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Post-Earnings Announcement Drift in U.S. Technology Stocks: Evidence from Earnings Surprises from 2023 to 2025

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ABSTRACT

This paper examines whether post-earnings announcement drift (PEAD) exists among U.S. technology stocks during the 2023-2025 period, a time marked by heightened investor attention, artificial intelligence-driven speculation, and rapid information dissemination.

Using an initial sample of 50 U.S. technology firms and 600 quarterly earnings announcements, this study retains 310 qualifying earnings-surprise events from 44 firms after applying a minimum absolute surprise threshold of 5%. Cumulative abnormal returns (CAR) are estimated using the market model across pre-announcement, immediate, and post-announcement event windows. The analysis separates earnings surprises by direction, magnitude, and firm market capitalization to evaluate whether abnormal returns persist after announcements or are incorporated earlier.

The results show limited evidence of systematic post-earnings announcement drift. Post-announcement abnormal returns (AR) are generally weak, inconsistent, and short-lived, with only isolated significance in selected subgroups. In contrast, statistically significant abnormal returns appear more frequently in pre-announcement windows, especially immediately before earnings releases. These findings suggest that, in the modern technology sector, earnings information is often absorbed before or shortly after official announcements rather than producing a persistent delayed price adjustment. The paper contributes to research on market efficiency by showing that PEAD in recent U.S. technology stocks appears fragmented and conditional rather than broad, persistent, and tradable and that the modern market has become much more efficient in terms of price adjustment.

INTRODUCTION

Over the past two decades, the technology sector has evolved from a high-growth, high-risk investment area into one of the largest and most influential sectors shaping global financial markets (Invesco, 2026; Uwilingiye et al., 2019). The increasing concentration of market value within a small number of mega-technology firms like Apple Inc., NVIDIA, and Microsoft has amplified their impact on stock market performance, countries' capital flows, and overall market stability (Invesco, 2026; (MarketMinute, 2025; De Fiore et al., 2025). The impact has been reinforced by the growth of passive investing, where

index funds naturally allocate more capital to firms with larger market capitalizations. This causes more investment to flow into the largest tech firms regardless of their individual fundamentals (Jiang et al., 2025; Oksanen & Ollila, 2025). Consequently, stock prices become increasingly interconnected and markets become more vulnerable to shocks affecting these few dominant players (Kaye, 2025; Oksanen & Ollila, 2025).

Beyond markets, tech firms play a critical role in shaping innovation, productivity, and daily life (Rammal et al., 2025; Gao, 2023). Recently, the rapid acceleration of artificial intelligence (AI) development following the release of ChatGPT in late 2022 has triggered a wave of speculative enthusiasm, coined as the "AI hype cycle" (Maghyereh & Awartani, 2025; Floridi, 2024). This has further intensified investor attention toward the tech sector, contributing to heightened volatility and speculation (Invesco, 2026; Floridi, 2024). Such heightened attention, however, does not necessarily imply more effective information processing; rather, periods of concentrated investor focus can actually exacerbate cognitive biases, leading to potential systemic delays in price adjustment (Lan et al., 2024; Fink, 2020; Li et al., 2020).

One manifestation of this phenomenon is the Post-Earnings Announcement Drift (PEAD) - the observation that stock prices do not fully adjust immediately to earnings announcements. Instead, prices tend to drift in the direction of the earnings surprise for an extended period following the announcement. This phenomenon was first documented by Ray Ball and Philip Brown (1968), and later formalized by subsequent studies, most notably Bernard and Thomas (1990), as a persistent anomaly in financial markets. Despite its long-standing documentation, the magnitude of PEAD has declined significantly over time, with the effect becoming nearly negligible among large-cap firms (Fink, 2020). Several explanations have been proposed for this attenuation. This decline is commonly attributed to increased market efficiency, particularly the rise of institutional arbitrage and faster information dissemination through algorithmic trading and digital financial platforms. In addition, earnings surprises have become less persistent over time, reducing their predictive power and limiting the extent of delayed price adjustment (Chordia et al., 2014; Martineau, 2021; Kettell et al., 2022).

Despite decades of research on PEAD across different countries and time periods, existing studies have largely focused on broad cross-market samples rather than sector-specific dynamics (Fink, 2020). To the best of my knowledge, there is limited empirical evidence examining whether PEAD manifests differently within the U.S. tech sector, particularly during the recent AI boom period characterized by rapid technological advancement and increased retail participation. This represents a meaningful gap in the literature, as these sector-specific characteristics can influence PEAD's magnitude. Addressing this gap is meaningful because the unique characteristics of technology markets and investors such as speculative sentiment and complex information environment influence how efficiently earnings information is processed and incorporated into stock prices, providing insight into whether modern market structures have eliminated PEAD entirely or merely changed the conditions under which it persists.

By starting with an initial sample of 50 U.S. technology firms across five different market-capitalization groups during the 2023–2025 period, this study aims to provide a more granular understanding of the magnitude — here referring to the size of cumulative abnormal returns (CAR) — and persistence of PEAD following quarterly earnings surprises. The final event-study sample is narrower because only

earnings announcements with an absolute surprise magnitude of at least 5% and sufficient return data are retained, resulting in 310 qualifying events from 44 firms. To address the research question comprehensively, the analysis examines whether abnormal return (AR) varies by firm size and surprise magnitude, whether price adjustment is concentrated immediately after the announcement or persists over longer post-announcement windows, and whether there is evidence of pre-announcement price adjustment.

This study employs event study methodology to examine stock price reactions around quarterly earnings announcements. Using a sample of quarterly earnings data for U.S.-listed tech firms stratified by market capitalization (2023-2025), earning surprises were identified by using percentage deviation from analyst consensus forecasts. For each earnings event, AR is calculated using the market model with S&P 500 as the benchmark, and CAR is calculated across multiple event windows to capture immediate, short-term, and long-term price reactions. The analysis will examine cross-sectional variation by firm size (market cap) and earnings surprise magnitude, while also considering pre-announcement drifting behavior.

The findings are relevant for both researchers and market participants. For researchers, the study contributes to ongoing discussions regarding market efficiency in modern market structures. For market participants like investors and funds, it provides insight into the timing of earnings-related price adjustment. This can help investors and risk managers better understand post-earnings volatility and the limits of relying on traditional PEAD-based signals in recent technology stocks.

This paper proceeds as follows. Section 2 reviews the existing literature on PEAD, including its theoretical foundations, empirical evidence, and proposed explanations, and develops the hypotheses. Section 3 explains the data, event study methodology, and relevant calculations. Section 4 describes the dataset, including how earnings-surprise events are selected and classified, and presents summary statistics for the key variables. Section 5 presents the empirical results, including overall CAR patterns and cross-sectional findings by earnings surprise magnitude and market capitalization. Section 6 concludes by discussing the implications of the findings, addressing limitations, and suggesting directions for future research.

LITERATURE REVIEW & HYPOTHESIS DEVELOPMENT

PEAD represents a market anomaly in which stock prices adjust gradually rather than immediately to earnings announcements. This phenomenon directly violates the semi-strong form of the Efficient Market Hypothesis which asserts that all publicly available information is instantaneously reflected in prices (Bernard & Thomas, 1990). PEAD allows investors to potentially earn abnormal returns by exploiting predictable post-announcement price movements (Ball & Brown, 2018; Bernard & Thomas, 1990). However, the practical profitability of PEAD-based strategies is not automatic because transaction costs and risk exposure can reduce or even eliminate the abnormal returns observed in event-study tests (Ng et al., 2008; Zhang et al., 2013).

2.1 Empirical Evidence for the Existence of PEAD

The magnitude and duration of PEAD have been widely documented, with early studies documenting economically meaningful AR can persist over roughly 60 trading days after the announcement and up to two or three quarters (Bernard & Thomas, 1990; Fink, 2020). In addition, the phenomenon of pre-announcement drift is also confirmed as a nearly universal characteristic of markets, where approximately 85% of the total price revision associated with earnings news occurs prior to the announcement month, reflecting the anticipatory nature of the stock market (Ball & Brown, 2018). This suggests that investors partially incorporate expectations before the official release, likely through analyst forecasts, information leakage, or gradual updating of expectations (Gao, 2023; Martineau, 2021; Chen, 2012).

2.2 Explanations for the Existence of PEAD

2.2.1 General Theoretical Explanations

Researchers have proposed multiple explanations for why PEAD exists despite its apparent exploitability through two perspectives: behavioral biases and frictions in information dissemination and processing.

From a behavioral perspective, one of the most widely cited explanations is the conservatism heuristic (Chen, 2012). When firms announce earnings that deviate from expectations, under conservatism, investors place excessive weight on prior beliefs and underweight new earnings signals, leading to only partial adjustment at the time of announcement (Tversky & Kahneman, 1974). As a result, prices continue to drift in the direction of the earnings surprise over subsequent periods as investors gradually revise their expectations (Fink, 2020; Chen, 2012).

Another behavioral explanation is fragmented attention under information overload. Earnings announcements compete with a large volume of complementary information like analyst commentary, social-media discussion, ... When confronted with such an overwhelming volume of information - even if investors are highly attentive to the sector - they may not process the same information at the same speed or interpret the same earnings signal in the same way (Gao, 2023). As a result, some investors may react immediately to headline earnings figures, while others may gradually update their expectations after reconsideration (Hung et al., 2015). This heterogeneity in interpretation can create staggered responses over time and contribute to delayed or fragmented price adjustment.

Behavioral explanations also highlight an asymmetry in how investors respond to positive versus negative earnings surprises (Owen, n.d.). Positive surprises may reinforce investor optimism and overconfidence, especially when they already expect strong firm performance. Negative surprises, by contrast, likely trigger loss aversion because investors tend to be more sensitive to losses than gains (Lan et al., 2024; Gao, 2023; Pompian, 2012). These differing psychological responses can produce asymmetric drift

patterns; as a result, the magnitude and duration of PEAD may differ depending on whether the earnings surprise is positive or negative (Lan et al., 2024).

While behavioral biases explain why investors may fail to react optimally, information-based explanations focus on structural barriers that prevent immediate price adjustment even in the absence of irrationality. One key factor is asymmetric information. Earnings announcements are not interpreted uniformly across all market participants because investors differ in access to information and experience. Since PEAD has been primarily linked to less sophisticated noninstitutional investors who are typically less informed, take more time to understand the implications of earnings news, and update their beliefs accordingly, this can lead to gradual incorporation of earnings signals into prices (Tan et al., 2024; Chen, 2012; Hirshleifer et al., 2003).

2.2.2 Sector-Specific Amplifiers in the Technology Sector

The tech sector in 2023-2025 also exhibits several characteristics that may amplify the existence and persistence of PEAD.

A key factor is that retail investor participation reached historic levels during this period (Floridi, 2024). Increased market accessibility through trading platforms and the rise of online financial advice content have enabled a broader base of individual investors to participate in equity markets (Guo et al., 2025; Hvide et al., 2024). Since retail investors generally have fewer analytical resources than institutional investors, they may take longer to interpret earnings news, especially when announcements contain complex information, contributing to slower price adjustment (Fink, 2020). However, this gap may be smaller today because earnings information is widely distributed through financial websites, analyst summaries, media coverage, and company earnings reports that usually highlight key figures, including but not limited to revenue, EPS, guidance, and segment performance near the beginning of the reports. Prior research also finds that financial analysis on social media can help less-informed investors process earnings news more quickly, though not necessarily accurately or uniformly. As long as the public information environment remains informative rather than overwhelming, better public information environment reduces information asymmetry and – potentially – subsequent drift (Gomez et al., 2023; Chen & Wu, 2022). Therefore, retail participation may contribute to fragmented interpretation of earnings news, but it is unlikely to be the sole or dominant explanation for persistent PEAD in the tech sector recently.

A second factor is the prevalence of herding behavior among retail and institutional investors. Contrary to assumption, about 38% of large institutional investors intentionally engage in herding when it comes to tech stocks (Uwilingiye et al., 2019). Fear of missing out (FOMO) plays a significant role in reinforcing herding dynamics (Floridi, 2024). During periods of rapid price appreciation, investors may enter positions to avoid missing perceived opportunities (Sharma & Prajapati, 2024). Simultaneously, the widespread use of artificial intelligence (AI) also enables faster information dissemination and higher information volume through streams of signals, forecasts, and sentiment indicators also intensifies the

extent of herding (Rammal et al., 2025). AI creates information overload, leading investors, especially inexperienced retail investors, to rely on prevailing market sentiment rather than conducting independent analysis (Rammal et al., 2025; Lan et al., 2024). This factor weakens the efficiency of price discovery as price movements are driven more by collective behavior (Uwilingiye et al., 2019).

Another characteristic is the heightened role of speculative sentiment in periods of technological disruption (Maghyereh & Awartani, 2025). The period of 2023-2025 is marked by a major technological breakthrough, specifically the shift in AI from predictive to generative (Floridi, 2024). The number of notable AI models nearly doubled from 51 in 2023 to approximately 95–105 models by 2025, while organizational AI adoption increased sharply from 55% to 88% over the same period (The 2026 AI Index Report, 2026; The 2024 AI Index Report, 2024). The capabilities of frontier AI systems also improved substantially. For instance, Claude AI evolved from a largely text-based model with an approximately 100,000-token context window and limited agentic functionality in 2023 to the Claude Sonnet 3.7 and Claude 4 era in 2025, where models supported up to 1 million tokens alongside advanced coding, writing, and image-generation tools readily available (Anthropic, 2025).

Investors frequently perceive emerging technologies like AI as transformative breakthroughs with far-reaching and long-lasting economic implications, leading to inflated expectations about future growth and profitability (Job-Bazille, 2026). While AI promises productivity gains, projections remain modest (Walsh, 2025). Yet, AI-related investment and data-center spending were major contributors to U.S. growth in 2025. The St. Louis Fed estimates that AI-related categories contributed 0.97 percentage points, or 39% of total U.S. GDP growth, in the first three quarters of 2025, exceeding the comparable contribution of IT investment during the dot-com boom. (EVOTEK, 2025; Rubinton & Patro, 2026). Clearly, market valuations have become increasingly influenced by narratives and expectations rather than current fundamentals (Floridi, 2024).

This environment can also amplify behavioral biases such as novelty preference and overconfidence (Gao et al., 2010; Fenn & Raskino, 2008). Novelty preference refers to investors' tendency to pay disproportionate attention to new and innovative technologies, especially during the early or middle stages of development (Gao et al., 2010). This bias is especially relevant to the tech sector because firm valuations often depend heavily on expectations about future innovation. Overconfidence also arises when investors overestimate their ability to identify successful technologies and interpret complex information, drawing on highly salient past successes e.g. rise of the internet to form high expectations about current technological developments (Gao, 2023). Consequently, when earnings results are weaker than the optimistic narratives surrounding the firm, investors may initially maintain their prior beliefs rather than immediately revising valuations downward.

Finally, the inherent complexity of information in tech firms can further slow the process of price discovery (Chen, 2012). Unlike traditional industries, tech firms derive a significant portion of their value from intangible assets such as intellectual property and R&D (Ocean Tomo, 2020). As a result, evaluating earnings requires investors to assess not only current profitability but also uncertain future growth. This

complexity can slow the process of translating earnings news into accurate valuations. Simultaneously, a stronger public information environment, with more analysis available to investors, could lead to earlier expectation formation or more rapid immediate adjustment. Therefore, the effect of information complexity on PEAD is theoretically ambiguous.

2.3 The Recent Decline of PEAD

While PEAD has been extensively documented, recent research reveals evidence of its decline (Richardson et al., 2010). Quarterly hedge portfolio returns from PEAD strategies dropped from approximately 4-5% in the 1980s-90s to below 3% in the late 2010s (Kettell et al., 2022). For large stocks, the drift has been documented as nearly non-existent since 2006, as modern price discovery now occurs almost entirely on the announcement date rather than over subsequent months (Martineau, 2021). Interestingly, the decline concentrates in the "later window" following announcements (days +10 to +60), while the immediate market reaction within the first few days has actually strengthened over time. (Martineau, 2021; Kettell et al., 2022).

Three main explanations have been proposed for this observed decline in PEAD magnitude. First, the increase in market efficiency driven by greater arbitrage activity (Kettell et al., 2022). Over time, heightened participation by hedge funds and sophisticated institutional investors has led to more aggressive trading strategies that systematically exploit earnings-based signals (Martineau, 2021). As these investors act quickly on earnings surprises, information is incorporated into prices more rapidly, reducing the magnitude for delayed adjustment. As a result, opportunities to earn abnormal returns from post-announcement drift have diminished.

The second explanation for the decline in PEAD magnitude is the declining persistence of earnings news (Kettell et al., 2022). In other words, earnings surprises have become less indicative of future earnings performance over time. When this happens, there is inherently less information for the market to incorporate after the announcement, leading to a reduction in drift magnitude. This is contrast to historical data, where firms with high or low standardized unexpected earnings (SUE) tended to exhibit similar performance in subsequent quarters, allowing investors to underreact initially and gradually revise expectations (Kettell et al., 2022).

Thirdly, improvements in information dissemination driven by technological advances and broader access to financial information have significantly increased the rate at which earnings news is transmitted and interpreted. Hence, the speed at which information is processed and reflected in prices increases (Chordia et al., 2014; Martineau, 2021).

2.4 Hypothesis Development

The extent to which PEAD persists in modern markets, specifically in a sector susceptible to elevated PEAD like the technology, remains an empirical question. On one hand, improvements in market

efficiency, increased arbitrage activity, and faster information dissemination may enable prices to adjust rapidly. Under this view, persistent post-announcement drift should be weak or absent because investors adjust either before the announcement, as expectations are formed, or very shortly after the announcement, when official results become public.

On the other hand, the technology sector also contains characteristics that may slow or fragment price adjustment. These conditions could cause investors to update their beliefs gradually, resulting in observable post-announcement drift. Therefore, this study tests not only whether PEAD exists, but also where earnings-related price adjustment is concentrated across the event window.

Building on the theoretical explanations above, this study also develops directional expectations for the cross-sectional analyses. Regarding surprise magnitude, larger earnings surprises are expected to be associated with stronger and more persistent post-announcement drift, since larger surprises should convey more new information that requires additional time for investors to fully process (Fink, 2020; Lan et al., 2024). Regarding market capitalization, smaller firms are expected to exhibit stronger and more persistent PEAD than larger firms. This follows from the information-based explanations discussed above: smaller firms typically receive less analyst coverage, face greater informational frictions, and are more likely to be dominated by less-sophisticated retail investors, all of which should slow the incorporation of earnings information into prices (Fink, 2020; Martineau, 2021; Hirshleifer et al., 2003).

Accordingly, the hypotheses tested in this study are:

- H_0 (Null hypothesis): There is no significant post-earnings announcement drift in U.S. technology stocks with stock prices fully adjusting to earnings information at the time of announcement.
- H_a (Alternative hypothesis): U.S. technology stocks exhibit significant post-earnings announcement drift, with stock prices continuing to move in the direction of earnings surprises following the announcement.

H1: Post-announcement CAR is expected to increase in magnitude and persistence as earnings surprise size increases.
H2: Post-announcement CAR is expected to be larger and more persistent for smaller market-capitalization firms than for larger firms.

METHODOLOGY

3.1 Event Study Methodology

This study employs event study methodology to examine stock price reactions to quarterly earnings announcements. Event study methodology is a standard empirical approach in financial research used to isolate the impact of a specific event on asset prices (Gao, 2023; Katz et al., 2018). Contextually, it allows for the assessment of how quickly and to what extent earnings information is incorporated into stock

prices, making it particularly suitable for testing whether earnings-related price adjustment is concentrated before, immediately around, or after the announcement.

The central premise of this methodology is that, under market efficiency, new information should be reflected immediately in stock prices Any systematic deviation from this immediate adjustment, observed through AR, indicates that earnings-related information is being incorporated outside the announcement window. (Fink, 2020). By tracking stock performance before and after earnings announcements, this methodology allows prior, immediate market reactions and any subsequent drift to be identified.

The implementation of the event study follows these key steps. Earnings announcement dates were identified as event dates. Day 0 was defined as the first full trading day when investors could react to the announcement. If the announcement time was unavailable, the release was treated as after-market-close, so Day 0 was set as the next trading day. Expected returns were estimated for each stock using the market model with the window [-260, -61], after which abnormal returns (AR) and cumulative abnormal returns (CAR) were calculated to capture firm-specific price movements around the event.

Then, statistical significance was evaluated by testing whether mean CAR differs from zero across events. Because the sample includes repeated earnings announcements from the same firms, observations from the same company may be correlated rather than fully independent. To account for this, standard errors were clustered at the firm level for the main event-window test. Subgroup results by earnings surprise magnitude and market capitalization are reported using one-sample t-tests because some subgroups contain fewer observations and firm clusters. When this occurs, firm-clustered standard errors can become unstable and unreliable because the test has too few clusters to estimate within-firm correlation properly. To examine cross-sectional variation, CAR was then compared across groups defined by earnings surprise magnitude, firm size, and year, and, where the sample size permits, across industries in the tech sector.

To capture the temporal dynamics of price adjustment, multiple event windows are employed. The immediate reaction window is defined as [0, +1], followed by a short-term drift window of [+2, +10], a medium-term window of [+11, +30], and an extended drift window of [+31, +90]. The multiple event windows facilitate the analysis of the initial market reactions and subsequent price adjustments over time. To examine pre-announcement price adjustment, CAR was also calculated across four pre-announcement windows: [-90, -31], [-30, -11], [-10, -2], and [-1, 0].

3.2 PEAD-related Formula

To quantify post-earnings price behavior, this study employs the market model to estimate expected returns and derive abnormal returns. The market model is defined as:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_{it} \quad \text{(Eq. 1)}$$

where

- R_{it} : Return of stock i on day t
- R_{mt} : Return of the market index on day t
- α_i : Stock-specific intercept term
- β_i : Sensitivity of stock i to market movements
- ϵ_{it} : Idiosyncratic component of returns

AR are then calculated as the difference between actual returns and expected returns predicted by the market model:

$$AR_{it} = R_{it} - (\alpha_i + \beta_i R_{mt})$$

These AR isolate the portion of stock price movement that cannot be explained by general market fluctuations and is interpreted as firm-specific price movement around the event window. To assess the persistence of price adjustment, abnormal returns are aggregated into cumulative abnormal returns (CAR) over specified event windows:

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{it}$$

The presence of PEAD is inferred from statistically significant CAR in post-announcement windows. Under the null hypothesis of market efficiency, CAR should not differ significantly from zero after the announcement as prices would have already fully incorporated the information. Conversely, consistently positive or negative CAR following earnings surprises indicates the existence of PEAD. In addition, this study also examines CAR in pre-announcement windows to determine whether earnings-related information is incorporated before the official release. This allows the analysis to distinguish between delayed post-announcement adjustment, immediate adjustment, and pre-announcement price adjustment.

DATA

4.1 Sample and Variable Construction

The initial sample consists of 50 U.S.-listed technology firms selected from Finviz (Appendix A). Firms were selected using a stratified approach based on market-capitalization tiers, including mega-cap, large-cap, upper-mid-cap, mid-cap, and small-cap firms. Within each tier, firms were chosen to cover a broad range of market-cap values rather than clustering around a narrow size range. This allows the study to compare earnings-related price adjustment across firms of different sizes within the technology sector.

To be included in the initial sample, firms had to be listed on a major U.S. exchange, primarily NYSE or NASDAQ, have a clear technology-related business model, and have sufficient quarterly earnings history during the 2023–2025 period. Firms also needed adequate trading liquidity so that abnormal return estimates would not be heavily distorted by thin trading. For smaller firms, a minimum average daily trading volume threshold of 300,000 shares was applied.

Earnings data, including reporting dates, actual diluted non-GAAP EPS, analyst consensus EPS forecasts, and earnings surprise percentages, were collected from MSN Money. Public filing and announcement-date information was checked using SEC filings. Market index and firm classification data, including industry category and market capitalization, were collected from Finviz. Market-cap tiers were assigned using market capitalization data collected on 29th March, 2026 as a fixed classification point. Although this classification date falls after the event period, it is used only to group firms for cross-sectional comparison and not to calculate event-time returns.

The raw dataset contained nearly 600 potential firm-quarter earnings events, based on 50 firms across 12 quarterly announcements from 2023 to 2025. The final event-study sample was constructed by applying two main filters. First, earnings announcements were retained only if the absolute earnings surprise was at least 5%, since smaller surprises were unlikely to represent economically meaningful earnings news. Second, events with missing EPS forecasts, missing price data, or insufficient return observations around the estimation or event windows were excluded.

Earnings surprise percentage was calculated as:

$$\text{Surprise } (\%) = \left(\frac{\text{Actual EPS} - \text{Consensus EPS}}{|\text{Consensus EPS}|} \right) \times 100$$

Events were classified as

- Positive surprises if the surprise percentage was at least +5%
- Negative surprises if the surprise percentage was -5% or lower.
- Events with surprise percentages between -5% and +5% were excluded from the analysis.

Event dates were also adjusted to ensure that Day 0 represents the first full trading day available for market reaction. If the announcement time was unavailable, the event was treated as after-market-close and shifted to the next trading day.

4.2 Descriptive Statistics

The final sample consists of 44 U.S. technology firms and 310 quarterly earnings announcement events spanning the 2023 - 2025 period. Of these events, 217 (70.00%) were classified as positive earnings surprises, while 93 (30.00%) were negative surprises. The substantially higher proportion of positive surprises is consistent with broader earnings-reporting trends in equity markets, where firms frequently issue conservative forward guidance prior to earnings announcements, allowing actual earnings to exceed

analyst expectations more easily. As a result, reported "earnings beats" may be structurally inflated, making positive surprises significantly more common than negative ones (Ng et al., 2024).

Table 1. Distribution of Earnings Surprise Events Panel A. Distribution by Surprise Magnitude

Panel A. Distribution by Surprise Magnitude				
Surprise magnitude	Number of events	Positive surprises (Number / %)	Negative surprises (Number / %)	% of Total
5–15%	112	89 / 79.46	23 / 20.54	36.13
15–30%	74	54 / 72.97	20 / 27.03	23.87
30–100%	66	45 / 68.18	21 / 31.82	21.29
100%+	58	29 / 50.00	29 / 50.00	18.71
Total	310	217 / 70.00	93 / 30.00	100.00
Panel B. Distribution by Year				
Year	Number of events	Positive surprises (Number / %)	Negative surprises (Number / %)	% of Total
2023	81	56 / 69.14	25 / 30.86	26.13
2024	101	72 / 71.29	29 / 28.71	32.59
2025	128	89 / 69.53	39 / 30.47	41.29
Panel C. Distribution by Market Capitalization				
Market capitalization	Number of events	Positive surprises (Number / %)	Negative surprises (Number / %)	% of Total
Mega-cap (200B+)	43	38 / 88.37	5 / 11.63	13.87
Large-cap (50–200B)	59	48 / 81.36	11 / 18.64	19.03
Upper-mid cap (10–50B)	44	37 / 84.09	7 / 15.91	14.19
Mid-cap (2–10B)	70	48 / 68.57	22 / 31.43	22.58

Small-cap (<2B)	94	46 / 48.94	48 / 51.06	30.32
Panel D. Distribution by Industry Composition				
Industry	Number of events	Positive surprises (Number / %)	Negative surprises (Number / %)	% of Total
Software - Infrastructure & Application	182	131 / 71.98	51 / 28.02	58.71
Information Technology Services	40	26 / 65.00	14 / 35.00	12.90
Semiconductor (Semiconductors, Semiconductor Equipment & Materials)	61	45 / 73.77	16 / 26.23	19.68
Hardware Technology (including Computer Hardware, Consumer Electronics)	21	14 / 66.67	7 / 33.33	6.77
Internet Content & Information	6	6 / 100.00	0 / 0.00	1.94

The distribution of earnings announcement events exhibits several notable patterns across time and firm characteristics. First, the number of surprise events observed increases steadily from 2023 to 2025. One possible explanation is the rapid acceleration of AI development and adoption between 2023 and 2025, which significantly increased investor attention toward technology firms. Increased market attention does not imply stronger PEAD effects, as greater analyst coverage typically increases volume of closely monitored earnings announcements over time and improves forecast accuracy. This should reduce surprise magnitude. Therefore, this trend should be interpreted primarily as a characteristic of the sample period rather than direct evidence of stronger post-announcement drift.

A second pattern emerges across market capitalization groups. Small-cap firms account for the largest proportion of earnings events of 30.29%, while mega-cap firms represent the smallest share of the sample of 13.36%. There is a gradual increase in the number of surprise events from mega-cap firms to small-cap firms even though the difference in proportion between mega-cap and upper-mid-cap firms is small only 0.97%. This trend can be explained by the level of analyst coverage and operational and financial stability across different market capitalization groups. Smaller firms generally exhibit greater earnings volatility because they tend to have less diversified revenue streams and weaker financial buffers, thus their growth trajectories are more unstable (Calvino et al., 2018; Chatterjee & Eyigungor, 2022; Davis et al., 2007; Liu et al., 2026). They also receive less investor attention and, hence, less analyst coverage (Bashir & Kumar, 2026). These characteristics likely increase the frequency and magnitude of earnings surprises.

At the same time, positive surprises are substantially more dominant among mega-cap and large-cap firms, whereas small-cap firms display a more balanced distribution between positive and negative surprises. One possible explanation is that larger firms have stronger incentives and greater ability to manage market expectations through conservative guidance and regular communication with analysts (Call et al., 2023; Kaplan et al., 2021). As a result, consensus forecasts may be set at levels that are easier to exceed or analyst estimates that are relatively optimistic may be excluded from the consensus measure, increasing the reported earnings beat rate (Kaplan et al., 2021; Ng et al., 2024). In contrast, analysts covering smaller firms have fewer incentives or opportunities to strategically lower expectations, potentially leading forecasts to reflect firm performance more objectively (Nilsson & Svensson, 2019). Combined with the greater uncertainty and volatility typically faced by smaller firms, this makes both positive and negative surprises more equally likely (Dichev & Tang, 2009; Johnson et al., 2019).

Industry composition is concentrated primarily in software-related firms accounting for 57.65% of observations. This concentration likely reflects the central role of software companies in recent technology market expansion, especially amid the rapid commercialization of artificial intelligence and cloud-based services during the 2023–2025 period (Invesco, 2026; Kaye, 2025). Semiconductor-related firms also comprise a significant portion of the sample with 17.26%, consistent with increased demand for computational hardware supporting AI development (Gao, 2023; Invesco, 2026). The concentration of firms in AI- and software-related industries is particularly relevant to this study's research question, as these sectors are characterized by high investor attention, rapid information flows, and elevated speculative sentiment, all of which can increase the magnitude and/or persistence of PEAD (Chen, 2012; Lan et al., 2024; Rammal et al., 2025).

Table 2. Summary Statistics of Key Variables (n = 310)

Variable	Mean	Median	Std Dev	Min	Max

Positive surprise % (winsorized)	102.32	20.35	316.36	5.00	2102.79
Negative surprise % (winsorized)	-142.90	-36.36	275.71	-1201.11	-5.16
CAR_pre_extended	0.0108	0.0106	0.3605	-1.3002	3.7277
CAR_pre_med	0.0114	0.0007	0.2276	-0.8437	2.6430
CAR_pre_short	0.0147	-0.0090	0.1753	-0.6631	1.6377
CAR_pre_imme	-0.0082	-0.0055	0.0400	-0.1536	0.2267
CAR_imme	-0.0010	-0.0033	0.0716	-0.2287	0.8009
CAR_short	0.0112	0.0083	0.1134	-0.5236	0.7230
CAR_med	-0.0113	-0.0132	0.2161	-1.1445	0.9092
CAR_extended	0.0161	-0.0012	0.4535	-1.7142	3.7250

Table note:

- Earnings surprise percentages are winsorized at the 1st and 99th percentiles to reduce the influence of extreme observations. CAR variables are reported using raw values.

- CAR_pre_extended: the CAR over the extended pre-announcement window [-90, -31].
- CAR_pre_medium: the CAR over the medium pre-announcement window [-30, -11].
- CAR_pre_short: the CAR over the short pre-announcement window [-10, -2].
- CAR_pre_immediate: the CAR over the immediate pre-announcement window [-1, 0].
- CAR_pre: the CAR over the pre-announcement window [-60, 0]
- CAR_imme: the CAR over the immediate reaction window [0, +1].
- CAR_short: the CAR over the short-term reaction window [+2, +10].
- CAR_med: the CAR over the medium-term reaction window [+11, +30].
- CAR_extended: the CAR over the extended drift [+31, +90].

Table 2 shows substantial dispersion in earnings surprise magnitudes across the sample, even after winsorizing surprise percentages at the 1st and 99th percentiles. Positive surprises have a winsorized mean of 102.32%, but a much lower median of 20.35%, while negative surprises have a winsorized mean of -142.90% and a median of -36.36%. The large gap between mean and median values suggests that the mean remains highly right-skewed and influenced by a relatively small number of extreme observations, especially for positive surprises. This is also reflected in the high standard deviations of 316.36% for

positive surprises and 275.71% for negative surprises. Therefore, although winsorization reduces the influence of extreme observations, the typical surprise is better represented by the median than by the mean. The substantial dispersion in earnings surprises reflects the heterogeneous and volatile nature of technology firms during the 2023–2025 period, where rapidly evolving technologies contributed to highly uneven earnings outcomes across firms with different market capitalization amount.

The presence of these extreme values is particularly relevant to this study's research question because prior literature suggests that PEAD magnitude may vary systematically with the size of the earnings surprise. Larger surprises should attract greater investor attention and trigger stronger post-announcement price adjustments, while smaller surprises may be incorporated into prices more efficiently. However, because the surprise variables remain highly dispersed, results based on surprise magnitude should be interpreted cautiously. The winsorized summary statistics show that the sample contains highly uneven earnings outcomes across technology firms, but they do not by themselves indicate a clear PEAD pattern.

The CAR variables show little consistent movement across event windows. In the post-announcement period, CAR_imme has a slightly negative median of -0.0033, followed by a positive median of 0.0083 in CAR_short, before turning negative again in CAR_med (-0.0132) and CAR_extended (-0.0012). The mean values also fluctuate constantly [0, 90]. This alternating pattern provides little descriptive evidence of a uniform or persistent PEAD effect. Instead, abnormal returns appear mixed across different announcements and time horizons. Coupled with the wide range between minimum and maximum values, it is also indicated that while some announcements generated strong price reactions, others - or most - produced little AR.

The pre-announcement CAR variables exhibit a slightly more consistent trend over time. Median CAR gradually decreases from 0.0106 in the extended pre-announcement window [-90, -31] to 0.0007 in the [-30, -11] window, before reaching -0.0090 in the [-10, -2] window and becoming slightly less negative at -0.0055 at the [-1, 0] window. Pre-announcement price movement is not a simple downward trend with some evidence of weakening or reversal in the final days before the announcement.

RESULTS

Statistical significance in this study is evaluated primarily using the 5% significance level ($p < 0.05$), which is commonly adopted in economic research. However, results significant at the 10% level ($p < 0.10$) are also discussed as marginally significant, as they may still indicate weaker but potentially meaningful evidence of post/ pre-announcement price adjustment.

Table 3: Mean CAR across Event Windows

Event window	Mean CAR	Std dev	t-stat	p-value
[-90, -31]	0.0108	0.3605	0.8131	0.4206
[-30, -11]	0.0114	0.2276	1.6198	0.1126
[-10, -2]	0.0147	0.1753	1.6730	0.1016
[-1, 0]	-0.0082	0.0400	-3.8395	0.0004
[0, +1]	-0.0010	0.0716	-0.4203	0.6764
[+2, +10]	0.0112	0.1134	1.4468	0.0952
[+11, +30]	-0.0113	0.2161	-1.0150	0.3158
[+31, +90]	0.0161	0.4535	0.8232	0.4149

Table note: Statistical significance is calculated using firm-clustered standard errors to account for repeated earnings events from the same firm. Mean CAR and standard deviation are reported using raw CAR values.

Table 3 shows limited evidence of systematic abnormal returns across the event windows after applying firm-clustered standard errors. Within the pre-announcement period, mean CAR increases slightly from 0.0108 in the extended window to 0.0114 in the medium window and 0.0147 in the short window. However, these positive CARs are not statistically significant, so they should not be interpreted as strong evidence of a consistent anticipation effect. At most, they suggest that some earnings-related expectations may begin forming before the official announcement, but the evidence is weak.

The only statistically significant result appears in the immediate pre-announcement window [-1, 0], where mean CAR is -0.0082 with a clustered p-value of 0.0004. This suggests that stock prices declined by approximately 0.82% immediately before earnings announcements on average. Thus, rather than steadily increasing their optimistic expectations, investors seemingly progressively reduce exposure.

One possible interpretation for this phenomenon is pre-announcement risk reduction. Earnings announcements for small tech firms can be high-information and high-volatility events. As the announcement date approaches, some investors may reduce their positions to avoid exposure to large price swings if earnings disappoint. This selling pressure shortly before the announcement can contribute to negative median CAR in the final pre-announcement windows (Gao et al., 2018; Gao et al., 2025). A second possible reason is short-term reversal after a pre-announcement price run-up. If investors become

more optimistic in the weeks leading up to earnings announcements, they may extrapolate past growth trends or recent positive news too aggressively into future earnings expectations and buy a lot of shares, pushing stock prices upward (Ertan et al., 2016). However, as the announcement date approaches and uncertainty becomes more immediate, some investors may reassess whether these expectations have become too optimistic. This can lead to partial correction in the short and immediate pre-announcement windows, as investors reduce positions or adjust valuations downward before the release (Ertan et al., 2016).

However, these two explanations are not mutually exclusive, and the event study design used here cannot distinguish between them or rule out other contributing factors, such as firm-specific news or information leakage occurring independently of earnings anticipation. Because AR captures only the portion of returns unexplained by market-wide movements, it identifies that an abnormal price movement occurred but not why. Adjudicating between these explanations would require additional data, such as analyst forecast revision timing or trading volume patterns, which is beyond the scope of this study.

The post-announcement pattern is much less consistent. Mean CAR alternates across the post-announcement windows: -0.0010 in [0, +1], 0.0112 in [+2, +10], -0.0113 in [+11, +30], and 0.0161 in [+31, +90]. This fluctuation suggests the absence of a stable drift across the full sample. The immediate [0, +1] window is near zero and statistically insignificant, suggesting that there is little systematic abnormal return immediately after earnings announcements on average. However, this does not prove that all information is fully incorporated immediately; rather, it indicates that there is no consistent average reaction in that window.

The only post-announcement window with marginal significance is [+2, +10], where mean CAR is 0.0112 with a clustered p-value of 0.0952. This suggests a weak short-term positive adjustment after earnings announcements. One possible explanation is that while headline earnings figures may be processed quickly, investors may require additional time to interpret more complex information (Hung et al., 2015). In the tech sector, where earnings announcements are often interpreted alongside broader narratives about innovation and future growth, this can create a limited delayed reaction even when the core earnings news is absorbed quickly (Floridi, 2024).

However, this short-term effect does not persist as all later windows are insignificant. This weakens the case for traditional PEAD, which requires a persistent continuation of AR after earnings announcements, but aligns with recent literature highlighting that PEAD has declined significantly over time. This implies that the theoretical sector-specific amplifiers in the technology sector discussed above did not translate into strong post-announcement drift in this sample. The small size of the mean CAR values further supports this interpretation: even when abnormal returns are statistically significant, their economic magnitude remains modest.

Overall, Table 3 suggests any PEAD effect in the full sample is weak, short-lived, and inconsistent. The strongest statistical evidence appears immediately before the announcement, while post-announcement evidence is limited to a marginal short-term effect in [+2, +10]. This suggests that recent U.S. technology

stocks do not exhibit persistent PEAD; instead, earnings-related adjustment appears more concentrated before the announcement, with only weak evidence of delayed adjustment afterward.

This lack of pattern has two implications for market efficiency. First, the lack of a drift implies that the modern market has become more efficient in processing earnings information after announcements, leaving little room for sustained AR. Second, the stronger evidence immediately prior to the announcement implies that investors tend to form expectations through analyst forecasts, media coverage, firm guidance, and other public signals and take actions much earlier. Thus, while modern technology markets are not perfectly efficient, they appear efficient enough to prevent a stable, persistent PEAD pattern from forming.

Table 4. CAR by Earnings Surprise Magnitude

Surprise Magnitude	Surprise Direction	Event Window	Mean CAR	Std. Dev.	t-stat	p-value
5–15%	**Positive**	[-90, -31]	-0.0083	0.1624	-0.4794	0.6328
		[-30, -11]	0.0021	0.0906	0.2169	0.8288
		[-10, -2]	-0.0075	0.0556	-1.2786	0.2044
		[-1, 0]	-0.0042	0.0327	-1.2028	0.2323
		[0, +1]	-0.0055	0.0289	-1.8019	0.0750
		[+2, +10]	0.0014	0.0622	0.2176	0.8282
		[+11, +30]	-0.0043	0.1650	-0.2455	0.8066
		[+31, +90]	0.0330	0.4728	0.6568	0.5130
	Negative	[-90, -31]	0.0247	0.1918	0.9532	0.3483
		[-30, -11]	0.0458	0.1479	2.2887	0.0292
		[-10, -2]	-0.0395	0.0763	-3.8358	0.0006
		[-1, 0]	0.0005	0.0383	0.1027	0.9188
		[0, +1]	-0.0040	0.0395	-0.7533	0.4570
		[+2, +10]	0.0227	0.0938	1.7915	0.0832

		[+11, +30]	-0.0242	0.2014	-0.8894	0.3811
		[+31, +90]	0.0895	0.4517	1.4668	0.1524
15–30%	**Positive**	[-90, -31]	0.0304	0.2777	0.8180	0.4170
		[-30, -11]	0.0003	0.1307	0.0184	0.9854
		[-10, -2]	-0.0041	0.0554	-0.5475	0.5868
		[-1, 0]	-0.0081	0.0264	-2.2922	0.0265
		[0, +1]	-0.0056	0.0314	-1.3283	0.1908
		[+2, +10]	0.0133	0.0894	1.1106	0.2728
		[+11, +30]	0.0206	0.1667	0.9220	0.3613
		[+31, +90]	0.0530	0.4588	0.8607	0.3937
	Negative	[-90, -31]	-0.0533	0.2216	-1.1842	0.2457
		[-30, -11]	-0.0217	0.1596	-0.6682	0.5092
		[-10, -2]	-0.0382	0.0693	-2.7005	0.0113
		[-1, 0]	-0.0131	0.0304	-2.1105	0.0434
		[0, +1]	-0.0056	0.0406	-0.6759	0.5043
		[+2, +10]	-0.0108	0.1037	-0.5114	0.6128
		[+11, +30]	-0.0318	0.1918	-0.8126	0.4232
		[+31, +90]	-0.0974	0.2715	-1.7587	0.0892
30–100%	**Positive**	[-90, -31]	0.0606	0.3323	1.3719	0.1762
		[-30, -11]	-0.0136	0.1597	-0.6399	0.5252
		[-10, -2]	0.0440	0.2406	1.3690	0.1769
		[-1, 0]	-0.0013	0.0346	-0.2789	0.7814
		[0, +1]	0.0135	0.1106	0.9128	0.3655

		[+2, +10]	-0.0067	0.1062	-0.4706	0.6398
		[+11, +30]	-0.0202	0.1798	-0.8393	0.4051
		[+31, +90]	0.0848	0.3396	1.8631	0.0682
	Negative	[-90, -31]	0.0367	0.4012	0.5275	0.6017
		[-30, -11]	0.0278	0.1714	0.9367	0.3558
		[-10, -2]	0.0070	0.1846	0.2198	0.8274
		[-1, 0]	-0.0098	0.0433	-1.3094	0.1990
		[0, +1]	0.0182	0.1046	1.0040	0.3222
		[+2, +10]	0.0185	0.1122	0.9525	0.3477
		[+11, +30]	-0.0268	0.1940	-0.7977	0.4307
		[+31, +90]	-0.0108	0.2849	-0.2195	0.8275
100%+	**Positive**	[-90, -31]	0.1025	0.7006	0.9243	0.3607
		[-30, -11]	0.0799	0.5347	0.9450	0.3503
		[-10, -2]	0.1583	0.3227	3.1055	0.0035
		[-1, 0]	-0.0024	0.0587	-0.2619	0.7948
		[0, +1]	0.0112	0.1087	0.6515	0.5180
		[+2, +10]	0.0537	0.1975	1.7193	0.0928
		[+11, +30]	0.0257	0.3543	0.4592	0.6485
		[+31, +90]	0.0105	0.6633	0.1003	0.9206
	Negative	[-90, -31]	-0.0917	0.4938	-0.9818	0.3349
		[-30, -11]	-0.0397	0.2967	-0.7067	0.4858
		[-10, -2]	0.0094	0.2475	0.2014	0.8149
		[-1, 0]	-0.0378	0.0482	-4.1516	0.0003

		[0, +1]	-0.0222	0.0879	-1.3341	0.1933
		[+2, +10]	0.0207	0.1619	0.6770	0.5042
		[+11, +30]	-0.0656	0.3167	-1.0960	0.2828
		[+31, +90]	-0.1037	0.5001	-1.0972	0.2823
Surprise Magnitude	**Surprise Direction**	**Event Window**	**Mean CAR**	**Std. Dev.**	**t-stat**	**p-value**
5–15%	**Positive**	[-90, -31]	-0.0083	0.1624	-0.4794	0.6328
		[-30, -11]	0.0021	0.0906	0.2169	0.8288
		[-10, -2]	-0.0075	0.0556	-1.2786	0.2044
		[-1, 0]	-0.0042	0.0327	-1.2028	0.2323
		[0, +1]	-0.0055	0.0289	-1.8019	0.0750
		[+2, +10]	0.0014	0.0622	0.2176	0.8282
		[+11, +30]	-0.0043	0.1650	-0.2455	0.8066
		[+31, +90]	0.0330	0.4728	0.6568	0.5130
	Negative	[-90, -31]	0.0247	0.1918	0.9532	0.3483
		[-30, -11]	0.0458	0.1479	2.2887	0.0292
		[-10, -2]	-0.0395	0.0763	-3.8358	0.0006
		[-1, 0]	0.0005	0.0383	0.1027	0.9188
		[0, +1]	-0.0040	0.0395	-0.7533	0.4570
		[+2, +10]	0.0227	0.0938	1.7915	0.0832

Table note: Two-tailed one-sample t-tests were conducted against a null hypothesis of mean CAR = 0 for each subgroup.

Table 4 shows that statistically significant CARs are sparse across the surprise magnitude subgroups. The clearest pattern is significant results appear more often in pre-announcement windows than in post-announcement windows. In particular, several significant CARs occur in the [-10, -2] and [-1, 0] windows for all surprise magnitude subgroups except the 30-100% group, while post-announcement

significance is limited and mostly marginal. This suggests that the subgroup results are more consistent with pre-announcement price adjustment than with traditional PEAD, providing further support for the anticipatory nature of the modern U.S. stock market. While the existence of a short pre-announcement drift of at least 10 days prior can be safely concluded since short pre-announcement movement appears across most surprise-magnitude groups, the size of this drift is generally modest, so the evidence points to limited anticipatory adjustment rather than a large or highly tradable pattern.

More importantly, there is no clear relationship between surprise magnitude and the strength or persistence of PEAD. Larger earnings surprises are expected to generate more statistically significant and more persistent post-announcement CARs as they should contain more new information for investors to process (Fink, 2020; Lan et al., 2024). However, smaller and larger surprise categories both contain mostly insignificant post-announcement results, and the few significant results appear in isolated windows rather than increasing steadily with surprise size.

A possible explanation is that extreme surprise values are noisy and may reflect unusual firm-specific circumstances rather than clean earnings information. This is especially relevant because surprise percentages in the sample are highly skewed even after winsorization. Another potential explanation is larger surprises actually can attract faster market reaction rather than stronger delayed reaction. Although the tech sector can create information overload with such a complex information environment, extreme earning surprises provide a clearer directional signal to investors: Large negative surprises are unfavorable and encourage investors to sell, and vice versa with large positive surprises. This may encourage faster trading responses, especially in highly monitored tech stocks, leaving less room for persistent drift after the announcement. Therefore, larger surprise magnitude does not automatically translate into stronger PEAD.

A second pattern is a slight asymmetry between positive and negative surprises in the pre-announcement windows. Across the pre-announcement windows, negative surprises show five statistically significant CARs, compared with only two for positive surprises. Negative-surprise significance appears in three of the four magnitude groups: 5%–15%, 15%–30%, and 100%+, with the only exception being the 30%–100% group. By contrast, positive-surprise significance appears only in two groups: 15%–30% and 100%+. This reveals that pre-announcement adjustment is somewhat more frequent for negative surprises than for positive surprises. This observation is consistent with the idea that investors reacts more strongly to expected bad news than good news because of loss aversion and risk reduction incentives. As earnings announcements approach, investors who suspect downside risk may reduce exposure earlier to avoid larger losses, especially in tech firms where valuations often depend heavily on growth expectations. However, the number of significant cases remains sparse, so this asymmetry should be treated as suggestive rather than conclusive. Regarding post-announcement windows, there is no asymmetry between negative and positive surprises.

If this asymmetry is meaningful, the implication is investors are more willing to reduce exposure before expected bad news than to increase exposure before expected good news. This is consistent with downside-risk management: investors prioritize avoiding earnings-related losses over capturing additional gains from positive surprises. For funds, the implication is that monitoring downside earnings risk before

announcements may be more useful for risk management than relying on post-announcement drift. This connects to broader portfolio-management strategies such as event-risk control and tail-risk hedging.

Across both positive and negative surprise categories, there is very limited and inconsistent evidence of statistically significant PEAD. Smaller surprise magnitudes largely exhibit insignificant PEAD across all windows, while larger surprise magnitudes only display isolated instances of marginal significance. Overall, these findings suggest persistent PEAD is largely absent within the sample, supporting recent literature arguing that PEAD has attenuated substantially in modern financial markets.

Table 5. CAR by Market Capitalization

Market Capitalization (USD)	Surprise Direction	Event Window	Mean CAR	Std. Dev.	t-stat	p-value
Small-cap (<2B)	**Positive**	[-90, -31]	0.0683	0.7374	0.6281	0.5331
		[-30, -11]	-0.0002	0.2746	-0.0044	0.9965
		[-10, -2]	0.0897	0.3589	1.6944	0.0971
		[-1, 0]	-0.0016	0.0610	-0.1791	0.8587
		[0, +1]	0.0052	0.0999	0.3536	0.7253
		[+2, +10]	0.0145	0.1578	0.6216	0.5373
		[+11, +30]	-0.0408	0.2680	-1.0320	0.3076
		[+31, +90]	-0.0175	0.5760	-0.2061	0.8376
	Negative	[-90, -31]	-0.1043	0.3998	-1.6084	0.1162
		[-30, -11]	0.0416	0.4829	0.5312	0.5984
		[-10, -2]	-0.0147	0.2534	-0.3588	0.7218
		[-1, 0]	-0.0236	0.0515	-2.8252	0.0076
		[0, +1]	0.0010	0.1502	0.0419	0.9000
		[+2, +10]	-0.0235	0.1284	-1.1273	0.2669

		[+11, +30]	-0.0604	0.3324	-1.1201	0.2699
		[+31, +90]	0.0745	0.9309	0.4936	0.6245
Mid-cap (2–10B)	**Positive**	[-90, -31]	0.0219	0.1995	0.8437	0.4023
		[-30, -11]	0.0146	0.1271	0.8794	0.3828
		[-10, -2]	0.0126	0.0643	1.5099	0.1365
		[-1, 0]	0.0004	0.0363	0.0918	0.9272
		[0, +1]	0.0028	0.0360	0.6071	0.5462
		[+2, +10]	0.0038	0.1197	0.2429	0.8089
		[+11, +30]	-0.0073	0.1792	-0.3145	0.7542
		[+31, +90]	-0.0239	0.3138	-0.5853	0.5606
	Negative	[-90, -31]	-0.0136	0.4356	-0.1283	0.8995
		[-30, -11]	0.0298	0.2873	0.4277	0.6746
		[-10, -2]	0.0306	0.1402	0.9005	0.3812
		[-1, 0]	-0.0238	0.0488	-2.0077	0.0619
		[0, +1]	-0.0066	0.0844	-0.3231	0.7508
		[+2, +10]	0.0605	0.1485	1.6809	0.1122
		[+11, +30]	0.0005	0.2428	0.0089	0.9930
		[+31, +90]	0.0300	0.2662	0.4640	0.6489
Upper-mid-cap (10–50B)	**Positive**	[-90, -31]	0.0076	0.1577	0.3433	0.7328
		[-30, -11]	-0.0076	0.1012	-0.5380	0.5929
		[-10, -2]	-0.0146	0.0508	-2.0568	0.0449

		[-1, 0]	-0.0059	0.0258	-1.6329	0.1088
		[0, +1]	-0.0021	0.0284	-0.5187	0.6062
		[+2, +10]	0.0314	0.0798	2.8099	0.0071
		[+11, +30]	0.0051	0.1875	0.1932	0.8476
		[+31, +90]	-0.0320	0.2369	-0.9636	0.3399
	Negative	[-90, -31]	0.0603	0.3165	0.4262	0.6919
		[-30, -11]	0.0174	0.2001	0.1944	0.8554
		[-10, -2]	0.0967	0.0756	2.8598	0.0459
		[-1, 0]	-0.0318	0.0402	-1.7652	0.1523
		[0, +1]	-0.0007	0.0439	-0.0354	0.9735
		[+2, +10]	-0.0092	0.2086	-0.0988	0.9261
		[+11, +30]	-0.1074	0.2889	-0.8315	0.4524
		[+31, +90]	0.1686	0.2189	1.7218	0.1602
Large-cap (50–200B)	**Positive**	[-90, -31]	0.0167	0.1398	0.7265	0.4722
		[-30, -11]	0.0100	0.0728	0.8362	0.4086
		[-10, -2]	0.0004	0.0553	0.0390	0.9691
		[-1, 0]	-0.0041	0.0204	-1.2205	0.2302
		[0, +1]	-0.0039	0.0259	-0.9081	0.3698
		[+2, +10]	-0.0028	0.0494	-0.3403	0.7356
		[+11, +30]	0.0151	0.1589	0.5796	0.5658
		[+31, +90]	0.0343	0.2814	0.7425	0.4626
	Negative	[-90, -31]	0.0277	0.1563	0.6629	0.5190

		[-30, -11]	0.0114	0.0913	0.4672	0.6481
		[-10, -2]	-0.0056	0.0392	-0.5330	0.6030
		[-1, 0]	-0.0030	0.0249	-0.4445	0.6640
		[0, +1]	0.0001	0.0263	0.0196	0.9847
		[+2, +10]	0.0026	0.0704	0.1370	0.8931
		[+11, +30]	0.0050	0.1506	0.1230	0.9040
		[+31, +90]	0.0077	0.1741	0.1644	0.8719
Mega-cap (200B+)	**Positive**	[-90, -31]	0.0553	0.1739	1.5586	0.1328
		[-30, -11]	0.0108	0.1288	0.4117	0.6843
		[-10, -2]	-0.0030	0.0465	-0.3165	0.7544
		[-1, 0]	-0.0094	0.0273	-1.6879	0.1049
		[0, +1]	-0.0103	0.0287	-1.7588	0.0919

Based on Table 5, only upper-mid-cap and mega-cap firms exhibit statistically significant post-announcement abnormal returns, while small-cap and mid-cap firms show virtually no significant PEAD across post-announcement windows. Upper-mid-cap firms with positive surprises record a significant CAR of 0.0314 in the [+2, +10] window ($p = 0.007$), while mega-cap firms with positive surprises record a marginally significant CAR of 0.0363 in the same window ($p = 0.050$). This suggests that any remaining PEAD within the technology sector is concentrated primarily among larger firms rather than smaller firms.

Mega-cap firms exhibit the clearest evidence of PEAD among all market-cap groups. Positive surprises display marginally significant short-term drift in the [+2, +10] window, whereas negative surprises display significant extended drift only in the [+31, +90] window, with a CAR of 0.1032 ($p = 0.042$). A possible explanation is investors may be slower to revise long-term growth expectations for mega-cap tech firms following negative earnings news. Due to their dominant market positions, investors may perceive disappointing earnings announcements as temporary deviations rather than fundamental deterioration, causing negative information to be incorporated more gradually over longer horizons for larger, more established firms.

While this implies timing of PEAD differs depending on surprise direction, these results should be interpreted very cautiously for two reasons: i) Mega-cap firms only have 5 negative surprise events. Basing insights on such a small sample size risks overgeneralization and reduces the reliability of the results. ii) the [+31, +90] window is far from the earnings announcement date, so AR in this period is likely affected by confounding firm-specific or market-wide factors rather than earnings news alone. Therefore, although mega-cap results provide limited evidence of delayed adjustment, they should not be treated as strong proof of persistent PEAD.

Interestingly, large-cap firms display consistently insignificant CAR across all windows regardless of surprise direction and regardless of whether the window is pre- or post-announcement. None of the large-cap categories record statistically significant abnormal returns at either the 5% or 10% level. Compared to other market-cap groups, a possible interpretation is large-cap firms occupy a "middle ground" where earnings information is incorporated efficiently, but without the extreme investor attention associated with mega-cap firms or the speculative uncertainty surrounding smaller firms. As a result, earnings announcements in this group do not generate a clear pattern of either pre-announcement adjustment or post-announcement drift.

Moving on to firms with smaller market caps, small-cap and mid-cap firms exhibit statistically significant abnormal returns only within pre-announcement windows. Small-cap firms with negative surprises record a significant CAR of -0.0236 in the [-1, 0] window ($p = 0.008$), while mid-cap firms with negative surprises record a marginally significant CAR of -0.0238 in the same window ($p = 0.062$). One possible explanation is that smaller technology firms are followed by a narrower and more specialized investor base that monitors firm-specific developments more closely before earnings announcements. As a result, prices may adjust relatively quickly once earnings information is released, leaving little residual underreaction to generate PEAD. The lack of post-announcement drift is not definitive evidence that these small firms are more informationally efficient although, theoretically, higher information efficiency is a plausible reason. Smaller tech firms typically receive less continuous media and analyst coverage than mega-cap firms, potentially creating a less information-saturated environment in which investors face fewer competing narratives and can process earnings information more directly.

CONCLUSION

This study examined whether post-earnings announcement drift exists in U.S. technology stocks during the 2023–2025 AI boom, and whether earnings-related abnormal returns vary by event window, earnings surprise magnitude, and market capitalization. Using 310 qualifying earnings-surprise events from 44 U.S. technology firms, overall, the findings suggest that PEAD in recent U.S. technology stocks is weak, fragmented, and conditional rather than broad and persistent, leading to limited real-world application and adoption in trading strategies. The theoretical sector-specific amplifiers discussed earlier, including retail participation, speculative sentiment, herding, and information complexity, did not lead to stronger post-announcement drift (Chen, 2012; Floridi, 2024; Maghyereh & Awartani, 2025; Uwilingiye et al.,

2019). These findings aligns with recent literature showing that PEAD has declined over time substantially as markets have become faster at processing earnings information through greater institutional arbitrage, wider analyst coverage, and faster digital information dissemination (Chordia et al., 2014; Martineau, 2021; Kettell et al., 2022).

In contrast, earnings-related price adjustment in recent U.S. technology stocks is more concentrated before the announcement. This can be explained by the fact that the modern market has become increasingly anticipatory: investors do not simply wait for official earnings releases, but form expectations earlier through an abundance of information sources like analyst forecasts and company guidance (Ball & Brown, 2018). For the technology sector specifically during this period, this anticipatory behavior is likely even stronger because valuations are often driven by expectations about future growth, AI adoption, product cycles, and long-term innovation rather than current earnings alone (Floridi, 2024; (Gao, 2023). As a result, by the time earnings are officially announced, a large part of the information may already be reflected in prices.

In terms of surprise magnitude, the results reveal statistically significant post-announcement CARs are sparse and appear only in isolated windows, rather than increasing consistently with surprise magnitude. This suggests that earnings surprise size alone is not enough to explain PEAD in tech firms recently. One possible explanation is that larger surprises may attract faster market reaction rather than stronger delayed reaction, especially in a highly monitored sector like technology (Uwilingiye et al., 2019). Another possibility is that extreme surprise percentages are noisy and partly reflect unusual firm-specific conditions rather than durable information about future earnings.

In terms of market capitalization, the results are also mixed and fragmented. While upper-mid-cap and mega-cap firms are shown to provide the clearest, though still limited, evidence of post-announcement abnormal returns, small-cap and mid-cap firms show significant price adjustment prior to the announcement. This appears to contrast with PEAD literature, which generally expects smaller firms to show stronger drift because they have lower analyst coverage and higher trading frictions (Fink, 2020; Martineau, 2021). However, the contrast should not be overstated because no market-cap group exhibits reliable and consistent PEAD across post-announcement windows. The broader result still aligns with the general attenuation of PEAD in modern markets. A possible explanation is that market capitalization is not the only driver of delayed price adjustment. Larger firms have more complex information environments. This is consistent with research showing that firm complexity can slow earnings-information processing and increase PEAD (Barinov, Park, & Yildizhan, 2022).

Finally, in terms of surprise direction, the results provide only limited evidence of asymmetry. Negative surprises show somewhat more frequent significant CARs in pre-announcement windows. While this pattern is not strong enough to support a broad conclusion, it does appear that downside earnings risk is incorporated earlier. This is consistent with the idea that investors are likely to react more strongly to expected bad news because of behavioral biases like loss aversion, which leads to risk reduction incentives (Gao, 2023; Gao et al., 2025). Additionally, positive and negative surprises show little difference in their post-announcement effects, which partly contrasts with the behavioral expectations established in the literature review. Positive surprises would be expected to generate continued upward

drift if investors gradually strengthened optimistic growth expectations, while negative surprises could generate stronger or more persistent downward drift if investors initially resisted incorporating unfavorable information, a phenomenon called conservatism (Chen, 2012; Gao et al., 2010; Lan et al., 2024). However, the results do not show a clear post-announcement asymmetry. A possible justification is that since technology stocks are so heavily driven by narratives of future growth, investors may focus less on whether EPS was positive or negative and more on the company's forward guidance and management commentary, for instance. This can blur the clean positive-vs-negative asymmetry predicted.

Despite these contributions, this study has several limitations. First, the analysis relies on the market model to estimate abnormal returns, which assumes a stable linear relationship between individual stock returns and market returns throughout the event period. However, technology firms during the 2023–2025 period were exposed to high volatility and rapid shifts in investor sentiment due to major AI breakthroughs and continuous product launches. Consequently, the model may not fully capture abnormal returns driven by sector-specific sentiment shocks rather than earnings information alone.

Second, many of the subgroup findings are suggestive rather than conclusive, and this deserves further explanation. The main event-window test in Table 3 uses firm-clustered standard errors, which adjust for the fact that multiple earnings events from the same firm are not fully independent observations. However, this adjustment requires a sufficient number of distinct firms to estimate reliably. Several subgroups in Tables 4 and 5 contain too few firms for clustering to function properly e.g. the mega-cap negative-surprise category includes only 5 events, so this study instead reports these subgroups using one-sample t-tests.

However, one-sample t-tests assume independent observations, an assumption not strictly satisfied here. Because individual firms contribute multiple earnings events across the 2023–2025 period, events from the same firm may share firm-specific characteristics, such as typical volatility or analyst coverage, that are not captured by the market model. This within-firm dependence is exactly what firm-clustering is designed to address, but cannot be corrected for once the sample is too small to cluster. Thus, statistical significance in the smallest subgroups should be interpreted more cautiously than in the full-sample results. Reported p-values in these subgroups can overstate the author’s actual confidence in the finding since they do not fully account for repeated observations from the same firm. This limitation applies most directly to subgroups with both few distinct firms and multiple events per firm, and least to the full-sample results in Table 3, where firm-clustered standard errors are used directly.

To address these limitations, future research could use multifactor models, such as the Fama-French three-factor or five-factor model, instead of relying only on the market model. This would help separate earnings-related abnormal returns from broader risk factors and sector-wide movements. In addition, future studies could use a larger sample of U.S. technology firms and more earnings events within each subgroup to enhance statistical reliability. A larger sample would also allow subgroup tests to use firm-clustered standard errors more consistently, rather than relying on one-sample t-tests when the number of firm clusters is too small.

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APPENDIX

Appendix A. Full Firm Sample

No.	Firm name	Ticker	Industry	Market cap (USD billions)	Market-cap tier	Included in the final sample?
1	NVIDIA	NVDA	Semiconductors	4380	Mega-cap	No
2	Apple	AAPL	Consumer Electronics	3676	Mega-cap	Yes
3	Intel Corp	INTC	Semiconductors	228.62	Mega-cap	Yes
4	Advanced Micro Devices Inc	AMD	Semiconductors	325.2	Mega-cap	Yes
5	Microsoft	MSFT	Software - Infrastructure	2939	Mega-cap	Yes
6	Google	GOOG	Internet Content & Information	3646	Mega-cap	Yes
7	Oracle	ORCL	Software - Infrastructure	445.8	Mega-cap	Yes
8	Broadcom	AVGO	Semiconductors	1527	Mega-cap	Yes
9	Micron Technology	MU	Semiconductors	479.61	Mega-cap	Yes
10	Palantir	PLTR	Software - Infrastructure	361.02	Mega-cap	Yes

11	KLA Corp	KLAC	Semiconductor Equipment & Materials	185.95	Large-cap	Yes
12	Shopify Inc	SHOP	Software - Application	160.35	Large-cap	Yes
13	Qualcomm, Inc	QCOM	Semiconductors	138.52	Large-cap	No
14	Intuit Inc	INTU	Software - Application	121.67	Large-cap	Yes
15	ServiceNow Inc	NOW	Software - Application	118.85	Large-cap	Yes
16	Dell Technologies Inc	DELL	Computer Hardware	100.48	Large-cap	Yes
17	Western Digital Corp	WDC	Computer Hardware	92.32	Large-cap	Yes
18	Synopsys, Inc	SNPS	Software - Infrastructure	79.04	Large-cap	Yes
19	Marvell Technology Inc	MRVL	Semiconductors	76.82	Large-cap	No
20	Snowflake Inc	SNOW	Software - Application	61.14	Large-cap	Yes
21	Strategy Inc	MSTR	Software - Application	46.62	Upper-mid-cap	Yes
22	Teradyne, Inc	TER	Semiconductor Equipment & Materials	44.84	Upper-mid-cap	Yes
23	Datadog Inc	DDOG	Software -	43.93	Upper-mid-ca	Yes

			Application		p	
24	Roper Technologies Inc	ROP	Software - Application	36.13	Upper-mid-cap	No
25	Fiserv, Inc	FISV	Information Technology Services	30.34	Upper-mid-cap	Yes
26	Fair Isaac Corp	FICO	Software - Application	26.83	Upper-mid-cap	Yes
27	Corpay Inc	CPAY	Software - Infrastructure	21.61	Upper-mid-cap	Yes
28	Global Payments, Inc	GPN	Software - Infrastructure	19.22	Upper-mid-cap	Yes
29	Entegris Inc	ENTG	Semiconductor Equipment & Materials	16.46	Upper-mid-cap	Yes
30	Jack Henry & Associates, Inc	JKHY	Information Technology Services	12.18	Upper-mid-cap	Yes
31	Onto Innovation Inc	ONTO	Semiconductor Equipment & Materials	9.42	Mid-cap	No
32	Skyworks Solutions, Inc	SWKS	Semiconductors	8.23	Mid-cap	Yes
33	Arrow Electronics Inc	ARW	Electronics & Computer Distribution	7.37	Mid-cap	No
34	DigitalOcean	DOCN	Software -	6.31	Mid-cap	Yes

	Holdings Inc		Infrastructure			
35	Cipher Digital Inc	CIFR	Information Technology Services	5.7	Mid-cap	Yes
36	Elastic N.V.	ESTC	Software - Application	5.33	Mid-cap	Yes
37	Shift4 Payments Inc	FOUR	Software - Infrastructure	4.43	Mid-cap	Yes
38	GitLab Inc	GTLB	Software - Infrastructure	3.78	Mid-cap	Yes
39	Diodes, Inc	DIOD	Semiconductors	2.93	Mid-cap	Yes
40	Ambarella Inc	AMBA	Semiconductor Equipment & Materials	2.25	Mid-cap	Yes
41	Alkami Technology Inc	ALKT	Software - Application	1.91	Small-cap	Yes
42	BigBear.ai Holdings Inc	BBAI	Information Technology Services	1.88	Small-cap	Yes
43	Quantum Computing Inc	QUBT	Computer Hardware	1.64	Small-cap	Yes
44	Flywire Corp	FLYW	Software - Infrastructure	1.51	Small-cap	Yes
45	PDF Solutions Inc	PDFS	Software - Application	1.33	Small-cap	Yes

46	Cohu, Inc	COHU	Semiconductor Equipment & Materials	1.28	Small-cap	Yes
47	Penguin Solutions Inc	PENG	Information Technology Services	0.94503	Small-cap	Yes
48	Aeva Technologies Inc	AEVA	Software - Infrastructure	0.80353	Small-cap	Yes
49	Sabre Corp	SABR	Software - Infrastructure	0.63029	Small-cap	Yes

The 6 excluded firms are: NVDA, QCOM, MRVL, ROP, ONTO, and ARW. Final included firm sample is 44 firms.