

Save The Date:

Analyst/Investor Days as a Trading Signal^{*}

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

This revision: April 28, 2026

Abstract

Firms increasingly use Analyst/Investor (A/I) days as discretionary disclosure channels. We show that announcing an A/I day leads to positive abnormal returns and a sustained pre-event price run-up. The run-up is more pronounced when firms issue additional pre-event voluntary disclosures and is followed by return reversals after the event. In contrast, events without any incremental disclosures exhibit positive post-event returns driven by event informativeness and changes in risk expectations. Exploiting these patterns, we design implementable long-short trading strategies that earn economically and statistically significant abnormal returns. A strategy based solely on the announcement yields positive alphas of around 0.095% before and 0.08% after transaction and borrowing costs. A deep-reinforcement-learning optimal stopping rule further improves performance, generating a positive alpha of 0.13% before costs, highlighting the importance of A/I days as a voluntary disclosure channel and the role of announcement and pre-event behaviour in shaping market prices.

JEL Classification: G14, G17, M41

Keywords: analyst/investor days; voluntary disclosure; trading strategy; linguistic complexity; risk expectations

^{*}We are grateful for the comments and suggestions from Kevin Aretz, Alfonso Dufour, Nadya Malenko, Ser-Huang Poon, Alex Taylor, Simone Varotto, Martin Walker, Shen Zhao, and all participants at the seminar at the ICMA Centre, Henley Business School, University of Reading, and the 5th Frontiers of Factor Investing Conference.

[†]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

Analyst/Investor (A/I) days provide a prominent and strategically important voluntary disclosure channel for managers to communicate strategic plans, showcase innovation, and shape investor perception outside of mandatory reporting channels. In addition to its importance for sell-side analysts (Brown et al., 2015), prior research has also shown significant market impact and improvements in information environment after A/I days (Kirk and Markov, 2016; Park, 2024). 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, reflecting the discrepancy in investor expectations before and after the event.¹

In contrast to mandatory and other voluntary disclosure channels, 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 (Bushee et al., 2022) in alignment with temporary incentive mechanisms and strategic information releases (cf. Edmans et al., 2018, 2022). In contrast to existing work on A/I days that largely focuses on the post-event performance, we further consider how the announcement of the event and pre-event disclosures shape market anticipation and the nature of price formation around the event.

In this paper, we demonstrate how the price dynamics around A/I days hosted by more than 1,000 unique publicly listed firms are shaped by the announcement, pre-event disclosures, event informativeness and changes in market risk expectations. Exploiting the timing of the announcement and the event themselves, we demonstrate that the decision to host an A/I day constitutes a value-enhancing signal that can be exploited using an implementable trading strategy. We further show that additional disclosures prior to the event are the main deter-

¹See Forbes (2023): “Tesla Stock Tanks After ‘Disjointed’ Investor Day Draws Mixed Reviews” (<https://www.forbes.com/sites/dereksaul/2023/03/02/tesla-stock-tanks-after-disjointed-investor-day-draws-mixed-reviews/>)

minants of pre-event abnormal returns. The events with such incremental disclosures exhibit significantly larger price run-ups prior to the event and pronounced post-event reversals.

In contrast, post-event returns are more strongly related to the information-related measures during the event. Particularly for events without prior incremental disclosures, post-event returns exhibit a stronger relationship with changes in risk expectations that affect their discount rates (Penman and Yehuda, 2019), as well as overall informativeness of the event. We capture event informativeness using a latent information component following Bushee et al. (2018b) extracted from the event transcripts and measure the risk-related expectations using the change in return variance implied by options maturing after the announcement, as proposed by Smith and So (2022).

To assess the economic relevance of these patterns, we construct implementable long-short trading strategies based on A/I day announcements under realistic investment conditions. 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 Sharpe ratios of around 1.06 annualised and positive daily alphas (relative to the q5 factor model) of approximately 0.095%, which remain around 0.08% and statistically significant 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 value enhancing trading signal. Allowing early closures of the positions in events with incremental disclosures or using the optimal closure time predicted by a deep-reinforcement-learning (DRL) algorithm further increases the daily alpha to 0.13% and the annualised Sharpe ratio to 1.22. Based on a dictionary-based sentiment measure by Loughran and McDonald (2011), we find that the strategy’s positive performance is concentrated in events with a positive tone. The long leg still delivers modest positive returns for events with a negative tone, suggesting that even “negative” A/I days serve as value enhancing signals and the downside risk of acting on the announcement alone is limited.

We contribute to the voluntary disclosure literature by showing that A/I days represent a disclosure channel that is distinct from both mandatory reporting and other discretionary communication formats. Unlike earnings calls or conference presentations, A/I days are firm-organised, infrequent, and fully discretionary events that combine strategic prepared remarks with extended, interactive Q&A sessions, making A/I days particularly suited for conveying forward-looking information. The long lead time between announcement and the event itself further enables shaping investor expectations well before the event occurs. [Brown et al. \(2015\)](#) report on survey evidence that sell-side analysts consider A/I days to be among their most important information sources, ranking them third for earnings forecasting, ahead of roadshows and industry conferences. [Kirk and Markov \(2016\)](#) established that A/I days are complementary to other voluntary disclosure channels, such as conference presentations which are typically hosted by third parties (see [Bushee et al., 2011](#); [Green et al., 2014](#); [Bushee et al., 2022](#)). [Park \(2024\)](#) further characterises short- and long-term effects on hosting firms' information environment.

We contribute to the wider literature on managerial communication in voluntary interactive disclosure events, such as earnings conference calls. Complementing existing studies, we demonstrate that the announcement of an upcoming A/I day triggers a pronounced and persistent price run-up, indicating that the announcement to host the event itself is value-enhancing but that there may be other short-term factors contributing to short-horizon under-reaction and an extended price run-up (as documented for earnings announcements by [Kimbrough, 2005](#); [Hirshleifer et al., 2009](#); [Daniel et al., 2020](#)).

We further demonstrate that event informativeness and sentiment as well as changes in market risk expectations are important determinants of post-event returns. As voluntary and face-to-face disclosure events, A/I days offer an interactive platform where managers are more compelled to discuss and share forward-looking insights than in backward-looking settings such as earnings calls. Particularly the inclusion of a Q&A session allows analysts and investors to ask direct questions and draw on verbal cues, such as silence and emotion ([Hollander et al.,](#)

2010; Hobson et al., 2012), to evaluate the informativeness and tone of managerial responses, thereby reducing information asymmetry (Matsumoto et al., 2011; Price et al., 2012; Brockman et al., 2015; Druz et al., 2020). As a result, stock prices may rise independent from 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). We thus contribute to the wider discussion on the role of face-to-face communication and interactive formats as well as other communication channels for managers, such as private meetings with analysts and investors (Solomon and Soltes, 2015), for price discovery.

By demonstrating that announcements of A/I days serve as a value-relevant trading signal that is both economically meaningful and implementable in real time, we further contribute to the literature on event-driven investment and trading strategies. In contrast to 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.² 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. While Hou et al. (2018) highlight a replication crisis, Jensen et al. (2023), on the contrary, argue 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).

²While 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. Getmansky et al. (2015) provide an overview of hedge fund strategies, including event-driven strategies, while 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.

Building on the event-driven paradigm, we develop a novel trading signal based on A/I day announcements applied to long-short trading strategies, with all strategies delivering positive risk-adjusted returns even after incorporating trading and borrowing costs for the short legs. Our baseline strategy relies solely on the announcement of A/I days and a fixed holding period. Our disclosure-adjusted strategy closes positions early depending on pre-event disclosure behaviour. The best performing strategy optimises early closure timing using a DRL algorithm. Specifically, we implement a Trading Deep Q-Network (TDQN) algorithm (Théate and Ernst, 2021), where position exit decisions are guided by a rule set derived from a two-year training period’s multi-factor analysis. In contrast to existing machine learning studies (such as Gu et al., 2020), we apply the TDQN algorithm to an existing long-short portfolio and optimise the exit timing, thus applying machine learning techniques in a different setting.

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, further enhanced by our insights on the heterogeneity of A/I days. Our detected price patterns have further implications for market integrity and regulatory oversight. Selective disclosure regulations such as Regulation Fair Disclosure (RegFD), adopted by the SEC in 2000, were intended to prevent firms from providing material non-public information selectively to institutional investors ahead of public announcements (Bailey et al., 2003; Eleswarapu et al., 2004; Gintschel and Markov, 2004). While voluntary 8-K filings and A/I days fall within the scope of fair disclosure, the strategic timing of such disclosures may fall in a regulatory grey area.

The rest of the paper is organised as follows: Section 2 outlines the empirical methodology and economic mechanisms. Section 3 describes the data sources and reports the summary statistics. Section 4.2 discusses the results related to the determinants of market responses around A/I days, while Section 4.3 develops and evaluates long-short trading strategies based on A/I days. Section 5 concludes.

2. Methodology and economic mechanisms

Methodologically, our analysis is split into two parts. First, we investigate market responses around A/I day announcements and examine the underlying economic mechanisms. Second, we develop an implementable trading strategy that leverages the documented performance patterns.

2.1 Market responses around A/I days

We begin by documenting market responses around the A/I day announcement and the event date using cumulative average abnormal returns (CAARs) of hosting firms. We compute abnormal returns relative to the [Carhart \(1997\)](#) four-factor model. The model parameters are estimated using 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. CAARs are aggregated over two windows – one following the announcement and one preceding the event itself – to capture the full dynamics of investor reaction.

Panel A in [Figure 1](#) 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 announcement of an A/I day serves as a value-enhancing 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 five trading days after the event.

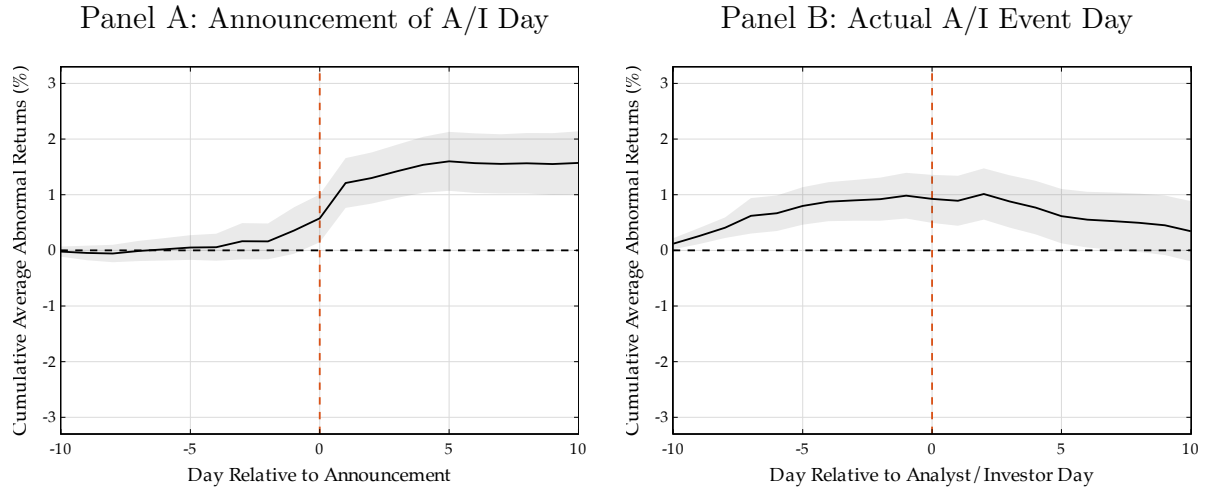


Figure 1. Cumulative Average Abnormal Returns Over Time

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 $t = 0$.

Since firms self-select into hosting A/I days, simple CAARs risk confounding event effects with pre-existing systematic differences between hosting and non-hosting firms. To address this selection concern, we employ propensity score matching (PSM) to construct a control group of observationally similar firms that do not host A/I days and assess market responses based on buy-and-hold abnormal returns (BHARs) as the difference between the compounded returns of the hosting firm and its matched control over predefined event windows.

The matching procedure is based on a logit model incorporating lagged firm characteristics as follows:

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

where Λ 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. 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 (Green et al., 2014; Kirk and Markov, 2016; Bushee et al., 2018a, 2022; Hoberg and Maksimovic, 2022; Chen et al., 2023). We provide a detailed discussion of the control variables and their definitions 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. By matching on lagged firm characteristics using only information available prior to each announcement, we ensure that differences in BHARs around A/I days are not driven by pre-existing firm characteristics, allowing us to interpret the resulting BHARs as capturing return dynamics attributable to the A/I day disclosure process rather than cross-sectional differences in firm fundamentals. 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.

We then assess the financial performance of the matched sets of firms based on BHARs for different time periods τ : (1) announcement period $BHAR[t_0, t_0 + 3]$ (from the announcement date t_0 to three days after the announcement), (2) pre-event period excluding event day $BHAR[t_0, t_1 - 1]$ (from the announcement day to the day before the event) and (3) pre-event period including event day $BHAR[t_0, t_1]$ (from the announcement day to the event day), and (4) post-event period $BHAR[t_1, t_1 + 1 \text{ Week}]$ (from the event date t_1 to one week after the event).

2.2 Determinants of market responses

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

$$\begin{aligned}
BHAR_i[\tau] = & \alpha + \beta_1 Incremental_Disclosure_i \\
& + \beta_2 Tone(Presentation)_i + \beta_3 Tone(Q\&A)_i \\
& + \beta_4 Info(Manager)_i + \beta_5 Obfu(Manager)_i \\
& + \beta_6 RiskInfo_{30,i} + I_i + Y_t + \varepsilon_i
\end{aligned} \tag{2}$$

The explanatory variables are chosen to capture several potential mechanisms that drive $BHAR$ dynamics. First, we capture potentially opportunistic managerial behaviour through pre-event disclosures and promotion, measured by the variable *Incremental_Disclosure*. Second, we control for event-day sentiment of both managers and analysts using a *Tone* variable constructed separately from the presentation and Q&A transcripts. Third, we account for the informativeness of the event. *Info(Manager)* measures informativeness of both managerial presentation and responses to questions, while *Obfu(Manager)* measures the obfuscation component of those sections. Fourth, we control for changes in the market’s perception of the hosting firm’s implied risk (*RiskInfo₃₀*). Finally, we include industry and year fixed effects (I_i, Y_t) to capture any further unobserved industry-specific or year-specific shocks to

the returns. Standard errors are clustered at the firm level. In what follows, we discuss the rationale and definitions of the key variables of interest.

To assess the importance of different determinants, we compute the SHapley Additive exPlanations (SHAP) values, which quantify the marginal contribution of each variable to the model’s R^2 (Lundberg and Lee, 2017). By averaging over all possible orderings of predictors, SHAP values provide a robust measure of each variable’s relative importance in the context of linear regression.³

2.2.1 *Pre-event disclosures and promotion*

Prior to high-visibility disclosure events such as A/I days, managers may have incentives to strategically influence investor expectations by engaging in strategic news releases and disclosures and benefit from their market responses (Edmans et al., 2018). Consistent with this view, Bushee et al. (2022) document that firms often issue discretionary disclosures prior to presentations at broker-organised conferences (i.e. conference presentations). In the context of A/I days, the long and variable lead time between the announcement and the event itself provides managers with a particularly fertile setting for strategic information release in the weeks preceding the event, thus strategically increasing attention toward the hosting firm (as documented by Edmans et al. (2022) before share repurchases) and potentially exacerbating investor biases (cf. Barber and Odean, 2008; Hirshleifer et al., 2009; Solomon et al., 2014). (Bushee et al., 2022) further show that large positive returns prior to disclosure events is typically followed by return reversals (negative returns) after the event, implying price inflation prior to the event.

We define *Incremental_Disclosure* as an indicator variable taking a value of one if a firm filed at least one voluntary 8-K disclosure between the A/I day announcement and the event date,

³Formally, the SHAP value for variable i is $\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|! (|F| - |S| - 1)!}{|F|!} [v(S \cup \{i\}) - v(S)]$, where F is the full set of predictors, S is a subset excluding i , and $v(\cdot)$ denotes the model R^2 evaluated on a given subset. For recent applications of SHAP and related interpretability methods in finance, see Pedersen (2022), Bali et al. (2023), and DeMiguel et al. (2023).

capturing the supply of promotional information by the companies. Voluntary disclosures are identified through EDGAR by extracting the relevant “Item Information” sections (Items 2.02, 7.01, or 8.01).

2.2.2 Event sentiment

To account for the sentiment of the event, we measure linguistic *Tone* using the proportion of “*Positive*” and “*Negative*” words, using an updated version of the finance-oriented Loughran and McDonald (2011) Master Dictionary.⁴ We compute *Tone* measures for each segment k of transcript j , at the level of individual speaker interventions n as follows:

$$Tone_{k,j} = \frac{Positive_{k,j} - Negative_{k,j}}{Positive_{k,j} + Negative_{k,j}} \quad (3)$$

where $Positive_{k,j} = \frac{\sum_{n=1}^N \frac{No. \text{ of Positive Words}_n}{Total \text{ No. of Words}_n}}{N}$, $Negative_{k,j} = \frac{\sum_{n=1}^N \frac{No. \text{ of Negative Words}_n}{Total \text{ No. of Words}_n}}{N}$, N is the total number of speaker interventions within segment k of transcript j , and $Tone_{k,j}$ is bounded between -1 and 1 .⁵ 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.

2.2.3 Event informativeness

To measure the informativeness of managerial presentation and responses during Q&A, we measure information and obfuscation component based on linguistic complexity during the event, following 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

⁴We use only the sub-set of words that can be unambiguously classified of positive or negative.

⁵Averaging 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.

$Fog(Analyst)$.⁶ 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:

$$\begin{aligned} Fog(Presentation) &= \varphi_0 + \varphi_1 Info^* + \varphi_2 Obfu^* + \epsilon, \\ Fog(Analyst) &= \delta_0 + \delta_1 Info^* + \nu, \end{aligned} \tag{4}$$

and then estimating the regression $Fog(Presentation) = \beta_0 + \beta_1 Fog(Analyst) + \eta$, allows recovering the required latent information and obfuscation components. The fitted values $Info(Presentation) = \hat{\beta}_0 + \hat{\beta}_1 Fog(Analyst)$ capture the information component, while the residuals capture the obfuscation component $Obfu(Presentation)$.

We repeat the procedure replacing $Fog(Presentation)$ by $Fog(Response)$ to estimate the two latent components of the managerial responses $Info(Response)$ and $Obfu(Response)$ during Q&A sessions. Finally, $Info(Manager)$ is computed as the first principal component of $Info(Presentation)$ and $Info(Response)$; similarly, $Obfu(Manager)$ is the first principal component of $Obfu(Presentation)$ and $Obfu(Response)$.

Intuitively, the information component of remarks by managers with favourable private information is likely to be higher, as such managers are more likely to engage constructively with analysts and offer detailed presentations and clear responses to complex questions during the Q&A session ([Bushee et al., 2018b](#); [Bushee and Huang, 2024](#)). In contrast, managers who anticipate poor performance may resort to obfuscation to delay or soften investors’ reactions ([Li, 2008](#); [Suslava, 2021](#)). Informative managerial disclosures are therefore more likely to trigger upward revisions in expected future cash flows and increase the stock price, while obfuscatory disclosures would be expected to produce the opposite effect.

⁶ $Fog = 0.4 \times \left(ASL + 100 \times \frac{n_{wsy \geq 3}}{n_w} \right)$, 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.

2.2.4 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 a horizon of h days, in terms of the firm's betas and idiosyncratic risk exposure, based on options with maturities m_1 and m_2 .⁷ The measure for horizon h is calculated as:

$$\begin{aligned} RiskInfo_h &= h \times \Delta IV_t + \mathbb{E}_{\tau_D^-}^Q[\tilde{J}^2] \\ &= h \times \Delta IV_t + \frac{m_2}{m_2 - m_1} \mathbb{E}_{\tau_D^-}^Q \left[\int_{\tau_D}^{\tau_D + m_1} \tilde{\sigma}_{D,s}^2 ds \right] - \frac{m_1}{m_2 - m_1} \mathbb{E}_{\tau_D^-}^Q \left[\int_{\tau_D}^{\tau_D + m_2} \tilde{\sigma}_{D,s}^2 ds \right], \end{aligned} \quad (5)$$

where the term $h \times \Delta IV_t$ captures the change in at-the-money (ATM) Black-Scholes implied variance per day around the event date τ_D for options with h days to maturity, reflecting the unexpected revision in expected future variance following the event. $\tilde{\sigma}$ is the instantaneous return volatility. The second term $\mathbb{E}_{\tau_D^-}^Q[\tilde{J}^2]$ —the risk-neutral expected event-date return variance prior to the event—corrects for the predictable decline in implied variance associated with anticipated announcement day variance.⁸

For a 30-day horizon, we measure the pre-event-implied variance based on implied variances of ATM options with $h = 30$ day maturity, two days prior to the event date τ_D (to account for information leakage), $IV_{\tau_D-2,30}$. The second correction term is estimated as the difference between the implied variance from a short-term option, $IV_{m_1} = IV_{30}$, and that from a long-

⁷As 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.

⁸[Patell and Wolfson \(1979\)](#) show that implied variance rises ahead of anticipated events and predictably declines once uncertainty is resolved, implying that raw changes in implied variance mechanically understate informational content; we therefore adjust for the expected announcement-date variance, $\mathbb{E}_{\tau_D^-}^Q[\tilde{J}^2]$, following [Smith and So \(2022\)](#).

term option, $IV_{m_2} = IV_{60}$, following [Dubinsky et al. \(2019\)](#). The measure for the 30-day horizon is thus calculated as:

$$RiskInfo_{30} = 30 \times [IV_{\tau_D+1,30} - IV_{\tau_D-2,30}] + \frac{IV_{\tau_D-2,30} - IV_{\tau_D-2,60}}{\frac{1}{30} - \frac{1}{60}}, \quad (6)$$

where the first term captures the announcement-induced change in expected return variance scaled over the subsequent 30 days and the second component corrects for the predictable decline in implied variance associated with anticipated announcement-day volatility. In line with empirical predictions of [Smith and So \(2022\)](#), we anticipate that higher levels of risk information will negatively affect BHARs, as greater risk perceptions are positively associated with the firm’s discount rate and return volatility, consistent with a higher required risk premium.

2.3 *Trading strategy and portfolio construction*

To demonstrate the economic value of A/I days, we implement 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 (motivated by the CAAR reversals after trading day 5 in [Figure 1](#)), capturing potential pre- and post-event drifts in stock prices.

Our previous discussion suggests that events accompanied by additional prior disclosures may experience a stronger pre-event run-up followed by subsequent return reversals. We therefore apply differentiated holding periods for events with and without additional disclosures, implementing a “Disclosure-Adjusted” strategy. Specifically, the portfolio is liquidated one day before the event when *Incremental_Disclosure* is identified in the window between the

announcement and one day prior to the event; otherwise, the position is held until one week after the event.

Our third strategy employs deep reinforcement learning (DRL) to determine optimal investment horizons, enabling a more dynamic and adaptive approach to portfolio exit decisions following [Hambly et al. \(2023\)](#). We apply the TDQN algorithm of [Théate and Ernst \(2021\)](#), in which exit and hold decisions are informed by historical stock performance, market conditions, and risk-adjusted return expectations, estimated over a two-year training period prior to the event. We label this strategy “Optimal-Timing”. The position is closed at any point between the announcement day and one week after the event, as recommended by the TDQN algorithm, with one week post-event serving as the maximum holding period. A detailed discussion of the algorithm can be found in Internet Appendix Section [A](#).

Figure [2](#) illustrates the timing structure and exit rules of the three strategies under consideration.

2.3.1 Performance evaluation and transaction costs

To evaluate the performance of the trading strategies described above, we estimate a comprehensive range of performance and risk measures commonly used in portfolio management separately for the long and short leg of our strategies. 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 95% confidence level, as well as maximum drawdown (*MDD*), the manipulation-proof performance measure (*MPPM*) from [Goetzmann et al. \(2007\)](#). 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, for firms hosting the A/I day and their matched peers. The measures are formally defined in Appendix Table [A.1](#).

We further evaluate the performance of the long-short portfolio relative to several factor models. We first 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

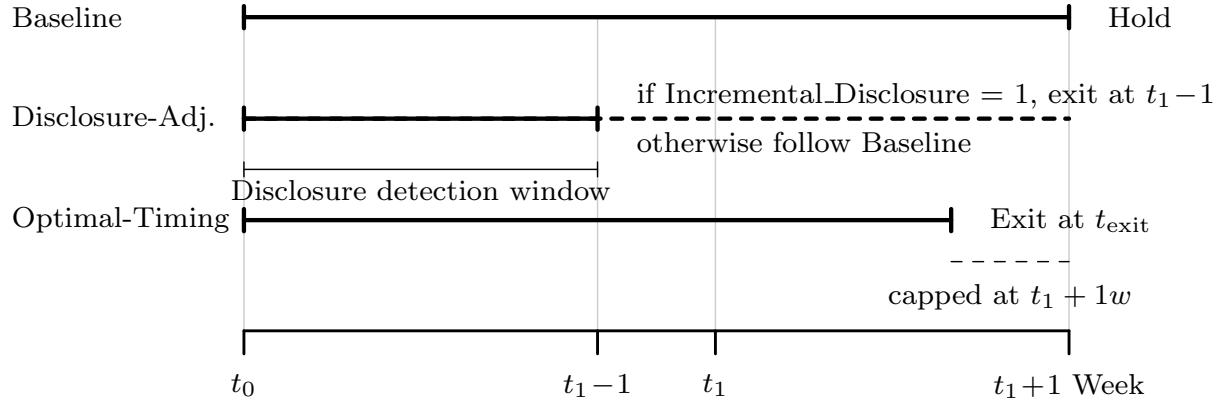


Figure 2. Trading Strategies Around A/I Days

This figure illustrates the timing structure of the three trading strategies examined in Section 2.3. The horizontal axis denotes event time, where t_0 is the A/I day announcement date, t_1 is the event date, and $t_1 + 1 \text{ Week}$ is one week after the event. The *Baseline* strategy initiates a long (short) position in announcing (matched non-announcing) firms at t_0 and holds the position until one week after the event. The *Disclosure-Adjusted* strategy modifies the exit rule based on the identification of *Incremental_Disclosure* between t_0 and $t_1 - 1$. If *Incremental_Disclosure* equals one the position is closed at $t_1 - 1$, otherwise, it follows the Baseline holding period. The *Optimal-Timing* strategy employs the TDQN algorithm to dynamically determine the exit date using information from a two-year pre-event training window. Positions may be closed at any time between t_0 and $t_1 + 1 \text{ Week}$, subject to a maximum holding period of one week after the event.

momentum factor (**MOM**) and further use the Fama-French 5-factor model (FF5), which adds profitability (**RMW**) and investment (**CMA**) to FF4, and 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. \(2021\)](#).

To demonstrate implementability under real-world conditions, we account for transaction costs following [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 [B](#).

3. Data and summary statistics

3.1 *Firm and A/I data sources*

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 2,525 transcripts from A/I days held by 1,052 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 find 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.⁹

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.¹⁰

Our data on institutional holdings come from the Thomson Reuters Institutional (13F) Holdings database (CDA/Spectrum s34). The text-based measure identifying the third stage of the product life cycle, which is used as one of the determinants of the probability of hosting an A/I day, is sourced from Hoberg and Maksimovic’s Data Library.¹¹ Finally, we use standardized option data from OptionMetrics to construct the risk information measures.

3.2 *Summary statistics*

Our final sample consists of 935 A/I days transcripts from firms with complete financial information, 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. Table 1 reports summary statistics, including tests of mean and median differences for both groups of firms. The statistics are based on firm-level observations.

⁹Only 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.

¹⁰The corresponding websites are http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html and <http://global-q.org/index.html>.

¹¹<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 intensity, which may reflect their position in a later stage of the product life cycle, where R&D spending typically declines. They have lower earnings volatility and higher stock returns. Differences in all of these covariates are significant at the 1% level. These descriptive results support our use of a matching approach, as hosting and non-hosting firms are found to be systematically different across a broad range of characteristics.

[Insert Table 1 About Here]

Summary statistics for event-level 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 $Obfu(Presentation)$ and $Obfu(Response)$ are zero by construction, as they are regression residuals. Their standard deviations are 1.564 and 1.146, respectively. The

mean of $Info(Presentation)$ is 11.241, while $Info(Response)$ averages 9.628. The higher value in the presentation segment reflects the planned and structured nature of prepared remarks, while the lower value in the Q&A session may come from its more spontaneous format and the use of strategic ambiguity in managerial responses.

The mean of $RiskInfo_{30}$ equals 0.003, indicating the average impact of A/I days on investors' expectations of the future return variance. To demonstrate the economic significance of the variable, we also report the scaled risk information $SRiskInfo_{30}$ by dividing $RiskInfo_{30}$ by the firms' diffusive return variance which reflects the units of variance expected over the remaining life of the option (Dubinsky et al., 2019). The $SRiskInfo_{30}$ of -1% indicates that the firms' expected riskiness is reduced by approximately 1% of the expected variance of stock returns over the 30 days following the event. The distribution of $SRiskInfo_{30}$ further suggests that A/I days can both lower and increase the hosting firms' expected risk over a 30 day horizon, with a median reduction of around 5%. At the same time, analyst activity increases in the run-up to the event, with an average of four analysts issuing at least one forecast during this period.

In our sample, 52% of A/I days have pre-event incremental disclosures, defined as instances in which voluntary 8-K filings occur between the announcement date and the event date. Figure 3 illustrates the distribution of timing of 8-K filings. We can see that additional filings become more frequent as the event date approaches, with median timings of 22 days prior to the A/I day.

Overall, A/I days are perceived positively by the market, with gains largely realised prior to the event. Market responses reveal a clear pattern of market anticipation prior to the event. The average $BHAR[t_0, t_0 + 3 \text{ Days}]$ in the three days following the announcement is 1.34%, approximately 0.45% per day. The marginal increase then slows down, with $BHAR[t_0, t_1 - 1]$ being 3.7% in the pre-event window, approximately 0.09% per day given an average time length between the announcement and the event of 39 days. $BHAR[t_0, t_1]$ reaches 3.79% when the event day is included, indicating that the event date $BHAR$ is similarly around

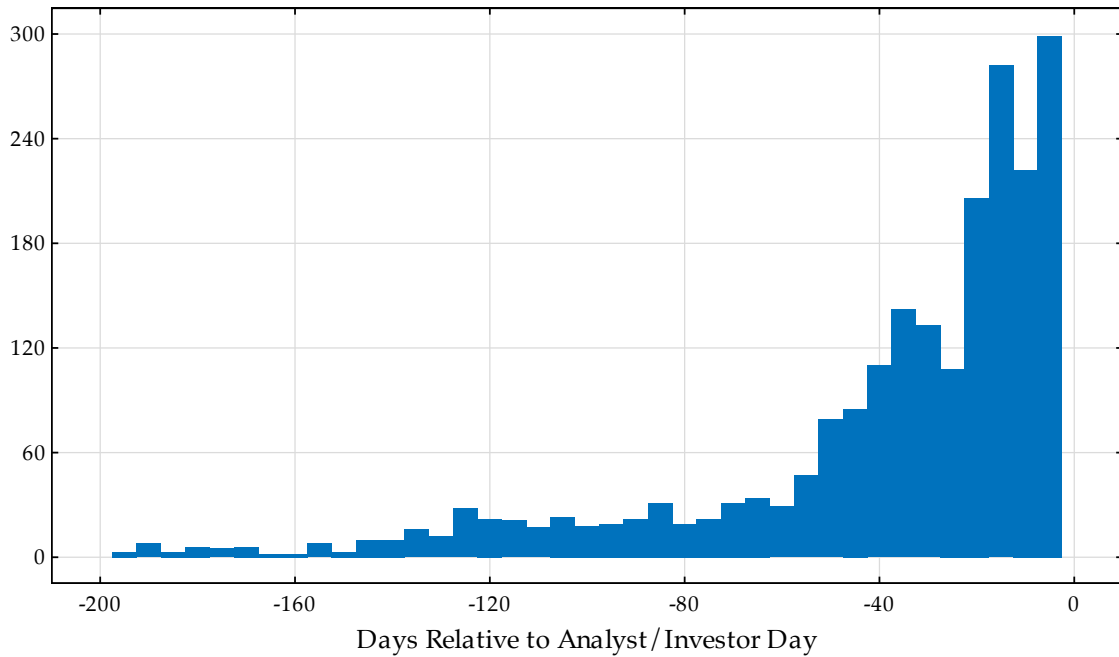


Figure 3. Timing of 8-K Filings Before A/I Day

This figure displays the distribution of voluntary 8-K filings in the pre-event window relative to analyst/investor (A/I) days. The horizontal axis reports event time in calendar days, where 0 denotes the A/I day and negative values indicate days prior to the event. The vertical axis shows the frequency of occurrences.

0.09%. Abnormal returns decline sharply to 0.08% in the week after the event, amounting to just 0.016% per day if equally distributed over a 5-day trading week. These findings indicate that most of the value is realised before the event, consistent with a strong announcement effect together with strategic pre-event disclosures and a post-announcement price drift due to potential behavioral biases and investor expectations.

[Insert Table 2 About Here]

4. Results

4.1 Cross-sectional determinants of the probability of hosting A/I days

To illustrate the cross-sectional determinants of hosting A/I days based on firm characteristics, we estimate a single regression as defined in Eq. (1) using the full sample and include industry and year fixed effects. This specification captures the general effects that internal benefits and external pressure/demand for disclosure have on the probability of hosting an A/I day.¹² Table A.2 in the Appendix reports the estimation results. The %STDY 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.

In terms of magnitude, *Financing* and *Bid-Ask Spread* exhibit the largest marginal effects among internal factors. A one standard deviation increase in *Bid-Ask Spread* reduces the odds of hosting an A/I day by 83.28%, while issuing debt or equity (*Financing* = 1) raises the odds of hosting an event by 54.57%, relative to firms that do not seek external financing.

¹²For the estimation of BHAR and the implementation of the trading strategy, we account for any look-ahead bias by re-estimating the logit model in Eq. (1) used for PSM every time a new A/I day is announced, and we are not relying on the full-sample estimation discussed here.

External demand factors also play an important role. Larger and older firms with broader analyst coverage are more likely to host A/I days, as indicated by the positive and significant coefficients on $\ln(1+Size)$, $\ln(1+Age^{Firm})$, and $\ln(1+No. \text{ of Analysts})$. High-tech firms exhibit a significantly higher likelihood of hosting (0.183, t -stat = 2.729), and the positive, significant coefficient on *Intangibles* (0.185, t -stat = 2.421) suggests that firms facing greater valuation uncertainty are more proactive in providing forward-looking information, consistent with [Kirk and Markov \(2016\)](#). The negative association with *Book-to-Market* and the positive coefficients on *Leverage* and *Loss* suggest that growth-oriented and more leveraged firms, as well as those that have recently experienced a negative net income, are more inclined to engage in active investor communication. Institutional ownership ($Ownership^{INS}$) has a positive albeit statistically insignificant sign.

4.2 Market responses around A/I days

Table 3 summarises the estimation results for the determinants of market responses for pre-event and post-event BHARs, as defined in Eq. (2).

Pre-event returns, both excluding and including the event day itself, are heavily influenced by *Incremental_Disclosure*. Firms associated with pre-event *Incremental_Disclosure* experience significantly higher BHARs during the pre-event windows, with an average increase of approximately 3.68 percentage points between the announcement date (t_0) and one day before the event ($t_1 - 1$), and 3.65 percentage points between the announcement date and the event date (t_1). These effects approximately double the average BHAR over these windows. We find, however, no effect of the incremental disclosure on post-event returns.

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 approximately 0.40 percentage point

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 (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 incorporated into the prices swiftly, as no significant effect can be detected for the week-long $BHAR[t_1, t_1 + 1 \text{ Week}]$ after the event.

The post-event returns are primarily driven by the informativeness of the event and changes in expected risk. $Info(Manager)$, which captures the overall informativeness of managerial speech, is positively related to post-event BHAR, reflecting the gradual processing of value-relevant information by investors following A/I day disclosures. A one standard deviation increase in managerial informativeness leads to a 0.77 percentage point increase in the BHAR after the event. Increases in market risk expectations, on the contrary, are related to increases in risk premia and discount rates, thereby reducing abnormal returns. A one standard deviation increase in $RiskInfo_{30}$ is associated with a 0.06 percentage point decline in post-event BHARs. While the tone of the event seems to be reflected promptly in the event-day returns, overall informativeness based on linguistic complexity and risk expectations show more persistent effects with post-event BHAR one week after the event.

To assess the relative importance of different determinants, we present the SHAP values of the individual determinants, which represent the percentage of the model’s explained variance attributable to each explanatory variable, in Panel B of Table 3. In the pre-event windows, particularly from the announcement date (t_0) to the day before the event, $Incremental_Disclosure$ is the most important predictor, explaining on average over 66% of the model’s R^2 for $BHAR[t_0, t_1 - 1]$. In contrast, during the post-event window (from t_1 to $t_1 + 1 \text{ Week}$), the relative importance shifts to information- and risk-related variables. The influence of $Incremental_Disclosure$ drops to 3.4%, while $Info(Manager)$ captures 48%, followed by $RiskInfo$ (20%).

These results suggest that incremental disclosure activities contribute to market anticipation before the event, while market responses during and after the event are more influenced by event informativeness and changes in market risk perceptions.

[Insert Table 3 About Here]

4.3 Trading strategy and performance

To demonstrate the economic value of market responses around A/I days, we identify 1,203 matched pairs of firms (each pair consisting of a hosting firm and a non-hosting firm) using the PSM described in Section 2¹³ and implement three long-short strategies exploiting A/I day-related signals, (1) a *Baseline* strategy holds the portfolio from the day of the event announcement until one week after the event, (2) a *Disclosure-Adjusted* strategy that holds the portfolio in the baseline strategy, unless *Incremental Disclosure* 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.¹⁴ Table 4 compares the average performance of the trading strategies buying stocks of firms that hold A/I days while going short their PSM-matched peers.

[Insert Table 4 About Here]

¹³Table A.3 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, with the differences in propensity scores smaller than 0.01. We thus account for the differences between hosting and non-hosting firms, illustrated in Figure A.1 in the Appendix. After matching, the matched and control samples are statistically indistinguishable from one another across all these dimensions.

¹⁴Our 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 (SR) increases from 0.019 for non-hosts to 0.076 for hosts, with the difference being 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 also exhibit slightly less negative tail-risk measures (VaR and ES) compared to non-hosting firms, indicating lower exposure to extreme losses and a more favourable risk profile. They display a significantly higher $MPPM$, reflecting stronger performance after adjusting for investor risk aversion.

Compared to the benchmark, the *Disclosure-Adjusted* strategy delivers higher mean returns for hosting firms (0.136%) and a larger long-short spread (0.114%), whilst the risk profile in terms of standard deviation, downside risk, VaR and ES remain similar. The *Optimal-Timing* strategy delivers strong performance too. It achieves similar long-leg returns as the *Disclosure-Adjusted* strategy, and the largest long-short spread (0.133%), driven predominantly by weaker performance of the short leg. This strategy performs well on the risk-adjusted measures, but its performance is generally comparable with that of the *Disclosure-Adjusted* strategy. The TDQN algorithm closes approximately 62% of positions before the A/I day, as shown in Figure 4. Hence, it seems to be able to capture the pre-event run-up and avoid any potential price reversals after the event, or even shortly before it. Investors, thus, have a choice between purely statistically driven closing time in *Optimal-Timing* and heuristic-based exits based on economic indicators, like in the *Disclosure-Adjusted* strategy to achieve similar performance patterns.

Table 5 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. Relative to the factor models, the *Disclosure-Adjusted* strategy performs better than the baseline strategy, and the *Optimal-*

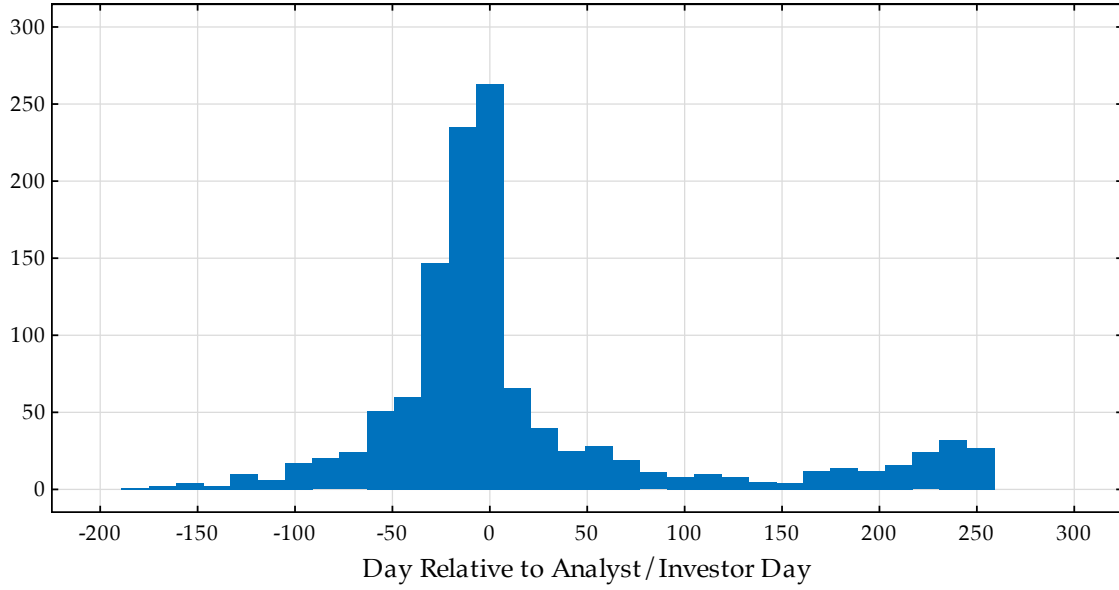


Figure 4. Optimal Stopping Distribution by the TDQN Algorithm

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.

Timing performing best of all three strategies, delivering, for example, an alpha of 0.125% per day relative to the q5 model. 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 5 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 Table 6. 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 further check if the performance of these trading strategies is driven by a particular segment of our data. Table 7 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 had prior disclosure 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 7 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 experience losses on average, 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.

The long-short alpha associated with positive Q&A tone is higher than that of the negative tone in the Baseline and Disclosure-Adjusted strategies. 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, possibly due to the fact that the Optimal-Timing strategy closes positions prior to the event, thus avoiding any negative post-event effects from negative-tone events. In particular, 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, high-tech firms consistently demonstrate better performance than non-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 with higher growth potential. Given their reliance on intangible assets and R&D, high-tech firms may exhibit higher valuation uncertainty which may be alleviated by A/I days that are likely to provide forward-looking insights.

Finally, when splitting the sample into events with and without incremental disclosures, we find that portfolios that include event firms without prior disclosure yield higher alphas compared to disclosure-preceding events. This pattern suggests that, by holding an A/I day, non-disclosing firms may be signalling an intention to release new, forward-looking information, in contrast to firms that have already provided updates through earlier disclosures. The market may perceive these A/I events as more informative, particularly when little prior guidance has been given.

5. Conclusion

This paper examines A/I days as strategic voluntary disclosure events and shows that both the decision to hold such an event and the way firms manage the disclosure environment prior to the event can affect market responses. We find a price run-up prior to the event, predominantly driven by incremental voluntary disclosures of hosting companies prior to the event, and an information-driven price adjustment for events without prior disclosure. We further illustrate

the economic value of A/I day announcements by developing trading strategies that generate positive risk-adjusted returns.

Our findings deepen the understanding of A/I days as a voluntary disclosure channel, by demonstrating the economic value of the announcement of the event itself and the role of pre-event disclosures and event informativeness in shaping market responses. These findings highlight the importance of modelling disclosure as a dynamic, multi-stage process with both informational and promotional components. Moreover, the differential market reaction to prepared remarks versus spontaneous Q&A highlights the role of interactive communication in extracting information from speech and reducing information asymmetry. Furthermore, by demonstrating that return dynamics around A/I days reflect both event informativeness and changes in expectations of the firm risk, our results conceptualise disclosure as influencing multiple components of firm value.

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 with robust performance even after accounting for trading and borrowing costs. The distinction between events with and without incremental voluntary disclosures provides a practical tool for risk management, as monitoring voluntary 8-K filings may help investors anticipate return run-ups and refine exit timing. For analysts, our results highlight the informational role of the Q&A session, emphasising the value of real-time assessment of managerial informativeness and tone. For regulators, the evidence of the link between pre-event additional disclosures and post-announcement drifts raises concerns about the potential for short-term price inflation around voluntary disclosures.

References

- Ali, A., Klasa, S., and Yeung, E. (2014). Industry concentration and corporate disclosure policy. *Journal of Accounting and Economics*, 58(2-3):240–264.
- Bailey, W., Li, H., Mao, C. X., and Zhong, R. (2003). Regulation Fair Disclosure and Earnings Information: Market, Analyst, and Corporate Responses. *The Journal of Finance*, 58(6):2487–2514.
- Bali, T. G., Beckmeyer, H., Moerke, M., and Weigert, F. (2023). Option return predictability with machine learning and big data. *The Review of Financial Studies*, 36(9):3548–3602.
- Bali, T. G., Engle, R. F., and Murray, S. (2016). *Empirical asset pricing: The cross section of stock returns*. John Wiley & Sons.
- Barber, B. M. and Odean, T. (2008). All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors. *Review of Financial Studies*, 21(2):785–818.
- Barroso, P. and Detzel, A. (2021). Do limits to arbitrage explain the benefits of volatility-managed portfolios? *Journal of Financial Economics*, 140(3):744–767.
- Barroso, P. and Santa-Clara, P. (2015). Momentum has its moments. *Journal of Financial Economics*, 116(1):111–120.
- Brockman, P., Li, X., and Price, S. M. (2015). Differences in conference call tones: Managers vs. analysts. *Financial Analysts Journal*, 71(4):24–42.
- Brown, L. D., Call, A. C., Clement, M. B., and Sharp, N. Y. (2015). Inside the “Black Box” of Sell-Side Financial Analysts. *Journal of Accounting Research*, 53(1):1–47.
- Bushee, B., Taylor, D. J., and Zhu, C. (2022). The dark side of investor conferences: Evidence of managerial opportunism. *The Accounting Review*.

- Bushee, B. J., Gerakos, J., and Lee, L. F. (2018a). Corporate jets and private meetings with investors. *Journal of Accounting and Economics*, 65(2-3):358–379.
- Bushee, B. J., Gow, I. D., and Taylor, D. J. (2018b). Linguistic complexity in firm disclosures: Obfuscation or information? *Journal of Accounting Research*, 56(1):85–121.
- Bushee, B. J. and Huang, Y. (2024). Do analysts and investors efficiently respond to managerial linguistic complexity during conference calls? *The Accounting Review*, 99(4):143–168.
- Bushee, B. J., Jung, M. J., and Miller, G. S. (2011). Conference presentations and the disclosure milieu. *Journal of Accounting Research*, 49(5):1163–1192.
- Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, 52(1):57–82.
- Chen, J., Li, N., and Zhou, X. (2023). Equity financing incentive and corporate disclosure: new causal evidence from seo deregulation. *Review of Accounting Studies*, 28(2):1003–1034.
- Cochrane, J. H. (2011). Discount rates. *NBER Working Paper No. w16972*.
- Daniel, K., Hirshleifer, D., and Sun, L. (2020). Short- and Long-Horizon Behavioral Factors. *The Review of Financial Studies*, 33(4):1673–1736.
- DeMiguel, V., Gil-Bazo, J., Nogales, F. J., and Santos, A. A. (2023). Machine learning and fund characteristics help to select mutual funds with positive alpha. *Journal of Financial Economics*, 150(3):103737.
- Druz, M., Petzev, I., Wagner, A. F., and Zeckhauser, R. J. (2020). When managers change their tone, analysts and investors change their tune. *Financial Analysts Journal*, 76(2):47–69.
- Dubinsky, A., Johannes, M., Kaeck, A., and Seeger, N. J. (2019). Option pricing of earnings announcement risks. *The Review of Financial Studies*, 32(2):646–687.

- Edmans, A., Fang, V. W., and Huang, A. H. (2022). The Long-Term Consequences of Short-Term Incentives. *Journal of Accounting Research*, 60(3):1007–1046.
- Edmans, A., Goncalves-Pinto, L., Groen-Xu, M., and Wang, Y. (2018). Strategic News Releases in Equity Vesting Months. *The Review of Financial Studies*, 31(11):4099–4141.
- Eleswarapu, V. R., Thompson, R., and Venkataraman, K. (2004). The Impact of Regulation Fair Disclosure: Trading Costs and Information Asymmetry. *Journal of Financial and Quantitative Analysis*, 39(2):209–225.
- Fama, E. F. and French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance*, 47(2):427–465.
- Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, 33(1):3–56.
- Farrelly, C. and Lhabitant, F.-S. (2017). Event-driven hedge fund strategies. In *Hedge Funds: Structure, Strategies, and Performance*. Oxford University Press.
- Getmansky, M., Lee, P. A., and Lo, A. W. (2015). Hedge Funds: A Dynamic Industry in Transition. *Annual Review of Financial Economics*, 7(Volume 7, 2015):483–577.
- Gintschel, A. and Markov, S. (2004). The effectiveness of Regulation FD. *Journal of Accounting and Economics*, 37(3):293–314.
- Goetzmann, W., Ingersoll, J., Spiegel, M., and Welch, I. (2007). Portfolio performance manipulation and manipulation-proof performance measures. *The Review of Financial Studies*, 20(5):1503–1546.
- Green, T. C., Jame, R., Markov, S., and Subasi, M. (2014). Broker-hosted investor conferences. *Journal of Accounting and Economics*, 58(1):142–166.
- Gu, S., Kelly, B., and Xiu, D. (2020). Empirical Asset Pricing via Machine Learning. *The Review of Financial Studies*, 33(5):2223–2273.

- Gunning, R. (1952). Technique of clear writing. *McGraw-Hill*.
- Hambly, B., Xu, R., and Yang, H. (2023). Recent advances in reinforcement learning in finance. *Mathematical Finance*, 33(3):437–503.
- Hasbrouck, J. (2009). Trading costs and returns for us equities: Estimating effective costs from daily data. *The Journal of Finance*, 64(3):1445–1477.
- Hirshleifer, D., Lim, S. S., and Teoh, S. H. (2009). Driven to Distraction: Extraneous Events and Underreaction to Earnings News. *The Journal of Finance*, 64(5):2289–2325. _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.2009.01501.x>.
- Hoberg, G. and Maksimovic, V. (2022). Product life cycles in corporate finance. *The Review of Financial Studies*, 35(9):4249–4299.
- Hobson, J. L., Mayew, W. J., and Venkatachalam, M. (2012). Analyzing Speech to Detect Financial Misreporting. *Journal of Accounting Research*, 50(2):349–392.
- Hollander, S., Pronk, M., and Roelofsen, E. (2010). Does silence speak? an empirical analysis of disclosure choices during conference calls. *Journal of Accounting Research*, 48(3):531–563.
- Hou, K., Mo, H., Xue, C., and Zhang, L. (2021). An augmented q-factor model with expected growth. *Review of Finance*, 25(1):1–41.
- Hou, K., Xue, C., and Zhang, L. (2015). Digesting anomalies: An investment approach. *The Review of Financial Studies*, 28(3):650–705.
- Hou, K., Xue, C., and Zhang, L. (2018). Replicating anomalies. *The Review of Financial Studies*, 33(5):2019–2133.
- Jensen, T. I., Kelly, B., and Pedersen, L. H. (2023). Is there a replication crisis in finance? *The Journal of Finance*, 78(5):2465–2518.

- Kimbrough, M. D. (2005). The effect of conference calls on analyst and market underreaction to earnings announcements. *The Accounting Review*, 80(1):189–219.
- Kirk, M. P. and Markov, S. (2016). Come on over: Analyst/investor days as a disclosure medium. *The Accounting Review*, 91(6):1725–1750.
- Kolokolova, O. and Xu, X. (2024). Enhancing betting against beta with stochastic dominance. *Journal of Empirical Finance*, 76:101465.
- Li, F. (2008). Annual report readability, current earnings, and earnings persistence. *Journal of Accounting and Economics*, 45(2-3):221–247.
- Loughran, T. and McDonald, B. (2011). When is a liability not a liability? textual analysis, dictionaries, and 10-ks. *The Journal of Finance*, 66(1):35–65.
- Lundberg, S. M. and Lee, S.-I. (2017). A unified approach to interpreting model predictions. *Advances in neural information processing systems*, 30.
- Matsumoto, D., Pronk, M., and Roelofsen, E. (2011). What makes conference calls useful? the information content of managers’ presentations and analysts’ discussion sessions. *The Accounting Review*, 86(4):1383–1414.
- Moreira, A. and Muir, T. (2017). Volatility-managed portfolios. *The Journal of Finance*, 72(4):1611–1644.
- Park, M. (2024). Analyst/investor days and firms’ information environment. *Accounting Horizons*, pages 1–22.
- Patell, J. M. and Wolfson, M. A. (1979). Anticipated information releases reflected in call option prices. *Journal of accounting and economics*, 1(2):117–140.
- Pedersen, L. H. (2022). Big data asset pricing 5: Machine learning in asset pricing. *Available at SSRN 4068797*.

- Penman, S. H. and Yehuda, N. (2019). A Matter of Principle: Accounting Reports Convey Both Cash-Flow News and Discount-Rate News. *Management Science*, 65(12):5584–5602.
- Price, S. M., Doran, J. S., Peterson, D. R., and Bliss, B. A. (2012). Earnings conference calls and stock returns: The incremental informativeness of textual tone. *Journal of Banking & Finance*, 36(4):992–1011.
- Smith, K. C. and So, E. C. (2022). Measuring risk information. *Journal of Accounting Research*, 60(2):375–426.
- Solomon, D. and Soltes, E. (2015). What Are We Meeting For? The Consequences of Private Meetings with Investors. *The Journal of Law and Economics*, 58(2):325–355.
- Solomon, D. H., Soltes, E., and Sosyura, D. (2014). Winners in the spotlight: Media coverage of fund holdings as a driver of flows. *Journal of Financial Economics*, 113(1):53–72.
- Suslava, K. (2021). Stiff business headwinds and uncharted economic waters: The use of euphemisms in earnings conference calls. *Management Science*, 67(11):7184–7213.
- Swade, A., Hanauer, M. X., Lohre, H., and Blitz, D. (2024). Factor zoo (.zip). *The Journal of Portfolio Management*, 50(3):11–31.
- Théate, T. and Ernst, D. (2021). An application of deep reinforcement learning to algorithmic trading. *Expert Systems with Applications*, 173:114632.

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

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	***
Ownership ^{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+Age ^{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: Event Characteristics

This table presents event-level 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). BHARs (%) are computed as the difference in compounded returns between A/I-day firms and their matched firms, described in Section 2.1. (1,203 observations are due to event-based matching, as firms that host more than one A/I day can be matched to different firms for individual events.) All the variables are defined in Table A.1.

	N	Mean	Std.	IQR	25%	50%	75%
<u>Sentiment</u>							
Tone	2,525	0.026	0.279	0.378	−0.166	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	0.358	−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
<u>Linguistic Complexity</u>							
Fog	2,525	12.498	1.344	1.856	11.532	12.397	13.389
Fog(Presentation)	2,525	13.173	1.726	2.359	11.941	12.946	14.300
Fog(Q&A)	2,525	10.821	2.207	1.367	10.363	11.055	11.729
Fog(Response)	2,525	10.899	2.309	1.579	10.330	11.150	11.909
Fog(Analyst)	2,525	9.151	4.122	1.778	9.351	10.338	11.129
<u>Latent Components of Linguistic Complexity</u>							
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	1.253	−0.684	0.000	0.569
Info(Response)	2,525	9.628	3.954	0.261	11.048	11.193	11.309
Obfu(Manager)	2,525	0.000	0.925	1.060	−0.565	0.000	0.495
Info(manager)	2,525	0.000	0.925	0.620	−0.381	0.000	0.239
<u>Market Responses</u>							
Incremental Disclosure	2,525	0.517	0.500	1.000	0.000	1.000	1.000
RiskInfo ₃₀	1,908	0.003	0.134	0.005	−0.003	−0.001	0.002
SRiskInfo ₃₀	1,908	−0.010	0.826	0.375	−0.231	−0.049	0.144
<u>BHARs (%)[†]</u>							
BHAR[t_0 , $t_0 + 3$ Days]	1,203	1.343	8.425	7.041	−2.570	0.865	4.471
BHAR[t_0 , $t_1 - 1$]	1,203	3.704	16.375	14.281	−4.204	1.970	10.077
BHAR[t_0 , t_1]	1,203	3.789	17.426	15.867	−4.709	2.275	11.159
BHAR[t_1 , $t_1 + 1$ Week]	1,203	0.077	9.492	9.599	−4.808	0.022	4.790

Table 3. Analyst/Investor Days BHARs

Panel A of this table reports OLS regression results of buy-and-hold abnormal returns (BHARs) 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. *Incremental Disclosure* is a dummy equal to one if the firm issues a voluntary 8-K (Items 2.02, 7.01, or 8.01). *Tone(Presentation)* and *Tone(Q&A)* measure sentiment in the manager’s presentation and Q&A session, respectively. *Info(Manager)* (*Obfu(Manager)*) represents the first principal component of the latent information (obfuscation) dimension, following [Bushee et al. \(2018b\)](#). *RiskInfo*₃₀ measures implied risk over a 30-day horizon, following [Smith and So \(2022\)](#). 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. Panel B reports the relative importance of the explanatory variables in predicting BHARs based on the Shapley (SHAP) value decomposition, that quantifies the marginal contribution of each variable to the model’s R-squared by 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 $[t_0, t_0 + 3 \text{ Days}]$	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: Regression Results				
Incremental Disclosure	0.623 (1.217)	3.684*** (3.652)	3.645*** (3.421)	0.345 (0.591)
Tone(Presentation)	−0.180 (−0.588)	−0.400 (−0.752)	−0.582 (−1.043)	0.223 (0.577)
Tone(Q&A)	0.257 (0.892)	0.865 (1.558)	1.456** (2.393)	0.350 (1.013)
Info(Manager)	0.428 (1.501)	0.738 (1.331)	0.598 (0.927)	0.835** (2.439)
Obfu(Manager)	0.268 (1.090)	1.228 (1.548)	1.454 (1.608)	0.448 (1.518)
RiskInfo ₃₀	0.096 (0.330)	−0.282 (−1.070)	−0.287 (−1.113)	−0.472** (−2.116)
Observations	935	935	935	935
Industry & Year FE	✓	✓	✓	✓
R ² (%)	3.444	5.827	5.666	2.918
Panel B: Explanatory importance (SHAP values)				
Incremental Disclosure	28.95	66.04	51.56	3.44
Tone(Presentation)	6.36	2.21	3.40	4.97
Tone(Q&A)	16.87	14.61	31.78	8.23
Info(Manager)	43.45	8.27	3.47	47.98
Obfu(Manager)	1.75	7.33	8.79	15.85
RiskInfo ₃₀	2.63	1.54	1.01	19.52

Table 4. Trading Strategies: Risk and Return Measures

This table reports the risk and return measures for the Baseline, Disclosure-Adjusted, and Optimal-Timing long-short strategies, based on 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. Disclosure-Adjusted refers to the strategy in which the portfolio is held until one day before the event if *Incremental Disclosure* 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				Disclosure-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***	0.114	0.136	0.022	0.114***	0.133	0.133	0.000	0.133***
Std. (%)	1.422	1.674	1.653	0.021	1.464	1.689	1.675	0.014	1.734	1.685	1.814	-0.129
SR	0.067	0.076	0.019	0.057***	0.078	0.080	0.013	0.067***	0.077	0.079	0.000	0.079***
DR (%)	0.931	1.139	1.199	-0.060	0.948	1.145	1.222	-0.077	1.092	1.139	1.354	-0.214
Sortino	0.102	0.111	0.027	0.085***	0.120	0.119	0.018	0.101***	0.122	0.117	0.000	0.117***
Omega (%)	1.238	1.268	1.063	0.205***	1.286	1.288	1.043	0.246***	1.275	1.268	1.000	0.268***
Upside (%)	0.531	0.527	0.449	0.078**	0.541	0.531	0.438	0.092***	0.565	0.552	0.416	0.136***
VaR	-0.022	-0.026	-0.027	0.001	-0.023	-0.026	-0.027	0.001	-0.027	-0.026	-0.030	0.003**
ES	-0.028	-0.033	-0.034	0.001	-0.029	-0.033	-0.034	0.001	-0.034	-0.033	-0.037	0.004**
MDD (%)	27.544	41.807	47.490	-5.683	30.367	45.949	67.143	-21.194	37.763	48.463	74.858	-26.395
MPPM (%)	0.050	0.065	-0.029	0.095***	0.066	0.073	-0.041	0.114***	0.069	0.070	-0.074	0.144***

Table 5. Trading Strategies: Performance Relative to Factor Models

This table reports the average excess returns and risk-adjusted returns of the Baseline, Disclosure-Adjusted, and Optimal-Timing long-short strategies using matched firms, calculated via out-of-sample PSM. Baseline refers to the strategy that holds the portfolios from the day of the event announcement until one week after the event is held. Disclosure-Adjusted refers to the strategy in which the portfolio is held until one day before the event if *Incremental Disclosure* 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					Disclosure-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*** (3.553)	0.089*** (3.306)	0.090*** (3.371)	0.090*** (3.357)	0.089*** (3.348)	0.114*** (4.133)	0.108*** (3.919)	0.111*** (4.003)	0.111*** (3.995)	0.109*** (3.975)	0.133*** (3.959)	0.130*** (3.834)	0.126*** (3.731)	0.125*** (3.686)	0.125*** (3.691)
MKT		0.114*** (2.736)	0.108** (2.484)	0.108** (2.483)	0.109** (2.477)		0.119*** (2.718)	0.103** (2.217)	0.103** (2.225)	0.107** (2.322)		-0.031 (-0.401)	-0.006 (-0.080)	-0.002 (-0.027)	0.009 (0.113)
SMB		-0.169** (-2.420)	-0.179** (-2.539)	-0.177** (-2.440)	-0.165** (-2.447)		-0.128 (-1.465)	-0.134 (-1.579)	-0.132 (-1.517)	-0.122 (-1.437)		-0.102 (-1.199)	-0.063 (-0.696)	-0.042 (-0.471)	-0.072 (-0.805)
HML		-0.038 (-0.600)	-0.020 (-0.266)	-0.015 (-0.179)			-0.050 (-0.838)	0.015 (0.197)	0.020 (0.254)			0.247*** (3.173)	0.080 (0.802)	0.139 (1.517)	
UMD		0.004 (0.087)		0.008 (0.179)			-0.009 (-0.220)		0.008 (0.180)			0.105 (1.448)		0.089 (1.213)	
RMW			-0.026 (-0.295)	-0.025 (-0.286)				0.004 (0.049)	0.005 (0.056)				0.185* (1.904)	0.193** (1.982)	
CMA			-0.048 (-0.423)	-0.054 (-0.446)				-0.191 (-1.506)	-0.198 (-1.471)				0.285** (2.068)	0.215 (1.618)	
IA					-0.059 (-0.608)					-0.134 (-1.343)					0.434*** (3.221)
ROE					0.013 (0.125)					0.038 (0.346)					0.039 (0.241)
EG					0.010 (0.082)					-0.011 (-0.098)					0.089 (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	1.1	1.1	1.08		0.96	1.11	1.11	1.07		1.58	1.72	1.93	1.61

Table 6. Trading Strategies: Factor-Model Alphas Including Transaction Costs

This table reports the average excess returns and risk-adjusted returns of the Baseline, Disclosure-Adjusted, and Optimal-Timing long-short strategies using matched firms, calculated via out-of-sample PSM, 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 (1)	FF5 (2)	FF6 (3)	q5 (4)	FF4 (5)	FF5 (6)	FF6 (7)	q5 (8)	FF4 (9)	FF5 (10)	FF6 (11)	q5 (12)
Panel A: Proportional trading costs												
Baseline	0.089*** (3.303)	0.090*** (3.368)	0.090*** (3.354)	0.089*** (3.344)	0.088*** (3.273)	0.089*** (3.337)	0.089*** (3.324)	0.088*** (3.314)	0.087*** (3.259)	0.088*** (3.324)	0.088*** (3.310)	0.088*** (3.300)
Disclosure-Adjusted	0.108*** (3.916)	0.111*** (4.000)	0.110*** (3.992)	0.109*** (3.972)	0.108*** (3.887)	0.110*** (3.971)	0.110*** (3.963)	0.109*** (3.943)	0.107*** (3.874)	0.109*** (3.959)	0.109*** (3.950)	0.108*** (3.930)
Optimal-Timing	0.129*** (3.826)	0.126*** (3.723)	0.125*** (3.679)	0.124*** (3.683)	0.127*** (3.756)	0.123*** (3.653)	0.122*** (3.610)	0.122*** (3.613)	0.126*** (3.725)	0.122*** (3.623)	0.121*** (3.579)	0.121*** (3.582)
Panel B: Proportional trading costs and borrowing costs												
Baseline	0.080*** (2.972)	0.081*** (3.035)	0.081*** (3.022)	0.080*** (3.011)	0.079*** (2.942)	0.080*** (3.004)	0.080*** (2.991)	0.079*** (2.980)	0.078*** (2.928)	0.080*** (2.991)	0.079*** (2.978)	0.079*** (2.966)
Disclosure-Adjusted	0.099*** (3.568)	0.101*** (3.652)	0.101*** (3.644)	0.100*** (3.623)	0.098*** (3.539)	0.100*** (3.624)	0.100*** (3.616)	0.099*** (3.594)	0.098*** (3.527)	0.100*** (3.611)	0.100*** (3.603)	0.099*** (3.581)
Optimal-Timing	0.125*** (3.702)	0.122*** (3.598)	0.121*** (3.555)	0.120*** (3.558)	0.123*** (3.632)	0.119*** (3.529)	0.118*** (3.486)	0.118*** (3.488)	0.122*** (3.601)	0.118*** (3.498)	0.117*** (3.455)	0.117*** (3.457)

Table 7. Trading Strategies: Factor-Model Alphas, Subsample Analysis

This table reports the average excess returns and risk-adjusted returns of the Baseline, Disclosure-Adjusted, and Optimal-Timing long-short strategies by subsamples using matched firms, calculated via out-of-sample PSM. Baseline refers to the strategy that holds the portfolios from the day of the event announcement until one week after the event is held. Disclosure-Adjusted refers to the strategy in which the portfolio is held until one day before the event if *Incremental Disclosure* 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 and during Q&A separately, firms belonging to high-tech and non-high-tech industries, and firms experiencing incremental disclosure and not prior to the 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				Disclosure-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 Tone ^{Overall}	0.131*** (2.594)	0.136*** (2.671)	0.136*** (2.671)	0.132*** (2.599)	0.169*** (3.196)	0.173*** (3.249)	0.174*** (3.268)	0.171*** (3.214)	0.157** (2.558)	0.149** (2.403)	0.148** (2.400)	0.144** (2.339)
Negative Tone ^{Overall}	0.057 (1.237)	0.060 (1.304)	0.056 (1.224)	0.062 (1.356)	0.062 (1.253)	0.068 (1.374)	0.063 (1.272)	0.070 (1.405)	0.097 (1.389)	0.105 (1.481)	0.099 (1.405)	0.103 (1.466)
Positive Tone ^{Q&A}	0.059 (1.205)	0.064 (1.294)	0.063 (1.278)	0.062 (1.245)	0.082 (1.610)	0.085* (1.669)	0.085* (1.658)	0.085* (1.656)	0.116** (2.213)	0.106** (2.040)	0.106** (2.039)	0.109** (2.094)
Negative Tone ^{Q&A}	0.018 (0.329)	0.012 (0.219)	0.013 (0.238)	0.004 (0.069)	0.047 (0.843)	0.052 (0.925)	0.048 (0.860)	0.050 (0.907)	0.161** (2.173)	0.171** (2.286)	0.163** (2.199)	0.176** (2.346)
High Tech.	0.164*** (3.812)	0.173*** (3.993)	0.172*** (3.980)	0.173*** (3.958)	0.177*** (4.098)	0.186*** (4.294)	0.186*** (4.284)	0.188*** (4.309)	0.263*** (4.232)	0.266*** (4.246)	0.263*** (4.182)	0.263*** (4.162)
Non-High Tech.	0.090*** (3.375)	0.088*** (3.344)	0.088*** (3.311)	0.088*** (3.267)	0.106*** (4.029)	0.105*** (4.025)	0.105*** (3.997)	0.105*** (3.915)	0.121*** (3.504)	0.116*** (3.393)	0.116*** (3.362)	0.118*** (3.430)
With Incremental Discl.	0.080*** (2.697)	0.081*** (2.768)	0.081*** (2.759)	0.083*** (2.818)	0.096*** (2.986)	0.099*** (3.069)	0.099*** (3.058)	0.101*** (3.101)	0.106*** (2.789)	0.103*** (2.726)	0.101*** (2.672)	0.101*** (2.680)
Without Incremental Discl.	0.123** (2.564)	0.120** (2.515)	0.120** (2.499)	0.122** (2.549)	0.123** (2.564)	0.120** (2.515)	0.120** (2.499)	0.122** (2.549)	0.127** (2.070)	0.126** (2.081)	0.126** (2.045)	0.126** (2.062)

Appendix A. Additional tables

Table A.1. Variable Definitions and Data Sources

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

Variable	Description
<u>Analyst/Investor Day</u>	
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.
<u>Internal Benefits for Disclosure</u>	
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) .
<u>External Demand for Disclosure</u>	
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.
Ownership ^{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+Age ^{Firm})	The natural logarithm of one plus the number of years that the stock has been listed on the CRSP database.
High Tech.	1 if the firm belongs to one of the following SIC codes: 2833-2836 (drugs), 8731-8734 (R&D services), 7371-7379 (programming), 3570-3577 (computers), 3600-3674 (electronics), or 3810-3845 (precise measurement instruments), and 0 otherwise.
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).

Continued...

Variable	Description
<u>Sentiment</u>	
Tone($\cdot$)	Sentiment measure defined as $(Positive - Negative) / (Positive + Negative)$, where <i>Positive</i> and <i>Negative</i> represent the proportions of <i>Positive</i> and <i>Negative</i> words in a given transcript, as defined by the Loughran and McDonald (2011) Master Dictionary. Tone(Presentation) captures sentiment in management's prepared remarks, while Tone(Q&A) reflects sentiment in the question-and-answer portion of the event.
<u>Linguistic Complexity</u>	
Fog($\cdot$)	Fog index measuring the linguistic complexity of the respective portion of the event. Specifically, Fog(Presentation) captures the complexity of management's prepared remarks, Fog(Q&A) reflects the overall complexity of the Q&A session, Fog(Response) measures the complexity of managers' responses to analyst questions, and Fog(Analyst) measures the complexity of analysts' questions and statements during the Q&A segment. Higher values indicate greater linguistic complexity.
<u>Latent Components of Linguistic Complexity</u> (based on Bushee et al., 2018b)	
Obfu($\cdot$)	Latent obfuscation component. Obfu(Presentation) represents the latent obfuscation component from the presentation segment, while Obfu(Q&A) refers to the latent obfuscation component from the Q&A segment.
Info($\cdot$)	Latent information component. Info(Presentation) represents the latent information component from the presentation segment, while Info(Q&A) refers to the latent information component from the Q&A segment.
Obfu(Manager)	Latent manager obfuscation component as the first principal component of Obfu(Presentation) and Obfu(Response).
Info(Manager)	Latent manager information component as the first principal component of Info(Presentation) and Info(Response).
<u>BHARs</u>	
BHAR[τ]	The difference in buy-and-hold returns between the hosting firm and its matched peer over 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).
<u>Market Responses</u>	
Incremental Disclosure	A dummy equal to one if the firm issues a voluntary 8-K (Items 2.02, 7.01, or 8.01) between the announcement and the event.
RiskInfo ₃₀	Implied risk over a 30-day horizon, following Smith and So (2022) .
SRiskInfo ₃₀	Defined as RiskInfo ₃₀ scaled by diffusive variance, where diffusive variance reflects the units of variance expected over the remaining life of the option (Smith and So, 2022 ; Dubinsky et al., 2019).
<u>Performance measures</u>	
Sharpe ratio	Average excess return of firm i (<i>Mean</i>) per unit of total risk (<i>Std.</i>), defined as $Sharpe_i = \frac{\frac{1}{T} \sum_{t=1}^T (r_{i,t} - r_{f,t})}{\sigma_i}$, where $r_{i,t}$ is the return of firm i during period t , $r_{f,t}$ is the risk-free rate during period t , and σ_i is the standard deviation of excess returns.
Downside risk	$DR_i = \sqrt{\sum_{t=1}^T (r_{i,t})^2 I_{r_{i,t} < 0} / T}$, 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.
Omega	Expected gains over expected losses, defined as $\Omega_i = \frac{\sum_{t=1}^T r_{i,t} I_{r_{i,t} > 0}}{\sum_{t=1}^T r_{i,t} I_{r_{i,t} < 0}}$.
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 .
VaR	Value at Risk under the assumption of normally distributed returns, defined as $VaR_i = \mu_i + z_{0.05} \sigma_i$, where μ_i is the mean return of firm i , σ_i is the standard deviation of returns, and $z_{0.05}$ is the 5th percentile of the standard normal distribution.
ES	Expected Shortfall under the assumption of normally distributed returns, defined as $ES_i = \mu_i - \sigma_i \frac{\phi(z_{0.05})}{0.05}$, where μ_i is the mean return of firm i , σ_i is the standard deviation of returns, $z_{0.05}$ is the 5th percentile of the standard normal distribution, and $\phi(\cdot)$ denotes the standard normal density.
Maximum drawdown (<i>MDD</i>)	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

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. %STDY 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: $((e^{\hat{\beta} \cdot (\bar{X} + \sigma)} / e^{\hat{\beta} \cdot \bar{X}}) - 1) \times 100$, where $\hat{\beta}$ is the estimated logit coefficient, $\bar{X}$ is the mean of the independent variable, and σ is its standard deviation. For dummy variables, %STDY captures the change of the independent variable from 0 to 1. The regression includes year and industry fixed effects, and it estimated using the complete sample. The t -statistics are in parentheses. *, **, and *** denote the statistical significance at 10%, 5%, and 1%, respectively. All the variables are defined in Table A.1. 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 it excludes year and industry fixed effects.

	1 (Analyst/Investor Day)		
	Coef.	t -stat	%STDY
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
$\ln(1+No. \text{ of Analysts})$	0.063*	(1.728)	5.32
Ownership ^{INS}	0.083	(0.964)	2.91
$\ln(1+Age^{\text{Firm}})$	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. 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	<i>t</i> -statistic
<u>Analyst/Investor Day</u>				
No. of AI Days	0.126	0.122	1.219	0.313
<u>Internal Benefits for Disclosure</u>				
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
<u>External Demand for Disclosure</u>				
ln(1+Size)	8.118	8.076	2.245	0.691
ln(1+No. of Analysts)	0.622	0.613	1.036	0.243
Ownership ^{INS}	0.698	0.680	5.249	1.320
ln(1+Age ^{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

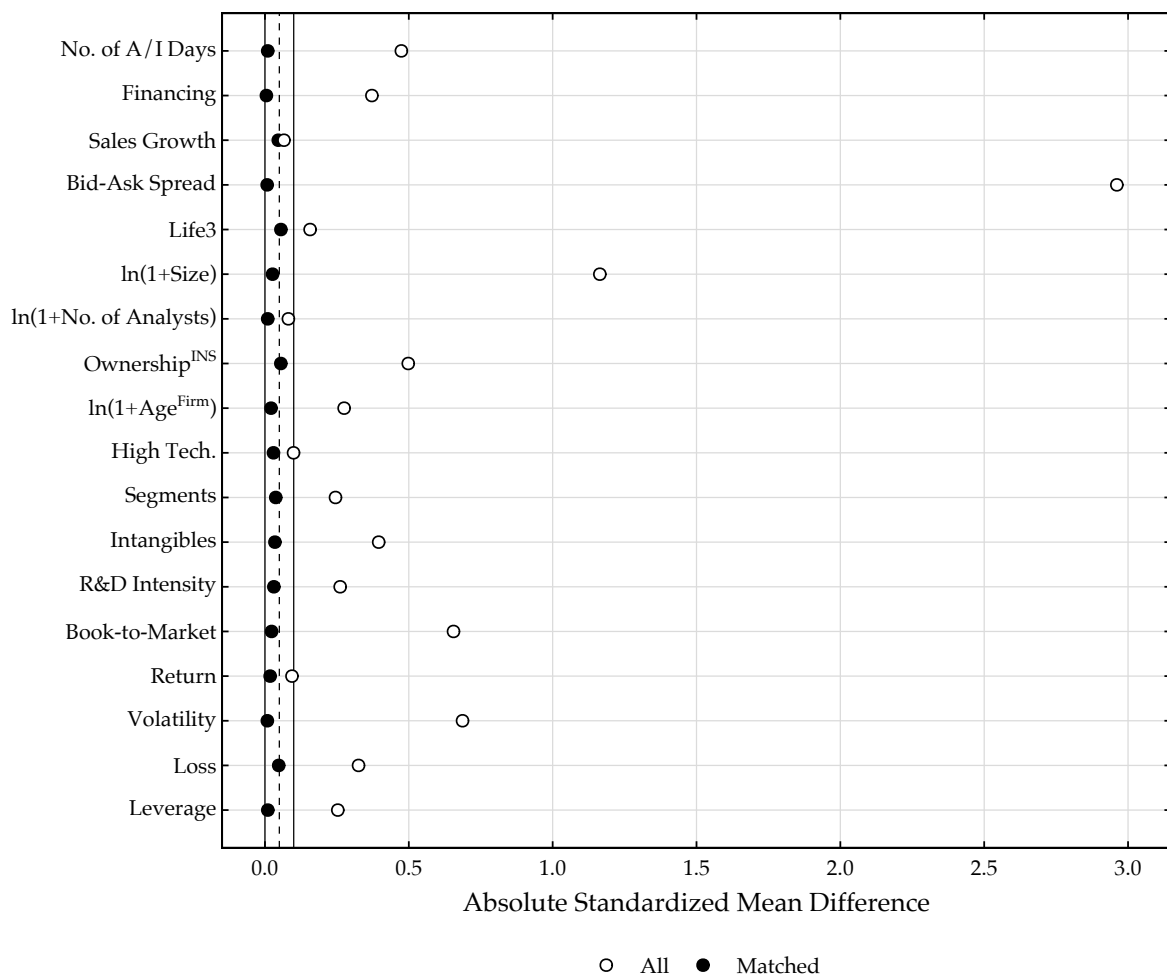


Figure A.1. PSM Matching Balance

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).

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. 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.

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 $h_t = \{(o_\tau, a_\tau, r_\tau) | \tau = 0, 1, \dots, t\}$ 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](#).

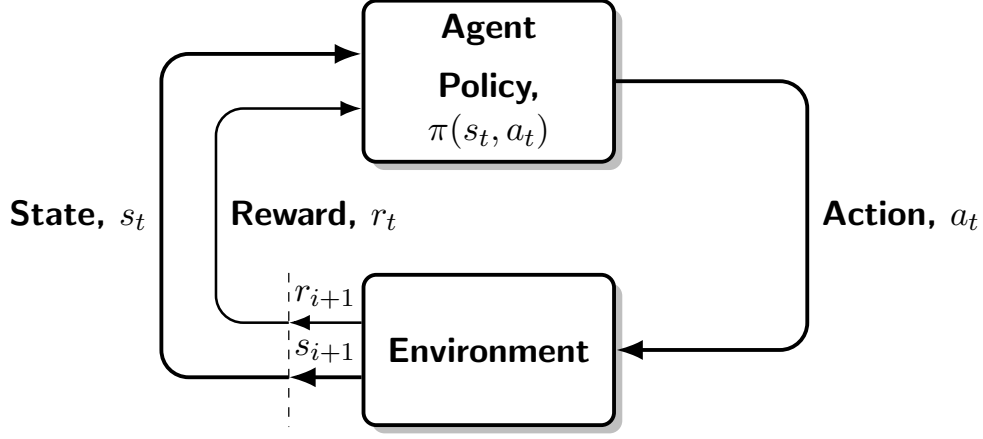


Figure IA.1. Reinforcement Learning Core Building Blocks

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:

$$Q^{(n+1)}(s, a) = \underbrace{Q^{(n)}(s, a)}_{\text{Current estimate}} + \underbrace{\alpha}_{\text{Learning rate}} \left[\underbrace{r(s, a)}_{\text{Reward}} + \underbrace{\gamma}_{\text{Discount rate}} \underbrace{\max_{a'} Q^{(n)}(s', a')}_{\text{Maximum predicted reward, given new state and all possible actions}} - Q^{(n)}(s, a) \right] \quad (\text{A.1})$$

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_{t+1}^c , and share value, v_{t+1}^s , defined as:

$$v_{t+1}^c = v_t^c - Q_t p_t - C |Q_t| p_t \quad (\text{A.2})$$

$$v_{t+1}^s = (n_t + Q_t) p_{t+1} = n_{t+1} p_{t+1} \quad (\text{A.3})$$

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.¹

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.

¹Eq. (A.2) allows the cash value to decrease after purchasing shares, while Eq. (A.3) 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).

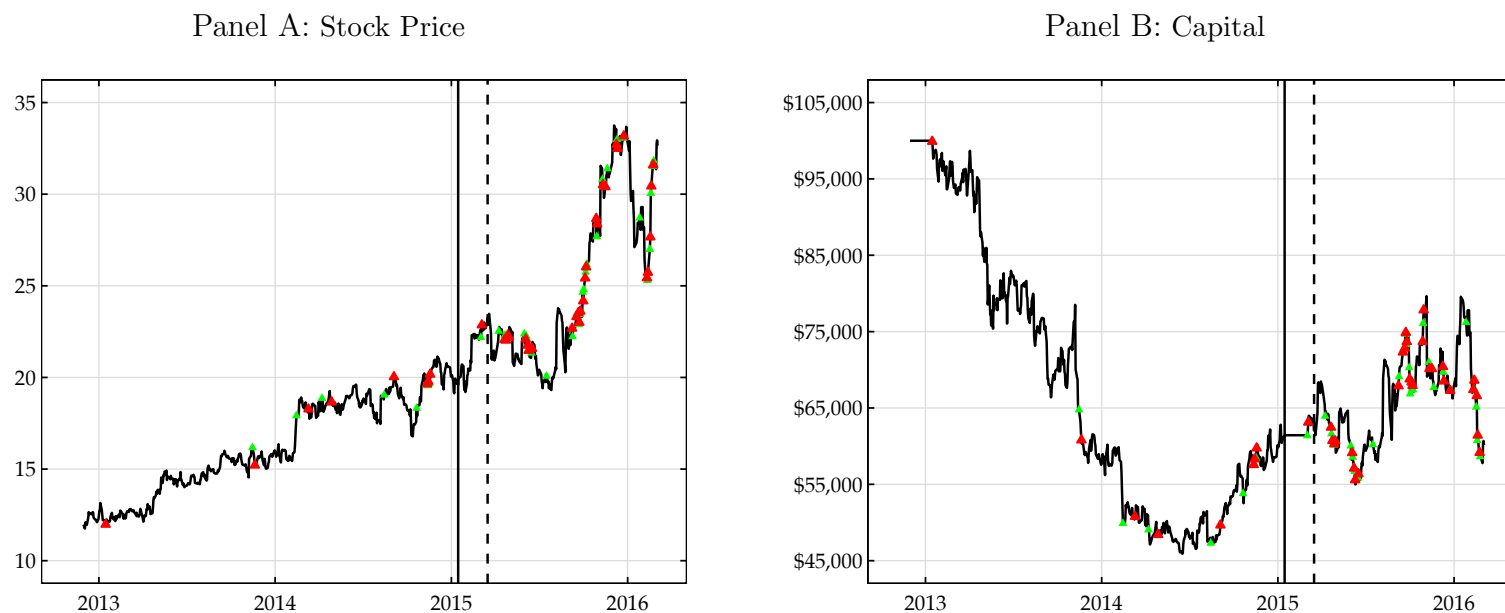


Figure IA.2. TDQN Algorithm Execution for Nvidia's A/I Day on March 17, 2015

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 B. Transaction Cost Modeling

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:

$$TC_{long,t} = \sum_{i=1}^{N_t} |w_{i,t} - \tilde{w}_{i,t-1}| c_{i,t}, \quad (\text{B.4})$$

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:

$$\tilde{w}_{i,t-1} = \frac{w_{i,t-1}(1 + r_{i,t})}{\sum_{j=1}^{N_t} w_{j,t-1}(1 + r_{j,t})}, \quad (\text{B.5})$$

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:

$$TC_{short,t}^{BOR} = \sum_{i=1}^{N_t} w_{i,t} c_{i,t}^{BOR} / 252, \quad (\text{B.6})$$

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

References

- Barroso, P. and Detzel, A. (2021). Do limits to arbitrage explain the benefits of volatility-managed portfolios? *Journal of Financial Economics*, 140(3):744–767.
- Barroso, P. and Santa-Clara, P. (2015). Momentum has its moments. *Journal of Financial Economics*, 116(1):111–120.
- Bekjarovski, F. (2018). How do short selling costs and restrictions affect the profitability of stock anomalies? *Available at SSRN 3066750*.
- Brockman, P., Li, X., and Price, S. M. (2015). Differences in conference call tones: Managers vs. analysts. *Financial Analysts Journal*, 71(4):24–42.
- Hambly, B., Xu, R., and Yang, H. (2023). Recent advances in reinforcement learning in finance. *Mathematical Finance*, 33(3):437–503.
- Hasbrouck, J. (2009). Trading costs and returns for us equities: Estimating effective costs from daily data. *The Journal of Finance*, 64(3):1445–1477.
- Kimbrough, M. D. (2005). The effect of conference calls on analyst and market underreaction to earnings announcements. *The Accounting Review*, 80(1):189–219.
- Kolokolova, O. and Xu, X. (2024). Enhancing betting against beta with stochastic dominance. *Journal of Empirical Finance*, 76:101465.
- Matsumoto, D., Pronk, M., and Roelofsen, E. (2011). What makes conference calls useful? the information content of managers’ presentations and analysts’ discussion sessions. *The Accounting Review*, 86(4):1383–1414.
- Price, S. M., Doran, J. S., Peterson, D. R., and Bliss, B. A. (2012). Earnings conference calls and stock returns: The incremental informativeness of textual tone. *Journal of Banking & Finance*, 36(4):992–1011.

Théate, T. and Ernst, D. (2021). An application of deep reinforcement learning to algorithmic trading. *Expert Systems with Applications*, 173:114632.