Strategic Competition Timing of Voluntary Disclosure: Evidence from Analyst/Investor Days*

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This revision: December 15, 2023

Abstract

Firms use analyst/investor (AI) days to discuss their performance and present corporate strategies to AI day attendees and capital market participants. Our findings show that firms host AI days strategically, adhering to a competition timing strategy. The likelihood of hosting AI days increases when levels of current industry competition is low and levels of threats from potential rivals are high. Measures of competition timing, together with linguistic complexity and tone of the Q&A section of the event, predict higher short-term abnormal returns of these firms. Over a longer post-event horizon, firms that host AI days outperform similar firms that choose not to hold AI days in terms of stock market performance (measured by, for example, Sharpe ratio) and future profitability (captured by return on equity).

Keywords: voluntary disclosure, competition timing, potential rivals, analyst/investor days, financial performance

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1. Introduction

Analyst/investor days (AI days) have become an important disclosure channel for management to effectively communicate information on the organization's performance and strategic outlook to buy- and sell-side analysts and existing and potential investors (Kirk and Markov, 2016). Similar to other investor relations activities, AI days aim to enable interactions with investors and analysts for the purpose of broadening the shareholder base, decreasing information asymmetry and, consequently, reducing the cost of capital (Brennan and Tamarowski, 2000). More recently, AI days have attracted considerable attention of analysts and capital market participants, raising the stakes for a successful vs not successful AI day. For example, on March 1st, 2023, Tesla hosted its highly-anticipated first AI day, which was met with disappointment by market participants and resulted in a 7% drop in its share price next day according to Forbes[1], highlighting the economic significance of the information conveyed or not during the event.

Despite their significance as a disclosure channel, AI days remain relatively unexplored in the literature. While systematic empirical evidence on the determinants of firms' decision to host AI days is scarce, anecdotal evidence indicates that the timing of such events depends on the competitive environment in which the firm operates. In this paper, we investigate whether the decision to host an AI day is strategically driven and whether the economic effects of hosting an AI day are contingent on these strategic considerations.

Using information from the transcripts of AI days spanning from 2011 to 2022 and text-based competition proxies[2], we find that firms seem to strategically time competition when scheduling an AI day. Firms are more likely to host an AI day when facing higher threats from potential entrants into the markets. Conversely, the likelihood of hosting such an event diminishes when firms face competitive threats from existing rivals. The market seems to view such "competition timing" positively: the cumulative abnormal returns of the host firm around the event increase if

[1] https://www.forbes.com/sites/dereksaul/2023/03/02/tesla-stock-tanks-after-disjointed-investor-day-draws-mixed-reviews/?sh=49adf2697078

[2] We use Hoberg and Phillips (2016)'s text-based measure of product similarity to proxy for competitive threats of existing competitors, and Hoberg et al. (2014)'s measure of product fluidity to proxy for product substitutability and threats from potential new entrants.

the event is held under higher threats from potential entrants into the market and lower threats from current competitors. This evidence supports the notion that, in the presence of proprietary costs affecting product market competition, firms' incentives to disclose information depends on the presence of existing competitors or the threat of entry by new competitors, and the disclosure under these circumstances is seen positively by investors.

We further focus on information transmission channels during the AI days and analyze the role of tone and linguistic complexity of the presentation and Q&A parts of the AI day separately. AI days usually commence with prearranged statements by the managers (e.g., CEO and CFO) and subsequently transitions into a Q&A session that fosters active involvement from attendees. In contrast to the scripted nature of the first part of the AI day, the latter segment allows for unscripted interactions, granting attendees the opportunity to seek clarification on any aspect pertaining to the firm's future or other relevant topics that may have been omitted during managers' presentations. Our evidence suggests that the actual new information conveyed during the scripted part of the AI day is limited and its characteristics are not related to firm's market performance. The Q&A section, on the contrary, seems to be informative. We find that the fraction of positive words in the questions from the attendees predicts higher abnormal returns of firm's stock up to a week after the event, while the fraction of negative words in the answers of managers predicts lower abnormal returns. These results point to the efficient assimilation of new information disclosed in the Q&A session. Regarding the linguistic complexity of both managers and attendees, we find that during the Q&A part of AI days, attendees do not tend to obfuscate with their questions and information conveyed by managers is higher when firms host AI days in accordance to the competition timing scenario. Over longer term, firms that hold AI days tend to outperform similar firms that choose not to hold such events in terms of their stock market performance over three months after the announcement of an AI day, as captured by the return Sharpe ratio. Additionally, these firms exhibit better accounting performance across a range of performance measures at the end of the fiscal year in which the event is held.

Our study contributes to the literature on the relationship between voluntary disclosure, proprietary cost, and market competition, by providing evidence of strategic competition timing of voluntary disclosure through hosting AI days. Verrecchia (1983, 1990)[3] shows that, in the presence of proprietary costs and the threat from existing rivals, disclosure can be costly if the revealed information exposes company-relevant details, thus discouraging firm disclosure. In contrast, Darrough and Stoughton (1990) predict that in the presence of potential entrants, firms will disclose *more* information to deter entry.

Empirical studies, in line with Verrecchia (1983)'s findings, consistently indicate that the intensity of competition significantly influences disclosure occurrences, though the evidence varies due to differences in the nature of competition and measurement methods (Botosan and Stanford, 2005; Verrecchia and Weber, 2006; Beyer et al., 2010). In particular, Clinch and Verrecchia (1997) find that industries marked by heightened competition among incumbent firms typically exhibit reduced disclosure levels. In the same vein, Ali et al. (2014) find a negative relationship between industry concentration and disclosure in their sample of manufacturing firms. In contrast, Glaeser and Landsman (2021) find evidence that managers time the disclosure of good news about innovative successes to deter product market competitors, specifically through patent disclosure. Li (2010) reconcile the conflicting findings by separately measuring competition from potential entrants and existing rivals. Consistent with the underlying theories, her findings suggest that competition from potential entrants increases disclosure quantity while competition from existing rivals decreases disclosure quantity. Lang and Sul (2014) highlight the primary challenges in establishing a compelling empirical connection between competition, proprietary costs, and disclosure, particularly when comparing different measures of industry competition. Our paper complements this literature by providing novel evidence that the decision to host an AI day is negatively affected by threats of existing competitors but positively affected by threats of potential competitors, confirming previous opposing effects. We further find that a competition timing strategy of voluntary disclosure yields better economic performance for the hosting firm compared to firms that do not host or do not follow a competition timing strategy.

[3]See Cheynel and Ziv (2021) for a detail product market foundation for the proprietary cost hypothesis.

Furthermore, our study contributes to the literature on AI days and the wider literature on face-to-face interactions between managers and influential market participants. In comparison to other more formal voluntary disclosure channels, AI days distinguish themselves by their unique attributes, including face-to-face interactions between managers and capital markets participants, more flexible formats, extended duration, and a broader range of attendees. Bushee et al. (2011) find that "disclosure milieu", i.e. the physical and social setting in which voluntary disclosures occur, and other characteristics of conference presentations (such as the nature of the audience or sponsor) are significantly associated with the market reaction and changes in subsequent analyst and institutional investor following. These results demonstrate the benefits to firms and analysts of engaging in face-to-face conferences compared to private events. Compared to conference presentations (see Bushee et al., 2011, 2022), AI days are organized and paid for by the company, allowing it complete control over the time and duration of the events, as well as the speakers and invitees.[4] AI days are a distinct disclosure channel, leading to 3-day abnormal absolute returns and abnormal turnover approximately four to six times larger than the effects of conference presentations (Kirk and Markov, 2016). They convey additional information beyond what is disclosed at other events and are influenced by factors such as valuation uncertainty, the size, and significance of the firm's analyst and investor base (Kirk and Markov, 2016; Wu and Yaron, 2018; Park, 2022; Miwa, 2023). We complement this literature by showing that information transmission predominantly happens through the interactions between the manager and the attendees during the Q&A session of the event. This information is valuable for the capital market participants and it is incorporated into stock prices within days following the event.

Overall, our findings enhance understanding of the dynamics underlying the decision to host an AI day and the determinants of short-term and longer-term economic outcomes associated with using AI days as a disclosure channel.

[4]The information provided during AI days complies with Fair Disclosure (Reg FD) rules enforced by the Securities and Exchange Commission (SEC) under the Securities Exchange Act of 1934. This mandates companies to share non-public information to reduce information imbalances between managers and investors. As a result, any company-hosted event, like a conference call, must promptly share its content (e.g., transcripts) with the public.

2. Hypotheses development and methodology

2.1 Competition timing of voluntary disclosure

Firms can choose to disclose voluntary information to reduce information asymmetry with stakeholders (Verrecchia, 2001), improve stock returns, and increase the number of analysts following and institutional investors allocating capital to the firm (Francis et al., 1997; Bushee et al., 2011). Nevertheless, in the presence of valuable proprietary information, firms face the trade-off between the costs and benefits of transparency, as disclosing detailed information can reveal sensitive information to rivals firms, potentially affecting firms' market position. Existing empirical research on voluntary disclosure suggests that the decision to disclosure information is contingent not only upon proprietary costs but also on the competitive environment within which firms operate (Botosan and Stanford, 2005; Verrecchia and Weber, 2006; Beyer et al., 2010; Li, 2010; Ali et al., 2014; Lang and Sul, 2014).

In his seminal paper, Verrecchia (1983) postulates that firms with greater proprietary costs of disclosure withhold more information compared to those companies incurring lower proprietary costs when the competition within the industry is high. Contrary to Verrecchia (1983), Darrough and Stoughton (1990) show that if the cost of entering the product market is low (e.g., due to low barriers to entry), incumbent firms are more likely to disclose *more* information to deter potential entrants in the same product market. Thus, considering the incentives of incumbent firms, increased competition promotes more disclosure. These studies focus on different sources of competition, however: Darrough and Stoughton (1990)'s conclusions stem from potential threats (e.g., pre-entry), whereas Verrecchia (1983) assumes that firms are already in competition (e.g., post-entry) and thus disclosure would reduce their competitive advantage. Li (2010) applies a principle component analysis to extract multiple measures of competitive pressures by existing rivals and potential entrants, confirming that firms reduce voluntary disclosure in the presence of intense product market competition and increase disclosure activities with greater threats of new entrants.

This reasoning leads to our *competition timing of voluntary disclosure* hypothesis in the context of AI days as a channel of voluntary disclosure:

Hypothesis H1. *Disclosure through AI days is more beneficial for companies facing higher threats from potential rivals and lower threats from existing rivals.*

Such competition timing would have implications for the likelihood of holding the AI day, as well as its perception by direct participants in the event and investors in general. In particular, firms should be more likely to hold AI days in accordance to competition timing, as well as to disclose more information with less obfuscation and vagueness in these cases. If such events indeed help firms to stay ahead of competition, the capital market participants should see such disclosures positively and abnormal returns of the hosting firm should increase following the event. Hence, we formulate several testable predictions, directly stemming from our competition timing hypothesis:

- **Empirical Prediction 1**: Firms are more likely to hold AI days to time competition, when the treat of potential rivals is higher and the threat from existing rivals is lower.
- **Empirical Prediction 2**: The information component of linguistic complexity of managers' presentation increases if the event is hosted in accordance with competition timing.
- **Empirical Prediction 3**: Short-term abnormal returns of a hosting firm increase if the event is hosted in accordance with competition timing.
- **Empirical Prediction 4**: More positive (negative) tone during the Q&A is related to more positive (negative) market reaction.

Any information disclosed during the AI day will be taking in account strategic considerations to discourage new entrants and improve firm valuation. The structured environment and focused discussion help to improve the quality and relevance of the information shared, ultimately leading to capital market outcomes through analyst and investor activities. Hence, we should expect that AI days will have a positive impact on capital markets, enhanced by the clearly defined physical and social surroundings, as well as the verbal communication and audience engagement during the event, including the manager's presentation and Q&A session.

The manager's interaction with analysts and investors during the Q&A session of the AI day provides a unique opportunity to shape this type of disclosure channel. Unlike scripted presentations, manager have less control over the content of their responses to questions, which can convey a mixed impression to the audience. Consequently, the language used in a face-to-face event is more likely to reflect an intentional disclosure choice by managers compared to mandatory disclosures (e.g., SEC filings), which are more constrained by regulatory and accounting requirements (Bushee et al., 2018b; Li, 2008; Guay et al., 2016). To this point, if analysts and investors are aware of the current context in which the firm is operating, they might have stronger information demands during the Q&A session, leading to an increase in the linguistic complexity and higher informational value.

Related to the implications of linguistic complexity, we further hypothesize that differences in tone should result in significant differences in capital market reactions. For instance, Healy and Palepu (2001) suggest that managers generally possess better insight into their company's future performance compared to external investors. Frankel et al. (2010) employed conference call tone as a measure reflecting the existing relationship between a firm and its investors when studying investor relations costs. They observed a positive association between conference call returns and linguistic tone. In addition, Verrecchia (2001) suggests a potential link between disclosure and economic consequences via the reduction of information asymmetry. Mayew and Venkatachalam (2012) provide evidence that short-term stock returns are linked to both positive and negative sentiments displayed by managers during the question and answer segment of earnings conference calls. Compared to earnings conference calls, AI days enable a more flexible and extended interaction, thereby conveying more valuable information (e.g., Kirk and Markov 2016). Consequently, we anticipate that investors will efficiently assimilate information conveyed during the AI day, particularly information disclosed during the Q&A session, in the short-term.

2.2 Measures of industry competition

Our hypothesis of competition timing of voluntary disclosure hinges on the opposing impact of existing and potential competition on voluntary disclosure, and by extension, on hosting an AI day. Following Boone et al. (2016) and Fei (2022), we use *Fluidity* measure by Hoberg et al. (2014) to capture dynamic competitive threats from potential rivals in the product market and the *Similarity* measure from Hoberg and Phillips (2016) to capture the static competitive threats posed by existing rivals in the product market.[5]

Hoberg et al. (2014) introduced a "product market fluidity" (*Fluidity*) measure based on firms' 10-K filings, in particular business descriptions where firms give detail on the products they offer. According to Hoberg et al. (2014), *Fluidity* assesses how potential rivals are changing the words that intersect with firm i's vocabulary, reflecting the dynamics within the product space. In the same vein, Hoberg and Phillips (2016) created a text-based network industry classification (TNIC-3). This classification is based on how similar each firm is to every other firm, calculated by determining firm-by-firm pairwise word similarity scores using the 10-K product words. Given that each firm possesses a unique set of rivals, it is possible to generate an aggregate "product market similarity" (*Similarity*) measure by summing the pairwise similarities between the focal firm and all other firms in their sample for a given year.

In our context, *Fluidity* and *Similarity* emerge as promising candidates as both measures are customized to each firm, utilizing each firm's unique product market vocabulary and TNIC-3 industry classification.

2.3 Test of competition timing of voluntary disclosure

To test our prediction related to the probability of hosting an AI day, we estimate the following probit model:

[5] These text-based competition proxies are downloaded from Hoberg-Phillips Data Library: https://hobergphillips.tuck.dartmouth.edu/. Another well-established approach involves using, concentration measures, such as the Herfindahl-Hirschman Index (HHI), as a proxy for competition (Ali et al., 2014) at industry level.

$$\Pr(AIDAY_{i,t} = 1) = \beta_0 + \beta_1\, Fluidity_{i,t-1} + \beta_2\, Similarity_{i,t-1} + \Gamma \cdot \mathbf{X}_{i,t-1} + \alpha_t + \epsilon_{i,t}, \tag{1}$$

where $AIDAY_{i,t}$ is an indicator that takes the value of one if the firm i hosts at least one AI day in the year t and zero otherwise. $\mathbf{X}_{i,t-1}$ is a set of lagged control variables, $\epsilon_{i,t}$ is the error term, and α_t stands for year-industry fixed effects.

To measure the effects of competition on the decision to host an AI day, we use two text-based measures of market competition: *Fluidity* and *Similarity*. We predict $\beta_1 > 0$ and $\beta_2 < 0$. These coefficients capture the potential proprietary costs of disclosure and, by extension, hosting an AI day based on the two competition measures.

Motivated from prior work, we identify a set of explanatory variables, potentially related to information disclosure. Kirk and Markov (2016) argue that organizing an AI day is linked to institutional holdings and the level of valuation uncertainty, thus, we include institutional ownership ($Ownership^{INS}$), intangible assets (*Intangibles*), and annualized return volatility (*Volatility*). Additionally, we control for market participants' demand for information by including firm size based on the marke value of equity (*Ln(Size)*), book-to-market ratio (*Book-to-Market*), and leverage[6] (*Leverage*) (see Bushee et al., 2022). Prior research has shown that events, such as broker conferences, conferences presentation (Bushee et al., 2011), and private meetings (Bushee et al., 2018a) lead to higher-quality analyst forecast activities, hence, we include analyst following (*Ln(Analysts)*) and earnings surprise (*Surprise*) as additional controls. To account for the influence of proprietary information held by the firm, we include R&D intensity (*R&D Intensity*) and high-tech industry dummies (*High Tech*).[7] We also include annualized stock return (*Return*), loss indicator if annual net income is negative (*Loss*), and capital intensity based on relative

[6]In accordance with Ali et al. (2014), we define the leverage ratio as total liabilities minus deferred taxes scaled by total book assets, as corporate cash reserves offer financial flexibility.

[7]Note, that industry-year fixed effects are based on industry classification of Bali et al. (2016), while *High Tech* dummy spans across different industries, and the two do not completely overlap. For example, all firms with SIC codes 2000-3999 will be classified as Manufacturing. Out of them only those with codes 2833-2836 (drugs), 3570-3577 (computers), 3600-3674 (electronics), and 3810-3845 (precise measurement instruments) are classified as High Tech.

capital expenditures (*Capital Intensity*). We further control for information asymmetry (Bushee et al., 2018b; Schoenfeld, 2017), proxied by the daily Amihud (2002) illiquidity measure (*Illiq.*$\times 10^7$) and for the total number AI days held by the firm in the fiscal year. Following Humphery-Jenner et al. (2016), we employ proxies to control for CEO characteristics and CEO compensation, in particular the natural logarithm of CEO age ($Ln(Age^{CEO})$), CEO gender ($Gender^{CEO}$) that takes a value of 1 for male CEOs and 0 for female CEOs, CEO tenure as the natural logarithm of one plus the number of years since the start of the current CEO's tenure (*Tenure*), continuous options-based CEO confidence (*Confidence*), number of vested options (*Ln(# of Options)*), and CEO's ownership ($Ownership^{CEO}$). All the aforementioned variables are defined in Table 1.

[Insert Table 1 About Here]

2.4 Role of linguistic complexity during AI days

To test if and how competition timing is related to perception of participants of AI days and linguistic complexity, including the willingness to reveal "pure" information vs an attempt to obscure the listeners, we estimate the following regression model:

$$LC^{l}_{k,i,t} = \beta_0 + \beta_1\, Fluidity_{i,t-1} + \beta_2\, Similarity_{i,t-1} + \Gamma \cdot \mathbf{X}_{i,t-1} + \alpha_t + \epsilon_{i,t}, \tag{2}$$

where $LC^{l}_{k,i,t}$ is the latent component l capturing information or obfuscation (*Info* or *Obfu*) of different portions k of an AI day of the firm's transcript i at year t. k captures structurally different parts of the event, including a manager's presentation, manager's responses to Q&A, and analyst's questions and statements during the Q&A. $\mathbf{X}_{i,t-1}$ is a set of lagged explanatory variables, $\epsilon_{i,t}$ is the error term, and α_t are year-industry fixed effects.

We expect a positive value of β_1 and a negative value of β_2 for the manager's presentation information component. We also expect the same signs but higher magnitudes of the estimates for the Q&A's information component. In other words, if the AI day is hosted to time competition, the linguistic complexity is used to inform in the manager's presentation and Q&A session and not to obfuscate the interaction between the manager and attendees.

To assess linguistic complexity, we begin by identifying the manager's presentation, manager's response to Q&A, and analysts' questions and statements during the Q&A portion of the AI day. Following Bushee et al. (2018b), we measure linguistic complexity using the Gunning's Fog index defined by Gunning (1952) as:

$$Fog = 0.4 \times \left(ASL + 100 \times \frac{n_{wsy} \geq 3}{n_w} \right), \tag{3}$$

where ASL is the average sentence length defined as the number of words (n_w) over the number of sentences and $n_{wsy} \geq 3$ the number of words with 3-syllables or more. The original Fog index is based on just a sample of 100 words; hence, we scale it by 100. According to Bushee et al. (2018b), linguistic complexity can be decomposed into two latent components: information ($Info^*$) and obfuscation ($Obfu^*$). The former is associated with informative technical disclosure (absence of obfuscation), while the latter aims to reduce the informativeness of the disclosure. As the informativeness of linguistic complexity can also differ between scripted and spontaneous language, we follow the approach of Bushee et al. (2018b) and separately examine the presentation and the response portions during the Q&A session. We derive different Fog indices separately for the presentation and Q&A portions of the AI day, as well as mangers and analysis. Managerial fog is captured by the Fog index of managers' language during the presentation, $Fog(Presentation)$, and the Fog of managers' responses to questions, $Fog(Response)$. We measure analysts' Fog as $Fog(Analyst)$, representing the analysts' questions and statements during the Q&A portion of the call.

To estimate the two latent components ($Info^*$ and $Obfu^*$), we formally represent the manager's presentation linguistic complexity as:

$$Fog(Presentation) = \varphi_0 + \varphi_1 Info^* + \varphi_2 Obfu^* + \epsilon, \tag{4}$$

and the linguistic complexity of the analyst questions during the Q&A session as:

$$\textit{Fog(Analyst)} = \delta_0 + \delta_1 \textit{Info}^* + v, \tag{5}$$

We follow the notion of Bushee et al. (2018b) that while "managers may seek to obfuscate information provided on the call, analysts should not seek to do so", as reflected in Eq. (5). Regressing Eq. (4) on Eq. (5) allows recovering an estimate of the latent information component (*Info*) and an estimate of the latent obfuscation component (*Obfu*) (See, Appendix A of Bushee et al. (2018b) for a detailed derivation). We repeat the procedure replacing $Fog(Presentation)$ by $Fog(Response)$ to estimate the two latent components of the managerial responses during Q&A sessions. In the presence of multiple AI days during one fiscal year, we average each latent component to obtain corresponding yearly measures.

2.5 Market reaction to AI days

To test the short-them market reactions after AI days, we estimate the following regression:

$$CAR_{k,i,t} = \beta_0 + \beta_1\, \textit{Sentiment}_{i,t} + \beta_2\, \textit{Fluidity}_{i,t-1} + \beta_3\, \textit{Similarity}_{i,t-1} + \beta_4\, \textit{FogIndex} + \mathcal{B} \cdot \mathbf{X}_{i,t-1} + \alpha_t + \epsilon_{i,t} \tag{6}$$

where $CAR_{k,i,t}$ represents the cumulative abnormal returns in firm i over horizons $k \in \{CAR(-5,-1), CAR(-1,+1), CAR(0,0), CAR(0,+4)\}$ around the AI day held in year t. $\textit{Sentiment}_{i,t}$ refers to the corresponding proportion of *Positive* and *Negative* words as defined in Eq. (7) and *Tone* as defined in Eq. (8), $\textit{Similarity}_{i,t-1}$ and $\textit{Fluidity}_{i,t-1}$ are two text-based competition proxies. $\textit{FogIndex}$ is an overall measure of linguistic complexity as described in the previous section, applied to the transcript of the whole AI day (both presentation and Q&A component). $\mathbf{X}_{i,t-1}$ is a set of lagged explanatory variables, α_t is the year fixed effects, γ_j is the industry fixed effects, and $\epsilon_{i,t}$ the error term of the regression. Following Guay et al. (2016) and Bushee et al. (2022), we further control for firms' voluntary disclosure with two dummy variables: *Forecast* and *Voluntary 8-k*. *Forecast* is equal to one if the firm revises any type of forecast ten days before the event day, as reported by I/B/E/S. *Voluntary 8-k* is equal to one if the firm issues any 8-K filling containing Item 2.02, 7.01, or 8.01 ten days before the event day. To do this, we downloaded all 8-K forms filed in the SEC's EDGAR system for each firm in our sample between 2011 and 2022, and through a text parser, we identified the corresponding item.

The measures for linguistic $Sentiment_{i,t}$ are based on the proportion of "*Positive*" and "*Negative*" words in the transcripts, and $Tone$. The proportion of "*Positive*" and "*Negative*" words is defined based on Loughran and McDonald (2011):

$$Positive_{k,j} = \frac{Word\ count\ for\ Positive_{k,j}}{Total\ Aiday\ word\ count_{k,j}} \qquad Negative_{k,j} = \frac{Word\ count\ for\ Negative_{k,j}}{Total\ Aiday\ word\ count_{k,j}}, \tag{7}$$

where subscript k is the portion of the transcript j.

We further construct a $Tone$ variable for each portion k of transcript j using:

$$Tone_{k,j} = \frac{Positive_{k,j} - Negative_{k,j}}{Positive_{k,j} + Negative_{k,j}}, \tag{8}$$

where $Tone$ is bounded between -1 and 1. As tone is derived from positive and negative word classifications which can depend on the context, word classification requires a context-specific dictionary. To compute Eq. (7) and Eq. (8), we use an updated version of the finance-oriented Loughran and McDonald (2011) Master Dictionary, focusing only on the categories that contain words that are either positive or negative.

CARs are computed relative to the Carhart (1997) four-factor model using stock return data from the Center for Research in Security Prices (CRSP). We use an estimation period of 100 days with a minimum of 70 observations with a gap of 10 days between the end of estimation period to compute expected and abnormal returns. We calculate the abnormal returns as differences between the raw daily returns for stock i on the day of interest and the expected returns, and then cumulate them over different time intervals around the AI day to obtain the corresponding CARs.

Disclosure events are typically scheduled weeks before they take place. This means that the management's prepared statements at the beginning of such events may contain information that has already been meticulously crafted and announced in press releases (Kimbrough, 2005; Matsumoto et al., 2011; Price et al., 2012). Thus, we reestimate Eq. (6) decomposing $Sentiment_{i,t}$ into their respective portion of the transcript. Accordingly, we construct *Positive(Present)*, *Negative(Present)*, *Positive(Question)*, *Negative(Question)*, *Positive(Answer)*, and *Negative(Answer)* as Eq. (7), where *Present* is the manager's presentation, and *Question* and *Answer* represent the Q&A portion of the transcript. We repeat the same procedure for $Tone$.

The decision to host an AI day is an endogenous choice and systematic differences may exist between firms hosting an AI day compared to firms that do not, which may introduce potential bias due to self-selection in our estimates in the regressions for CARs and LC. To mitigate this concern, we employ a self-selection correction model proposed by Heckman (1976). We use the estimation results of the probit model in Eq. (1) and include an inverse Mills ratio (*IMR*) as an additional control in all the regressions for CARs, linguistic complexity and tone.

2.6 Longer-term measures of economic performance and risk

We next assess the economic value of hosting AI days and the differences in performance between firms hosting AI days and firms that do not host while controlling for the self-selection. We use propensity score matching (PSM) and the entropy balancing method by Hainmueller (2012) to construct samples of comparable firm that hold and not hold AI days.

We implement PSM in three steps. In the first step, we reestimate the probit model in Eq. (1) that relates the probability of hosting an AI day to a set of lagged explanatory variables, which includes our two text-based competition proxies, along with firm characteristics, CEO characteristics, and CEO compensation. In the second step, we obtain the propensity score as the probability of hosting an AI day given the aforementioned variables. Finally, in the third step, we perform a one-to-one matching using the nearest neighbour algorithm without replacement within the same year and industry. We retain only those matches for which the difference in the score is smaller than 0.01 resulting. For the entropy balancing method, we set it to find weights directly adjusted to the first and second moments based on industry, year, and the set of lagged explanatory variables. This approach involves mitigating pre-existing category differences by weighting treatment and control observations, following the methodology established by Hainmueller (2012). We then evaluate performance of the matched sets of firms using measures related to their stock market performace, as well as accounting performace measures.

Together with the commonly used mean returns, return volatility, and Sharpe ratio, we compute the downside risk measures (*DR*), Sortino ratio, maximum drawdown and manipulation-proof performance measure (*MPPM*) of Goetzmann et al. (2007). All these measures are computed using 3 months of daily return observations starting from the announcement date of an AI day for firms hosting the AI day and their matched peers.

The downside risk is computed as $DR = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\min(r_{i,t},0)^2}$, where $r_{i,t}$ is the return of firm i during period t. The Sortino ratio is the average firm return per unit of the downside risk. Maximum drawdown (*MDD*) is the difference between cumulative returns and the peak cumulative return. Whenever cumulative returns dip below the highest point, it signifies a drawdown. These drawdowns are then expressed as a percentage of the highest cumulative return. Manipulation-proof performance measure (*MPPM*) is computed as:

$$MPPM = \frac{1}{(1-\rho)}\ln\left[\frac{1}{T}\sum_{t=1}^{T}\left(\frac{1+r_{i,t}}{1+r_{f,t}}\right)^{1-\rho}\right], \tag{9}$$

where $r_{i,t}$ is the return of firm i during period t, $r_{f,t}$ is the risk-free rate, and ρ the curvature coefficient, which we set at 4. *MPPM* quantifies the continuously compounded certainty equivalent return exceeding the risk-free return for an investor with power-utility preferences.

Accounting performance measures include return on assets (*ROA (%)*), return on equity (*ROE (%)*), and net profit margin (*NPM (%)*) at the end of the fiscal year during which the AI was held. Further to capture potential institutional reaction on these events we compute the quarterly change in institutional holdings ($\Delta Ownership^{INS}(\%)$) from q to $q-1$, where q is the quarter when the AI day was hosted.

3. Data and Descriptive Statistics

Our main data source for historical AI day transcripts is the Capital IQ Transcripts database provided by S&P Global Market Intelligence. The data are collected from around 8,000 public companies and contain over 400,000 unique transcripts divided in twenty different events. Our data is composed of North American public firms from the first quarter of 2011 through the fourth quarter of 2022, comprising 3,061 transcripts from AI days held by 1,242 unique firms. After excluding events hosted by multiple firms, we found that nearly 50% of the firms (672) have hosted more than one AI day in our sample.

Figure 1 displays the total number of AI day hosted quarterly from 2011 to 2022 and Table 2 reprots the number of conferences held each year-by-quarter, together with the numbers of unique participating companies. Figure 1 and Table 2 show, with the exception of the first quarter affected by the COVID-19 pandemic, an upward trend in the utilization of this type of conference over the years, the observation consistent with (Kirk and Markov, 2016; Karolyi et al., 2020). We observe a higher number of AI days in the second and fourth quarters of each year. Each transcript contain at least one of the following speaker: analysts, attendees, executives, operators, shareholders, and unidentified. Executives have the most participation, followed by analysts.[8]

[Insert Figure 1 and Table 2 About Here]

We obtain information on the firm's executives from the Execucomp database, maintained by Standard & Poor's. The Execucomp database obtains compensation data from firms' annual proxy statements (specifically, form DEF 14A). Alongside compensation details, Execucomp also provides information on executives' age, their respective positions within the firm, and their gender. We restrict our sample to years 2011 to 2022 using only executives with a current position identified

[8] In Table A.2 of Appendix B, we describe the composition of each type of speaker in terms of their participation, the number of words and characters used in their interventions during the event in our sample. On average, the executives' transcripts contain 23,621 characters (23,210 words and 411 numbers) and involve eight of them.

as CEO. After restricting the sample to the aforementioned time period, the Execucomp database spans 11,484 firms.

Our stock returns data are from the Center for Research in Security Prices (CRSP) Daily Stock File and Monthly Stock File. To ensure consistency, we include only those stocks that have been listed on US stock exchanges and traded on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), or NASDAQ, over the period spanning January 2010 to December 2022. Only stocks with share codes 10 and 11 are included in the sample. The listing exchange codes (1, 2, or 3) are converted into explicit exchange names, following the methodology suggested by Bali et al. (2016). The additional year of data (2010) is necessary to compute lagged values of the control variables for the regressions.

Monthly returns are adjusted for delistings, whereas no adjustments are made to the Daily Stock File, as there are no aggregation issues. Using the GVKEY-PERMNO links provided by the merged CRSP-Compustat database, we merge our sample with Compustat to compute companies' yearly financial variables and I/B/E/S for analyst and management forecast data. Additional factors required for the analysis are collected from Kenneth French's data library.[9] We exclude utility firms (those with standard industrial classification (SIC) codes from 4900 to 4999) and financial firms (those with SIC codes from 6000 to 6999) as is common in the literature. Our data on institutional holdings are from the Thomson Reuters Institutional (13f) Holding database (CDA/Spectrum s34). The text-based competition measures *Fluidity* and *Similarity* are downloaded from Hoberg-Phillips Data Library.[10] Since the text-based competition measures are constructed annually, we test our main hypotheses at the firm-year level.

3.1 Summary statistics

Table 3 reports summary statistics, including tests of mean differences, for firms that host at least one AI day and firms that do not host any AI day in the fiscal year. Firms hosting AI days

[9] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data library.html.

[10] The Hoberg-Phillips Data Library can be found here: https://hobergphillips.tuck.dartmouth.edu/.

have an average *Fluidity* of 5.521 and an average *Similarity* of 6.326. In contrast, companies that do not host any AI day show a higher average *Fluidity* (5.826), and a higher average *Similarity* (7.378), with these differences being statistically significant at the 1% level. Furthermore, firms that host at least one AI day have on average higher institutional ownership and greater number of analyst following. These firms tend to be larger, have lower R&D expenditures, and a higher leverage. These firms exhibit less volatile earnings and slightly lower stock returns. As for CEO characteristics and compensation, firms holding AI days have younger CEOs with shorter tenure who are more confident but have lower ownership. Finally, firms in high-tech industries are more likely to host AI days.

[Insert Table 3 About Here]

To illustrate the market reaction around AI days, we report a set of measures used in the literature to provide insights into the informativness embedded in the event. These metrics include: abnormal absolute return *ABS MAR* of Bushee et al. (2011) and Cready and Hurtt (2002), abnormal share turnover *ABN TURN* of Kirk and Markov (2016), and abnormal analyst forecast activity *ABN FRAC* of Cotter et al. (2006). For all the measures, we calculate their cumulative sums over rolling 3-day periods (starting from day -3 to day +3) using an estimation period s from day -100 to day -10 relative to the event.

Abnormal absolute return is computed as:

$$ABS\ MAR = (|R_{i,t} - R_t| - \overline{x}_{1i,s})/\sigma_{1i,s}, \tag{10}$$

where $|R_{i,t} - R_t|$ is the market adjusted returns based on the CRSP value-weighted market index, $\overline{x}_{1i,s}$ is the mean value of $|R_{i,t} - R_t|$ over estimation period s and $\sigma_{1i,s}$, the standard deviation of $|R_{i,t} - R_t|$ over estimation period s.

Abnormal share turnover is computed as:

$$ABN\ TURN = (Turnover_{i,t} - \overline{x}_{2i,s})/\sigma_{2i,s}, \tag{11}$$

where $Turnover_{i,t}$ is the daily volume divided by shares outstanding, $\overline{x}_{2i,s}$ is the mean value of $Turnover_{i,t}$ during the estimation period s and $\sigma_{i,s}$, the standard deviation of $Turnover_{i,t}$ over estimation period s.

Abnormal analyst forecast activity is captured by:

$$ABN\ FRAC = (Fraction_{i,t} - \overline{x}_{3i,s})/\sigma_{3i,s}, \tag{12}$$

where $Fraction_{i,t}$ is calculated as the proportion of unique analysts who revised their forecasts out of the total number of unique analysts who revised forecasts, $\overline{x}_{3i,s}$ is the mean value of $Fraction_{i,t}$ during the estimation period s and $\sigma_{i,s}$ the standard deviation of $Fraction_{i,t}$ over the estimation period s.

Table 4 reports the mean and median values of these market reaction measures around the AI day. We observe a significant increase in *ABS MAR*, *ABN TURN*, and *ABN FRAC* during a three day window around the AI day (-1,+1), as well as significantly positive levels in the three days prior to the presentation (-4,-2). The mean abnormal returns, turnover and analyst coverage are positive and statistically significant, consistent with Kirk and Markov (2016), highlighting that AI days provide new information for market participants.

[Insert Table 4 About Here]

4. Empirical results

4.1 Competition timing and probability of hosting AI days

Table 5 reports the estimation results for the probit model in Eq. (1), which includes our two text-based competition proxies, along with firm characteristics, CEO characteristics, and CEO compensation variables as controls. Consistent with our main hypotheses, we find a positive and significant coefficient on $Fluidity$ (0.022, t-statistic 2.364), indicating that firms facing higher threats from potential entrants are more likely to host an AI day. In contrast, we observe a negative and significant coefficient on *Similarity* (-0.009, *t*-statistic -2.905), hence firms are less likely to host such events in the case of competitive threat from existing rivals. These results align with the theoretical literature suggesting that competition affects a firm's propensity to make proprietary disclosures and, by extension, host an AI day (Verrecchia, 1983; Darrough and Stoughton, 1990).

Regarding the control variables, firms in the high-tech industry are more likely to host an AI day (0.086, *t*-statistic 1.777). Additionally, we find significantly positive coefficients on *Book-to-Market* (0.126, *t*-statistic 1.754), *Intangibles* (0.101, *t*-statistic 1.704), and *Tobin's Q* (0.030, *t*-statistic 2.395), which capture valuation uncertainty and firms with a high-level of investment in growth (Kirk and Markov, 2016). As Kirk and Markov (2016), we find evidence of the importance of the firm's analyst base and firm size, as the coefficients on *ln(Analyst)*, *ln(Size)*, and $Ownership^{INS}$[11] are positive, even though not statistically significant. Regarding CEO characteristics and CEO compensation variables, the number of vested options (*ln(# of Options)*) is associated with a higher probability of hosting an AI day (0.011, *t*-statistic 1.477), while CEO age is negatively related to the probability of hosting an AI day (-0.608, *t*-statistic -3.364).

[Insert Table 5 About Here]

4.2 Tone, linguistic complexity and short-term performance during AI days

Table 6 reports the estimation of the regression in Eq. (2) for latent components of linguistic complexity of AI days. While neither *Fluidity* nor *Similarity* are statistically significant for *Info(Presentation)*, these variables seem to be linked to *Obfu(Presentation)*. The corresponding coefficient on *Fluidity* is negative and significant at the 10% level (-0.057, *t*-statistic -1.7), while the coefficient on *Similarity* is positive and significant at the 5% level (0.040, *t*-statistic 2.224).

[11] In Table A.1 of Appendix A, we examine the baseline model considering different institutional holdings. Following the classification system of Bushee and Noe (2000) and Bushee (2001), we distinguish three types of institutional investors based on their portfolio turnover, diversification, and investment horizon: transient (TRAs), quasi-indexers (QIXs), and dedicated (DEDs). Consistent with Boone and White (2015), we observe a positive relationship between quasi-indexer investors and a firm's decision to host an AI day. In contrast, transient investors are found to be less inclined to host such an event. Similarly, dedicated investors, with a preference for private information sources, are also less likely to host an AI day.

These results are consistent with our prediction: if the AI day is hosted to time competition (i.e. when levels of fluidity are high and levels of similarity are low), we observe less obfuscation in CEO speech. When firms do not host AI days in accordance to competition timing, the reverse applies and the obfuscation level increases when fluidity is low (low chance of potential new entrants) and decreases when similarity is high (greater competitive threats by existing competitors). Our results are validated by the Q&A portion of the event (column 3 and 4), where the coefficients have the same signs with *Similarity* being significantly negative for *Info(Response)* and significantly positive for *Obfu(Response)*, suggesting that attendees do not seek to obfuscate with their question and therefore manager intentionally disclose information (Li, 2008; Bushee et al., 2018b).

[Insert Table 6 About Here]

Table 7 reports the mean and median CARs sorted according to *Tone* quintiles, with *Tone* based on Loughran and McDonald (2011) Master Dictionary. The differences in mean and median CARs between events with the highest tone and lowest tone are always positive, and in most cases statistically significant, indicating that more positive discussions during AI days are related to greater changes in firm returns.

[Insert Table 7 About Here]

Figure 2 illustrates the differences in cumulative average abnormal returns (CAARs) between the high and low Tone quintile portfolios, plotted alongside the overall AI days in the sample. For each subfigure, we calculate the corresponding average abnormal return (AAR) for each day between -10 days before and 10 days after the event, aggregating the abnormal returns (ARs) for all firms to obtain the average at each point in time. We then cumulate the AARs over all days t within the window. We see an increase in CAARs before an AI day for all cases, but more pronounced for AI days with higher tone. After the AI day, CAARs remain high for high tone AI days, but decline and are not significantly different from zero for low tone AI days.

[Insert Figure 2 About Here]

The regression results for individual firms' CARs estimated as in Eq. 6 are reported in Table 8. The results show that the market reaction in the short-term is related to the firm's competitive environment, consistent with our prediction on competition timing. CAR(-1,+1), CAR(0,0), and CAR(0,+4) increase with *Fluidity* (threat from new competitors) and decrease with *Similarity* (threat from existing competitors), with the effects being statistically significant at the 1% level and 5% level. These effects are economically large. An increase in *Fluidity* by one standard deviation leads to an increase in CAR(-1,1) by around 0.42 percentage points, almost 5 times the average level of CAR(-1,1) of 0.089. An increase in *Similarity* by one standard deviation leads to a decrease in CAR(-1,1) by around 0.83 percentage points, which is around 10 times of its mean value. As a foresight exercise to measure the stock price run-up to the event, we include CAR(-5,-1) along with our text-based sentiment and competition proxies measures. This inclusion potentially captures expectations of what might occur during the event as well as possible information leakages. While our findings suggest an anticipation of higher sentiment values, it's noteworthy that the sign of our text-based competition proxies is reversed.

As for linguistic tone, we find a positive but not significant reaction of CARs to the overall *Tone* in the short-term. Remarkably, the market seems to react stronger on the negative information compared to positive one. While coefficients on *Positive* are all positive but not statistically significant, the coefficients on *Negative* are much larger in absolute values, they are negative and significant at the 5% level and 10% level for CAR(-1,+1) and CAR(0,+4). The effect of "negativity" during the AI day has a strong economic impact on the CARs. An increase in the fraction of negative words by one standard deviation leads to a decrease of 0.32 percentage point on average for CAR(-1,1), which is 3.6 times larger than the mean value of CAR(-1,1).

The results in Table 9 take a more granular approach and measure tone and its components for the manager's presentation and the Q&A session separately. The tone of the questions (*Tone(Question)*) exhibits a positive and significant coefficient for CAR(-1,1). The effect is predominantly driven by the fraction of positive words in questions from the analysts

(*Positive(Question)*), which has a positive and significant effect on CARs for all horizons. The tone of answers (*Tone(Answer)*) is also positively but not significantly related to CARs. Interestingly, its effect is driven the fraction of negative words in answers (*Negative(Answer)*), with the coefficients for CAR(-1,1) and CAR(0,+4) being statistically significant. The coefficient of our text-based competition proxies remains unchanged.

Overall, the results suggest that a considerable portion of the information content contained in the presentation is already known to the audience, which is confirmed or supplemented in the manager's presentation, consistent with Bushee et al. (2011). The unscripted part of the event – the Q&A session – provides new insights into firm's performance and prospects and, consequently, triggers market reactions.

[Insert Tables 8 and 9 About Here]

4.3 Longer-term economic implications of hosting AI days

We start by implementing the PSM for firms that hold and not AI days. We retain in total 1,289 matched pairs of firms, with the differences in the scores smaller than 0.01. The resulting treated firms (Hosted AI Day) and control firms (Did Not Host AI Day) are indistinguishable in terms of all the characteristics we use as the basis for matching, as reported in Table 10.

[Insert Table 10 About Here]

Figure 3 further illustrates that, in the absence of matching through PSM, the firms that hosted an AI day are different from the full sample of firms on a number of observable dimensions, including firm characteristics, CEO characteristics, and CEO compensation. After matching, the matched control sample is statistically indistinguishable from the sample with AI days across all these dimensions.

[Insert Figure 3 About Here]

Tables 11 and 12 compare the differences in performance between the firms that hold AI days and their PSM matched peers (in Panels A) or entropy balancing weighted firms (in Panels B). Panel A of Table 11 indicates that firms with AI days exhibit a significantly higher mean return at the 5% level, enhanced risk-adjusted returns (Sharpe ratio and Sortino ratio), and higher manipulation-proof performance measure (*MPPM*) over three months after the event day is announced. Using the entropy balancing technique in Panel B of Table 11, we similarly find that firms that host AI day display higher mean returns and higher Sharpe ratios compared to firms that do not host such events.

Interestingly, all these results are mainly driven by the pre-event drift, as we do not observe any significant differences in performance in the three months after the actual event is held. This suggests that the market incorporates expectations about the new information that may be released during the AI day gradually before the event. Any price adjustments are made immediately after the event (as our results for short-term CARs) when the information becomes public, without any further drifts.

[Insert Table 11 About Here]

Economically, firms that hold AI days do seem to benefit. The results in Panel A of Table 12 show that firms hosting AI days are more likely to have higher return on asset, return on equity, and net profit margin at the end of the fiscal year. However, the corresponding differences are only significant at the 5% level for the return on equity (3.368 vs. 2.234). Regarding the quarterly change in institutional holdings, firms hosting such an event witness a higher change in holdings (0.620 vs. 0.165), though non-significant. Overall, the results from the matching and weighting analysis support our hypotheses and predictions, indicating that hosting an AI day offers benefits in relation to portfolio and financial performance.

[Insert Table 12 About Here]

4.4 Trading strategy based on AI day hosting/non-hosting firms

Previous findings indicate superior performance of firms hosting AI days within the matched sample. In the attempt to capitalize on this, we develop the following trading strategy: starting from the event announcement date, we hold a long-short (Long-Short) portfolio for six months, rebalancing semi-annually. We take a long (Long Leg) position in the firms that host an AI day and a short (Short Leg) position in the matched control firm (did not host an AI day). We take the equally weighted averages across the portfolios held at the same time.

Table 13 reports the average excess returns and risk-adjusted returns of the trading strategy, as well as its individual legs relative to the Carhart (1997) four-factor model. We use daily returns from CRSP and the risk-free rate from Kenneth French's data library. Over the 2011 to 2022 investment period, the long-short strategy alpha is 0.005% per day, but it is not statistically significant. Also reported in Table 13 are the average and risk-adjusted returns of the long and short-leg portfolios of our trading strategy, with the long leg of the portfolio delivering slightly higher alpha.

[Insert Table 13 About Here]

4.5 Robustness checks: Alternative competition measures

As a robustness check, we use three different types of measures to assess potential product market competition: "Barrier to entry", the Lerner Index, and the Herfindahl-Hirschman Index.

The "Barrier to entry" measure is the costs necessary for selling, assuming that all firms in the same industry face the same cost curve. Consequently, we can expect that a higher "Barrier to entry" implies a diminished threat from potential rivals, leading to a decrease in voluntary disclosure. We proxy it by the costs of sales (COGS) divided by the total sales (SALES) as reported by Compustat.

Another way to measure competition is to use a Lerner Index. A firm with a lower pricing power faces more intense competition within its industry. A lower Lerner Index indicates higher competition, while a higher index indicates lower competition. Following Grullon et al. (2019), we define an industry-adjusted Lerner Index for firm i in year t as follows:

$$LI_{i,t} = \frac{Profit_{i,t}}{Sales_{i,t}} - \sum_{i=1}^{N} W_{i,t} \times \frac{Profit_{i,t}}{Sales_{i,t}}, \tag{13}$$

where, *Profit* is the operating income before depreciation (OIADAP) minus depreciation (DP), *Sales* is the total sales (SALE), and $W_{i,t}$ is the proportion of sales of firm i in total industry sales in year t — all reported by Compustat. This approach enables us to account for industry-specific factors that are unrelated to the pricing power of the firm (for a comprehensive review of measures related to product market competition, see, Babar and Habib, 2021).

Finally, we include the Herfindahl-Hirschman Index (*HHI*) calculated as the square of firms' market shares based on the text-based network industry classification (TNIC-3) following Hoberg et al. (2014) and Hoberg and Phillips (2016) to measure factors such as pricing power and market concentration. The *HHI* scale ranges from 0 to 1, with higher values indicating greater market concentration and therefore, less competition. For ease of interpretation as competition (rather than concentration) measure, we use (1 - *HHI*) as the independent variable.

We use the same specification as in Eq. (1), but replace *Fluidity* with Barrier to entry in Model (1), and then *Similarity* with Lerner Index in Model (2) and with 1-HHI in Model (3). Results in Table 14 show estimates for the coefficient on *Barrier to Entry* is negative as expected, but not statistically significantly. On the other hand, the coefficients on the *Lerner Index* and (1 - *HHI*) are 0.087 (t-statistic 1.714) and -0.123 (t-statistic -1.475), respectively. Unlike *Similarity* (-0.006, t-statistic -2.139), we do not observe statistical significance for *Fluidity* after incorporating *Barrier to Entry* and (1 - *HHI*). In general, our text-based competition proxies are mostly in line with our baseline findings, although with smaller coefficients, and only *Similarity* is statistically significant.

[Insert Table 14 About Here]

5. Conclusion

In this paper, we examine whether the decision to host an AI day by firms is strategically driven by competition timing. Our key findings show that firms are more inclined to host AI days when confronting lower levels of industry competition and facing a higher threat from potential rivals. As an implication of competition timing, we find that during the event, attendees are less likely to seek obfuscation with their questions, leading managers to intentionally disclose information. Additionally, we observe differences in the predictive ability of the Q&A section of the AI day for the market reaction after the event. The tone and fractions of positive words in the questions are positively related to abnormal returns in the short term, while the fraction of negative words in the answers predicts lower abnormal returns. We find a similar pattern for negative fractions of the words in the answers. This aligns with the notion that the initial prepared statements by management during such events might consist of information that has already been carefully formulated and made public in press releases (Bushee et al., 2011). After the event is held, firms outperform similar firms that choose not to hold AI days in terms of their end-of-year financial performance.

Our paper highlights the importance of AI days in relation to proprietary costs and voluntary disclosure, emphasizing the role of competition timing and its associated benefits. We demonstrate that institutional and market-level characteristics, such as competition, also drive linguistic attributes in disclosures, reflected in the market reactions when firms engage in competition timing. We complement existing findings of Kirk and Markov (2016) who have provided an important foundation for the analysis of AI days and further highlight the importance of the social and physical "disclosure milieu" whose effects are just beginning to be explored (Bushee et al., 2011). Our findings also provide valuable practical insights for managers into a relatively new channel of corporate disclosure, by emphasizing the role of the unscripted Q&A part of the AI day and the information content and sentiment of answers and responses during the Q&A, reflected in the market reaction after the event.

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Figure 1: Analyst/Investor Day Hosted, 2011 - 2022

Notes. This figure displays the number of analyst/investor days hosted from 2011 to 2022. We exclude analyst/investor days hosted by more than one firm. Our final sample contains 3,061 unique transcripts and 1,242 uniques firms. All of them are North American public companies.

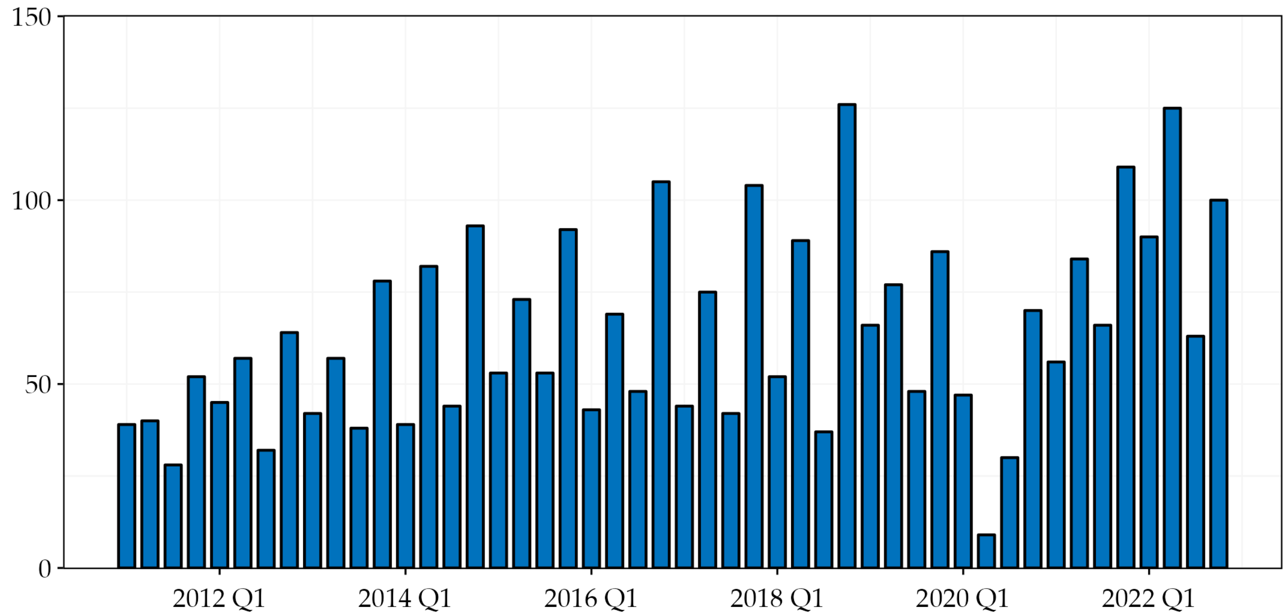
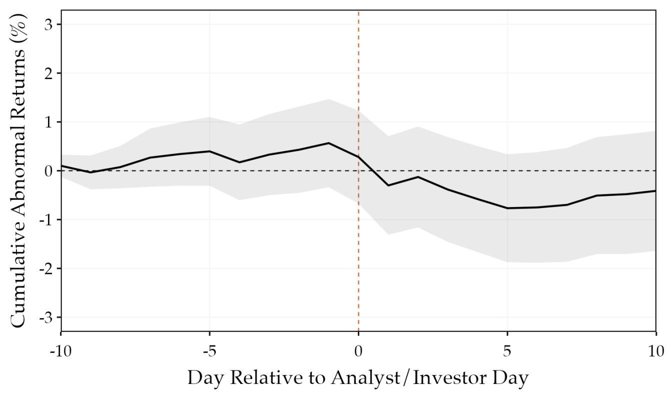


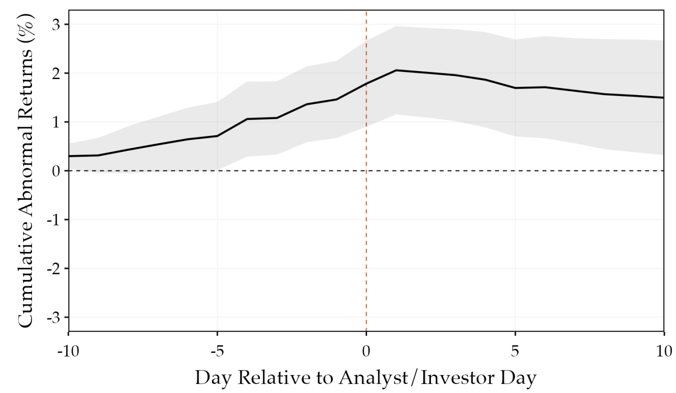
Figure 2: Cumulative Avarage Abnormal Returns Over Time

Notes. This figure plots the cumulative average abnormal returns (CAARs) and the 95% confidence intervals related to analyst/investor days, covering the [-10, +10] day windows before and after the event. For each subfigure, we calculate the corresponding average abnormal return for each day within the window across all firms and then cumulate the average abnormal returns over all days within the window. Sub-figure (a) plots CAARs for the lower tone quintile of AI days. Sub-figure (b) plots CAARs for the highest tone quintile AI days. Sub-figure (c) uses the complete sample of AI days. The shaded areas in each figure represent 95% confidence bands.

(a) Low Tone AI days



(b) High Tone AI days



(c) All AI days

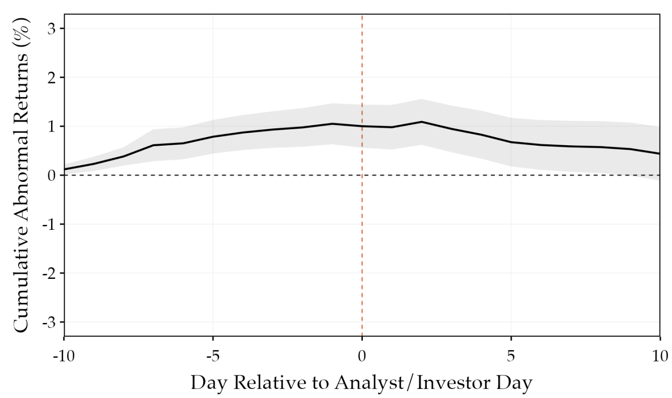


Figure 3: PSM Matching Balance

Notes. This figure summarizes the covariate balance of the propensity score matching (PSM) procedure, comparing treated (holding AI days) and matched (not holding AI day) observations (solid points) as well as treated observations and the full sample (hollow points).

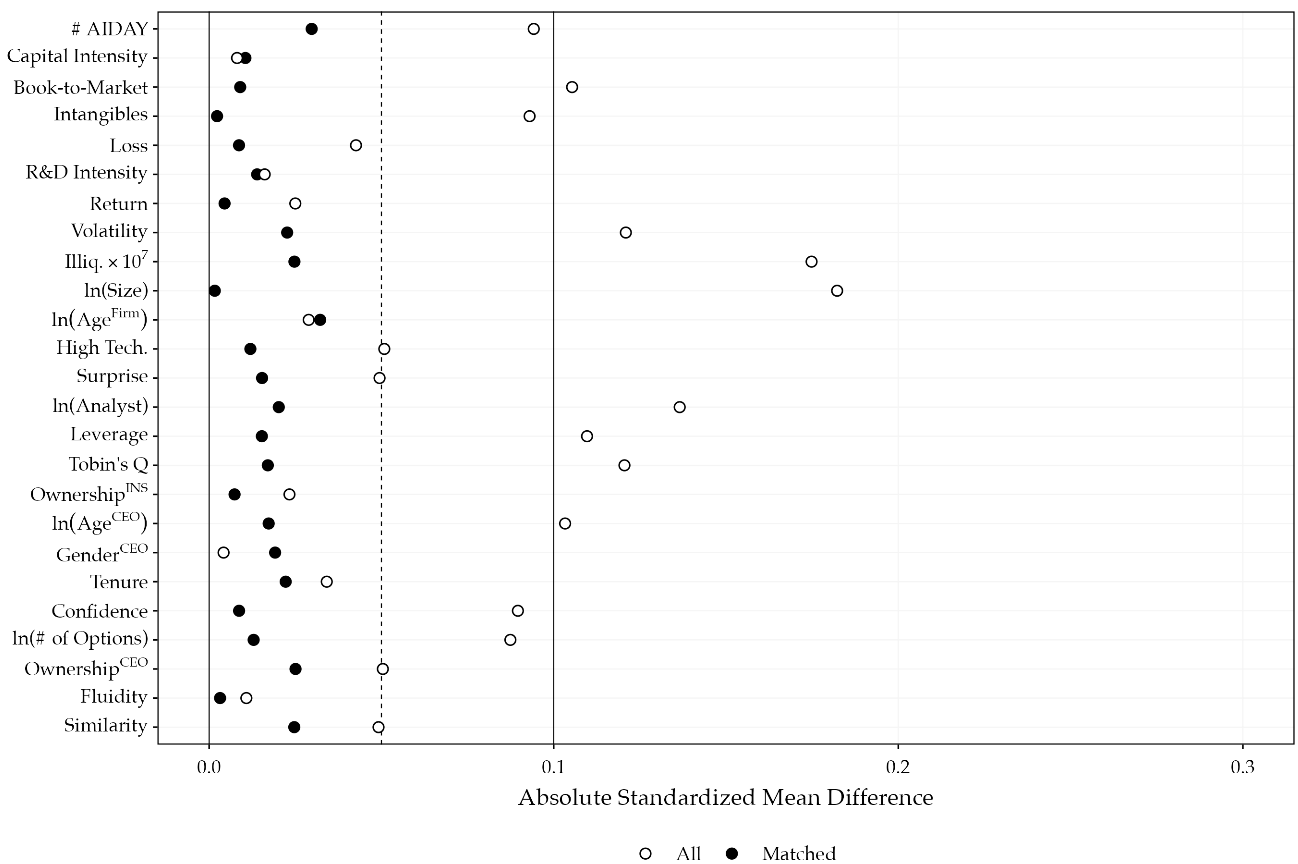


Table 1: Variable Definitions and Data Sources

Notes. This table lists the variables and their definitions in the order of their usage within their respective categories.

Variable	Description
Analyst/Investor Day	
AIDay	1 if a firm hosted an analyst/investor day during the fiscal quarter, and 0 otherwise.
# AIDay	Total number of hosted analyst/investor days in the fiscal year.
Firm Characteristics	
Capital Intensity	The capital expenditures (CAPX) scaled by the lagged of total assets (AT).
Book-to-Market	The book value of common equity (CEQ) scaled by the market value of equity (MKVALT).
Intangibles	Recognized intangibles (INTAN) plus goodwill (GDWL) scaled by total assets (AT).
Loss	1 if the prior fiscal year's net income (NI) is negative, and 0 otherwise.
R&D Intensity	Firm spends on R&D (XRD) scaled by the lagged of total assets (AT). We replace spends on R&D (XRD) with zero if is missing in Compustat.
Return	The firm's average stock returns over the year, annualized by multiplying by 252.
Volatility	The firm's stock return volatility, measured using the daily stock returns over the year, annualized by multiplying by $\sqrt{252}$.
Illiq.$\times 10^7$	The ratio of the absolute daily stock return (RET) to daily dollar trading volume (ABS(PRC) $\times$ VOL), where the average is taken over all trading days over the year (see Amihud, 2002).
ln(Size)	The natural logarithm of one plus the market value of equity (see, Fama and French, 1992).
ln(Age^{Firm})	The natural logarithm of one plus the number of years that the stock has been listed on the CRSP database.
High Tech.	1 if the firm belongs to one of the following SIC codes: 2833-2836 (drugs), 8731-8734 (R&D services), 7371-7379 (programming), 3570-3577 (computers), 3600-3674 (electronics), or 3810-3845 (precise measurement instruments), and 0 otherwise.
Surprise	Difference between the earnings-per-share (ACTUAL) and analyst's mean forecast for the firm fiscal year (MEANEST) as reported by I/B/E/S, scaled by the stock price at the close of the fiscal year (PRCC_F).
ln(Analyst)	The natural logarithm of one plus the number of analysts (NUMEST) issuing earnings forecasts for the next company fiscal year. Assumed to be 0 for any period in which the company is listed on an exchange, but no data are available on I/B/E/S.
Leverage	The total liabilities (LT) minus deferred taxes (TXDB) scaled by total assets (AT) (see, Ali et al., 2014).
Tobin's Q	Total assets (AT) plus the market value of equity (MKVALT) minus the book value of common equity (CEQ), scaled by total assets (AT).
$\text{Ownership}^{\text{INS}}$	The Institutional Investor's percentage ownership in the firm. This is derived by dividing the Institutional Investor's stock ownership by the number of shares outstanding as reported in the Institutional Holding (13f) database.
CEO Characteristics	
ln(Age^{CEO})	The natural logarithm of one plus the CEO's age as reported in ExecuComp.
$\text{Gender}^{\text{CEO}}$	1 if the CEO's gender is equal to male, and 0 otherwise (ExecuComp).
Tenure	The natural logarithm of one plus the time between year t and the year in which the CEO became CEO (ExecuComp).
Confidence	The "value per vested option," scaled by the "average strike price" of those options, is calculated as follows. In year t, the "value per vested option" is defined as the total value of vested but unexercised options (OPT_UNEX_EXER_EST_VAL) divided by the number of those options (OPT_UNEX_EXER_NUM). The average strike price is determined by subtracting the value per vested option from the stock price at the time the option-value is assessed (PRCC_F).
CEO Compensation	
ln(# of Options)	The natural logarithm of one plus the number of vested but unexercised options.
$\text{Ownership}^{\text{CEO}}$	The CEO's percentage ownership in the firm. This is derived by dividing the CEO's stock ownership (SHROWN) by the number of common shares outstanding (CSHO).
Competition proxies	
Fluidity	A text-based, firm-specific similarity measure of competitive threat from existing rivals developed by Hoberg et al. (2014).
Similarity	A text-based, firm-specific fluidity measure of competitive threat from potential rivals developed by Hoberg and Phillips (2016).

Table 2: Number of Analyst/Investor Days Hosted and Unique Hosting Companies, 2011 - 2022

Notes. This table reports the number of analyst/investor days by year. The column Companies shows the number of unique firms per year, whereas the column $AIDAY_t > 1$ shows the number of unique firms that host more than one analyst/investor day in the same year.

						Unique	
Year	1st Qtr.	2nd Qtr.	3rd Qtr.	4th Qtr.	Total	Companies	$\text{AIDAY}_t > 1$
2011	39	40	28	52	159	154	5
2012	45	57	32	64	198	190	8
2013	42	57	38	78	215	204	10
2014	39	82	44	93	258	245	13
2015	53	73	53	92	271	256	15
2016	43	69	48	105	265	256	9
2017	44	75	42	104	265	257	8
2018	52	89	37	126	304	293	10
2019	66	77	48	86	277	272	4
2020	47	9	30	70	156	148	8
2021	56	84	66	109	315	307	8
2022	90	125	63	100	378	373	5
Total	616	837	529	1,079	3,061	1,242	672

Table 3: Summary Statistics for the Fiscal Year in Which a Firm Hosts an Analyst/Investor Day

Notes. This table displays firm level summary statistics for the fiscal year in which a firm hosted an analyst/investor day (did not host analyst/investor day). ***, **, * indicate statistical significance difference in means (medians based on Wilcoxon rank sum test) between the samples at the 1%, 5% and 10% levels, respectively. All the variables are defined in Table 1.

	Did Not Host Analyst/Investor Day							Hosted Analyst/Investor Day							Difference Tests			
	N	Mean	Std.	IQR	25%	50%	75%	N	Mean	Std.	IQR	25%	50%	75%	Mean	Sign.	Median	Sign.
Analyst/Investor Day																		
# AIDAY	11,863	0.000	0.000	0.000	0.000	0.000	0.000	2,578	1.030	0.178	0.000	1.000	1.000	1.000	−1.030	***	−1.000	***
Firm Characteristics																		
Capital Intensity	8,251	0.135	8.397	0.036	0.014	0.027	0.050	2,370	0.042	0.053	0.035	0.014	0.028	0.050	0.094		−0.001	
Book-to-Market	8,271	0.331	2.476	0.378	0.161	0.314	0.539	2,376	0.343	0.414	0.333	0.142	0.287	0.475	−0.012		0.029	***
Intangibles	8,168	0.420	0.376	0.618	0.072	0.338	0.691	2,347	0.473	0.377	0.621	0.139	0.415	0.760	−0.053	***	−0.044	***
Loss	8,275	0.700	0.458	1.000	0.000	1.000	1.000	2,376	0.744	0.436	1.000	0.000	1.000	1.000	−0.044	***	0.000	***
R&D Intensity	8,276	0.080	0.160	0.087	0.000	0.014	0.087	2,376	0.070	0.120	0.090	0.000	0.018	0.090	0.010	***	0.000	***
Return	8,276	0.172	0.538	0.448	−0.059	0.169	0.389	2,376	0.149	0.462	0.439	−0.062	0.158	0.377	0.023	**	0.009	
Volatility	8,276	0.451	0.266	0.272	0.279	0.387	0.551	2,376	0.403	0.226	0.225	0.256	0.348	0.481	0.047	***	0.034	***
Illiq.$\times 10^7$	8,276	0.256	3.229	0.037	0.002	0.008	0.039	2,376	0.062	0.497	0.015	0.001	0.004	0.016	0.194	***	0.002	***
ln(Size)	8,276	7.863	1.808	2.405	6.652	7.833	9.056	2,376	8.374	1.669	2.143	7.302	8.314	9.445	−0.511	***	−0.510	***
ln(Age^{Firm})	8,276	2.825	1.004	1.350	2.203	2.973	3.552	2,376	2.891	0.973	1.434	2.211	3.029	3.644	−0.065	***	−0.052	**
High Tech.	8,276	0.266	0.442	1.000	0.000	0.000	1.000	2,376	0.293	0.455	1.000	0.000	0.000	1.000	−0.027	**	0.000	***
Surprise	8,200	−0.026	2.299	0.003	0.000	0.001	0.002	2,361	−0.006	0.216	0.002	0.000	0.001	0.002	−0.020		0.000	
ln(Analyst)	8,276	2.245	0.674	0.981	1.792	2.303	2.773	2,376	2.418	0.599	0.944	1.946	2.485	2.890	−0.174	***	−0.167	***
Leverage	7,689	0.548	0.328	0.319	0.361	0.524	0.680	2,161	0.571	0.333	0.301	0.390	0.546	0.691	−0.022	***	−0.021	***
Tobin's Q	8,241	2.505	2.155	1.486	1.338	1.831	2.824	2,370	2.766	2.388	1.729	1.419	1.952	3.149	−0.262	***	−0.118	***
$\text{Ownership}^{\text{INS}}$	6,653	0.754	0.210	0.232	0.655	0.787	0.888	1,893	0.785	0.183	0.199	0.693	0.805	0.893	−0.031	***	−0.020	***
CEO Characteristics																		
ln(Age^{CEO})	5,785	4.050	0.114	0.157	3.970	4.060	4.127	1,646	4.044	0.106	0.141	3.970	4.043	4.111	0.006	**	0.000	**
$\text{Gender}^{\text{CEO}}$	5,788	0.953	0.211	0.000	1.000	1.000	1.000	1,646	0.954	0.209	0.000	1.000	1.000	1.000	−0.001		0.000	
Tenure	5,670	1.736	0.856	1.204	1.099	1.792	2.303	1,605	1.673	0.870	1.204	1.099	1.792	2.303	0.063	**	0.000	**
Confidence	5,788	0.728	1.634	0.811	0.000	0.202	0.811	1,646	0.912	1.992	0.968	0.000	0.312	0.968	−0.184	***	0.000	***
CEO Compensation																		
ln(# of Options)	5,786	4.331	2.763	6.426	0.000	5.288	6.426	1,646	4.371	2.767	4.527	1.999	5.306	6.525	−0.040		0.000	
$\text{Ownership}^{\text{CEO}}$	5,748	0.017	0.040	0.012	0.001	0.004	0.013	1,636	0.014	0.035	0.009	0.001	0.003	0.011	0.003	***	0.001	***
Competition proxies																		
Fluidity	7,493	5.826	3.402	4.000	3.374	4.984	7.374	2,045	5.521	3.287	3.730	3.207	4.771	6.937	0.305	***	0.245	***
Similarity	7,493	7.378	16.947	2.048	1.124	1.517	3.172	2,045	6.326	15.191	1.898	1.115	1.502	3.014	1.052	***	0.013	

Table 4: Information Content of Analyst/Investor Days

Notes. This table reports the means and medians of stock market and analyst forecast reaction variables during 3-day windows around an analyst/investor day following Cready and Hurtt (2002), Bushee et al. (2011), and Kirk and Markov (2016). Day 0 is the event day. ABN ABSMAR, ABN TURN, and ABN FRAC are standardized measures of the abnormal 3-day absolute value of market-adjusted returns, abnormal share turnover, and fraction of unique analysts revising any forecast. The estimation period used in the standardization is [-100, -10]. *, **, and *** denote the statistical significance at 10%, 5%, and 1%, respectively.

Variable	Window	Mean	Median	Pct.> 0	N
ABS MAR	(−7, −5)	0.423***	−0.239	44.1	2,413
	(−4, −2)	0.267***	−0.251**	44.2	2,413
	(−1, +1)	1.364***	0.632***	62.4	2,413
	(+2, +4)	0.126***	−0.250***	43.2	2,413
	(+5, +7)	−0.130***	−0.520***	35.1	2,413
ABN TURN	(−7, −5)	0.768***	−0.175**	45.3	2,413
	(−4, −2)	0.799***	−0.075***	48.4	2,413
	(−1, +1)	2.375***	1.200***	70.6	2,413
	(+2, +4)	1.046***	0.187***	54.0	2,413
	(+5, +7)	0.487***	−0.290	42.5	2,413
ABN FRAC	(−7, −5)	0.136***	−0.771***	31.8	2,396
	(−4, −2)	0.310***	−0.609***	38.1	2,396
	(−1, +1)	5.073***	4.770***	91.9	2,396
	(+2, +4)	1.097***	0.525***	59.1	2,396
	(+5, +7)	−0.293***	−0.826***	27.0	2,396

Table 5: Probability of Hosting an Analyst/Investor Day

Notes. This table reports the estimation results of the probit regression for the probability of hosting an analyst/investor day during the fiscal year. The dependent variable is a dummy variable indicating whether or not a firm hosted at least one analyst/investor day during the fiscal year. *, **, and *** denote the statistical significance at 10%, 5%, and 1%, respectively. All the variables are defined in Table 1.

	$\mathbb{1}$ (Analyst/Investor Day)	
	Coef.	t-statistic
Competition proxies		
Fluidity	0.022**	(2.364)
Similarity	−0.009***	(−2.905)
Analyst/Investor Day		
# AIDAY	0.051	(1.233)
Firm Characteristics		
Capital Intensity	0.820**	(1.992)
Book-to-Market	0.126*	(1.754)
Intangibles	0.101*	(1.704)
Loss	−0.054	(−0.879)
R&D Intensity	0.131	(0.455)
Return	0.074	(1.173)
Volatility	−0.398**	(−2.168)
Illiq.$\times 10^7$	−0.070	(−0.997)
ln(Size)	0.030	(1.316)
ln(Age$^{\text{Firm}}$)	0.029	(1.137)
High Tech.	0.086*	(1.777)
Surprise	2.535	(1.612)
ln(Analyst)	0.032	(0.665)
Leverage	0.374***	(4.913)
Tobin's Q	0.030**	(2.395)
Ownership$^{\text{INS}}$	0.064	(0.501)
CEO Characteristics		
ln(Age$^{\text{CEO}}$)	−0.608***	(−3.364)
Gender$^{\text{CEO}}$	−0.021	(−0.234)
Tenure	0.001	(0.049)
Confidence	0.007	(0.597)
CEO Compensation		
ln(# of Options)	0.011	(1.477)
Ownership$^{\text{CEO}}$	0.066	(0.120)
Observations	5,888	
Year × Industry FE	✓	

Table 6: Latent Components of Linguistic Complexity

Notes. This table reports the estimation results of the relationship between our text-based competition proxies and the latent components of linguistic complexity, as measured by the Fog Index defined by Gunning (1952). *Info*($\cdot$) is the latent information component, while *Obfu*($\cdot$) represents the latent obfuscation component. *Presentation* refers to the manager's presentation and *Response* indicate the managers responses during the Q&A portion of the analyst/investor day. *, **, and *** denote the statistical significance at 10%, 5%, and 1%, respectively.

	(1) Info(Presentation)	(2) Obfu(Presentation)	(3) Info(Response)	(4) Obfu(Response)
Fluidity	0.001	−0.057*	0.003	−0.021
	(0.278)	(−1.700)	(0.653)	(−0.830)
Similarity	−0.002	0.040**	−0.003*	0.019*
	(−1.286)	(2.224)	(−1.782)	(1.651)
IMR	0.096	−2.548**	0.205	−0.915
	(0.787)	(−2.294)	(1.131)	(−1.110)
Constant	12.478***	3.813*	9.875***	1.813
	(58.331)	(1.868)	(32.118)	(1.264)
Observations	1,259	1,259	1,259	1,259
R-squared	0.692	0.166	0.491	0.176
Firm Controls	✓	✓	✓	✓
Year × Industry FE	✓	✓	✓	✓

Table 7: Test of Differences of Means and Medians, by Tone Quintiles

Notes. This table reports the average values of CARs sorted into Tone portfolios. Tone is defined as (Positive - Negative)/(Positive + Negative) where Positive (Negative) reflects the proportions of Positive (Negative) words in a given transcript as defined by Loughran and McDonald (2011) Master Dictionary. Test statistics for the differences in means (t) and medians (z) are in parentheses. The abnormal returns are estimated using the Carhart (1997) four-factor model, and then cumulated across the respective horizons. *, **, and *** denote the statistical significance at 10%, 5%, and 1%, respectively.

Tone quintiles		CAR(-5,-1)	CAR(-1,+1)	CAR(0,0)	CAR(0,+4)
1 (Low)	Mean	0.224	−0.731	−0.286	−1.147
	Median	0.034	−0.669	−0.179	−0.711
2	Mean	0.075	0.114	−0.092	−0.010
	Median	−0.010	−0.086	−0.158	−0.023
3	Mean	0.291	−0.068	0.002	0.093
	Median	0.007	−0.081	0.050	−0.010
4	Mean	0.591	0.030	−0.186	−0.441
	Median	0.570	0.135	−0.078	−0.194
5 (High)	Mean	0.816	0.696	0.324	0.404
	Median	0.450	0.235	0.060	−0.087
Two sample t-test					
Mean Q5 - Q1		0.592	1.427***	0.610**	1.551***
t-Statistic		(1.521)	(3.629)	(2.194)	(3.198)
Wilcoxon rank-sum test					
Median Q5 - Q1		0.536*	1.013***	0.341**	0.956**
z-Statistic		(1.932)	(3.549)	(2.087)	(2.777)

Table 8: Regression Results of Cumulative Abnormal Returns

Notes. This table reports the estimation results of the cross-sectional regression model in Equation 6 of CARs on the Fog Index, measures of Sentiment, competition measures *Fluidity* and *Similarity* and a set of control variables. For sentiment, we use *Tone* and fraction of *Positive* and *Negative* words in the AI day transcript. All other variables are defined in Table 1. The t-statistics are in parenthesis. All regressions include year-industry fixed effects. *, **, and *** denote the statistical significance at 10%, 5%, and 1%, respectively.

	CAR(-5,-1)		CAR(-1,+1)		CAR(0,0)		CAR(0,+4)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tone	1.962**		0.960		0.322		0.631	
	(2.476)		(1.097)		(0.601)		(0.671)	
Positive		5.810		0.301		0.829		9.149
		(0.513)		(0.022)		(0.098)		(0.579)
Negative		−22.243**		−20.086**		−6.165		−16.546*
		(−2.387)		(−2.082)		(−0.908)		(−1.661)
Fog Index	−0.078	−0.087	0.047	0.019	0.011	0.004	0.068	0.049
	(−0.756)	(−0.850)	(0.415)	(0.182)	(0.163)	(0.057)	(0.565)	(0.424)
Fluidity	−0.114*	−0.118*	0.127**	0.124**	0.134***	0.133***	0.083	0.082
	(−1.662)	(−1.721)	(2.036)	(1.994)	(2.707)	(2.692)	(1.058)	(1.046)
Similarity	0.058*	0.054*	−0.059**	−0.061**	−0.046**	−0.047**	−0.028	−0.029
	(1.852)	(1.721)	(−2.096)	(−2.182)	(−2.317)	(−2.366)	(−0.660)	(−0.685)
IMR	1.130	1.214	1.388	1.467	1.091	1.115	1.215	1.279
	(0.858)	(0.928)	(1.161)	(1.238)	(1.301)	(1.337)	(0.873)	(0.918)
Constant	−3.499	−2.660	−1.506	−1.033	−5.631	−5.507	−1.500	−1.711
	(−0.549)	(−0.415)	(−0.218)	(−0.151)	(−1.244)	(−1.229)	(−0.212)	(−0.244)
Observations	1,410	1,410	1,410	1,410	1,410	1,410	1,410	1,410
R-squared	0.054	0.055	0.043	0.045	0.061	0.061	0.041	0.043
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year × Industry FE	✓	✓	✓	✓	✓	✓	✓	✓

Table 9: Regression Results of Cumulative Abnormal Returns, by Portions of The Transcripts

Notes. This table reports the estimation results of cross-sectional regressions of CARs on the Fog Index, measures of Sentiment, and a set of control variables as in Equation 6. For sentiment, we use *Tone* and fraction of *Positive* and *Negative* words. We separate the transcript into manager's presentation (Presentation), analyst questions (Question) and manager answers (Answer) during the Q&A session and include sentiment variables *Tone* and fraction of *Positive* and *Negative* words for each part of the transcript. The t-statistics are are in parenthesis. All regressions include year-industry fixed effects. *, **, and *** denote the statistical significance at 10%, 5%, and 1%, respectively.

	CAR(-5,-1)		CAR(-1,1)		CAR(0,0)		CAR(0,+4)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tone(Present)	0.258		−0.060		0.077		0.327	
	(0.410)		(−0.090)		(0.159)		(0.413)	
Tone(Answer)	2.256***		0.658		0.113		0.037	
	(3.219)		(0.835)		(0.232)		(0.043)	
Tone(Question)	0.014		1.248***		0.507		0.840	
	(0.031)		(2.882)		(1.604)		(1.503)	
Positive(Present)		−3.743		−7.212		−2.732		−8.860
		(−0.493)		(−0.872)		(−0.551)		(−0.954)
Positive(Answer)		7.133		1.909		0.431		0.290
		(0.929)		(0.219)		(0.076)		(0.027)
Positive(Question)		9.430		27.012***		9.059*		26.378***
		(1.290)		(3.231)		(1.652)		(2.635)
Negative(Present)		−4.331		−1.842		2.628		−7.154
		(−0.548)		(−0.233)		(0.358)		(−0.607)
Negative(Answer)		−14.685***		−11.509*		−6.449		−13.310**
		(−2.828)		(−1.950)		(−1.334)		(−2.162)
Negative(Question)		−0.327		−6.492		−0.144		0.451
		(−0.060)		(−1.234)		(−0.040)		(0.080)
Fog Index	−0.054	−0.064	0.046	0.054	0.010	0.011	0.066	0.068
	(−0.529)	(−0.622)	(0.414)	(0.509)	(0.140)	(0.163)	(0.570)	(0.581)
Fluidity	−0.116*	−0.114*	0.125**	0.128**	0.133***	0.134***	0.083	0.087
	(−1.687)	(−1.684)	(1.984)	(2.070)	(2.697)	(2.749)	(1.061)	(1.129)
Similarity	0.061*	0.052*	−0.056**	−0.064**	−0.045**	−0.048**	−0.027	−0.033
	(1.906)	(1.667)	(−2.007)	(−2.301)	(−2.277)	(−2.437)	(−0.632)	(−0.802)
IMR	1.100	1.190	1.266	1.347	1.047	1.102	1.150	1.238
	(0.834)	(0.908)	(1.057)	(1.128)	(1.249)	(1.311)	(0.824)	(0.888)
Constant	−4.200	−3.743	−1.182	−2.591	−5.517	−6.127	−1.312	−3.028
	(−0.665)	(−0.580)	(−0.172)	(−0.379)	(−1.223)	(−1.363)	(−0.187)	(−0.436)
Observations	1,410	1,410	1,410	1,410	1,410	1,410	1,410	1,410
R-squared	0.059	0.057	0.048	0.054	0.062	0.064	0.043	0.050
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year × Industry FE	✓	✓	✓	✓	✓	✓	✓	✓

Table 10: Balancing Tests of Propensity Score Matching

Notes. This table reports the balancing test results of propensity score matching. The treated group includes firms that hosted at least one analyst/investor day within the period spanning from 2011 and 2022. The control group includes firms that did not host an analyst/investor day during the same timeframe. *, **, and *** denote the statistical significance at 10%, 5%, and 1%, respectively. All the variables are defined in Table 1.

	Hosted AI Day	Did Not Host AI Day	% Bias	t-statistic
Analyst/Investor Day				
# AIDAY	0.250	0.264	−0.030	−0.772
Firm Characteristics				
Capital Intensity	0.042	0.042	−0.011	−0.302
Book-to-Market	0.357	0.360	−0.009	−0.242
Intangibles	0.501	0.500	0.002	0.058
Loss	0.849	0.846	0.009	0.219
R&D Intensity	0.044	0.043	0.014	0.361
Return	0.197	0.196	0.004	0.118
Volatility	0.357	0.353	0.023	0.575
Illiq.$\times 10^7$	0.023	0.029	−0.025	−0.870
ln(Size)	8.578	8.580	−0.002	−0.041
ln(Age$^{\text{Firm}}$)	3.153	3.125	0.032	0.827
High Tech.	0.303	0.298	0.012	0.301
Surprise	0.001	0.001	0.015	0.295
ln(Analyst)	2.446	2.457	−0.020	−0.503
Leverage	0.546	0.540	0.015	0.609
Tobin's Q	2.376	2.414	−0.017	−0.577
Ownership$^{\text{INS}}$	0.786	0.787	−0.007	−0.191
CEO Characteristics				
ln(Age$^{\text{CEO}}$)	4.043	4.045	−0.017	−0.436
Gender$^{\text{CEO}}$	0.960	0.956	0.019	0.489
Tenure	1.724	1.705	0.022	0.569
Confidence	0.796	0.813	−0.009	−0.268
CEO Compensation				
ln(# of Options)	4.405	4.440	−0.013	−0.331
Ownership$^{\text{CEO}}$	0.015	0.014	0.025	0.700

Table 11: Performance Comparison of Matched Firms

Notes. This table reports the propensity score matching (Panel A) and entropy balancing by Hainmueller (2012) (Panel B) results for the period spanning from 2011 and 2022. Mean (%) is the firm's mean stock returns minus risk-free return (excess return). Volatility (%) is the firm's stock return minus risk-free return (excess return) standard deviation. Sharpe ratio is the Mean (%) over the Volatility (%). DR is the downside risk (semi-standard deviation) measured using the subset of returns that are less than the target (or Minimum Acceptable Returns (MAR) that equal to zero). The Sortino ratio is the average firm return over DR. MPPM is the Goetzmann et al. (2007) manipulation-proof performance measure for a relative risk aversion coefficient of four. Each measure is computed for 3-months daily returns from CRSP, starting from the event announcement day (Announcement) or from the event day (Analyst/Investor Day). *, **, and *** denote the statistically significant differences in means between the treated (Host AI Day) and controls (Did Not Host AI Day) firms at the 1%, 5%, and 10% levels, respectively.

	Announcement				Analyst/Investor Day			
	Host AI Day	Did Not Host AI Day	Difference	*t*-statistic	Host AI Day	Did Not Host AI Day	Difference	*t*-statistic
Panel A: Propensity Score Matching								
Mean (%)	0.084	0.056	0.028	2.510**	0.045	0.049	−0.003	−0.301
Volatility (%)	2.165	2.139	0.026	0.629	2.127	2.134	−0.007	−0.174
Sharpe ratio	0.047	0.037	0.010	2.154**	0.030	0.035	−0.004	−0.911
DR (%)	1.457	1.448	0.008	0.268	1.461	1.456	0.005	0.163
Sortino ratio	0.101	0.086	0.015	1.843*	0.078	0.080	−0.002	−0.162
MDD (%)	15.106	15.398	−0.292	−0.755	15.262	15.402	−0.140	−0.358
MPPM (%)	−0.032	−0.059	0.027	2.047**	−0.070	−0.067	−0.003	−0.223
Panel B: Entropy Balancing								
Mean (%)	0.095	0.073	0.022	1.891*	0.057	0.063	−0.006	−0.496
Volatility (%)	2.085	2.075	0.010	0.236	2.056	2.097	−0.041	−0.906
Sharpe ratio	0.052	0.043	0.009	1.717*	0.036	0.041	−0.005	−1.097
DR (%)	1.394	1.388	0.006	0.209	1.405	1.415	−0.009	−0.286
Sortino ratio	0.110	0.098	0.012	1.391	0.079	0.092	−0.013	−1.542
MDD (%)	14.386	14.696	−0.310	−0.789	14.833	15.151	−0.318	−0.780
MPPM (%)	−0.014	−0.035	0.021	1.600	−0.051	−0.049	−0.003	−0.187

Table 12: Financial Performance Comparison of Matched and Weighted Firms

Notes. This table reports the propensity score matching (Panel A) and entropy balancing by Hainmueller (2012) (Panel B) results for the period spanning from 2011 and 2022. ROA (%) is the return on assets, calculated as net income (NI) scaled by market value of equity (MKVALT). ROE (%) is the return on equity, calculated as net income (NI) scaled by total assets (AT). NPM (%) is the net profit margin, calculated as net income (NI) over sales (SALE). All these measures are calculated at the end of the fiscal year according to Compustat. $\Delta\text{Ownership}^{\text{INS}}$(%) represents the quarterly change in institutional holdings, sourced from I/B/E/S, comparing quarter q to q - 1, where q is the quarter when the AI day was hosted. *, **, and *** denote the statistically significant differences in means between the treated (Host AI Day) and control (Did Not Host AI Day) firms at the 1%, 5%, and 10% levels, respectively

	Host AI Day	Did Not Host AI Day	Difference	t-statistic
Panel A: Propensity Score Matching				
ROA (%)	5.461	5.285	0.176	0.476
ROE (%)	3.368	2.234	1.134	2.001**
NPM (%)	4.831	3.107	1.723	0.637
$\Delta\text{Ownership}^{\text{INS}}$(%)	0.620	0.165	0.455	1.111
Panel B: Entropy Balancing				
ROA (%)	5.474	5.236	0.238	0.621
ROE (%)	3.213	2.544	0.670	1.269
NPM (%)	4.697	3.401	1.296	0.492
$\Delta\text{Ownership}^{\text{INS}}$(%)	0.624	0.169	0.455	1.104

Table 13: Performance Analysis of Long-Short Portfolio Strategy by Matched Firms

Notes. This table reports the average excess returns and risk-adjusted returns of the matched firm through propensity score matching. The benchmark model is the Carhart (1997) four-factor model, which includes MKT (market minus risk free), SMB (small minus big), HML (high minus low), and UMD (momentum). For each matched firm, we calculated the excess return using daily returns from CRSP and the risk-free rate from Kenneth French's data library. We hold a long-short (Long-Short) portfolio for six months, rebalancing semi-annually. The long leg (Long Leg) is the long position in the firms that host an AI day, and the short leg (Short Leg) is the short position in the matched firms that do not host an AI day. For multiple portfolios at any point in time, we take a simple average of their returns. Newey-West t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. The investment period spanning from 2011 to 2022.

		Carhart (1997) Fama-French four-factor model					
	Mean (%)	Alpha	MKT	SMB	HML	UMD	R^2(%)
Equal weighting, i.e., portfolio weight = $\frac{1}{N}$							
Long-Short	0.005	0.005	0.008	−0.017	−0.015	−0.009	0.08
	(0.539)	(0.513)	(0.597)	(−0.880)	(−1.067)	(−0.637)	
Long Leg	0.082***	0.032***	1.048***	0.502***	0.157***	−0.032**	90.09
	(3.375)	(4.172)	(81.482)	(23.084)	(9.887)	(−2.182)	
Short Leg	0.077***	0.027***	1.041***	0.519***	0.172***	−0.022**	87.45
	(3.109)	(3.013)	(116.844)	(30.001)	(12.655)	(−2.214)	

Table 14: Robustness - Probability of Hosting an Analyst/Investor Day

Notes. This table displays the coefficients of the probit regression estimating the probability of hosting an analyst/investor day during the fiscal year, controlling for the barrier to entry, Lerner Index, and HHI. The dependent variable is a dummy variable indicating whether or not a firm hosted an analyst/investor day. Barrier to entry is defined as costs of sales (COGS) divided by total sales (AT). HHI is 1 minus the Herfindahl-Hirschman index calculated as the square of firms' market shares based on the text-based network industry classification (TNIC-3) by Hoberg et al. (2014) and Hoberg and Phillips (2016). Lerner Index is calculated as the profit over sales (SALE) minus profit over sales scaled by proportion of sales of firm i to total industry sales. Profit is the operating income before depreciation (OIADAP) minus depreciation (DP). Except for the HHI variable, the rest are computed using Compustat. The t-statistics are reported below the coefficients. *, **, and *** denote the statistical significance at 10%, 5%, and 1%, respectively. See Table 1 for more details on the variables construction.

	$\mathbb{1}$ (Analyst/Investor Day)		
	(1)	(2)	(3)
Fluidity		0.011	0.013
		(1.333)	(1.483)
Similarity	-0.006^{**}		
	(-2.139)		
Barrier to Entry	-0.054		
	(-1.346)		
Lerner Index		0.087^{*}	
		(1.714)	
(1 - HHI)			-0.123
			(-1.475)
Observations	5,888	5,883	5,883
Firm Controls	✓	✓	✓
Year × Industry FE	✓	✓	✓

Internet Appendix for

Strategic Competition Timing of Voluntary Disclosure: Evidence from Analyst/Investor Days

Gabriel Cabrera Olga Kolokolova S. Sarah Zhang

SUPPLEMENTARY RESULTS

This Internet Appendix provides additional information supporting the results reported in the paper. Appendix A examines whether our main results remain consistent when considering different institutional holdings. This Internet Appendix also includes 7 tables:

- Table A.1: Probability of Hosting an Analyst/Investor Day Based on Bushee (2001)
- Table A.2: Analyst/Investor Day by Speaker Type, 2011:Q1 - 2022:Q4
- Table A.3: Sentiment by Speaker Type, 2011:Q1 - 2022:Q4
- Table A.4: Readability by Speaker Type, 2011:Q1 - 2022:Q4
- Table A.5: Variable Correlations, 2011 - 2022
- Table A.6: Sentiment Variable Correlations, 2011 - 2022
- Table A.7: Kirk and Markov (2016) Logit Model

Appendix A. Institutional Investors

Bushee and Noe (2000) and Bushee (2001), discern three prominent categories of institutional investors based on their portfolio characteristics of turnover, diversification, and investment horizon, namely transient (TRAs), quasi-indexers (QIXs), and dedicated (DEDs). As argued by Boone and White (2015), distinct institutional types exhibit different preferences when it comes to disclosure. A transient institutional investor is characterized by a highly-diversified portfolio, albeit with a higher frequency of turnover, primarily engaging in short-term trading strategies. Thus, are less likely to influence management disclosure decisions. On the other hand, a quasi-indexer can be defined as an institutional investor that exhibits an elevated level of portfolio diversification, maintains a low rate of portfolio turnover, and implements buy-and-hold strategies that are index-based. Their strategies rely on public disclosure to mitigate information asymmetry, thereby reducing the costs of both monitoring management and trading, as Boone and White (2015) document. Finally, a dedicated institutional investor is associated with a lower portfolio turnover rate, indicative of longer investment horizons akin to quasi-indexers. Moreover, their focused portfolio holdings allow dedicated institutions to engage on private sources of information in contrast to public disclosures (Bushee and Noe, 2000). Consequently, they are also less likely to influence management disclosure decisions. For each type of trader and quarter, we compute quarterly fractional holdings of each stock as:

$$StockHold_{i,t}^{k} = \sum_{s} \frac{StockHold_{i,q}^{k}}{TSO_{i,q}}, \tag{14}$$

where $StockHold_{i,q}^{k}$ is the holding of stock i by all investor $k \in \{\text{TRAs}, \text{QIXs}, \text{DEDs}\}$ at the end of quarter q and $TSO_{i,q}$ is the total number of outstanding shares of firm i at the end of quarter q. In Table A.1, we present the re-estimation of Eq. (1) employing the four quarter as our annual measure of institutional ownership, respectively. The table is divided into three panels, each representing a distinct type of institutional investor. Panel A comprises transient investors, Panel B consists of quasi-indexers, and Panel C focuses on dedicated investors.

Our findings indicate that there is a positive relationship between transient ($Ownership^{TRA}$) and quasi-indexer ($Ownership^{QIX}$) investors and a firm's decision to host an AI day. However, only the latter is significant in the full sample (0.005, t-statistic 1.825) and within the non-overconfident subset (0.007, t-statistic 2.004), consistent with prior literature. In contrast, we observe that the coefficient related to dedicated ($Ownership^{DED}$) investor ownership is significantly negative (-0.008, t-statistic -2.511), suggesting preference for private source of information rather than public disclosure (Bushee and Noe, 2000). All other control variables remain unchanged, including our text-based competition proxies.

Table A.1: Probability of Hosting an Analyst/Investor Day Based on Bushee (2001)

Notes. This table reports the coefficients of the probit regression estimating the probability of hosting an analyst/investor day during the fiscal year following Bushee (2001) investor's ownership classification. The dependent variable is a dummy variable indicating whether or not a firm hosted at least one analyst/investor day during the fiscal year. The t-statistics are reported below the coefficients. *, **, and *** denote the statistical significance at 10%, 5%, and 1%, respectively. See Table 1 in the main text for more details on the variables construction.

	$\mathbb{1}$ (Analyst/Investor Day)		
	(1)	(2)	(1)
Fluidity	0.023**	0.022**	0.022**
	(2.440)	(2.372)	(2.413)
Similarity	−0.009***	−0.009***	−0.009***
	(−2.832)	(−2.896)	(−2.850)
$\text{Ownership}^{\text{INS}}$	−0.231	0.086	0.203
	(−1.029)	(0.617)	(1.425)
$\text{Ownership}^{\text{CEO}}$	0.067	0.067	0.082
	(0.122)	(0.121)	(0.149)
$\text{Ownership}^{\text{QIX}}$	0.440		
	(1.631)		
$\text{Ownership}^{\text{TRA}}$		−0.126	
		(−0.395)	
$\text{Ownership}^{\text{DED}}$			−0.763**
			(−2.152)
Observations	5,888	5,888	5,888
Firm Controls	✓	✓	✓
Year × Industry FE	✓	✓	✓

Appendix B. Additional Tables

Table A.2: Analyst/Investor Day by Speaker Type, 2011:Q1 - 2022:Q4

Notes. This table reports statistics that summarize analyst/investor day participation, words, number and characters in its transcripts.

		Mean						
	N	$\bar{\mathbf{x}}$	%	Std.	IQR	25%	50%	75%
Participants per Call								
Analysts	2,707	7	-	4	6	4	7	10
Attendees	1,800	2	-	2	1	1	1	2
Executives	3,125	8	-	3	4	6	8	10
Operator	465	1	-	0	0	1	1	1
Shareholders	44	1	-	0	0	1	1	1
Unidentified	38	1	-	0	0	1	1	1
Words								
Analysts	2,707	1,316	5%	974	981	737	1,212	1,718
Attendees	1,800	2,136	8%	3,421	2078	236	735	2,314
Executives	3,125	23,210	91%	8,719	11,208	17,242	22,687	28,450
Operator	465	93	1%	95	116	22	63	138
Shareholders	44	231	1%	330	197	66	118	263
Unidentified	38	1,501	5%	1,706	2,075	286	687	2,360
Numbers								
Analysts	2,707	24	5%	20	22	11	20	33
Attendees	1,800	33	8%	60	31	3	11	34
Executives	3,125	411	91%	186	220	288	387	508
Operator	465	1	0%	1	1	0	0	1
Shareholders	44	4	1%	6	4	0	1	4
Unidentified	38	19	4%	25	21	2	9	24
Characters								
Analysts	2,707	1,340	5%	990	1,003	750	1,232	1,753
Attendees	1,800	2,169	8%	3,476	2,101	239	750	2,340
Executives	3,125	23,621	91%	8,856	11,454	17,549	23,097	29,003
Operator	465	93	1%	96	116	22	65	138
Shareholders	44	234	1%	334	206	66	120	272
Unidentified	38	1,520	5%	1,728	2,088	288	696	2,376

Table A.3: Sentiment by Speaker Type, 2011:Q1 - 2022:Q4

Notes. This table reports statistics that summarize the sentiment measures. Tone is defined as (Positive - Negative)/(Positive + Negative) where Positive (Negative) reflects the proportions of Positive (Negative) words in a given transcript as defined by Loughran and McDonald (2011) Master Dictionary.

	N	Mean	Std.	IQR	25%	50%	75%
Tone							
Analysts	2,613	-0.123	0.335	0.405	-0.333	-0.121	0.071
Attendees	1,649	-0.026	0.490	0.637	-0.328	-0.013	0.309
Executives	3,061	0.199	0.197	0.262	0.069	0.208	0.330
Shareholders	36	0.052	0.677	1.070	-0.423	0.088	0.647
Positive							
Analysts	2,613	0.030	0.020	0.017	0.020	0.027	0.036
Attendees	1,649	0.035	0.032	0.023	0.019	0.029	0.043
Executives	3,061	0.038	0.013	0.014	0.029	0.036	0.044
Shareholders	36	0.049	0.070	0.035	0.016	0.024	0.052
Negative							
Analysts	2,613	0.037	0.023	0.018	0.025	0.033	0.043
Attendees	1,649	0.042	0.050	0.029	0.019	0.031	0.048
Executives	3,061	0.037	0.019	0.022	0.024	0.033	0.046
Shareholders	36	0.029	0.029	0.030	0.008	0.025	0.038

Table A.4: Readability by Speaker Type, 2011:Q1 - 2022:Q4

Notes. This table reports statistics that summarize the readability measure. The Gunning's Fog Index is defined by Gunning (1952) as $0.4 \times (ASL + 100 \times (n_{wsy} \geq 3)/n_w)$. Where $n_{wsy} \geq 3$ is the number of words (n_w) with 3-syllables or more. The original Fog Index is based on just a sample of 100 words; hence, we scale it by 100.

	N	Mean	Std.	IQR	25%	50%	75%
Fog Index							
Analysts	2,649	11.470	2.982	2.123	10.055	11.039	12.178
Attendees	1,765	12.554	4.806	3.567	10.294	11.836	13.861
Executives	3,061	10.478	1.515	1.940	9.446	10.384	11.386
Shareholders	43	10.952	3.412	3.147	9.557	11.676	12.704

Table A.5: Variable Correlations, 2011 - 2022

Notes. The table displays Pearson correlation.(1) Analyst/ Investor Day, (2) # AIDAY, (3) Capital Intensity, (4) Book-to-Market, (5) Intangibles, (6) Loss, (7) R&D Intensity, (8) Return, (9) Volatility, (10) Illiq.$\times 10^7$, (11) ln(Size), (12) ln(Age$^{\text{Firm}}$), (13) High Tech., (14) Surprise, (15) ln(Analyst), (16) Leverage, (17) Tobin's Q, (18) Ownership$^{\text{INS}}$, (19) ln(Age$^{\text{CEO}}$), (20) Gender$^{\text{CEO}}$, (21) Tenure, (22) Confidence, (23) ln(# of Options), (24) Ownership$^{\text{CEO}}$, (25) Fluidity, and (26) Similarity. * indicate statistical significance at the 5% level in a two-tailed test. See Table 1 in the main text for more details on the variables construction.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)
(1)																										
(2)	0.980																									
(3)	−0.005	−0.005																								
(4)	0.002	0.002	0.000																							
(5)	0.058*	0.055*	0.007	0.021*																						
(6)	0.040*	0.041*	−0.015	0.025*	0.190*																					
(7)	−0.028*	−0.027*	0.062*	−0.023*	−0.270*	−0.450																				
(8)	−0.018	−0.017	−0.001	0.026*	−0.048*	0.064*	0.091*																			
(9)	−0.076*	−0.078*	0.016	−0.045*	−0.280*	−0.510	0.390	0.140*																		
(10)	−0.028*	−0.028*	0.002	−0.002	−0.011	−0.091*	0.069*	−0.003	0.120*																	
(11)	0.120*	0.120*	0.005	0.006	0.230*	0.410	−0.290*	0.120*	−0.480	−0.160*																
(12)	0.027*	0.027*	−0.024*	−0.001	0.120*	0.310*	−0.330*	−0.042*	−0.310*	−0.068*	0.350*															
(13)	0.025*	0.023*	−0.007	−0.001	0.058*	−0.096*	0.210*	0.005	0.040*	0.009	−0.055*	0.022*														
(14)	0.004	0.004	0.000	0.008	0.008	0.018	−0.025*	−0.018	−0.018	−0.014	0.027*	0.027*	−0.019*													
(15)	0.110*	0.110*	−0.023*	−0.008	0.100*	0.250*	−0.180*	−0.013	−0.330*	−0.140*	0.730	0.160*	−0.062*	0.036*												
(16)	0.028*	0.030*	−0.014	−0.150*	−0.007	−0.020*	−0.077*	−0.054*	0.046*	0.000	0.059*	0.065*	−0.140*	−0.042*	0.053*											
(17)	0.049*	0.052*	0.005	−0.074*	−0.180*	−0.120*	0.360	0.260*	0.091*	−0.016	0.130*	−0.230*	0.130*	−0.089*	0.086*	0.110*										
(18)	0.063*	0.061*	−0.029*	0.039*	0.160*	0.170*	−0.240*	0.029*	−0.200*	−0.190*	0.200*	0.150*	−0.039*	−0.045*	0.230*	−0.004	−0.030*									
(19)	−0.023*	−0.016	0.007	0.000	−0.007	0.055*	−0.120*	−0.031*	−0.083*	−0.064*	0.120*	0.140*	−0.062*	0.017	0.069*	0.013	−0.038*	0.025*								
(20)	0.002	0.006	−0.016	−0.002	0.072*	−0.028*	0.027*	−0.010	−0.029*	0.005	−0.002	0.010	0.027*	0.007	0.015	−0.053*	−0.011	−0.011	0.015							
(21)	−0.030*	−0.025*	0.005	−0.014	−0.036*	0.076*	0.076*	0.016	−0.035*	−0.031*	−0.014	0.010	0.052*	0.015	0.046*	−0.130*	0.082*	0.009	0.330*	0.099*						
(22)	0.044*	0.042*	0.079*	−0.020	−0.033*	0.012	0.220*	0.240*	0.054*	−0.016	0.062*	−0.200*	0.024*	−0.002	0.035*	0.001	0.440	−0.024*	−0.077*	0.012	0.110*					
(23)	0.006	0.009	−0.016	−0.005	0.012	0.007	0.110*	−0.005	−0.088*	−0.010	0.130*	0.043*	0.028*	−0.005	0.170*	0.045*	0.046*	−0.045*	0.019	0.046*	0.200*	0.270*				
(24)	−0.033*	−0.030*	0.081*	−0.003	−0.130*	−0.013	0.120*	0.033*	0.073*	0.035*	−0.180*	−0.210*	0.029*	−0.002	−0.082*	−0.120*	0.079*	−0.150*	0.068*	0.048*	0.380*	0.130*	0.021			
(25)	−0.037*	−0.036*	−0.008	−0.015	−0.200*	−0.340*	0.480	−0.004	0.290*	0.035*	−0.210*	−0.310*	0.130*	−0.005	−0.076*	−0.095*	0.140*	−0.150*	−0.049*	0.014	0.062*	0.069*	0.110*	0.098*		
(26)	−0.026*	−0.027*	−0.004	−0.009	−0.260*	−0.380	0.610	0.033*	0.370*	0.022*	−0.230*	−0.260*	0.060*	0.011	−0.130*	−0.054*	0.190*	−0.110*	−0.018	0.014	0.048*	0.150*	0.110*	0.047*	0.620	

Table A.6: Sentiment Variable Correlations, 2011 - 2022

Notes. The table displays Pearson correlation. (1) CAR(+5,+1), (2) CAR(-1,+1), (3) CAR(0,0), (4) CAR(0,+4), (5) Fog Index, (6) Tone, (7) Tone(Present), (8) Tone(Question), (9) Tone(Answer), (10) Positive, (11) Positive(Present), (12) Positive(Question), (13) Positive(Answer), (14) Negative, (15) Negative(Present), (16) Negative(Question), and (17) Negative(Answer). * indicate statistical significance at the 5% level in a two-tailed test.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1)																	
(2)	0.120*																
(3)	−0.069*	0.700															
(4)	−0.077*	0.720	0.640*														
(5)	−0.025	−0.032	−0.042*	−0.022													
(6)	0.034	0.076*	0.056*	0.078*	0.088*												
(7)	0.040	0.056*	0.041*	0.062*	−0.012	0.570*											
(8)	−0.011	0.037	0.035	0.040	0.031	0.420*	0.130*										
(9)	0.035	0.060*	0.048*	0.068*	0.022	0.720	0.330*	0.170*									
(10)	0.014	0.069*	0.057*	0.072*	−0.150*	0.560*	0.350*	0.250*	0.430*								
(11)	0.010	0.044*	0.030	0.041	−0.110*	0.330*	0.450*	0.082*	0.200*	0.550*							
(12)	−0.004	0.035	0.026	0.055*	−0.130*	0.081*	0.019	0.420*	0.096*	0.200*	0.018						
(13)	0.017	0.037	0.036	0.032	−0.190*	0.290*	0.210*	0.076*	0.470*	0.740	0.230*	0.110*					
(14)	−0.025	−0.059*	−0.043*	−0.061*	−0.140*	−0.620*	−0.320*	−0.200*	−0.500*	−0.200*	−0.120*	−0.002	−0.052*				
(15)	−0.025	−0.042*	−0.021	−0.061*	−0.041*	−0.300*	−0.600*	−0.080*	−0.170*	−0.099*	−0.084*	−0.010	−0.071*	0.380*			
(16)	−0.004	−0.015	0.002	−0.006	−0.050*	−0.300*	−0.120*	−0.460*	−0.091*	−0.150*	−0.055*	0.110*	0.017	0.310*	0.072*		
(17)	−0.020	−0.040	−0.037	−0.057*	−0.190*	−0.450*	−0.170*	−0.130*	−0.530*	−0.110*	−0.044*	0.051*	0.014	0.760	0.160*	0.170*	

Table A.7: Kirk and Markov (2016) Logit Model

Notes. This table displays the coefficients of the logit regression estimating the probability of hosting an analyst/investor day during the fiscal year. The dependent variable is a dummy variable indicating whether or not a firm hosted an analyst/investor day. %STDX is the percentage change in odds of hosting an analyst/investor day for a standard deviation increase in the independent variable (from the mean). The p-values are reported below the coefficients based on robust standard errors clustered by firm. *, **, and *** denote the statistical significance at 10%, 5%, and 1%, respectively. See Table 1 in the main text for more details on the variables construction.

	$\mathbb{1}$ (Analyst/Investor Day)	
	(1)	%STDX
Book-to-Market	−0.038	−3.7
	(0.089)	
Intangibles	0.130	13.9
	(0.092)	
Loss	−0.110	−10.4
	(0.086)	
R&D Intensity	0.147	15.9
	(0.260)	
Return	0.051	5.2
	(0.07)	
Volatility	−0.528*	−41.0
	(0.222)	
ln(Size)	0.092**	9.6
	(0.033)	
Leverage	0.155	16.7
	(0.139)	
ln(Age^{Firm})	−0.115**	−10.9
	(0.036)	
High Tech.	0.151	16.3
	(0.084)	
ln(Analyst)	0.103	10.9
	(0.076)	
$Ownership^{INS}$	0.145	15.6
	(0.177)	
Observations	7,776	
Year FE	✓	