis is crucial for further clarifying the role of verbal communication with corporate insiders.

2.2. Hypotheses development

In this study, I predict that verbal communication with corporate insiders reduces communicators' discount rates for the company and eventually affects the firm's stock price. To test this prediction, this study focuses on the influence of sell-side analysts' verbal communication with corporate insiders on their estimates because they play a major role during interactive discussions, and their earnings and fair value estimates for the hosting company are observable. Hence, to test this prediction, I develop several hypotheses regarding the influence of verbal communication on analysts' estimations.

2.2.1. Updates of active analysts' estimation

In this study, I initially verify the existence of the influence of verbal communication on communicators' estimates. I particularly focus on the disparity in responses to AI days between analysts who communicate with corporate insiders (active analysts) and those who do not (non-active analysts). If verbal communication significantly impacts communicators' expectations, active analysts should demonstrate a more pronounced revision of their estimates (e.g., price targets and earnings forecasts) than non-active ones. Therefore, the following hypothesis is proposed:

H1: The degree of revision in analysts' estimates is higher for active analysts than for non-active analysts on AI days.

2.2.2. Influence on fair value estimation

Verbal communication with corporate insiders can reduce communicators' (active analysts') uncertainty about company performance. Given that analysts' discount rates often reflect their subjective perceptions of information uncertainty, verbal communication may decrease active analysts' discount rates. Furthermore, as the fair value of a stock is determined by discounted future cash flows, verbal communication ultimately triggers positive revisions in communicators' (active analysts') fair value estimations. Therefore, a significant difference in fair value estimate revisions can be observed between active and non-active analysts on AI days. Hence, I propose the following hypothesis:

H2: Active analysts are more likely than non-active analysts to revise their fair value estimations upward for hosting companies on AI days.

By contrast, analysts' earnings expectations are not typically influenced by their discount rates. Therefore, even if verbal communication reduces discount rates, it is unlikely to affect the earnings estimates. Additionally, as Miwa (2023a) argues, the information shared on AI days is not confined to positive aspects; participants freely discuss both positive and negative topics regarding company performance during Q&A sessions. Thus, verbal communication does not always positively affect communicators' earnings expectations. Hence, the following hypothesis is proposed:

H3: Verbal communication with corporate insiders does not always increase earnings forecasts of active analysts.

2.2.3. Influence on stock prices

Although financial analysts do not trade stocks directly, studies (e.g., Brav and Lehavy, 2003; Feldman et al., 2012; Miwa, 2023b) show that stock prices react significantly to revisions in analysts' fair value estimates. Therefore, the reactions of active analysts, as reflected in their fair value estimates on AI days, could have a significant impact on the stock prices of the hosting firms. Thus, the following hypothesis is proposed:

H4: More positive revisions in fair value estimates by active analysts (relative to those by non-active analysts) induce higher returns for host firms on AI days.

If all hypotheses (H1, H2, H3, and H4) are satisfied, verbal communication with corporate insiders is likely to affect stock prices by influencing communicators' discount rates.

3. Determinant of Verbal Communication

3.1. Definition of active analysts on AI days

For this study, I form a sample of AI days for U.S. firms using company-level event calendar data from FactSet. When an AI day spans multiple days, only the first day is included in the sample. Following Kirk and Markov (2016), we exclude the AI days on which a firm announces earnings within two trading days.

For each observation, I categorize active analysts as those who provide comments or ask questions to corporate insiders during the Q&A session. The identification of these analysts is based on transcripts collected from the FactSet transcript database, where the names and affiliations of speakers are available. I classify non-active analysts as those who cover the host firm but do not comment on AI days[2]. Subsequently, I match the collected analysts' names and affiliations with the FactSet analysts' estimates data to construct my sample.

[2] Non-active analysts include analysts who does not participate in the event.

3.2. Characteristics of active analysts

It is unlikely that analysts randomly decide whether to verbally communicate with corporate insiders. Specifically, analysts' characteristics and prior activities could influence their decision to engage in verbal communication. Therefore, as a preliminary analysis, I examine the differences in characteristics and prior activities between active and non-active analysts.

- Methodology

To analyze the differences in the differences in characteristics and ex-ante activities, the following logit model with AI day fixed effects is estimated:

$$Prob\left(Active\_analyst_{i,s} = 1\right) = f(X_{i,s}) \tag{1}$$

$Active\_analyst_{i,s}$ is a dummy variable that takes a value of one if analyst i had any comments or asked questions to corporate insiders on AI day s. $X_{i,s}$ represents explanatory valuables, including several characteristics of analyst i for AI day s. The model includes AI day fixed effects, allowing us to compare analyst characteristics on the same AI day.

First, I predict that the willingness to communicate with corporate insiders could be higher for financial analysts who update their estimations more frequently because more frequent updates reflect their greater willingness to collect information. In addition, analysts' abilities and experience may be closely related to their willingness to ask questions. Mayew et al. (2013) show that analysts who ask questions at public conferences possess superior information about a firm. Brown et al. (2014) argue that analysts purposely avoid asking questions when they have no information at all.

Thus, I analyze the differences in several analysts' abilities and update frequency measures. Following Clement and Tse (2005), I include the following measures:

Exp: Analysts' general experience, calculated as the number of years of experience as a financial analyst issuing reports on stock recommendations.

$Freq$: Analysts' forecast frequency for a firm, calculated as the number of updates on the firm's price targets made by the analyst in the previous 12 months.[3]

Brk_Size: Size of the analysts' brokerage firm, calculated as the number of analysts employed by the brokerage firm.

N_Cov : Number of firms covered by the analyst, calculated as the number of stocks followed by the analyst.

Ind_Cov: Number of industries covered by the analyst, calculated as the number of two-digit SICs followed by the analyst.

$Star$: Analyst's star status, defined as a dummy variable that takes the value of one if an analyst has the AA title of the Institutional Investor magazine.

Furthermore, Mayew (2008) suggests that analysts who issue more favorable recommendations for the hosting firm are more likely to ask questions during earnings conference calls. Previous studies (Francis et al., 1997; Das et al., 1998) show that analysts issue optimistic estimates to maintain access to firm management. Therefore, I also analyze the differences in stock recommendations and price targets between active and non-active analysts. The model includes the analyst's stock recommendation and price target relative to the corresponding consensus (Rec and PT).

Additionally, I include a dummy variable for analysts' investment banking relationships with the hosting firm ($Bank\_Rel$). Since Dugar and Nathan (1995) show that such a relationship induces financial analysts' optimism, it might affect analysts' motivation to communicate with the hosting firm.

Finally, because an analyst's revisions immediately before the events may indicate that the analyst has new information about the firm, such an analyst has a strong motivation to communicate with corporate insiders on AI days. Thus, I include the magnitude of lagged revisions in earnings forecasts (for current unreported [FY1] and next fiscal years [FY2]), stock

[3] This measure is time-varying and varies across firms. Its value is controlled by subtracting it from the minimum number, with this difference scaled by the range in the number.

recommendations, and price target ($Abs\_RevEPS1[-9,-1]$, $Abs\_RevEPS2[-9,-1]$, $Abs\_RevRec[-9,-1]$, and $Abs\_RevPT[-9,-1]$, respectively). Additionally, because analysts' motivation to communicate with corporate insiders could differ depending on whether their information is positive or negative, I also include lagged revisions in earnings forecasts (for current unreported and next fiscal years), stock recommendations, and price targets ($RevEPS1[-9,-1]$, $RevEPS2[-9,-1]$, $RevRec[-9,-1]$, and $RevPT[-9,-1]$, respectively).[4] Detailed definitions of the explanatory variables used in this study are provided in Table A1(a).

・ Descriptive statistics

This study's sample includes 56,277 AI day-analyst observations (for a total of 3,699 AI days hosted by 1,403 firms) over the period 2010–2022. I set 2010 as the starting date because sufficient transcript data for the AI days is available only from 2010 onwards.

According to the descriptive statistics in Table 1(a), 37.2% of the sample are active analysts (and the rest are non-active analysts). In the "$RevPT[0,1]$" columns, the ratio of positive revisions in price targets (11.56%) exceeds that of negative revisions (3.81%). For " $RevRec[0,1]$", only 0.46% and 0.38% of stock recommendations are revised positively and negatively, respectively, suggesting infrequent revisions by analysts. This may be because recommendations are constrained to a few categories (strong buy, buy, hold, sell, and strong sell)[5]. Thus, $Abs\_RevRec[0,1]$ (the absolute value of $RevRec[0,1]$) may not be a suitable indicator regarding the degree of updates in analysts' fair price estimations.

Table 1(b) reveals that in terms of correlation between control variables, Rec (stock recommendation relative to consensus) has a significantly positive correlation with PT (stock recommendation relative to consensus); N_Cov (number of stocks that an analyst cover) has a

[4] I winsorized the bottom and top 1% of the revision variables (except for stock recommendation measures) to reduce the effect of outliers.

[5] Additionally, analysts' recommendations infrequently fall into the last two categories (sell and strong sell).

significantly positive correlation with Cov_Ind (number of industries that an analyst cover); $RevEPS1[-9,-1]$ (revisions in analysts' FY1 EPS forecasts from days t-9 to t-1) has a significantly positive correlation with $RevEPS2[-9,-1]$ (revisions in analysts' FY2 EPS forecasts from days t-9 to t-1). These strong correlations emphasize the necessity of checking the severity of multicollinearity in the regression analysis.

D_Comm (a dummy variable of an analyst's communication with corporate insiders) is positively correlated with $Star$, Brk_Size, N_Cover, $Freq$, and Exp, $Star$ indicating that analysts that communicate with corporate insiders are likely to possess a star analyst status, have extensive experience, be employed by large brokerage firms, frequently update their estimates, and cover a significant number of firms. Because these features represent analysts' abilities, the results indicate that analysts with higher abilities tend to communicate actively with corporate insiders.

[Table 1]

- Regression results

The results of the probit model with AI day fixed effects presented in Table 2 generally support the previously mentioned indications. Higher Brk_Size, N_Cover, $Freq$, Exp, $Star$ values increase the probability of communicating with corporate insiders. These results indicate that analysts employed by larger brokerage houses, who cover more stocks, update their forecasts more frequently, have longer experience, and possess star-analyst status, tend to communicate more, supporting the view that analysts with higher abilities tend to communicate. The significant positive coefficient of $Bank\_rel$ indicates that analysts who have an investment banking relationship with the hosting firm are more likely to engage in active verbal communication with management on AI days. In addition, the positive coefficient of Rec suggests that analysts who issue favorable recommendations actively communicate with corporate insiders.

In summary, the results highlight significant differences in characteristics between active and non-active analysts. In other words, analyst backgrounds and ex-ante forecasts affect whether analysts interact with corporate insiders on AI days. Therefore, when analyzing the impact of verbal communication on active analysts' estimates, it is crucial to include these characteristics as control variables for alleviating the concern that the impact of verbal communication is attributed to the active analysts' characteristics.

[Table 2]

4. Influence on Analysts' Estimates

4.1. Research designs

- Magnitude of active analysts' updates

I first test H1, which posits that verbal communication induces significant updates in communicators' estimates (e.g., price targets and earnings forecasts). To this end, the absolute value of analysts' estimates is regressed on a dummy variable of analysts' communication (D_Comm) with several control variables and AI-day fixed effects, where D_Comm takes the value of one if an analyst comments on or questions the event (otherwise 0). Specifically, the following regression model with AI-day fixed effects is estimated:

$$Abs\_Rev_{i,s} = \beta_0 D\_Comm_{i,s} + (Controls) \qquad (2)$$

where the dependent variable ($Abs\_Rev_{i,s}$) is the absolute value of the revision in analysts i's earnings forecasts (for current unreported and next fiscal years), stock recommendations, or price targets for the hosting firm of AI day s for days t through t+1 (denoted as $Abs\_RevEPS1[0,1]_{i,s}$, $Abs\_RevEPS2[0,1]_{i,s}$, $Abs\_RevRec[0,1]_{i,s}$, and $Abs\_RevPT[0,1]_{i,s}$, respectively). I estimate the model with AI day fixed effects, which allows for comparing participant responses on the same AI day.[6] This approach alleviates the possibility that differences in hosting firms' conditions and incentives, analysts' characteristics, and the

[6] I also estimate the regression model with fixed analyst effects to account for analyst-specific impacts. The results hold in this case (details of the results are available upon request).

information provided across AI days could affect the regression results. Since Section 3 demonstrates that analyst characteristics and ex-ante activities can influence whether analysts interact with corporate insiders, the model includes the following control variables: analyst experience (Exp), update frequency ($Freq$), brokerage size (Brk_Size), the number of covered firms (N_Cov), the number of covered industries (Ind_Cov), an analyst's star status ($Star$), a dummy variable of the analyst's investment banking relationship ($Bank\_Rel$), analyst's relative stock recommendation (Rec), relative price target (PT), lagged revisions in earnings forecasts for current unreported and next fiscal years, stock recommendations, and price target ($RevEPS1[-9,-1]$, $RevEPS2[-9,-1]$, $RevREC[-9,-1]$, and $RevPT[-9,-1]$, respectively), and the absolute value of these lagged revisions. The positive coefficient of D_Comm indicates that analysts who interact with corporate insiders (active analysts) update their estimates more significantly than non-active analysts, supporting H1.

- Revisions of active analysts' estimates

Next, I test H2 and H3, which posit that verbal communication increases fair price estimations but does not increase earnings forecasts. To test these hypotheses, I analyze whether and how active analysts revise their fair price estimations differently from non-active analysts. To this end, I regress the revision of active analysts' estimates on a dummy variable of the analyst's communication (D_Comm) with several control variables and AI day fixed effects.

$$Rev_{i,s} = \beta_0 D\_Comm_{i,s} + (Controls), \qquad (3)$$

where the dependent variable ($Rev_{i,s}$) is the revision of analyst *i*'s earnings forecasts for the current unreported and following fiscal years, stock recommendations, or price targets for the hosting firm of AI day *s* for days *t* through *t*+1 (denoted as $RevEPS1[0,1]_{i,s}$, $RevEPS2[0,1]_{i,s}$, $RevRec[0,1]_{i,s}$, and $RevPT[0,1]_{i,s}$, respectively). The model includes AI day fixed effects, allowing us to compare participant responses on the same AI day.[7] To mitigate the possibility

[7] The results hold when I estimate the regression model with fixed analyst effects (details of the results are available upon request).

that t the coefficient of D_Comm is influenced by differences in analyst characteristics and ex-ante activities between active and non-active analysts, the model includes control variables for these factors (i.e., Exp, $Freq$, Brk_Size, N_Cov, Ind_Cov, $Star$, $Bank\_Rel$, Rec, PT, $RevEPS1[-9,-1]$, $RevEPS2[-9,-1]$, $RevREC[-9,-1]$, and $RevPT[-9,-1]$).

If H2 and H3 are satisfied, then the revisions in price targets and stock recommendations ($RevPT[0,1]$ and $RevRec[0,1]$) would be positively associated with D_Comm, while revisions in earnings forecasts ($RevEPS1[0,1]$ and $RevEPS2[0,1]$) would not be positively associated with D_Comm.

4.2. Results

- Magnitude of active analysts' updates

Table 3 presents the estimated coefficients of model (2) for $Abs\_RevPT[0,1]$, $Abs\_RevEPS1[0,1]$, $Abs\_RevEPS2[0,1]$, and $Abs\_RevRec[0,1]$, respectively. The highest variance inflation factor (VIF) is 2.08, which is well below the tolerance limit of 10, indicating no serious multicollinearity issues with any of the variables in the regressions.

$Abs\_RevPT[0,1]$, $Abs\_RevEPS1[0,1]$, and $Abs\_RevEPS2[0,1]$ are positively associated with $Freq$. These positive associations are reasonable because analysts who frequently updated their estimates in the last 12 months could also frequently update their estimates on AI days. Additionally, $Abs\_RevPT[0,1]$, $Abs\_RevEPS1[0,1]$, and $Abs\_RevEPS2[0,1]$ exhibit negative associations with $Abs\_RevPT[-9,-1]$, $Abs\_RevEPS1[-9,-1]$, and $Abs\_RevEPS1[-9,-1]$, respectively. These negative associations make sense because significant revisions in analysts' estimates just before AI days reduce the likelihood and magnitude of revisions on AI days.

The coefficient of D_Comm is significantly positive for $Abs\_RevPT[0,1]$, $Abs\_RevEPS1[0,1]$, $Abs\_RevEPS2[0,1]$ (at the 1% level), indicating that active communication with corporate insiders induces a significant change in communicators' (active analysts') price targets and forecasts of FY1 and FY2 earnings.

The coefficient of D_Comm is insignificant for $Abs\_RevRec[0,1]$. Furthermore, the other variables have much weaker explanatory power for $Abs\_RevRec[0,1]$ than for $Abs\_RevPT[0,1]$, $Abs\_RevEPS1[0,1]$, and $Abs\_RevEPS2[0,1]$. As discussed in Section 3.2., $Abs\_RevRec[0,1]$ (the degree of change in stock recommendations) may not be a suitable indicator of the degree of revision in analysts' fair value estimates because stock recommendations fall into a limited number of categories. This characteristic may contribute to the weaker explanatory power of D_Comm and the control variables for $Abs\_RevRec[0,1]$.

Overall, the results support the view that analysts' active communication with corporate insiders affects their estimates by altering their perspectives on a company's performance and stock valuations, supporting H1.

[Table 3]

- Influence on fair price estimations of communicators

Table 4 presents the estimated coefficients of model (3) for $RevPT[0,1]$, $RevEPS1[0,1]$, $RevEPS2[0,1]$, and $RevRec[0,1]$, respectively, showing whether and how verbal communication with corporate insiders raises communicators' earnings and fair price estimates. The highest VIF is 2.08, which is below 10, indicating that there are no serious multicollinearity problems related to the explanatory variables.

$RevPT[0,1]$, $RevEPS1[0,1]$, and $RevEPS2[0,1]$ are negatively associated with $RevPT[-9,-1]$, $RevEPS1[-9,-1]$, and $RevEPS2[-9,-1]$, respectively. These negative associations are reasonable because significant positive (negative) revisions of analysts' estimates reduce the possibility of further positive (negative) revisions. [8]

The coefficient of D_Comm is significantly positive for $RevPT[0,1]$ and $RevRec[0,1]$,

[8] Additionally, $RevPT[0,1]$ is positively associated with Rec (stock recommendations relative to consensus) and negatively associated with PT (price targets relative to consensus). Meanwhile, $RevRec[0,1]$ is positively associated with PT and negatively associated with Rec.

indicating that verbal communication with corporate insiders increases the price targets and stock recommendations. Meanwhile, the coefficient of D_Comm is insignificant for $RevEPS1[0,1]$ and $RevEPS2[0,1]$, indicating that active communication with corporate insiders does not increase earnings forecasts. These results support H2 and H3. Because reductions in analysts' discount rates do not affect their earnings forecasts, but elevate their price targets and stock recommendations, the overall result indicates that active communication with corporate insiders influences (reduces) their discount rate.

[Table 4]

5. Price Impacts

5.1. Research design

The previous section offers evidence of the influence of verbal communication on communicators' discount rates, highlighting that active analysts tend to make more positive revisions to stock recommendations and price targets than non-active analysts do on AI days. In this section, I examine whether the difference in reactions to AI days between active and non-active analysts impacts the hosting firm's stock price. Specifically, I investigate whether differences in the revisions of price targets and stock recommendations between active and non-active analysts on AI days are positively associated with abnormal stock returns. To this end, I first calculate the differences in $RevPT[0,1]$ and $RevRec[0,1]$ between active and non-active analysts for each AI day (referred to as $Diff\_RevPT[0,1]$ and $Diff\_RevRec[0,1]$, respectively). Following this, I analyze whether these differences are positively associated with abnormal returns around the AI day. This analysis is conducted by estimating the following regression model with firm fixed effects:

$$CAR[0,1]_s = \beta_0 \text{Diff\_RevPT}[0,1]_s + \beta_1 \text{Diff\_RevRec}[0,1]_s + (Controls), \quad (4)$$

where the dependent variable $CAR[0,1]_s$ represents the abnormal return of the hosting firm on AI day *s* for days *t* through *t* +1, where *t* is the date of AI day *s* (if it takes place on multiple days,

t is its first day). Abnormal returns are calculated using the Fama-French three-factor model with the Carhart momentum factor (Carhart four-factor model).

Control variables encompass differences in revisions in FY1 and FY2 EPS forecasts between active and non-active analysts ($Diff$_RevEPS1[0,1] and $Diff$_RevEPS2[0,1]), as these differences may influence stock returns on AI days.[9] Additionally, to account for the overall level of revisions in analysts' estimates affecting stock returns, the regression model includes the average values of $RevPT[0,1]$, $RevRec[0,1]$, $RevEPS1[0,1]$, and $RevEPS2[0,1]$ of non-active analysts (denoted as $RevPT\_NoComm[0,1]$, $RevRec\_NoComm[0,1]$, $RevEPS1\_NoComm[0,1]$, and $RevEPS2\_NoComm[0,1]$, respectively). Thus, $\beta_0 Diff\_RevPT[0,1]$ and $\beta_1 Diff\_RevRec[0,1]$ can be interpreted as the price impact of the additional positivity in active analysts' revisions to price targets and stock recommendations (relative to non-active analysts) on AI days.

In addition, I consider several lagged revisions. As demonstrated in Section 4, analysts' estimate revisions are significantly influenced by the lagged revisions in their estimates. The model specifically includes differences in revisions in price target, stock recommendation, FY1, and FY2 EPS forecasts from t-9 to t-1 between active and non-active analysts (denoted as $Diff\_RevPT[-9,-1]$, $Diff\_RevRec[-9,-1]$, $Diff\_RevEPS1[-9,-1]$, $Diff\_RevEPS2[-9,-1]$, respectively) and the average values of $RevPT[-9,-1]$, $RevRec[-9,-1]$, $RevEPS1[-9,-1]$, and $RevEPS2[-9,-1]$ of non-active analysts (denoted as $RevPT\_NoComm[-9,-1]$, $RevRec\_NoComm[-9,-1]$, $RevEPS1\_NoComm[-9,-1]$, and $\mathrm{RevEPS2\_NoComm}[-9,-1]$, respectively. The control variables also encompass the difference in price targets (denominated by stock price) and stock recommendations ($Diff\_PT$ and $\mathrm{Diff\_Rec}$, respectively), non-active analysts' price targets denominated by stock price

[9] There is a significant difference in the analyst's characteristics between active and non-active analysts. However, these differences vary across firms but not across time. Since the regression model consider AI-day fixed effects, it is not necessary to include differences in the analyst's characteristics as a control variable.

(PT_NoComm), and their stock recommendations (Rec_NoComm). This incorporation is based on the findings in Section 4, which demonstrate that the level of stock recommendations and price targets (relative to their consensus) is associated with subsequent revisions in price targets and stock recommendations. Furthermore, considering that dispersion in earnings forecasts and price targets might affect the difference in these revisions between active and non-active analysts, the model also includes dispersion in price targets, FY1 and FY2 EPS forecast (denoted as $\mathrm{Disp\_PT}$, $\mathrm{Disp\_EPS1}$, and $\mathrm{Disp\_EPS2}$, respectively). To mitigate the influence of analysts' piggybacking on recent news or price movements (Abarbanell, 1991), the model incorporates the abnormal stock returns of the hosting firm on nine prior trading days ($CAR[-9,-1]$). The returns are calculated using the Fama-French three-factor model with a Carhart momentum factor. To control for direct information flow from earnings announcements, I include SUE (i.e., earnings surprise measures for the most recent earnings announcement of the hosting firm). Finally, the regression model includes firm size ($SIZE$) and the book-to-market ratio (BM). Table A1(b) provides detailed definitions of the explanatory variables used in this section.

5.2. Results

・ Descriptive statistics and correlations

The analysis includes 3,699 AI day observations (for 1,403 firms from 2010 to 2022). According to the descriptive statistics in Table 5(a), the ratio of positive $Diff\_RevPT[0,1]$ (32.7%) is larger than that of negative $Diff\_RevPT[0,1]$ (31.6%). Here, a positive (negative) $Diff$_RevPT[0,1] indicates that RevPT[0,1] is higher (lower) for active analysts than for non-active analysts. In addition, the ratio of positive $Diff$_RevRec[0,1] (5.6%) is larger than that of negative $Diff$_RevRec[0,1] (5.1%). The column "Diff_PT" and "Diff_Rec" indicate that the price target and stock recommendation are higher for active analysts than for non-active analysts, consistent with the findings in Section 4.

The correlation matrix presented in Table 5(b) indicates that $Diff\_RevPT[0,1]$ and $Diff\_RevRec[0,1]$ are negatively associated with $RevPT\_NoComm[0,1]$ and

$RevRec\_NoComm[0,1]$, respectively. Additionally, noteworthy correlations exist among the control variables: a negative correlation between Rec_NoComm and $Diff\_Rec$, and a positive correlation between $RevEPS1\_NoComm[-9,-1]$ and $RevEPS2\_NoComm[-9,-1]$. Thus, it is necessary to check for the severity of multicollinearity in the regression analysis.

[Table 5]

- Influence on stock prices

Table 6 displays the estimated coefficients of model (4) for $CAR[0,1]$. Concerning the control variables, the coefficients of PT_NoComm are significantly positive, whereas those of $Diff\_PT$ are insignificant, indicating that an analyst's price target (denominated by stock price) affects stock returns, but the impact does not differ between active and non-active analysts.

The coefficients of the differences in revisions in price targets and stock recommendations between active and non-active analysts ($Diff\_RevPT[0,1]$ and $Diff\_RevRec[0,1]$, respectively), as well as the coefficients of revisions in price targets and stock recommendations by non-active analysts ($RevPT_NoComm[0,1]$and $RevRec\_NoComm[0,1]$, respectively), are significantly positive. These positive coefficients indicate that the difference in these revisions between active and non-active analysts has an additional impact on stock prices. In other words, the results suggest that active analysts' positive responses to AI days induce more positive abnormal returns, supporting H4.

Given that active communication with corporate insiders induces a positive revision in communicators' (active analysts) price targets and stock recommendations (resulting in higher $Diff\_RevPT[0,1]$ and $Diff\_RevRec[0,1]$), the positive association of $Diff\_RevPT[0,1]$ and $Diff\_RevRec[0,1]$ with abnormal returns on AI days supports the view that active communication with corporate insiders can positively impact stock prices by influencing communicators' price targets and stock recommendations.

Regarding multicollinearity, the highest VIF is 4.45, which is below the common threshold of 10, suggesting no severe multicollinearity problem concerning the explanatory variables.

However, as the highest VIF (4.45) exceeds 4, there is a possibility of a slight bias in the coefficients. To investigate this, I exclude the variable with the highest VIF (i.e., $Diff\_PT$) and re-estimate the coefficients of the regression model. The results are presented in the second column of Table 6. The highest VIF decreases to 2.72, indicating little multicollinearity in the re-estimated model. Notably, the estimated coefficients of $Diff\_RevPT[0,1]$ and $Diff\_RevRec[0,1]$ a remain significantly positive and are not substantially affected by the exclusion of Diff_PT. Thus, multicollinearity in the full model is unlikely to have a substantial impact on the estimated coefficients of $Diff\_RevPT[0,1]$ and $Diff\_RevRec[0,1]$.

[Table 6]

6. Additional Evidence and Discussion

This section presents further discussions and additional analyses to provide more evidence in support of the hypotheses.

6.1. Endogeneity concern regarding verbal communication

I suggest that verbal communication can influence analysts' estimations, particularly by reducing their discount rates, which in turn leads to upward revisions in fair value estimates. However, a potential endogeneity issue arises: analysts who are inclined to revise their estimates may be more likely to actively interact with corporate insiders on AI days. In this scenario, such analysts might revise their estimates even if their estimations are not directly influenced by verbal communication. This reverse causality could explain why active analysts tend to make more significant revisions around AI days. However, it does not account for the observed reduction in the discount rate among active analysts for the following reasons.

Analysts who are inclined to increase their discount rates (reflecting heightened concern about the company's performance) are more likely to seek active communication with management to address their increased uncertainty. Conversely, those whose ex-ante discount rates have decreased (indicating reduced concern about the company's performance) are less likely to seek additional interaction due to the decreased uncertainty. Therefore, if verbal communication were driven by ex-ante revisions in the discount rate, contrary to the empirical findings, active analysts (those who engage more with corporate insiders) would increase their discount rates immediately after AI days, leading to negative revisions in their target prices.

Thus, it is more plausible to interpret the findings as indicating that verbal communication reduces analysts' concerns about company performance, leading to a reduction in the discount rate.

6.2. Analyst fixed effects

To address the concern that differences in responses between active and non-active analysts may be attributed to differences in analysts' characteristics, the regression model includes analysts' characteristics as control variables. However, there remain concerns that analysts who are more inclined to communicate with corporate insiders may tend to reduce their discount rates, regardless of whether they actually engage in communication with corporate insiders.

To address this concern, I additionally include analyst fixed effects (and exclude analyst characteristic variables [10]) when estimating Model (3). The revisions of active analysts' estimates are regressed on a dummy variable for the analyst's communication (D_Comm), along with several control variables, AI day fixed effects, and analyst fixed effects.

Table 7 presents the estimated coefficients of model (3) for $RevPT[0,1]$, $RevEPS1[0,1]$, $RevEPS2[0,1]$, and $RevRec[0,1]$, respectively. The coefficient of D_Comm remains significantly positive for $RevPT[0,1]$ and $RevRec[0,1]$, indicating that verbal communication with corporate insiders increases the price targets and stock recommendations. Meanwhile, the coefficient of D_Comm remains not significantly positive for $RevEPS2[0,1]$ and it is significantly negative for $RevEPS2[0,1]$. It at least suggests that active communication with corporate insiders does not positively impact earnings forecasts. These regression results

[10] Variables regarding analyst characteristics are excluded because these variables are almost stable over time.

continue to support Hypotheses 2 and 3, even after controlling for analyst fixed effects.

[Table 7]

6.3. Long-run reactions

Section 4 demonstrates that communication with corporate insiders leads to positive revisions in price targets and stock recommendations. My next aim is to examine whether this influence is temporary.

- Hypotheses developments

If corporate insiders faithfully communicate with investors and analysts to provide information about company performance, a reduction in the discount rate would not be temporary. Therefore, positive revisions in analysts' price targets and stock recommendations induced by verbal communication would not be subsequently reversed. Consequently, the following hypothesis is proposed:

H5a: Active analysts' positive reactions to AI days are not reversed subsequently.

However, we must consider the possibility of active analysts being misled by the host firm through interactive discussions, although no study has provided evidence of such misguidance during AI days. In such cases, positive revisions to price targets and stock recommendations would be subsequently reversed. Therefore, the following alternative hypothesis is proposed:

H5b: Active analysts' positive reactions to AI days are reversed subsequently.

Next, I analyze the long-run price reactions to differences in the revisions of price targets and stock recommendations between active and non-active analysts ($Diff\_RevPT[0,1]$ and $Diff\_RevRec[0,1]$). If corporate insiders faithfully provide information through interactive communication with analysts and investors, a reduction in the discount rate is not temporary. In other words, the price reaction to $Diff\_RevPT[0,1]$ and $Diff\_RevRec[0,1]$ will not be reversed in subsequent periods. Thus, the following hypothesis is proposed:

H6a: Price reactions to the difference in revisions of price targets and stock recommendations between active and non-active analysts are not reversed.

If active analysts are misled by the host firm through active communication on an AI day, price reactions to differences in revisions of price targets and stock recommendations between active and non-active analysts would be subsequently reversed. Hence, the following alternative hypothesis is proposed:

H6b: Price reactions to the difference in revisions of price targets and stock recommendations between active and non-active analysts are reversed.

- Methodology

To test H5a and H5b, I examine the association of the dummy variable representing verbal communication (D_Comm) with prolonged revisions in price targets and stock recommendations using AI day-analyst observations of the sample (employed to test H1, H2, and H3). Specifically, I investigate the association between revisions in price targets and stock recommendations for t+2 through t+60 ($RevPT[2,60]$ and $RevRec[2,60]$) by estimating regression model (3):

To test H6a and H6b, I assess the association of $Diff\_RevPT[0,1]$ and $Diff\_RevRec[0,1]$ with extended abnormal returns using all AI day observations (utilized for testing H4). Specifically, I examine the association with cumulative abnormal return for t+2 through t+60 (CAR[2,60]) by estimating the regression model (4). Additionally, recognizing that price corrections might occur more rapidly than corrections in analysts' estimates, I also analyze the association with cumulative abnormal return for t+2 through t+20 (CAR[2,20]).

- Results

Table 8 presents the estimated coefficients of model (3) for $RevPT[2,60]$ and $RevRec[2,60]$. Concerning the control variables, $RevPT[2,60]$ and $RevRec[2,60]$ are significantly associated with stock recommendations and price targets relative to their consensus (Rec and PT). Notably, the negative associations between $RevPT[2,60]$ and PT and between $RevRec[2,60]$ and Rec indicate mean-reverting behavior in price targets and stock recommendations. Additionally, there is a strong negative association between $RevPT[-9,-1]$ and $RevPT[2,60]$ and between

$RevRec[-9,-1]$ and $RevRec[2,60]$.

Importantly, the coefficients of D_Comm for $RevPT[2,60]$ and $RevRec[2,60]$ are insignificant. This finding suggests that analysts' reactions to price targets and stock recommendations following active communication are unlikely to be reversed subsequently, supporting H5a.

Tables 9(a) and 9(b) present the estimated coefficients of model (4) for $CAR[2,20]$ and $CAR[2,60]$, respectively. Compared with the results of the regression for $CAR[0,1]$, the explanatory variables exhibit weaker explanatory power for $CAR[2,20]$ and $CAR[2,60]$. Notably, the coefficients of $Diff\_RevPT[0,1]$ and $Diff\_RevRec[0,1]$ for $CAR[2,20]$ and $CAR[2,60]$ are insignificant. Given that the coefficients of $Diff\_RevPT[0,1]$ and $Diff\_RevRec[0,1]$ for $CAR[0,1]$ are significantly positive, these results indicate that price reactions to $Diff\_RevPT[0,1]$ and $Diff\_RevRec[0,1]$ are not reversed in the subsequent period, supporting H6a.

In summary, the results suggest that active communication has a lasting impact on active analysts' fair value estimates and stock prices. These findings support the notion that communication between investors (including financial analysts) and corporate insiders plays an essential role in reducing discount rates by faithfully providing information, rather than misleading them.

[Table 8]

[Table 9]

6.3. Price reactions outside AI days

I demonstrate that stock prices significantly respond to variations in price target revisions and stock recommendation revisions between active and non-active analysts. Given that verbal communication with corporate insiders triggers communicators' (active analysts') revisions of both price targets and stock recommendations, the findings support the notion that verbal communication can affect stock prices by influencing the fair value estimations of active communicators. However, we should note that, as shown in Section 3, analysts with more ability tend to communicate actively with corporate insiders. Hence, these price reactions to active analysts' revisions can be attributed to stronger reactions to superior analysts' estimates. Specifically, significant price reactions to differences in revisions of price targets and stock recommendations between active and non-active analysts could be observed, even if stock prices do not react to revisions prompted by verbal communication. This possibility is partially refuted by my finding that stock prices do not react to the differences in earnings forecast revisions between active and non-active analysts[11]. However, further evidence is required to exclude this possibility.

In such a scenario, a more pronounced price reaction to differences in revisions should be observed outside AI days than on AI days because active analysts' revisions on AI days include revisions induced by verbal communication, which have no price impact. Hence, if the price reaction to the difference in revisions between active and non-active analysts does not differ significantly between AI days and outside AI days, it is likely that the stock price reacts to analysts' revisions induced by verbal communication.

Therefore, I assess the price reaction to the difference in revisions between active and non-active analysts outside of AI days. To this end, I analyze the price reaction to the difference in revisions between them several days before AI days. Subsequently, I compare price reactions between AI days and non-AI days. As Table 4 illustrates, revisions in price targets and stock recommendations ($\mathrm{RevPT}[0,1]$ and $\mathrm{RevRec}[0,1]$) are negatively associated with the corresponding revisions over the nine prior trading days ($\mathrm{RevPT}[-9,-1]$ and $\mathrm{RevRec}[-9,-1]$). Furthermore, as Table 6 indicates, abnormal returns around AI days ($\mathrm{CAR}[0,1]$) demonstrate a negative association with abnormal stock returns over the nine prior trading days

[11] If the price reaction to active analysts' price targets and stock recommendations is attributed to their superior ability, prices should also react to active analysts' revisions in earnings forecasts beyond other analysts' revisions in them.

$(\mathrm{CAR}[-9,-1]))$[12]. Thus, to maintain the independence of observations, I analyze the price reaction to the difference in revisions between active and non-active analysts 11 days before AI days. I form the 11-day lagged observations (of the AI day sample) as the non-AI day sample.[13, 14] Then, I combine both the AI day and non-AI day samples and estimate the following regression model:[15]

$$CAR[0,1]_s = \beta_0 D\_AIDay_s * Diff\_RevPT[0,1]_s + \beta_1 D\_AIDay_s * Diff\_RevRec[0,1]_s + \gamma_0 Diff\_RevPT[0,1]_s + \gamma_1 Diff\_RevRec[0,1]_s + (Controls) \quad (5)$$

In the equation, D_AIDay is a dummy variable that takes the value of one if the observation is included in the AI day sample (0 if the observation is included in the non-AI day sample). The significantly positive or non-significant coefficients of $D\_AIDay *$ Diff_RevPT[0,1] and $D\_AIDay *$ Diff_RevRec[0,1] indicate that the (positive) price responses to $Diff\_RevPT[0,1]$ and $Diff\_RevRec[0,1]$ are not significantly weaker on AI days.

Table 10 displays the estimated coefficients of model (5). The coefficient of $D\_AIDay *$ Diff_RevRec[0,1] is significantly positive, suggesting a stronger price response to $Diff\_RevRec[0,1]$ on AI days than on non-AI days. The coefficient of $D\_AIDay * Diff\_RevPT[0,1]$ is not significantly negative. These results reject the possibility of weakened price reactions to differences in price targets and stock recommendations between active and non-active analysts on AI days. Thus, stock prices are likely to react to analysts' revisions induced through verbal communication.

[Table 10]

6.4. Additional evidence from virtual AI days

[12] The additional analysis reveals that the negative autocorrelation in stock returns significantly weakens when I consider a lag of more than 10 days.

[13] If there are additional AI days from t-11 to t-1, the observation is excluded from the sample.

[14] $CAR[0,1]$, $Diff\_RevRec[0,1]$ and $Diff\_RevPT[0,1]$ for a non-AI day sample is equivalent to $CAR[-11,-10]$, $Diff\_RevRec[-11,-10]$ and $Diff\_RevPT[-11,-10]$ for the corresponding AI day sample, respectively.

[15] I also compare the samples with lags of 16, 21, 26, and 31 days to the AI-day sample. I confirm that the result's implication remains unaffected by the number of lags.

This study highlights that verbal communication with corporate insiders affects communicators' fair value estimation, potentially influencing the host firm's stock price. However, the reactions from these active analysts could be attributed to additional events during AI days. Particularly, before the COVID-19 pandemic, AI days were conducted face-to-face, providing participants, especially active communicators, with opportunities to partake in company and factory tours and meals with corporate insiders. According to Brown et al. (2014), visits to companies or plants are useful for generating stock recommendations. Therefore, these opportunities may alleviate analysts' concerns about a company's performance, potentially leading to a decrease in their discount rates.

To investigate this possibility, I examine the impact of communication with corporate insiders on virtual AI days. Before the COVID-19 pandemic, the vast majority of AI days were conducted face-to-face. However, because of the pandemic, many companies have shifted to hosting AI days. These virtual AI days consist of management presentations and corresponding Q&A sessions, thus lacking additional components such as factory tours or meals with corporate insiders.

- Hypotheses developments

If the response from active analysts is linked to the supplementary face-to-face events, their response and the resulting price impact might significantly diminish for virtual AI days compared with face-to-face AI days. Conversely, if the active analysts' responses and their impact on stock prices remain consistent between face-to-face and virtual AI days, interactive communication with corporate insiders rather than supplementary face-to-face events holds significant importance for participants. In light of this, the following hypothesis is proposed:

H7: The impact of verbal communication with corporate insiders on communicators' fair value estimations does not differ between face-to-face and virtual settings.

The following hypothesis is proposed regarding the influence of active analysts' responses on stock prices:

H8: The price impact of active analysts' revisions on fair value estimates does not differ between face-to-face and virtual settings.

- Methodology

To test H7 and H8, I determine whether AI days during COVID-19 and post-COVID-19 periods (from 2020 to 2022) were held in a virtual or face-to-face format by examining their transcripts using the following steps.

1) Identifying expressions commonly used on virtual AI days and face-to-face AI days based on a randomly selected sample of 100 transcripts. These expressions are listed in Table 11(a).
2) Classifying an AI day as a virtual event if the participant comments include any expressions associated with virtual AI days (listed in the virtual format column of Table 11[a]), along with their synonyms or orthographic variants.
3) Classifying an AI day as a face-to-face event if participant comments include any expressions associated with face-to-face AI days (listed in the "Face-to-Face format" column of Table 11[a]), along with their synonyms or orthographic variants.
4) Determining the categorization of AI days that fit into both the face-to-face and virtual event categories [16] or do not fit into either category through qualitative assessment.
5) Conducting a manual check to ensure the logical consistency and validity of all categorizations.

As indicated in Table 11(b), out of the 1,123 AI days held after 2020, 675 are categorized as virtual AI days. The highest ratio of the virtual format is observed in the first quarter of 2021. However, even during the post-Covid period, a substantial number of AI days continued to be conducted in the virtual format.

To test H7, I analyze the interaction effect of D_Comm with $D\_Virtual$ for revisions of price targets and stock recommendations, where $D\_Virtual$ is a dummy variable that takes the

[16] This situation may arise, particularly in the case of AI days conducted in a hybrid format. In such instances, given that the majority of active analysts participate in-person, I categorize hybrid AI days as non-virtual (face-to-face) AI days.

value of one if AI days are held in a virtual format (otherwise 0). Specifically, I estimate the following regression model using all the AI day-analyst observations:

$$Rev_{i,s} = \beta_0 D\_Comm_{i,s} * D\_Virtual_s + \gamma_1 D\_Comm_{i,s} + \gamma_2 D\_Virtual_s + \gamma_3 D\_Comm_{i,s} * D\_Year[2020{,}2022]_s + \gamma_4 D\_Year[2020{,}2022]_s + (Controls) \quad (6)$$

where the dependent variable (Rev) represents $RevPT[0,1]$ and $RevRec[0,1]$. The interaction effect with $D\_Virtual$ may include the effect of the COVID-19 and post-COVID-19 period. Thus, I include $D\_Year[2020,2022]$, and the interaction term between D_Comm and $D\_Year[2020,2022]$, where $D\_Year[2020,2022]$ is a dummy variable that takes the value of one if an AI day is held between 2020 and 2022. The other control variables are the same as those in Equation (3). The negative coefficient of the interaction term ($D\_Comm * D\_Virtual$) suggests that the impact of verbal communication on communicators' fair value estimates is less pronounced on virtual AI days than on face-to-face AI days.

To test H8, I examine whether price reactions to $Diff\_RevPT[0,1]$ and $Diff\_RevRev[0,1]$ differ between virtual and face-to-face AI days. I assess whether stock returns are associated with the interaction effects of $Diff\_RevPT[0,1]$ and $Diff\_RevRev[0,1]$ with $D\_Virtual$. Specifically, I estimate the following regression model using all AI day observations:

$$CAR_s = \beta_1 D\_Virtual_s * Diff\_RevPT[0,1]_s + \beta_2 D\_Virtual_s * Diff\_RevRec[0,1]_s + \gamma_1 D\_Year[2020{,}2022]_s * Diff\_RevPT[0,1]_s + \gamma_2 D\_Year[2020{,}2022]_s * Diff\_RevRec[0,1]_s + \gamma_3 D\_Virtual_s + \gamma_4 Diff\_RevPT[0,1]_s + \gamma_5 Diff\_RevRev[0,1]_s + \gamma_6 D\_Year[2020{,}2022]_s + (Controls) \quad (7)$$

The dependent variables are $CAR[0,1]$, $CAR[2,20]$, or $CAR[2,60]$. The other control variables are the same as those in Equation (4). The negative coefficients of $D\_Virtual * Diff\_RevPT[0,1]$ and $D\_Virtual * Diff\_RevRec[0,1]$ indicate that price reactions to $Diff\_RevPT[0,1]$ and $Diff\_RevRec[0,1]$ are less pronounced for virtual AI days than for face-to-face AI days.

・ Result

Table 12 (a) shows the estimated coefficients of the regression model (6) for $RevPT[0,1]$ and $RevRec[0,1]$. These findings indicate that the interaction term between D_Comm and $D\_Virtual$ has little influence on $RevPT[0,1]$ and $RevRec[0,1]$. This suggests that the impact of verbal communication with corporate insiders on communicators' price targets and stock recommendations remains consistent, regardless of whether communication occurs virtually or face-to-face.

Table 12 (b) presents the estimated coefficients of the regression model (7). The coefficients associated with the interaction terms between $Diff\_RevRec[0,1]$ and $D\_Virtual$ as well as $Diff\_RevPT[0,1]$ and $D\_Virtual$ are found to be insignificant. This implies that the price impact resulting from differences in revisions in price targets and stock recommendations between active and non-active analysts is unrelated to the format of an AI day.

In summary, these findings suggest that the influence of communication with corporate insiders on communicators' fair value estimates (discount rates) and the subsequent impact on stock prices remains substantial, even in a virtual format. Given that both virtual and face-to-face AI days typically encompass management presentations and Q&A sessions (providing an opportunity for verbal interactive discussions with management), these results support the notion that verbal communication with corporate insiders during Q&A sessions, rather than other face-to-face events such as factory tours, non-virtual product demonstrations, or meals with managers, plays a crucial role in influencing fair value estimation (and discount rates) of event participants.

[Table 11]

[Table 12]

7. Conclusions

This study aims to clarify the influence of verbal communication with corporate insiders on communicators' expectations of hosting firms, particularly concerning their discount rates and their subsequent impact on stock prices. To achieve this, I have identified participants engaging in communication with corporate insiders and analyzed whether and how these active participants, compared to non-active ones, revise their fair price estimations, consequently affecting the stock prices of the hosting firm.

This study reveals that active analysts tend to make more substantial revisions to their estimates, including earnings forecasts and price targets, compared to non-active analysts. This indicates that verbal communication with corporate insiders has sufficient influence to alter communicators' expectations regarding the host firm. Furthermore, verbal communication has a unidirectional impact solely on analysts' price targets and stock recommendations; verbal communication raises communicators' fair value estimates but does not raise their earnings forecasts [17]. This result indicates that verbal communication with corporate insiders shifts communicators' discount rates, rather than company performance estimates. In addition, the difference in revisions of price targets and stock recommendations between active and non-active analysts positively affects stock prices, supporting the view that the additional positive reaction of active analysts to AI days raises stock prices. Finally, I confirm that these reactions are not temporal and do not differ between virtual and face-to-face AI days.

This study contributes to the existing research in several ways. First, it highlights a novel effect of verbal communication with corporate insiders. While previous studies have focused on verbal communication's influence on participants' short-term earnings expectations, this study reveals that verbal communication can decrease discount rates and increase fair value estimates for hosting firms. Second, this study contributes to corporate disclosure studies by demonstrating the advantages of events involving interactions with corporate insiders. Analysts who communicate with management raise fair value estimates, and their revisions can positively

[17] Exactly to say, the influence of verbal communication on communicators" earnings forecasts is not positively biased.

affect stock prices and potentially reduce their cost of capital. Finally, the study clarifies the role of virtual investor meetings. Despite their increased prevalence after COVID-19, few studies have examined whether and how participants' reactions differ between virtual and face-to-face meetings. This study reveals that virtual meetings can reduce informational uncertainty similar to face-to-face meetings. Widespread adoption of virtual formats in interactions with investors does not deteriorate their information environment.

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Table 1

Descriptive Statistics and Correlations for the Analyst Revision Analysis

Panel(a) reports 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. Pr(>0)" and "Pr(<0)" indicate the probability that a value is greater than zero or negative, respectively. Panel (b) shows the Pearson's correlations between the variables used for testing H1, H2, and H3.

(a) Descriptive statistics

	Mean	Std. Dev.	Median	Skew	kurtosis	5th	25th	75th	95th	Pr(>0)	Pr(<0)
RevPT[0,1]	0.008	0.038	0.000	2.800	12.791	0.000	0.000	0.000	0.083	0.116	0.038
RevEPS1[0,1]	0.000	0.001	0.000	-1.438	22.950	0.000	0.000	0.000	0.000	0.082	0.073
RevEPS2[0,1]	0.000	0.002	0.000	-1.818	18.370	-0.001	0.000	0.000	0.001	0.105	0.098
RevRec[0,1]	0.001	0.084	0.000	0.062	163.217	0.000	0.000	0.000	0.000	0.005	0.004
D_Comm	0.372	0.483	0.000	0.529	-1.721	0.000	0.000	1.000	1.000	0.372	0.000
Rec	0.044	0.496	0.167	-0.679	0.144	-0.783	-0.333	0.412	0.700	0.560	0.412
PT	0.001	0.130	0.004	0.979	16.377	-0.197	-0.062	0.064	0.185	0.513	0.482
Star	0.104	0.305	0.000	2.602	4.769	0.000	0.000	0.000	1.000	0.086	0.000
Brk_Size	43.927	31.217	46.000	0.236	-0.950	1.000	15.000	68.000	94.000		
N_Cover	14.243	8.391	14.000	1.209	8.188	1.000	9.000	19.000	28.000		
Freq	0.016	0.011	0.016	1.235	6.189	0.000	0.008	0.020	0.036		
Exp	1.797	1.754	2.580	-0.011	-1.939	0.000	0.000	3.582	3.827		
Cover_Ind	3.391	2.704	3.000	1.133	3.780	0.000	2.000	5.000	8.000		
Bank_Rel	0.029	0.168	0.000	5.612	29.491	0.000	0.000	0.000	0.000		
RevEPS1[-9,-1]	0.000	0.002	0.000	0.058	16.441	-0.002	0.000	0.000	0.002	0.119	0.096
RevEPS2[-9,-1]	0.000	0.002	0.000	-0.217	16.066	-0.002	0.000	0.000	0.002	0.105	0.095
RevPT[-9,-1]	0.007	0.046	0.000	2.158	12.343	0.000	0.000	0.000	0.091	0.092	0.041
RevRec[-9,-1]	0.003	0.109	0.000	2.352	94.597	0.000	0.000	0.000	0.000	0.007	0.005
D_Virtual	0.172	0.377	0.000	1.739	1.025	0.000	0.000	0.000	1.000		

(b) Correlations

	Rec	PT	Star	Brk_Size	N_Cover	Freq	Exp	Cover _Ind	Bank _Rel	RevEPS1 [-9,-1]	RevEPS2 [-9,-1]	RevPT [-9,-1]	RevRec [-9,-1]	D_Virtual
D_Comm	0.07	0.05	0.13	0.30	0.21	0.15	0.17	0.11	0.06	0.01	0.02	0.01	0.01	0.08
Rec		0.61	0.00	-0.03	0.06	0.06	0.07	0.05	-0.02	-0.01	-0.01	0.02	0.09	0.00
PT			0.00	-0.05	0.04	0.03	0.04	0.03	-0.01	0.01	0.03	0.13	0.04	0.00
Star				0.35	0.19	0.11	0.16	0.12	0.09	0.01	0.01	0.00	0.00	-0.01
Brk_Size					0.27	0.23	0.16	0.15	0.17	0.00	0.00	0.00	0.00	-0.07
N_Cover						0.26	0.40	0.55	0.05	0.01	0.02	0.01	0.00	0.21
Freq							0.16	0.18	0.03	0.02	0.01	0.05	0.00	0.08
Exp								0.25	0.02	0.02	0.02	0.01	0.01	0.17
Cover_Ind									0.04	-0.01	0.02	0.02	0.00	0.08
Bank_Rel										0.01	0.00	0.00	0.00	0.00
RevEPS1[-9,-1]											0.62	0.32	0.04	0.02
RevEPS2[-9,-1]												0.37	0.07	0.03
RevPT[-9,-1]													0.19	0.03
RevRec[-9,-1]														0.00

Table 2

Characteristics of Participants

This table presents the results of estimating Equation (1) for D_Comm. 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.

Rec	0.2343	***	(12.16)
PT	0.2176	***	(2.98)
Brk_Size	0.0150	***	(51.71)
N_Cov	0.0075	***	(5.25)
Freq	22.7000	***	(22.52)
Exp	0.0535	***	(11.24)
Cover_Ind	0.0060		(1.21)
Bank_Rel	0.1586	***	(3.51)
Star	0.0963	***	(3.78)
RevEPS1[-9,-1]	1.0360		(0.17)
RevEPS2[-9,-1]	7.3740		(1.46)
RevPT[-9,-1]	-0.1724		(0.64)
RevRec[-9,-1]	0.0141		(0.19)
Abs_RevEPS1[-9,-1]	-17.0900	**	(2.33)
Abs_RevEPS2[-9,-1]	12.3200	**	(2.08)
Abs_RevPT[-9,-1]	0.6944	**	(2.53)
Abs_RevRec[-9,-1]	-0.0262		(0.35)
Adjusted R2	13.9%		

Table 3

Influence on the Degree of Analyst Revisions

This table shows the results of estimating Equation (2) for $Abs\_RevPT[0,1]$, $Abs\_RevEPS1[0,1]$, $Abs\_RevEPS2[0,1]$, and $Abs\_RevRec[0,1]$. 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.

	Abs_RevPT[0,1]		Abs_RevEPS1[0,1]		Abs_RevEPS2[0,1]		Abs_RevREC[0,1]	
D_Comm	0.0028 ***	(7.42)	0.0000 ***	(3.63)	0.0001 ***	(5.60)	0.0006	(0.60)
Rec	0.0048 ***	(9.52)	0.0000	(1.85)	0.0000	(1.35)	-0.0048 **	(2.88)
Star	-0.0007	(1.42)	0.0000	(0.09)	0.0000	(0.60)	-0.0001	(0.05)
PT	-0.0321 ***	(13.87)	0.0000	(0.60)	0.0000	(0.28)	-0.0044	(0.96)
Brk_Size	0.0000 *	(2.28)	0.0000	(1.52)	0.0000	(0.09)	0.0000	(1.34)
N_Cov	0.0000	(0.10)	0.0000 ***	(4.14)	0.0000 *	(2.37)	0.0002 *	(2.20)
Freq	0.0783 ***	(3.79)	0.0076 ***	(10.96)	0.0117 ***	(9.57)	0.0730	(1.33)
Exp	0.0000	(0.29)	0.0000	(1.55)	0.0000	(1.55)	-0.0005	(1.60)
Cover_Ind	-0.0003 **	(2.64)	0.0000	(1.27)	0.0000 **	(2.62)	0.0003	(0.98)
Bank_Rel	-0.0008	(0.86)	0.0000	(0.41)	-0.0001	(1.86)	-0.0004	(0.14)
RevEPS1[-9,-1]	0.0579	(0.45)	0.0142 *	(2.48)	0.0051	(0.54)	-0.2919	(0.84)
RevEPS2[-9,-1]	0.0593	(0.53)	-0.0055	(1.58)	0.0001	(0.02)	0.2687	(0.99)
RevPT[-9,-1]	-0.0384 ***	(5.47)	-0.0002	(1.16)	-0.0002	(0.67)	0.0159	(0.80)
RevRec[-9,-1]	0.0046 **	(3.19)	0.0000	(1.10)	0.0000	(0.14)	-0.0069	(0.57)
Abs_RevEPS1[-9,-1]	0.1553	(1.05)	-0.0386 ***	(5.62)	-0.0105	(0.95)	-0.4091	(0.95)
Abs_RevEPS2[-9,-1]	-0.6816 ***	(5.10)	-0.0164 ***	(4.03)	-0.0744 ***	(7.81)	-0.7023 *	(2.54)
Abs_RevPT[-9,-1]	-0.0884 ***	(11.66)	-0.0003 *	(2.02)	-0.0013 ***	(3.65)	-0.0290	(1.49)
Abs_RevRec[-9,-1]	0.0001	(0.11)	0.0000		0.0002 *	(2.00)	0.0175	(1.43)
Controls for AI days Effects	Yes		Yes		Yes		Yes	
Adjusted R2	3.47%		1.74%		1.57%		0.26%	

Table 4

Influence on Analyst Revisions

This table shows the results of estimating Equation (3) for $RevPT[0,1]$, $RevEPS1[0,1]$, $RevEPS2[0,1]$, and $RevRec[0,1]$. 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.

	RevPT[0,1]			RevEPS1[0,1]			RevEPS2[0,1]			RevREC[0,1]		
D_Comm	0.0020	***	(5.13)	0.0000		(1.72)	0.0000		(0.87)	0.0052	***	(4.85)
Rec	0.0067	***	(12.00)	0.0000		(0.94)	0.0000		(0.83)	-0.0196	***	(11.99)
PT	-0.0425	***	(14.58)	-0.0001	*	(2.36)	-0.0006	***	(4.97)	0.0286	***	(6.20)
Star	-0.0005		(0.97)	0.0000		(0.11)	0.0000		(0.48)	0.0027		(1.80)
Brk_Size	0.0000	*	(2.44)	0.0000		(0.16)	0.0000		(1.41)	-0.0001	***	(3.81)
N_Cov	0.0000		(0.36)	0.0000		(1.83)	0.0000		(0.26)	-0.0001		(1.52)
Freq	0.0139		(0.67)	-0.0001		(0.17)	0.0014		(1.12)	0.0131		(0.24)
Exp	0.0000		(0.02)	0.0000		(1.63)	0.0000		(0.37)	0.0000		(0.05)
Cover_Ind	-0.0001		(1.25)	0.0000		(1.46)	0.0000		(0.03)	0.0007	*	(2.45)
Bank_Rel	-0.0008		(0.88)	0.0000		(0.91)	0.0000		(0.11)	0.0029		(1.08)
RevEPS1[-9,-1]	0.1237		(0.95)	-0.0442	***	(7.03)	-0.0013		(0.13)	0.0056		(0.02)
RevEPS2[-9,-1]	-0.0931		(0.85)	-0.0081	*	(2.23)	-0.0758	***	(8.92)	-0.4164		(1.51)
RevPT[-9,-1]	-0.1087	***	(15.09)	-0.0002		(1.31)	-0.0010	***	(4.07)	0.0260		(1.83)
RevRec[-9,-1]	0.0073	***	(4.97)	0.0000		(1.17)	0.0000		(0.20)	-0.0158		(1.61)
Controls for AI days Effects	Yes			Yes			Yes			Yes		
Adjusted R2	4.07%			1.02%			1.21%			1.13%		

Table 5

Descriptive statistics and correlations for the price impact analysis

Panel(a) reports 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. Pr(>0)” and “Pr(<0)” indicate the probability that a value is greater than zero or negative, respectively. Panel (b) shows the Pearson’s correlations between the variables used for testing H4.

(a) Descriptive statistics

	Mean	Std. Dev.	Median	Skew	kurtosis	5th	25th	75th	95th	Pr(>0)	Pr(<0)
CAR[0,1]	0.171	7.752	-0.002	31.73	1,517.6	-6.235	-1.725	1.903	6.317	49.8%	50.0%
Diff_RevEPS1[0,1]	0.000	0.001	0.000	-0.71	31.2	-0.001	0.000	0.000	0.001	33.6%	34.0%
Diff_RevEPS2[0,1]	0.000	0.001	0.000	-0.38	21.5	-0.002	0.000	0.000	0.002	36.1%	37.1%
Diff_RevPT[0,1]	0.001	0.028	0.000	0.75	12.7	-0.037	-0.004	0.006	0.043	32.7%	31.6%
Diff_RevRec[0,1]	0.002	0.070	0.000	1.42	100.4	0.000	0.000	0.000	0.037	5.6%	5.1%
Diff_Rec	0.076	0.349	0.083	-0.35	1.1	-0.500	-0.111	0.289	0.625	57.9%	34.1%
Diff_PT	0.012	0.124	0.013	-0.27	14.3	-0.162	-0.035	0.062	0.179	57.6%	42.1%
Diff_RevEPS1[-9,-1]	0.000	0.001	0.000	2.08	36.8	-0.001	0.000	0.000	0.002	34.2%	34.5%
Diff_RevEPS2[-9,-1]	0.000	0.002	0.000	1.47	28.9	-0.002	0.000	0.000	0.002	35.5%	36.0%
Diff_RevPT[-9,-1]	0.002	0.027	0.000	1.05	19.2	-0.032	-0.002	0.005	0.041	32.2%	28.9%
Diff_RevRec[-9,-1]	0.003	0.078	0.000	3.68	96.4	-0.059	0.000	0.000	0.071	7.7%	7.1%
RevEPS1_NoComm[0,1]	0.000	0.001	0.000	-3.60	43.1	-0.001	0.000	0.000	0.001	28.1%	24.6%
RevEPS2_NoComm[0,1]	0.000	0.001	0.000	-2.65	28.9	-0.001	0.000	0.000	0.001	31.8%	27.4%
RevPT_NoComm[0,1]	0.008	0.026	0.000	2.41	13.8	-0.014	0.000	0.009	0.056	36.9%	12.5%
RevRec_NoComm[0,1]	-0.001	0.039	0.000	-6.25	171.1	0.000	0.000	0.000	0.000	3.6%	3.2%
Rec_NoComm	-0.002	0.150	0.000	-0.10	3.8	-0.250	-0.075	0.071	0.222	45.1%	47.5%
RevEPS1_NoComm[-9,-1]	0.000	0.002	0.000	-0.20	19.9	-0.002	0.000	0.000	0.002	29.2%	27.0%
RevEPS2_NoComm[-9,-1]	0.000	0.001	0.000	-0.78	24.5	-0.002	0.000	0.000	0.001	28.9%	28.3%
RevPT_NoComm[-9,-1]	0.005	0.025	0.000	2.51	18.8	-0.017	0.000	0.004	0.045	32.4%	14.8%
RevRec_NoComm[-9,-1]	0.921	6.830	0.735	0.30	7.6	-8.971	-2.155	3.801	11.443	5.3%	4.3%
CAR[-9,-1]	0.001	0.015	0.001	-4.79	278.4	-0.005	0.000	0.002	0.009	57.6%	42.2%
SUE	3.902	0.756	3.907	-0.17	0.1	2.662	3.413	4.405	5.199		
Size	0.363	0.405	0.294	1.93	37.6	0.010	0.148	0.505	1.028		
BM	0.000	0.046	0.000	24.04	1,143.1	-0.008	0.000	0.001	0.009		
Disp_EPS1	-0.001	0.216	0.001	-39.60	2,190.2	-0.015	0.000	0.002	0.015		
Disp_EPS2	0.005	0.012	0.002	6.81	65.8	0.000	0.001	0.005	0.020		
Disp_PT	0.193	0.395	0.000	1.55	0.4	0.000	0.000	0.000	1.000		
D_Virtual	0.000	0.000	0.000	0.00	0.0	0.000	0.000	0.000	0.000	0.195	0.000

(b) Correlations

	Diff_RevEPS2[0,1]	Diff_RevPT[0,1]	Diff_RevRec[0,1]	Diff_Rec	Diff_RevEPS1[-9,-1]	Diff_RevEPS2[-9,-1]	Diff_RevPT[-9,-1]	Diff_RevRec[-9,-1]	RevEPS1_NoComm[0,1]	RevEPS2_NoComm[0,1]	RevPT_NoComm[0,1]	RevRec_NoComm[0,1]	Rec_NoComm	RevEPS1_NoComm[-9,-1]	RevEPS2_NoComm[-9,-1]	RevPT_NoComm[-9,-1]	RevRec_NoComm[-9,-1]	CAR[-9,-1]	SUE	Size	BM	Disp_EPS1	Disp_EPS2	Disp_PT	D_Virtual
Diff_RevEPS1[0,1]	0.472	0.075	0.034	-0.006	-0.043	-0.032	-0.015	0.001	-0.286	-0.144	0.038	-0.005	-0.004	0.052	0.041	0.014	-0.012	0	-0.014	0.003	-0.038	0.019	-0.019	-0.026	0.003
Diff_RevEPS2[0,1]		0.132	0.06	-0.027	0.026	-0.049	-0.022	-0.012	-0.124	-0.308	0.056	0.011	0.019	0.064	0.1	0.046	-0.027	-0.013	0.036	-0.018	-0.016	0.02	-0.014	-0.02	-0.013
Diff_RevPT[0,1]			0.135	0.004	-0.025	-0.022	-0.098	0.016	0.049	0.045	-0.331	-0.084	0.011	0.038	0.042	0.044	-0.037	0.022	0.024	-0.011	0.005	-0.029	-0.006	-0.029	-0.018
Diff_RevRec[0,1]				-0.116	0	-0.013	-0.021	-0.025	0.024	0.016	-0.048	-0.544	0.076	0.002	0.011	0.01	-0.059	0.017	-0.01	0.008	0.056	-0.005	-0.001	-0.049	0.014
Diff_Rec					-0.011	-0.028	0.014	0.078	0.028	0.046	-0.019	0.05	-0.779	-0.006	-0.002	-0.016	-0.025	-0.006	-0.025	0.091	-0.04	0.022	0.018	-0.006	-0.084
Diff_RevEPS1[-9,-1]						0.497	0.039	0.033	0.062	0.017	0.02	0.006	0.031	-0.262	-0.151	0.133	-0.008	0.027	0.057	-0.021	0.024	-0.009	0.014	0.002	0.012
Diff_RevEPS2[-9,-1]							0.193	0.057	0.036	0.052	0.015	0.007	0.03	-0.088	-0.274	0.081	0.018	0.056	0.046	-0.035	0.022	-0.044	0	0.044	0.044
Diff_RevPT[-9,-1]								0.191	0.037	0.033	0.099	0.011	0.002	0.087	0.05	-0.2	-0.044	0.128	0.042	-0.023	-0.01	-0.008	0.005	0.017	0.049
Diff_RevRec[-9,-1]									0.036	0.03	0.019	-0.02	-0.053	-0.013	-0.008	-0.036	-0.468	0.031	0.009	-0.009	-0.006	-0.033	-0.005	0.015	-0.002
RevEPS1_NoComm[0,1]										0.487	0.123	0.039	-0.007	0.075	0.075	0.062	-0.013	0.04	0.039	0.014	-0.025	-0.017	0.016	-0.04	0.043
RevEPS2_NoComm[0,1]											0.249	0.069	-0.035	0.034	0.095	0.073	0.001	0.073	-0.016	0.028	0.021	-0.012	0.004	-0.054	0.043
RevPT_NoComm[0,1]												0.155	0.011	0.059	0.106	0.209	0.01	0.18	0.022	-0.088	-0.039	0.015	0.021	-0.021	0.074
RevRec_NoComm[0,1]													-0.057	-0.01	0.005	0.019	0.006	-0.045	0.019	-0.003	0.013	-0.013	0	0.009	-0.015
Rec_NoComm														0.015	0.012	0.033	0.031	0.017	0.039	-0.011	0.013	-0.012	-0.007	-0.027	0.072
RevEPS1_NoComm[-9,-1]															0.682	0.295	0.061	0.2	0.054	0.011	-0.001	-0.01	-0.011	-0.066	0.008
RevEPS2_NoComm[-9,-1]																0.37	0.063	0.194	0.036	0.035	0.017	0.007	0.006	-0.051	0.023
RevPT_NoComm[-9,-1]																	0.102	0.248	0.031	-0.038	-0.026	-0.019	0.006	-0.072	0.046
RevRec_NoComm[-9,-1]																		0.079	0.013	0.015	-0.013	-0.005	0.003	-0.006	0.017
CAR[-9,-1]																			0.079	-0.058	0.027	-0.053	-0.008	0.046	-0.001
SUE																				-0.032	0.053	-0.009	-0.008	0.04	0.076
Size																					-0.033	0.033	0.004	-0.387	-0.106
BM																						-0.001	-0.013	0.077	-0.029
Disp_EPS1																							0.008	0.043	-0.024
Disp_EPS2																								-0.009	-0.007
Disp_PT																									0.146

Table 6

Price Impact of Active Analysts' Revisions

This table shows the results of estimating Equation (4) for $CAR[0,1]$. The second column reports the estimated coefficients when $Diff\_PT$ is excluded from the model. 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.

	CAR[0,1]			
Diff_RevPT[0,1]	20.29 ***	(3.69)	19.00 ***	(3.47)
Diff_RevRec[0,1]	8.86 ***	(5.46)	9.23 ***	(5.67)
Diff_RevEPS1[0,1]	250.94	(1.01)	258.41	(1.04)
Diff_RevEPS2[0,1]	200.19	(1.42)	191.61	(1.35)
Diff_PT	4.84 .	(1.86)		
Diff_Rec	-0.03	(0.06)	0.75 .	(1.86)
Diff_RevPT[-9,-1]	11.43 *	(2.10)	13.56 *	(2.49)
Diff_RevRec[-9,-1]	0.60	(0.50)	0.23	(0.19)
Diff_RevEPS1[-9,-1]	-338.00 **	(2.71)	-335.71 **	(2.65)
Diff_RevEPS2[-9,-1]	31.17	(0.31)	30.57	(0.30)
RevPT_NoComm[0,1]	60.42 ***	(8.17)	59.49 ***	(8.13)
RevRec_NoComm[0,1]	13.28 ***	(3.61)	13.63 ***	(3.71)
RevEPS1_NoComm[0,1]	142.75	(0.59)	138.23	(0.57)
RevEPS2_NoComm[0,1]	690.00 ***	(4.65)	695.26 ***	(4.61)
PT_NoComm	25.52 ***	(3.44)	17.71 **	(3.24)
Rec_NoComm	-3.83 **	(2.82)	-2.66 *	(2.15)
RevPT_NoComm[-9,-1]	-3.78	(0.70)	-3.11	(0.58)
RevRec_NoComm[-9,-1]	2.68	(1.02)	2.37	(0.89)
RevEPS1_NoComm[-9,-1]	-23.23	(0.20)	-23.21	(0.20)
RevEPS2_NoComm[-9,-1]	-102.25	(0.65)	-103.42	(0.66)
Disp_EPS1	-3.34 *	(2.28)	-3.49 *	(2.42)
Disp_EPS2	-0.35 .	(1.95)	-0.35 .	(1.88)
Disp_PT	77.87 **	(2.60)	76.45 *	(2.53)
CAR[-9,-1]	-0.09 ***	(4.12)	-0.09 ***	(4.03)
SUE	-24.19	(1.11)	-25.08	(1.15)
Size	1.24 **	(2.63)	1.19 *	(2.53)
BM	0.90 .	(1.82)	0.86 .	(1.72)
Controls for Firm Effects	Yes		Yes	
Adjusted R2	24.73%		24.42%	

Table 7

Influence on Analyst Revisions after considering analyst fixed effects

This table shows the results of estimating Equation (3) for $RevPT[0,1]$, $RevEPS1[0,1]$, $RevEPS2[0,1]$, and $RevRec[0,1]$, when I additionally include analyst fixed effects and exclude analyst characteristic variables. 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.

	RevPT[0,1]			RevEPS1[0,1]			RevEPS2[0,1]			RevREC[0,1]		
D_Comm	0.00179	***	(3.90)	-0.00003	**	(2.82)	-0.00001		(0.30)	0.00562	***	(4.81)
Rec	0.00753	***	(15.71)	0.00002		(1.47)	0.00003		(1.27)	-0.02132	***	(10.48)
PT	-0.04966	***	(19.65)	-0.00015	**	(2.80)	-0.00064	***	(5.62)	0.02449	***	(5.25)
RevEPS1[-9,-1]	0.10238		(0.80)	-0.04310	***	(7.81)	-0.00062		(0.06)	0.08435		(0.26)
RevEPS2[-9,-1]	-0.13666		(1.27)	-0.01023	**	(2.71)	-0.08094	***	(10.05)	-0.54530	*	(2.14)
RevPT[-9,-1]	-0.10669	***	(13.49)	-0.00013		(1.23)	-0.00106	***	(4.80)	0.02693		(1.91)
RevRec[-9,-1]	0.00721	***	(4.50)	0.00005		(1.47)	0.00002		(0.17)	-0.01543		(1.61)
Controls for AI days & Analyst Effects	Yes			Yes			Yes			Yes		
Adjusted R2	4.53%			1.02%			1.35%			1.23%		

Table 8

Influence on Long-run Revisions

This table shows the estimation results of Equation (3) for $RevPT[2,60]$, and $RevRec[2,60]$. 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.

	Rev_PT[2,60]			Rev_REC[2,60]		
D_Comm	-0.0003		(0.29)	0.0044		(1.52)
Rec	0.0163	***	(11.79)	-0.1344	***	(32.90)
PT	-0.1912	***	(23.47)	0.1376	***	(10.78)
Star	0.0010		(0.77)	-0.0042		(0.94)
Brk_Size	-0.0001	***	(4.29)	0.0000		(0.07)
N_Cov	0.0000		(0.03)	0.0002		(0.98)
Freq	0.1262	*	(2.44)	0.5523	**	(3.27)
Exp	0.0002		(1.03)	0.0032	***	(4.05)
Cover_Ind	0.0001		(0.36)	-0.0006		(0.77)
Bank_Rel	-0.0024		(1.07)	-0.0142		(1.81)
RevEPS1[-9,-1]	-0.3806		(0.95)	-0.6495		(0.64)
RevEPS2[-9,-1]	-0.3456		(1.10)	1.4430		(1.69)
RevPT[-9,-1]	-0.1150	***	(8.37)	0.0534		(1.45)
RevRec[-9,-1]	0.0156	***	(3.84)	-0.0191		(1.29)
Controls for AI day Effects	Yes			Yes		
Adjusted R2	8.32%			5.87%		

Table 9

Long-run Price Impact

Panels (a) and (b) show the estimation results of Equation (4) for $CAR[2,20]$ and $CAR[2,60]$, respectively. The second column of each table reports the estimated coefficients when $Diff\_PT$ is excluded from the model. 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) CAR[2,20]

	CAR[2,20]					
Diff_RevPT[0,1]	-9.44		(1.18)	-11.40		(1.43)
Diff_RevRec[0,1]	0.34		(0.13)	0.90		(0.33)
Diff_RevEPS1[0,1]	835.82	*	(2.32)	847.13	*	(2.35)
Diff_RevEPS2[0,1]	-394.88	*	(2.22)	-407.86	*	(2.27)
Diff_PT	7.32	.	(1.66)			
Diff_Rec	-0.57		(0.61)	0.61		(0.71)
Diff_RevPT[-9,-1]	-9.74		(1.04)	-6.51		(0.68)
Diff_RevRec[-9,-1]	-0.97		(0.47)	-1.52		(0.71)
Diff_RevEPS1[-9,-1]	-180.51		(0.66)	-177.05		(0.65)
Diff_RevEPS2[-9,-1]	26.88		(0.13)	25.97		(0.13)
RevPT_NoComm[0,1]	14.09		(1.46)	12.68		(1.31)
RevRec_NoComm[0,1]	-2.73		(0.38)	-2.20		(0.31)
RevEPS1_NoComm[0,1]	206.51		(0.57)	199.66		(0.55)
RevEPS2_NoComm[0,1]	-225.72		(1.09)	-217.76		(1.05)
PT_NoComm	5.74		(0.54)	-6.09		(0.88)
Rec_NoComm	2.55		(1.18)	4.32	*	(2.06)
RevPT_NoComm[-9,-1]	5.40		(0.51)	6.42		(0.62)
RevRec_NoComm[-9,-1]	4.30		(0.78)	3.83		(0.69)
RevEPS1_NoComm[-9,-1]	-212.55		(0.78)	-212.52		(0.78)
RevEPS2_NoComm[-9,-1]	237.04		(0.75)	235.28		(0.75)
Disp_EPS1	-6.30	*	(2.32)	-6.53	*	(2.34)
Disp_EPS2	0.02		(0.04)	0.02		(0.05)
Disp_PT	158.25	*	(2.38)	156.11	*	(2.33)
CAR[-9,-1]	-0.04		(1.02)	-0.03		(0.96)
SUE	95.86	**	(2.61)	94.51	**	(2.59)
Size	-0.41		(0.44)	-0.49		(0.52)
BM	-0.09		(0.08)	-0.15		(0.13)
Controls for Firm Effects	Yes			Yes		
Adjusted R2	5.18%			4.93%		

(b) CAR[2,60]

	CAR[2,60]					
Diff_RevPT[0,1]	5.64		(0.34)	4.37		(0.27)
Diff_RevRec[0,1]	0.84		(0.16)	1.20		(0.23)
Diff_RevEPS1[0,1]	1,605.80	*	(2.02)	1,613.13	*	(2.03)
Diff_RevEPS2[0,1]	-636.39		(1.59)	-644.81		(1.61)
Diff_PT	4.75		(0.52)			
Diff_Rec	-2.55		(1.32)	-1.79		(1.13)
Diff_RevPT[-9,-1]	-50.98	**	(2.88)	-48.89	**	(2.83)
Diff_RevRec[-9,-1]	0.57		(0.14)	0.21		(0.05)
Diff_RevEPS1[-9,-1]	-118.27		(0.23)	-116.01		(0.22)
Diff_RevEPS2[-9,-1]	384.31		(1.24)	383.67		(1.24)
RevPT_NoComm[0,1]	37.57		(1.60)	36.65		(1.58)
RevRec_NoComm[0,1]	0.44		(0.04)	0.78		(0.07)
RevEPS1_NoComm[0,1]	-33.63		(0.04)	-38.06		(0.05)
RevEPS2_NoComm[0,1]	-558.26		(1.30)	-553.12		(1.28)
PT_NoComm	-16.69		(0.93)	-24.36	*	(1.99)
Rec_NoComm	3.16		(0.78)	4.31		(1.14)
RevPT_NoComm[-9,-1]	18.57		(0.92)	19.22		(0.95)
RevRec_NoComm[-9,-1]	8.32		(0.73)	8.01		(0.71)
RevEPS1_NoComm[-9,-1]	145.73		(0.27)	145.77		(0.27)
RevEPS2_NoComm[-9,-1]	374.21		(0.67)	373.06		(0.67)
Disp_EPS1	-6.00		(1.14)	-6.14		(1.17)
Disp_EPS2	1.43	*	(2.01)	1.43	*	(2.03)
Disp_PT	195.65	.	(1.70)	194.26	.	(1.69)
CAR[-9,-1]	-0.24	**	(2.86)	-0.23	**	(2.87)
SUE	-7.25		(0.10)	-8.12		(0.11)
Size	-6.44	***	(3.80)	-6.49	***	(3.84)
BM	-1.81		(0.80)	-1.85		(0.82)
Controls for Firm Effects	Yes			Yes		
Adjusted R2	6.14%			6.11%		

Table 10

Comparing with non-AI Days Sample

The table shows the results of estimating Equation (5) for $CAR[0,1]$. 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.

	CAR[0,1]	
D_AIDay X Diff_RevPT[0,1]	-3.80	(0.40)
D_AIDay X Diff_RevRec[0,1]	7.16 **	(2.84)
Diff_RevPT[0,1]	27.77 **	(3.19)
Diff_RevRec[0,1]	-1.46	(0.65)
Diff_RevEPS1[0,1]	-41.42	(0.76)
Diff_RevEPS2[0,1]	118.32	(1.28)
Diff_PT	2.36	(1.47)
Diff_Rec	0.01	(0.04)
Diff_RevPT[-9,-1]	3.74	(1.50)
Diff_RevRec[-9,-1]	0.28	(0.33)
Diff_RevEPS1[-9,-1]	0.79	(0.03)
Diff_RevEPS2[-9,-1]	-20.99	(0.93)
RevPT_NoComm[0,1]	52.47 ***	(8.46)
RevRec_NoComm[0,1]	7.36 **	(3.04)
RevEPS1_NoComm[0,1]	-206.53	(1.29)
RevEPS2_NoComm[0,1]	570.89 ***	(4.69)
PT_NoComm	13.16 **	(2.82)
Rec_NoComm	-2.34 *	(2.57)
RevPT_NoComm[-9,-1]	0.21	(0.09)
RevRec_NoComm[-9,-1]	4.89 **	(3.06)
RevEPS1_NoComm[-9,-1]	23.46	(0.96)
RevEPS2_NoComm[-9,-1]	-26.77	(0.92)
Disp_EPS1	0.01	(0.23)
Disp_EPS2	-0.42	(1.41)
Disp_PT	57.40 **	(3.10)
D_AIDay	-0.49 ***	(5.19)
CAR[-9,-1]	-0.07 ***	(5.69)
SUE	-8.15	(0.52)
Size	0.45	(1.46)
BM	0.30	(0.78)
Controls for Firm Effects	Yes	
Adjusted R2	13.60%	

Table 11

Definition of Virtual Meeting

Panel (a) shows the word lists used to identify virtual and face-to-face AI days. Panel (b) shows the number of AI days categorized as virtual AI days and the ratio for each quarter (between 2020 and 2022).

a) Words/Expressions for Identifying Virtual Meeting

Virtual Format	Face-to-Face Format
can you hear	in person
line is live	being here
line is now live	being with us here
line is now open	in the room
line is open	take your seats
listen-only	raise your hand
Q&A button	Microphone
submit question	mic-runner
today's call	
today's webinar	
Unmute	
virtual analyst and investor day	
virtual analyst day	
virtual event	
virtual investor day	
virtual setting	

b) Number of Virtual Meetings from the First Quarter (Q1) of 2020 to Q4 of 2022

	Virtual Format	All Format	Ratio
Q1 2020	14	35	40.0%
Q2 2020	32	68	47.1%
Q3 2020	42	62	67.7%
Q4 2020	116	138	84.1%
Q1 2021	80	89	89.9%
Q2 2021	122	143	85.3%
Q3 2021	72	105	68.6%
Q4 2021	90	143	62.9%
Q1 2022	27	55	49.1%
Q2 2022	34	141	24.1%
Q3 2022	21	66	31.8%
Q4 2022	15	78	19.2%
2020 to 2022	675	1123	60.1%

Table 12

Influence of Virtual Format

Panels (a) and (b) show the results of estimating Equations (6) and (7) for Rev_EPS (the results for the year dummies are not reported). 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) Active analyst's revisions

	Rev_PT[0,1]			Rev_REC[0,1]		
D_Comm X D_Virtual	-0.0003		(0.19)	0.0008		(0.25)
D_Comm X D_Year[2020,2022]	-0.0001		(0.11)	0.0000		(0.01)
D_Comm	0.0021	***	(4.67)	0.0051	***	(3.84)
Rec	0.0067	***	(12.00)	-0.0196	***	(11.99)
PT	-0.0425	***	(14.58)	0.0286	***	(6.18)
Star	-0.0005		(0.97)	0.0027		(1.80)
Brk_Size	0.0000	*	(2.44)	-0.0001	***	(3.80)
N_Cov	0.0000		(0.34)	-0.0001		(1.53)
Freq	0.0141		(0.68)	0.0128		(0.23)
Exp	0.0000		(0.02)	0.0000		(0.06)
Cover_Ind	-0.0001		(1.24)	0.0007	*	(2.45)
Bank_Rel	-0.0008		(0.88)	0.0029		(1.08)
RevEPS1[-9,-1]	0.1240		(0.95)	0.0055		(0.02)
RevEPS2[-9,-1]	-0.0928		(0.84)	-0.4167		(1.51)
RevPT[-9,-1]	-0.1090	***	(15.08)	0.0260		(1.83)
RevRec[-9,-1]	0.0073	***	(4.97)	-0.0158		(1.61)
Controls for AI day Effects	Yes			Yes		
Adjusted R2	4.07%			1.13%		

(b) Price impact

	CAR[0,1]					
D_Virtual X Diff_RevPT[0,1]	19.15		(0.89)	19.44		(0.91)
D_Virtual X Diff_RevRec[0,1]	2.80		(0.31)	2.28		(0.26)
D_Year[2020,2022] X Diff_RevPT[0,1]	-17.51		(1.25)	-18.46		(1.31)
D_Year[2020,2022] X Diff_RevRec[0,1]	-1.14		(0.15)	-1.11		(0.14)
D_Virtual	-0.67	*	(2.04)	-0.67	*	(2.05)
Diff_RevPT[0,1]	22.69	***	(4.60)	21.66	***	(4.41)
RevPT_NoComm[0,1]	60.99	***	(7.90)	60.05	***	(7.87)
Diff_PT	4.77	.	(1.85)			
PT_NoComm	25.25	***	(3.41)	17.55	**	(3.22)
Diff_RevPT[-9,-1]	11.97	*	(2.14)	14.05	*	(2.50)
RevPT_NoComm[-9,-1]	-4.01		(0.72)	-3.32		(0.59)
Diff_RevRec[0,1]	8.75	***	(5.35)	9.16	***	(5.57)
Diff_Rec	0.02		(0.05)	0.79	.	(1.92)
RevRec_NoComm[0,1]	13.20	***	(3.68)	13.57	***	(3.79)
Rec_NoComm	-3.79	**	(2.80)	-2.63	*	(2.13)
Diff_RevRec[-9,-1]	0.54		(0.45)	0.19		(0.15)
RevRec_NoComm[-9,-1]	3.04		(1.15)	2.74		(1.03)
Diff_RevEPS1[0,1]	246.40		(1.01)	253.92		(1.03)
Diff_RevEPS2[0,1]	194.35		(1.39)	185.17		(1.31)
RevEPS1_NoComm[0,1]	170.92		(0.73)	167.84		(0.71)
RevEPS2_NoComm[0,1]	685.45	***	(4.57)	691.08	***	(4.54)
Diff_RevEPS1[-9,-1]	-331.62	**	(2.63)	-329.50	**	(2.58)
Diff_RevEPS2[-9,-1]	36.82		(0.36)	36.55		(0.36)
RevEPS1_NoComm[-9,-1]	-28.92		(0.26)	-28.80		(0.26)
RevEPS2_NoComm[-9,-1]	-103.90		(0.67)	-104.98		(0.68)
CAR[-9,-1]	-0.09	***	(4.16)	-0.09	***	(4.07)
SUE	-21.97		(1.04)	-22.76		(1.07)
Size	1.07	*	(2.01)	1.03	.	(1.91)
BM	0.91	.	(1.84)	0.87	.	(1.74)
Disp_EPS1	-3.16	*	(2.09)	-3.30	*	(2.21)
Disp_EPS2	-0.35	.	(1.94)	-0.35	.	(1.87)
Disp_PT	74.64	*	(2.43)	73.36	*	(2.36)
Controls for Firm Effects	Yes			Yes		
Adjusted R2	25.06%			24.76%		

Table A1

List of variables

(a) The variables for the Analyst Revision Analysis (Equation (1), (2), (3), and (6))

Variables	Definition
$RevPT[t_1, t_2]_{i,s}$	A revision in price target for the hosting firm of AI day *s* defined as the change in analyst i's price target for days t_1 through t_2 (from $t_1 - 1$ to t_2) deflated by the closing price on $t_1 - 1$.
$RevRec[t_1, t_2]_{i,s}$	A revision in stock recommendation for the hosting firm of AI day *s* defined as the change in analyst i's recommendation for days t_1 through t_2, where recommendation is coded as strong buy = 1, buy = 0.5, hold = 0, sell = -0.5, and strong sell= -1.
$RevEPS1[t_1, t_2]_{i,s}$	A revision in earnings per share (EPS) estimates for the current fiscal year (FY1) defined as the change in analyst i's FY1 EPS forecast for days t_1 through t_2, deflated by the closing price on $t_1 - 1$.
$RevEPS2[t_1, t_2]_{i,s}$	A revision in earnings per share (EPS) estimates for the next fiscal year (FY2) defined as the change in analyst i's FY2 EPS forecast for days t_1 through t_2, deflated by the closing price on $t_1 - 1$.
$Abs\_RevPT[t_1, t_2]_{i,s}$	Absolute value of $RevPT[t_1, t_2]_{i,s}$.
$Abs\_RevRec[t_1, t_2]_{i,s}$	Absolute value of $RevRec[t_1, t_2]_{i,s}$.
$Abs\_RevEPS1[t_1, t_2]_{i,s}$	Absolute value of $RevEPS1[t_1, t_2]_{i,s}$.
$Abs\_RevEPS2[t_1, t_2]_{i,s}$	Absolute value of $RevEPS2[t_1, t_2]_{i,s}$.
$PT_{i,s}$	The relative price target defined as the analyst *i*'s price target for the hosting firm of AI day *s* minus its consensus price target deflated by the closing price.
$Rec_{i,s}$	The relative stock recommendation defined as the analyst *i*'s stock recommendation (coded as strong buy = 1, buy = 0.5, hold = 0, sell = -0.5, and strong sell= -1) for the hosting firm of AI day *s* minus its consensus stock recommendation.
$Star_{i,s}$	A dummy variable that takes 1 if analyst *i* has the AA title of the Institutional Investor magazine and 0 otherwise.
$Brk\_Size_{i,s}$	The size of the brokerage firm of the analyst *i*, calculated as the number of analysts employed by the brokerage firm employing the analyst *i* on the date of AI day *s*.
$N\_Cov_{i,s}$	The number of stocks that the analyst *i* covers on the date of AI day *s*.
$Ind\_Cov_{i,s}$	The number of industries that the analyst *i* covers, calculated as the number of two-digit SICs that the analyst follows on the date of AI day *s*.
$Exp_{i,s}$	The measure of analyst *i*'s experience, calculated as the number of years of experience as a financial analyst as of the date of AI day s.
$Freq_{i,s}$	The measure of the analyst *i*'s forecast frequency for a firm, calculated as the number of updates for price targets of the firm made by analyst *i* in the last twelve months (as of the date of AI day *s*).
$Bank\_Rel_{i,s}$	A dummy variable of the analyst *i*'s investment banking relationship with the hosting firm of AI day *s* (as of the date of AI day *s*).
$D\_Virtual_s$	A dummy variable that takes a value of one if AI day *s* is held in a virtual format.

(b) The variables for the Price Impact Analysis (Equation (4), (5), (7))

Variables	Definition
$CAR[t_1, t_2]_s$	Abnormal stock returns of the hosting firm of AI day s for days t_1 through t_2, calculated using the Fama-French three-factor model with the Carhart momentum factor.
$Diff\_RevPT[t_1, t_2]_s$	Difference in $RevPT[t_1, t_2]_{i,s}$ between active and non-active analysts (for AI day *s*).
$Diff\_RevRec[t_1, t_2]_s$	Difference in $RevRec[t_1, t_2]_{i,s}$ between active and non-active analysts (for AI day *s*).
$Diff\_RevEPS1[t_1, t_2]_s$	Difference in $RevEPS1[t_1, t_2]_{i,s}$ between active and non-active analysts (for AI day *s*).
$Diff\_RevEPS2[t_1, t_2]_s$	Difference in $RevEPS2[t_1, t_2]_{i,s}$ between active and non-active analysts (for AI day *s*).
$Diff\_PT_s$	Difference in $PT_{i,s}$ between active and non-active analysts (for AI day *s*).
$Diff\_Rec_s$	Difference in $Rec_{i,s}$ between active and non-active analysts (for AI day *s*).
$RevPT\_NoComm[t_1, t_2]_s$	Average value of $RevPT[t_1, t_2]_{i,s}$ of non-active analysts (for AI day *s*).
$RevRec\_NoComm[t_1, t_2]_s$	Average value of $RevRec[t_1, t_2]_{i,s}$ of non-active analysts (for AI day *s*).
$RevEPS1\_NoComm[t_1, t_2]_s$	Average value of $RevEPS1[t_1, t_2]_{i,s}$ of non-active analysts (for AI day *s*).
$RevEPS2\_NoComm[t_1, t_2]_s$	Average value of $RevEPS2[t_1, t_2]_{i,s}$ of non-active analysts (for AI day *s*).
PT_NoComm_s	Average value of $PT_{i,s}$ of non-active analysts (for AI day *s*).
Rec_NoComm_s	Average value of $Rec_{i,s}$ of non-active analysts (for AI day *s*).
$Disp\_PT_s$	Dispersion in price targets calculated as one standard division of analysts' price targets for the hosting firm deflated by its closing price (as of the date of AI day *s*).
$Disp\_EPS1_s$	Dispersion in FY1 EPS forecasts calculated as one standard division of analysts' FY1 EPS forecasts for the hosting firm deflated by its closing price (as of the date of AI day *s*).
$Disp\_EPS2_s$	Dispersion in FY2 EPS forecasts calculated as one standard division of analysts' FY2 EPS forecasts for the hosting firm deflated by its closing price (as of the date of AI day *s*).
SUE_s	Earnings surprise measures, calculated as the difference between analysts' consensus forecast and the reported EPS (deflated by its closing price) for the most recent quarterly earnings announcement of the hosting firm of AI day *s*.
$SIZE_s$	Log of the market value of the hosting firm of AI day *s*.
BM_S	Book-to-market ratio (book value of equity/market value of equity) of the hosting firm of AI day *s*.
D_AIday_s	A dummy variable that takes a value of one if the sample s is included in the AI day's sample.
$D\_Year[2020{,}2022]_s$	A dummy variable that takes a value of one if AI day s is held between 2020 and 2022
$D\_Virtual_s$	A dummy variable that takes a value of one if AI day s is held in a virtual format.