Verbal Communication with Corporate Insiders

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Abstract

This study examines the impact of direct verbal communication between analysts and corporate insiders on analysts' discount rates and stock prices. The analysis shows that active analysts who communicate with corporate insiders during analyst and investor days (AI Days) make more positive revisions to price targets and stock recommendations than non-active analysts, while no comparable effect is observed for earnings forecasts. Because price targets and stock recommendations are affected by discount rates, whereas earnings forecasts are not, the findings suggest that direct verbal communication primarily reduces analysts' discount rates. Finally, hosting firms' abnormal returns are positively associated with revisions in active analysts' price targets and stock recommendations. Overall, the evidence indicates that direct communication reduces discount rates and, in turn, positively affects stock prices, thereby partially contributing to the positive price reaction to AI Days.

Keywords: direct communication; financial analyst; discount rate

JEL classification: G14 , G24 ,G32

1. Introduction

As an increasing number of analysts and investors underscore the significance of access to corporate management (Kary, 2005; Wagner, 2005; Brinkley, 2012), companies are correspondingly expanding opportunities for market participants to engage directly with corporate insiders (Valentine, 2011; Brown et al., 2014). Prior research (e.g., Bowen et al., 2002; Kimbrough, 2005; Kirk & Markov, 2016; Park, 2019; Miwa, 2023a) has predominantly examined the effects of such direct communication on short-term earnings expectations. These studies demonstrate that interactive discussions often prompt revisions in earnings forecasts; however, the direction of these revisions tends to be neutral, as both positive and negative earnings-related information is conveyed in equal measure (Park, 2019; Miwa, 2023a).

Hence, these prior studies seem to suggest that firms derive little benefit from interactive communication with market participants, including financial analysts and investors. However, several studies (e.g., Botosan, 1997; Lambert et al., 2007) argue that voluntary disclosure can lower firms' cost of capital and discount rates. Thus, firms may still benefit from interactive communication, which is a specific type of voluntary disclosure, by reducing their discount rate and increasing their stock prices.

Hence, this study clarifies the influence of such communication on communicators' discount rates. It empirically investigates the effect on discount rates and the subsequent impact on stock prices. Specifically, I analyze the influence of direct communication that occurs during AI days on sell-side analysts' estimates, given their prominent role in these events and the observability of their forecasts.

Sapienza and Korsgaard (1996) suggest that direct and timely interaction between firm management and investors enhances investors' trust in the company. Furthermore, Gennaioli et al. (2015) argue that such trust lowers the required risk premium. Hence, the direct and timely interaction can reduce the discount rates applied to future cash flows and ultimately exert a positive influence on stock prices.

To test this prediction, I compare the impact on discount rates between two groups of analysts: those who engage in direct verbal communication with corporate insiders (hereinafter referred to as active analysts) and those who do not (non-active analysts). Since analysts' discount rates are not directly observable, I assess them indirectly by examining their effects on both fair value-related and earnings-related estimates.

First, to confirm the informational value of direct communication with corporate insiders for analysts, I examine whether such communication induces changes in communicators' estimates.

Second, because a reduction in discount rates typically increases fair-value-related estimates, namely price targets and stock recommendations, I investigate whether active analysts revise these estimates more positively than non-active analysts on AI Days. In addition, because discount rates do not directly affect earnings forecasts, I examine whether such differential revisions are absent for earnings forecasts. If both conditions are met, that is, if more positive revisions by active analysts are observed only for price targets and stock recommendations, the results would suggest that active analysts' discount rates are reduced more substantially than those of non-active analysts. This, in turn, would indicate that direct communication with corporate insiders primarily reduces communicators' discount rates.

Finally, 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.

First, the analysis confirms that analysts who actively engage in direct communication with corporate insiders more significantly revise their earnings forecasts and price targets on AI days, supporting the significant influence of direct 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 direct communication with corporate insiders reduces communicators' discount rates, resulting in an upward revision of price targets and stock recommendations.

Next, 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 direct communication.

This study contributes to the existing literature in three primary ways. First, it advances the understanding of the effects of direct communication by corporate insiders. While prior research has predominantly examined how such communication influences participants' short-term earnings expectations and corresponding earnings forecasts, this study extends the analysis beyond earnings-related impacts. Specifically, it demonstrates that direct communication also affects communicators' discount rates, thereby altering their fair value estimates for the hosting firms.

Second, this study contributes to corporate disclosure research. Several studies (e.g., Botosan, 1997; Lambert et al., 2007) argue that voluntary disclosure can lower firms' cost of capital and discount rates. I extend this argument by providing evidence that interactions with corporate insiders, categorized as voluntary disclosure channels, lower the discount rate applied to the firm.

Finally, this paper contributes to research on analysts' access to management and selective disclosure. Prior studies show that analysts do not receive equal access to corporate managers and that such differences in access can shape unequal information production. This study extends this literature by showing that analysts who actively communicate with managers respond differently from those who do not.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature. Section 3 describes the sample selection and presents preliminary tests on the determinants of direct communication. Sections 4, 5, and 6 examine the influence of communication on communicators' estimate updates, fair value estimates, and stock prices, respectively. Section 7 discusses additional analyses. Finally, Section 8 summarizes the findings.

2. Related Literature

Interactive discussions with corporate insiders have recently gained importance as a source of information for capital market participants (Valentine, 2011; Brown et al., 2014). Traditionally, short-term interactions occur at the end of earnings calls, which are usually held immediately after earnings announcements. Accordingly, a considerable number of studies have analyzed earnings conference 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 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. Mayew et al. (2013) find that analysts who actively participate in these discussions produce annual earnings forecasts that are both more accurate and timelier than those of non-participating analysts. Brockman et al. (2015) demonstrate that both managerial and analyst tones significantly affect abnormal returns.

Meanwhile, in response to the growing demand for intensive interactions with corporate insiders (Kary, 2005; Wagner, 2005; Brinkley, 2012), firms have increasingly provided opportunities for engagement through a new disclosure channel: AI Days. Today, practitioners regard this channel as a significant component of corporate disclosure and investor relations activities (Rossi, 2010; Buckley, 2011). Valentine (2011) argues that AI Days serve as a valuable source of information for institutional investors and sell-side analysts. Compared with earnings calls, AI Days offer a more extended period of interaction with corporate insiders. Analyzing these prolonged, interactive discussions is therefore critical for understanding the influence of direct communication with insiders (Kirk & Markov, 2016). Moreover, unlike earnings calls, AI Days are seldom held in conjunction with earnings announcements, thereby mitigating concerns that participants' reactions are confounded by responses to contemporaneous earnings disclosures.

Reflecting the growing recognition of AI Days, an increasing number of academic studies have examined its informational role. Kirk and Markov (2016) argue that AI Days serve a crucial informational role for investors. They document substantial increases in stock price variability, trading volume, and analyst activity around these events, reinforcing the informational value of AI Days. Park (2019) finds that hosting AI Days enhances the informativeness of subsequent quarterly earnings announcements. Wu and Yaron (2018) report positive stock price reactions to these events, supporting the view that direct communication has favorable valuation effects. Miwa (2023a) shows that the positive (negative) tone of Q&A sessions during AI Days significantly prompts positive (negative) revisions in analysts' earnings forecasts.

Despite the expanding body of research analyzing the effects of direct interactions between analysts and firms during such events, most existing studies concentrate on earnings-related information and its impact on participants' earnings forecasts. However, the broader voluntary-disclosure literature suggests that disclosure can reduce information asymmetry and estimation risk, thereby lowering firms' cost of capital or discount rates. Botosan (1997) provides early evidence that firms with more extensive voluntary disclosure have a lower cost of equity capital, particularly when analyst following is low. Botosan and Plumlee (2002) further show that different types of disclosure are associated with the cost of equity in different ways, highlighting the importance of distinguishing among disclosure channels and disclosure formats. Lambert et al. (2007) develop a theoretical framework showing that accounting information can affect the discount rate applied to the firm through corporate disclosure. This line of research provides the theoretical foundation for the argument that voluntary disclosure, including direct communication between analysts and corporate insiders as a specific form, may influence firm value not only through expected future cash flows but also through discount rates.

Hence, this study addresses this gap by investigating the effect of direct communication on participants' discount rates. Such an analysis is crucial for deepening our understanding of the economic function of direct interaction with corporate insiders.

This study also relates to research on analysts' access to management and selective disclosure. Analysts do not receive access to firms uniformly. Brown et al. (2014) emphasize that private communication with management is an important input into analysts' research process. More directly, Cohen et al. (2020) show that firms strategically allocate access to management. They argue that such inequal access to corporate managers can shape unequal information production. This study extends these studies by clarifying whether analysts who actively communicate with managers respond differently from those who do not.

3. Sample Selection and Characteristics

3.1. Sample Selection

This study focuses on direct communication during AI days for several reasons. Compared to earnings calls, AI days provide longer and more substantive opportunities for interaction between corporate insiders and financial analysts or investors. Furthermore, unlike earnings calls, AI days are seldom scheduled alongside earnings announcements, thereby minimizing the risk that investor responses to these interactions are confounded by reactions to contemporaneous financial disclosures (Kirk & Markov, 2016).

I construct a sample of AI days for U.S. firms using company-level event calendar data from FactSet. If an AI day spans multiple days, only the first day is included in the sample. Following Kirk and Markov (2016), I exclude AI days on which a firm announces earnings within two trading days. The final sample comprises 56,277 AI day–analyst observations, covering 3,699 AI days hosted by 1,403 firms during the period from 2010 to 2022. The year 2010 is chosen as the starting point due to the availability of sufficiently comprehensive transcript data from that year onward.

This study focuses on the influence of sell-side analysts' direct 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.

For each observation, analysts are classified as active if they provide comments or ask questions during the Q&A session with corporate insiders. These analysts are identified using transcripts from the FactSet transcript database, which records both speaker names and affiliations. Non-active analysts are defined as those who cover the host firm but do not engage in communication during the AI day. I then match these identified names and affiliations with the FactSet analyst estimates database to build the full sample. Approximately 37.2% of the sample consists of active analysts, while the remainder are classified as non-active. On average, each AI day involves 4.9 active analysts and 10.3 non-active analysts.

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 direct communication. Therefore, as a preliminary analysis, I examine the differences in the characteristics and prior activities between active and non-active analysts.

3.2.1. Key Variables

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' characteristics 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. [1]

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

[1] 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.

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, 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 recommendations, and price target for days t-9 through t-1, where t is the date of AI day s [2] (denoted as $Abs\_RevEPS1[-9,-1]$, $Abs\_RevEPS2[-9,-1]$, $Abs\_RevRec[-9,-1]$, 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).[3] Detailed definitions of the explanatory variables used in this study are provided in Table A1(a).

3.2.2. Analysis of Analyst Characteristics

To analyze the association of D_Comm with the characteristics, the following probit model with AI day fixed effects is estimated:

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[2] If it takes place on multiple days, t is its first day.

[3] To mitigate the effect of outliers, I winsorize the bottom and top 1% of the variables related to analysts' estimate revisions (excluding stock recommendation measures).

$$Prob(D\_Comm_{i,s} = 1) = f(X_{i,s}) \quad (1)$$

$D\_Comm_{i,s}$ is a dummy variable of analysts' communication (in other words, an active analyst dummy variable) that takes a value of one if analyst i had any comments or asked questions to corporate insiders on AI day s (otherwise 0). $X_{i,s}$ represents explanatory variables, 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.

The regression result presented in Table 1 reveals that higher Brk_Size, N_Cover, $Freq$, Exp, $Star$ values increase the probability of communicating with corporate insiders. These findings indicate that analysts employed by larger brokerage houses, those who cover more stocks, update their forecasts more frequently, have longer experience, and hold star-analyst status, are more likely to engage in communication on AI days. This supports the view that analysts with higher abilities tend to communicate more actively. The significant positive coefficient of $Bank\_rel$ suggests that analysts with an investment banking relationship with the hosting firm are more likely to engage in active direct communication. Additionally, the positive coefficients of Rec and PT indicate that analysts who issue favorable recommendations and aggressive price targets tend to communicate more actively.

In summary, the results highlight significant differences in characteristics between active and non-active analysts. In other words, analysts' backgrounds and ex-ante forecasts influence whether they interact with corporate insiders on AI days. Therefore, when analyzing the impact of direct communication on active analysts' estimates, it is crucial to include these characteristics as control variables to mitigate concerns that the observed impact is merely attributable to active analysts' inherent traits. Additionally, to address endogeneity concerns, specifically the self-selection of informed analysts into active communication with corporate insiders, I perform Heckman's (1979) two-stage procedure in Section 7.1 for the analysis of hypotheses related to ex-post revision activity.

[Table 1]

4. Impact on Analysts' Updates

In this section, I confirm the informational value of direct communication with corporate insiders for analysts, by examining whether such communication induces updates in communicators' estimates.

4.1. Hypothesis

I predict that direct communication has informational value for analysts and, therefore, influences communicators' expectations. Consequently, analysts who communicate with corporate insiders, i.e., active analysts, may exhibit more pronounced unsigned revisions in their estimates, such as target prices and earnings forecasts, than non-active analysts. Hence, I propose the following hypothesis:

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

4.2. Methodology

To test H1, the absolute value (magnitude) of analysts' estimate revisions is regressed on a dummy variable of analysts' communication (D_Comm) with several control variables and AI-day fixed effects. Specifically, the following regression model with AI-day fixed effects is estimated:

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

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, where t is the date of AI day s (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). Detailed definitions of these revision variables are provided in Table A1(a).

Although it is not theoretically clear whether and how analysts' estimate revisions on AI days are directly related to their ability,[4] these revisions may be indirectly influenced by analyst ability, as such characteristics can affect whether they interact with firms (as explained in Section 3). Hence, the model includes the following control variables regarding analyst abilities: analyst experience (Exp), update frequency ($Freq$), brokerage size (Brk_Size), the number of covered firms (N_Cov),

[4] Consistent with this argument, as shown in Table 3, the magnitude of the revisions are largely unrelated to the analyst ability measures, with the exception of the frequency of their updates ($Freq$).

the number of covered industries (Ind_Cov), and an analyst's star status ($Star$). In addition, the model includes a dummy variable of the analyst's investment banking relationship ($Bank\_Rel$), analyst's relative stock recommendation (Rec), and relative price target (PT). Since analyst ex-ante activities can influence whether analysts interact with firms, 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.

I estimate the model with AI day fixed effects, which allows for comparing participant responses on the same AI day.[5] This approach alleviates the possibility that differences in hosting firms' conditions and incentives, characteristics of analysts who cover the firm, and the information provided across AI days affect the regression results. H1 predicts a positive coefficient of D_Comm.

4.3. Results

- Descriptive Statistics

The descriptive statistics of the sample for testing analysts' updates are shown in Table 2 (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 (11.6%) exceeds that of negative revisions (3.8%). For "$RevRec[0,1]$", only 0.5% and 0.4% 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)[6]. 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 2(b) reveals that D_Comm (the communication dummy variable) is positively correlated with $Star$, Brk_Size, N_Cover, $Freq$, and Exp indicating that analysts that communicate with corporate insiders are likely to possess a star analyst status, be employed by large brokerage firms, cover a significant number of firms, frequently update their estimates, and have extensive experience.

[5] 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).

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

Because these features represent analysts' abilities, the results indicate that analysts with higher abilities tend to communicate actively with corporate insiders. 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 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.

[Table 2]

- Main Result

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 among the variables in the regressions.

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

The coefficient of D_Comm is insignificant for $Abs\_RevRec[0,1]$. Furthermore, the other explanatory variables exhibit much weaker predictive 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 5.1, $Abs\_RevRec[0,1]$ (the degree of change in stock recommendations) may not be a suitable indicator of analysts' fair value estimate revisions because stock recommendations fall into a limited number of discrete 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 influences their estimates by altering their perspectives on a company's performance and stock valuation, thereby supporting H1.

[Table 3]

5. Positive Influence on Fair Value Estimation

In this section, I investigate the influence of direct communication on the fair value estimates

5.1. Hypothesis

Several business communication and management studies (e.g., Sapienza & Korsgaard, 1996; Becerra & Gupta, 2003; Thomas et al., 2009) suggest that direct communication enhances communicators' trust. Specifically, Sapienza and Korsgaard (1996) argue that interaction between firm management and investors fosters greater investor trust in the company. Such trust may reduce investors' perception of the riskiness of future cash flows (Gennaioli et al., 2015), thereby lowering the required risk premium (i.e., discount rates) applied to the firm's cash flows. Since the fair value of a stock is determined by the discounted value of its expected future cash flows, the direct communication could primarily induce positive revisions in communicators' (i.e., active analysts') fair value estimates. Therefore, even if the content of these communications is shared with other analysts and investors, revisions in fair value estimates are likely to be more positive for active analysts who engage in direct communication with corporate insiders than for non-active analysts who do not. Based on this reasoning, I propose the following hypothesis:

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

By contrast, analysts' earnings expectations are not typically influenced by their discount rates. Therefore, even if direct communication reduces discount rates, this reduction is unlikely to increase 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. Thus, although earnings forecasts are more likely to be revised in either direction on AI days, there is unlikely to be a consistent upward trend in these revisions. Hence, the following hypothesis is proposed:

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

5.2. Methodology

To test H2 and H3, 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.

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

where the dependent variable ($Rev_{i,s}$) represents 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 over 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). Detailed definitions of these revision variables are provided in Table A1(a). The model includes AI day fixed effects, allowing for a comparison of participant responses on the same AI day.

It is not logically clear whether and how signed revisions in analysts' estimates on AI days are directly related to the analyst's ability.[7] However, since measures of analyst ability can influence whether analysts interact with firms, their signed revisions may be indirectly affected by such characteristics. Hence, to mitigate the possibility that the coefficient of D_Comm is influenced by analyst characteristics and ex-ante activities, the model includes control variables for these factors (Exp, $Freq$, Brk_Size, N_Cov, Ind_Cov, $Star$, $Bank\_Rel$, Rec, PT, $RevEPS1[-9,-1]$, $RevEPS2[-9,-1]$, $RevREC[-9,-1]$, and $RevPT[-9,-1]$).

H2 and H3 predict that the revisions in price targets and stock recommendations ($RevPT[0,1]$ and $RevRec[0,1]$) are positively associated with D_Comm, while revisions in earnings forecasts

[7] Consistent with this argument, as shown in Table 6, the signed revisions are largely unrelated to the analyst ability measures.

($RevEPS1[0,1]$ and $RevEPS2[0,1]$) are not positively associated with D_Comm.

5.3. Result

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 direct communication with corporate insiders raises communicators' earnings and fair price estimates. The highest VIF is 2.08, which is below 10, indicating that there is 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 coefficients regarding analyst characteristic measures (Exp, $Freq$, Brk_Size, N_Cov, Ind_Cov, $Star$, $Bank\_Rel$) are largely insignificant, indicating that the signed revisions are not directly associated with the analyst characteristics.

The coefficient of D_Comm is significantly positive for $RevPT[0,1]$ and $RevRec[0,1]$, indicating that direct 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 always increase earnings forecasts. [9] These results support H2 and H3. [10]

[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.

[9] I cannot rule out the possibility that the communication affects long-term growth expectations, thereby influencing target prices and stock recommendations. Therefore, as an additional test, I examine the effect of communication on revisions in EPS forecasts for the fiscal year after next (FY3) and on changes in long-term growth forecasts. The untabulated results (available upon request) show that the coefficient on D_Comm is not statistically significant for either revisions in FY3 EPS forecasts or changes in long-term growth forecasts. Therefore, the possibility that communication increases stock recommendations and target prices through changes in long-term forecasts is not supported.

[10] The stock price effect may reflect a simpler explanation: firms hold AI Days when they have favorable information to disclose, and active analysts are those who conduct more research on these firms. This timing × analyst-effort explanation can account for larger revisions by active analysts around AI Days. However, it cannot explain why the positive effect appears only in target prices and stock recommendations, not in forecasts of firm performance.

If AI Days primarily conveyed positive information, active analysts should also revise earnings forecasts upward. Yet I find no positive effects on FY1, FY2, or FY3 EPS forecasts, or on long-term growth forecasts. Moreover, Miwa

[Table 4]

6. Influence on Stock Prices

In this section, I investigate whether responses to AI days by active analysts affect stock prices.

6.1. Hypothesis

Although financial analysts do not trade stocks directly, prior studies (e.g., Brav & Lehavy, 2003; Feldman et al., 2012; Miwa, 2023b) show that stock prices react significantly to revisions in analysts' fair value estimates. Therefore, revisions in active analysts' fair value estimates, which may be induced by direct communication, could significantly affect the stock prices of hosting firms on AI Days. 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 supported, direct communication with corporate insiders is likely to elevate stock prices by decreasing communicators' discount rates.

6.2. Methodology

To test H4, 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).[11] Then, I analyze whether these differences are positively associated with abnormal returns around the AI day, by estimating the following regression model with firm fixed effects:

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

(2023a) shows that AI Days provide supplemental information, which is especially useful for uninformed analysts, rather than entirely new information. These findings support our interpretation that direct communication lowers the discount rate used in fair value estimation, rather than merely reflecting AI Day timing × analyst effort.

[11] Detailed definitions of these variables regarding the difference in revision are provided in Table A1(b).

where the dependent variable $CAR[0,1]_s$ represents the abnormal return of the hosting firm on AI day s over days t through t +1, where t is the date of AI day s (if it spans 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). $\beta_0 Diff\_RevPT[0,1]$ and $\beta_1 Diff\_RevRec[0,1]$ capture 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.

Control variables include differences in FY1 and FY2 EPS forecast revisions (forecast revisions of earnings per share for the current unreported and next fiscal years) 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.[12] Additionally, to account for the level of analysts estimate revisions that are not attributed direct communication, the regression model includes $RevPT[0,1]$, $RevRec[0,1]$, $RevEPS1[0,1]$, 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).

In addition, I consider several lagged revisions. As demonstrated in Section 4, analysts' estimate revisions are significantly influenced by prior revisions in their estimates. The model specifically includes differences in revisions of price targets, stock recommendations, and 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). It also incorporates the average values of $RevPT[-9,-1]$, $RevRec[-9,-1]$, $RevEPS1[-9,-1]$, and $RevEPS2[-9,-1]$ for non-active analysts (denoted as $RevPT\_NoComm[-9,-1]$, $RevRec\_NoComm[-9,-1]$, $RevEPS1\_NoComm[-9,-1]$, and RevEPS2_NoComm$[-9,-1]$, respectively). The control variables also include the difference in price targets relative to stock price and stock recommendations ($Diff\_PT$ and $Diff\_Rec$, respectively), as well as non-active analysts' price targets relative to stock price (PT_NoComm), and their stock recommendations (Rec_NoComm). This incorporation is based on the findings in Section

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

5, which demonstrate that the level of stock recommendations and price targets is associated with subsequent revisions in price targets and stock recommendations. Furthermore, considering that dispersion in earnings forecasts and price targets may influence the difference in the revisions between active and non-active analysts, the model also includes dispersion in price targets and FY1 and FY2 EPS forecasts (denoted as Disp_PT, Disp_EPS1, and 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 over the nine prior trading days ($CAR[-9,-1]$). 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 accounts for firm size ($SIZE$) and the book-to-market ratio (BM). Table A1(b) provides detailed definitions of the explanatory variables used in this section.

6.3. Results

- Descriptive Statistics

The descriptive statistics for testing price reactions (H4) are shown 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%). In addition, the ratio of positive $Diff$_RevRec[0,1] (5.6%) is larger than that of negative $Diff$_RevRec[0,1] (5.1%). These results indicate that RevPT[0,1] and RevREC[0,1]are likely to be higher for active analysts than for non-active analysts. In other words, these results support the view that active analysts are more likely to upwardly revise their price targets and stock recommendations than non-active analysts. The positive $Diff$_PT and $Diff$_Rev indicate that the price target and stock recommendation are higher for active analysts than for non-active analysts, consistent with the findings in Section 5. The mean $CAR[0,1]$is 17 basis points (0.0017), indicating that abnormal returns on AI Days tend to be positive. This result is consistent with Wu and Yaron (2018), although the magnitude is smaller than theirs (29 basis points).

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]

- Main Results

Table 6 presents the estimated coefficients of Model (4) for CAR[0,1].

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 findings indicate that while revisions in non-active analysts' fair value estimates impact stock prices, revisions made by active analysts have an additional impact beyond those of non-active analysts, supporting H4.

Since active communication with corporate insiders leads to positive revisions in communicators' price targets and stock recommendations, resulting in higher $Diff_RevPT[0,1]$and $Diff\_RevRec[0,1]$, the positive association between these variables and abnormal returns on AI Days supports the view that active communication with corporate insiders can positively influence stock prices by increasing communicators' price targets and stock recommendations.

The coefficient on $Diff\_RevPT[0,1]$ and $Diff\_RevRec[0,1]$ are 0.20 and 0.09 respectively, indicating that an additional 1% increase in $Diff_RevPT[0,1]$is associated with abnormal stock returns of 0.20%, while a one-unit increase in $Diff_RevREC[0,1]$is associated with abnormal stock returns of 9%. Section 5 and Table 4 show that direct communication increases target prices and stock recommendations by 0.20% of the stock price and 0.0052, respectively. These increases could translate into abnormal stock returns of approximately 9 basis points ($= 0.20\% \times 0.20 + 0.0052 \times 0.09$). This magnitude is approximately 53% of the average $CAR[0,1]$, suggesting that about half of the positive stock price reaction to AI Days can be explained by interactive communication with corporate insiders.

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, since the highest VIF exceeds 4, there is a possibility of slight bias in the coefficients. To investigate this, I exclude the variable with the highest VIF ($Diff\_PT$) and re-estimate the regression model. The results, presented in the second column of Table 6, show that 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 $Diff\_RevRec[0,1]$ 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]

7. Additional Evidence

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

7.1. Endogeneity Concern Regarding Direct Communication

The findings shown in Section 5 suggest that direct communication can influence analysts' estimations, 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 engage with corporate insiders. In this scenario, such analysts might revise their estimates even if direct communication has no direct impact on their estimations.[13] To alleviate the endogeneity concern, I first employ the Heckman (1979) treatment effects model to estimate Model (2) and (3). Moreover, to further mitigate endogeneity concerns, I instrument the focal analyst's communication variable using the leave-one-out communication

[13] This reverse causality does not account for the observed reduction in discount rates among active analysts. Analysts inclined to increase (or decrease) their discount rates—perhaps due to heightened (or reduced) skepticism about the company—are more (or less) likely to proactively seek communication with management in response to such skepticism. Therefore, if verbal communication were primarily driven by analysts' ex-ante intentions to revise their discount rates, we would expect active analysts to raise their discount rates following AI days, resulting in downward revisions to their price targets.

propensity among other analysts of the same brokerage on other AI days.

7.1.1. Heckman Treatment Effect Model

Since D_Comm is a binary variable, I address this endogeneity concern using the Heckman (1979) treatment effects estimation approach to test Models (2) and (3). In the first stage, for Model (2), I estimate a probit model where the dependent variable is the communication dummy (D_Comm). Several analyst characteristics, such as Exp, Brk_Size, N_Cov, $Star$, and $Bank\_Rel$, are strongly associated with whether analysts communicate with firms. However, as shown in Tables 3 and 4, these characteristics are not directly associated with signed or unsigned revisions. Therefore, the explanatory variables in the probit model include the control variables used in Model (2), including the aforementioned analyst characteristics. I then calculate the inverse Mills ratio (IMR) based on the first-stage regression and include it in the second stage. Similarly, to apply the Heckman procedure to Model (3), I estimate a probit model in which the dependent variable is D_Comm and the control variables are those used in Model (3). I then calculate the IMR from this probit model and include it in the second stage.

Table 7 (a) presents the second-stage regression results for Model (2). The coefficient for D_Comm remains positive for revisions in price targets and earnings forecasts, significant at the 1% level. These findings confirm that direct communication induces significant changes (revisions) in analysts' estimates, supporting H1.

Table 7 (b) presents the second-stage regression results for Model (3), showing that the coefficient for D_Comm remains significantly positive for revisions in price targets and stock recommendations but is insignificant for earnings forecasts. These results confirm that direct communication induces a positive revision in analysts’ fair value estimates, supporting H2 and H3.

[Table 7]

7.1.2. Broker-Level Communication Likelihood

To further address the endogeneity of the communication indicator, I construct an instrumental variable based on the leave-one-out brokerage house level access propensity. Specifically, for each analyst a and firm i, I compute the fraction of analysts within the same brokerage who comment on other AI days during the one-year window preceding the focal AI day, excluding analyst a as well as AI days of firm i and of firms in the same two-digit SIC industry as firm i.

This instrument captures brokerage-level variation in access to corporate management, which directly affects an analyst's likelihood of communicating with corporate insiders on AI days. The underlying idea follows Soltes (2014), who shows that analysts' opportunities to interact with corporate management depend importantly on the institutional characteristics and relationships of the brokerage houses for which they work. Because the instrument is constructed using other analysts' communication on AI days of firms outside the focal firm's industry, it is expected to be orthogonal to firm-specific and industry-specific information shocks affecting the focal firm on the focal AI day. This identification strategy follows the logic of leave-one-out (Hausman-type) peer instruments and within-network IV designs, which exploit variation in peers' behavior while excluding the focal observation to satisfy the exclusion restriction (Bramoullé et al., 2009; Borusyak et al., 2024). Therefore, brokerage-level variation in communication likelihood could affect the focal analyst's assessment of the firm through its effect on the analyst's access to corporate management.

In the first stage, I examine whether the brokerage-level access propensity, P_Comm_Brk, predicts the likelihood that the focal analyst communicates with corporate insiders on AI day, P_Comm. I calculate P_Comm_Brk, as the probability that peer analysts, defined as analysts employed by the same brokerage as the focal analyst but excluding those covering firms in the same two-digit SIC industry, communicate with corporate insiders on AI days hosted by firms in different two-digit SIC industries during the one-year window preceding the focal AI day. The untabulated results show that P_Comm is significantly positively associated with P_Comm_Brk. The Kleibergen–Paap Wald rk F statistic is 2333.4, suggesting that concerns about weak identification are limited.

Next, to examine the association between P_Comm_Brk and both unsigned and signed forecast revisions, I estimate regression Models (2) and (3) after replacing P_Comm with P_Comm_Brk.

Table 8(a) reports the results for the modified Model (2). The coefficient on P_Comm_Brk is positive and statistically significant for both target price revisions and earnings forecast revisions.

These findings indicate that P_Comm_Brk is positively associated with the magnitude of forecast revisions, supporting H1.

Table 8(b) presents the results for the modified Model (3). The coefficient on P_Comm_Brk remains significantly positive for target price revisions and is insignificant for earnings forecasts. Although the coefficient on P_Comm_Brk is statistically insignificant for stock recommendation revisions, the results remain consistent with the view that direct communication induces positive revisions in analysts' fair value estimates, supporting H2 and H3.

Overall, the results using brokerage-level communication likelihood as an instrument alleviate concerns that the influence of direct communication documented in Section 5 is driven by endogeneity. [14]

[Table 8]

7.2. Analyst Fixed Effects

This section further addresses the concern that differences in responses between active and non-active analysts are driven by differences in analysts' characteristics. To do so, I estimate a regression model that includes analyst fixed effects while excluding analyst characteristic variables from Model (3) [15]. In this model, the revisions of active analysts' estimates are regressed on a dummy variable for analyst communication (D_Comm), along with several control variables, AI day fixed effects, and analyst fixed effects.

Table 9 presents the estimated coefficients 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 direct communication with corporate insiders increases the price targets and stock recommendations. Meanwhile, the coefficient of D_Comm

[14] The IV variable might capture brokerage-level information production technology, brokerage culture, and client relationships. These factors may affect the update frequency of both earnings forecasts and stock recommendations. However, to the best of my knowledge, no study shows that asymmetric or inconsistent revisions between target prices or stock recommendations and earnings forecasts are attributable to these factors. Thus, these factors do not provide a reasonable explanation for my finding that positive revisions by active analysts are more pronounced for stock recommendations and target prices than for earnings forecasts.

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

remains insignificantly positive for $RevEPS2[0,1]$ and is significantly negative for $RevEPS1[0,1]$. This at least suggests that active communication with corporate insiders does not positively impact earnings forecasts. These regression results continue to support H2 and H3, even when controlling for analyst-fixed effects.

[Table 9]

7.3. Price Reactions outside AI Days

This section addresses the concern that active analysts' revisions prompted by direct communication have no price impact. In particular, as shown in Section 3, analysts with greater ability tend to communicate actively with corporate insiders. Hence, the stronger price reactions to active analysts' revisions, observed in Section 6, could be solely attributed to stronger market responses to superior analysts' estimates. If this were the case, significant price reactions to differences in revisions of price targets and stock recommendations between active and non-active analysts could still be observed, even if revisions prompted by direct communication had no direct price impact.

To mitigate this concern, I assess the price reaction to differences in revisions between active and non-active analysts outside of AI days. If revisions prompted by direct communication have no price impact, then the price reaction to active analysts' revisions on AI days—where revisions include those induced by direct communication—should be weaker than on non-AI days.

To examine this, I analyze the price reaction to these differences several days before AI days and subsequently compare price reactions between AI days and non-AI days. As illustrated in Table 4, 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 prior nine trading days ($\mathrm{RevPT}[-9,-1]$ and $\mathrm{RevRec}[-9,-1]$). Furthermore, as indicated in Table 6, abnormal returns around AI days ($\mathrm{CAR}[0,1]$) show a negative association with abnormal stock returns over the prior nine trading days ($\mathrm{CAR}[-9,-1]$))[16]. 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

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

AI days. I construct an 11-day lagged sample of AI days as the non-AI day sample.[17, 18] Then, I combine both the AI day and non-AI day samples and estimate the following regression model:[19]

$$CAR[0,1]_s = \beta_0 D\_AIDay_s * Diff\_RevPT[0,1]_s + \beta_1 D\_AIDay_s * Diff\_RevRec[0,1]_s + \gamma_0 Diff\_RevPT[0,1]_s + \gamma_1 Diff\_RevRec[0,1]_s + (Controls) + \varepsilon_{i,s} \qquad (5)$$

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

Table 10 presents 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, indicating that the price response to $Diff\_RevPT[0,1]$ is not weaker on AI days than on non-AI days. These results reject the possibility that active analysts' revisions prompted by direct communication have no price impact.

[Table 10]

7.4. Long-Run Reactions

I demonstrate that communication with corporate insiders leads to positive revisions in price targets and stock recommendations. However, it is important to consider the possibility that active analysts may be misled by the host firm or incorrectly interpret interactive discussions. In such cases, positive revisions to price targets and stock recommendations, as well as the subsequent price reactions to active analysts' revisions, could eventually be reversed. To address this concern, I analyze long-run analyst and price reactions.

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

[18] $CAR[0,1]$, $Diff\_RevRec[0,1]$ 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.

[19] 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.

To examine long-run analyst reactions, I analyze the association between the dummy variable representing direct communication (D_Comm) and prolonged revisions in price targets and stock recommendations using AI day-analyst observations from the sample employed to test H1, H2, and H3. Specifically, I investigate the association between revisions in price targets and stock recommendations over t+2 through t+60 ($RevPT[2,60]$ and $RevRec[2,60]$) by estimating Model (3).

To examine long-run price reactions, I assess the association of $Diff\_RevPT[0,1]$ and $Diff\_RevRec[0,1]$ with extended abnormal returns using all AI day observations employed to test H4. Specifically, I estimate regression Model (4) to analyze the association with cumulative abnormal returns over t+2 through t+60 (CAR[2,60]). Additionally, recognizing that price corrections may occur more rapidly than analysts' estimate adjustments, I also analyze the association with cumulative abnormal returns over t+2 through t+20 (CAR[2,20]).

Table 11 presents the estimated coefficients of Model (3) for $RevPT[2,60]$ and $RevRec[2,60]$. The coefficients of D_Comm for both variables are insignificant, suggesting that analysts' revisions to price targets and stock recommendations following active communication are unlikely to be reversed over time.

Tables 12(a) and 12(b) present the estimated coefficients of Model (4) for $CAR[2,20]$ and $CAR[2,60]$, respectively. The coefficients of $Diff\_RevPT[0,1]$ and $Diff\_RevRec[0,1]$ for both $CAR[2,20]$ 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 findings suggest that price reactions to $Diff\_RevPT[0,1]$ and $Diff\_RevRec[0,1]$ are not reversed in the subsequent period.

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 a crucial role in reducing discount rates by providing meaningful information rather than misleading market participants.

[Table 11]

[Table 12]

7.5. Influence on Virtual AI Days

Before the COVID-19 pandemic, AI days were conducted face-to-face, offering participants—particularly active communicators—opportunities to tour companies and factories and to share meals with corporate insiders. In contrast, virtual AI days primarily focus on direct communication between firms and investors (or analysts). According to Brown et al. (2014), site visits to companies or production facilities provide valuable insights for generating stock recommendations. Thus, these in-person events may alleviate analysts' concerns about a company's performance or enhance their trust in the firm, potentially leading to a reduction in their discount rates.

However, while most face-to-face AI days include extended Q&A sessions, they do not consistently feature supplementary in-person activities such as company tours or shared meals. Thus, I argue that direct interactive communication with corporate insiders—rather than the supplementary face-to-face elements—plays a central role in building trust between communicators and management, thereby lowering communicators' discount rates. If this is the case, the effects of active analysts' fair value estimations and their impact on stock prices should be consistent across both face-to-face and virtual AI days. Hence, the impact of direct communication with corporate insiders on communicators' fair value estimations is not weakened by holding meetings in a virtual format, which focuses on direct direct verbal communication between market participants and firms. In addition, the price impact of active analysts' revisions on fair value estimates is not weakened by holding meetings in a virtual format, which focuses on direct communication.

・ Methodology

To test the hypothesis, I determine whether AI days during the COVID-19 and post-COVID-19 periods (from 2020 to 2022) were held in a virtual or face-to-face format by analyzing 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 13 (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 13 [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 13 [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 [20], 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 13 (b), out of the 1,123 AI days held between 2020 and 2022, 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 (in 2022), a substantial number of AI days continued to be conducted in a virtual format.

Then, 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 value of one if AI days are held in a virtual format and zero otherwise. Specifically, I estimate the following regression model using all AI day-analyst observations[21]:

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

where the dependent variable (Rev) represents $RevPT[0,1]$ and $RevRec[0,1]$. The interaction effect with $D\_Virtual$ may also capture the broader impact of the COVID-19 and post-COVID-19 periods (2020–2022). Therefore, I include $D\_Year[2020,2022]$, along with the interaction term $D\_Comm \times D\_Year[2020,2022]$, where $D\_Year[2020,2022]$ is a dummy variable that takes the value of one if an AI day occurred between 2020 and 2022. The other control variables remain the same as those in Equation (3). A negative coefficient of the interaction term $D\_Comm \times D\_Virtual$

[20] 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.

[21] I also estimate the regression model using the sample from 2020 to 2022 without including variables related to $D\_Year[2020,2022]$. The results confirm that the overall findings remain consistent.

would suggest that the impact of direct communication on communicators' fair value estimates is less pronounced on virtual AI days than on face-to-face AI days. H5 predicts that this coefficient is not significantly negative.

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

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

Where the dependent variable is $CAR[0,1]$. The other control variables remain the same as those in Equation (4). Negative coefficients for $D\_Virtual \times Diff\_RevPT[0,1]$ and $D\_Virtual \times Diff\_RevRec[0,1]$ would 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. I predict that these coefficients are not significantly negative.

[Table 13]

- Result

Table 14 (a) presents 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 $RevRec[0,1]$.[22] This suggests that the impact of direct communication on communicators' price targets and stock recommendations remains consistent, regardless of whether communication occurs virtually or face-to-face.

Table 14 (b) reports 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

[22] The untabulated result (available upon request) shows that the positive association between communication and revisions in target prices and stock recommendations remains statistically significant even in the virtual-meeting subsample.

$Diff\_RevPT[0,1]$ 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 direct communication on communicators' fair value estimates (discount rates) and the subsequent impact on stock prices remains substantial, even in a virtual format. Since both virtual and face-to-face AI days typically include management presentations and Q&A sessions—providing opportunities for verbal interactive discussions with management— these findings support the notion that direct communication with corporate insiders during Q&A sessions, rather than other face-to-face events such as factory tours, in-person product demonstrations, or meals with managers, plays a crucial role in raising participants' fair value estimates (by decreasing their discount rates).

[Table 14]

8. Conclusion

This study aims to clarify the influence of direct communication with corporate insiders on communicators' expectations of hosting firms, particularly with respect to their discount rates. It identifies analysts who engage in such communication on AI Days and examines whether, and in what ways, these active analysts revise their fair value estimates relative to non-active analysts, thereby potentially affecting the stock prices of the hosting firms.

The findings reveal that active analysts tend to make more substantial revisions to their estimates, including earnings forecasts and price targets, compared to non-active analysts. This suggests that direct communication provides sufficient information for communicators to update their expectations regarding the host firm. Furthermore, while active analysts' price targets and stock recommendations are more elevated than those of non-active analysts on AI days, no such tendency is observed for earnings forecasts. Given that a reduction in discount rates can raise fair value estimates without affecting earnings forecasts, these results support the view that direct communication with corporate insiders can reduce communicators' discount rates.

This study contributes to the literature in the following ways. First, it extends research on direct communication between firms and capital market participants. Prior studies on earnings calls and AI Days have mainly examined whether such communication affects analysts' earnings forecasts and short-term earnings expectations. This study provides evidence that the economic role of direct communication is not limited to the transmission of earnings-related information, but also includes reducing the discount rate applied to the host firm

Second, this study contributes to the voluntary disclosure and cost-of-capital literature. Prior studies argue that voluntary disclosure can reduce information asymmetry, estimation risk, and firms' cost of capital. This study extends that argument by examining a specific disclosure channel: direct interaction with corporate insiders. The results suggest that such interaction lowers the discount rate applied by communicators and has a positive impact on the focal firm's stock price. Thus, this study provides empirical evidence on one mechanism through which voluntary disclosure may reduce the cost of equity and enhance firm value.

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Table 1

Characteristics of Communicators

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 2

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 3

Influence on the Magnitude 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 Signed 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]	0.0017	0.0775	0.0000	0.3173	15.1763	-0.0624	-0.0173	0.0190	0.0632	49.8%	50.0%
Diff_RevEPS1[0,1]	0.0000	0.0010	0.0000	-0.7120	31.2090	-0.0010	0.0000	0.0000	0.0010	33.6%	34.0%
Diff_RevEPS2[0,1]	0.0000	0.0010	0.0000	-0.3830	21.5470	-0.0020	0.0000	0.0000	0.0020	36.1%	37.1%
Diff_RevPT[0,1]	0.0010	0.0280	0.0000	0.7510	12.6650	-0.0370	-0.0040	0.0060	0.0430	32.7%	31.6%
Diff_RevRec[0,1]	0.0020	0.0700	0.0000	1.4180	100.4260	0.0000	0.0000	0.0000	0.0370	5.6%	5.1%
Diff_Rec	0.0760	0.3490	0.0830	-0.3450	1.1370	-0.5000	-0.1110	0.2890	0.6250	57.9%	34.1%
Diff_PT	0.0120	0.1240	0.0130	-0.2720	14.2810	-0.1620	-0.0350	0.0620	0.1790	57.6%	42.1%
Diff_RevEPS1[-9,-1]	0.0000	0.0010	0.0000	2.0750	36.7930	-0.0010	0.0000	0.0000	0.0020	34.2%	34.5%
Diff_RevEPS2[-9,-1]	0.0000	0.0020	0.0000	1.4720	28.8640	-0.0020	0.0000	0.0000	0.0020	35.5%	36.0%
Diff_RevPT[-9,-1]	0.0020	0.0270	0.0000	1.0510	19.2140	-0.0320	-0.0020	0.0050	0.0410	32.2%	28.9%
Diff_RevRec[-9,-1]	0.0030	0.0780	0.0000	3.6840	96.4080	-0.0590	0.0000	0.0000	0.0710	7.7%	7.1%
RevEPS1_NoComm[0,1]	0.0000	0.0010	0.0000	-3.5980	43.1060	-0.0010	0.0000	0.0000	0.0010	28.1%	24.6%
RevEPS2_NoComm[0,1]	0.0000	0.0010	0.0000	-2.6490	28.8870	-0.0010	0.0000	0.0000	0.0010	31.8%	27.4%
RevPT_NoComm[0,1]	0.0080	0.0260	0.0000	2.4050	13.7670	-0.0140	0.0000	0.0090	0.0560	36.9%	12.5%
RevRec_NoComm[0,1]	-0.0010	0.0390	0.0000	-6.2540	171.0740	0.0000	0.0000	0.0000	0.0000	3.6%	3.2%
Rec_NoComm	-0.0020	0.1500	0.0000	-0.0950	3.7910	-0.2500	-0.0750	0.0710	0.2220	45.1%	47.5%
RevEPS1_NoComm[-9,-1]	0.0000	0.0020	0.0000	-0.2020	19.9310	-0.0020	0.0000	0.0000	0.0020	29.2%	27.0%
RevEPS2_NoComm[-9,-1]	0.0000	0.0010	0.0000	-0.7780	24.4630	-0.0020	0.0000	0.0000	0.0010	28.9%	28.3%
RevPT_NoComm[-9,-1]	0.0050	0.0250	0.0000	2.5090	18.8050	-0.0170	0.0000	0.0040	0.0450	32.4%	14.8%
RevRec_NoComm[-9,-1]	0.9210	6.8300	0.7350	0.3030	7.5560	-8.9710	-2.1550	3.8010	11.4430	5.3%	4.3%
CAR[-9,-1]	0.0010	0.0150	0.0010	-4.7910	278.3560	-0.0050	0.0000	0.0020	0.0090	57.6%	42.2%
SUE	3.9020	0.7560	3.9070	-0.1680	0.1320	2.6620	3.4130	4.4050	5.1990		
Size	0.3630	0.4050	0.2940	1.9310	37.6020	0.0100	0.1480	0.5050	1.0280		
BM	0.0000	0.0460	0.0000	24.0410	1,143.131	-0.0080	0.0000	0.0010	0.0090		
Disp_EPS1	-0.0010	0.2160	0.0010	-39.5990	2,190.219	-0.0150	0.0000	0.0020	0.0150		
Disp_EPS2	0.0050	0.0120	0.0020	6.8130	65.7940	0.0000	0.0010	0.0050	0.0200		
Disp_PT	0.1930	0.3950	0.0000	1.5540	0.4140	0.0000	0.0000	0.0000	1.0000		
D_Virtual	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	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]	0.20	***	(3.69)	0.19	***	(3.47)
Diff_RevRec[0,1]	0.09	***	(5.46)	0.09	***	(5.67)
Diff_RevEPS1[0,1]	2.51		(1.01)	2.58		(1.04)
Diff_RevEPS2[0,1]	2.00		(1.42)	1.92		(1.35)
Diff_PT	0.05	.	(1.86)			
Diff_Rec	0.00		(0.06)	0.01	.	(1.86)
Diff_RevPT[-9,-1]	0.11	*	(2.10)	0.14	*	(2.49)
Diff_RevRec[-9,-1]	0.01		(0.50)	0.00		(0.19)
Diff_RevEPS1[-9,-1]	-3.38	**	(2.71)	-3.36	**	(2.65)
Diff_RevEPS2[-9,-1]	0.31		(0.31)	0.31		(0.30)
RevPT_NoComm[0,1]	0.60	***	(8.17)	0.59	***	(8.13)
RevRec_NoComm[0,1]	0.13	***	(3.61)	0.14	***	(3.71)
RevEPS1_NoComm[0,1]	1.43		(0.59)	1.38		(0.57)
RevEPS2_NoComm[0,1]	6.90	***	(4.65)	6.95	***	(4.61)
PT_NoComm	0.26	***	(3.44)	0.18	**	(3.24)
Rec_NoComm	-0.04	**	(2.82)	-0.03	*	(2.15)
RevPT_NoComm[-9,-1]	-0.04		(0.70)	-0.03		(0.58)
RevRec_NoComm[-9,-1]	0.03		(1.02)	0.02		(0.89)
RevEPS1_NoComm[-9,-1]	-0.23		(0.20)	-0.23		(0.20)
RevEPS2_NoComm[-9,-1]	-1.02		(0.65)	-1.03		(0.66)
Disp_EPS1	-0.03	*	(2.28)	-0.03	*	(2.42)
Disp_EPS2	0.00	.	(1.95)	0.00	.	(1.88)
Disp_PT	0.78	**	(2.60)	0.76	*	(2.53)
CAR[-9,-1]	0.00	***	(4.12)	0.00	***	(4.03)
SUE	-0.24		(1.11)	-0.25		(1.15)
Size	0.01	**	(2.63)	0.01	*	(2.53)
BM	0.01	.	(1.82)	0.01	.	(1.72)
Controls for Firm Effects	Yes			Yes		
Adjusted R2	24.73%			24.42%		

Table 7

Heckman Two-stage Procedure

Panel (a) shows the results of estimating Equation (2) for Abs_RevPT[0,1], Abs_RevEPS1[0,1], and Abs_RevEPS2[0,1], using the Heckman two-stage procedure. Panel (b) shows the results of estimating Equation (3) for RevPT[0,1], RevEPS1[0,1], RevEPS2[0,1], and RevRec[0,1], using the Heckman two-stage procedure. *IMR* is the inverse Mills ratio calculated based on the corresponding probit 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) Influence on the Degree of Analyst Revisions

	Abs_RevPT[0,1]		Abs_RevEPS1[0,1]		Abs_RevEPS2[0,1]	
D_Comm	0.0029 ***	(7.71)	0.0000 ***	(4.11)	0.0001 ***	(6.03)
IMR	0.0225 ***	(3.97)	0.0008 ***	(5.75)	0.0016 ***	(5.71)
Rec	0.0077 ***	(8.60)	0.0001 ***	(4.10)	0.0002 ***	(4.23)
Star	-0.0012 *	(2.30)	0.0000	(1.20)	-0.0001	(1.92)
PT	-0.0294 ***	(12.26)	0.0001	(1.21)	0.0002 *	(2.04)
Brk_Size	0.0002 ***	(3.64)	0.0000 ***	(5.50)	0.0000 ***	(5.65)
N_Cov	0.0003 ***	(3.66)	0.0000 ***	(3.79)	0.0000 ***	(4.46)
Freq	0.2304 ***	(5.30)	0.0132 ***	(10.14)	0.0228 ***	(9.22)
Exp	0.0012 ***	(3.81)	0.0000 ***	(5.01)	0.0001 ***	(5.05)
Cover_Ind	-0.0002 *	(2.07)	0.0000	(0.38)	0.0000	(1.73)
Bank_Rel	0.0003	(0.29)	0.0000 *	(2.01)	0.0000	(0.15)
RevEPS1[-9,-1]	-0.0070	(0.05)	0.0118 *	(2.07)	0.0004	(0.04)
RevEPS2[-9,-1]	0.2181	(1.81)	0.0003	(0.09)	0.0117	(1.47)
RevPT[-9,-1]	-0.0383 ***	(5.46)	-0.0002	(1.14)	-0.0002	(0.65)
RevRec[-9,-1]	0.0047 ***	(3.30)	0.0000	(1.25)	0.0000	(0.02)
Abs_RevEPS1[-9,-1]	0.1448	(0.98)	-0.0390 ***	(5.69)	-0.0113	(1.02)
Abs_RevEPS2[-9,-1]	-0.6855 ***	(5.13)	-0.0166 ***	(4.08)	-0.0746 ***	(7.86)
Abs_RevPT[-9,-1]	-0.0885 ***	(11.68)	-0.0003 *	(2.05)	-0.0014 ***	(3.68)
Abs_RevRec[-9,-1]	0.0002	(0.11)	0.0000		0.0002 *	(2.00)
Controls for AI days Effects	Yes		Yes		Yes	
Adjusted R2	3.51%		1.74%		1.68%	

(b) Influence on Signed Analyst Revisions

	RevPT[0,1]		RevEPS1[0,1]		RevEPS2[0,1]		RevREC[0,1]	
D_Comm	0.0020 ***	(5.27)	0.0000	(1.71)	0.0000	(0.96)	0.0051 ***	(4.72)
IMR	0.0120 *	(2.07)	0.0000	(0.01)	-0.0004	(1.10)	-0.0220	(1.17)
Rec	0.0082 ***	(8.83)	0.0000	(0.43)	0.0000	(0.53)	-0.0224 ***	(7.63)
PT	-0.0410 ***	(13.77)	-0.0001 *	(2.24)	-0.0006 ***	(5.06)	0.0259 ***	(5.06)
Star	-0.0008	(1.43)	0.0000	(0.11)	0.0000	(0.21)	0.0032 *	(2.04)
Brk_Size	0.0001	(1.74)	0.0000	(0.03)	0.0000	(1.24)	-0.0002	(1.61)
N_Cov	0.0001	(1.74)	0.0000	(0.59)	0.0000	(1.11)	-0.0004	(1.48)
Freq	0.0946 *	(2.14)	-0.0001	(0.09)	-0.0009	(0.34)	-0.1351	(0.96)
Exp	0.0006	(1.93)	0.0000	(0.47)	0.0000	(1.17)	-0.0011	(1.12)
Cover_Ind	-0.0001	(0.95)	0.0000	(1.46)	0.0000	(0.15)	0.0006 *	(2.29)
Bank_Rel	-0.0002	(0.24)	0.0000	(0.85)	0.0000	(0.24)	0.0018	(0.66)
RevEPS1[-9,-1]	0.0894	(0.68)	-0.0442 ***	(7.05)	-0.0003	(0.03)	0.0687	(0.19)
RevEPS2[-9,-1]	-0.0083	(0.07)	-0.0082 *	(2.15)	-0.0783 ***	(8.82)	-0.5722	(1.83)
RevPT[-9,-1]	-0.1087 ***	(15.08)	-0.0002	(1.31)	-0.0010 ***	(4.07)	0.0260	(1.83)
RevRec[-9,-1]	0.0074 ***	(5.02)	0.0000	(1.17)	0.0000	(0.18)	-0.0159	(1.62)
Controls for AI days Effects	Yes		Yes		Yes		Yes	
Adjusted R2	4.08%		1.02%		1.21%		1.14%	

Table 8

Broker-level Communication Likelihood

Panel (a) shows the results of estimating Equation (2) for Abs_RevPT[0,1], Abs_RevEPS1[0,1], and Abs_RevEPS2[0,1], when P_Comm is replaced with P_Comm_Brk. Panel (b) shows the results of estimating Equation (3) for RevPT[0,1], RevEPS1[0,1], RevEPS2[0,1], and RevRec[0,1], when P_Comm is replaced with P_Comm_Brk. 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.

(c) Influence on the Degree of Analyst Revisions

	Abs_RevPT[0,1]			Abs_RevEPS1[0,1]			Abs_RevEPS2[0,1]		
D_Comm_Brk	0.0062	***	(5.77)	0.0001	*	(2.16)	0.0002	***	(4.53)
Rec	0.0052	***	(9.87)	0.0000		(0.58)	0.0000		(0.06)
Star	-0.0011	*	(2.09)	0.0000		(0.95)	0.0000		(1.74)
PT	-0.0320	***	(13.42)	0.0000		(0.71)	0.0000		(0.01)
Brk_Size	0.0000	*	(2.52)	0.0000		(0.29)	0.0000		(0.74)
N_Cov	0.0000		(0.58)	0.0000	*	(2.11)	0.0000		(1.08)
Freq	0.1280	***	(5.38)	0.0101	***	(12.18)	0.0168	***	(11.27)
Exp	0.0001		(1.10)	0.0000		(0.05)	0.0000		(0.08)
Cover_Ind	0.0000		(0.38)	0.0000		(0.94)	0.0000		(0.48)
Bank_Rel	-0.0009		(1.01)	0.0000		(0.35)	-0.0001	*	(2.05)
RevEPS1[-9,-1]	0.0621		(0.47)	0.0140	*	(2.35)	0.0043		(0.43)
RevEPS2[-9,-1]	0.0158		(0.13)	-0.0063		(1.65)	-0.0002		(0.02)
RevPT[-9,-1]	-0.0391	***	(5.28)	0.0000		(0.25)	0.0000		(0.06)
RevRec[-9,-1]	0.0046	**	(2.96)	0.0000		(0.38)	-0.0001		(0.86)
Abs_RevEPS1[-9,-1]	0.1645		(1.04)	-0.0406	***	(5.70)	-0.0077		(0.66)
Abs_RevEPS2[-9,-1]	-0.7109	***	(5.05)	-0.0169	***	(3.92)	-0.0804	***	(7.89)
Abs_RevPT[-9,-1]	-0.0916	***	(11.66)	-0.0004	**	(2.64)	-0.0015	***	(4.14)
Abs_RevRec[-9,-1]	0.0006		(0.41)	0.0000		(1.13)	0.0001		(1.56)
Controls for AI days Effects	Yes			Yes			Yes		
Adjusted R2	3.67%			2.08%			1.95%		

(d) Influence on Signed Analyst Revisions

	RevPT[0,1]			RevEPS1[0,1]			RevEPS2[0,1]			RevREC[0,1]		
D_Comm_Brk	0.0037	***	(3.44)	0.0000		(0.73)	0.0000		(0.91)	0.0030		(0.94)
Rec	0.0068	***	(11.28)	0.0000		(0.51)	0.0000		(0.14)	-0.0199	***	(11.88)
PT	-0.0425	***	(13.38)	-0.0001	*	(1.98)	-0.0005	***	(4.56)	0.0269	***	(5.72)
Star	-0.0006		(1.22)	0.0000		(0.06)	0.0000		(0.29)	0.0038	*	(2.52)
Brk_Size	0.0000	*	(2.28)	0.0000		(1.10)	0.0000		(1.31)	-0.0001	**	(3.23)
N_Cov	0.0000		(0.00)	0.0000		(1.50)	0.0000		(0.01)	-0.0002	*	(2.12)
Freq	0.0422		(1.78)	0.0003		(0.33)	0.0021		(1.36)	-0.0051		(0.08)
Exp	0.0001		(0.54)	0.0000		(1.65)	0.0000		(0.19)	-0.0001		(0.37)
Cover_Ind	0.0000		(0.19)	0.0000		(0.61)	0.0000		(0.25)	0.0005		(1.62)
Bank_Rel	-0.0009		(0.92)	0.0000		(0.94)	0.0000		(0.35)	0.0033		(1.23)
RevEPS1[-9,-1]	0.1068		(0.80)	-0.0470	***	(7.09)	0.0028		(0.26)	0.1691		(0.43)
RevEPS2[-9,-1]	-0.1452		(1.25)	-0.0056		(1.38)	-0.0801	***	(8.61)	-0.3724		(1.29)
RevPT[-9,-1]	-0.1125	***	(15.14)	-0.0002		(1.86)	-0.0010	***	(3.90)	0.0272		(1.76)
RevRec[-9,-1]	0.0078	***	(5.04)	0.0001		(1.37)	0.0001		(0.72)	-0.0196		(1.79)
Controls for AI days Effects	Yes			Yes			Yes			Yes		
Adjusted R2	4.25%			1.04%			1.25%			1.13%		

Table 9

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 10

Compared with the 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]	-0.04		(0.40)
D_AIDay X Diff_RevRec[0,1]	0.07	**	(2.84)
Diff_RevPT[0,1]	0.28	**	(3.19)
Diff_RevRec[0,1]	-0.01		(0.65)
Diff_RevEPS1[0,1]	-0.41		(0.76)
Diff_RevEPS2[0,1]	1.18		(1.28)
Diff_PT	0.02		(1.47)
Diff_Rec	0.00		(0.04)
Diff_RevPT[-9,-1]	0.04		(1.50)
Diff_RevRec[-9,-1]	0.00		(0.33)
Diff_RevEPS1[-9,-1]	0.01		(0.03)
Diff_RevEPS2[-9,-1]	-0.21		(0.93)
RevPT_NoComm[0,1]	0.52	***	(8.46)
RevRec_NoComm[0,1]	0.07	**	(3.04)
RevEPS1_NoComm[0,1]	-2.07		(1.29)
RevEPS2_NoComm[0,1]	5.71	***	(4.69)
PT_NoComm	0.13	**	(2.82)
Rec_NoComm	-0.02	*	(2.57)
RevPT_NoComm[-9,-1]	0.00		(0.09)
RevRec_NoComm[-9,-1]	0.05	**	(3.06)
RevEPS1_NoComm[-9,-1]	0.23		(0.96)
RevEPS2_NoComm[-9,-1]	-0.27		(0.92)
Disp_EPS1	0.00		(0.23)
Disp_EPS2	0.00		(1.41)
Disp_PT	0.57	**	(3.10)
D_AIDay	0.00	***	(5.19)
CAR[-9,-1]	0.00	***	(5.69)
SUE	-0.08		(0.52)
Size	0.00		(1.46)
BM	0.00		(0.78)
Controls for Firm Effects	Yes		
Adjusted R2	13.60%		

Table 11

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 12

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]	-0.09	(1.18)	-0.11	(1.43)
Diff_RevRec[0,1]	0.00	(0.13)	0.01	(0.33)
Diff_RevEPS1[0,1]	8.36 *	(2.32)	8.47 *	(2.35)
Diff_RevEPS2[0,1]	-3.95 *	(2.22)	-4.08 *	(2.27)
Diff_PT	0.07 .	(1.66)		
Diff_Rec	-0.01	(0.61)	0.01	(0.71)
Diff_RevPT[-9,-1]	-0.10	(1.04)	-0.07	(0.68)
Diff_RevRec[-9,-1]	-0.01	(0.47)	-0.02	(0.71)
Diff_RevEPS1[-9,-1]	-1.81	(0.66)	-1.77	(0.65)
Diff_RevEPS2[-9,-1]	0.27	(0.13)	0.26	(0.13)
RevPT_NoComm[0,1]	0.14	(1.46)	0.13	(1.31)
RevRec_NoComm[0,1]	-0.03	(0.38)	-0.02	(0.31)
RevEPS1_NoComm[0,1]	2.07	(0.57)	2.00	(0.55)
RevEPS2_NoComm[0,1]	-2.26	(1.09)	-2.18	(1.05)
PT_NoComm	0.06	(0.54)	-0.06	(0.88)
Rec_NoComm	0.03	(1.18)	0.04 *	(2.06)
RevPT_NoComm[-9,-1]	0.05	(0.51)	0.06	(0.62)
RevRec_NoComm[-9,-1]	0.04	(0.78)	0.04	(0.69)
RevEPS1_NoComm[-9,-1]	-2.13	(0.78)	-2.13	(0.78)
RevEPS2_NoComm[-9,-1]	2.37	(0.75)	2.35	(0.75)
Disp_EPS1	-0.06 *	(2.32)	-0.07 *	(2.34)
Disp_EPS2	0.00	(0.04)	0.00	(0.05)
Disp_PT	1.58 *	(2.38)	1.56 *	(2.33)
CAR[-9,-1]	0.00	(1.02)	0.00	(0.96)
SUE	0.96 **	(2.61)	0.95 **	(2.59)
Size	0.00	(0.44)	0.00	(0.52)
BM	0.00	(0.08)	0.00	(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]	0.06	(0.34)	0.04	(0.27)
Diff_RevRec[0,1]	0.01	(0.16)	0.01	(0.23)
Diff_RevEPS1[0,1]	16.06 *	(2.02)	16.13 *	(2.03)
Diff_RevEPS2[0,1]	-6.36	(1.59)	-6.45	(1.61)
Diff_PT	0.05	(0.52)		
Diff_Rec	-0.03	(1.32)	-0.02	(1.13)
Diff_RevPT[-9,-1]	-0.51 **	(2.88)	-0.49 **	(2.83)
Diff_RevRec[-9,-1]	0.01	(0.14)	0.00	(0.05)
Diff_RevEPS1[-9,-1]	-1.18	(0.23)	-1.16	(0.22)
Diff_RevEPS2[-9,-1]	3.84	(1.24)	3.84	(1.24)
RevPT_NoComm[0,1]	0.38	(1.60)	0.37	(1.58)
RevRec_NoComm[0,1]	0.00	(0.04)	0.01	(0.07)
RevEPS1_NoComm[0,1]	-0.34	(0.04)	-0.38	(0.05)
RevEPS2_NoComm[0,1]	-5.58	(1.30)	-5.53	(1.28)
PT_NoComm	-0.17	(0.93)	-0.24 *	(1.99)
Rec_NoComm	0.03	(0.78)	0.04	(1.14)
RevPT_NoComm[-9,-1]	0.19	(0.92)	0.19	(0.95)
RevRec_NoComm[-9,-1]	0.08	(0.73)	0.08	(0.71)
RevEPS1_NoComm[-9,-1]	1.46	(0.27)	1.46	(0.27)
RevEPS2_NoComm[-9,-1]	3.74	(0.67)	3.73	(0.67)
Disp_EPS1	-0.06	(1.14)	-0.06	(1.17)
Disp_EPS2	0.01 *	(2.01)	0.01 *	(2.03)
Disp_PT	1.96 .	(1.70)	1.94 .	(1.69)
CAR[-9,-1]	0.00 **	(2.86)	0.00 **	(2.87)
SUE	-0.07	(0.10)	-0.08	(0.11)
Size	-0.06 ***	(3.80)	-0.06 ***	(3.84)
BM	-0.02	(0.80)	-0.02	(0.82)
Controls for Firm Effects	Yes		Yes	
Adjusted R2	6.14%		6.11%	

Table 13

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 14

Influence of Virtual AI Days

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]	0.19		(0.89)	0.19		(0.91)
D_Virtual X Diff_RevRec[0,1]	0.03		(0.31)	0.02		(0.26)
D_Year[2020,2022] X Diff_RevPT[0,1]	-0.18		(1.25)	-0.18		(1.31)
D_Year[2020,2022] X Diff_RevRec[0,1]	-0.01		(0.15)	-0.01		(0.14)
D_Virtual	-0.01	*	(2.04)	-0.01	*	(2.05)
Diff_RevPT[0,1]	0.23	***	(4.60)	0.22	***	(4.41)
RevPT_NoComm[0,1]	0.61	***	(7.90)	0.60	***	(7.87)
Diff_PT	0.05	.	(1.85)			
PT_NoComm	0.25	***	(3.41)	0.18	**	(3.22)
Diff_RevPT[-9,-1]	0.12	*	(2.14)	0.14	*	(2.50)
RevPT_NoComm[-9,-1]	-0.04		(0.72)	-0.03		(0.59)
Diff_RevRec[0,1]	0.09	***	(5.35)	0.09	***	(5.57)
Diff_Rec	0.00		(0.05)	0.01	.	(1.92)
RevRec_NoComm[0,1]	0.13	***	(3.68)	0.14	***	(3.79)
Rec_NoComm	-0.04	**	(2.80)	-0.03	*	(2.13)
Diff_RevRec[-9,-1]	0.01		(0.45)	0.00		(0.15)
RevRec_NoComm[-9,-1]	0.03		(1.15)	0.03		(1.03)
Diff_RevEPS1[0,1]	2.46		(1.01)	2.54		(1.03)
Diff_RevEPS2[0,1]	1.94		(1.39)	1.85		(1.31)
RevEPS1_NoComm[0,1]	1.71		(0.73)	1.68		(0.71)
RevEPS2_NoComm[0,1]	6.85	***	(4.57)	6.91	***	(4.54)
Diff_RevEPS1[-9,-1]	-3.32	**	(2.63)	-3.29	**	(2.58)
Diff_RevEPS2[-9,-1]	0.37		(0.36)	0.37		(0.36)
RevEPS1_NoComm[-9,-1]	-0.29		(0.26)	-0.29		(0.26)
RevEPS2_NoComm[-9,-1]	-1.04		(0.67)	-1.05		(0.68)
CAR[-9,-1]	0.00	***	(4.16)	0.00	***	(4.07)
SUE	-0.22		(1.04)	-0.23		(1.07)
Size	0.01	*	(2.01)	0.01	.	(1.91)
BM	0.01	.	(1.84)	0.01	.	(1.74)
Disp_EPS1	-0.03	*	(2.09)	-0.03	*	(2.21)
Disp_EPS2	0.00	.	(1.94)	0.00	.	(1.87)
Disp_PT	0.75	*	(2.43)	0.73	*	(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
$D\_Comm_{i,s}$	A dummy variable of analysts' communication that takes a value of one if analyst i had any comments or asked questions to corporate insiders on AI day s (otherwise 0)
$RevPT[t_1, t_2]_{i,s}$	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*).

$D\_Year[2020,2022]_s$	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.

(b) The variables for the Price Impact Analysis (Equation [4], [5], and [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.