Save The Date: Analyst/Investor Days as a Trading Signal*

Gabriel Cabrera†, Olga Kolokolova‡, and S. Sarah Zhang§

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Abstract

Firms use voluntary disclosure channels, such as Analyst/Investor (A/I) days, for both information disclosure and company promotion. Using transcripts of over 1,000 A/I days between 2011 and 2022, we find a positive abnormal stock market response on the announcement of such events and a further run-up in stock prices between the announcement date and the actual A/I day. Firms that "hype" the A/I day by releasing additional disclosures prior to the event experience a greater pre-event run-up in stock price and a return reversal after the event. Stock prices around "non-hyped" events, on the contrary, react positively to the actual event too, with the event returns driven by the release of both cash-flow and discount-rate related information. A long-short trading strategy that exploits these price patterns between the announcements and the actual A/I days for both hyped and non-hyped events using a deep reinforcement learning algorithm, generates a positive alpha of 0.13% per day.

Keywords: analyst/investor days; buy-and-hold abnormal returns; linguistic complexity; stock hyping; risk information

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†Email: gabriel.cabreraguzman@postgrad.manchester.ac.uk. Address: Alliance Manchester Business School, The University of Manchester, Booth Street West, Manchester, M15 6PB UK.

‡Email: o.kolokolova@lancaster.ac.uk. Address: Lancaster University Management School, Lancaster University, Bailrigg, Lancaster, LA1 4YX UK.

§Email: sarah.zhang@manchester.ac.uk. Corresponding author. Address: Alliance Manchester Business School, The University of Manchester, Booth Street West, Manchester, M15 6PB UK.

1. Introduction

Firms increasingly rely on voluntary disclosure events, such as Analyst/Investor (A/I) days, not only to inform capital market participants and analysts about firms' performace or plans, but also to exert influence on stock market sentiment and valuation. A/I days provide a platform for managers to communicate strategic plans, showcase innovation, and shape investor perception outside of mandatory reporting channels.[1]

Prior research has established A/I days as a voluntary disclosure channel distinct from other channels like conference presentations (Kirk and Markov, 2016). Using a dataset of A/I day transcripts from 2011 to 2022, we extend this research along two different dimensions. First, we examine how additional disclosures prior to the event, such as voluntary 8-K filings, and insider trading shape both the nature and informational value of A/I days. Second, we suggest an implementable trading strategy that exploits stock price dynamics around such events.

In contrast to other disclosure channels, such as conference presentations which are typically hosted by third parties (see Bushee et al., 2011, 2022), A/I days are organised and funded by the firm itself, giving it full control over the timing, content, structure, and guest list. This control enables not only strategic messaging but also opportunistic behaviour, such as releasing additional disclosures in the lead-up to the event and engaging in insider trading ahead of anticipated market reactions, practices often labelled as "hype" (Bushee et al., 2022). We decompose the overall market reaction around A/I days into pre-event and post-event reaction. We find that hype explains over 56% of the variance in pre-event abnormal returns, while post-event returns are more strongly driven by the informativeness of the disclosures and perceived changes in firm risk after the event. Hyped A/I days are associated with signifi-

[1] A prominent example is Tesla's highly-anticipated first A/I day on March 1st, 2023, which triggered a considerable price run-up but was followed by a 7% decline in share price the next day due to disappointment on the day of the event. See https://www.forbes.com/sites/dereksaul/2023/03/02/tesla-stock-tanks-after-disjointed-investor-day-draws-mixed-reviews/

cantly higher pre-event returns and pronounced post-event reversals in contrast to non-hyped events, consistent with short-term stock price inflation and managerial opportunism.

During an A/I day, firms can disclose valuable information that affects the valuation of their future cash flows and forward-looking exposures to various risk factors, affecting their discount rates (Penman and Yehuda, 2019). We capture event informativeness using a latent information component following Bushee et al. (2018b) extracted from the event transcripts and we measure the risk-related information using the change in return variance implied by options maturing after the announcement, as proposed by Smith and So (2022). We find that for non-hyped events, post-event returns exhibit a stronger relationship with these variables that reflect the firm's underlying fundamentals. Notably, more informative disclosures are associated with significantly higher post-event returns.

Building on these insights, we investigate whether the price patterns of A/I days can be exploited using a long-short trading strategy under realistic investment conditions. We find that firms announcing A/I days outperform their otherwise identical peers that do not hold A/I days over a horizon beginning at the announcement and ending one week after the event. Our baseline strategy of going long on hosting firms and short on matched non-hosting firms on the announcement date, and then closing the position one week after the event yields positive daily alphas (relative to the q5 factor model) of approximately 0.095% and Sharpe ratios of around 1.06 annualised, even after accounting for transaction and borrowing costs. The returns are primarily driven by the long leg, suggesting that the decision to host an A/I day serves as a positive trading signal and conveys meaningful informational content. The performance of the baseline strategy is further enhanced by allowing early closures of the positions in hyped events or using the optimal closure time predicted by the deep reinforcement learning. Such early closures, that allow avoiding return reversals of hyped events, increase the daily alpha to 0.13% and the annualised Sharpe ratio to 1.22.

Using a finance-domain-specific textual sentiment measure, we find that the strategy's positive performance is concentrated in events with a positive tone. For A/I days with a negative tone, the long-short alpha becomes statistically insignificant; however, the long leg still delivers modest positive returns. This suggests that even "negative" A/I days may help communicate valuable information, providing valuation benefits relative to silence. Our findings thus indicate that the downside risk of acting on the announcement alone is limited: events with a negative tone do not erase gains from the strategy, while events with a positive tone significantly enhance them. Interestingly, the strategy with optimal early closure also shows stronger performance when the tone of the Q&A session is negative; it seems to be able to correctly identify the events to close early, thereby avoiding exposure to negative disclosures but still profiting from pre-event run-up.

Our study broadly contributes to several strands of literature, related to voluntary disclosure, A/I days, and trading signal extraction for portfolio allocation.

Kirk and Markov (2016) established that A/I days differ meaningfully from conference presentations, and Wu and Yaron (2018) and Park (2024) explored their post-event effects. We shift the focus to pre-event dynamics and informational characteristics of the events. In particular, we demonstrate that the decision to hold an A/I day, and not only the content and tone of the actual disclosure, can serve as a valuable market signal. We document a new form of pre-event drift driven by discretionary firm actions and promotional hyping activities. Post-event returns, on the contrary, are driven by information characteristics of the actual event, related to both cash-flow and risk news.

We further show that a negative tone of the event or a Q&A session does not necessarily erode hosting firm performance, contributing to the discussion on the importance of direct communication for information discovery. A/I days, as voluntary and face-to-face disclosure events, offer a discretionary platform where managers are typically more inclined to share forward-looking insights than in backward-looking settings such as earnings calls. Even when the presentation content is not especially positive, the inclusion of a Q&A session allows analysts and investors to ask direct questions, drawing on verbal cues to evaluate the quality and informativeness of managerial responses (Kimbrough, 2005; Matsumoto et al., 2011; Price et al., 2012; Brockman et al., 2015; Druz et al., 2020). This interactive format limits the possibilities of managers to remain silent or evasive, which reduces information asymmetry and may allow investors to infer both positive and negative news (Hollander et al., 2010). As a result, stock prices may rise independent of the tone during the presentation or Q&A, but mostly due to reduction in information asymmetry and newly disclosed information about the firm's strategy and outlook and changing perceptions of the firm's growth and risk exposure (Bushee et al., 2018b; Bushee and Huang, 2024; Smith and So, 2022).

As for extraction of trading signals, the financial literature has seen a proliferation of return predictive signals, with Cochrane (2011) characterising this phenomenon as a "factor zoo". The field remains divided on the replicability and out-of-sample performance of these factors, with Hou et al. (2018) highlighting a replication crisis, while Jensen et al. (2023), on the contrary, finds that not only most of the factors can be replicated in large international datasets, their predictive power does not erode over time. Professional asset managers typically rely on a subset of approximately 15 factors that capture the strongest market anomalies (Swade et al., 2024). Beyond traditional factor investing, event-driven strategies represent a distinct approach to returns generation, often used by asset managers working with high-net-worth individuals or institutional investors, like hedge funds or family offices. Farrelly and Lhabitant (2017) discuss how event-driven hedge funds exploit information surrounding special corporate events such as mergers and acquisitions, distressed securities trading, and other special situations. While hedge funds in this broad category are very heterogeneous, they attract around a quarter of capital within alternative investments. Such trades usually have an identifiable trigger (e.g., a corporate event), and a specified time frame. Hence, they often provide uncorrelated performance to strategies based on classical factor investing.

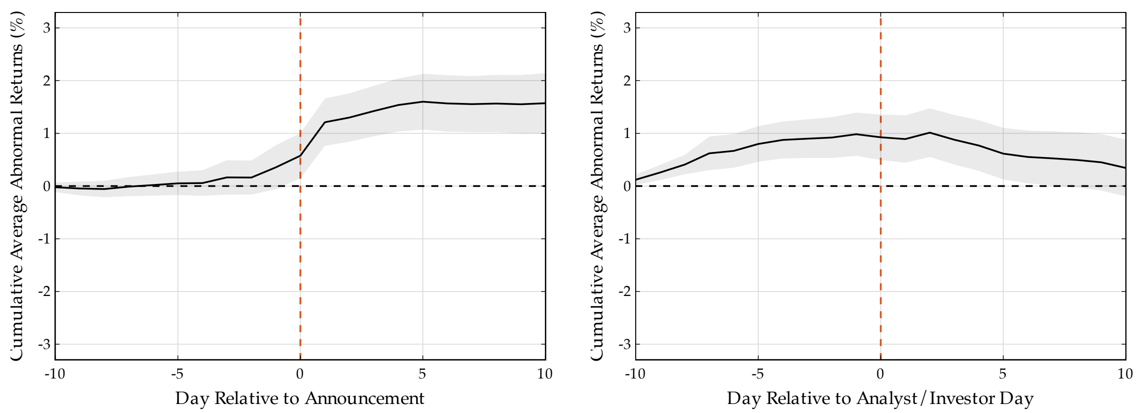
We extend this event-driven paradigm by developing a novel trading signal based on A/I day announcements. We propose three long-short trading strategies: a baseline strategy that solely relies on the announcement of A/I days, a hype-adjusted strategy that closes positions before the actual event if there is evidence of managers proactively hyping stock prices before the event, and a strategy that optimises early closure using a deep reinforcement learning algorithm. Specifically, we implement a Trading Deep Q-Network (TDQN) algorithm (Théate and Ernst, 2021), where position exit decisions are guided by a ruleset derived from a two-year training period's multi-factor analysis. All three strategies deliver positive risk-adjusted returns even after incorporating trading and borrowing costs for the short legs, with the optimal-stopping-time strategy delivering the strongest performance.

Our results provide novel insights into A/I days as a valuable yet under-explored disclosure channel and trading signal, which is of practical relevance for institutional investors and portfolio managers. Our results related to hyped events allow further enhancing the performance of the trading strategies. These results may be of interest to regulators too, who may be concerned with the short-term effects on market prices by strategic voluntary disclosure by companies.

The rest of the paper is organised as follows: Section 2 outlines the empirical methodology. Section 3 describes the data sources and reports the summary statistics. Section 4 discusses the results related to the information content of A/I days, while Section 5 develops and evaluates long-short trading strategies based on A/I day announcements. Section 6 concludes.

2. Methodology

To motivate our analysis, Figure 1 plots cumulative average abnormal returns (CAARs) of hosting firms around the announcement and the A/I day event. We compute cumulative abnormal returns (CARs) using the Carhart (1997) four-factor model. Abnormal returns are estimated over a 100-day window prior to the event announcement, requiring a minimum of 70 valid trading days, and excluding the 10 days immediately preceding the announcement. CARs are aggregated over two windows surrounding the announcement and the event itself, to capture the complete dynamics of investor reaction.



Panel A: Announcement of A/I Day   Panel B: Actual A/I Event Day

Figure 1. Cumulative Average Abnormal Returns Over Time

Note: 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. Panel A uses the complete sample of A/I announcement days in $t = 0$. Panel B uses the complete sample of A/I days in $t = 0$.

The figure in Panel A reveals a pronounced announcement effect, with CAARs rising sharply in the days immediately following the disclosure of an upcoming A/I day. The positive drift continues all the way until the actual event (Panel B), suggesting that the mere act of announcing an A/I day serves as a credible signal to the market, triggering investor anticipation and price appreciation even before any substantive information is released. With respect to the actual event, CAARs show a reversal soon after the event, with the CAARs turning insignificant from about 5 trading days after the event.

2.1 Roadmap of empirical analysis

While the CAAR analysis intuitively illustrates the returns patterns surrounding the announcement and A/I day event, it may be subject to a self-selection bias, as firms voluntarily decide to hold an A/I day at a particular time. To address these potential concerns, we employ propensity score matching (PSM) to define a control group of comparable firms that do not host A/I days. Based on the matched sample, we calculate Buy-and-Hold Abnormal Returns (BHARs) as the difference in compounded returns between firms that host A/I days and their matched non-hosting peers, over different event windows after the announcement of A/I days and around the actual event.

The matching procedure is based on a logit model incorporating lagged firm characteristics as described in Section 2.2 below, ensuring that matched firms are statistically indistinguishable across key covariates. The matching is always performed using only past information. That is, every time a firm announces an A/I day, the logit model is re-estimated using the information on only past A/I days, hence, avoiding forward-looking bias in the estimated coefficients. This approach allows us to isolate the effect of hosting A/I days on market outcomes and later evaluate trading strategies under realistic, out-of-sample conditions.

We decompose BHARs into announcement, pre-event and post-event periods: (1) announcement period: from the announcement date (t_0) to three days after the announcement, $BHAR[t_0, t_0 + 3]$, (2) pre-event period: from the announcement date to the day before the event date $BHAR[t_0, t_1 - 1]$ and to the event itself $BHAR[t_0, t_1]$, (3) post-event period: from the event date (t_1) to one week after the event $BHAR[t_1 + 1 \text{ Week}]$.

To understand the drivers of market responses around the announcement and the actual A/I day, we examine the determinants of pre-event and post-event abnormal returns using a regression framework. We focus on two channels that can affect stock prices around A/I days: managerial opportunism (as captured by hyping activities of the hosting firm prior to the event) and information disclosure. For information disclosure, we distinguish between the event's information precision and changes in the market's perception of the firm's risk. The details are provided in Section 2.3.

Last but not least, we evaluate trading strategy that invests in firms announcing A/I days and shorts their PSM-matched peers, with the details on strategy construction and performance evaluation provided in Section 2.4.

2.2 Propensity score matching

We apply PSM to construct a matched sample of comparable firms that do not hold A/I days, by calculating the propensity score based on the following logit model:

$$\Pr(A/I\ Day_{i,t} = 1) = F(\beta_0 + \Gamma \cdot \mathbf{X}_{i,t-1} + I_t), \tag{1}$$

where F is the logistic distribution function. $A/I\ Day_{i,t}$ is an indicator variable equal to one if firm i hosts at least one A/I day in fiscal year t, and zero otherwise. $\mathbf{X}_{i,t-1}$ is a vector of lagged control variables, and I_t represent industry fixed effects. As control variables, we include factors that are likely to affect firms' decisions to hold A/I days, which capture both internal benefits of disclosure as well as external pressure/demand for disclosure (Chen et al., 2023; Hoberg and Maksimovic, 2022; Kirk and Markov, 2016; Bushee et al., 2018a, 2022). All the variables are defined in Appendix Table A.1.

We conduct a one-to-one matching using the nearest neighbour algorithm without replacement, restricted to the same year and industry, and retain only matches with a score difference smaller than 0.01. We then assess the financial performance of the matched sets of firms. To ensure real-time implementability and to avoid any look-ahead bias, we re-estimate the logit model in Eq. (1) each time an investment decision is made, using an expanding window. This approach yields propensity scores based solely on data available prior to each decision date.

2.3 Determinants of market responses

To understand the determinants of market anticipation and responses around the events, we estimate the following OLS regression model for BHARs at different horizons τ.

$$\begin{aligned} BHAR_i[\tau] = \alpha &+ \beta_1 \mathit{Tone(Presentation)}_i + \beta_2 \mathit{Tone(Q\&A)}_i + \beta_3 \mathit{Info(Both)}_i \\ &+ \beta_4 \mathit{Obfu(Both)}_i + \beta_5 \mathit{Hype}_i + \beta_6 \mathit{Numest}_i + \beta_7 \mathit{RiskInfo}_{30,i} + FE + \varepsilon_i \end{aligned} \tag{2}$$

The explanatory variables capture potential pre-event hype (*Hype*), event-day sentiment (*Tone* from presentation and Q&A), information content and obfuscation (*Info*(*Both*), *Obfu*(*Both*)), changes in market perception of the hosting company's implied risk ($RiskInfo_{30}$), and the number of analysts following (*Numest*) the firm as an additional control. Year and industry fixed effects (denoted FE) are included, and standard errors are clustered at the firm level. In what follows, we explain the rationale and the definitions of the key variables of interest.

Pre-event disclosures and managerial opportunism

Prior to any high-visibility events, managers may "frame the narrative" and provide additional voluntary disclosures intended to positively skew market perceptions in advance of the event. As documented by Bushee et al. (2022), company insiders may even bet on the price run-up and sell shares prior to the event at higher prices.

To capture this mechanism, we define *Hype* as an indicator equal to one if, between the event announcement and the event date, the firm files at least one voluntary 8-K disclosure and insiders engage in net selling prior to the event.[2] If managers engage in stock hyping prior to the event, we expect to observe a positive impact on buy-and-hold abnormal returns before the event and a subsequent return reversal after the event.

Managerial informativeness and linguistic complexity

To account for information content and precision revealed during the event, we apply linguistic measures, such as the tone of speakers and information and obfuscation component based on linguistic complexity during the event. We measure linguistic *Tone* using the proportion of

[2] Voluntary disclosures are identified through EDGAR by extracting the relevant "Item Information" sections (Items 2.02, 7.01, or 8.01), while insider trading activity is determined based on Forms 3, 4, and 5. Net selling is recorded when insider sales ("S" transactions) exceed purchases ("P" transactions) during this window.

"*Positive*" words, the proportion of "*Negative*" words. These measures are computed for each segment k of transcript j, at the level of individual speaker interventions n. Using an updated version of the finance-oriented Loughran and McDonald (2011) Master Dictionary, we compute *Tone* as $Tone_{k,j} = \frac{Positive_{k,j} - Negative_{k,j}}{Positive_{k,j} + Negative_{k,j}}$, where $Positive_{k,j} = \frac{\sum_{n=1}^{N} \frac{\textit{No. of Positive Words}_n}{\textit{Total No. of Words}_n}}{N}$, $Negative_{k,j} = \frac{\sum_{n=1}^{N} \frac{\textit{No. of Negative Words}_n}{\textit{Total No. of Words}_n}}{N}$, N is the total number of speaker interventions within segment k of transcript j, and $Tone_{k,j}$ is bounded between -1 and 1.[3] As sentiment can vary for different speakers and sections of the event, we construct $Positive_{i,t}$, $Negative_{i,t}$, and $Tone_{i,t}$ variables for the *Presentation* part, for asked *Questions* of attendees and *Answers* provided by the hosting firm's managers.

To measure information and obfuscation levels of managerial presentation and responses during Q&A, we adopt the methodology of Bushee et al. (2018b). First, we measure the linguistic complexity for the presentation, managerial responses and analysts' questions during Q&A using the Gunning's Fog index defined by Gunning (1952), and obtain *Fog*(*Presentation*), *Fog*(*Response*), and *Fog*(*Analyst*).[4] Next, we decompose linguistic complexity into two latent components: information ($Info^*$) and obfuscation ($Obfu^*$), and use the linguistic complexity of analyst questions as a "benchmark level of complexity that one would expect in the absence of obfuscation" (p.92 Bushee et al., 2018b).

Representing the linguistic complexity of managers and analysts as:

$$
\begin{aligned}
\textit{Fog(Presentation)} &= \varphi_0 + \varphi_1 \textit{Info}^* + \varphi_2 \textit{Obfu}^* + \epsilon, \\
\textit{Fog(Analyst)} &= \delta_0 + \delta_1 \textit{Info}^* + \nu,
\end{aligned}
\tag{3}
$$

[3]Averaging the proportion of positive and negative words across speaker interventions captures variation among speakers and prevents any single speaker from disproportionately influencing the overall measure due to longer or more frequent contributions.

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

and then estimating the regression $\textit{Fog(Presentation)} = \beta_0 + \beta_1 \textit{Fog(Analyst)} + \eta$, allows recovering the required latent information and obfuscation components.

The fitted values $\textit{Info}(\textit{Presentation}) = \hat{\beta}_0 + \hat{\beta}_1 \textit{Fog(Analyst)}$ capture the information component, while the residuals capture the obfuscation component $\textit{Obfu}(\textit{Presentation})$. We repeat the procedure replacing $\textit{Fog}(\textit{Presentation})$ by $\textit{Fog}(\textit{Response})$ to estimate the two latent components of the managerial responses $\textit{Info}(\textit{Response})$ and $\textit{Obfu}(\textit{Response})$ during Q&A sessions.

Intuitively, the information component of managerial responses reflects the linguistic complexity of responses of managers with favourable private information about future earnings, as they are more likely to engage constructively with analysts and offer detailed responses to complex questions during the Q&A session (Bushee et al., 2018b; Bushee and Huang, 2024). In contrast, managers that anticipate poor performance may resort to obfuscation to delay or soften investors' reactions (Li, 2008; Lee, 2016; Suslava, 2021), thus reflected in the obfuscation component. Informative (obfuscatory) managerial disclosures during the event are therefore more likely to trigger upward (downward) revisions in expected future cash flows, thereby increasing (decreasing) the stock price.

Changes in risk expectations

To capture the role of A/I days' impact on investors' risk expectations of the hosting firm, we construct an option-based risk information measure. According to Smith and So (2022), the measure reflects how much investors' beliefs about a firm's total return variance change in response to information disclosed during the event date, τ_d, over the subsequent t days, in terms of the firm's betas and idiosyncratic risk exposure.[5] The measure for horizon t is calculated as:

[5] As the authors highlight, exposure to market-wide risk should be relatively small compared to the information revealed about firm-level risk, understood as a firm's specific exposures to systematic factors. This assumption is reasonable in our context, given that A/I days primarily focus on firm-specific disclosures.

$$
\begin{aligned}
RiskInfo_t &= t \times \Delta IV_t + \mathbb{E}^{\mathbb{Q}}_{\tau_D^-}[\tilde{J}^2] \\
&= t \times \Delta IV_t + \frac{t_2}{t_2 - t_1}\mathbb{E}^{\mathbb{Q}}_{\tau_D^-}\left[\int_{\tau_D}^{\tau_D+t_1} \tilde{\sigma}^2_{T,s} ds\right] - \frac{t_1}{t_2 - t_1}\mathbb{E}^{\mathbb{Q}}_{\tau_D^-}\left[\int_{\tau_D}^{\tau_D+t_2} \tilde{\sigma}^2_{T,s} ds\right],
\end{aligned} \tag{4}
$$

where the term $t \times \Delta IV_t$ captures the change in at-the-money (ATM) Black-Scholes implied variance per day around the event date, τ_d, and $\mathbb{E}^{\mathbb{Q}}_{\tau_D^-}[\tilde{J}^2]$ represents the risk-neutral expected event-date return variance documented by Patell and Wolfson (1979).[6] This term can be estimated using the difference between the implied variance from a short-term option, IV_{t_1}, and that from a long-term option, IV_{t_2}, prior to the event, following Dubinsky et al. (2019). We apply the measure over a 30-day horizon.

Empirically, to compute this measure for a 30-day horizon following an event-study approach, it is necessary to define a window of d days around the event to prevent information leakage affecting the estimates. Accordingly, we set the window to one day after and two days before the event date, τ_d. Based on this setup, the measure for the 30-day horizon is calculated as:

$$
RiskInfo_{30} = 30 \times [IV_{Event+1,30} - IV_{Event-2,30}] + \frac{IV_{Event-2,30} - IV_{Event-2,60}}{\frac{1}{30} - \frac{1}{60}}, \tag{5}
$$

where the first component reflects the use of 30-day standardised options, and the second component estimates $\mathbb{E}^{\mathbb{Q}}_{\tau_D^-}[\tilde{J}^2]$ by considering the option term structure, converting daily implied variances into variances over the life of the option using $\frac{1}{30} - \frac{1}{60}$. We anticipate that higher levels of risk information will negatively affect BHARs, as greater perceived risk raises the discount rate and lowers stock prices, consistent with a higher required risk premium.

[6] Patell and Wolfson (1979) show that implied variance tends to rise ahead of anticipated information events and revert to normal levels afterward. This pattern reflects the temporary uncertainty surrounding such events, which is priced into options through higher implied volatility. Once the event occurs and uncertainty is resolved, implied variance predictably declines. As a result, relying on raw changes in implied variance can underestimate the informational content of the event, since part of the decline is mechanical. To recover the true risk information, we adjust for this expected drop following Smith and So (2022).

Assessment of economic effects of different factors

To assess the importance of different determinants, we estimate SHAP values (Lundberg and Lee, 2017). SHapley Additive exPlanations (SHAP) is an additive method that quantifies the marginal contribution of each variable to the model's R-squared. It does so by averaging over all possible orderings of predictors, thereby providing a robust measure of each attribute's relative importance in linear regression as in our case.[7]

2.4 Trading strategy and portfolio construction

We now investigate if hosting an A/I day can be used as a valuable trading signal. We propose a long-short trading strategy, taking a long position (Long Leg) in firms that announce an A/I day and a short position (Short Leg) in the matched firms that have not announced an A/I day on the announcement date.

In our baseline specification, we use a fixed investment horizon that starts on the announcement date of an A/I day and extends to one week after the event, capturing potential pre- and post-event drifts in stock prices, labelling it "Baseline" strategy. The one week post-event cut off is motivated by the CAAR reversals after trading day 5 in Figure 1.

We further incorporate insights from hyped and non-hyped events by applying different exit timings for both types of events. In particular, we implement a "Hype-Adjusted" strategy in which the portfolio is held until one day before the event if *Hype* is identified between the announcement and one day prior to the event, with *Hype* being a dummy equal to one if the firm issues a voluntary 8-K (Items 2.02, 7.01, or 8.01) and net insider selling occurs between the announcement and the event, following Bushee et al. (2022); otherwise, the position is held until one week after the event.

Our third strategy enables a more dynamic and adaptive decision-making process for position closures. We adopt a data-driven approach using deep reinforcement learning (DRL) to

[7] For recent applications of SHAP and related interpretability methods in finance, see Pedersen (2022), Bali et al. (2023), and DeMiguel et al. (2023).

determine optimal investment horizons following Hambly et al. (2023). Specifically, we apply the Trading Deep Q-Network (TDQN) algorithm introduced by Théate and Ernst (2021), where the decision to exit or hold a position is guided by a set of rules based on multiple factors from a 2-year training period prior to the event, including historical stock performance, market conditions, and risk-adjusted return expectations described in detail in the Internet Appendix Section B. We label the strategy as "Optimal-Timing", where the position is closed anytime between the announcement day when the TDQN algorithm recommends it and up to one week after the event day if the TDQN algorithm recommends a holding period longer than one week.

Performance evaluation

To compare the performance of the firms that hold and not hold A/I days, we estimate a comprehensive range of performance and risk measures commonly used in portfolio management separately for portfolios of firms that host and firms that do not host. In particular, we calculate mean returns, return volatility (*Std.*), Sharpe ratio (*SR*), downside risk (*DR*), Sortino, Omega, and Upside ratios. We further consider tail-risk measures, including Value-at-Risk (*VaR*) and Expected Shortfall (*ES*) at the 5% level, as well as maximum drawdown (*MDD*), the manipulation-proof performance measure (*MPPM*) from Goetzmann et al. (2007), and average buy-and-hold (*Avg. Buy-and-Hold*). We calculate buy-and-hold abnormal returns (BHAR) as the difference between the compounded return from continuously holding the hosting firm and that of its matched firm over the strategy period. All these measures are computed using daily return observations, starting from the announcement date of an A/I day until the designated strategy exit point (i.e., one week after the event is hosted), for firms hosting the A/I day and their matched peers. Details are provided in Appendix Table A.1.

We further evaluate the performance of the long-short portfolio relative to several factor models. First, we consider the Fama-French 4-factor model (FF4), which includes the market excess return over the risk-free rate (`MKT_RF`), size (`SMB`), value (`HML`), and the Carhart momentum factor (MOM). Second, we use the Fama-French 5-factor model (FF5), which adds profitability (RMW) and investment (CMA) to FF4. Third, we employ the Fama-French 6-factor model (FF6), which extends FF5 by incorporating the momentum factor (MOM). Finally, we consider the q-factor model (q5), which includes the market excess return (MKT_RF), size (SMB), investment (IA), return on equity (ROE), and expected growth (EG), following Hou et al. (2021).

Transaction costs

To account for transaction costs, we adopt the methodologies proposed by Hasbrouck (2009), Barroso and Santa-Clara (2015), Barroso and Detzel (2021) and Kolokolova and Xu (2024). In particular, we assume that transaction costs are proportional to trade size and turnover and include borrowing costs for the short leg. We apply fixed transaction costs of 1 bp, 10 bps, and 14 bps for the turnover-based cost component, and borrowing costs ranging from 0.35% per year (for the largest stocks) to 21.85% (for the smallest stocks) (cf. Kolokolova and Xu, 2024). Further details are outlined in Internet Appendix Section A.

3. Data and Summary Statistics

3.1 Firm and A/I data

Our main data sample consists of U.S. public firms that have held A/I days during the period from the first quarter of 2011 to the fourth quarter of 2022. We collect historical A/I day transcripts from Capital IQ Transcripts database provided by S&P Global Market Intelligence, comprising 3,061 transcripts from A/I days held by 1,242 unique firms. Each transcript includes the manager's presentation and the Q&A portion of the event. After excluding events hosted by multiple firms, we found that nearly 50% of the firms (672) have hosted more than one A/I day in our sample.

Our stock returns data are obtained from the Center for Research in Security Prices (CRSP). To ensure consistency, we include only those stocks that have been listed on U.S. stock exchanges and traded on the NYSE, AMEX, or NASDAQ, over the period spanning January 2010 to December 2022 (including one additional year of data (2010) to compute lagged variables). 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 due to their highly regulated environment.[8]

We merge our sample with companies' yearly financial variables from Compustat and analyst data from I/B/E/S. For the performance analysis, we include various risk factors, such as the market (`MKT_RF`), size (`SMB`), and value (`HML`) factors from Fama and French (1993), the momentum (`MOM`) factor from Carhart (1997), and the profitability (`RMW`) and investment (`CMA`) factors, sourced from Kenneth French's data library. We also include the investment (`IA`) and return on equity (`ROE`) by Hou et al. (2015), and expected growth (`EG`) factors by Hou et al. (2021), obtained from Lu Zhang's global-q data library.[9]

Our data on institutional holdings come from the Thomson Reuters Institutional (13F) Holdings database (CDA/Spectrum s34). The text-based measure used to identify the third stage of the product life cycle is obtained from Hoberg and Maksimovic's Data Library.[10] Finally, we use standardized option data from OptionMetrics to construct the risk information measures.

3.2 Summary statistics

Table 1 reports summary statistics, including tests of mean and median differences, for firms that have hosted at least one A/I day and firms that have never hosted an A/I day during the period of our sample. The statistics are based on firm-level observations.

[8]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). Any adjustments are made to the Daily Stock File, as there are no aggregation issues.

[9]The corresponding websites are `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data library.html` and `http://global-q.org/index.html`.

[10]`http://faculty.marshall.usc.edu/Gerard-Hoberg/HobergMaxLifeCycles/index.html`

In our sample, firms hosting A/I days, on average, have higher financing requirements, lower sales growth, and lower bid-ask spreads, suggesting that these companies tend to show greater transparency in their information disclosure. Additionally, firms holding A/I days are often in the third stage of their product life cycle, indicating that they offer stable and more mature products. All these internal benefits of disclosure are significant at the 1% level.

Furthermore, regarding external pressure/demand for disclosure, firms hosting A/I days significantly differ from those that do not. For instance, hosting firms in our sample generally have higher institutional ownership, a greater number of analysts following them, and more business segments. These firms also tend to be larger, have higher leverage, and exhibit lower book-to-market ratio. Additionally, hosting firms are more likely to operate in high-tech industries and hold more intangible assets. In contrast to the findings of Kirk and Markov (2016), our hosting firms exhibit lower R&D expenditures, which may reflect their position in a later stage of the product life cycle, where R&D spending typically declines. Moreover, they show lower earnings volatility and higher stock returns. All of these covariates are significant at the 1% level.

[Insert Table 1 About Here]

Summary statistics for sentiment are shown in Table 2. The sentiment measures indicate that the overall tone of the event is positive, driven primarily by the manager's presentation, with an average value of 0.352. On average, the participants use similar fractions of positive and negative words, with the fraction of positive words being higher during the manager's presentation. In contrast, during the Q&A session, the fraction of negative words is higher than that of positive words.

The means of $\mathit{Obfu}(\mathit{Presentation})$ and $\mathit{Obfu}(\mathit{Response})$ are zero by construction, as they are regression residuals. Their standard deviations are 1.564 and 1.146, respectively. The mean of $\mathit{Info}(\mathit{Presentation})$ is 11.241, while $\mathit{Info}(\mathit{Response})$ averages 9.627. The higher value in the presentation segment may reflects the planned and structured nature of prepared remarks, while the lower value in the Q&A session may come from from its more spontaneous format and the use of strategic ambiguity in managerial responses.

[Insert Table 2 About Here]

3.3 Logit model: a full sample results

As mentioned in Section 2.1, the logit model used for PSM is re-estimated every time when a new A/I day is announced. In this section, however, for the illustrative purpose, we estimate a single regression as defined in Eq. (1) using the full sample, and include year fixed effects. The purpose of this exercise is to illustrate the general effect of internal benefits and external pressure/demand for disclosure have on the probability of hosting an A/I day. Table A.2 in Appendix reports the estimation results. The %STDX column reports the percentage change in the odds of hosting an A/I day associated with a one standard deviation increase in each independent variable.

The number of A/I days (*No. of A/I Days*) hosted in the previous year is highly significant, indicating persistence in hosting behaviour. This suggests that once firms establish such events as part of their disclosure strategy, they tend to repeat them — possibly as part of institutionalised investor relations practices.

Among the internal drivers, the likelihood of hosting is positively associated with a firm's stage in the product life cycle, as captured by *Life3*. Firms with greater financing needs are also more likely to host such events, as reflected in the strong positive coefficient on *Financing* (0.435, t-statistic = 2.961) and the large negative coefficient on *Bid-Ask Spread* (−1.693, t-statistic = −6.478), consistent with efforts to reduce information asymmetries. The negative association with *Book-to-Market* and the positive coefficient on *Leverage* suggest that growth-oriented and more leveraged firms are more inclined to engage in active investor communication.

In terms of magnitude, *Financing* and *Bid-Ask Spread* exhibit the largest marginal effects among internal factors: a one standard deviation increase in *Financing* raises the odds of hosting by 54.57%, while a similar increase in *Bid-Ask Spread* reduces the odds by 83.28%.

External demand factors also play a key role. Larger and older firms are more likely to host A/I days, as indicated by the positive and significant coefficients on *ln(1+Size)* and *ln(1+Age*^{Firm}*)*. Analyst coverage (*ln(1+No. of Analysts)*) is also positively associated with hosting and is significant at the 10% level. High-tech firms show a significantly higher likelihood of hosting (0.183, t-statistic = 2.729), and the positive, significant coefficient on *Intangibles* (0.185, t-statistic = 2.421) suggests that firms facing greater valuation uncertainty are more proactive in providing forward-looking information, consistent with Kirk and Markov (2016). While institutional ownership (*Ownership*^{INS}) is positively signed, it is not statistically significant.

4. Market responses around A/I days

Panel A of Table 3 reports the average BHARs across four event windows surrounding A/I days. The results show a clear pattern of market anticipation and reaction: BHARs average 1.15% in the three days following the announcement, increase to 3.70% in the pre-event window, and peak at 3.83% when including the event day itself. However, returns drop sharply to just 0.23% in the post-event week. These findings indicate that most of the value is realised before the event, consistent with potential strategic pre-event disclosures and investor expectations. The post-event fade supports the hypothesis that some firms may engage in short-term stock hyping, with limited lasting impact on valuation.

[Insert Table 3 About Here]

Panel B of Table 3 summarises the estimation results for the determinants of BHAR as defined in Eq. (2).[11] We find that pre-event and post-event BHARs are influenced by different factors. For example, the immediate market reaction to the announcement of the event $BHAR[t_0, t_0 + 3]$ is negatively related to the number of analysts following the company. This suggests that for companies heavily followed by analysts, the market perceives any additional promised disclosure as relatively less valuable, leading to a weaker announcement reaction.

Pre-event returns, both excluding and including the event day itself, are heavily influenced by *Hype*. Firms associated with pre-event *Hype* experience significantly higher BHARs during the pre-event windows, with an average increase of approximately 4.5 pp between the announcement date (t_0) and one day before the event ($t_1 - 1$), and 3.9 pp between the announcement date and the event date (t_1). These effects represent an increase of around 1.2 times the average BHAR over these windows. Consistent with managerial opportunism, we find that the effect reverses in the post-event period, and the coefficient on *Hype* for post-event returns is negative, although not statistically significant. This evidence suggests that insiders may have the opportunity to benefit from hype by selling shares ahead of the A/I day, consistent with the opportunistic behaviour of managers documented by Bushee et al. (2022).

Another important finding is that the Q&A portion of the A/I day induces stronger market responses after the event compared to prepared statements and presentations. In particular, there is a positive and statistically significant relationship between the tone during the Q&A session and BHAR from the announcement date (t_0) to the event day (t_1), as a one standard deviation increase in $Tone^{Q\&A}$ is associated with an approximate 1.5 pp increase in BHARs. This effect is primarily driven by the event itself, as it disappears when the event day is excluded. This suggests that the spontaneous disclosures made during the interactive portion of the event are more informative, as managers may reveal insights they would not otherwise disclose in prepared remarks, in line with previous findings on earnings conference calls

[11] Appendix Table A.4 reports the summary statistics of the additional control variables used in the BHARs regression analysis.

(Kimbrough, 2005; Matsumoto et al., 2011; Price et al., 2012; Brockman et al., 2015). The information from the tone of Q&A seems to be almost instantly incorporated into the prices, as no significant effect can be detected for the week-long $BHAR[t_t, t_1 + 1 \text{ Week}]$ after the event.

The post-event returns are driven by the informativeness of the event. *Info*(*Both*), which captures the overall informativeness of the event, is positively related to post-event BHAR, reflecting the gradual processing of cash-flow relevant information by investors following A/I day disclosures. Information related to firms risk, on the contrary, reduces the abnormal returns. A one-unit increase in $RiskInfo_{30}$, is associated with a 0.482 pp decline in post-event BHARs. Intuitively, if the A/I day signals higher firm risk, investors demand higher returns, which lowers the current stock price. While the tone of the event seems to be reflected immediately in the returns on the event date, the factual information (related to both cash flows and risk) seems to require longer processing times, and hence its effect is significant for the weekly BHAR.

To assess the relative importance of different determinants, we calculate the SHAP values of the individual determinants which represent the percentage of the model's explained variance attributable to each explanatory variable. The SHAP values are presented in Table 4. In the pre-event windows, particularly from the announcement date (t_0) to the day before the event (from t_0 to $t_1 - 1$), *Hype* is the most important predictor, explaining on average over 56% of the model's R^2 for BHAR[t_0, $t_1 - 1$] (i.e., over 3.7% of the explained variance for an overall model R^2 of 6.646%) in BHARs. In contrast, during the post-event window (from t_1 to $t_1 + 1$ Week), the relative importance shifts to information-related variables. The influence of *Hype* drops to less than 1%, while variables related to both *Info*(*Both*) and *Obfu*(*Both*), become much more important, explaining over 48% and 14% of the variance, respectively. Risk information also gains relevance post-event, with $RiskInfo_{30}$ accounting for nearly 20%. These results suggest that pre-disclosure activities/hype contribute to market anticipation before the event, while market responses during and after the event are more influenced by the information content during the event and market perceptions.

[Insert Table 4 About Here]

To assess the role of pre-event disclosure (hyping activities), we replicate Table 3 by splitting the sample into A/I days with *Hype* (*Hype* $= 1$) and without (*Hype* $= 0$). The results presented in Table 5 show distinctive differences between hyped and non-hyped events: while for hyped events pre-event returns are mainly driven by hype, for non-hyped events post-event returns are explained by managerial informativeness and risk resolution. Tone of the Q&A sessions impacts returns of non-hyped events only.

In the subsample with hype, we observe on average a large positive BHAR, around 7.66%, before the event, suggesting that hype builds investor expectations early. As a result, there is a clear run-up in prices leading up to the event, followed by an average reversal of -0.03% afterward.

In the case of non-hyped events, post-event returns are stronger and better explained by variables related to informativeness and risk. For example, a one standard deviation increase in $\mathit{RiskInfo}_{30}$ reduces BHAR by 0.548 pp, approximately 1.7 times the average BHAR over that window. At the same time, higher informativeness, captured by *Info(Both)*, is related to higher BHARs of roughly four times the average. Both effects are larger than those observed in the full sample. This suggests that if there is no hype, the market responses correlate more with the actual content of the event.

[Insert Table 5 About Here]

We further consider the importance of information-related and non-information-related determinants for the overall BHARs from announcement up to one week after the event for all A/I days, and separately for hyped and non-hyped events. The results presented in Table 6 confirm that price patterns around hyped events are mostly unrelated to informativeness variables. In contrast, stock returns around non-hyped events are mostly related to both the tone and informativeness during the event. Interestingly, obfuscation is positively related to BHARs of hyped events, which may suggest that managers who engage in hype activities prior to the event also tend to conceal the lack of meaningful content during the event itself.

[Insert Table 6 About Here]

5. Trading strategy and performance

Based on the PSM described in Section 2.2, we identify 1,174 matched pairs of firms, with the differences in propensity scores smaller than 0.01.[12] Table 7 compares the average performance of a trading strategies buying stocks of firms that hold A/I days while going short their PSM-matched peers. We implement three strategies, (1) a baseline strategy that holds the portfolio from the day of the event announcement until one week after the event (Baseline), (2) a strategy that holds the portfolio in the baseline strategy, unless *Hype-Adjusted* is identified between the announcement and one day prior to the event, in which case the positions are closed the day before the event, and (3) a deep learning strategy using the TDQN algorithm (Optimal-Timing) that dynamically determines how long to hold the investment and that defaults to one week after the event if the TDQN algorithm suggests a longer holding period.[13]

[Insert Table 7 About Here]

[12] Table IA.1 in Appendix reports that the treated firms (those that hosted A/I days) and the control firms (those that did not host A/I days) are indistinguishable in terms of all the characteristics used for matching. While, Figure IA.3 in Appendix, further illustrates that in the absence of matching through PSM, the firms that hosted an A/I day are different from the full sample of firms on a number of observable dimensions, including factors related to internal benefits as well as external demand for disclosure. After matching, the matched and control samples are statistically indistinguishable from one another across all these dimensions.

[13] Our baseline portfolio is constructed by holding a position that begins with the announcement and closes one week after the event takes place. In this case, our first matched firm is Advanced Micro Devices, Inc., which hosted its A/I day on February 2, 2012, with the announcement made on September 20, 2011. Therefore, September 20, 2011, serves as our starting date.

In our baseline strategy, hosting firms earn a significantly higher mean excess return (0.127%) compared to matched non-hosting firms (0.032%), with a long-short difference of 0.095%, statistically significant at the 1% level. The Sharpe Ratio increases from 0.019 for non-hosts to 0.076 for hosts, with a long-short difference of 0.067, also significant at the 1% level. The higher Sortino Ratio (0.111 vs. 0.027) further indicates that hosting firms achieve superior returns with less downside volatility. This is supported by the higher Upside Ratio (0.527 vs. 0.449), which reflects greater gains per unit of downside risk.

Hosting firms exhibit slightly less negative tail-risk measures – Value-at-Risk (VaR) and Expected Shortfall (ES) – compared to non-hosting firms, indicating lower exposure to extreme losses and a more favourable risk profile. They also display a significantly higher Manipulation-Proof Performance Measure ($MPPM$), reflecting stronger performance after adjusting for investor risk aversion. Furthermore, hosting firms generate higher average buy-and-hold returns, suggesting a positive market response to the information disclosed during A/I day events.

Compared to the benchmark, the Hype-Adjusted strategy delivers higher mean returns for hosting firms (0.133%) and a larger long-short spread (0.109%), whilst the risk profile in terms of standard deviation, downside risk, VaR and ES remain similar.

The Optimal-Timing strategy delivers the strongest overall performance. It achieves both the highest mean return for hosting firms and the largest long-short spread (0.133%), with both estimates statistically significant at the 1% level and primarily driven by the long leg. This strategy also outperforms on risk-adjusted measures, exhibiting the highest Sharpe, Sortino, and Omega ratios. The TDQN algorithm closes approximately 62% of positions before the A/I day, as shown in Figure 2. Hence, it seems to be able to avoid more price reversals after the event, or even shortly before it.

[Insert Figure 2 About Here]

We further implement an extended strategy $Hype(Flipped)$ that reverts the position one day prior to the event (i.e., goes long the short leg, and vice versa) and holds this "flipped" position up to 1 week after the event in the cases when Hype is detected before the event. The results are reported in the Internet Appendix IA.2. While it improvs performance relative to the Hype-Adjusted strategy, it still underperforms the Optimal-Timing strategy.

Table 8 further reports the performance of the trading strategies relative to four daily benchmark factor models: FF4, FF5, FF6, and q5. All the strategies deliver positive alphas significant at the 1% level relative to all four models. Similar to the previously discussed results, the Hype-Adjusted strategy performs slightly better than the baseline strategy, with the Optimal-Timing performing best of all three strategies, delivering an alpha of 0.125% per day. Remarkably, since the long and short legs of the portfolio have similar exposures to the market factors, the resulting long-short strategy is close to being market-neutral. It delivers pure alpha while not being strongly correlated with the factors in each specification. This is also supported by the low R-squared values across all factor models.

[Insert Table 8 About Here]

To account for trading costs of implementing the trading strategy, we report abnormal returns (alphas) relative to the daily benchmark models, adjusted for proportional trading costs of 1, 10, and 14 bps, as well as borrowing costs, across the three trading strategies. The results are reported in Appendix Table A.3. Panel A shows that after accounting for proportional transaction costs, all strategies continue to deliver statistically significant alphas. For the Baseline strategy, alpha declines slightly from 0.089% to 0.087% (FF4) as trading costs increase from 1 bp to 14 bps, with similar pattern across the benchmark models. The Optimal-Timing strategy consistently delivers the highest alphas, from 0.129% to 0.126%, in line with previous findings. Panel B includes both trading and borrowing costs. The Baseline strategy remains strong, with alpha falling to 0.078% at 14 bps. As before, the Optimal-Timing strategy performs best, with alphas between 0.125% and 0.117% across the daily benchmark models.

We now check if the good performance of these trading strategies is driven by a particular segment of our data. Table 9 reports abnormal returns (alphas) relative to daily benchmark models for different subsamples of the events. We segmented the full sample by whether $Tone^{Overall}$ or $Tone^{Q\&A}$ are positive or negative, whether the hosting firm is a high-tech company, or whether the events were hyped or not. Events with positive (negative) $Tone^{Overall}$ are defined as those with tone values in the top (bottom) quintile of the distribution. The same classification is applied to $Tone^{Q\&A}$.

[Insert Table 9 About Here]

The strong performance of the long-short strategies appears to be concentrated among the events with a positive overall tone, with the alphas of all three strategies relative to all models considered being positive and statistically significant. This reinforces the notion that positive tone during events is also reflected in prices around the event (Brockman et al., 2015; Druz et al., 2020). Importantly, portfolios based on A/I days with negative tone do not exhibit negative alphas. They remain positive, though not statistically significant. This result indicates that investors in the proposed long-short strategies do not lose even for events that are dominated by a negative tone. This observation is likely to be particularly important for practical implementation, since one cannot condition on the event tone in real life, when the investment decision is made on the announcement day.

Interestingly, although the long-short alpha associated with positive Q&A tone is higher than that of the negative tone in the baseline strategy, it is not statistically significant. In contrast, under the Optimal-Timing strategy, the negative Q&A tone subsample surprisingly yields higher and statistically significant alphas compared to the positive tone subsample. This result may be driven by the fact that the Optimal-Timing strategy effectively avoids negative-tone events. For example, among the 245 negative-tone cases, 58% of positions were closed before the event took place, based on the TDQN algorithm.

In terms of industry classification, outperformance is predominantly concentrated in high-tech firms. Across all strategies and models, these firms exhibit consistently higher and more significant alphas, for instance, 0.263% (FF4, Optimal-Timing) versus 0.121% for non-high-tech firms. This pattern may reflect greater investor responsiveness to A/I day disclosures in high-tech sectors, where such events are more likely to provide forward-looking insights. Given their reliance on intangible assets and R&D, high-tech firms may exhibit higher valuation uncertainty. As a result, investors may place greater emphasis on qualitative disclosures to evaluate future earnings prospects and strategic investments.

6. Conclusion

This paper examines Analyst/Investor (A/I) days as strategic voluntary disclosure events and demonstrates their value as an exploitable trading signal. Using transcripts of over 1,000 A/I days between 2011 and 2022, it documents economically significant market reactions and develop trading strategies that generate positive risk-adjusted returns.

Our analysis reveals distinct price dynamics around A/I days. Firms announcing such events experience average buy-and-hold abnormal returns of 1.15% within three days of the announcement and 3.70% in the pre-event period, indicating that the mere decision to host an A/I day conveys meaningful information to the market. We decompose these returns by distinguishing between "hyped" and "non-hyped" events. Hyped events – characterised by voluntary 8-K filings and net insider selling prior to the event – exhibit substantially higher pre-event returns (averaging 7.56%) followed by post-event reversals, consistent with short-term stock price inflation and managerial opportunism. Hype explains over 56% of the variance in pre-event abnormal returns. In contrast, non-hyped events generate positive post-event returns that are significantly associated with the informativeness of disclosures and changes in market perceptions of firm risk. Notably, the tone of the Q&A portion of the event drives stronger market responses than prepared presentations, suggesting that spontaneous disclosures are more informative to investors.

A long-short trading strategy that goes long on hosting firms and short on propensity-score-matched non-hosting firms yields annualised Sharpe ratios of 1.06 and daily alphas of approximately 0.089% relative to the q5 factor model before transaction costs, and 0.079% after accounting for transaction and borrowing costs. Performance is primarily driven by the long leg, reinforcing the interpretation that hosting an A/I day conveys positive information. Incorporating insights about hyped events or using deep reinforcement learning to optimise exit timing further enhances performance, with daily alphas reaching 0.13% and annualised Sharpe ratios of 1.22. Importantly, events with negative tone do not generate negative alphas; the strategy remains profitable regardless of disclosure tone, though returns are concentrated in events with positive tone and in high-tech firms where valuation uncertainty is greater.

We contribute to several strands of literature. First, we extend prior work on A/I days (Kirk and Markov, 2016; Wu and Yaron, 2018; Park, 2024) by shifting focus to pre-event dynamics and demonstrating that the decision to hold an A/I day–not merely its content–serves as a valuable market signal. Second, we document a new form of pre-event drift driven by discretionary firm actions and promotional hyping activities, contributing to the voluntary disclosure literature (Bushee et al., 2022). Third, we show that post-event returns are explained by both cash-flow news (captured by our informativeness measure) and discount-rate news (captured by option-implied risk information), consistent with the framework of Penman and Yehuda (2019). Fourth, we contribute to the event-driven investing literature by developing a novel trading signal based on A/I day announcements and demonstrating its profitability under realistic investment conditions.

Our findings have implications for multiple stakeholders. For institutional investors and portfolio managers, A/I days represent an interpretable market signal that can be incorporated into event-driven strategies. Monitoring pre-event disclosures and insider trading activity allows investors to distinguish between hyped and non-hyped events and adjust position timing accordingly. For analysts, our results underscore the importance of the Q&A session as a venue for information discovery, even when overall tone is negative. For regulators concerned with market integrity, our evidence of pre-event hyping behaviour and its association with insider selling warrants attention, as it suggests that some firms may strategically use voluntary disclosure to facilitate short-term stock price inflation.

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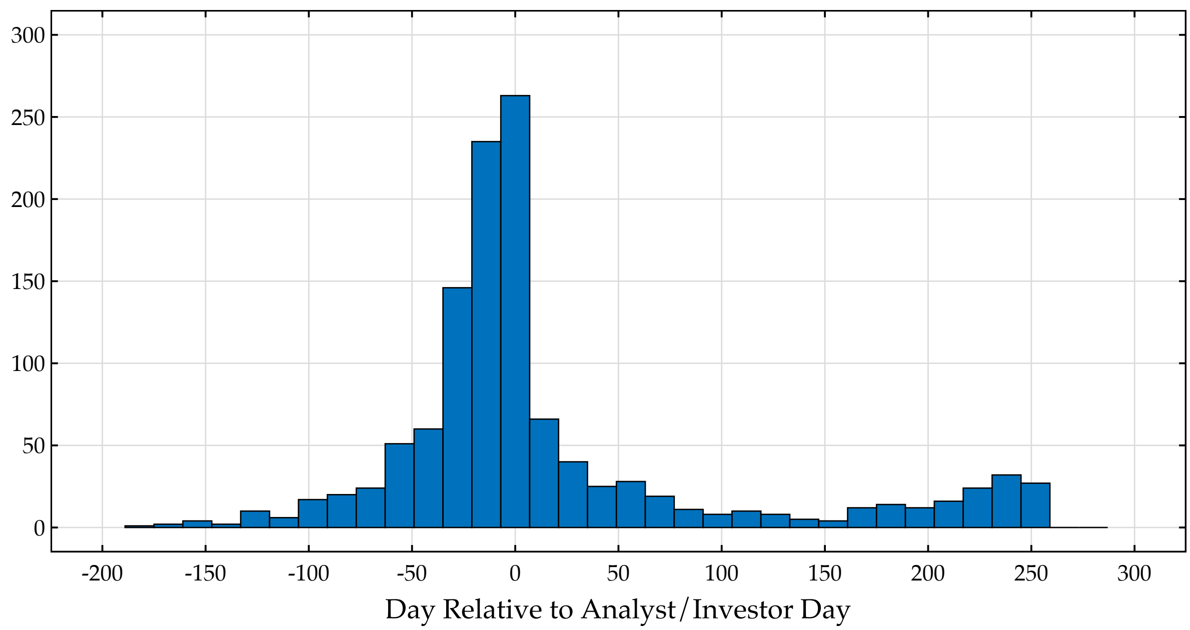


Figure 2. Optimal Stopping Distribution by the TDQN Algorithm

Note: This figure displays the distribution of the optimal stopping times for the Trading Deep Q-Network (TDQN) algorithm by Théate and Ernst (2021), segmented into 14-day intervals relative to the analyst/investor (A/I) day.

Table 1. Summary Statistics for Firms Hosting Analyst/Investor Days

Note: This table displays firm-level summary statistics for firms that hosted at least one analyst/investor day (Host A/I Day) and firms that have never hosted an analyst/investor day (Did Not Host A/I Day) from 2011 through 2022. For each firm, we calculate the summary statistics based on the average values for each variable per firm. N represents unique firms in each group. ***, **, * indicate statistical significance of the 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 A.1.

	Host A/I Day							Did Not Host A/I Day							Difference Tests			
	N	Mean	Std.	IQR	25%	50%	75%	N	Mean	Std.	IQR	25%	50%	75%	Mean	Sign.	Median	Sign.
Analyst/Investor Day																		
No. of A/I Days	1,052	0.209	0.149	0.195	0.091	0.167	0.286	5,381	0.000	0.000	0.000	0.000	0.000	0.000	0.209	***	0.167	***
Internal Benefits for Disclosure																		
Financing	1,046	0.952	0.121	0.000	1.000	1.000	1.000	4,784	0.889	0.233	0.091	0.909	1.000	1.000	0.063	***	0.000	***
Sales Growth	1,034	0.279	0.845	0.173	0.045	0.099	0.218	4,276	0.435	1.477	0.278	0.026	0.114	0.304	−0.157	***	−0.005	
Bid-Ask Spread	1,052	0.197	0.304	0.155	0.040	0.080	0.195	5,380	1.025	1.193	1.383	0.157	0.529	1.540	−0.829	***	−0.377	***
Life3	1,038	0.270	0.089	0.121	0.210	0.269	0.331	4,350	0.258	0.104	0.147	0.180	0.252	0.327	0.012	***	0.015	***
External Pressure/Demand for Disclosure																		
ln(1+Size)	1,051	7.801	1.708	2.291	6.656	7.747	8.948	4,810	5.568	1.913	2.782	4.110	5.524	6.891	2.234	***	2.278	***
ln(1+No. of Analysts)	1,052	0.727	0.807	1.454	0.000	0.327	1.454	5,381	0.487	0.599	0.947	0.000	0.118	0.947	0.240	***	0.000	***
$\text{Ownership}^{\text{INS}}$	1,052	0.647	0.215	0.295	0.523	0.695	0.818	5,381	0.370	0.268	0.472	0.117	0.360	0.590	0.277	***	0.293	***
$\ln(1+\text{Age}^{\text{Firm}})$	1,049	2.585	1.027	1.725	1.642	2.733	3.367	4,803	1.953	1.057	1.910	1.020	1.696	2.931	0.632	***	0.625	***
High Tech.	1,052	0.265	0.441	1.000	0.000	0.000	1.000	5,381	0.196	0.397	0.000	0.000	0.000	0.000	0.069	***	0.000	***
Segments	1,052	5.367	4.020	5.857	2.500	2.786	8.357	5,381	3.075	2.807	1.744	1.333	2.167	3.077	2.291	***	1.396	***
Intangibles	1,048	0.409	0.352	0.559	0.089	0.339	0.648	4,799	0.259	0.333	0.417	0.000	0.102	0.417	0.150	***	0.132	***
R&D Intensity	1,052	0.090	0.120	0.098	0.014	0.042	0.112	5,381	0.136	0.169	0.150	0.028	0.076	0.178	−0.047	***	−0.026	***
Book-to-Market	1,041	0.492	1.049	0.400	0.215	0.374	0.615	4,623	0.696	1.026	0.583	0.284	0.534	0.867	−0.204	***	−0.139	***
Return	1,052	0.144	0.229	0.130	0.093	0.163	0.223	5,381	0.041	0.711	0.389	−0.098	0.135	0.291	0.103	***	0.032	***
Volatility	1,052	0.492	0.231	0.274	0.323	0.431	0.597	5,378	0.694	0.420	0.517	0.397	0.605	0.914	−0.202	***	−0.148	***
Loss	1,051	0.364	0.376	0.714	0.000	0.214	0.714	4,802	0.572	0.416	0.900	0.100	0.667	1.000	−0.208	***	−0.167	***
Leverage	1,025	0.551	0.239	0.298	0.385	0.538	0.683	4,719	0.514	0.376	0.414	0.266	0.459	0.680	0.036	***	0.069	***

Table 2. Summary Statistics for Sentiment and Linguistic Complexity

Note: This table presents summary statistics for analyst/investor (A/I) day sentiment, linguistic complexity, and latent components of linguistic complexity, excluding utility firms (those with Standard Industrial Classification (SIC) codes from 4900 to 4999) and financial firms (SIC codes from 6000 to 6999). Sentiment is measured by *Tone*, defined as (*Positive* - *Negative*) / (*Positive* + *Negative*), where *Positive* and *Negative* represent the proportions of *Positive* and *Negative* words in a given transcript, as defined by the Loughran and McDonald (2011) Master Dictionary. *Presentation* refers to the manager's presentation, while *Q&A* refers to the question-and-answer section of the event. *Fog(.)* is the Fog index of the respective portion of the event, where *Fog(Response)* is the Fog index of managers' responses to questions, and *Fog(Analyst)*, the Fog index of analysts' questions and statements during the Q&A portion of the call. *Obfu(.)* is the latent obfuscation component during the respective section of the event and *Info(.)* is the latent information component during the respective section of the event.

	N	Mean	Std.	IQR	25%	50%	75%
Sentiment							
Tone	2,525	0.026	0.278	0.377	−0.165	0.028	0.212
Tone(Presentation)	2,525	0.352	0.318	0.401	0.178	0.416	0.579
Tone(Q&A)	2,525	−0.059	0.274	0.357	−0.244	−0.047	0.114
Positive	2,525	0.020	0.008	0.008	0.015	0.018	0.022
Positive(Presentation)	2,525	0.021	0.013	0.009	0.015	0.019	0.024
Positive(Q&A)	2,525	0.018	0.009	0.008	0.013	0.017	0.021
Negative	2,525	0.019	0.010	0.010	0.013	0.017	0.023
Negative(Presentation)	2,525	0.010	0.009	0.006	0.006	0.008	0.012
Negative(Q&A)	2,525	0.021	0.012	0.011	0.014	0.020	0.026
Linguistic Complexity							
Fog	2,525	12.498	1.344	1.856	11.532	12.397	13.389
Fog(Presentation)	2,525	13.199	1.769	2.416	11.941	12.996	14.357
Fog(Q&A)	2,525	10.820	2.207	1.367	10.363	11.055	11.729
Fog(Response)	2,525	9.151	4.122	1.778	9.351	10.338	11.129
Fog(Analyst)	2,525	10.898	2.309	1.578	10.330	11.150	11.908
Latent Components of Linguistic Complexity							
Obfu(Presentation)	2,525	0.000	1.564	1.857	−1.025	0.000	0.833
Info(Presentation)	2,525	11.241	4.610	0.172	12.999	13.095	13.171
Obfu(Response)	2,525	0.000	1.146	1.254	−0.685	0.000	0.569
Info(Response)	2,525	9.627	3.954	0.261	11.047	11.193	11.309

Table 3. Analyst/Investor Days BHARs

Note: This table reports average buy-and-hold abnormal returns (BHARs) in Panel A and OLS regressions in Panel B across four event windows: the announcement period $[t_0,\ t_0 + 3\ \text{Days}]$, the pre-event period $[t_0,\ t_1 - 1]$, including the event period $[t_0,\ t_1]$, and the post-event period $[t_1,\ t_1 + 1\ \text{Week}]$. BHARs are calculated as the difference in buy-and-hold returns between the hosting firm and its matched peer over the corresponding period. $RiskInfo_{30}$ measures implied risk over a 30-day horizon, following Smith and So (2022). *Hype* is a dummy equal to one if the firm issues a voluntary 8-K (Items 2.02, 7.01, or 8.01) and if net insider selling occurs between the announcement and the event, following Bushee et al. (2022). *Tone(Presentation)* and *Tone(Q&A)* measure sentiment in the manager's presentation and Q&A session, respectively. *Info(Both)* (*Obfu(Both)*) represents the first principal component of the latent information (obfuscation) dimension, following Bushee et al. (2018b). *Numest* is the number of analysts who issued any forecast between the announcement date and the event date. All regressions include year and industry fixed effects. Standard errors are clustered at the firm level. The t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Variable:	BHAR$[t_0,\ t_0 + 3\ \text{Days}]$	BHAR$[t_0,\ t_1 - 1]$	BHAR$[t_0,\ t_1]$	BHAR$[t_1,\ t_1 + 1\ \text{Week}]$
	(1)	(2)	(3)	(4)
Panel A: Average BHAR				
Avg. BHAR (%)	1.146	3.703	3.826	0.233
Panel B: BHAR Determinants				
Tone(Presentation)	−0.173	−0.422	−0.611	0.222
	(−0.567)	(−0.798)	(−1.101)	(0.575)
Tone(Q&A)	0.255	0.831	1.433**	0.375
	(0.867)	(1.498)	(2.339)	(1.070)
Info(Both)	0.488*	0.776	0.612	0.867**
	(1.681)	(1.420)	(0.956)	(2.515)
Obfu(Both)	0.233	1.105	1.344	0.439
	(0.945)	(1.412)	(1.511)	(1.486)
Hype	1.133	4.492***	3.901**	−0.149
	(1.600)	(3.053)	(2.468)	(−0.201)
Numest	−0.479**	0.822	1.086	−0.265
	(−2.142)	(0.845)	(0.991)	(−0.944)
$RiskInfo_{30}$	0.074	−0.311	−0.306	−0.483**
	(0.254)	(−1.143)	(−1.197)	(−2.147)
Observations	935	935	935	935
Industry FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2 (%)	3.758	6.646	6.333	2.985

Table 4. Characteristic Importance on BHARs

This table reports the relative importance of key explanatory variables in predicting buy-and-hold abnormal returns (BHARs) during the announcement period $[t_0,\, t_0 + 3$ Days$]$, the pre-event period $[t_0,\, t_1 - 1]$, including the event period $[t_0,\, t_1]$, and the post-event period $[t_1,\, t_1 + 1$ Week$]$. Variable importance is computed using the Shapley value decomposition approach. This method quantifies the marginal contribution of each variable to the model's R-squared, averaging over all possible predictor orderings. All values are expressed as percentages of explained variance. Higher values indicate greater explanatory importance in the regression model.

Dep. Variable:	BHAR$[t_0,\, t_0 + 3$ Days$]$	BHAR$[t_0,\, t_1 - 1]$	BHAR$[t_0,\, t_1]$	BHAR$[t_1,\, t_1 + 1$ Week$]$
	(1)	(2)	(3)	(4)
Tone(Presentation)	3.66	1.62	2.68	4.83
Tone(Q&A)	10.11	9.31	22.68	8.57
Info(Both)	30.45	5.84	2.59	48.07
Obfu(Both)	1.65	4.59	6.17	14.41
Hype	27.72	56.64	41.74	0.85
Numest	25.16	20.86	23.33	3.96
RiskInfo_{30}	1.24	1.14	0.80	19.30

Table 5. Analyst/Investor Days BHARs: Subsamples by Hype

Note: This table reports average buy-and-hold abnormal returns (BHARs) in Panel A and OLS regressions in Panel B across four event windows: (1) from the announcement date (t_0) to three days after the announcement (t_0 + 3 Days), (2) from the announcement date (t_0) to the day before the event date ($t_1 - 1$), (3) from the announcement date (t_0) to the event date (t_1), and (4) from the event date (t_1) to one week after the event (t_1 + 1 Week), by subsamples based on *Hype*. BHARs are calculated as the difference in buy-and-hold returns between the hosting firm and its matched peer over the corresponding period. The first column includes A/I days with *Hype* (*Hype* = 1), while the second column focuses on cases with no *Hype* over the same window (*Hype* = 0). *RiskInfo*$_{30}$ measures implied risk over a 30-day horizon, following Smith and So (2022). *Hype* is a dummy equal to one if the firm issues a voluntary 8-K (Items 2.02, 7.01, or 8.01) and if net insider selling occurs between the announcement and the event, following Bushee et al. (2022). *Tone(Presentation)* and *Tone(Q&A)* measure sentiment in the manager's presentation and Q&A session, respectively. Both are computed as (*Positive* - *Negative*) / (*Positive* + *Negative*) using the Loughran-McDonald dictionary. *Info(Both)* (*Obfu(Both)*) represents the first principal component of the latent information (obfuscation) dimension, following Bushee et al. (2018b). *Numest* is the number of analysts who issued any forecast between the announcement date and the event date. All regressions include year and industry fixed effects. Standard errors are clustered at the firm level. The t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Hype = 1				Hype = 0			
	BHAR[t_0, t_0+3 Days]	BHAR[t_0, t_1-1]	BHAR[t_0, t_1]	BHAR[t_1, t_1+1 Week]	BHAR[t_0, t_0+3 Days]	BHAR[t_0, t_1-1]	BHAR[t_0, t_1]	BHAR[t_1, t_1+1 Week]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Average BHAR								
Avg. BHAR (%)	1.686	7.559	7.556	-0.027	0.976	2.489	2.651	0.315
Panel B: BHAR Determinants								
Tone(Presentation)	0.366	0.651	0.490	0.019	−0.315	−0.678	−0.890	0.346
	(0.643)	(0.461)	(0.331)	(0.036)	(−0.895)	(−1.201)	(−1.455)	(0.697)
Tone(Q&A)	−0.345	0.309	0.857	0.341	0.457	1.095*	1.680**	0.331
	(−0.565)	(0.221)	(0.605)	(0.526)	(1.380)	(1.818)	(2.449)	(0.806)
Info(Both)	0.367	0.832	0.425	−0.487	0.560	0.711	0.576	1.297***
	(0.703)	(0.685)	(0.341)	(−0.781)	(1.618)	(1.156)	(0.770)	(3.265)
Obfu(Both)	0.155	4.820	5.611	0.581	0.240	0.126	0.235	0.411
	(0.255)	(1.567)	(1.584)	(0.839)	(0.868)	(0.270)	(0.489)	(1.221)
Numest	−0.670**	1.174	1.676	−0.183	−0.376	−0.480	−0.468	−0.294
	(−1.985)	(0.851)	(1.085)	(−0.499)	(−1.118)	(−0.398)	(−0.345)	(−0.645)
RiskInfo$_{30}$	0.136	−0.628*	−0.348	−0.351	−0.034	−0.088	−0.203	−0.548**
	(0.701)	(−1.795)	(−0.939)	(−1.198)	(−0.089)	(−0.281)	(−0.649)	(−2.077)
Observations	223	223	223	223	711	711	711	711
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2 (%)	7.382	12.904	14.504	5.862	4.786	6.210	5.461	3.829

Table 6. Analyst/Investor Days BHARs: Window [t_0, t_1 + 1 Week]

Note: This table reports average buy-and-hold abnormal returns (BHARs) in Panel A and OLS regressions in Panel B over the windows from the announcement date (t_0) to one week after the event (t_1 + 1 Week). Results are presented for the full sample, hyped events (*Hype* = 1), and non-hyped events (*Hype* = 0). BHARs are calculated as the difference in buy-and-hold returns between the hosting firm and its matched peer over the corresponding period. $RiskInfo_{30}$ measures implied risk over a 30-day horizon, following Smith and So (2022). *Hype* is a dummy equal to one if the firm issues a voluntary 8-K (Items 2.02, 7.01, or 8.01) and if net insider selling occurs between the announcement and the event, following Bushee et al. (2022). *Tone(Presentation)* and *Tone(Q&A)* measure sentiment in the manager's presentation and Q&A session, respectively. Both are computed as (*Positive* - *Negative*) / (*Positive* + *Negative*) using the Loughran-McDonald dictionary. *Info(Both)* (*Obfu(Both)*) represents the first principal component of the latent information (obfuscation) dimension, following Bushee et al. (2018b). *Numest* is the number of analysts who issued any forecast between the announcement date and the event date. All regressions include year and industry fixed effects. Standard errors are clustered at the firm level. The t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Full Sample	Hype = 1	Hype = 0
	(1)	(2)	(3)
Panel A: Average BHAR			
Avg. BHAR (%)	3.952	7.589	2.806
Panel B: BHAR Determinants			
Tone(Presentation)	−0.231	0.488	−0.317
	(−0.364)	(0.339)	(−0.442)
Tone(Q&A)	1.182*	0.626	1.399**
	(1.863)	(0.413)	(1.990)
Info(Both)	1.677**	0.279	2.092***
	(2.573)	(0.200)	(2.786)
Obfu(Both)	1.546**	5.154*	0.600
	(2.101)	(1.926)	(1.064)
Hype	4.415**		
	(2.553)		
Numest	0.567	0.958	−0.749
	(0.595)	(0.754)	(−0.558)
$RiskInfo_{30}$	−0.827***	−1.009**	−0.696**
	(−3.234)	(−2.336)	(−2.093)
Observations	935	223	711
Industry FE	✓	✓	✓
Year FE	✓	✓	✓
R^2 (%)	6.425	13.920	5.920

Table 7. Trading Strategies: Risk and Return Measures

This table reports the risk and return measures for the Baseline, Hype-Adjusted, and Optimal-Timing strategies, constructed using firms that held A/I days (Long) and matched firms that did not hold A/I days (Short), identified via out-of-sample PSM. The columns present the results for the Long-Short portfolio, its individual Long and Short legs, and the differences between them over the period from 2011 to 2022. Baseline refers to the strategy that holds the portfolios from the day of the event announcement until one week after the event is held. Hype-Adjusted refers to the strategy in which the portfolio is held until one day before the event if *Hype* is identified between the announcement and one day prior to the event; otherwise, it is held until one week after the event. Optimal-Timing refers to the strategy where the optimal stopping point is set to one week after the event if the TDQN algorithm suggests a stopping time beyond one week. Mean (%) is the average excess return over the risk-free rate, Std. (%) is the standard deviation of excess returns. The Sharpe Ratio is calculated as Mean (%) divided by Std. (%). DR (downside risk) is the semi-standard deviation using returns below the Minimum Acceptable Return (MAR) of zero. Sortino is the average firm return divided by DR, and Omega (%) is the ratio of expected gains to expected losses. Upside (%) is the ratio of gains per unit of downside risk (DR). VaR is the 5% Value-at-Risk, ES represents the 5% Expected Shortfall, and MDD in maximum drawdown. MPPM is the manipulation-proof performance measure as defined by Goetzmann et al. (2007), assuming a relative risk aversion coefficient of four. One-sided p-values for the differences are obtained using 1,000 bootstrap samples. *, **, and *** denote statistically significant at the 1%, 5%, and 10% levels, respectively.

	Baseline				Hype-Adjusted				Optimal-Timing			
	Long-Short	Long	Short	Difference	Long-Short	Long	Short	Difference	Long-Short	Long	Short	Difference
Mean (%)	0.095	0.127	0.032	0.095***	0.109	0.133	0.024	0.109***	0.133	0.133	0.000	0.133***
Std. (%)	1.422	1.674	1.653	0.021	1.422	1.649	1.663	−0.013	1.734	1.685	1.814	−0.129
SR	0.067	0.076	0.019	0.057***	0.077	0.080	0.014	0.066***	0.077	0.079	0.000	0.079***
DR (%)	0.931	1.139	1.199	−0.060	0.921	1.113	1.217	−0.104	1.092	1.139	1.354	−0.214
Sortino	0.102	0.111	0.027	0.085***	0.118	0.119	0.019	0.100***	0.122	0.117	0.000	0.117***
Omega (%)	1.238	1.268	1.063	0.205***	1.277	1.284	1.046	0.238***	1.275	1.268	1.000	0.268***
Upside (%)	0.531	0.527	0.449	0.078**	0.546	0.539	0.440	0.099***	0.565	0.552	0.416	0.136***
VaR	−0.022	−0.026	−0.027	0.001	−0.022	−0.026	−0.027	0.001	−0.027	−0.026	−0.030	0.003**
ES	−0.028	−0.033	−0.034	0.001	−0.028	−0.033	−0.034	0.001	−0.034	−0.033	−0.037	0.004**
MDD (%)	27.544	41.807	47.490	−5.683	27.544	40.799	58.783	−17.984	37.763	48.463	74.858	−26.395
MPPM (%)	0.050	0.065	−0.029	0.095***	0.064	0.073	−0.038	0.111***	0.069	0.070	−0.074	0.144***

Table 8. Trading Strategies: Performance Relative to Factor Models

Note: This table reports the average excess returns and risk-adjusted returns of the Baseline, Hype-Adjusted, and Optimal-Timing strategies using matched firms, calculated via out-of-sample propensity score matching. Baseline refers to the strategy that holds the portfolios from the day of the event announcement until one week after the event is held. Hype-Adjusted refers to the strategy in which the portfolio is held until one day before the event if *Hype* is identified between the announcement and one day prior to the event; otherwise, it is held until one week after the event. Optimal-Timing refers to the strategy where the optimal stopping point is set to one week after the event if the TDQN algorithm suggests a stopping time beyond one week. The benchmark models are Fama-French 4-factor, 5-factor, 6-factor, and q5 factor model. 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. Newey-West t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Baseline					Hype-Adjusted					Optimal-Timing				
	Mean	FF4	FF5	FF6	q5	Mean	FF4	FF5	FF6	q5	Mean	FF4	FF5	FF6	q5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Alpha	0.095***	0.089***	0.090***	0.090***	0.089***	0.109***	0.105***	0.107***	0.107***	0.106***	0.133***	0.130***	0.126***	0.125***	0.125***
	(3.553)	(3.306)	(3.371)	(3.357)	(3.348)	(4.064)	(3.908)	(3.955)	(3.948)	(3.924)	(3.959)	(3.834)	(3.731)	(3.686)	(3.691)
MKT		0.114***	0.108**	0.108**	0.109**		0.077**	0.068	0.068	0.070		−0.031	−0.006	−0.002	0.009
		(2.736)	(2.484)	(2.483)	(2.477)		(1.969)	(1.603)	(1.601)	(1.638)		(−0.401)	(−0.080)	(−0.027)	(0.113)
SMB		−0.169**	−0.179**	−0.177**	−0.165**		−0.138*	−0.142*	−0.143*	−0.127		−0.102	−0.063	−0.042	−0.072
		(−2.420)	(−2.539)	(−2.440)	(−2.447)		(−1.755)	(−1.831)	(−1.798)	(−1.636)		(−1.199)	(−0.696)	(−0.471)	(−0.805)
HML		−0.038	−0.020	−0.015			−0.066	−0.024	−0.025			0.247***	0.080	0.139	
		(−0.600)	(−0.266)	(−0.179)			(−1.165)	(−0.328)	(−0.333)			(3.173)	(0.802)	(1.517)	
UMD		0.004		0.008			−0.011		−0.002			0.105		0.089	
		(0.087)		(0.179)			(−0.277)		(−0.037)			(1.448)		(1.213)	
RMW			−0.026	−0.025				−0.006	−0.006				0.185*	0.193**	
			(−0.295)	(−0.286)				(−0.071)	(−0.072)				(1.904)	(1.982)	
CMA			−0.048	−0.054				−0.115	−0.114				0.285**	0.215	
			(−0.423)	(−0.446)				(−0.968)	(−0.916)				(2.068)	(1.618)	
IA					−0.059					−0.104					0.434***
					(−0.608)					(−1.085)					(3.221)
ROE					0.013					0.020					0.039
					(0.125)					(0.188)					(0.241)
EG					0.010					0.020					0.089
					(0.082)					(0.185)					(0.485)
Observations	2,822	2,822	2,822	2,822	2,822	2,813	2,813	2,813	2,813	2,813	2,659	2,659	2,659	2,659	2,659
R^2 (%)		1.08	1.10	1.10	1.08		0.66	0.72	0.72	0.69		1.58	1.72	1.93	1.61

Table 9. Trading Strategies: Factor-Model Alphas, Subsample Analysis

Note: This table reports the average excess returns and risk-adjusted returns of the Baseline, Hype-Adjusted, and Optimal-Timing strategies by subsamples using matched firms, calculated via out-of-sample propensity score matching. Baseline refers to the strategy that holds the portfolios from the day of the event announcement until one week after the event is held. Hype-Adjusted refers to the strategy in which the portfolio is held until one day before the event if *Hype* is identified between the announcement and one day prior to the event; otherwise, it is held until one week after the event. Optimal-Timing refers to the strategy where the optimal stopping point is set to one week after the event if the TDQN algorithm suggests a stopping time beyond one week. The benchmark models are FF4, FF5, FF6, and q5. The long-short portfolio strategy is implemented for the following subsamples: firms with positive and negative speaker tone during A/I days, firms belonging to high-tech and non-high-tech industries, and firms that disclosed (or did not disclose) through conference presentations in the quarter prior to the analyst/investor (A/I) days. Firms with a positive (negative) *Tone* are those in the 5th (1st) quintile of the *Tone* distribution. The same classification applies to $Tone^{Q\&A}$. Newey-West t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Baseline				Hype-Adjusted				Optimal-Timing			
	FF4	FF5	FF6	q5	FF4	FF5	FF6	q5	FF4	FF5	FF6	q5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Positive $\text{Tone}^{\text{Overall}}$	0.131***	0.136***	0.135***	0.132***	0.147***	0.153***	0.152***	0.150***	0.156**	0.148**	0.148**	0.143**
	(2.588)	(2.665)	(2.665)	(2.593)	(2.869)	(2.946)	(2.946)	(2.899)	(2.547)	(2.392)	(2.389)	(2.329)
Negative $\text{Tone}^{\text{Overall}}$	0.064	0.067	0.064	0.069	0.053	0.056	0.053	0.059	0.104	0.112	0.106	0.111
	(1.402)	(1.470)	(1.390)	(1.519)	(1.112)	(1.179)	(1.108)	(1.244)	(1.496)	(1.594)	(1.517)	(1.572)
Positive $\text{Tone}^{\text{Q\&A}}$	0.059	0.064	0.063	0.062	0.077	0.082	0.082	0.082	0.116**	0.106**	0.106**	0.109**
	(1.205)	(1.294)	(1.278)	(1.245)	(1.563)	(1.643)	(1.633)	(1.631)	(2.213)	(2.040)	(2.039)	(2.094)
Negative $\text{Tone}^{\text{Q\&A}}$	0.018	0.012	0.013	0.004	0.034	0.027	0.029	0.019	0.161**	0.171**	0.163**	0.176**
	(0.329)	(0.219)	(0.238)	(0.069)	(0.607)	(0.480)	(0.515)	(0.351)	(2.173)	(2.286)	(2.199)	(2.346)
High Tech.	0.164***	0.173***	0.172***	0.173***	0.173***	0.181***	0.181***	0.184***	0.263***	0.266***	0.263***	0.263***
	(3.812)	(3.993)	(3.980)	(3.958)	(3.964)	(4.143)	(4.132)	(4.168)	(4.232)	(4.246)	(4.182)	(4.162)
Non-High Tech.	0.090***	0.088***	0.088***	0.088***	0.106***	0.103***	0.103***	0.101***	0.121***	0.116***	0.116***	0.118***
	(3.375)	(3.344)	(3.311)	(3.267)	(3.997)	(3.929)	(3.908)	(3.751)	(3.504)	(3.393)	(3.362)	(3.430)

Appendix A. Additional tables

Table A.1. Variable Definitions and Data Sources

Note: This table lists the variables and their definitions within their respective categories.

Variable	Description
Analyst/Investor Day	
A/I Day	1 if a firm hosted an analyst/investor (A/I) day during the fiscal year, and 0 otherwise.
No. of A/I Days	Total number of hosted analyst/investor days (A/I) in the fiscal year.
Internal Benefits for Disclosure	
Financing	1 if a firm issues debt or equity, as reported in Compustat. Equity issuance (`SSTK`) scaled by the total assets (`AT`) and Debt issuance (`DLTIS`) scaled by the total assets (`AT`).
Sales Growth	Growth rate of sales, measured as the change in sales in the fiscal year scaled by sales in the prior fiscal year.
Bid-Ask Spread	Average daily bid-ask spread over the year. The bid-ask spread is the difference between the ask and bid price of each stock over the mean of ask and bid (midpoint) from CRSP daily data. We exclude bid-ask spreads greater than 50% of the quote midpoint.
Life3	A text-based, firm-specific measure of the intensity of stable and mature products developed by Hoberg and Maksimovic (2022).
External Demand for Disclosure	
ln(1+Size)	The natural logarithm of one plus the market value of equity (see, Fama and French, 1992).
ln(1+No. of Analysts)	The natural logarithm of 1 plus the average number of analysts (`NUMEST`) issuing earnings forecasts for any horizon during 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.
$\text{Ownership}^{\text{INS}}$	Institutional investors' percentage ownership at the end of fiscal year t. This is calculated by dividing institutional investors' stock holdings by the number of shares outstanding, as reported in the Thomson Reuters Institutional (13F) Holdings database (CDA/Spectrum s34). The value is assumed to be 0 for any period in which the company is listed on an exchange but no ownership data are available.
$\ln(1+\text{Age}^{\text{Firm}})$	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.
Segments	The number of unique business segments reported in a company's annual filings from Compustat. If missing, it is assumed to be 1.
Intangibles	Recognized intangibles (`INTAN`) plus goodwill (`GDWL`) scaled by total assets (`AT`).
R&D Intensity	Firm spends on R&D (`XRD`) scaled by the total assets (`AT`). We replace missing values with the industry median of R&D Intensity for the same year, if the latter is also missing, we then set R&D Intensity to 0.
Book-to-Market	The book equity scaled by the market equity (`MKVALT`). Book equity is calculated as the sum of shareholders' equity (`SEQ`) and deferred taxes and investment tax credit (`TXDITC`) minus the preferred stock redemption value (`PSTKRV`). If shareholders' equity (`SEQ`) is missing, the sum of common equity (`CEQ`) and preferred stock (`PSTK`), or total assets (`AT`) minus total liabilities (`LT`), is used. If deferred taxes and investment tax credit (`TXDITC`) are missing, deferred tax credits (`TXDB`) plus investment tax credits (`ITCB`) are added, defaulting to 0 if all are missing. If the preferred stock redemption value (`PSTKRV`) is missing, the preferred stock liquidation value (`PSTKL`) or preferred stock (`PSTK`) is subtracted, defaulting to 0 if all are missing.
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 $\sqrt{252}$.
Loss	1 if the firm's net income (`NI`) at the end of the fiscal year is negative, and 0 otherwise.
Leverage	The total liabilities (`LT`) minus deferred taxes (`TXDB`) scaled by total assets (`AT`) (see, Ali et al., 2014).
Performance measures	
Downside risk	$DR_i = \sqrt{\sum_{t=1}^{T}(\lvert r_{i,t}\rvert)^2 I_{r_{i,t}<0}/T}$, where $r_{i,t}$ is the return of firm i during period t, and $I_{r_{i,t}<0}$ is an indicator equal to 1 if $r_i, t < 0$ and 0 otherwise.
Sortino ratio	Average return of firm i per unit of downside risk.
Upside	Expected gains per unit downside risk, defined as $Upside_i = \frac{\frac{1}{T}\sum_{t=1}^{T} r_{i,t} I_{r_{i,t}>0}}{DR_i}$, where $r_{i,t}$ is the return of firm i during period t, $I_{r_{i,t}>0}$ is an indicator equal to 1 if the return is positive, and DR_i is the downside risk of firm i.
Omega	Expected gains over expected losses, defined as $Omega_i = \frac{\sum_{t=1}^{T} r_{i,t} I_{r_{i,t}>0}}{\sum_{t=1}^{T} \lvert r_{i,t}\rvert I_{r_{i,t}<0}}$.
Maximum drawdown (*MDD*)	Difference between cumulative returns and the peak cumulative return.
MPPM	Manipulation-proof performance measure, defined as $MPPM_i = \frac{1}{(1-\rho)}\ln\left[\frac{1}{T}\sum_{t=1}^{T}\left(\frac{1+r_{i,t}}{1+r_{f,t}}\right)^{1-\rho}\right]$, 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.

Table A.2. Probability of Hosting an Analyst/Investor Day

Note: This table reports the estimation results of the logit regression for the probability of hosting an analyst/investor (A/I) day during the fiscal year. The dependent variable is a dummy variable indicating whether or not a firm hosted at least one A/I day during the fiscal year. %STDX represents the percentage change in the odds of hosting an A/I day for a one-standard-deviation increase in the independent variable from its mean. It is computed as: $((e^{\hat{\beta}\cdot(\bar{X}+\sigma)}/e^{\beta\cdot\bar{X}}) - 1) \times 100$, where $\hat{\beta}$ is the estimated logit coefficient, $\bar{X}$ is the mean of the independent variable, and σ is its standard deviation. The t-statistics are in parentheses. The regression includes year and industry fixed effects, and it estimated using the complete sample. Note, the results are reported for illustrative purpose only. For the matching procedure used in the paper, the model is re-estimated every time a new A/I day is announced using only past data, and excluding year fixed effects. *, **, and *** denote the statistical significance at 10%, 5%, and 1%, respectively. All the variables are defined in Table A.1.

	$\mathbb{1}$ (Analyst/Investor Day)		
	Coef.	*t*-stat	%STDX
Analyst/Investor Day			
No. of A/I Days	1.225***	(17.931)	34.41
Internal Benefits for Disclosure			
Financing	0.435***	(2.961)	54.57
Sale Growth	−0.003	(−0.123)	−0.40
Bid-Ask Spread	−1.693***	(−6.478)	−83.28
Life3	0.545**	(1.985)	5.82
External Pressure/Demand for Disclosure			
ln(1+Size)	0.207***	(9.299)	55.35
ln(1+No. of Analysts)	0.063*	(1.728)	5.32
$\text{Ownership}^{\text{INS}}$	0.083	(0.964)	2.91
$\ln(1+\text{Age}^{\text{Firm}})$	0.071*	(1.884)	7.45
High Tech.	0.183***	(2.729)	20.10
Segments	0.006	(1.033)	2.54
Intangibles	0.185**	(2.421)	6.95
R&D Intensity	0.058	(0.175)	0.73
Book-to-Market	−0.147*	(−1.882)	−31.34
Return	0.032	(0.476)	1.91
Volatility	−0.277	(−1.534)	−8.32
Loss	0.194***	(2.642)	21.39
Leverage	0.230*	(1.831)	5.36
Observations	26,648		
Industry FE	✓		
Year FE	✓		

Table A.3. Trading Strategies: Factor-Model Alphas Including Transaction Costs

Note: This table reports the average excess returns and risk-adjusted returns of the Baseline, Hype-Adjusted, Hype (Flipped), and Optimal-Timing strategies using matched firms, calculated via out-of-sample propensity score matching, and based on three assumptions for trading costs: 1 bp, 10 bps, and 14 bps. Strategies are as defined previously Following Moreira and Muir (2017), Panel A presents results without short-selling costs, while Panel B incorporates short-selling borrowing costs within each panel. The benchmark models are Fama-French 4-factor model (market, size, value, and momentum), Fama-French 5-factor model (market, size, value, profitability, and investment), Fama-French 6-factor model (market, size, value, momentum, robust operating profitability, and conservative investment), and q5 factor model (market, size, investment, return on equity, and expected growth). 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. Newey-West t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The investment period spans from 2011 to 2022.

	1 bp				10 bps				14 bps			
	FF4	FF5	FF6	q5	FF4	FF5	FF6	q5	FF4	FF5	FF6	q5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Proportional trading costs												
Baseline	0.089***	0.090***	0.090***	0.089***	0.088***	0.089***	0.089***	0.088***	0.087***	0.088***	0.088***	0.088***
	(3.303)	(3.368)	(3.354)	(3.344)	(3.273)	(3.337)	(3.324)	(3.314)	(3.259)	(3.324)	(3.310)	(3.300)
Hype-Adjusted	0.105***	0.107***	0.107***	0.106***	0.104***	0.106***	0.106***	0.105***	0.104***	0.105***	0.105***	0.104***
	(3.905)	(3.952)	(3.945)	(3.921)	(3.875)	(3.922)	(3.915)	(3.891)	(3.862)	(3.909)	(3.902)	(3.877)
Hype (Flipped)	0.111***	0.112***	0.112***	0.110***	0.110***	0.111***	0.111***	0.109***	0.110***	0.110***	0.111***	0.109***
	(4.168)	(4.210)	(4.207)	(4.155)	(4.137)	(4.179)	(4.177)	(4.124)	(4.124)	(4.166)	(4.163)	(4.111)
Optimal-Timing	0.129***	0.126***	0.125***	0.124***	0.127***	0.123***	0.122***	0.122***	0.126***	0.122***	0.121***	0.121***
	(3.826)	(3.723)	(3.679)	(3.683)	(3.756)	(3.653)	(3.610)	(3.613)	(3.725)	(3.623)	(3.579)	(3.582)
Panel B: Proportional trading costs and borrowing costs												
Baseline	0.080***	0.081***	0.081***	0.080***	0.079***	0.080***	0.080***	0.079***	0.078***	0.080***	0.079***	0.079***
	(2.972)	(3.035)	(3.022)	(3.011)	(2.942)	(3.004)	(2.991)	(2.980)	(2.928)	(2.991)	(2.978)	(2.966)
Hype-Adjusted	0.095***	0.097***	0.097***	0.096***	0.095***	0.096***	0.096***	0.095***	0.094***	0.096***	0.096***	0.095***
	(3.545)	(3.592)	(3.586)	(3.560)	(3.515)	(3.562)	(3.556)	(3.530)	(3.502)	(3.549)	(3.543)	(3.517)
Hype (Flipped)	0.102***	0.102***	0.102***	0.100***	0.101***	0.101***	0.101***	0.100***	0.101***	0.101***	0.101***	0.099***
	(3.811)	(3.851)	(3.849)	(3.795)	(3.781)	(3.820)	(3.819)	(3.764)	(3.767)	(3.807)	(3.805)	(3.751)
Optimal-Timing	0.125***	0.122***	0.121***	0.120***	0.123***	0.119***	0.118***	0.118***	0.122***	0.118***	0.117***	0.117***
	(3.702)	(3.598)	(3.555)	(3.558)	(3.632)	(3.529)	(3.486)	(3.488)	(3.601)	(3.498)	(3.455)	(3.457)

Table A.4. Summary Statistics for RiskInfo_{30}, Hype, and Numest

Note: This table reports summary statistics for the $RiskInfo_{30}$, Hype, and Numest variables, based on the matched sample used in the BHARs regression analysis. $RiskInfo_{30}$ measures implied risk over a 30-day horizon, following Smith and So (2022). *Hype* is a dummy equal to one if the firm issues a voluntary 8-K (Items 2.02, 7.01, or 8.01) and if net insider selling occurs between the announcement and the event, following Bushee et al. (2022). *Numest* is the number of analysts who issued any forecast between the announcement date and the event date.

	N	Mean	Std.	IQR	25%	50%	75%
RiskInfo_{30}	935	0.009	0.123	0.006	-0.003	-0.001	0.002
Hype	935	0.240	0.427	0.000	0.000	0.000	0.000
Numest	935	2.939	4.699	4.000	0.000	1.000	4.000

Internet Appendix for

Save The Date: Analyst/Investor Days as a Trading Signal

Gabriel Cabrera Olga Kolokolova S. Sarah Zhang

SUPPLEMENTARY RESULTS

This Internet Appendix provides supplementary information to support the results presented in the paper.

Appendix A. Transaction cost

To account for transaction costs, we adopt the methodologies proposed by Hasbrouck (2009), Barroso and Santa-Clara (2015), and Barroso and Detzel (2021), assuming that transaction costs are proportional to trade size.

The proportional transaction cost (TC) associated with long leg of trades is computed as:

$$TC_{long,t} = \sum_{i=1}^{N_t} |w_{i,t} - \tilde{w}_{i,t-1}| c_{i,t}, \tag{A.1}$$

where N_t is the number of valid stocks in day t, $w_{i,t}$ is the weight of stock i in the long leg of day t after rebalancing, and $\tilde{w}_{i,t-1}$ is its weight before rebalancing defined as:

$$\tilde{w}_{i,t-1} = \frac{w_{i,t-1}(1 + r_{i,t})}{\sum_{j=1}^{N_t} w_{j,t-1}(1 + r_{j,t})}, \tag{A.2}$$

with $r_{i,t}$ denoting the raw return of stock i. $c_{i,t}$ refers to the one-way transaction cost as defined by Hasbrouck (2009).

Following the methodology outlined in Kolokolova and Xu (2024), we consider three fixed trading cost levels: 1 bp, 10 bps, and 14 bps. The transaction cost for the short leg is calculated in the same manner, using the same $w_{i,t}$ and $\tilde{w}_{i,t-1}$ as in the long leg. The total transaction cost for the portfolio is the sum of the costs associated with both the long and short legs.

We estimate the portfolio weights $w_{i,t}$ based on the sizes of the matched firms involved. Since portfolio construction depends on the timing of A/I days, there may be instances where only one matched firm is available between the announcement and one week after the event, without any overlap. In such cases, the weight $w_{i,t}$ is set to 1 by construction. The proportional TC of the short leg is computed similarly.

We incorporate borrowing costs into the short leg, as documented by Bekjarovski (2018) and Kolokolova and Xu (2024), which range from as low as 0.35% per year for the largest 10% of stocks to 21.85% for the smallest 10%. To achieve this, we utilise the average borrowing costs for stocks across different size deciles and adjust the resulting returns of our long-short portfolios accordingly.

At each daily instance, prior to investing, all available stocks are sorted into deciles from smallest to largest based on NYSE size breakpoints. Since NYSE size breakpoints are available monthly while our portfolio is constructed daily, we use the corresponding monthly decile classification for each day within that month. Then, the annual borrowing costs for each stock are determined according to its size decile. The costs for the size deciles (from smallest to largest stocks) are as follows: 21.85%, 10.90%, 3.40%, 2.37%, 0.92%, 0.58%, 0.44%, 0.38%, 0.37%, and 0.35% per year, respectively. The daily costs for the short leg of our portfolios are calculated as:

$$TC^{BOR}_{short,t} = \sum_{i=1}^{N_t} w_{i,t} c^{BOR}_{i,t} / 252, \tag{A.3}$$

We subtract proportional trading costs and the borrowing costs from the returns of the long-short portfolios to obtain post-TC returns.

Appendix B. Trading strategy using deep learning algorithm

Following Hambly et al. (2023), we implement a DRL-based method to determine the optimal stopping time. Specifically, we apply the Trading Deep Q-Network (TDQN) algorithm introduced by Théate and Ernst (2021), where the decision to exit or hold a position is guided by a set of rules derived from the trading strategy. These rules incorporate multiple factors, including historical stock performance, market conditions, risk-adjusted return expectations, and information precision, enabling a dynamic and adaptive decision-making process.

To simulate a real out-of-sample (OOS) trading decision using the TDQN algorithm, we split the sample into training and testing subsets. The training subsample is used to fit the model, while the testing subsample evaluates its performance. Our empirical analysis begins with a fixed training period of two years prior to the event announcement for each firm pair and a one-year testing subsample.

At each training step (i.e., using all available data before the announcement date, 2 years in our case), the DRL agent sequentially processes past stock returns and event-related characteristics to form a dynamic view of the market environment. Using the TDQN framework, it learns whether to exit a position or continue holding it, based on estimates of long-term performance measured by the Sharpe ratio. We force the agent to always open a long position on the announcement date of the hosted firm. A reward function is designed to guide the agent toward decisions that maximise risk-adjusted returns, explicitly encouraging improvements in the Sharpe ratio over the holding period. To address data limitations and improve the stability of the learning process, we use artificial trajectory generation, allowing the agent to simulate trading along historical price paths under the assumption that its actions do not influence market prices. Additionally, the DRL agent uses experience replay, allowing it to revisit and learn from its own past decisions by analysing stored scenarios — particularly those involving suboptimal actions like exiting too early or missing a post-event price reversal — to improve future performance.[1]

Under a reinforcement learning framework, the trading problem can be modelled as a Partially Observable Markov Decision Process (POMDP), where an RL agent i_t interacts with the RL environment at time step t by observing internal market states s_t, retrieving an observation o_t, and selecting an action a_t according to its policy $\pi(a_t|h_t)$, where $h_t = \{(o_\tau, a_\tau, r_\tau)|\tau = 0, 1, ..., t\}$ represents the RL agent's history. After taking action a_t the agent transitions to a new state s_{t+1} and receives a reward r_t. This interaction between the agent (policy) and the environment is summarised and illustrated in Figure IA.1.

[1] Appendix B provides a detailed description of the TDQN algorithm's implementation and parameter settings at each stage.

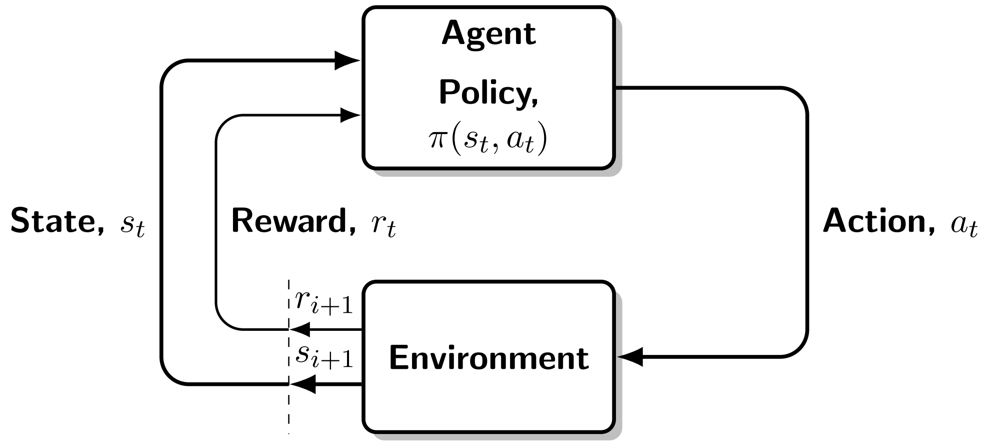


Figure IA.1. Reinforcement Learning Core Building Blocks

Note: This figure illustrates the interaction between an agent (policy) and its environment within a reinforcement learning (RL) framework. At each time step t, the agent observes a state s_t and selects an action a_t based on its policy $\pi(s_t, a_t)$. In response, the environment transitions to the next state s_{t+1} and provides an immediate reward r_t. This reward guides the agent's learning process, allowing the policy to iteratively improve and ultimately maximise cumulative rewards over time. In the context of our trading strategy, the environment represents the financial market, where the agent makes decisions about whether to buy, sell, or hold a given number of shares. The agent's state is defined by market features such as OHLCV data and event-related information precision, while the reward corresponds to the realised daily return. Through repeated interaction with the environment, the TDQN agent learns to refine its policy to optimise exit timing and ultimately maximise the Sharpe ratio of the trading strategy.

The RL agent updates its action-value function $Q(s_t, a_t)$ using the Q-learning update rule, which iteratively refines the estimated future reward of taking action a_t in state s_t. In each Q-learning iteration n, for a given time step t, the update is computed as follows:

$$Q^{(n+1)}(s,a) = \overbrace{Q^{(n)}(s,a)}^{\text{Current estimate}} + \underset{\text{Learning rate}}{\alpha} \Big[\underbrace{r(s,a)}_{\text{Reward}} + \underset{\text{Discount rate}}{\gamma} \overbrace{\max_{a'} Q^{(n)}(s',a')}^{\substack{\text{Maximum predicted reward, given} \\ \text{new state and all possible actions}}} - Q^{(n)}(s,a)\Big] \tag{B.4}$$

The learning rate α controls the extent to which new information updates the existing Q-value, which is calculated using the sample (s, a, r, s'), where s' is drawn from the transition probability distribution $P(s'|s,a)$. While the discount rate γ determines the RL agent's weighting of future rewards. When $\gamma = 0$, the RL agent is myopic, focusing only on the immediate reward while completely ignoring future rewards. As γ increases ($\gamma > 0$), the agent becomes more long-term oriented. When $\gamma = 1$, the RL agent values all rewards equally, regardless of when they occur.

A key challenge in designing a trading strategy under a POMDP framework, as in real-world markets, is the imbalance between the information available to the RL agent and the complexity of the market environment. Specifically, the RL agent cannot fully observe the true market state (e.g., due to information asymmetry), making it difficult to accurately assess market conditions and optimise decision-making.

Therefore, the agent must process observations o_t sequentially, integrating past information gathered in previous steps (e.g., the trading position at time step t, whether long or short) with newly available data at time step t to refine its belief about the underlying market dynamics. The RL observations consist of features capturing past price movements, including OHLCV (Open, High, Low, Close, and Volume), as well as information precision from A/I days. The action space, a_t, is defined by the number of shares Q_t traded in each decision, including holding (i.e., neither buying nor selling, $Q_t = 0$), entering (e.g., buying shares, $Q_t > 0$), or exiting (e.g., selling shares, $Q_t < 0$) a position.

The goal of the RL trading agent is to maximise the portfolio value over time. The portfolio value consists of cash value, v^c_{t+1}, and share value, v^s_{t+1}, defined as:

$$v^c_{t+1} = v^c_t - Q_t\, p_t - C\, |Q_t|\, p_t \tag{B.5}$$

$$v^s_{t+1} = (n_t + Q_t)\, p_{t+1} = n_{t+1}\, p_{t+1} \tag{B.6}$$

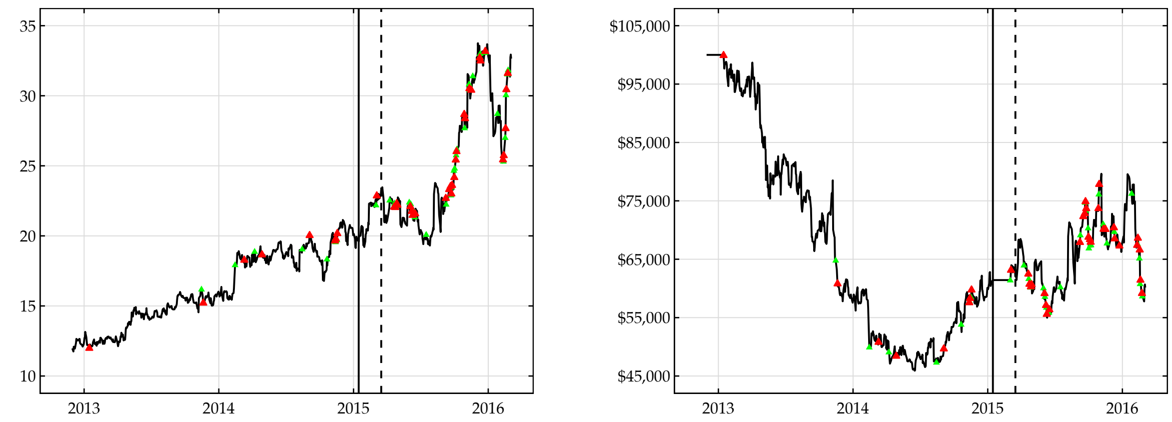
Where n_t is the number of shares held by the trading agent at time step t, p_t (p_{t+1}) is the closing market price at time t ($t+1$), and $C\, |Q_t|\, p_t$ represents the trading cost. Following a simplified rule-based approach, the model assumes that a fixed percentage of the trade's value, denoted by C and set to 0.1%, is lost whenever a trade occurs.[2]

The reward function, defined as daily returns, is designed to optimise long-term profitability by maximising the Sharpe ratio, as proposed by Théate and Ernst (2021). To address the challenges of limited market data and non-stationary environments, artificial trajectory generation and experience replay are employed to enhance the robustness of the learning process.

The TDQN algorithm extends the classical Deep Q-Network (DQN) by incorporating double Q-learning to mitigate overestimation bias and a duelling architecture to improve action-value estimation. Additionally, we leverage prioritised experience replay to sample transitions more efficiently, ensuring that the agent learns from the most informative past experiences. The DQN serves as the policy executor, $\pi(s_t, a_t)$, selecting actions that maximise the estimated Q-values given the current market state, thereby guiding optimal trading decisions. Our implementation is trained on historical stock data, with performance evaluated based on risk-adjusted returns, drawdowns, and execution efficiency. By adapting to evolving market dynamics, the TDQN-based strategy offers a more flexible and data-driven approach to optimising trade execution and exit timing.

Figure IA.2 shows the application of the trading strategy to Nvidia's A/I Day on March 17, 2015, illustrating the evolution of both the stock price (p_t) and the RL agent's portfolio value (v_t) over the full sample period, based on an initial investment of \$100,000.

[2]Eq. (B.5) allows the cash value to decrease after purchasing shares, while Eq. (B.6) captures the updated value of the position at the next time step. Although the number of shares n_t can be negative, corresponding to a short position, two constraints apply: (i) the cash value v_t^c must remain non-negative to prevent over-leveraging, and (ii) when short selling, the agent must retain enough cash to repurchase the borrowed shares even under adverse price movements. To enforce this, the agent assumes a maximum daily price change $\varepsilon > 0$, ensuring it can always return to a neutral position ($n_t = 0$) without default risk. For a full formalisation of these constraints and the resulting bounds on the action space, see Théate and Ernst (2021, p.5).



Panel A: Stock Price

Panel B: Capital

Figure IA.2. TDQN Algorithm Execution for Nvidia's A/I Day on March 17, 2015

Note: This figure displays the performance of the trading strategy applied to Nvidia's A/I day on March 17, 2015, showing both the stock market price p_t (Panel A) and the RL agent's portfolio value v_t (Panel B), assuming an initial capital of $100,000. Green triangles indicate long positions, while red triangles indicate short positions. The solid line marks the end of the testing sample, and the dotted line denotes the event date.

Appendix C. Additional Tables and Figures

Table IA.1. Balancing Tests of Propensity Score Matching

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

	Hosted A/I Day	Did Not Host A/I Day	% Bias	t-statistic
Analyst/Investor Day				
No. of AI Days	0.126	0.122	1.219	0.313
Internal Benefits for Disclosure				
Financing	0.970	0.971	−0.357	−0.122
Sales Growth	0.209	0.256	−3.592	−0.809
Bid-Ask Spread	0.099	0.100	−0.184	−0.229
Life3	0.279	0.273	5.394	1.407
External Demand for Disclosure				
ln(1+Size)	8.118	8.076	2.245	0.691
ln(1+No. of Analysts)	0.622	0.613	1.036	0.243
$\text{Ownership}^{\text{INS}}$	0.698	0.680	5.249	1.320
$\ln(1+\text{Age}^{\text{Firm}})$	2.875	2.854	2.096	0.513
High Tech.	0.327	0.313	3.032	0.707
Segments	6.778	6.590	3.984	0.922
Intangibles	0.478	0.465	3.533	0.833
R&D Intensity	0.067	0.070	−2.414	−0.666
Book-to-Market	0.415	0.408	0.484	0.565
Return	0.188	0.196	−1.441	−0.419
Volatility	0.401	0.399	0.597	0.193
Loss	0.249	0.228	4.472	1.162
Leverage	0.507	0.505	0.932	0.236

Table IA.2. Performace of "Hype Flipped" Trading Strategy

Note: This table presents the risk and return measures and trading performance of the Hype flipped strategy in which the portfolio is reversed (going long in the matched firm and short in the hosting firm) between the event date and one week after the event if *Hype* is identified between the announcement and one day before the event; otherwise, the portfolio is held until one week after the event without flipping. The first four columns present the results for the Long-Short portfolio, its individual Long and Short legs, and the differences between them, with the same performance measures as in Table 7. The five columns in the middle report the average excess returns and risk-adjusted returns of the Hype (flipped) strategy, with benchmark models FF4, FF5, FF6, and q5. The last five columns reports the same returns for different subsamples (firms with positive and negative tone during A/I days, belonging to high-tech and non-high-tech industries, and firms that disclosed (or did not disclose) through conference presentations in the quarter prior to the analyst/investor (A/I) days) as in Table 9. Newey-West t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All the variables are defined in Table A.1.

	Risk/Return			
	Long-Short (1)	Long (2)	Short (3)	Difference (4)
Mean (%)	0.113	0.137	0.024	0.113***
Std. (%)	1.424	1.625	1.703	−0.078
SR	0.079	0.084	0.014	0.070***
DR (%)	0.929	1.087	1.238	−0.151
Sortino	0.121	0.126	0.019	0.106***
Omega (%)	1.290	1.297	1.047	0.250***
Upside (%)	0.539	0.550	0.437	0.113***
VaR	−0.022	−0.025	−0.028	0.002**
ES	−0.028	−0.032	−0.035	0.003**
MDD (%)	27.544	35.740	56.010	−20.27
MPPM (%)	0.067	0.079	−0.041	0.119***

	Performance relative to factor models				
	Mean (1)	FF4 (2)	FF5 (3)	FF6 (4)	q5 (5)
Alpha	0.113***	0.111***	0.112***	0.112***	0.110***
	(4.202)	(4.171)	(4.213)	(4.211)	(4.158)
MKT		0.027	0.024	0.023	0.026
		(0.697)	(0.586)	(0.564)	(0.590)
SMB		−0.168**	−0.163**	−0.168**	−0.135*
		(−2.321)	(−2.223)	(−2.227)	(−1.860)
HML		−0.104*	−0.073	−0.086	
		(−1.824)	(−1.003)	(−1.137)	
UMD		−0.024		−0.019	
		(−0.574)		(−0.437)	
RMW			0.009	0.008	
			(0.100)	(0.084)	
CMA			−0.069	−0.054	
			(−0.600)	(−0.439)	
IA					−0.08
					(−0.731)
ROE					0.004
					(0.040)
EG					0.097
					(0.754)

	Alphas in subsamples			
	FF4 (1)	FF5 (2)	FF6 (3)	q5 (4)
Positive Tone$^{\text{Overall}}$	0.129**	0.135***	0.134***	0.132***
	(2.550)	(2.640)	(2.640)	(2.593)
Negative Tone$^{\text{Overall}}$	0.064	0.066	0.064	0.069
	(1.390)	(1.437)	(1.397)	(1.501)
Positive Tone$^{\text{Q\&A}}$	0.065	0.069	0.069	0.069
	(1.309)	(1.397)	(1.384)	(1.381)
Negative Tone$^{\text{Q\&A}}$	0.043	0.036	0.039	0.029
	(0.784)	(0.647)	(0.700)	(0.522)
High Tech.	0.170***	0.179***	0.178***	0.181***
	(3.911)	(4.098)	(4.088)	(4.133)
Non-High Tech.	0.118***	0.114***	0.114***	0.112***
	(4.415)	(4.328)	(4.317)	(4.226)

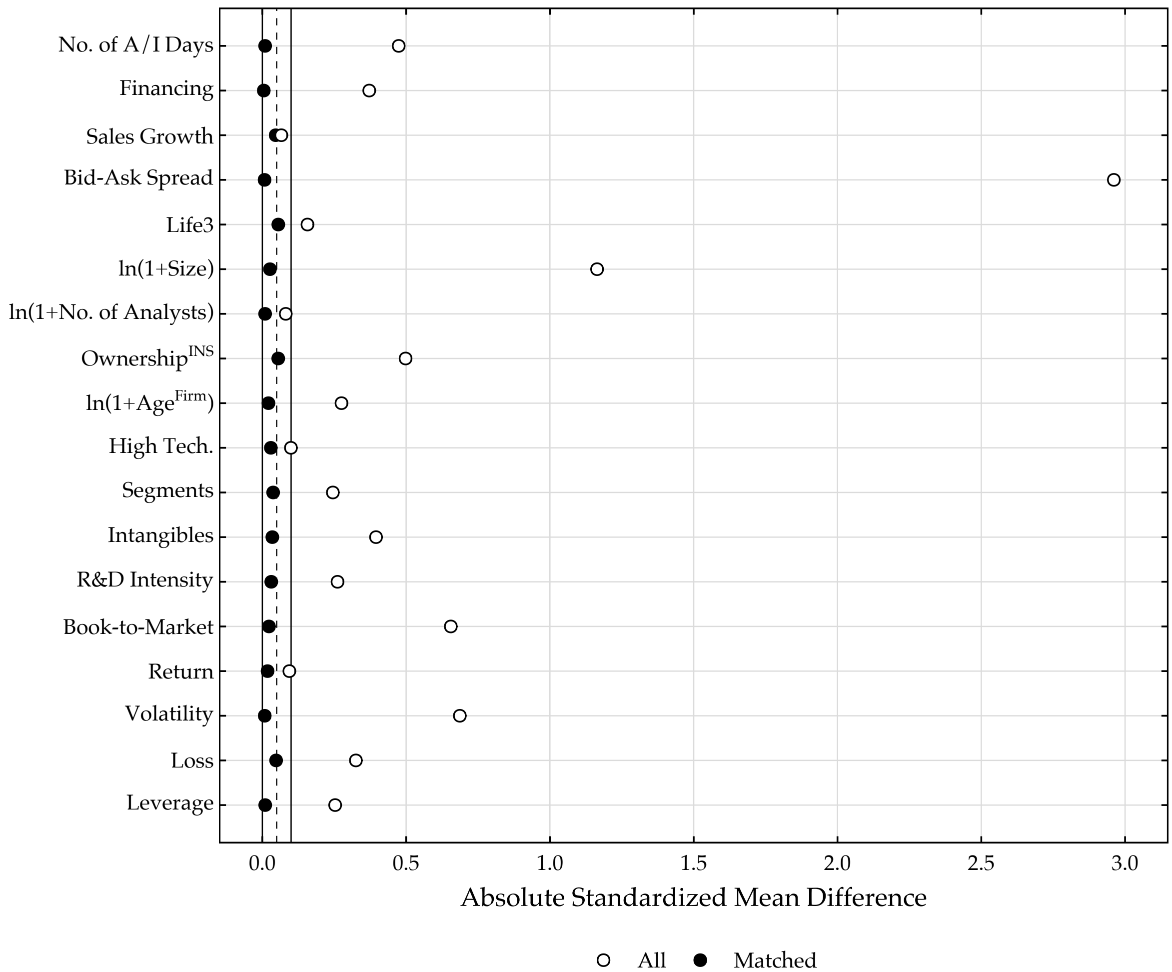


Figure IA.3. PSM Matching Balance

Note: This figure summarises the covariate balance of the propensity score matching (PSM) procedure, comparing treated (holding A/I day) and matched (not holding A/I day) observations (solid points) as well as treated observations and the full sample (hollow points).

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