Original Research Article

AI Disclosure Intensity and Short-Term Stock Returns Evidence from Spring 2026 Earnings Calls

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ABSTRACT

This study explores whether the intensity of AI (artificial intelligence) related language used during the Spring 2026 earnings calls is associated with short-term abnormal stock returns and whether this relationship differs between technology-oriented and comparison firms. Using a cross-sectional event study framework, this study analyzes a sample of 50 publicly traded large-cap U.S. firms, consisting of 25 technology-oriented firms and 25 comparison firms from non-technology industries. AI disclosure intensity was measured as the proportion of AI-related terminology relative to total transcript word count. In contrast, market reactions were measured using cumulative abnormal returns (CAR) over a three-day [-1,+1] event window surrounding each earnings announcement. The results indicated that technology-oriented firms exhibited higher average AI disclosure intensity and greater dispersion in cumulative abnormal returns than firms in the comparison cohort. Regression analysis suggested that the association between AI disclosure intensity and short-term abnormal returns varies across industry groups, with AI-related communication appearing to have a stronger relationship with market reactions, particularly among technology-oriented firms. However, these findings should be interpreted as statistical associations rather than any evidence of causality. Moreover, other earnings-related information released simultaneously may also influence stock-price movements. Overall, the study provides exploratory evidence that investors may evaluate AI-related corporate disclosures differently depending on industry context. These findings are consistent with theories of corporate signaling and information credibility, although additional research using larger samples, longer time periods, and more comprehensive control variables is required to establish the underlying mechanisms.

Keywords: Asset Pricing; Corporate Finance; Abnormal returns; Earnings calls; Artificial Intelligence; Event Study; Textual Analysis

INTRODUCTION

The rapid and exponential development of artificial intelligence (AI) within the 21st century has positioned AI as a central component of corporate strategy, investment decisions, and financial communication. As firms begin to increasingly integrate AI into products, operations, infrastructure, and long-term growth strategies, management teams have begun emphasizing AI-related initiatives during their quarterly earnings calls (or known as quarterly earnings calls) to communicate future

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opportunities and competitive positioning. Because these earnings calls contain both mandatory financial information and voluntary qualitative disclosures, they provide an important setting for examining how investors will process new information and revise their expectations regarding future firm performance and valuation.

Financial markets are expected to incorporate this publicly available information rapidly into asset prices, as proposed by the Efficient Market Hypothesis (EMH) developed by Fama (1). Under the semi-strong form of market efficiency, corporate disclosures and earnings announcements should be reflected in stock prices shortly after their release, making earnings calls an appropriate environment for studying investor reactions to new information. However, the degree to which individual disclosures are separately reflected in prices remains difficult to isolate when multiple forms of information are released simultaneously. Previous research has also demonstrated that market responses are influenced not only by quantitative financial results but also by the language and content used by corporate management. Textual analysis studies have shown that corporate language contains economically meaningful information capable of influencing investor sentiment and stock returns (2, 3). Loughran and McDonald (2) further demonstrated that disclosure language can be systematically analyzed to extract information relevant to financial outcomes.

Beyond information disclosure, signaling theory also provides an additional framework for understanding how investors interpret voluntary corporate communication. According to Spence (4), firms may attempt to communicate quality through observable signals underlying quality when information asymmetry exists between firms and investors. However, Crawford and Sobel (5) highlight that disclosures without sufficient credibility may instead represent “cheap talk” and provide limited informational value. Therefore, identical AI-related statements may be interpreted differently depending on a firm’s perceived ability to implement AI technologies and generate future value. Research on technological innovation similarly demonstrates that emerging technologies can influence firm valuation and investor expectations, with technological developments often generating significant market reactions (6, 7).

Despite the growing importance of AI within corporate communication, limited empirical evidence exists regarding whether AI-specific language intensity within earnings calls is associated with short-term stock market reactions. Existing literature primarily examines general disclosure sentiment, innovation, or technological communication rather than AI-focused discussions during earnings announcements. Furthermore, little evidence exists regarding whether investors evaluate AI disclosures differently across industries where AI represents either a core operational capability or a supporting business technology.

This study examines whether AI disclosure intensity is associated with cumulative abnormal returns around earnings announcements and whether this association differs between technology-oriented and comparison cohorts. AI disclosure intensity is measured through textual analysis of earnings-call transcripts, while market reactions are evaluated using a short-window event-study framework. Expected returns are estimated using a market model based on historical firm and market returns. This study contributes to the existing literature in three ways. First, it provides empirical evidence on AI-related corporate communication during a recent reporting period characterized by widespread AI adoption. Second, it evaluates whether AI disclosure intensity provides explanatory power for abnormal returns after controlling for firm-specific market exposure and transcript characteristics. Third, it combines transcript-based textual analysis with an event-study methodology to investigate the relationship between AI disclosure intensity and short-term market reactions.

The study tests two hypotheses. First, it examines whether AI disclosure intensity is associated with cumulative abnormal returns surrounding earnings announcements. Second, it evaluates whether this relationship differs between the technology-oriented and comparison cohorts.

METHODS AND MATERIALS

Financial Data Sets and variables

Within this study, multiple credible and highly developed financial data sets are utilized to construct the empirical framework of AI (artificial intelligence) within earnings calls to short-term changes in stock price. The objective when conducting this research was to develop a dataset that captured both (i) firm responses following the announcement call, and (ii) the variation in language used by management in relation to AI during earnings calls. The final dataset combines stock-return variables derived from an event-study framework with textual measures extracted from earnings-call transcripts.

In order to measure the stock price, this research relies mainly/heavily on public data extracted via Yahoo Finance. Created in 1997 and based on its parent company Yahoo, the platform directly provides detailed and comprehensive information regarding daily markets for publicly traded US companies. The dataset contains daily-level stock prices and trade volumes. Firms are matched according to their market ticker and are verified alongside their ISIN (international securities identification numbers) and CUSIP identifiers, ensuring an alignment of precise trading across different firms and periods of time. Using Yahoo Finance, daily closing prices were extracted from various stocks to compute the short-term stock return regarding earnings calls. Adjusted closing prices were used when calculating returns in order to account for stock splits and dividend adjustments, ensuring that measured price movements represent economically meaningful shareholder returns rather than mechanical changes caused by corporate actions. In addition, in order to construct the benchmark for broader changes in the market, this paper employs the S&P 500 index from Yahoo finance, which acted as a representative for the aggregate portfolio in the market. Controlling the market allows for abnormal returns to be estimated in relation to a widely recognized, investable benchmark (8).

The central exploration of this study focuses on the intensity of AI communication within a corporate earnings announcement in order to assess and identify AI disclosure intensity within earnings calls. This paper utilized the Stock Analysis platform, which provides standardized, historic earnings call transcripts alongside timestamped dates, ensuring the window of events is directly centered on actual disclosure dates. This dataset includes full records of earnings calls, with both remarks by corporate management and question-and-answer sessions with analysts (9). These publicly available transcripts act as one of the most information-rich channels within financial markets. To operationalize the amount of AI disclosure intensity within these earnings calls, each earnings call announcement was processed to measure the volume of AI disclosure intensity. This measure is created by the frequency and context of AI-related language within each company's earnings calls. Keywords include AI, artificial intelligence, automation, machine learning, LLM (large language models), and other related language. Figure 1 plots the percentage of S&P 500 firms from Q1 2018 to Q1 2026 in which AI is mentioned within their earnings calls; the graph overall demonstrates a positive trend in corporate discussion revolving around AI. At the beginning of the sample, in Q1 2018, the mention of AI remained extremely uncommon. Less than 10% of S&P 500 companies mentioned AI in their earnings announcements. Despite slight fluctuations

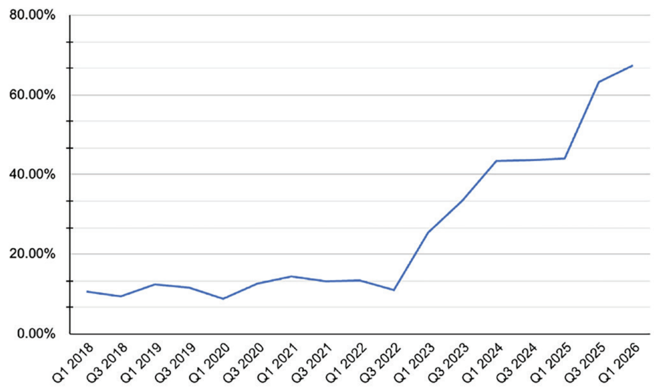

Figure 1. *The percentage of S&P 500 companies mentioning AI within their earnings calls from Q1 2018-Q1 2026. The percentage is a measure of the n.o of firms which reference AI. The data is derived from earnings calls transcripts. Created by the author after receiving permission, using data derived from "HIGHEST NUMBER OF S&P 500 EARNINGS CALLS CITING "AI" OVER THE PAST 10 YEARS" VIA FACTSET (10).*

Between 2018 and 2021, the number of firms mentioning AI generally increased slightly, as experimentation around machine learning, automation, and AI analytics had started to become more popular. From 2023 onwards, the AI narrative in corporate disclosures began to exponentially accelerate, with the number of firms referencing AI rising sharply from 20% to 40% by 2024. The 2026 first quarter, however, can be emphasized as the AI narrative became dominant within the industry. Slightly over 70% of firms had mentioned AI within their earnings calls, the highest point in all of the entire graph.

GICS Classifications and Restrictions

This study analyzes a cross-sectional sample of 50 large-cap publicly traded U.S. companies. The sample size consisted of all S&P 500 constituent companies that reported quarterly earnings between March and June 2026. To minimize selection bias, firms were selected before any return analysis was conducted. Candidate firms were first screened based on membership in the

S&P 500 Index and a market capitalization exceeding approximately USD 10 billion, measured as of March 1, 2026. From the eligible firms, companies were first classified as either the technology-oriented cohort or comparison cohort according to the predefined industry criteria described below. Firms were then selected prior to any return analysis to obtain 25 firms from each cohort while maintaining representation across the relevant industries and ensuring complete availability of earning-call transcripts and financial data. Selection was conducted independently of the observed stock-return outcomes; criterion separation is further explained in Table 1 below. For the purposes of this study, large-cap firms were therefore defined as companies with a market capitalization exceeding approximately USD 10 billion at the time of sample selection.

Table 1. *Sample Screening Procedure summarizes the eligibility criteria and number of firms retained at each stage, resulting in a final sample of 25 technology-oriented and 25 comparison firms.*

Screening Stage	Firms Remaining	Additional notes
S&P 500 constituent (March 1, 2026)	500	N/A
Reported quarterly earnings between March and June 2026	485	Accounting for typical late/missing filers
Market capitalization exceeding approximately USD 10 Billion	485	S&P 500 cap is well above this threshold
Complete earnings-call transcript available	380	Accounting for missing/unindexed third-party transcripts
Eligible technology-oriented cohort	74	Total tech-sector firms surviving previous filters
Eligible comparison cohort	306	Remaining non-tech firms available for matching
Final technology-oriented cohort	25	Firms were randomly selected from the available cohort
Final comparison cohort	25	Firms were randomly selected from the available cohort
Final analytical sample	50	N/A

Technology-oriented firms were selected from industries in which artificial intelligence forms an important component of business operations, including software, semiconductors, cloud computing, enterprise technology, and digital infrastructure. The comparison cohort was selected from industries where AI is generally considered a supporting technology rather than a primary revenue generating activity, which includes healthcare, consumer goods, transportation, financial services, industrials, and energy. Industry classifications were based primarily on the Global Industry Classification Standard (GICS) published jointly by MSCI and S&P Global (11). Where necessary, company annual reports and official business descriptions were consulted to verify each firm's primary source of revenue and principal business activities.

Because several firms commonly associated with technology are classified outside the Information Technology sector under GICS, additional classification criteria were applied. Alphabet and Meta Platforms, although classified under Communication Services, were included in the technology-oriented cohort because their principal business activities rely heavily on artificial intelligence, large-scale computing infrastructure, and digital platforms. Similarly, Amazon, although classified within Consumer Discretionary, was included in the technology-oriented group because Amazon Web Services (AWS), cloud infrastructure, and AI development constitute major components of the company's operations and long-term investment strategy.

Companies classified in Communication Services or Consumer Discretionary were therefore assigned to the technology-oriented cohort only when AI-related products, cloud infrastructure, software platforms, or digital services represented a substantial component of their core business model (Each firm appears only once within the final sample), the subsequent definition of each firm in the final sample is visible in Table 2.

Table 2. *Sample Firms and GICS Classifications. The table lists the 50 sampled firms and their Global Industry Classification Standard (GICS) sectors. Firms 1–25 comprise the technology-oriented cohort, and Firms 26–50 comprise the comparison cohort.*

Title	Firm	Classification (GICS based)	Title	Firm	Classification (GICS based)
1	Microsoft	Information Technology	26	Coca-Cola	Consumer Staples
2	Alphabet	Communication Services	27	Procter & Gamble	Consumer Staples
3	Meta Platforms	Communication Services	28	Johnson & Johnson	Healthcare
4	Amazon	Consumer Discretionary	29	Delta Air Lines	Industrials
5	Apple	Information Technology	30	ExxonMobil	Energy
6	NVIDIA	Information Technology	31	Chevron	Energy
7	AMD	Information Technology	32	McDonald’s	Consumer Discretionary
8	Salesforce	Information Technology	33	PepsiCo	Consumer Staples
9	Adobe	Information Technology	34	Costco	Consumer Staples
10	Oracle	Information Technology	35	Home Depot	Consumer Discretionary
11	Palantir	Information Technology	36	Lowe’s	Consumer Discretionary
12	IBM	Information Technology	37	Target	Consumer Discretionary
13	Intel	Information Technology	38	Caterpillar	Industrials
14	Qualcomm	Information Technology	39	Union Pacific	Industrials
15	ServiceNow	Information Technology	40	Honeywell	Industrials
16	Intuit	Information Technology	41	CSX Corp	Industrials
17	Arista Networks	Information Technology	42	Centene Corporation	Healthcare
18	Micron	Information Technology	43	Northern Trust Corporation	Financials
19	Marvell Tech	Information Technology	44	AbbVie	Healthcare
20	Broadcom	Information Technology	45	Eli Lilly	Healthcare
21	Cisco Systems	Information Technology	46	Merck & Co.	Healthcare
22	Snowflake	Information Technology	47	Norfolk Southern Corporation	Industrials
23	MongoDB	Information Technology	48	The Allstate Corporation	Financials
24	Dell Tech	Information Technology	49	The Progressive Corporation	Financials
25	HP Enterprise	Information Technology	50	BlackRock	Financials

Once all the firms are defined, they are mapped to their respective earnings call release dates, focusing specifically on spring 2026, allowing for the event-time structure to be formulated. Each return calculated is aligned directly to a base information period; thus, it allows comparisons to be made across different firms despite differences within their earnings announcements. Approaching the research in this way avoids any possible distortions arising from interest or compounding, providing a more thorough and accurate image of total stock price changes during earnings calls. The market-adjusted returns are subsequently calculated by subtracting the S&P 500 benchmark, ensuring only firm-specific changes from expected movements in the market are maintained throughout the analysis. Therefore, the dataset created reflects a structure where every firm-to-event observation contains identical information on the timing of the earnings calls, equity returns, benchmark performance of the market, and the intensity of AI extracted from each disclosure. The subsequent earnings-call dates and event details recorded for each firm are listed in Table 3. The baseline date (t0) represents the public release date of the earnings announcement, while the event reaction period is aligned according to whether the disclosure occurred before market

This adjustment ensures that the calculated returns correspond to the period when investors were first able to respond to the information.

Table 3. *Earnings announcement dates and timing. The table reports the baseline date (t0), post-announcement date (t+1), announcement timing, and reported quarter for each sampled firm. Event timing was aligned to the first trading session in which investors could respond to the earnings disclosure.*

Firm	Baseline Date (t0)	Post Date (t+1)	Reporting Window	Reported Quarter
Microsoft	Apr 29, 2026	Apr 30, 2026	After Market Close	Q3 2026
Alphabet	Apr 29, 2026	Apr 30, 2026	After Market Close	Q1 2026
Meta Platforms	Apr 29, 2026	Apr 30, 2026	After Market Close	Q1 2026
Amazon	Apr 29, 2026	April 30, 2026	After Market Close	Q1 2026
Apple	Apr 30, 2026	May 01, 2026	After Market Close	Q2 2026
NVIDIA	May 20, 2026	May 21, 2026	After Market Close	Q1 2027
AMD	May 5, 2026	May 6, 2026	After Market Close	Q1 2026
Salesforce	May 27, 2026	May 28, 2026	After Market Close	Q1 2027
Adobe	Mar 12, 2026	Mar 13, 2026	After Market Close	Q1 2026
Oracle	Mar 10, 2026	Mar 11, 2026	After Market Close	Q3 2026
Palantir	May 04, 2026	May 05, 2026	After Market Close	Q1 2026
IBM	Apr 22, 2026	Apr 23, 2026	After Market Close	Q1 2026
Intel	Apr 23, 2026	Apr 24, 2026	After Market Close	Q1 2026
Qualcomm	April 29, 2026	April 30, 2026	After Market Close	Q2 2026
ServiceNow	Apr 22, 2026	Apr 23, 2026	After Market Close	Q1 2026
Intuit	May 20, 2026	May 21, 2026	After Market Close	Q3 2026
Arista Networks	May 05, 2026	May 06, 2026	After Market Close	Q1 2026
Micron	Mar 18, 2026	Mar 19, 2026	After Market Close	Q2 2026
Marvell Tech	May 27, 2026	May 28, 2026	After Market Close	Q1 2027
Broadcom	Jun 03, 2026	Jun 04, 2026	After Market Close	Q2 2026
Cisco Systems	May 13, 2026	May 14, 2026	After Market Close	Q3 2026
Snowflake	May 27, 2026	May 28, 2026	After Market Close	Q1 2027
MongoDB	May 28, 2026	May 29, 2026	After Market Close	Q1 2027
Dell Tech	May 28, 2026	May 29, 2026	After Market Close	Q1 2027
HP Enterprise	Jun 01, 2026	Jun 02, 2026	After Market Close	Q2 2026
Coca-Cola	Apr 28, 2026	Apr 29, 2026	Before Market Open	Q1 2026
Procter & Gamble	Apr 24, 2026	Apr 27, 2026	Before Market Open	Q3 2026
Johnson & Johnson	Apr 14, 2026	Apr 15, 2026	Before Market Open	Q1 2026
Delta Air Lines	April 8, 2026	April 9, 2026	Before Market Open	Q1 2026
ExxonMobil	May 1, 2026	May 4, 2026	Before Market Open	Q1 2026
Chevron	May 1, 2026	May 4, 2026	Before Market Open	Q1 2026

Continued Table 3. *Earnings announcement dates and timing. The table reports the baseline date (t0), post-announcement date (t+1), announcement timing, and reported quarter for each sampled firm. Event timing was aligned to the first trading session in which investors could respond to the earnings disclosure.*

Firm	Baseline Date (t0)	Post Date (t+1)	Reporting Window	Reported Quarter
McDonald's	May 7, 2026	May 8, 2026	Before Market Open	Q1 2026
PepsiCo	Apr 16, 2026	Apr 17, 2026	Before Market Open	Q1 2026
Costco	May 28, 2026	May 29, 2026	After Market Close	Q3 2026
Home Depot	May 19, 2026	May 20, 2026	Before Market Open	Q1 2026
Lowe's	May 20, 2026	May 21, 2026	Before Market Open	Q1 2026
Target	May 20, 2026	May 21, 2026	Before Market Open	Q1 2026
Caterpillar	May 18, 2026	May 19, 2026	Before Market Open	Q1 2026
Union Pacific	Apr 23, 2026	Apr 24, 2026	Before Market Open	Q1 2026
Honeywell	Apr 23, 2026	Apr 24, 2026	Before Market Open	Q1 2026
CSX Corp	Apr 22, 2026	Apr 23, 2026	After Market Close	Q1 2026
Centene Corporation	Apr 28, 2026	Apr 29, 2026	Before Market Open	Q1 2026
Northern Trust Corporation	April 21, 2026	April 22, 2026	Before Market Open	Q1 2026
AbbVie	Apr 29, 2026	Apr 30, 2026	Before Market Open	Q1 2026
Eli Lilly	Apr 30, 2026	May 1, 2026	Before Market Open	Q1 2026
Merck & Co.	Apr 30, 2026	May 1, 2026	Before Market Open	Q1 2026
Norfolk Southern Corporation	Apr 24, 2026	Apr 27, 2026	After Market Close	Q1 2026
The Allstate Corporation	Apr 30, 2026	May 1, 2026	After Market Close	Q1 2026
The Progressive Corporation	May 5, 2026	May 6, 2026	After Market Close	Q1 2026
BlackRock	Apr 14,	Apr 15, 2026	Before Market Open	Q1 2026

Theoretical Design/Framework

The Empirical framework for this research is built on the premise that earnings calls serve as a rich and important mechanism for transmitting financial information in markets. Unlike mandatory core financial statements such as balance sheets or internal reports, earnings calls are structured in a way that allows management at firms to communicate specific strategies, priorities, expectations, investment plans and developments operationally directly to all investors. As a result, these disclosures consequently maintain both quantitative data and qualitative information that result in investors changing their expectations regarding the company's future in the market. Following the outline of the research listed previously, each firm to event observation is in combination with the intensity of AI related discussion in the earnings call's transcripts. The general objective is to observe if variation in the communication of AI (artificial intelligence) results in differences in abnormal returns near the earnings calls.

Cash flow signals and value function

The beginning point of this framework is represented by the DCF or discounted cash formula, in which the value of a firm V_0 is represented as the sum of its potential discounted future cash flow adjusted to fit the value of today, represented by the model:

$$V_0 = \sum_{t=1}^{\infty} \frac{E(CF_t)}{(1+k)^t} \qquad \text{Eq. 1}$$

In which $E(CF_t)$ represents the expectations of the market for the firms cash flow within year t, and k is a representation of the interest rate in which is used to negatively penalize cash flow within the future, due to time/risk.

This formula is widely used throughout asset pricing and corporate finance as it links a firm's value directly to the expectation of future investors regarding risk or profit within a company's stock. If a firm's management team explicitly emphasizes the deployment strategy of using AI during a quarterly earnings call, it introduces new information potentially causing investors to either change or revise the expected cash flow in the future or discount rates associated with these new cash flows. To put it more broadly, it introduces an information shock aimed at changing the market (and investors) overall interpretation of the company's trajectory within the future. If investors view this signal as credible/reliable, it results in an upward positive adjustment of the cash flow rate in the long-term, as successful AI incorporation results in improved productivity, reduced costs, and new revenue opportunities; therefore, investors may revise their expectations regarding future profits:

$$\Delta E(CF_t) > 0 \qquad \text{Eq. 2}$$

In addition, investors may also interpret the success of employing AI as evidence of a better position among competitive firms. A greater operational efficiency results in larger future growth prospects. In this circumstance, the investors' perceived risk of future cash flow thus declines, reducing the value of k, the discount rate:

$$k^{new} > k^{old} \qquad \text{Eq. 3}$$

Similarly, if the discount rate increases as well, the firm's values simultaneously increase through the discounted cash flow formula/mechanism. However, consequently, AI-related disclosures which are positive can change market valuations through both the ECF and changes in investors' perceived risk. The immediate reaction observed regarding any earnings calls reflects the speed at which investors can update their expectations following the release of any new information. Regardless of the case, each signal results in a short-term and immediate positive change within the market price $\Delta V_0 > 0$ when the announcement occurs.

Differentiating between a change in equilibrium vs talk

While AI disclosures can have a significant influence on the expectations of investors, the influence of the content in each statement is heavily dependent on their credibility. Many firms do not possess identical capabilities, infrastructure, or incentives to properly deploy AI technologies. In turn, many investors interpret identical AI-related language differently depending on the association of the firm. Firms that typically operate within data analytics, software, cloud infrastructure, semiconductors, or information technology; investments related to AI are closely linked to the core of their business activities. These firms directly commit large amounts of resources towards researching and developing (R and D), product innovation, and capital investment. On the other hand, firms that operate outside any of these sectors, AI references may be less connected to their primary revenue-generating business activities; therefore, investors may associate AI-related statements with lower value, resulting in less response. This distinction is the primary reason for the division of firms into technology-oriented and comparison cohorts in analysis.

Furthermore, it can also be emphasized that for this qualitative signal within the earnings call to be fully valued, in a strong and efficient market, it needs to fulfill the requirements associated with a separating equilibrium. According to signal theory, if a signal created does not result in any costs to display, every single firm will emit the same signal regardless of their operational capacity. This action causes a filled equilibrium in which the market associates the disclosure as non-informative "cheap talk" (6), this results in value being immediately recognized as zero:

$$\Delta V_0 = 0 \qquad \text{Eq. 4}$$

In this empirical design, membership within the technology sector is used as an observable proxy for firms that are more likely to operate in environments where AI-related activities are strategically relevant. However, industry classification does not directly measure the cost of AI adoption, investment commitment, infrastructure development, or operational capability. Therefore, technology-sector membership should be interpreted as a firm characteristic associated with potential AI relevance instead of a direct measure of costly signaling. Consequently, AI-related disclosures from the comparison cohort may be interpreted differently by investors due to differences in perceived relevance, business models, and expected implementation capacity. However, the current empirical design does not assume that these disclosures are inherently non-informative or that they generate zero abnormal returns. Instead, the framework suggests that investors may evaluate similar AI-related disclosures differently depending on firm characteristics and their perceived ability to translate AI initiatives into future value.

Similarly, technology-oriented firms may receive different market reactions to AI-related disclosures due to their existing technological positioning, resources, and investor expectations. However, whether these differences represent credible signaling, differences in implementation capability, or other firm-specific factors cannot be directly identified within the current model. Therefore, the main empirical prediction is that the relationship between AI disclosure intensity and abnormal returns may differ between the technology-oriented cohort and comparison cohort. This prediction is tested through the interaction between AI disclosure intensity and technology-sector classification in the regression framework:

$$E[AI = 1] \neq E[AI = 0] \quad \text{Eq. 5}$$

Event Design and Abnormal Returns

To convert the theoretical framework into actual validity of the empirical data, a structured and organized dataset that links qualitative narratives with market returns was created. The dataset primarily focuses on the earnings calls of the spring 2026 reporting timeline, from March till June. The total sample size represents 50 large cap public companies/organizations (shown above), which are structured and broken down into 2 different categories based on their business strategies. The Technology-oriented cohort contains 25 technological firms, and the Comparison Cohort consists of 25 non-tech focused companies derived from sectors in which AI is not a primary factor in driving revenue. The independent variable within this study is tracked using a simple indicator, AI, isolating if a firm belongs to the technological-oriented cohort.

The methodology used in this study adopts a short-term event design that captures the market's immediate reaction to earnings announcements. For each firm denoted by i, stock returns are calculated over the interval surrounding the earnings announcement date, where t0 represents the announcement date and t+1 represents the subsequent return period used in the baseline specification. This approach allows the analysis to capture the immediate market response following the release of earnings-call information while reducing exposure to unrelated long-term market movements.

Announcement timing is also considered within the analysis. Earnings releases occurring before market opening and after market close provide investors with different periods to process and react to information. Therefore, the exact announcement timing is reported in Table 3, and this limitation is considered when interpreting abnormal returns. Future analysis could improve upon this framework by incorporating intraday price data or announcement-time-specific event windows that distinguish between announcements released before market opening and after market close.

This could be improved in future research by using intraday price data or narrower announcement time-based event windows to more precisely capture the immediate market reaction.

Daily continuous compounded returns are calculated as follows:

$$R_{i,t} = ln\ ln\ (P_{i,t}) \ - ln\ ln\ (P_{i,t-1}) \quad \text{Eq. 6}$$

In which $P_{i,t}$ represents the closing price of the firm's stock i on day t. By using natural logs, it ensures that consistency is maintained across various firms allowing for the returns to be collected over time.

To reduce any potential systemic movements within the market over the short period, S&P 500 market index values M_0, M_{+1} are used as a benchmark to identify the market return (MR)

$$R_{m,t} = ln\ ln\ (M_t) - ln\ ln\ (M_{t-1}) \quad \text{Eq. 7}$$

In which M_t represents the value of the market on day t, controlling the market is essential within this research as since the earnings calls slightly differ between firms, market control removes any systematic macroeconomic influences such as changes in interest rates, investor sentiment, resulting in the results representing simply firm level reactions to information shocks within earnings calls.

The valuation premium is then isolated by the cumulative abnormal return (CAR) over the event window which can be defined as:

$$CAR_{i,t} = \sum_{t=t_0}^{t_1} AR_{i,t} \quad \text{Eq. 8}$$

Written also as:

$$CAR_{i,t} = \sum_{t=t_0}^{t_1} (R_{i,t} - R_{m,t}) \quad \text{Eq. 9}$$

The CAR or cumulative abnormal returns thus is an illustration of the total abnormal price adjustment attributed to all the firm specific info released during the earnings call's announcement period. It acts as the main independent variable within this empirical investigation and is used throughout many different studies as a direct measure of intensity response by investors.

However, it is important to recognize that the calculated CAR does not represent the isolated market reaction to AI related communication alone. Earnings announcements contain multiple simultaneous sources of information, including earnings performance, revenue results, forward guidance, margin expectations, capital allocation decisions, and other firm specific developments. Although the event window captures the immediate market response surrounding the earnings call, the methodology cannot fully separate from the contribution of AI related disclosures in relation to other information released during the same period. Therefore, CAR can only be interpreted as the overall abnormal market reaction associated with the earnings announcement, with AI disclosure intensity examined as a potential explanatory factor rather than a direct measure of the causal effect of AI communication.

While these CAR calculations provide a transparent measure of abnormal performance relative to broad market movements, the methodology differs from conventional event-study approaches that estimate expected returns using a pre-event estimation window. The current study applies a market-adjusted return approach using the S&P 500 benchmark due to the exploratory nature of the analysis and the limited observation period. Although this method controls for general market movements, it does not fully capture firm-specific expected returns or differences in systematic risk exposure. Future research could extend this framework by incorporating market models or multifactor asset-pricing models estimated over longer pre-event periods.

One of the most important variables within this study is intensity around the AI narrative, not capturing whether AI is mentioned or not, but the extent in which it manages to dominate communication within earnings calls. The earnings calls transcripts which were obtained from Stock Analysis (9) are processed to identify the occurrence of AI and other related tech concepts referenced throughout. The AI disclosure intensity is defined by the following formula:

$$AIIntensity = \frac{AI\ Associated\ word\ count_{i,t}}{Total\ world\ count_{i,t}} \quad \text{Eq. 10}$$

This measure allows for comparisons to be made across all firms, regardless of differences within transcript length or the structure of the earnings call. The decision to create an intensity metric rather than a binary indicator was chosen as it more accurately depicts the variation in emphasis; thus, the model can differentiate between companies that only reference AI briefly and those that use AI as a central theme throughout the earnings calls.

To estimate the relationship between communication revolving around AI and the market's reactions, the following regression model is used:

$$CAR_{i,t} = AIIntensity_{i,t} + \epsilon_{i,t} \quad \text{Eq. 11}$$

In this equation $CAR_{i,t}$ measures the cumulative abnormal return and the $AIIntensity_{i,t}$ captures the amount of AI-related language used within the earnings calls, and the coefficient represents the marginal effect of the intensity of the AI narrative on short-term stock price changes. It's important to note that cumulative abnormal return (CAR) acts as the dependent variable, while AI disclosure intensity is the independent variable used to explain cross-sectional differences in stock price reactions following the earnings announcements. Furthermore, A positive coefficient indicates that more AI-related emphasis results in stronger positive market reactions, while a coefficient that is not significant suggests that the AI language itself does not carry new informational content beyond earnings. Lastly, the error term (ε) is used to explain any variation in cumulative abnormal returns arising from factors not included in the regression model.

Importantly, the main hypothesis contained within this study is that AI-related disclosures that are identical may be interpreted differently depending on the characteristics of the firm and its industry structure; to account for this, the model extends to allow for heterogeneous effects across both the technologically-oriented and comparison cohorts:

$$CAR_{i,t} = \alpha + \beta_1 AIIntensity_{i,t} + \beta_2 Tech_i + \beta_3(AIIntensity_{i,t} \times Tech_i) + \varepsilon_{i,t} \quad \text{Eq. 12}$$

$Tech_i$ is a binary indicator indicating 1 if firms operate in technology heavy industries and 0 if otherwise. The interaction happening at term β_3 identifies if the market gives a different differential value to AI-associated communication depending on if a firm operates within an environment where adopting AI is structurally essential to revenue growth and long-term production/competitiveness. A positive, significant value effect directly correlates with the AI narrative being more credible and strongly priced if issued by firms with the potential operational capacity to implement them at a large scale such as within software or digital infrastructure.

While these CAR formulas provide a transparent measure of short-term abnormal performance, it differs from a conventional event study methodology that estimates expected returns using a pre-event estimation window and models such as the market model or multifactor asset pricing models. Due to the exploratory nature of this study and the limited sample period, the current analysis applies to a market-adjusted benchmark using the S&P 500 index. However, this approach may not fully capture firm-specific expected returns or differences in systematic risk exposure.

RESULTS AND DISCUSSION

Before demonstrating the formal results conducted within this study, it's important to clarify what the event study is really identifying. The empirical design created isolates short-term price changes around the earnings calls; thus, the CAR or cumulative abnormal returns depict the market's immediate revision of expectations after new information is introduced. Thus, in this context, abnormal returns should not be solely interpreted as performance in a traditional manner, rather than new valuation effects caused by new information shocks. If new information revolving around AI carries specific details regarding potential productivity improvements or future cash flow, this may contribute to differences in cumulative abnormal returns across various firms. However, because earnings announcements contain multiple simultaneous disclosures, the observed CAR cannot be attributed exclusively to AI-related communication.

AI disclosure Intensity

AI disclosure intensity was measured using a predefined dictionary of AI-related keywords consisting of: AI, OpenAI, LLM (Large Language Modeling), Automation, Data Center, Generative AI, AI Agent/Agentic, and Model Training. Keyword matching was performed in a case insensitive manner, meaning that differences in capitalization (e.g., AI and ai) were treated identically (words which included perhaps the term 'ai' such as "gain" were excluded, with the single term being analyzed). Singular and plural forms of keywords were counted as the same term where applicable, while compound phrases such as Generative AI, Data Center, Model Training, and AI Agent were searched and recorded as complete phrases.

Some terms, specifically Automation, Agent, and Data Center, had the possibility of appearing in contexts unrelated to artificial intelligence. Therefore, these terms were manually reviewed within their surrounding sentences and were counted only when they clearly referred to artificial intelligence, machine learning, or related AI technologies. References unrelated to AI were excluded from the final keyword count. For the purpose of this paper, AI context is defined as adaptive systems that learn, make complex decisions, or use specialized infrastructure like GPUs for machine learning and autonomous agents.

The complete earnings-call transcript was analyzed, including both the prepared management presentation and the analyst question-and-answer session. Every validated keyword occurrence was assigned equal weight when calculating AI disclosure intensity; no weighting was applied based on keyword type, speaker, or transcript location. All transcript coding was performed by the author using the predefined keyword dictionary. Coding was completed independently of the statistical analysis and without reference to the abnormal-return results to minimize potential bias. Because the coding was conducted by a single researcher, formal inter-rater reliability was not assessed. This limitation is acknowledged and represents an opportunity for future research.

Moreover, it is essential before examining the exact market reactions related to AI disclosures to understand the variation within the distribution of AI across all 50 sample firms. Table 4 reveals the results of textual analysis and the significant variation in the extent to which firms discuss AI within their earnings calls. This variation is critical because this investigation aims to determine if investors react differently when firms place greater emphasis on AI-related topics. Taking a closer look at Table 4 reveals several meaningful economic patterns in correlation with AI and its discussion throughout earnings calls. Firstly, the differences which can be observed between the Technology-oriented cohort and Comparison Cohort in terms of AI mentions are not marginal by any means and are a representation of an extremely large magnitude.

To compare, Technology-oriented cohort (tech intensive) firms averaged 94.08 AI mentions per their spring 2026 earnings calls, while in contrast only 5.84 mentions were associated with the Comparison Cohort. This difference illustrates that AI-related language was substantially more prevalent among technology-oriented firms during the sampled earnings period. This pattern

Table 4. *Summary of AI disclosure measures by study cohort and distribution of AI-related vocabulary across earnings-call transcripts. Panel A represents the descriptive statistics for firms classified as technology intensive, while panel B reports the same measures for comparison firms. The variables included are AI related keywords mentioned, total word count for each earnings call transcript, and AI disclosure intensity measure. Additionally, Panel C provides a breakdown of the AI-specific vocabulary analyzed and used throughout firms' earnings calls. It's important to note that AI disclosure intensity is expressed as a proportion, not a percentage.*

Variable	Panel A: Technology-oriented cohort			
	Mean	Median	Min	Max
AI Mentions	94.08	92	29	163
Word Count	8989.04	9272	6,605	12,535
AI disclosure intensity	0.0105	0.010	0.003	0.02

Variable	Panel B: Comparison cohort			
	Mean	Median	Min	Max
AI Mentions	5.84	2	0	31
Word Count	9546.76	9256	5,989	12,816
AI disclosure intensity	0.0007	0.0000	0.000	0.003

Vocabulary	Panel C: AI specific vocabulary summary	
	Technology-oriented cohort	Comparison cohort
OpenAI	52	1
AI	1432	85
LLM	48	0
Automation	42	6
Data Center	139	24
Generative AI	37	3
AI agent / agentic	594	5
Model Training	0	0

suggests greater emphasis on AI-related communication within these firms. However, transcript frequency alone cannot determine the strategic importance or implementation level of AI initiatives.

This can be further emphasized by the median values of 92 recorded within the Technology-oriented cohort, implying the suggestion that AI is consistently involved across most general tech firms rather than influenced by an outlier. On the other hand, the Comparison Cohort's small median of only 2 indicates that comparison firms make minimal reference to AI with many not mentioning it at all. The importance of this distinction cannot be overstated, suggesting that the gap observed between firms is structural rather than pioneered by a small group of highly intensive AI firms.

The word count further helps to rule out any possibility of these differences being driven by variation in length, both the Comparison Cohort and Technology-oriented cohort exhibit generically similar average transcript length, with the Comparison Cohort being just slightly higher on average with 9546 words compared to 8989 words for the Technology-oriented cohort, this difference in word count implies higher AI mentions within the Technology-oriented cohort is not simply a function due to longer earnings calls, reflecting a higher density of AI related discussion in comparable settings between groups.

The AI disclosure intensity measure is calculated by dividing the number of AI mentions within a firm's earnings calls by the total word count. This standardization allows for the assurance of capturing relative emphasis rather than the absolute frequency of AI related language, therefore it allows meaningful comparisons to be made across different firms with varying levels of length in communication. Although its values remain extremely small due to sparse length of the earnings calls, the relative differences remain economically significant. Technology-oriented cohort firms showed higher levels of AI disclosure intensity than the comparison cohort firms meaning they devote significantly more time within their earnings calls around AI focused topics. The comparison cohort firms cluster near zero in AI disclosure intensity, indicating that AI-related terminology appeared less frequently within their earnings calls compared with technology-oriented firms. This difference reflects variation in AI-related disclosure emphasis but does not directly measure differences in actual AI adoption, implementation, or operational capability.

Throughout the study, words analyzed within earnings calls were specifically chosen based on common words often associated with AI development and deployment, this includes both technical and industry facing vocab which is standard language within corporate discussions revolving around AI, the initial dictionary used to gather these words was informed by AI glossaries and industry taxonomy as viewable in, (12) which includes many, common used terms in AI communication and development. Additionally, to ensure words were used within accurate context manual validation was conducted on broader terms such as "generation" and "Automation" where each word was reviewed in context with its surrounding structure to ensure it referred specifically to AI rather than other unrelated usage.

Building these differences, the analysis proceeds next by structuring the AI disclosure intensity into ranked groups to more accurately portray the variation in distribution across the sample size. While Table 4, previously highlighted the observed differences within average AI on average disclosures between both firm groups, it does not provide a detailed view of how firms are distributed across the full range of AI disclosure intensity. Specifically, the mean and median stats summarize tendencies, but do not capture the full picture of firm clusters at different levels. To account for this issue

Table 5 classifies firms according to AI disclosure intensity. The technology-oriented cohort is divided into five equal sized quintiles (five firms per quintile), while the comparison cohort is grouped into three mutually exclusive AI-disclosure-intensity categories. Equal-sized quintiles could not be constructed for the comparison cohort because many firms shared identical zero AI-disclosure-intensity values. Therefore, firms with identical values were retained within the same category rather then being arbitrarily separated. The transformation of this data allows a clearer framework for the empirical tests, by separating the firms into different

Table 5. *Firm Grouped Analysis. Technology-oriented firms are ranked into five equal-sized quintiles (five firms per quintile) based on AI disclosure intensity. Because many comparison firms reported identical AI disclosure intensity values of zero, equal-sized tertiles could not be constructed without arbitrarily separating tied observations. Therefore, comparison firms are classified into three mutually exclusive AI disclosure intensity categories based on the observed distribution of the data.*

Panel A: Technology-oriented cohort			
Quintile	**Firms**	**AI disclosure intensity Range, Approximate**	**Comparison**
Q1 (Lowest Intensity)	Apple, Micron, Intel, Intuit, Marvell Tech	0.003-0.007	Lowest 20%
Q2	Arista Networks, IBM, Cisco Systems, Dell Technologies, HP Enterprise	0.007-0.009	Low-Mid 20%
Q3	Meta Platforms, Palantir, Broadcom, Salesforce, Snowflake	0.009-0.011	Middle 20%
Q4	Microsoft, AMD, Adobe, MongoDB, Qualcomm	0.011-0.014	Mid-High 20%
Q5 (Highest AI disclosure intensity)	Oracle, NVIDIA, Alphabet, ServiceNow, Amazon	0.014-0.020	High 20%

Continued Table 5. *Firm Grouped Analysis. Technology-oriented firms are ranked into five equal-sized quintiles (five firms per quintile) based on AI disclosure intensity. Because many comparison firms reported identical AI disclosure intensity values of zero, equal-sized tertiles could not be constructed without arbitrarily separating tied observations. Therefore, comparison firms are classified into three mutually exclusive AI disclosure intensity categories based on the observed distribution of the data.*

Panel B: Comparison Cohort

Category	Firms	AI disclosure intensity Range, Approximate	Relative Position
Category 1	Coca-Cola, Johnson & Johnson, Delta Air Lines, Chevron, McDonald's, PepsiCo, CSX Corp, AbbVie, Eli Lilly, Norfolk Southern, ExxonMobil, Merck & Co., Target, Home Depot, Centene Corporation	0.000	No AI References
Category 2	Costco, Union Pacific, Honeywell, Northern Trust Corporation, BlackRock	0.001	Low AI disclosure intensity
Category 3	Lowe's, Caterpillar, Allstate Corporation, Progressive Corporation, Procter & Gamble	0.002+	Higher AI disclosure intensity

levels of AI communication. It reduces the influence of any possible small variations within individuals' observations by grouping various firms with smaller disclosures together. In turn, the quintile structure allows for a better representation of how AI is embedded within corporate strategies, simultaneously setting the dataset up for comparing the market reactions at low, medium, and high AI disclosure intensity levels.

Abnormal returns

Next, Figure 2 section presents the empirical finding revolving around the cumulative abnormal returns recorded (CAR) for each of 50 firms, the abnormal return measure captures deviations from expected performance after adjusting to market.

A first observation reveals substantial diversification in abnormal returns across the sample. The cumulative abnormal returns range significantly from deeply negative to strongly positive, thus the earnings calls sample period represents a section within the financial market which is highly informative for changes in equity valuation. On the upper end of the distribution, firms like DELL Technologies (42.98%), Snowflake (42.53%), Intel (25.65%) and Centene (23.38%) post the largest positive abnormal return among all firms recorded in this sample, these firms (except Centene, which stands as the largest outlier, are within the technology sector) exhibited the largest positive cumulative abnormal returns following their earnings announcements. One possible explanation is that investors revised expectations regarding future growth and profitability, although these price movements may also reflect other information released during the earnings announcement, including earnings surprises, revenue performance, or forward guidance.

Conversely, other firms experienced significant downward trends in the exact same window, this was led by Artista with –18.3%, Broadcom with a decline of –18.27%, Intuit at -16.37% and ServiceNow with a decline of -11.77%, indicating the opposite effect, these firms exhibited the largest negative cumulative abnormal returns following their earnings announcements. These reactions may reflect investors' responses to the overall information contained within the earnings announcement, including earnings performance and other firm-specific disclosures.

In examining the distribution of abnormal returns across both sample a notable pattern appears, the magnitude of price reactions within the technological sector is significantly more pronounced than comparison firms, Komenjumrus and Hamanee emphasize the sensitivity of technology stocks and the large influence caused by broader market conditions and macroeconomic factors, acting as a possible reason for the significant disparity between the technology-oriented and Comparison Cohorts (12). This economic asymmetry suggests that technology-oriented firms experienced larger stock price reactions during the sample period. One possible explanation is that AI related disclosures may be

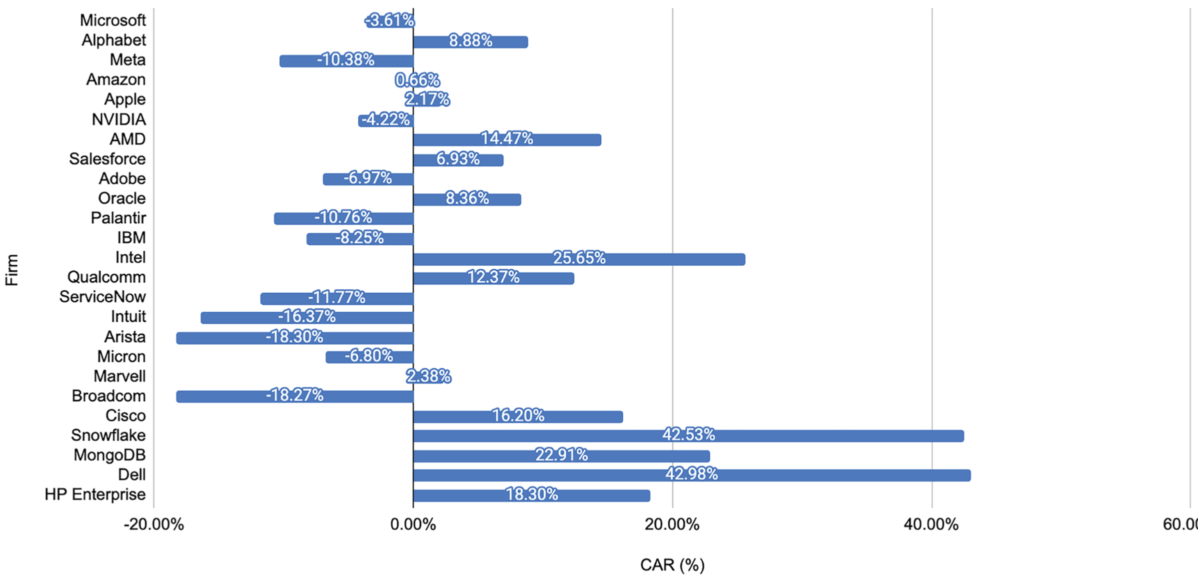

Figure 2. *Equity Return Log A (Technology-oriented cohort) presents the cumulative abnormal returns (CAR) for the technology-oriented cohort calculated using the baseline event window from the earnings announcement date (t0) to the subsequent trading period (t+1). This represents a one-interval return window rather than two calendar days. Stock returns are calculated using continuously compounded returns:*

$R_{i,t} = \ln \ln (P_{i,t}) - \ln \ln (P_{i,t-1})$, where $P_{i,t}$ represents the adjusted closing price of firm i. Market returns are calculated using the same approach for the S&P 500 benchmark $R_{i,t} = \ln \ln (M_t) - \ln \ln (M_{t-1})$. Abnormal returns are estimated as $AR_{i,t} = R_{i,t} - R_{m,t}$ and CAR represents the cumulative abnormal return over the defined event interval.

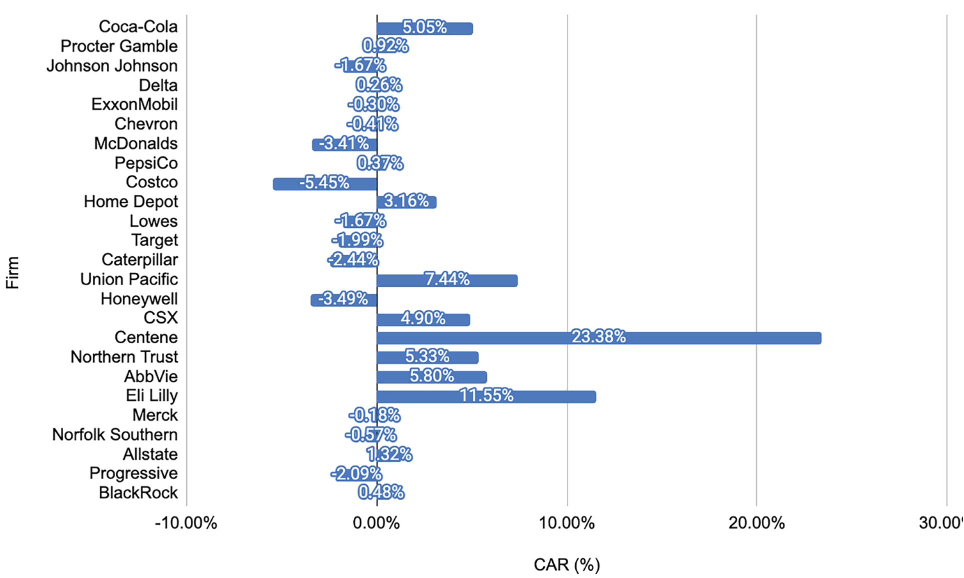

Figure 3. *Equity Return Log B (Comparison Cohort) presents the cumulative abnormal returns (CAR) for the comparison cohort calculated using the baseline event window from the earnings announcement date (t0) to the subsequent trading period (t+1). This represents a one-interval return window rather than two calendar days. Stock returns are calculated using continuously compounded returns:*

$R_{i,t} = \ln \ln (P_{i,t}) - \ln \ln (P_{i,t-1})$, where $P_{i,t}$ represents the adjusted closing price of firm i. Market returns are calculated using the same approach for the S&P 500 benchmark $R_{i,t} = \ln \ln (M_t) - \ln \ln (M_{t-1})$. Abnormal returns are estimated as $AR_{i,t} = R_{i,t} - R_{m,t}$ and CAR represents the cumulative abnormal return over the defined event interval.

more relevant for firms operating in technology-intensive industries, although other characteristics of these firms and their earnings announcements may also contribute to the observed differences. In such cases earnings calls are evidently more likely to contain more future looking information, especially regarding investment into services like Ai infrastructure or scalability in the long term. As a result, AI-related disclosures may receive greater attention within technology-oriented firms. However, technology-sector classification should not be interpreted as a direct measure of AI adoption or implementation capability. Firms within the same industry may differ substantially in their AI investment levels, infrastructure, and ability to generate value from AI-related initiatives.

Optimization of Regression

The data collected within the spring 2026 earnings calls yielded a noticeable difference in the empirical cohorts, as viewable above. The data is refined through optimizing a baseline cross sectional framework, to examine the association between AI mentions and cumulative abnormal returns or CAR. The evaluation of the parameters across all 50 different datasets created the following cross sectional OLS regression equation:

$$CAR_{i,t} = 0.0291 - 17.6412(AIIntensity_i) + \varepsilon_{i,t} \qquad \text{Eq. 13}$$

Equation (13) estimates the relationship between AI disclosure intensity and cumulative abnormal returns (CAR) using the baseline event window, CAR[0,+1]. The y-intercept of 0.0291 represents the expected cumulative abnormal return when AI disclosure intensity equals zero. The coefficient on AI intensity is -17.6412, indicating a negative association between AI-related disclosure intensity and short-term abnormal returns within the baseline specification. However, the coefficient is statistically insignificant, suggesting that higher AI-related language in earnings calls does not provide sufficient evidence of a consistent market valuation effect. This specification assumes that investors interpret AI-related disclosures similarly across all firms, regardless of industry classification.

To address this relevance, the regression model used in equation 12 is imposed. This model extends the equation into a diverse framework that specifcially allows the effect of AI disclosure intensity to change depending on the firm's allocation within the industry. The following equation is produced as such:

$$CAR_{i,t} = 0.0291 - 17.6412(AIIntensity_i) - 0.0852(Tech_i) + 27.0527(AIIntensity_{i,t} \times Tech_i) + \varepsilon_{i,t} \qquad \text{Eq. 14}$$

Equation 14 extends the baseline model by incorporating firm-level technology classification and the interaction between AI disclosure intensity and technology status. The intercept of 0.0291 represents the expected cumulative abnormal return for a non-technology firm with zero AI disclosure intensity. The AI intensity coefficient of -17.6412 captures the estimated effect of AI disclosure intensity among comparison firms, while the technology dummy coefficient of -0.0852 represents the difference in baseline abnormal returns between technology and non-technology firms when AI intensity equals zero. The interaction coefficient of 27.0527 indicates that the relationship between AI disclosure intensity and CAR is more positive for technology-oriented firms relative to comparison firms. However, the interaction term remains statistically insignificant, meaning the results do not provide strong evidence that investors systematically value AI disclosures differently across industries.

Furthermore, to evaluate the reliability and statistical significance of the regression estimates, additional regression diagnostics were conducted. Table 5 presents the complete regression outputs for both regression specifications, including coefficient estimates, standard errors, R-squared values, F-statistics, degrees of freedom, and residual variance measures.

For Equation 13, the baseline regression model produced an R^2 value of 0.0664, indicating that AI disclosure intensity alone explains approximately 6.64% of the variation in cumulative abnormal returns (CAR) across the sample. The AI disclosure intensity coefficient was estimated at -17.6412 with a standard error of 29.9380. The negative coefficient suggests that firms with higher levels of AI-related disclosure typically experienced lower cumulative abnormal returns within the baseline event window. However, the coefficient is statistically insignificant. The model produced an F-statistic of 1.0912 with 48 degrees of freedom, indicating limited explanatory power. Therefore, the results should not be interpreted as evidence of a causal relationship between AI disclosure intensity and short-term market performance.

For Equation 14, the interaction model was estimated to examine whether investors evaluate AI-related disclosures differently depending on industry classification. The interaction coefficient between AI disclosure intensity and technology classification was estimated at 27.0527 with a standard error of 30.5390. This coefficient represents the additional effect of AI disclosure intensity for technology-oriented firms compared with the comparison cohort. The model produced an R^2 value of 0.0664, indicating that incorporating industry classification and the interaction term does not substantially improve explanatory power relative to the baseline specification. Although the positive interaction coefficient suggests that technology-oriented firms may experience a relatively stronger market response to AI disclosures, the estimate remains statistically insignificant.

The estimated marginal effect of AI disclosure intensity was also calculated separately for each cohort. For the comparison cohort, the estimated effect corresponds to the coefficient on AI disclosure intensity alone:

$$\beta_{non\text{-}tech} = -17.6412 \quad \text{Eq. 15}$$

This indicates that, among non-technology firms, a one-unit increase in AI disclosure intensity is associated with an estimated 17.6412 decrease in cumulative abnormal returns, holding other factors constant. However, this relationship is not statistically significant.

For technology-oriented firms, the total AI effect is calculated as the sum of the AI disclosure intensity coefficient and the interaction coefficient:

$$\beta_{tech} = -17.6412 + 27.0527 = 9.4115 \quad \text{Eq. 16}$$

This suggests that the relationship between AI disclosure intensity and cumulative abnormal returns is less negative and becomes positive for technology-oriented firms relative to comparison firms. However, because the interaction term is statistically insignificant, there is insufficient evidence to conclude that investors systematically value AI disclosures differently across technology and non-technology firms. Table 6 presents the results regarding the regression optimization for the baseline model.

Table 6. *Regression Optimization Presents the regression results for the baseline and interaction model specifications used to examine the relationship between AI disclosure intensity and cumulative abnormal returns (CAR). Equation 13 estimates the association between AI disclosure intensity and CAR using the baseline specification. Equation 14 extends the model by incorporating a technology-industry indicator and an interaction term between AI disclosure intensity and technology classification to evaluate whether the relationship differs between technology-oriented and comparison firms. The table reports coefficient estimates, standard errors, R^2 values, F-statistics, degrees of freedom, and residual variance for each model. These statistics provide an assessment of model fit, estimation precision, and the statistical significance of the estimated relationships.*

Name of indicator	Baseline model (Eq. 13)	Interaction model (Eq. 14)	Definition of indicator
Slope (m1)	-17.64120	-17.64120	Estimated change in CAR associated with a one-unit increase in AI disclosure intensity
Technology coefficient (M2)		-0.08523	Estimated difference in CAR between technology and comparison firms when AI intensity equals zero
AI x Technology interaction coefficient (M2)		27.05265	Additional effect of AI disclosure intensity for technology-oriented firms
Y-intercept	0.029097	0.029097	Expected value of CAR when all explanatory variables equal zero
Standard error of AI Intensity coefficient	29.938000	29.938000	Precision measure of the AI intensity coefficient estimate
Standard error of Technology coefficient		0.075000	Precision measure of the technology classification coefficient
Standard error of Interaction coefficient		30.539000	Precision measure of the interaction coefficient estimate
Standard error of intercept	0.031000	0.031000	Precision measure of the intercept estimate

Continued Table 6. *Regression Optimization Presents the regression results for the baseline and interaction model specifications used to examine the relationship between AI disclosure intensity and cumulative abnormal returns (CAR). Equation 13 estimates the association between AI disclosure intensity and CAR using the baseline specification. Equation 14 extends the model by incorporating a technology-industry indicator and an interaction term between AI disclosure intensity and technology classification to evaluate whether the relationship differs between technology-oriented and comparison firms. The table reports coefficient estimates, standard errors, R² values, F-statistics, degrees of freedom, and residual variance for each model. These statistics provide an assessment of model fit, estimation precision, and the statistical significance of the estimated relationships.*

Name of indicator	Baseline model (Eq. 13)	Interaction model (Eq. 14)	Definition of indicator
R-squared value	0.0664	0.0664	Proportion of variance in CAR explained by the regression model
F-statistic	1.0912	1.0912	Overall significance test of the regression model
Degrees of freedom (dF)	48	46	Residual degrees of freedom after estimating model parameters

Robustness Checks

In order to evaluate whether the estimated relationship between AI disclosure intensity and cumulative abnormal returns (CAR) is sensitive to the choice of event-window specification, additional robustness tests were conducted using alternative event windows. The baseline specification uses the [0,+1] event window, which captures the immediate market reaction following the first trading session in which investors could respond to the earnings disclosure. Two additional specifications were estimated: CAR[-1,+1] and CAR[0,+2]. The CAR[-1,+1] specification extends the event window by including the trading day immediately preceding the announcement reaction period. This approach captures potential information leakage, investor anticipation, or market adjustments occurring prior to the official earnings disclosure. The CAR[0,+2] specification extends the post-announcement period by an additional trading day, allowing the analysis to examine whether investor reactions persist beyond the immediate earnings announcement response.

Table 7 presents the robustness regression results using alternative event-window specifications. Across the new specifications, the estimated coefficients vary in magnitude, reflecting differences in the information period captured by each event window. The CAR[-1,+1] specification produces the highest explanatory power with an R^2 of 0.181, suggesting that including the trading day preceding the announcement captures additional variation in market reactions. However, the interaction coefficient remains statistically insignificant, indicating limited evidence that technology-oriented firms experience systematically different market responses to AI disclosure intensity. The CAR[0,+2] specification produces lower explanatory power compared with the baseline and CAR[-1,+1] models, with an R^2 of 0.0627. This suggests that extending the post-announcement

Table 7. *Robustness Check presents the robustness regression results using the extended event window's. The cumulative abnormal returns (CAR) used as the dependent variable were recalculated by extending the baseline event window to include additional trading day's. Stock returns were calculated using continuously compounded logarithmic returns, while S&P 500 returns were used as the market benchmark. Abnormal returns were calculated as the difference between firm returns and market returns, with CAR representing the sum of abnormal returns across the window. The same cross-sectional regression specification used in the baseline model was then re-estimated using the updated CAR values, including AI disclosure intensity, technology classification, and the interaction between AI disclosure intensity and technology classification as explanatory variables.*

Regression Specification	Event window	AI Intensity Coefficient	AI Intensity Standard Error	Technology Interaction Coefficient	R²	F-Statistic	Degrees of Freedom
Robustness model 1	CAR[-1, +1]	-7.2497	9.7510	0.0254	0.1810	3.3960	46
Robustness model 2	CAR[0 +2]	-8.3328	32.4942	-0.0854	0.0627	1.0256	46

window does not substantially improve the ability of AI disclosure intensity to explain cumulative abnormal returns. Overall, the direction and magnitude of coefficients remain sensitive to event-window selection, reinforcing that the results should be interpreted as exploratory evidence rather than definitive causal estimates.

These robustness tests strengthen the reliability of the analysis by demonstrating that the findings are not dependent on a single event-window definition. However, the results also highlight the limitations of the market-adjusted return approach. Future analysis using a conventional market model or multifactor expected-return framework estimated over a pre-event estimation window would provide a more precise measurement of abnormal returns.

To further evaluate the reliability of the event-study methodology, an additional robustness test was conducted using a predicted market model approach. Unlike the baseline specification, which estimates abnormal returns relative to direct S&P 500 movements, the market model accounts for each firm's historical sensitivity to market-wide fluctuations by incorporating firm-specific alpha and beta coefficients.

The expected return for each firm was estimated as:

$$E(R_{i,t}) = a_i + \beta_i R_{m,t} \quad \text{Eq. 17}$$

Where a_i represents the firm's average excess return independent of market movements and β_i captures the firm's systematic exposure to the S&P 500 index. Abnormal returns were then calculated as:

$$AR_{i,t} = R_{i,t} - E(R_{i,t}) \quad \text{Eq. 18}$$

and cumulative abnormal returns were obtained by aggregating abnormal returns across the event window:

$$CAR_i = \Sigma AR_{i,t} \quad \text{Eq. 19}$$

The predicted market model generates substantial variation in estimated firm-level market exposure across the sample. Technology-oriented firms generally exhibit higher beta coefficients, indicating greater sensitivity to movements in the S&P 500 benchmark. For example, Micron (β = 3.1041), AMD (β = 2.4212), Arista Networks (β = 2.3060), and Intel (β = 2.2922) demonstrate relatively high systematic exposure compared with the broader market. This suggests that these firms historically experienced amplified responses to overall market movements during the estimation period. In contrast, several comparison firms display lower or negative beta estimates, including Coca-Cola (β = -0.0645), Procter & Gamble (β = -0.1257), Chevron (β = -0.2014), and Progressive (β = -0.2716), indicating weaker or inverse co-movement with the S&P 500 benchmark.

After controlling for expected market movements through the predicted market model, the resulting cumulative abnormal returns continue to demonstrate substantial cross-sectional variation. Among technology-oriented firms, Qualcomm produced the largest positive market-model adjusted CAR at 12.08%, followed by HP Enterprise (11.38%), Broadcom (11.16%), Micron (8.55%), and Intuit (8.12%). These results indicate that, after accounting for systematic market exposure, several technology firms experienced positive abnormal price movements surrounding their earnings announcements. However, other technology-oriented firms experienced negative abnormal reactions, including Intel (-6.06%), ServiceNow (5.20%), Adobe (-2.84%), and NVIDIA (-3.17%), demonstrating that technology-sector classification alone does not guarantee positive market responses. Within the comparison cohort, abnormal returns were generally less concentrated but still displayed notable variation. Centene recorded the largest positive market-model adjusted CAR among non-technology firms at 11.31%, followed by Target (2.99%), Chevron (2.81%), and ExxonMobil (2.65%). Conversely, firms including Honeywell (-6.52%), Delta Air Lines (-3.87%), Costco (-3.53%), and Eli Lilly (-3.76%) experienced negative abnormal returns after controlling for expected market performance, further detail regarding the results is displayed in Table 8.

The persistence of heterogeneous CAR values following adjustment for firm-specific market exposure suggests that earnings announcements contain information beyond broad market movements. The predicted market model therefore provides a more rigorous robustness specification by accounting for differences in systematic risk across firms. However, these abnormal returns cannot be attributed exclusively to AI-related disclosures, as earnings announcements contain multiple simultaneous information signals, including earnings surprises, revenue performance, management guidance, industry conditions, and future growth expectations. Therefore, while the market-model adjustment strengthens the reliability of the event-study methodology, it does not establish a causal relationship between AI disclosure intensity and short-term equity valuation.

Table 8. *Predicted Market Model Robustness Check Results presents the market-model adjusted cumulative abnormal returns used in the robustness analysis. Compared with the baseline S&P 500 benchmark approach, the predicted market model accounts for firm-specific systematic exposure through estimated alpha and beta coefficients. The persistence of cross-sectional variation after this adjustment suggests that the observed earnings announcement reactions cannot be fully explained by broad market movements.*

Firm	Announcement Date	Alpha (α)	Beta (β)	Market-Model CAR
Microsoft	2026-04-29	-0.0027	0.8875	3.65%
Alphabet	2026-04-29	0.0009	1.2725	2.38%
Meta	2026-04-29	-0.0001	1.5364	1.24%
Amazon	2026-04-29	-0.0012	1.3762	1.63%
Apple	2026-04-30	-0.0002	0.8159	0.09%
NVIDIA	2026-05-20	0.0001	1.7141	-3.17%
AMD	2026-05-05	0.0005	2.4212	-0.77%
Salesforce	2026-05-27	-0.0024	0.5976	0.82%
Adobe	2026-03-12	-0.0036	0.7474	-2.84%
Oracle	2026-03-10	-0.0069	1.9321	3.62%
Palantir	2026-05-04	-0.0008	2.1982	-0.43%
IBM	2026-04-22	-0.0016	1.3879	1.87%
Intel	2026-04-23	0.0031	2.2922	-6.06%
Qualcomm	2026-04-29	-0.0025	1.2942	12.08%
ServiceNow	2026-04-22	-0.0052	0.5469	5.20%
Intuit	2026-05-20	-0.0045	0.5783	8.12%
Arista Networks	2026-05-05	0.0007	2.3060	0.01%
Micron	2026-03-18	0.0090	3.1041	8.55%
Marvell	2026-05-27	0.0048	2.0634	0.93%
Broadcom	2026-06-03	-0.0003	2.1292	11.16%
Cisco	2026-05-13	0.0003	1.0966	6.55%
Snowflake	2026-05-27	-0.0056	1.4236	6.10%
MongoDB	2026-05-28	-0.0044	1.9320	-0.35%
Dell Technologies	2026-05-28	0.0042	1.4940	4.22%
HP Enterprise	2026-06-01	0.0019	1.4238	11.38%
Coca-Cola	2026-04-28	0.0011	-0.0645	0.80%
Procter & Gamble	2026-04-24	-0.0004	-0.1257	-2.66%
Johnson & Johnson	2026-04-14	0.0025	-0.0879	-1.99%
Delta Air Lines	2026-04-08	0.0001	1.9451	-3.87%
ExxonMobil	2026-05-01	0.0036	-0.2498	2.65%
Chevron	2026-05-01	0.0029	-0.2014	2.81%
McDonald’s	2026-05-07	0.0003	0.1580	-1.26%
PepsiCo	2026-04-16	0.0003	-0.0996	-1.20%
Costco	2026-05-28	0.0009	0.0331	-3.53%

Continued Table 8. *Predicted Market Model Robustness Check Results presents the market-model adjusted cumulative abnormal returns used in the robustness analysis. Compared with the baseline S&P 500 benchmark approach, the predicted market model accounts for firm-specific systematic exposure through estimated alpha and beta coefficients. The persistence of cross-sectional variation after this adjustment suggests that the observed earnings announcement reactions cannot be fully explained by broad market movements.*

Firm	Announcement Date	Alpha (α)	Beta (β)	Market-Model CAR
Home Depot	2026-05-19	-0.0003	0.8622	-0.31%
Lowe's	2026-05-20	0.0003	0.9319	-0.60%
Target	2026-05-20	0.0043	0.4468	2.99%
Caterpillar	2026-05-18	0.0025	1.8093	-3.52%
Union Pacific	2026-04-23	0.0014	0.5423	-1.22%
Honeywell	2026-04-23	0.0016	0.7362	-6.52%
CSX	2026-04-22	0.0013	0.8076	0.88%
Centene	2026-04-28	-0.0003	0.2715	11.31%
Northern Trust	2026-04-21	0.0014	1.1474	0.04%
AbbVie	2026-04-29	0.0005	0.1908	-1.87%
Eli Lilly	2026-04-30	0.0010	0.6306	-3.76%
Merck	2026-04-30	0.0040	0.3322	-1.90%
Norfolk Southern	2026-04-24	0.0006	0.4718	-1.59%
Allstate	2026-04-30	0.0006	-0.1843	-0.49%
Progressive	2026-05-05	-0.0003	-0.2716	-0.37%
BlackRock	2026-04-14	-0.0019	1.3061	0.80%

CONCLUSION

Overall, this study demonstrated if AI disclosure intensity during Spring 2026 earnings calls was associated with short-term abnormal stock returns and if this relationship differed between either technology-oriented or comparison firms. By using a short-term event window study framework and transcript-based textual analysis, the results indicated that technology-oriented firms generally discussed AI more extensively than firms in the comparison cohort and experienced greater variation in cumulative abnormal returns following earnings announcements.

The data collected via the regression analysis suggests that the relationship between AI disclosure intensity and abnormal returns appears to vary across industry groups, although these results should not be interpreted as evidence that AI communication alone caused the observed market reactions industry groups. While these findings are broadly consistent with signaling theory and the concept that the credibility of corporate disclosures depends on firm characteristics, the empirical design does not have the ability to determine whether AI-related language itself caused the observed market reactions. Signaling theory should be viewed as a possible interpretive framework rather than a mechanism directly tested by the empirical design. As other information released during earnings announcements, including earnings surprises, forward guidance, and more, may also have contributed to the measured abnormal returns. In addition, all theoretical concepts discussed throughout this paper, including signaling theory, separating equilibrium, and cheap-talk theory should be interpreted as possible explanations for the observed patterns rather than conclusions directly demonstrated by the empirical analysis.

Several limitations should also be acknowledged. The study uses a relatively small, non-random sample of fifty firms from a single reporting period and applies to a short two-day event window. In addition, the analysis does not explicitly control variables such as earnings surprises, revenue surprises, valuation measures, or other firm-specific announcements that may influence stock-price movements. Consequently, the results should be interpreted as exploratory rather than causal. Furthermore, AI disclosure intensity was derived from manually coded transcript data using a predefined keyword dictionary. Although contextual validation was performed, some classification error may remain, particularly for terms that can appear in both AI and non-AI contexts. Future research should strengthen these findings by analyzing multiple earnings seasons, expanding the sample size, incorporating other comprehensive processing techniques, and applying conventional event-study methodologies using estimation windows, and multifactor expected-return benchmarks. Direct measures of AI investment, research and development expenditure, and implementation outcomes could also provide further insight into how investors evaluate AI-related corporate disclosures.

Additionally, membership within the technological sector is used as a proxy for firms operating in AI-intensive industries rather than a direct measure of operational AI capability. Firms within the technology sector vary substantially in their actual AI investment and implementation, while some comparison firms may also possess significant AI capabilities. Consequently, industry membership should not be interpreted as a direct measure of operational AI adoption.

Overall, this study contributes to the growing literature on AI disclosure by providing exploratory evidence that the relationship between AI-related communication and short-term market reactions differs across industries. While further research is required, the findings suggest that industry context may play an important role in how investors interpret AI-related corporate disclosures.

CONFLICT OF INTEREST

The author declares no conflict of interest related to this work

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