THE RESURGENCE OF POST-EARNINGS ANNOUNCEMENT DRIFT

INSIGHTS FROM POST-2020 U.S. EQUITY MARKETS

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Abstract

This study challenges the prevailing view that the Post-Earnings Announcement Drift (PEAD) anomaly has steadily diminished in modern U.S. equity markets. Instead, it suggests a resurgence since 2020, particularly among large-cap stocks. Analyzing data from 220,228 quarterly earnings announcements across 6,958 U.S. listed firms between 2005 and 2024, we observe that the average 60-day drift for large-cap equities appears to have increased by approximately 280% post-2020, yielding annualized returns exceeding 8% from a zero-cost hedge portfolio. Motivated by post-pandemic structural shifts, such as increased retail investor participation and the dominance of passive investment strategies, we explore whether these ownership changes contribute to PEAD resurgence. Although both retail and passive ownership show a positive correlation with PEAD, they do not seem to fully explain the intensified drift post-2020. Our findings suggest that broader structural changes in trading behavior, technology adoption, and information dissemination mechanisms likely drive these renewed market inefficiencies. This study contributes to ongoing discussions in the asset pricing and market efficiency literature, highlighting the dynamic and cyclical nature of market anomalies. It underscores the necessity of revisiting asset pricing models and efficiency frameworks in response to evolving market conditions shaped by investor demographics and technological advancements.

Keywords:

Post-Earnings Announcement Drift (PEAD), Market Anomalies,
Asset Pricing, Information Processing, Market Efficiency

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This study provides compelling indications of a notable resurgence in the post-earnings announcement drift (PEAD) anomaly in U.S. equity markets following the COVID-19 pandemic. This phenomenon appears to be particularly evident among large-cap stocks, a segment traditionally considered to be informationally efficient. PEAD, defined as the persistent tendency of stock prices to continue moving in the direction of an earnings surprise after its public announcement, poses a challenge to the semi-strong form of the Efficient Market Hypothesis (EMH) (Bernard & Thomas, 1990). First documented by Ball and Brown (1968) and formally characterized by Rendleman et al. (1982), Foster et al. (1984), and Bernard and Thomas (1989), PEAD has remained a prominent subject of empirical inquiry in financial economics.

Over recent decades, substantial evidence has pointed to a reduction in PEAD, particularly among large-cap stocks, due to factors such as improved liquidity, faster information dissemination, and enhanced arbitrage activities (Chordia et al., 2014; Milian, 2015). This apparent decline prompted Martineau (2021) to metaphorically declare an "elegy" for the anomaly, suggesting that it had effectively ceased to exist. However, material structural shifts since 2020, such as increased retail investor participation,[1] proliferation of commission-free trading platforms and widespread dissemination of financial information through media (Barber et al., 2022; Ozik et al., 2021; Cookson & Niessner, 2020), the rise of passive investing strategies (Haddad et al., 2025), the expansion of high-frequency trading (HFT) (Chakrabarty et al., 2022), and advances in artificial intelligence (AI)-based forecasting (Kim et al., 2024), have challenged established perceptions regarding the persistence and trajectory of market efficiency.

Motivated by these developments, this study reassesses the presence and extent of PEAD in U.S. equity markets post-2020. Using a comprehensive dataset encompassing 220,228 quarterly earnings announcements from firms listed on the NYSE, AMEX, and NASDAQ, spanning from 2005 to 2024, we empirically investigate the hypothesized reversal

[1] According to Vanda Research, net retail flows surged by 84% in 2023 compared to 2019, with a marked increase during the onset of the pandemic. See Appendix C for a visual depiction.

of PEAD's previously attenuating trend. To evaluate PEAD, we employ standardized unexpected earnings (SUE) as our principal earnings surprise metric, while cumulative abnormal returns (CAR) are calculated employing the Fama-French three-factor model. Our analytical framework incorporates a post-2020 temporal indicator to explicitly assess changes in the earnings-returns relationship, supplemented by additional analyses that explore whether shifts in the magnitude of PEAD systematically correlate with levels of retail and passive ownership.

This study addresses critical gaps in the existing literature by revisiting PEAD in U.S. equities during the post-pandemic period. First, previous research documenting the attenuation of PEAD predominantly relies on data collected before 2020 (Martineau and Gregoire, 2021; Chordia et al., 2014; Chordia & Miao, 2020), limited investor compositions (Luo et al., 2022), or non-U.S. settings (Bock & Geissel, 2024). As a result, the persistence or intensification of PEAD among U.S. equities in recent years remains largely unexplored. Second, previous studies have largely overlooked the implications of changing investor composition on PEAD dynamics, particularly the rise in passive investment strategies and retail trading. This omission is notable, given that recent literature suggests that increased passive investment can increase market inelasticity (Gabaix & Koijen, 2021; Haddad et al., 2025), thereby degrading price efficiency (Qin & Singal, 2015), while recent increases in retail participation (Ozik et al., 2021), characterized by behavioral biases and limited investor attention, may sustain or even amplify asset mispricing (Barber et al., 2022; Luo et al., 2022).

Our empirical findings reveal a significant resurgence of PEAD among large-cap U.S. stocks in the post-pandemic period, directly challenging previous claims about the anomaly's disappearance (Martineau, 2021). Specifically, the magnitude of the large-cap PEAD observed after 2020 is approximately 280% greater than the levels documented during 2005-2020, with the average 60-day drift increasing from 0.52% to 1.99%. These results remain robust across alternative return benchmarks, event windows, and earnings surprise definitions.

Our additional tests further reveal that retail and passive ownership impact PEAD, which is consistent with previous studies (Luo et al., 2022; Qin & Singal, 2015). However, contrary to initial expectations, our findings provide limited support to the hypothesis that increased retail participation or passive ownership explains the intensified drift observed post-2020. While changes in investor composition may alter market structures, the heightened PEAD is more likely attributable to broader structural changes in market dynamics and information processing behaviors than our methodology can capture in these tests. The precise mechanisms that drive this resurgence remain unclear and require further investigation.

This study contributes to existing research by providing the first comprehensive empirical evidence of intensified PEAD among large-cap stocks in the post-pandemic period, emphasizing the cyclical and dynamic nature of market efficiency. Our findings challenge static views of efficiency progression, demonstrating that even highly liquid, extensively monitored stocks can encounter significant informational frictions. Additionally, we provide novel insights into how technological advancements and evolving investor demographics influence price discovery mechanisms, highlighting that improvements in trading technology and information dissemination alone do not guarantee increased market efficiency.

Although endogeneity concerns are an inevitable aspect of empirical financial research, we have taken several steps to alleviate potential issues. Earnings surprises are treated as independent shocks to firm fundamentals, and the post-2020 indicator is calendar-driven, thus mitigating simultaneity bias. Furthermore, the window for measuring cumulative abnormal returns (CAR) begins two days after the earnings announcement to alleviate the effects of market anticipation. Nevertheless, we acknowledge that other contemporaneous factors beyond our control, such as management's earnings guidance or strategic press releases, may still affect reported earnings and subsequent CAR. We also recognize potential limitations in our analyses of ownership structures and interpret our additional test results with appropriate consideration of the complex relationships involved.

By documenting the re-emergence of PEAD in large-cap equities, this study emphasizes the necessity for continuous reassessment of market efficiency assumptions. Our findings carry important implications for asset pricing theories, investment strategies, and regulatory frameworks that rely on the concept of progressively improving informational efficiency.

The remainder of this paper is structured as follows: Section 2 reviews related literature on market efficiency, retail investor behavior, passive investing, algorithmic trading, and PEAD. Section 3 outlines the data sources, sample construction, and the primary empirical methodology. Section 4 presents the main empirical results and robustness analyses. Section 5 delves deeper into the effects of retail and passive ownership on PEAD, and Section 6 concludes the paper with a discussion of the implications and potential avenues for future research.

2 Previous Research

2.1 A Historical Perspective of Market Efficiency

The Efficient Market Hypothesis, articulated by Fama (1970), stands as a foundational paradigm in financial economics that classifies market efficiency into weak, semi-strong, and strong forms. These distinctions reflect the extent to which stock prices incorporate information from past prices, publicly available data, and private sources, respectively. However, scholars, such as Grossman and Stiglitz (1980), critique the EMH by highlighting its inherent paradox: full efficiency eliminates incentives for information acquisition, implying that markets must inherently exhibit some mispricing.

A significant manifestation of market mispricing is the post-earnings announcement drift, first identified by Ball and Brown (1968) and later formalized by scholars during the 1980s (Bernard and Thomas, 1989; 1990; Foster et al., 1984; Rendleman et al. 1982). PEAD refers to the persistent price movements that occur for months following earnings surprises, posing a direct challenge to the semi-strong EMH. Throughout the 1980s and the 1990s, PEAD became emblematic of a broader wave of return irregularities that challenged informational efficiency, which traditional asset pricing models struggled to fully explain (De Bondt & Thaler, 1985; Jegadeesh & Titman, 1993). Although Fama and French (1993) developed a multi-factor model addressing size and value anomalies, persistent irregularities such as PEAD continued to question the comprehensive explanatory power of existing frameworks.

By the late 1990s, academic discussions on market efficiency had become more nuanced. Fama (1998) defended the EMH, arguing that anomalies were either sporadic or stochastic, while scholars such as Thaler (1993) and Shiller (2000) argued that systematic investor psychology played a significant role. Simultaneously, a narrative emerged suggesting that increased competition, deregulation, and technological advancements, along with the documentation of irregularities in academic papers, would reduce arbitrage opportunities, thereby enhancing market efficiency (Schwert, 2002; Fink, 2021). Despite this viewpoint, contemporary research continues to revisit the anomaly, questioning the permanence of efficiency gains and suggesting that new inefficiencies may emerge (Barber et al., 2022; Haddad et al., 2025; Luo et al., 2022; Bock & Geissel, 2024).

This renewed scrutiny is particularly timely in light of the ongoing technological advancements and shifts in market composition. Specifically, the expansion of commission-free platforms and social media has amplified retail investor participation (Ozik et al., 2021; Barber et al., 2022), enhancing market access but also potentially exacerbating noise trading and herding behavior (Cookson & Niessner, 2020; Barber et al., 2022). Simultaneously, algorithmic and high-frequency trading have accelerated information integration (Hendershott et al., 2011; Brogaard et al., 2014; Chordia & Miao, 2020), whereas artificial intelligence models could outperform human analysts in certain forecasting tasks

(Kim et al., 2024). In addition to these developments, the continued growth of passive investment strategies has increased market elasticity, thereby altering the mechanisms of price formation (Haddad et al., 2025; Qin & Singal, 2015).

The following sections explore how changes in ownership structure, along with technological advancements, continue to influence market efficiency, using PEAD as a lens through which these changes are assessed.

2.2 Institutional vs. Retail Investors

The impact of technological and structural shifts depends largely on the type of investors involved. Retail and institutional investors engage with information in fundamentally distinct manners, and their respective influences determine how efficiently the markets react. Institutional investors generally benefit from access to information and advanced analytical tools, enabling them to identify and exploit mispricing more effectively than retail investors (Ke & Ramalingegowda, 2005). Moreover, substantial evidence suggests that firms with higher institutional ownership tend to exhibit more efficient pricing, with institutional ownership negatively correlated with PEAD (Bartov et al., 2000; Doyle et al., 2006; Ng et al., 2008).

Conversely, retail investor activity has been linked to decreased market efficiency (Luo et al., 2022), a relationship that has garnered renewed attention during the surge in retail participation following the COVID-19 pandemic (Barber et al., 2022). According to Vanda Research (2023), there has been a continuous increase in net retail flows starting in 2020, fueled by increased savings, direct stimulus payments, and zero-commission trading platforms such as Robinhood, with 2023 flows 84% above the 2019 levels. These elements, along with pandemic-induced lockdowns, boredom, and the growing influence of online investment communities, have spurred speculative trading activity, especially in small-cap and high-volatility stocks (Barber et al., 2022).

While traditional finance theory suggests that increased participation and liquidity should improve market efficiency (Fama, 1980), recent evidence suggests otherwise (Barber et al., 2022; Luo et al., 2022; Bock & Geissel, 2024). Retail traders often display a higher degree of behavioral biases than institutional investors, such as overreaction to salient news, engaging in herd behavior, and favoring speculative assets, which contribute to price inefficiencies and prolonged mispricing (Barber et al., 2022; Cookson & Niessner, 2020). Additionally, several authors (Kaniel et al., 2012; Barber et al., 2022) demonstrate that retail investors systematically act as contrarians around earnings announcements, selling stocks with strong earnings surprises and buying stocks that report weak earnings. This trading behavior directly contributes to the persistence of PEAD and other price momentum anomalies (Luo et al., 2022). Luo et al. (2022) find that the magnitude of retail net flows predicts PEAD, especially for stocks with the largest earnings surprises, whether positive or negative. This effect is even more pronounced for stocks in extreme momentum portfolios, particularly momentum losers, and for small-cap stocks, aligning with the findings of Hong et al. (2000). Collectively, this research indicates that retail trading actively sustains mispricing and prolongs inefficiencies.

However, the concept of retail-driven mispricing is not novel. As early as the 1980s, Black (1986) introduced the term "noise trading," which refers to trades influenced by non-informational factors, such as speculation, emotions, or rumors. In today's context, social media further complicates this landscape by serving as both an accelerant and distortionary force in price discovery (Barber et al., 2022; Cookson & Niessner, 2020). Cookson and Niessner (2020) observe that stocks frequently discussed in online forums often undergo exaggerated price swings, typically followed by reversals, reinforcing the idea that digital communities amplify noise rather than signal. Consequently, the rapid spread of information (both accurate and misleading) on these platforms means that, while markets may react swiftly, they do not always react efficiently. Similarly, Barber et al. (2022) emphasize how modern platforms could encourage herd behavior, thereby increasing volatility and reducing informational efficiency. Yan et al. (2022) even find that, in markets with significant retail participation, HFT reduces efficiency, contrary to its effect in markets dominated by institutional investors.

Thus, there seems to be a shift in market dynamics driven by the growing influence of retail investors and their interaction with technological platforms and trading mechanisms. Instead of uniformly enhancing efficiency through increased participation and liquidity, technological advancements have introduced new frictions and sources of mispricing, particularly in segments dominated by retail investors. The next section explores how the concurrent increase in passive investing further alters these dynamics.

2.3 Passive Investing as a Form of Institutional Investing

In addition to retail-driven dynamics, passive institutional investment strategies have surged, with passive U.S. domestic equity funds surpassing active funds in managed assets by 2018.[2] Unlike active institutional investors, who contribute to price discovery, passive investors allocate capital mechanically, causing price movements to be increasingly influenced by investor flows rather than fundamental analysis. This further weakens the market's "price discovery" function, ultimately making markets more homogenous and allowing mispricing to persist for longer periods (Gabaix & Koijen, 2021).

Gabaix and Koijen (2021) introduced the inelastic markets hypothesis to explain this phenomenon. Their research indicates that as more investors allocate capital passively without responding to changes in fundamental information, even minor demand shifts can cause disproportionate price movements. Empirically, they find that for every $1 of net inflow into the stock market, the total market value increases by approximately $5. This implies that stock prices are increasingly driven by investor flows rather than fundamentals. Supporting this, Haddad et al. (2025) argue that the rise in passive ownership over the last two decades has made the demand for individual stocks about 15% more inelastic, resulting in heightened volatility often disconnected from fundamental

[2] According to data from Morningstar, 2018.

values. Ke and Ramalingegowda (2005) and Docherty and Hurst (2018) also demonstrate that stocks with higher passive ownership incorporate less firm-specific news, increasing volatility and reducing efficiency. Concurrently, with retail inflows surging during the early 2020s, another layer of flow-driven volatility emerged. Alongside the rise in retail trading activity, this suggests that increased passive investments may introduce an element of inelastic demand, resulting in price distortions, increased volatility, the emergence of market feedback loops, and ultimately, reduced efficiency (Haddad et al., 2025). This erosion of price discovery raises the question of whether anomalies such as PEAD may resurge, sustained not by a lack of information but by structural inelasticity in how the information is processed.

2.4 High-Frequency Trading (HFT)

If passive flows and increased retail participation suggest a decline in price responsiveness, algorithmic trading has long been regarded as a corrective force that enhances informational efficiency through rapid processing and immediate execution, thereby fundamentally transforming the informational architecture of modern financial markets (Chakrabarty et al., 2022; Menkveld, 2013; O'Hara, 2015). High-frequency trading, in particular, has emerged as a central mechanism, allowing trades to be executed almost instantaneously in response to new information (Brogaard et al., 2014). At first glance, these advancements seem to improve market efficiency by reducing transaction costs, enhancing liquidity, and accelerating the incorporation of fundamental information into prices (Menkveld, 2013; O'Hara, 2015).

Indeed, a substantial body of the empirical literature supports this view. Hendershott et al. (2011) find that algorithmic trading is associated with narrower bid-ask spreads and improved price linkage across markets, both indicative of increased informational efficiency. Similarly, Chordia and Miao (2020) highlight how increased trading activity from HFT facilitates the swifter absorption of earnings announcements. Further research suggests that arbitrageurs, with the aid of HFT, are becoming increasingly adept at identifying and correcting pricing errors, contributing to a decline in the profitability of well-documented return anomalies such as value and momentum (Brogaard et al., 2014; Chordia & Miao, 2020). Schwert (2002) found that market anomalies weaken after academic publication, and McLean and Pontiff (2016) provide empirical support for this finding by documenting that abnormal returns decline by approximately 50% over the subsequent decade. More recently, Chakrabarty et al. (2022) found that HFT accelerates information diffusion and mitigates inefficiencies, particularly when human attention is limited. Similarly, Beschwitz et al. (2020) find that some HFT algorithms can parse structured textual earnings announcements, thereby reducing the lag in price response.

Chordia and Miao (2020) quantify this phenomenon using a measure of low latency frequency, which serves as a proxy for HFT, observing that HFT reduces the price response to earnings announcements. Specifically, stocks with low HFT activity exhibit a 4.7% price difference between positive and negative earnings news, whereas those with high HFT activity show a -0.8% difference. This suggests that increased HFT activity significantly reduces, if not eliminates, PEAD in stocks that are liquid and closely monitored by institutional investors.

However, the same technology that enhances efficiency under normal conditions can become a source of instability when the market dynamics shift. A striking example of this was the 2010 "Flash Crash," where HFT systems quickly withdrew from the market in response to volatility, intensifying the crash rather than dampening it (Brogaard et al., 2014). Malceniece et al. (2019) echo this concern, arguing that algorithmic traders, unlike traditional market makers, are not obligated to maintain liquidity and often pull back during times of stress, precisely when stability is most needed.

Moreover, the efficiency gains of HFT do not appear consistent across all markets. Yan et al. (2022) find that HFT enhances efficiency in markets dominated by institutional investors, where sophisticated participants are better equipped to interpret and trade on complex information. In contrast, in markets with high retail participation, where investors are more susceptible to behavioral biases and informational naivety, HFT may instead amplify noise, resulting in greater inefficiencies.

Collectively, previous research highlights the dual nature of HFT: while it can significantly enhance efficiency through faster information processing and enhanced liquidity, it may also contribute to instability under certain conditions, especially in volatile markets or those with high retail participation. This duality underscores the complex relationship between HFT and market efficiency, suggesting that while HFT can address some inefficiencies, it may inadvertently create or exacerbate others. One particularly persistent anomaly reflecting these inefficiencies is the post-earnings announcement drift. PEAD exemplifies how market inefficiencies can persist even in the presence of sophisticated trading mechanisms such as HFT. The following section delves deeper into this anomaly and explores its characteristics, potential causes, and implications for market efficiency.

2.5 Post-Earnings Announcement Drift (PEAD)

PEAD has long served as a benchmark for evaluating market efficiency, providing a concrete empirical framework to determine whether recent technological and structural changes have affected how information is incorporated into prices. Defined as the ongoing drift in stock returns following earnings announcements, PEAD challenges the idea that markets reflect public information fully and immediately. Foster et al. (1984) document that a portfolio, which is long in stocks within the most positive unexpected earnings decile and short in the most negative unexpected earnings decile during the 60 trading days after an earnings announcement, yields an annualized abnormal return of 25%.

However, over the past two decades, a growing body of research has observed a notable reduction in PEAD, especially in large-cap stocks in developed markets (Chordia et al., 2014; Chordia and Miao, 2020; Martineau and Gregoire, 2021; Martineau, 2021).

Chordia et al. (2014) find that PEAD-related returns declined sharply after the early 2000s, attributing this decline to increased market liquidity and the rise of HFT. Chordia and Miao (2020) demonstrate that the return spread during the 60 trading days following earnings announcements between the highest and lowest unexpected earnings deciles decreased from 4.7% in low-HFT to -0,8% in high-HFT environments, with SUE coefficients becoming statistically insignificant. This finding reinforces the view that HFT significantly reduces, if not eliminates, PEAD in liquid and institutionally monitored firms. Martineau and Gregoire (2021) noted that, while post-earnings announcement drift persists in mid- and small-cap stocks, it is effectively absent in the S&P 500, where prices adjust almost immediately to earnings news. In a subsequent paper, Martineau (2021) further elaborates, offering what he describes as an "elegy" for PEAD in the U.S. He documents a near-complete disappearance of the anomaly in large-cap stocks and concludes that PEAD, once a robust and persistent challenge to the EMH, may have finally reached its empirical endpoint.

Despite this long-term trend, several studies have indicated a potential resurgence of inefficiencies. Luo et al. (2022) demonstrates that retail investors act as contrarians around earnings announcements, buying on bad news and selling on good news. This behavior exacerbates mispricing, particularly in small-cap stocks and those with low institutional ownership, where arbitrageur activity is lower, and is found to predict sustained PEAD. Although their findings are based on U.S. retail brokerage data from 2010 to 2014 and do not incorporate post-pandemic dynamics, they suggest the capacity of recent retail flows to impair price discovery and contribute to sustained return drift. A more recent study by Bock and Geissel (2024) offers complementary findings from Europe, showing a 20% increase in market inefficiency between 2007 and 2022, as measured by their market inefficiency intensity measure (MIIM) with developed markets experiencing the largest rise (+32%). Although not specific to PEAD, their findings emphasize that structural shifts in trading behavior and market composition may compromise efficiency, even in developed markets.

While substantial evidence has documented the attenuation of PEAD in large-cap stocks through the mid-2010s (Chordia et al. 2014; Chordia & Miao, 2020; Martineau and Gregoire, 2021; Martineau, 2021), recent structural shifts in market dynamics warrant renewed investigation. The post-pandemic era has been characterized by significant changes, including a surge in retail participation (Ozik et al., 2021), the growing dominance of passive capital,[3] shifts in liquidity provision (Bond & García, 2022), and the emergence of AI models that are now capable of outperforming human analysts in forecasting earnings (Kim et al., 2024).

Yet, no published study has systematically assessed whether the decline in PEAD has continued or reversed in this new environment. Existing research either relies on pre-pandemic U.S. data (Chordia et al. 2014; Chordia & Miao, 2020; Martineau and Gregoire, 2021; Luo et al., 2022), is confined to specific segments such as retail flows (Luo et al., 2022), focuses on non-U.S. markets (Hung et al., 2015; Bock & Geissel, 2024), or examines related phenomena such as flow-driven inelasticity without directly assessing PEAD (Haddad et al., 2025). By revisiting PEAD in U.S. equities during the post-pandemic period, this study addresses a critical gap in the literature and provides timely insights into whether the informational efficiency gains of previous decades has remained intact amidst these evolving market forces. Or, as Martineau (2021) elegy suggests, "PEAD, as it has long been studied, may now rest in peace," we explore whether this declaration was, perhaps, premature.

[3] According to the Investment Company Institute (ICI), the combined net assets of index mutual funds and exchange-traded funds (ETFs) in the US increased from $865 billion in 2005 to $9.9 trillion in 2020, reaching $16.2 trillion by 2024. This represents a 63% increase in passive investment assets since the onset of the COVID-19 pandemic, collectively accounting for the majority (51%) of assets in long-term funds in the U.S. in 2024.

3 Data and Empirical Model

3.1 Data Sources and Sample Selection

This study draws on data from three primary sources: CRSP, Compustat, and I/B/E/S. Our initial sample includes both active and inactive publicly listed U.S. firms on the NYSE, AMEX, and NASDAQ exchanges, spanning from January 2005 to December 2024. To ensure consistency in earnings definitions, we sourced actual and consensus analyst forecast earnings per share (EPS), along with earnings announcement dates, from I/B/E/S. Although our analysis period is limited to 2005-2024, we retrieve an additional six years of historical I/B/E/S data (beginning January 1999) to calculate the historical standard deviation needed for computing SUE. Daily stock prices, returns, trading volumes, shares outstanding, and equal- and value-weighted market returns were obtained from CRSP's daily securities and index files for the period January 2004 to December 2024. Data on book value of equity were collected from Compustat. Additionally, the returns for the 25 portfolios formed on size and book-to-market used to estimate abnormal returns were sourced from Kenneth French's website.[4] To explore ownership effects in our additional analyses, we incorporate institutional ownership data from Thomson Reuters 13F filings,[5] Passive ownership is identified using Bushee's (2000) classification of quasi-indexer (QIX) institutions, collected from Brian Bushee's website.[6]

Our final sample is constructed using several filtering criteria to ensure data integrity and comparability. Initially, we exclude firm-quarter observations with incomplete data necessary for key variables, and exclude consensus estimates dated post-announcement. Next, we retain only the most recent available analyst consensus forecast prior to each earnings announcement from I/B/E/S, simplifying the analysis by focusing on the most

[4] Accessed publicly via Kenneth French's website.
[5] Accessed publicly via the Harvard Dataverse.
[6] Accessed publicly via Brian Bushee's website .

current expectations, in line with established practices (Bartov et al., 2000; Hirshleifer et al., 2009). Additionally, to mitigate confounding effects from overlapping event windows, we excluded announcements occurring within 60 days of a prior announcement. Furthermore, to calculate our SUE variable, we require at least 10 earnings announcements per firm during the 1999-2024 period, in line with Foster et al. (1984). Finally, we remove non-U.S. firms and those with share prices below $1 at the time of earnings announcements, as these entities may differ systematically due to regulatory frameworks or liquidity concerns (Atiase, 1985).

Following the application of these criteria, our dataset includes 220,228 quarterly earnings announcements from 6,958 unique firms. Of these, 105,896 observations originate from NYSE, 2,690 from AMEX, and 111,642 from NASDAQ-listed firms. Panel A of Table 1 outlines the sample selection process in more detail. Panel B presents the descriptive statistics of the variables used in our main analysis, and Panel D displays the correlation matrix. For further details on retail and passive ownership, as well as the control variables, refer to Appendix B.

To enable analyses related to firm size, companies are classified on a quarterly basis according to their market capitalization, as measured at the conclusion of the preceding quarter. Firms with market capitalizations below $2 billion are designated as small-cap, those exceeding $10 billion are identified as large-caps, and those falling between these thresholds are categorized as mid-caps. The descriptive statistics for each capitalization group are presented in Table 1, Panel C.

Table 1
Sample Construction and Descriptive Statistics

Panel A: Sample Selection Process

Step	Earnings Announcements	Unique Firms
Initial universe of firm-quarters from I/B/E/S	1,353,499	20,219
Drop observations with missing forecast or actual EPS	1,313,306	19,596
Drop if estimation date is after announcement date	1,290,174	19,520
Keep only the last forecast before earnings announcement	445,610	19,520
Exclude overlapping announcements within 60-day window	428,866	19,520
Drop if less than 10 announcements in the past 6 years	391,365	11,178
Limit to announcement years 2005–2024	297,553	9,655
Merge with CRSP	233,427	7,099
Drop firms with share price below $1	231,151	7,091
Drop if exchange $\neq$ NYSE, AMEX or NASDAQ	231,081	7,088
Keep if Compustat book value available	220,228	6,958
Final sample	**220,228**	**6,958**
Of which:		
NYSE	105,896	2,856
AMEX	2,690	165
NASDAQ	111,642	3,937

Panel B: Summary Statistics

Statistic	N	Mean	St. Dev.	25th pct.	Median	75th pct.
Baseline regression						
SUE	22,305,635	35.914	155.494	-25.000	25.000	101.000
DSUE	22,305,635	0.000	0.319	-0.278	0.0556	0.278
D	22,750,310	0.226	0.418	0.000	0.000	0.000
AR	17,634,614	0.010	3.285	-1.240	-0.050	1.160
CAR-2-60	220,228	0.551	19.042	-6.190	0.000	6.890
CAR-1-1	220,228	0.017	6.567	-1.770	0.000	1.700
CAR-2-30	220,228	0.324	13.140	-4.380	0.000	4.550
CAR-2-90	220,228	0.570	19.376	-6.320	0.000	7.075
Alternative SUE and AR measures						
EAR	16,142,964	16.172	6785.732	-0.093	0.051	0.263
SURP	22,750,310	0.226	0.418	0.000	0.000	0.000
UE	22,750,310	106.448	20493.560	-2.000	2.000	7.000
AR_VWM	22,749,230	0.009	3.042	-1.000	0.000	1.000
AR_VW	22,749,230	0.009	3.042	-1.000	0.000	1.000
AR_EW	22,749,230	0.008	3.019	-1.000	0.000	1.000
AR_S&P	22,749,230	0.020	3.058	-1.000	0.000	1.000

Panel C: Descriptive Statistics by Capitalization Group

	Large-cap	Mid-cap	Small-cap	Full sample
Firm-quarters (N)	122,745	66,443	31,040	220,228
Market capitalization ($m)				
N	16,526,462	9,122,435	4,377,656	30,026,553
Mean	15,500,000	519,767	106,972	8,716,494
Median	3,745,609	481,889	107,926	1,265,383
Number of analysts per firm				
Mean	11.050	5.090	2.810	8.040
Median	10.000	4.000	2.000	6.000
Earnings surprise (%)				
Mean	55.470	19.920	-11.740	35.090
Std. Dev.	153.520	148.040	151.040	153.550
25th perc.	-10.000	-33.000	-56.000	-25.000
Median	39.000	13.000	0.000	24.000
75th perc.	122.000	79.000	50.000	99.000
Earnings surprise distribution (deciles)				
Top decile	12.830	7.630	4.540	10.070
Decile 9	12.090	8.410	5.660	10.050
Decile 8	11.440	9.260	7.340	10.200
Decile 7	10.280	9.390	8.220	9.720
Decile 6	10.030	10.090	9.680	10.000
Decile 5	8.850	10.330	11.300	9.650
Decile 4	9.480	11.960	12.130	10.610
Decile 3	8.400	11.090	13.060	9.880
Decile 2	8.610	11.070	13.280	10.030
Bottom decile	7.990	10.760	14.790	9.800

Panel D: Correlation Matrix

	SUE	D	AR	CAR-2-60	CAR-1-1	CAR-2-30	CAR-2-90	EAR	SURP	UE	VWM	VW	EW	S&P500
SUE	1	0.0256	0.1752	0.0265	0.2062	0.0276	0.0265	0.0122	0.2335	0.0166	0.1082	0.1083	0.1084	0.1078
D	0.0256	1	-0.0085	-0.0265	-0.0007	-0.0144	-0.0257	-0.0032	0.0058	-0.0049	-0.0096	-0.0095	-0.0065	-0.0110
AR	0.1752	-0.0085	1	0.0117	0.0043	0.0162	0.0111	-0.0020	0.0399	-0.0009	0.9920	0.9918	0.9913	0.9896
CAR-2-60	0.0265	-0.0265	0.0117	1	0.0102	0.6786	0.9793	-0.0008	0.0044	-0.0010	0.0135	0.0134	0.0135	0.0134
CAR-1-1	0.2062	-0.0007	0.0043	0.0102	1	0.0145	0.0100	-0.0029	0.0416	-0.0005	0.0066	0.0069	0.0072	0.0069
CAR-2-30	0.0276	-0.0144	0.0162	0.6786	0.0145	1	0.6641	0.0036	0.0066	0.0032	0.0176	0.0176	0.0182	0.0178
CAR-2-90	0.0265	-0.0257	0.0111	0.9793	0.0100	0.6641	1	-0.0010	0.0046	-0.0020	0.0131	0.0129	0.0130	0.0129
EAR	0.0122	-0.0032	-0.0020	-0.0008	-0.0029	0.0036	-0.0010	1	-0.0004	0.7917	-0.0023	-0.0023	-0.0021	-0.0021
SURP	0.2335	0.0058	0.0399	0.0044	0.0416	0.0066	0.0046	-0.0004	1	-0.0018	0.0398	0.0397	0.0404	0.0395
UE	0.0166	-0.0049	-0.0009	-0.0010	-0.0005	0.0032	-0.0020	0.7917	-0.0018	1	0.0008	0.0008	0.0009	0.0010
AR_VWM	0.1082	-0.0096	0.9920	0.0135	0.0066	0.0176	0.0131	-0.0023	0.0398	0.0008	1	0.9996	0.9961	0.9982
AR_VW	0.1083	-0.0095	0.9918	0.0134	0.0069	0.0176	0.0129	-0.0023	0.0397	0.0008	0.9996	1	0.9974	0.9983
AR_EW	0.1084	-0.0065	0.9913	0.0135	0.0072	0.0182	0.0130	-0.0021	0.0404	0.0009	0.9961	0.9974	1	0.9943
AR_S&P500	0.1078	-0.0110	0.9896	0.0134	0.0069	0.0178	0.0129	-0.0021	0.0395	0.0010	0.9982	0.9983	0.9943	1

Notes: This table summarizes the sample construction and descriptive statistics for the data used in the empirical analysis. **Panel A** outlines the stepwise sample selection procedure, beginning with 1,353,499 firm-quarter observations from I/B/E/S between 2005 and 2024. We eliminate observations with missing forecast or actual EPS, discard those where forecast dates follow announcement dates, and retain only the final forecast preceding the announcement. To ensure clean event windows, we exclude earnings announcements occurring within 60 days of a prior event for the same firm. We then restrict the sample to firms with at least ten announcements over the 1999-2024 period, merge with CRSP to obtain stock returns, and exclude firms with prices below $1 or those not listed on NYSE, AMEX, or NASDAQ. We retain only observations with non-missing book values from Compustat. The resulting sample comprises 220,228 earnings announcements from 6,958 unique firms. **Panel B** reports descriptive statistics for the variables employed in the baseline specification and robustness checks. SUE denotes standardized unexpected earnings, defined as the analyst forecast error scaled by the standard deviation of prior surprises and ranked into deciles. D is a post-2020 indicator equal to one for announcements between 2021 and 2024. *CAR-2-60*, *CAR-1-1*, *CAR-2-30*, and *CAR-2-90* denote cumulative abnormal returns measured over 2 to 60, 0 to +1, 2 to 30, and 2 to 90 trading day windows, respectively, using the Fama-French three-factor model. Panel B also includes summary statistics for alternative measures of earnings surprise (EAR and UE) and alternative abnormal return benchmarks (AR_VWM, AR_VW, AR_EW, and $AR\_S\&P$). **Panel C** presents descriptive statistics by capitalization group. Market capitalization is measured at the end of the quarter preceding each announcement. We report sample sizes, average analyst coverage, earnings surprise distributions (in both percent and decile formats), and cross-sectional characteristics across large-, mid-, and small-cap firms. **Panel D** reports the Pearson correlation matrix among the key variables used in the analysis, including alternative specifications of abnormal returns and earnings surprises. $DSUE$ is the decile-scaled SUE, linearly scaled to range from -0.5 to $+0.5$. It is used as the primary explanatory variable in all regression models. All variable definitions are detailed in Appendix A. Additional information on data sources and construction procedures is provided in Section 3.

3.2 Variable Definitions

3.2.1 Abnormal Returns

Our primary dependent variable is the cumulative abnormal return (CAR), which captures the persistence of stock price drift following earnings announcements. Abnormal returns are defined as the difference between actual daily returns and expected returns, calculated using the Fama-French three-factor model, consistent with Hirshleifer et al. (2009). Stocks are assigned to one of the 25 portfolios formed on size and book-to-market at the end of June each year, with market capitalization assessed at the end of June and the book-to-market ratio determined using book equity from the previous fiscal year-end relative to market equity at the prior quarter-end. The abnormal return (AR) for each firm i on day k within a specified window from to T (where $\tau < T$) is computed as follows:

$$AR_{[\tau,T],\,i} \;=\; \prod_{k=\tau}^{T} R_{i,k} \;-\; \prod_{k=\tau}^{T} \mathbb{E}\big[R_{p,k}\big] \tag{1}$$

where $R_{i,k}$ is the daily return for firm i, and $R_{p,k}$ is the matched Fama–French portfolio daily return on day k.

The cumulative abnormal return (CAR) represents the sum of these daily abnormal returns over the period of interest. Our primary event window, defined as (CAR-*2-60*), captures the buy-and-hold abnormal returns from trading day two through trading day 60 following the earnings announcement. We exclude day 1 from the CAR window and analyze it separately, in line with Bernard and Thomas (1989), as the immediate market reaction is expected to be fully reflected on the announcement day in an efficient market. Robustness checks using alternative event windows (30-day and 90-day horizons) support our primary findings, as detailed in Section 4.3.1.

3.2.2 Earnings Surprise

Earnings surprises are proxied by standardized unexpected earnings (SUE), which are calculated using analyst consensus forecasts obtained from I/B/E/S. While traditional foundational studies on PEAD typically relied on time series data to forecast earnings (Rendleman et al., 1982; Bernard and Thomas, 1989; 1990; Foster et al., 1984), later empirical research shows that analyst-based forecasts offer superior predictive accuracy for quarterly earnings (Livnat & Mendenhall, 2006). For instance, extensive research has found significantly larger and more persistent PEAD effects when using analyst-based expectations from I/B/E/S (Livnat & Mendenhall, 2006; Doyle et al., 2006). They attribute this to the closer alignment of analysts' forecasts with the market's implicit expectations rather than differences in data construction. Supporting this view, Walther (1997) suggests that sophisticated investors rely more on analyst consensus estimates than historical earnings extrapolation.

Thus, by relying on analyst expectations, we reduce forecast noise and more accurately reflect true market expectations, aligning with contemporary methodologies in the PEAD literature (Martineau & Gregoire, 2021; Martineau, 2021; Chordia & Miao, 2020; Luo et al., 2022). Additionally, by standardizing unexpected earnings, we account for historical earnings volatility (Bernard & Thomas, 1989). Although scholars have employed various approaches to standardize unexpected earnings, Foster et al. (1984) demonstrate that the difference between these methods is negligible. We follow Bernard and Thomas (1989) by scaling with the stock-specific standard deviation of unexpected earnings and computing the SUE as follows:

$$\mathrm{SUE}_{i,t} = \frac{e_{i,t} - \mathbb{E}\left[e_{i,t}\right]}{\sigma_i} \tag{2}$$

where $e_{i,t}$ denotes the actual earnings before extraordinary items for firm i at announcement t, and $\mathbb{E}[e_{i,t}]$ is the consensus-analyst expected earnings reported in I/B/E/S. The standard deviation σ_i is estimated using unexpected earnings from the previous six years, requiring at least ten observations, in line with Foster et al. (1984). SUE is winsorized at the 1% and 99% levels to reduce the impact of extreme observation.

Despite the recognized benefits of analyst-based forecasts, potential biases may exist. For example, Johnson (2004) highlights potential biases arising from analysts' incentives, while Bradshaw et al. (2012) argue that random walk models occasionally outperform analyst forecasts over extended horizons. To thoroughly address these methodological concerns and strengthen the robustness of our empirical findings, we conduct supplementary analyses employing alternative definitions of earnings surprises in Section 4.3.2.

3.3 Empirical Model

To empirically examine temporal changes in PEAD, we estimate the following cross-sectional pooled regression model:

$$CAR_{[2,60],i,t} \;=\; \beta_0 \;+\; \beta_1\, DSUE_{i,t} \;+\; \beta_2\, D_T \;+\; \beta_3\, (DSUE_{i,t} \times D_T) \;+\; \varepsilon_{i,t} \tag{3}$$

where $CAR_{[2,60],i,t}$ is the cumulative abnormal return based on the Fama-French three-factor model for firm i from day two through day 60 post-announcement. The variable $DSUE_{i,t}$ is the decile rank of standardized unexpected earnings for firm i at quarter t, linearly scaled to range from -0.5 and 0.5. This design, consistent with PEAD literature (Livnat & Mendenhall, 2006; Johnson & Schwartz, 2000; Milian, 2015), scales $DSUE_{i,t}$ to have zero mean, and facilitates the interpretation of regression coefficients. Specifically, each coefficient can be interpreted as the abnormal return to a zero-investment (hedged) portfolio strategy: going long in the top five SUE deciles and short in the bottom five deciles. The indicator variable D_T equals one for announcements in the post-2020 period (2021-2024), and zero otherwise. Consequently, β_1 represents the abnormal return on a zero-investment portfolio for 2005-2020. Similarly, $\beta_1 + \beta_3$ represents the abnormal return for our key test variable, given by the interaction term $DSUE_{i,t} \times D_T$, and thus, also the simulated trading strategy in 2021-2024.

If the effect of underreaction to earnings announcement news is more pronounced in the latter period than in the former, then β_3 should be significantly positive. This would indicate an increased underreaction to earnings news from 2021 onward, consistent with a more pronounced PEAD effect, slower information diffusion, and prolonged mispricing.

This regression specification allows us to evaluate whether the degree of market underreaction to earnings announcements has changed post-2020, possibly due to shifts in market structure, investor composition, or trading dynamics.

4 Empirical Results

4.1 Empirical Replication and Size Effects

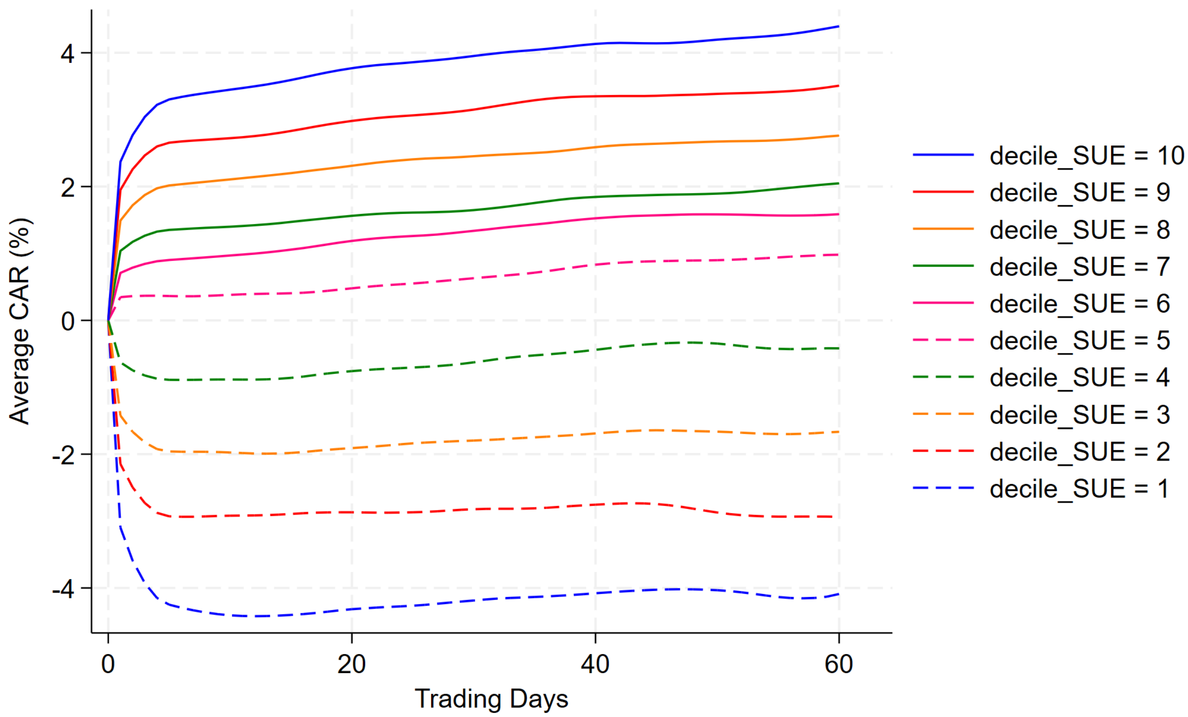
We begin by replicating previous findings within our sample. Next, we demonstrate that although the post-earnings announcement drift has been on a downward trajectory since its discovery, it has recently shown an increase. Finally, we show that this result cannot be attributed to our choice of drift period, the construction of the standardized earnings variable, or our method of calculating abnormal returns.

Our replication analysis, utilizing a comprehensive dataset of 220,228 quarterly earnings announcements from 2005 to 2024, reaffirms the persistent presence of post-earnings announcement drift, first documented by Ball and Brown (1968) and methodologically formalized during the 1980s by Rendleman et al. (1982), Foster et al. (1984), and Bernard and Thomas (1989). However, our findings reveal a noticeable reduction in both the magnitude and economic significance of PEAD compared with these seminal studies, underscoring important nuances in contemporary market dynamics.

Consistent with Foster et al. (1984) original findings, Figure 1 illustrates a largely monotonic relationship between cumulative abnormal returns and standardized unexpected earnings deciles. This pattern indicates that stocks with positive earnings surprises continue to drift upward in subsequent months, while those with negative surprises drift downward. However, we observe an intriguing deviation within portfolios with negative earnings surprises: these portfolios exhibit partial reversals in CAR a few weeks into the post-announcement window. This observation is in line with the findings of Doyle et al. (2006), who documented a stronger persistence of positive surprise drifts, and Martineau and Gregoire (2021), who noted similar reversals in negative surprise portfolios during his 2006-2015 sample period. These results suggest a potential structural evolution in the market responses to negative earnings surprises, which warrants further exploration.

Furthermore, we construct zero-investment portfolios by taking long positions in the highest-surprise deciles and short positions in the lowest-surprise deciles. Our findings for the full sample, presented in Table 2, Panel A, Column 4, reveal that this strategy yields abnormal returns of 1.45% over the 60-day post-announcement period, translating to an annualized return of 6.04%. In Panel B, we construct portfolios similar to those of Bernard and Thomas (1989), restricting the sample to only long positions in the highest SUE decile and short positions in the lowest SUE decile. The returns of these portfolios are comparable, as seen in Column 4, where abnormal returns of 1.47% (annualized 6.32%) are reported for the full sample. This outcome represents a significant decline from the 18% annualized returns reported by Bernard and Thomas (1989), and the 25% reported by Foster et al. (1984), highlighting a notable reduction in the economic significance and practical exploitation of PEAD. It is important to note, however, that these results are not directly comparable, mainly because we use FF3 abnormal returns, whereas

Figure 1
Post-Earnings Announcement Drift by SUE Decile



Notes: Figure 1 plots the average cumulative abnormal returns (CAR) over a 60-trading-day window following quarterly earnings announcements ($t = 0$). Firms are grouped into decile portfolios based on standardized unexpected earnings (SUE), from Decile 1 (lowest surprises) to Decile 10 (highest surprises). The sample comprises 220,228 quarterly earnings announcements from 6,958 U.S. firms listed on NYSE, AMEX, and NASDAQ between 2005 and 2024. Daily abnormal returns are calculated as the difference between actual stock returns and expected returns from the Fama-French three-factor model, using returns of matched 25 size–book-to-market portfolios from Kenneth French's data library. SUE is calculated as the forecast error from consensus analyst estimates scaled by its standard deviation of earnings surprises during the preceding six years. This figure illustrates the post-announcement drift pattern across the full sample.

Bernard and Thomas (1989), and Foster et al. (1984), employ abnormal returns from a market value-weighted model. Additionally, we use analyst-based forecasts instead of random-walk models. Nonetheless, even when similar calculations for abnormal returns and standardized unexpected earnings are used (see Section 4.3.2 and Section 4.3.3), we are unable to account for this substantial difference. The reduction in magnitude also aligns with the findings of other scholars, such as Chordia et al. (2014) and Martineau and Gregoire (2021), who attribute the attenuation to factors such as improved market liquidity, technological advancements, and increased arbitrage activity. Despite this, the magnitude of the drift remains economically significant and may still attract investors. For instance, some quantitative hedge funds that use sophisticated multi-factor or systematic models leverage PEAD as one of the many signals included in their models. The nuanced exploitation of anomalies within institutional trading is consistent with the empirical findings of Bartov et al. (2000) and Ng et al. (2008), who emphasize institutional investors' superior capabilities in systematically exploiting residual market inefficiencies.

Next, when the sample is divided into capitalization groups, significant differences emerge. As shown in Column 3 of Table 2, small-cap stocks exhibit a more pronounced drift, with abnormal returns of 6.81% over the same 60-day period, equivalent to an annualized return of 28.36%. While these potential returns might attract a wider range of investors looking to capitalize on them, it is important to consider that the higher drift in this segment may be attributed to factors that limit the exploitability of the drift, such as lower liquidity and higher trading costs (Ng et al., 2008), rather than solely exploitable factors such as limited analyst coverage and greater informational asymmetry (Hung et al., 2015; Hong et al., 2000). In the more specialized hedge portfolio, as seen in Panel B, the abnormal returns are estimated at 6.04% (annualized 27.95%), which is of similar magnitude to what Foster et al. (1984) found for his total sample across capitalization groups. In contrast, large-cap stocks, as observed in Column 1, exhibit substantially lower abnormal returns of just 0.83% (annualized 3.48%), supporting the assertions from

Bernard and Thomas (1989) and Martineau and Gregoire (2021) that enhanced scrutiny and efficient information dissemination mitigate drift among larger, more liquid firms.

Table 2
Post Earnings Announcement Drift 2005–2024

Panel A:	*Dependent variable:*				
	CAR-2-60				CAR-1-1
	Large-cap	Mid-cap	Small-cap	Full Sample	Full Sample
	(1)	(2)	(3)	(4)	(5)
DSUE	0.834***	1.853***	6.806***	1.450***	4.074***
	(0.121)	(0.277)	(0.571)	(0.130)	(0.046)
Observations	121,266	64,711	29,969	215,946	215,946
R^2	0.000	0.001	0.005	0.001	0.039

Panel B:	*Dependent variable:*				
	CAR-2-60				CAR-1-1
	Large-cap	Mid-cap	Small-cap	Full Sample	Full Sample
	(1)	(2)	(3)	(4)	(5)
DSUE	0.729***	2.044***	6.038***	1.471***	4.216***
	(0.182)	(0.413)	(0.915)	(0.192)	(0.069)
Observations	24,963	12,063	5,967	42,993	42,993
R^2	0.001	0.002	0.007	0.001	0.079

*p<0.05; **p<0.01; ***p<0.001

Notes: The table reports results from cross-sectional regressions of cumulative abnormal returns (*CAR*) on standardized unexpected earnings (*SUE*), in order to capture post-earnings announcement drift returns. The full sample includes 220,228 quarterly earnings announcements from 6,958 firms between January 2005 and December 2024. (*CAR-2-60*) denotes cumulative abnormal returns from trading day 2 to 60 after the earnings announcement, while (*CAR-1-1*) captures the immediate market reaction on the announcement day. Abnormal returns are calculated using the Fama-French three-factor model with expected returns based on the 25 portfolios formed on size and book-to-market from Kenneth French's data library. *DSUE* is defined as the earnings surprise standardized by the trailing six-year standard deviation of forecast errors and ranked into deciles each quarter, scaled to range from -0.5 to +0.5. In **Panel A**, we report estimates based on this continuous decile-scaled *DSUE* variable, which simulates a zero-cost hedge portfolio strategy going long in the top five deciles and short in the bottom five. In **Panel B**, we restrict this portfolio to the extreme deciles only, i.e., long in Decile 10 and short in Decile 1. Columns (1) through (3) show results separately for large-, mid-, and small-cap firms, defined based on their market capitalization at the end of the preceding quarter. Column (4) reports estimates for the full sample using (*CAR-2-60*), and Column (5) reports immediate price reactions (*CAR-1-1*). Robust standard errors are reported in parentheses. Full variable definitions are provided in Appendix A. Asterisks indicate statistical significance at the 5%, 1%, and 0.1% levels, respectively.

Overall, our empirical replication demonstrates that, although PEAD remains statistically significant, its magnitude, economic relevance, and practical utility for typical investors have notably diminished, especially in large-cap stocks.[7] In light of recent changes in investor composition and technological advancements, we raise a critical question: has the declining trend of PEAD persisted, or have recent shifts in market dynamics led to increased inefficiencies? This possibility is explored in greater detail in the following section.

4.2 Regression on PEAD Change Over Time

Our empirical analysis reveals a striking reversal in the magnitude of post-earnings announcement drift after 2020, challenging the previously well-documented decline in this anomaly. Historically, extensive empirical evidence has attributed the decreasing trajectory of PEAD to several interrelated market dynamics, including increased arbitrage activity (Chordia et al. 2014), improvements in market infrastructure and liquidity driven by algorithmic and high-frequency trading (Brogaard et al., 2014), and improvements in informational environments driven by regulatory and technological advancements (Hung et al., 2015). In contrast, our findings highlight a notable resurgence of PEAD, suggesting a critical inflection point that warrants further investigation of recent structural changes.

Table 3, Panel A, Column 4, shows that the average magnitude of PEAD increased significantly from 1.30% during the period 2005-2020 to 2.25% (1.30% + 0.95%) post-2020, representing a substantial increase of approximately 70%.[8] Notably, this rise coincides with a simultaneous decline in immediate market reactions, as evidenced by the negative coefficient β_3 observed for day-one abnormal returns in Column 5. This inverse relationship highlights a behavioral shift toward delayed price adjustments rather than heightened earnings surprises. Such behavior may be attributed to evolving market structures,

[7] When introducing both quarter- and year-time fixed effects into our model, the interpretation of the results remains unchanged.

[8] Given that we do not control for macro-level time-varying factors and that decile ranking only partially addresses potential quarter-specific shocks, we augment our baseline regression with a linear time trend (see Equation 3 Section 3.3). Re-estimating the model with this trend leaves the interpretation of our results unchanged. Because our main dummy D_T varies solely over time and lacks cross-sectional variation, it is collinear with conventional time fixed effects; therefore, we employ a continuous time trend.

including the growing influence of retail investors and passive investment strategies, which have introduced new dynamics of inelastic market behavior and amplified noise trading (Gabaix & Koijen, 2021; Luo et al., 2022). It also aligns with theoretical frameworks that emphasize bounded rationality and investor inattention, where structural market frictions rather than informational deficiencies slow the incorporation of news into prices (Bartov et al., 2000).

Of particular note, our findings indicate that large-cap stocks exhibit the most pronounced change in PEAD, challenging recent literature that claims its disappearance in this segment since 2006 (Martineau and Gregoire, 2021; Martineau, 2021; Milian, 2015). Specifically, as detailed in Table 3, Column 1, the large-cap PEAD significantly rises from a modest 0.52% during the period 2005-2020 to 1.99% (0.52% + 1.47%) during 2021-2024. This represents an approximately 280% increase in the magnitude of the drift. When annualized, this increase corresponds to hedge portfolio returns rising from 2.17% to 8.29%. This notable resurgence starkly contrasts with Martineau's (2021) claim that improved informational efficiency had effectively eliminated PEAD among large-cap stocks after 2006. Instead, our results suggest a resurgence of market inefficiencies, potentially driven by evolving market conditions.

Panel B reveals a nuance: When zero-investment portfolios are constructed with long positions in only the highest earnings surprise decile and short positions in the lowest, the previously observed increase in PEAD in the full sample disappears (Column 4). However, for large-cap stocks (Column 1), the coefficient β_3, which captures the post-2020 increase, remains significant and economically meaningful with a magnitude of 1.68%, reinforcing our conclusion that large-cap PEAD has experienced a meaningful resurgence in the recent period.

Conversely, as observed in Column 3 of Panel A in Table 3, small-cap stocks have not exhibited significant changes in drift magnitude post-2020, consistently maintaining elevated abnormal returns of approximately 6.38% (annualized 26.59%) throughout our

Table 3
Changes between 2005–2020 and 2021–2024

Panel A:	*Dependent variable:*				
	CAR-2-60				CAR-1-1
	Large-cap	Mid-cap	Small-cap	Full Sample	Full Sample
	(1)	(2)	(3)	(4)	(5)
DSUE	0.516***	1.666***	6.381***	1.301***	4.149***
	(0.133)	(0.295)	(0.605)	(0.144)	(0.050)
D	−1.264***	−1.212***	0.807	−1.145***	−0.129***
	(0.096)	(0.250)	(0.514)	(0.105)	(0.036)
DSUE × D	1.472***	1.152	2.468	0.948**	−0.310**
	(0.304)	(0.803)	(1.718)	(0.331)	(0.118)
Observations	121,266	64,711	29,969	215,946	215,946
R^2	0.002	0.001	0.005	0.001	0.040

Panel B:	*Dependent variable:*				
	CAR-2-60				CAR-1-1
	Large-cap	Mid-cap	Small-cap	Full Sample	Full Sample
	(1)	(2)	(3)	(4)	(5)
DSUE	0.409*	1.844***	5.284***	1.331***	4.334***
	(0.197)	(0.440)	(0.966)	(0.212)	(0.077)
D	−1.597***	−0.801	3.073*	−1.071***	−0.241**
	(0.244)	(0.614)	(1.422)	(0.255)	(0.092)
DSUE × D	1.680***	1.282	4.699	0.981	−0.494**
	(0.488)	(1.228)	(2.845)	(0.510)	(0.184)
Observations	24,963	12,063	5,967	42,993	42,993
R^2	0.003	0.002	0.008	0.002	0.080

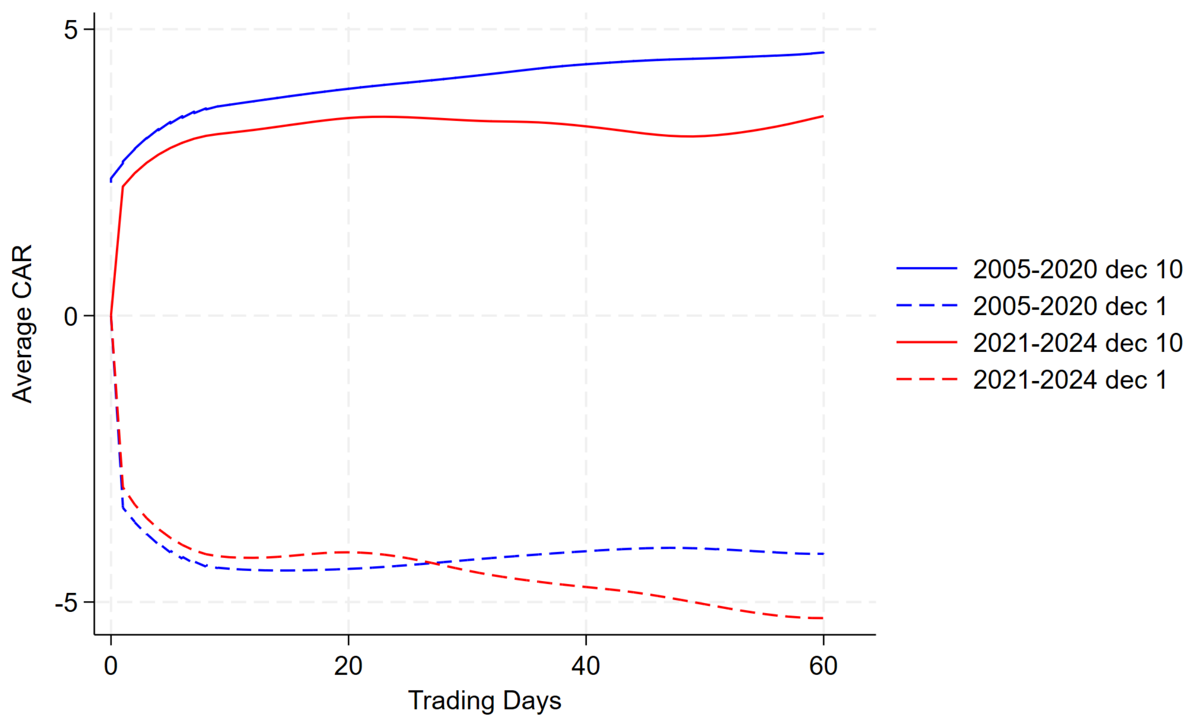
*p<0.05; **p<0.01; ***p<0.001

Notes: The table reports results from regressions of cumulative abnormal returns (CAR) on standardized unexpected earnings (SUE), a post-2020 indicator variable (D), and their interaction ($SUE \times D$), in order to assess changes in the magnitude of post-earnings announcement drift (PEAD) across two distinct periods: 2005-2020 and 2021-2024. The full sample includes 220,228 quarterly earnings announcements from 6,958 between January 2005 to December 2024. (*CAR-2-60*) denotes cumulative abnormal returns from trading day 2 to trading day 60 following the earnings announcement, while (*CAR-1-1*) captures the immediate price reaction on day 1. D is an indicator variable equal to one for firm-quarter observations in 2021-2024 and zero otherwise. The coefficient on SUE reflects the drift magnitude during the baseline period (2005-2020), while the interaction term ($SUE \times D$) reflects the incremental drift in the later subperiod. Abnormal returns are computed using the Fama-French three-factor model with expected returns estimated from 25 portfolios formed on size and book-to-market from Kenneth French's data library. SUE is defined as the earnings surprise standardized by the trailing six-year standard deviation of forecast errors and ranked into deciles each quarter, scaled to range from -0.5 to +0.5. In **Panel A**, we report estimates based on this continuous decile-scaled DSUE variable, which simulates a zero-cost hedge portfolio strategy going long in the top five deciles and short in the bottom five. In **Panel B**, we restrict this portfolio to the extreme deciles only, i.e., long in Decile 10 and short in Decile 1. Columns (1) to (3) show results separately for small-, mid-, and large-cap firms, based on their market capitalization at the end of the previous quarter. Column (4) presents results for the full sample, and Column (5) shows the immediate market reaction on the day following the earnings announcement (*CAR-1-1*) for the full sample. Robust standard errors are reported in parentheses. Full variable definitions are provided in Appendix A. Asterisks indicate statistical significance at the 5%, 1%, and 0.1% levels, respectively.

study period. This observation is also evident in Panel B. This persistent inefficiency among small-cap stocks, which is consistently higher than that observed in the large-cap sample, aligns closely with earlier research, indicating enduring structural limitations in information dissemination and processing within small-cap stocks (Hong et al., 2000; Grégoire & Martineau, 2022; Milian, 2015).

Figure 2

Post-Earnings Announcement Drift by SUE Decile



Notes: Figure 2 plots the average cumulative abnormal returns (CAR) over a 60-trading-day window following quarterly earnings announcements for firms in the top and bottom SUE deciles, separately for two sub periods: 2005-2020 and 2021-2024. The full sample includes 220,228 quarterly earnings announcements from 6,958 firms between January 2005 to December 2024. Cumulative abnormal returns are calculated using Fama-French three-factor adjusted returns. Solid lines correspond to firms in the highest SUE decile (decile 10), while dashed lines represent firms in the lowest SUE decile (decile 1). The horizontal axis denotes event time in trading days, where $t = 0$ is the earnings announcement date. The vertical axis displays average cumulative abnormal returns in percentage terms. The figure illustrates the time path of abnormal returns around earnings announcements and enables a visual comparison of the magnitude and persistence of post-earnings announcement drift (PEAD) across periods. All variables are explained in greater detail in Appendix A

Figure 2 further highlights the distinct temporal dynamics of PEAD across SUE deciles. Notably, the positive earnings surprise decile shows increasing abnormal returns during the 60 trading days post-announcement for both the 2005-2020 and 2021-2024 samples, although with a pattern suggesting potential investor profit-taking in the latter period. This behavior is consistent with prospect theory and is indicative of noise trading biases (Kahneman and Tversky, 1979; 1992; Black, 1986), which are likely to intensify as market dynamics evolve with the growing influence of retail investors, and the passive capital ownership share becoming more prominent. In contrast, the negative SUE decile exhibits notably greater declines in abnormal returns in the post-2020 period, without the partial reversals observed during the 2005-2020 period. Collectively, these patterns suggest that the increased hedge portfolio returns post-2020 are primarily derived from larger gains in negative drift positions.

Another notable trend in the post-2020 period is the rise and influence of the "Magnificent Seven" (Mag 7) stocks, which have become dominant drivers of aggregate index performance in the U.S.[9] This raises the question of whether these stocks, given their substantial market capitalizations, frequent positive earnings surprises, and high returns during this period, might be disproportionately influencing the observed resurgence in PEAD among the large-cap stocks. Although our empirical design should mitigate such biases through measures such as winsorization of extreme observations, the use of standardized unexpected earnings that accounts for historical volatility in surprises (Bernard & Thomas, 1989), and the size of our large-cap sample (see Section 3 for more details), it remains essential to test this directly. To address this, we re-estimate our main regression model after excluding all observations related to the Mag 7. The results, presented in Appendix D, confirm that the suggested increase in PEAD among large-cap stocks seems to persists even in the absence of these firms, with a similar magnitude. Furthermore, this holds true when the Mag-7 is expanded to include Netflix and Broadcom, which are part of two other influential acronyms: "FAANG" and "BATMAN." This underscores that the resurgence of drift is not merely a result of a narrow subset of

[9] The "Magnificent Seven" (Mag 7) stocks consists of Alphabet, Microsoft, Amazon, Meta, Apple, Tesla and Nvidia. According to Yahoo Finance, the Mag 7 accounted for one-third of the S&P 500 index as of year-end 2024, more than double their 14% at year-end 2019.

mega-cap equities but rather reflects broader structural changes in market behavior.

In summary, our findings highlight a notable shift in market behavior post-2020, characterized by a resurgence of PEAD, particularly among large-cap stocks. This observed shift prompts critical reconsideration of contemporary market efficiency, drawing attention to the substantial influence of recent technological advancements and structural transformations in investor composition. To support these insights and strengthen the robustness of our findings, the subsequent section provides comprehensive evaluations across alternative methodological frameworks including varied time horizons, definitions of earnings surprises, and benchmark models.

4.3 Robustness Tests

4.3.1 Alternative Time Horizons for CAR

Following Bernard and Thomas (1989) and the subsequent consensus in the PEAD literature (Chordia & Miao, 2020; Martineau and Gregoire, 2021; Martineau, 2021), we initially employ a 60-trading day post-announcement period to measure PEAD. However, while this 60-day window approximately corresponds to a quarter, selecting a specific time frame remains somewhat arbitrary and existing theoretical frameworks offer limited guidance. To test the robustness of our results, we extend our analysis to include alternative post-announcement windows, specifically examining cumulative abnormal returns over 30- and 90-trading day periods. Consistent with our primary methodology, we calculate abnormal returns using the Fama-French three-factor model and exclude returns from the first trading day after the announcements, as the immediate market reaction should capture the full price adjustment if markets are efficient.

Table 4, Panels A and B, demonstrate that our primary findings hold across these alternative time horizons. Notably, the increased drift among large-cap stocks remains statistically significant for both the 30- and 90-day windows, indicating a persistent delayed reaction to earnings announcements rather than a consequence of our choice of period. Similarly to our baseline regressions, the effect appears to be concentrated in the large-cap subsample, as no significant β_3 coefficients are present for mid-cap and small-cap stocks, observed in Column 2 and 3 of Panel A and B. Interestingly, the PEAD effect for large-caps during 2005-2020 vanished in the 30-day horizon (Panel A), suggesting that PEAD may be defined over longer time horizons. Among small-cap stocks, the primary results again appear to hold, with a relatively high post-announcement drift observed (5.11% for 30 days and 6.63% for 90 days), with no significant difference in the post-2020 period.

These findings suggest that while small-cap drift remains stable, it seems inefficiencies in large-cap stocks have seen a significant increase since 2020, regardless of the time horizon considered. Additionally, it appears that PEAD in large-cap stocks may require extended time frames to fully materialize. Our results challenge Martineau and Gregoire (2021), who linked PEAD solely to small, illiquid firms. Instead, our results suggest that even large, more widely monitored stocks are now more prone to underreaction, potentially due to changes in investor composition or attention (Haddad et al., 2025; Barber et al., 2022; Luo et al., 2022).

Table 4
Abnormal Returns Over Alternative Time Periods

Panel A:	*Dependent variable: CAR-2-30*			
	Large-cap	Mid-cap	Small-cap	Full Sample
	(1)	(2)	(3)	(4)
SUE	−0.043	1.147***	5.114***	0.869***
	(0.092)	(0.203)	(0.426)	(0.100)
D	−0.514***	−0.748***	1.013**	−0.461***
	(0.066)	(0.169)	(0.367)	(0.073)
DSUE × D	1.113***	0.717	1.276	0.588*
	(0.208)	(0.546)	(1.226)	(0.229)
Observations	121,266	64,711	29,969	215,946
R^2	0.001	0.001	0.007	0.001

Panel B:	*Dependent variable: CAR-2-90*			
	Large-cap	Mid-cap	Small-cap	Full Sample
	(1)	(2)	(3)	(4)
DSUE	0.505***	1.698***	6.633***	1.336***
	(0.136)	(0.300)	(0.617)	(0.147)
D	−1.275***	−1.135***	0.804	−1.136***
	(0.098)	(0.254)	(0.518)	(0.107)
DSUE × D	1.501***	1.377	2.570	1.007**
	(0.311)	(0.816)	(1.735)	(0.337)
Observations	121,266	64,711	29,969	215,946
R^2	0.002	0.001	0.005	0.001

*p<0.05; **p<0.01; ***p<0.001

Notes: The table presents regression estimates of cumulative abnormal returns (CAR) on standardized unexpected earnings (SUE), a post-2020 period indicator D, and their interaction $SUE \times D$. The full sample includes 220,228 quarterly earnings announcements from 6,958 between January 2005 to December 2024. Abnormal returns are computed using the Fama-French three-factor model with expected returns constructed from 25 portfolios formed on size and book-to-market from Kenneth French's data library. SUE is defined as the earnings surprise standardized by the trailing six-year standard deviation of forecast errors and ranked into deciles each quarter, scaled to range from -0.5 to +0.5. The coefficient on SUE corresponds to the abnormal return associated with a zero-cost hedge portfolio strategy: going long in the top five deciles and short in the bottom five. **Panel A** replicates the specifications of the baseline regression in Table 3 using an shortened event window of 30 trading days (*CAR-2-30*), capturing shorter-term post-announcement drift. Columns (1) to (3) show results separately for small-, mid-, and large-cap firms, based on their market capitalization at the end of the previous quarter while Column (4) presents results for the full sample. **Panel B** replicates the specifications of Panel A using an extended event window of 90 trading days (*CAR-2-90*), capturing longer-term post-announcement drift. As in Panel A, estimates are presented separately by firm size group (Columns 1-3) and for the full sample (Column 4). Robust standard errors are reported in parentheses. Asterisks indicate statistical significance at the 5%, 1%, and 0.1% levels, respectively. Variable definitions and additional methodological details are available in Appendix A.

4.3.2 Alternative SUE Measures

To safeguard against the possibility that our findings on post-earnings announcement drift (PEAD) are not artifacts of a specific earnings surprise construction, we perform a series of robustness checks by using three alternative definitions of unexpected earnings. These variations allow us to assess the stability of the drift across both analyst-based and time-series-based surprise measures, reflecting broader concerns in the literature regarding the empirical sensitivity of PEAD to how surprises are quantified (Livnat & Mendenhall, 2006; Bradshaw et al., 2012).

Our baseline SUE metric employs the standard approach of scaling unexpected earnings based on the historical volatility of the I/B/E/S consensus forecast errors. Additionally, we employ the contemporary approach of calculating unexpected earnings as the difference between the reported EPS and the latest I/B/E/S consensus forecast. This specification, widely adopted in the literature (Doyle et al., 2006; Livnat & Mendenhall, 2006), captures the unexpected component of earnings, while the scaling accounts for firm-specific variation in forecast accuracy (Bernard & Thomas, 1989). However, two limitations motivate our exploration of alternative ways of defining SUE. First, scaling unexpected earnings may understate the economic significance of large earnings shocks in firms that are inherently volatile. Second, its sole reliance on earnings forecasts may omit broader qualitative signals contained in earnings releases such as sales, margin adjustments, or strategic outlook statements (Jegadeesh & Titman, 1993).

To address these concerns, we first employ the Earnings Announcement Return (EAR) metric, which builds on the approach introduced by Liang (2003). This price-scaled surprise is computed as follows:

$$EAR_{i,t} = \frac{EPS_{i,t} - EPS_{i,t-4}}{P_{i,t-45}} \tag{4}$$

where $EPS_{i,q}$ and $EPS_{i,q-4}$ denote earnings per share in the current and the same quarter of the previous year, respectively, and $P_{i,t-45}$ is the stock price 45 trading days before the earnings announcement. By anchoring surprises to a seasonal random walk benchmark and scaling by lagged prices, EAR captures not only earnings content, but also other concurrent informational signals released during the earnings window, including forward guidance and qualitative information (Bradshaw et al., 2012). Moreover, as it bypasses analyst forecasts, it is robust to biases stemming from conflicts of interest, personal incentives, and herding behavior among sell-side analysts (Johnson, 2004). However, its dependence on lagged prices introduces some exposure to market-wide cycles, which may not reflect firm-level fundamentals.

Second, we adopt a seasonal random walk model with standardized forecast errors, which we refer to as $SURP$, following Foster et al. (1984) and Bernard and Thomas (1989). Here, unexpected earnings are defined as follows:

$$SURP_{i,t} = \frac{EPS_{i,t} - EPS_{i,t-4}}{\sigma_i} \tag{5}$$

where $EPS_{i,t}$ denotes the actual earnings before extraordinary items for firm i at announcement t, and expected earnings are those reported in the same fiscal quarter one year earlier: $EPS_{i,t-4}$. To standardize the surprises, we scale unexpected earnings by the standard deviations of forecast errors. These are computed using data from the prior six years, requiring at least 10 quarters of data per firm. This approach offers a purer model-based surprise that does not rely on analyst projections and could be argued to be well-suited for capturing shifts in underlying firm performance over time. Although both $SURP$ and EAR rely on the same benchmark expectation and only differ in scaling, we include both to distinguish between two conceptually different aspects of earnings news: EAR emphasizes the economic magnitude of the surprise by scaling with price, whereas $SURP$ emphasizes its unexpectedness relative to historical volatility by standardizing with firm-specific forecast error variance.

Third, we consider unexpected earnings (UE) without any standardization, defined as the raw difference between the reported EPS and the analyst consensus forecast. While we acknowledge that omitting standardization may introduce additional variance, its practical impact is alleviated by condensing the variable into decile ranks and by employing robust standard errors. Using absolute earnings surprises retains the absolute magnitude of the surprise, which is particularly pertinent for high-volatility firms, where large earnings deviations might be downplayed in standardized SUE metrics, potentially leading to an underestimation of their market impact. In such cases, SUE may potentially serve more as a proxy for firm opacity than for the surprise itself, as discussed by Livnat and Mendenhall (2006). Thus, UE offers a complementary perspective by emphasizing the size of informational shocks rather than their relative unexpectedness.

The results of these robustness checks, reported in Table 5 (Panels A-C), corroborate our findings on the persistence and statistical significance of PEAD across all the surprise definitions. Drift magnitudes remain consistent, regardless of whether earnings surprises are defined by analyst expectations (SUE, UE) or time-series benchmarks (EAR, $SURP$). Notably, the post-2020 resurgence in drift among large-cap stocks holds under each metric, reinforcing the view that the resurgence of PEAD may reflect a genuine structural shift in market behavior rather than measurement sensitivity. Consistent with previous findings that analyst-based surprises tend to exhibit stronger drift effects (Doyle et al., 2006; Livnat & Mendenhall, 2006), our baseline and UE-based models yield slightly higher magnitudes. Overall, these results support our findings that post-2020 markets, even among large-caps, appear to have seen an increase in PEAD, a trend that is robust to both conceptual and empirical choices in earnings surprise construction.

Table 5
Different Measures of SUE

Panel A: EAR	*Dependent variable:*				
	CAR-2-60				CAR-1-1
	Large-cap	Mid-cap	Small-cap	Full Sample	Full Sample
	(1)	(2)	(3)	(4)	(5)
EAR	0.503**	1.612***	5.034***	1.957***	4.345***
	(0.188)	(0.305)	(0.478)	(0.179)	(0.056)
D	−1.305***	−1.377***	0.445	−1.256***	−0.203***
	(0.093)	(0.252)	(0.491)	(0.104)	(0.036)
EAR × D	1.455***	0.478	−0.197	0.476	−0.499***
	(0.379)	(0.716)	(1.197)	(0.381)	(0.125)
Observations	122,740	66,437	31,033	220,210	220,210
R^2	0.002	0.001	0.005	0.002	0.042

Panel B: SURP	*Dependent variable:*				
	CAR-2-60				CAR-1-1
	Large-cap	Mid-cap	Small-cap	Full Sample	Full Sample
	(6)	(7)	(8)	(9)	(10)
SURP	−0.040	1.131***	3.234***	0.411**	2.111***
	(0.136)	(0.314)	(0.675)	(0.149)	(0.051)
D	−1.104***	−0.907***	1.140*	−0.917***	−0.031
	(0.092)	(0.257)	(0.542)	(0.103)	(0.037)
SURP × D	1.378***	0.971	2.444	1.152***	−0.131
	(0.281)	(0.812)	(1.747)	(0.317)	(0.114)
Observations	115,286	58,319	26,044	199,649	199,649
R^2	0.002	0.001	0.002	0.001	0.011

(Continued)

Panel C: UE	*Dependent variable:*				
	CAR-2-60				CAR-1-1
	Large-cap	Mid-cap	Small-cap	Full Sample	Full Sample
	(1)	(2)	(3)	(4)	(5)
UE	0.312^{*}	1.519^{***}	6.570^{***}	1.258^{***}	4.122^{***}
	(0.147)	(0.331)	(0.652)	(0.160)	(0.052)
D	-1.377^{***}	-1.350^{***}	0.402	-1.279^{***}	-0.295^{***}
	(0.098)	(0.250)	(0.502)	(0.106)	(0.036)
UE × D	1.494^{***}	1.071	0.199	0.768^{*}	-0.866^{***}
	(0.284)	(0.754)	(1.546)	(0.314)	(0.105)
Observations	122,745	66,443	31,040	220,228	220,228
R^2	0.002	0.001	0.005	0.001	0.036

*p<0.05; **p<0.01; ***p<0.001

Notes: The table reports regression estimates of cumulative abnormal returns (*CAR-2-60*) on alternative measures of earnings surprises, a post-2020 indicator variable (D), and their interaction ($SUE \times D$), across 220,228 quarterly earnings announcements from 6,958 firms between January 2005 and December 2024. **Panel A** employs the Earnings Announcement Return (EAR) metric, defined as the difference in earnings per share (EPS) between the current quarter and the corresponding quarter four quarters prior, scaled by the stock price 45 trading days prior to the announcement. **Panel B** reports results using the standardized unexpected earnings $SURP$ measure, based on the seasonal random walk model, in which the earnings surprise before scaling is given by $E(e_{i,t}) = e_{i,t-4}$, where $e_{i,t}$ denote the actual earnings before extraordinary items for firm i at announcement t. The measure is scaled by the standard deviation of forecast errors estimated over a rolling six-year window, requiring a minimum of 10 prior observations. **Panel C** utilizes the unstandardized forecast error UE, defined as the raw difference between actual EPS and the I/B/E/S consensus analyst forecast, without adjusting for historical volatility. In all panels, firms are sorted into categories by market capitalization measured at the end of the previous fiscal quarter. Columns (1) through (3) report estimates separately for large-cap, mid-cap, and small-cap firms, respectively, while Column (4) presents results for the full sample. Robust standard errors are reported in parentheses. Full variable definitions are provided in Appendix A. Asterisks indicate statistical significance at the 5%, 1%, and 0.1% levels, respectively.

4.3.3 Different Abnormal Return (AR) Benchmarks

Finally, acknowledging the potential limitations associated with our primary abnormal return calculation method, the Fama-French three-factor (FF3) model, we test alternative specifications to verify the robustness of our findings. Previous literature highlights the inherent risk that abnormal returns might simply reflect fair compensation for unmeasured or inadequately measured risk factors (Fama & French, 1993). To address this concern, we systematically assess four alternative benchmark models used to calculate abnormal returns to reinforce the credibility of our observed PEAD effects.

First, we employ a value-weighted market model (AR_VWM), a method widely employed in earlier PEAD studies, notably by Bernard and Thomas (1989). The AR_VWM captures systematic market risk using a single market factor (beta) estimated through firm-specific regressions against its representative market index (NYSE, AMEX, or NASDAQ), explicitly excluding size, value, and other risk factors. Under this specification, the daily abnormal returns are estimated as follows:

$$AR_{i,t} \;=\; R_{i,t} \;-\; \mathbb{E}\big[R_{m,t}\big] \tag{6}$$

where $R_{i,t}$ is the daily raw return of a firm i at day t, $R_{m,t}$, denotes the value-weighted market return for the NYSE, AMEX, and NASDAQ exchanges, and $\mathbb{E}\big[R_{m,t}\big]$ specifies the expected return based on the market factor in the benchmark model. The cumulative abnormal return is calculated as the sum of these daily abnormal returns over the designated 60-day post-announcement window.

Second, we assess market-adjusted abnormal returns by using a simpler benchmark that does not estimate firm-specific sensitivities. This model calculates abnormal returns directly as the difference between firm-specific returns and the value-weighted market index returns (AR_VW). This straightforward approach offers an intuitive measure of abnormal returns without the additional assumptions inherent in estimating the beta coefficients.

Third, we explore abnormal returns adjusted using an equal-weighted market index (AR_EW). By employing an equal-weighted index, we mitigate potential biases from large-cap stocks disproportionately affecting market index returns. This method reduces the likelihood that our findings are merely artifacts of index-weighting methodologies, especially given the increasing dominance of large-cap stocks in value-weighted indices.

Finally, we focus on specifically isolating and analyzing large-cap stocks, benchmarking their returns exclusively against the S&P 500 index ($AR\_S\&P$). This targeted analysis specifically addresses concerns that observed drift patterns among large-cap firms might stem from methodological issues such as inappropriate benchmarks or the inadvertent inclusion of small-firm anomalies within broader market indices. By using the S&P 500 as a benchmark, widely regarded as the most representative index for large-cap U.S. equities, we directly evaluate the robustness of our findings within a large-cap context. The formal specifications of the latter three approaches are uniformly defined by:

$$AR_{i,t} = R_{i,t} - R_{m,t} \tag{7}$$

where $R_{i,t}$ denotes the daily raw return for a firm i at day t, and $R_{m,t}$ represents the respective benchmark return (value-weighted, equal-weighted, or S&P 500). For the value- and equal-weighted specifications, stocks are matched to their respective exchanges: the NYSE, AMEX, or NASDAQ. In the S&P 500 specification, all stocks are compared against the S&P 500. The cumulative abnormal returns for each firm are aggregated over the standard 60-trading day event window.

Table 6 presents the results of these alternative abnormal return methodologies. Across all alternative benchmarks, the results consistently support our primary findings, affirming robust and statistically significant post-announcement drift effects of magnitudes similar to our original FF3-based analysis. Notably, due to the exclusion of size and value risk factors, the estimated abnormal returns under these alternative specifications are, in most cases, slightly higher in magnitude compared to our primary analysis. For instance, the abnormal drift identified among small-cap stocks (Column 3) ranges from 6.83% to 6.99% across alternative benchmarks compared to 6.38% in the baseline FF3 model (Table 3). Similarly, the incremental increase in drift for large-cap stocks (Column 1) between the 2005-2020 and 2021-2024 period ranges from 1.59% to 2.08%, slightly higher than the 1.47% observed under the FF3 specification.

Table 6
Different Measures of Abnormal Returns

Panel A: AR_VWM	*Dependent variable:*				
	CAR-2-60				CAR-1-1
	Large-cap	Mid-cap	Small-cap	Full Sample	Full Sample
	(1)	(2)	(3)	(4)	(5)
DSUE	0.888***	1.930***	6.934***	1.519***	4.551***
	(0.158)	(0.300)	(0.613)	(0.153)	(0.052)
D	−1.605***	−2.681***	−1.138*	−1.980***	−0.131***
	(0.114)	(0.253)	(0.518)	(0.112)	(0.039)
DSUE × D	2.073***	1.089	1.801	1.596***	0.063
	(0.366)	(0.811)	(1.728)	(0.357)	(0.127)
Observations	121,266	64,711	29,969	215,946	215,946
R^2	0.003	0.003	0.006	0.003	0.044
Panel B: AR_VW	*Dependent variable:*				
	CAR-2-60				CAR-1-1
	Large-cap	Mid-cap	Small-cap	Full Sample	Full Sample
	(6)	(7)	(8)	(9)	(10)
DSUE	0.879***	1.924***	6.924***	1.511***	4.551***
	(0.159)	(0.300)	(0.614)	(0.153)	(0.052)
D	−1.586***	−2.661***	−1.123*	−1.961***	−0.131***
	(0.114)	(0.253)	(0.518)	(0.112)	(0.039)
DSUE × D	2.082***	1.095	1.811	1.605***	0.064
	(0.366)	(0.811)	(1.728)	(0.357)	(0.127)
Observations	121,266	64,711	29,969	215,946	215,946
R^2	0.003	0.003	0.006	0.003	0.044

(Continued)

Panel C: AR_EW	*Dependent variable:*				
	CAR-2-60				CAR-1-1
	Large-cap	Mid-cap	Small-cap	Full Sample	Full Sample
	(1)	(2)	(3)	(4)	(5)
DSUE	0.630***	1.573***	6.831***	1.388***	4.549***
	(0.157)	(0.292)	(0.595)	(0.149)	(0.052)
D	0.998***	−0.002	1.798***	0.714***	−0.104**
	(0.112)	(0.247)	(0.510)	(0.110)	(0.039)
DSUE × D	1.721***	1.271	1.699	1.340***	0.001
	(0.360)	(0.791)	(1.704)	(0.350)	(0.127)
Observations	121,266	64,711	29,969	215,946	215,946
R^2	0.002	0.001	0.006	0.001	0.044
Panel D: AR_S&P	*Dependent variable:*				
	CAR-2-60				CAR-1-1
	Large-cap	Mid-cap	Small-cap	Full Sample	Full Sample
	(6)	(7)	(8)	(9)	(10)
DSUE	0.983***	1.965***	6.992***	1.569***	4.552***
	(0.159)	(0.301)	(0.616)	(0.154)	(0.052)
D	−1.883***	−2.902***	−1.317*	−2.245***	−0.152***
	(0.115)	(0.255)	(0.520)	(0.113)	(0.039)
DSUE × D	1.587***	0.780	1.569	1.166**	0.0547
	(0.369)	(0.818)	(1.738)	(0.360)	(0.128)
Observations	121,266	64,711	29,969	215,946	215,946
R^2	0.004	0.004	0.006	0.003	0.044

*p<0.05; **p<0.01; ***p<0.001

Notes: Table 6 presents estimates from cross-sectional regressions of cumulative abnormal returns (*CAR-2-60*) on standardized unexpected earnings (SUE), estimated under four alternative benchmark models for expected returns. The full sample includes 220,228 quarterly earnings announcements from 6,958 firms between January 2005 and December 2024. **Panel A** constructs abnormal returns using Fama-French three-factor adjusted returns with value-weighted 25 portfolios formed on size and book-to-market from Kenneth French's data library. **Panel B** computes abnormal returns using value-weighted (AR_VW) returns of the CRSP universe as the benchmark. **Panel C** uses equal-weighted (AR_EW) market returns, while **Panel D** employs S&P 500 index returns as the reference ($AR\_S\&P500$). In each panel, the dependent variable (*CAR-2-60*) reflects cumulative abnormal returns from trading day 2 through day 60 following quarterly earnings announcements. The variable SUE represents standardized unexpected earnings, scaled to decile ranks from −0.5 to +0.5 each quarter. The coefficient on SUE reflects the abnormal return to a zero-investment portfolio strategy: going long in the top five deciles and short in the bottom five deciles. The post-2020 indicator D identifies observations from the January 2021 to December 2024 subperiod. The interaction term $SUE \times D$ measures differences in the earnings-returns relation between the pre-2021 and post-2020 periods. Firms are sorted into groups by market capitalization at the end of the previous quarter, with Columns (1) to (3) displaying results for large-, mid-, and small-cap segments, respectively, and Column (4) reporting estimates for the full sample. Robust standard errors are reported in parentheses. Full variable definitions are provided in Appendix A. Asterisks indicate statistical significance at the 5%, 1%, and 0.1% levels, respectively.

Collectively, the comparable results across diverse abnormal return methodologies suggest that our documented PEAD results are not artifacts of omitted risk factors or methodological biases related to abnormal return estimation. Consequently, these results substantially challenge the explanations grounded in incomplete risk adjustment, instead providing compelling findings consistent with market underreaction and delayed price adjustments following earnings announcements. As the robustness checks in regard to time horizons, earnings surprises, and abnormal returns, presented throughout Section 4.3, collectively reinforce the empirical validity of our findings, they also prompt a more granular investigation into the drivers behind this drift. The next section explores the roles of investor composition, trading behavior, and structural ownership patterns in explaining this increased effect.

5 Additional Tests

5.1 Retail Ownership and Passive Investment

The COVID-19 pandemic has significantly reshaped the equity market landscape, leading to a notable increase in retail investor participation (Ozik et al., 2021). This surge was fueled by extended lockdowns, substantial fiscal stimuli that boosted personal savings, and the enhanced accessibility of user-friendly trading platforms such as Robinhood, alongside the emergence of influential online investor communities such as Reddit's r/wallstreetbets. According to Vanda Research (2023), retail flows surged by 84% in 2023 compared to 2019, with a marked increase during 2020 from a relatively stable level in the preceding years (see Appendix C for a visual depiction). Previous research suggests that retail investors often exhibit behavioral biases, such as contrarian strategies around earnings announcements, which can hinder efficient price discovery and contribute to market inefficiencies (Luo et al., 2022; Kaniel et al., 2012; Barber et al., 2022; Cookson & Niessner, 2020).

Concurrently, the growth of passive investment strategies signifies a major shift away from active institutional management. By design, passive funds systematically disregard firm-specific fundamentals, adjusting portfolios strictly based on index rebalancing, rendering them inelastic. Consequently, the increasing dominance of passive investment has raised concerns about its impact on market efficiency and price discovery (Gabaix & Koijen, 2021). Thus, these parallel developments of heightened retail activity and increased passive investment create an environment in which the assimilation of earnings information is delayed, providing an intuitive explanation for the recent rise in post-earnings announcement drift.

To formally investigate these hypotheses, we concentrate on two primary ownership metrics: Retail Ownership (RET_OWN) and Passive Ownership ($PASS\_OWN$). Panel A of Table 7 offers summary statistics for these ownership variables, alongside the baseline regression variables and additional control variables employed in the subsequent empirical analyses. Specifically, the control variables include illiquidity ($ILLIQ$), bid-ask spread (BAS), analyst coverage ($ANALYST$), earnings persistence ($PERS$), reporting lag ($REPLAG$), and the number of concurrent earnings announcements ($NCEA$). The theoretical justifications for using these particular controls are discussed in Section 5.1.1 and Section 5.1.2. The corresponding correlations among these variables are detailed in Panel B.

Table 7

Summary Statistics

Statistic	N	Mean	St. Dev.	25th perc.	Median	75th perc.
Baseline regression						
SUE	22,305,635	35.914	155.494	-25.000	25.000	101.000
DSUE	22,305,635	0.000	0.319	-0.278	0.0556	0.278
D	22,750,310	0.226	0.418	0.000	0.000	0.000
AR	17,634,614	0.010	3.285	-1.240	-0.050	1.160
CAR-2-60	220,228	0.551	19.042	-6.190	0.000	6.890
CAR-1-1	220,228	0.017	6.567	-1.770	0.000	1.700
CAR-2-30	220,228	0.324	13.140	-4.380	0.000	4.550
CAR-2-90	220,228	0.570	19.376	-6.320	0.000	7.075
Additional tests and controls						
RET_OWN	27,626,312	34.576	26.079	13.000	28.000	52.000
PASS_OWN	29,692,761	37.977	58.049	2.847	17.308	55.876
ILLIQ[1]	17,354,293	0.001	0.121	0.001	0.001	0.001
BAS	17,394,435	0.107	4.129	0.013	0.024	0.048
ANALYST	30,029,077	8.037	6.576	3.000	6.000	11.000
PERS	17,394,435	0.001	0.408	0.000	0.000	0.000
REPLAG	30,029,077	33.854	13.210	26.000	33.000	39.000
NCEA	17,394,435	167.658	99.176	89.000	168.000	240.000

[1] Amihud's (2002) illiquidity measure (ILLIQ) has been multiplied by 1,000 to facilitate interpretation.

Panel B: Correlation Matrix

	SUE	D	AR	CAR-2-60	CAR-1-1	CAR-2-30	CAR-2-90	EAR	SURP	UE	RET_OWN	PASS_OWN	BAS	ILLIQ	ANALYST	PERS	REPLAG	NCEA
SUE	1	0.0256	0.1752	0.0265	0.2062	0.0276	0.0265	0.0122	0.2335	0.0166	-0.1205	0.0548	-0.0041	-0.0005	0.1404	-0.0032	-0.0614	0.0237
D	0.0256	1	-0.0085	-0.0265	-0.0007	-0.0144	-0.0257	-0.0032	0.0058	-0.0049	-0.0372	0.3149	-0.0041	-0.0042	-0.0223	-0.0016	0.1093	0.1851
AR	0.1076	-0.0085	1	0.0117	0.0043	0.0162	0.0111	-0.002	0.0399	-0.0009	0.0011	0.0003	-0.0004	0.0002	-0.0022	-0.0005	-0.0004	0.0002
CAR-2-60	0.0136	-0.0265	0.0117	1	0.0102	0.6786	0.9793	-0.0008	0.0044	-0.001	0.0019	-0.0002	-0.0006	0.0024	0.0152	-0.005	0.0086	0.0091
CAR-1-1	0.1257	-0.0007	0.0043	0.0102	1	0.0145	0.01	-0.0029	0.0416	-0.0005	-0.0161	0.0097	0	0.0004	0.0005	-0.0036	-0.0115	0.0055
CAR-2-30	0.0241	-0.0144	0.0162	0.6786	0.0145	1	0.6641	0.0036	0.0066	0.0032	-0.0048	0.0108	-0.0006	0.0032	-0.0029	-0.0032	0.0089	0.0113
CAR-2-90	0.0141	-0.0257	0.0111	0.9793	0.01	0.6641	1	-0.001	0.0046	-0.002	0.0017	0.0018	-0.0007	0.002	-0.0108	-0.0054	0.0061	0.0067
EAR	0.0066	-0.0032	-0.002	-0.0008	-0.0029	0.0036	-0.001	1	-0.0004	0.7917	0.0062	-0.0007	-0.0001	0	0.0004	-0.0004	0.0012	0.0011
SURP	0.3088	0.0058	0.0399	0.0044	0.0416	0.0066	0.0046	-0.0004	1	-0.0018	-0.0019	0.0008	-0.0001	0.0002	0.0032	-0.0003	-0.002	0.002
UE	0.0091	-0.0043	0.001	0.0025	-0.0006	0.0064	0.0024	0.8428	-0.0018	1	0.0079	-0.0024	-0.001	-0.0001	-0.0018	-0.0002	0.0018	-0.0009
RET_OWN	-0.1205	-0.0372	0.0011	0.0019	-0.0161	-0.0048	0.0017	0.0062	-0.0019	0.0079	1	-0.21	0.0284	0.0154	-0.3374	0.008	0.0697	-0.0766
PASS_OWN	0.0548	0.3149	0.0003	-0.0002	0.0097	0.0108	0.0018	-0.0007	0.0008	-0.0024	-0.21	1	-0.0077	-0.0004	0.0896	-0.0009	0.063	0.1236
BAS	-0.0041	-0.0041	-0.0004	-0.0006	0	-0.0006	-0.0007	-0.0001	-0.0001	-0.001	0.0284	-0.0077	1	0.0552	-0.1922	0.0006	-0.055	-0.0517
ILLIQ	-0.0005	-0.0042	0.0002	0.0024	0.0004	0.0032	0.002	0	0.0002	-0.0001	0.0154	-0.0004	0.0552	1	-0.011	0	-0.0062	-0.0078
ANALYST	0.1404	-0.0223	-0.0022	0.0152	0.0005	-0.0029	-0.0108	0.0004	0.0032	-0.0018	-0.3374	0.0896	-0.1922	-0.011	1	-0.0031	-0.0748	0.0211
PERS	-0.0032	-0.0016	-0.0005	-0.005	-0.0036	-0.0032	-0.0054	-0.0004	-0.0003	-0.0002	0.008	-0.0009	0.0006	0	-0.0031	1	0.0055	-0.0015
REPLAG	-0.0614	0.1093	-0.0004	0.0086	-0.0115	0.0089	0.0061	0.0012	-0.002	0.0018	0.0697	0.063	-0.055	-0.0062	-0.0748	0.0055	1	-0.0582
NCEA	0.0237	0.1851	0.0002	0.0091	0.0055	0.0113	0.0067	0.0011	0.002	-0.0009	-0.0766	0.1236	-0.0517	-0.0078	0.0211	-0.0015	-0.0582	1

Notes: The table reports summary statistics and the correlation matrix for the key variables used in the additional tests examining the effects of retail and passive ownership on post-earnings announcement drift. **Panel A** presents descriptive statistics for the variables employed in both the baseline and extended specifications. SUE is the standardized unexpected earnings, measured as the analyst forecast error scaled by the standard deviation of historical forecast errors and ranked into deciles from -0.5 to +0.5. D is an indicator variable equal to one for earnings announcements between 2021 and 2024. *CAR-2-60*, *CAR-1-1*, *CAR-2-30*, and *CAR-2-90* denote cumulative abnormal returns measured over 2 to 60, 0 to 1, 2 to 30, and 2 to 90 trading day windows, respectively, calculated using the Fama-French three-factor model. RET_OWN is the percentage of shares not held by institutions, proxied as the residual of institutional ownership based on Thomson Reuters 13F filings. PASS_OWN is defined as the fraction of institutional ownership attributable to quasi-indexer (QIX) institutions, following Bushee's (2000) classification. Illiquidity ($ILLIQ$) is the Amihud (2002) measure, computed as the average daily ratio of absolute returns to dollar trading volume over the 30 trading days prior to the earnings announcement. BAS denotes the average bid-ask spread over the same period. Analyst coverage ($ANALYST$) is the number of I/B/E/S analysts providing forecasts in the announcement quarter. Earnings persistence ($PERS$) is the autocorrelation of quarterly earnings over the trailing four quarters. Reporting lag ($REPLAG$) is the number of calendar days between the fiscal quarter-end and the earnings announcement date. $NCEA$ denotes the number of earnings announcements occurring on the same day, used as a proxy for investor attention. **Panel B** reports the Pearson correlation matrix for these variables. Correlations between ownership structure, abnormal returns, information environment variables, and control variables confirm low to moderate multicollinearity and support the inclusion of these variables in multivariate regressions. $DSUE$ is the decile-scaled SUE, normalized to range from –0.5 to +0.5. It is used as the primary explanatory variable in all regression models. All variable definitions are provided in Appendix A, and further methodological detail is available in Section 3 and Section 5.

5.1.1 Retail Ownership's Effect on PEAD

Building on previous studies (Kaniel et al., 2012; Luo et al., 2022; Barber et al., 2022), we investigate whether the surge in retail investor activity from 2021 to 2024, as documented by Vanda Research (2023), plays a significant role in the increased PEAD observed after 2020 (Table 3). Utilizing an analytical framework adapted from Johnson and Schwartz (2000), we estimate the following pooled cross-sectional regression:

$$\begin{gathered} CAR\text{-}2\text{-}60 = \beta_0 + \beta_1\, SUE_t + \beta_2\, D_T + \beta_3\, (SUE_t \times D_T) \\ +\beta_4\, RET\_OWN_t + \beta_5\, (RET\_OWN_t \times SUE_t) \\ +\beta_6\, (RET\_OWN_t \times D_T) + \beta_7\, (RET\_OWN_t \times SUE_t \times D_T) + \varepsilon_t \end{gathered} \tag{8}$$

where *CAR-2-60* represents cumulative abnormal returns calculated using the FF3 model over the 60-day post-announcement window, SUE_t denotes the scaled decile-ranked earnings surprise derived from analyst forecast errors, and D_T is a dummy variable marking the post-2020 period. The estimated coefficients $\beta_1 + \beta_3$ thus represents the abnormal returns for a zero-investment strategy during the post-pandemic period for firms with low retail ownership, whereas $\beta_1 + \beta_3 + \beta_7$ captures the change in abnormal returns for high retail-ownership stocks during the same period. Retail ownership (RET_OWN) is proxied inversely by institutional ownership data derived from Thomson Reuters' 13F filings,[10] as follows:

$$RET\_OWN_t \;=\; 100\% \;-\; \textit{Institutional Ownership}_t \tag{9}$$

Although the measure aligns with existing practices in the literature (Chaieb et al., 2024), our RET_OWN measure is subject to several limitations. First, it may systematically overstate retail ownership due to the exclusion of smaller institutions, such as boutique

[10] Accessed publicly via the Harvard Dataverse.

hedge funds and family offices, which are not captured because of the 13F reporting threshold of $100 million in assets. Second, the quarterly data frequency and inherent reporting lags introduce potential mismatches, especially during highly volatile periods such as the immediate aftermath of the COVID-19 pandemic. Third, this proxy overlooks intermediated retail flows invested through ETFs and mutual funds, categorizing such investments as institutional despite the flows originating from retail investors. Consequently, the actual retail market influence may also be understated, as the flows from these institutional vehicles could result from retail investors exhibiting performance-chasing characteristics or other behavioral biases in their fund selection (Barber et al., 2022; Kaniel et al., 2012). Additionally, in selecting this measure, we assume that stocks with high retail ownership will experience higher retail flows.

Beyond measurement error, there may also be concerns regarding omitted-variable bias. To determine whether firm-level characteristics confound the relationship between retail ownership and PEAD, we incorporate a comprehensive set of control variables in Panel B of Table 8. These controls account for known determinants of liquidity, trading activity, earnings quality, information environment, and investor attention, which may simultaneously influence both abnormal returns and the explanatory variables RET_OWN and SUE.

Retail investors are often linked to contrarian behavior, limited attention, and slower information processing (Barber et al., 2022; Kaniel et al., 2012). However, these behavioral patterns can vary depending on stock-specific features such as liquidity, coverage, or volatility. To isolate the effect of retail ownership from these confounding characteristics, we control for the bid-ask spread (BAS) and Amihud's (2002) illiquidity measure ($ILLIQ$), which serve as proxies for transaction costs and price impact, respectively. Stocks with low liquidity may attract fewer institutional arbitrageurs, allowing retail-driven inefficiencies to persist for longer. By including these liquidity variables, we mitigate any concerns that the observed PEAD effects are not merely artifacts of illiquidity that correlate with higher retail participation. This approach is consistent with Qin and Singal (2015), who emphasize that liquidity-related controls are essential when estimating ownership effects, as liquidity can confound the relationship between investor type and return anomalies.

We also account for analyst coverage ($ANALYST$), which acts as a proxy for the quality and availability of public information. Retail investors often trade disproportionately in stocks with low coverage, where prices reflect firm-specific information to a lower degree and thus are more susceptible to drift. By controlling for coverage, we can better determine whether PEAD results from retail trading behavior or merely from weaker information environments. Additionally, we consider earnings persistence ($PERS$), which capture the reliability and noisiness of earnings signal. Firms with more stable and predictable earnings are easier for all investors, retail and institutional alike, to interpret, potentially affecting the likelihood of drift. We also include reporting lag ($REPLAG$), which reflects the timeliness of information release, and investor attention, proxied by the number of concurrent earnings announcements ($NCEA$). The latter two variables, highlighted in previous studies such as Ohlson (1979) and Bartov et al. (2000), are known to affect the speed and completeness of market reactions to earnings news. In incorporating these controls, we follow Chordia and Miao (2020), who adopt a similar structure to mitigate the risk that the effect of our key variable on PEAD is confounded by omitted variables. See Appendix A for further details on variable construction.

The empirical findings detailed in Panel A of Table 8 reveal distinct nuances. For firms with low retail ownership, significant PEAD effects are predominantly confined to small-cap stocks ($\beta_1 = 6.46\%$, which is comparable to baseline findings in Table 3). In contrast, high-retail ownership in small-caps does not amplify PEAD, as observed in the insignificant β_5 (Column 3). However, in mid- and large-cap firms, higher retail ownership correlates significantly with stronger PEAD during the 2005-2020 period (as observed in the positive and significant β_5 in Column 1 and 2), aligning with behavioral finance theories that suggest that retail investors incorporate earnings news into prices more slowly (Kaniel et al., 2012; Barber et al., 2022). Notably, this effect disappears among the large-cap stocks in Panel B when control variables are included.

Analyzing the post-2020 effects in Table 8 presents additional complexity. While a general increase in PEAD is supported by a significant positive coefficient across most groups, as observed in β_3, a notable negative interaction coefficient β_7 specifically appears among mid-cap firms, indicating a potentially accelerated price discovery among high-retail stocks. This shift may be driven by improved access to and dissemination of earnings information through digital platforms, social media, and emerging AI tools, which potentially help retail investors interpret financial disclosures more quickly (Barber et al., 2022; Ozik et al., 2021; Kim et al., 2024). Although the results observed in the mid-cap sample are also evident in the full sample, with both a larger immediate reaction (Column 5) and lower drift (Column 4), this is likely influenced by a capitalization bias with small-cap stocks having a higher retail ownership than large-cap stocks because of liquidity constraints imposed on most institutional investors. Furthermore, the effects are marginal for both the mid-cap stocks and the full sample, implying low economic significance. Additionally, the significant decrease in PEAD vanishes when controls are introduced in Panel B. Despite this mid-cap phenomenon, the broader findings across other capitalization groups and specifications remains inconclusive, suggesting that increased retail participation alone may not fully account for the observed post-pandemic PEAD resurgence.

Table 8
Effects of Retail Ownership Between 2005–2020 and 2021–2024

Panel A:	*Dependent variable:*				
	CAR-2-60				CAR-1-1
	Large-cap	Mid-cap	Small-cap	Full Sample	Full Sample
	(1)	(2)	(3)	(4)	(5)
DSUE	0.082	−0.223	6.455***	0.422	4.086***
	(0.027)	(0.508)	(1.702)	(0.224)	(0.082)
D	−11.045***	−22.953***	8.224	−16.044***	−1.265**
	(1.470)	(4.817)	(16.513)	(1.645)	(0.570)
DSUE × D	1.260**	4.021**	2.205	2.002***	−1.089***
	(0.452)	(1.519)	(5.756)	(0.504)	(0.183)
RET_OWN	−0.033	−0.002	−0.174**	0.097***	0.019***
	(0.020)	(0.037)	(0.083)	(0.020)	(0.006)
RET_OWN × DSUE	0.014*	0.053***	0.005	0.057***	−0.080
	(0.006)	(0.012)	(0.026)	(0.006)	(0.019)
RET_OWN × D	−0.017	0.249*	0.015	0.162**	0.003
	(0.050)	(0.103)	(0.242)	(0.047)	(0.014)
RET_OWN × D × DSUE	0.001	−0.063	−0.020	−0.030*	0.025***
	(0.002)	(0.032)	(0.084)	(0.015)	(0.005)
Controls	NO	NO	NO	NO	NO
Observations	111,279	63,351	31,740	206,370	206,370
R^2	0.021	0.019	0.053	0.021	0.391

(Continued)

Panel B:	*Dependent variable:*				
	CAR-2-60				CAR-1-1
	Large-cap	Mid-cap	Small-cap	Full Sample	Full Sample
	(1)	(2)	(3)	(4)	(5)
DSUE	0.145	−0.117	8.330***	−0.160	3.953***
	(0.225)	(0.587)	(1.975)	(0.247)	(0.092)
D	−9.982***	−28.800***	5.337	−17.164***	−0.895
	(1.591)	(5.654)	(20.661)	(1.801)	(0.620)
DSUE × D	0.915	3.711*	0.557	1.612**	−1.244***
	(0.488)	(1.752)	(7.183)	(0.545)	(0.198)
RET_OWN	−0.031	−0.042	−0.048	0.044*	0.001
	(0.022)	(0.045)	(0.101)	(0.023)	(0.007)
RET_OWN × DSUE	0.008	0.046***	−0.017	0.051***	0.001
	(0.007)	(0.014)	(0.031)	(0.007)	(0.002)
RET_OWN × D	−0.032	0.444***	0.052	0.210***	0.005
	(0.054)	(0.123)	(0.308)	(0.055)	(0.016)
RET_OWN × D × DSUE	0.016	−0.037	0.018	−0.011	0.039***
	(0.017)	(0.037)	(0.105)	(0.016)	(0.005)
Controls	YES	YES	YES	YES	YES
Observations	86,528	45,021	21,653	153,202	153,202
R^2	0.020	0.026	0.080	0.026	0.402

*p<0.05; **p<0.01; ***p<0.001

Notes: The table reports regression estimates of cumulative abnormal returns (*CAR-2-60*) and immediate price reactions (*CAR-1-1*) on standardized unexpected earnings (*SUE*), a post-2020 period indicator (*D*), retail ownership (*RET_OWN*), and their interactions to assess how PEAD varies with changes in investor composition. (*CAR-2-60*) is defined as the cumulative abnormal return from trading day 2 to 60 post-earnings announcement, while (*CAR-1-1*) captures the day-one market reaction. Abnormal returns are computed using the Fama-French three-factor model. *SUE* is scaled from -0.5 to +0.5 based on decile rankings of forecast errors, and *D* equals one for observations from 2021-2024. *RET_OWN* is computed as 100% minus institutional ownership, based on quarterly Thomson Reuters 13F filings. **Panel A** presents baseline regressions without control variables. **Panel B** adds a comprehensive set of firm-level controls: illiquidity (*ILLIQ*), bid-ask spread (*BAS*), analyst coverage (*ANALYST*), earnings persistence (*PERS*), reporting lag (*REPLAG*), and the number of concurrent earnings announcements (*NCEA*), all previously introduced in Table 7, with full variable definitions and construction procedures provided in Appendix A.

5.1.2 Passive Investments' Effect on PEAD

In light of the rapid growth of passive investing and its potential impact on market efficiency, as highlighted in recent literature (Gabaix & Koijen, 2021; Haddad et al., 2025), we investigate whether this trend might partly explain the observed resurgence of post-earnings announcement drift in recent years. Building on the established empirical framework in Section 5.1.1 and previous literature (Johnson & Schwartz, 2000), we estimate the following pooled cross-sectional regression:

$$\begin{aligned} CAR\text{-}2\text{-}60 = \beta_0 + \beta_1\, SUE_t + \beta_2\, D_T + \beta_3\,(SUE_t \times D_T) \\ +\beta_4\, PASS\_OWN_t + \beta_5\,(PASS\_OWN_t \times SUE_t) \\ +\beta_6\,(PASS\_OWN_t \times D_T) + \beta_7\,(PASS\_OWN_t \times SUE_t \times D_T) + \varepsilon_t \end{aligned} \tag{10}$$

where *CAR-2-60* represents the cumulative abnormal returns computed using the FF3 model over the 60 trading days following earnings announcements, SUE_t denotes the scaled decile-ranked earnings surprise based on analyst forecast errors, and D_T is a dummy variable capturing the post-2020 period. $PASS\_OWN$ quantifies the proportion of a firm's institutional holdings held by quasi-indexer (QIX) institutions, and serves as our proxy for passive ownership.

$PASS\_OWN$ is derived using Bushee's (2000) institutional investor classifications, which categorize investors into transient (TRA), dedicated (DED), and quasi-indexer (QIX) types based on their turnover rates and portfolio diversification.[11] QIX institutions, characterized by low turnover and high diversification, serve as a credible proxy for passively managed strategies. The use of this proxy is well-established and aligns with previous literature (Ke & Ramalingegowda, 2005; Appel et al., 2016; DeLisle et al., 2017). To construct our $PASS\_OWN$ variable, we integrate Bushee's (2000) classification data with quarterly stock-level holdings data from Thomson Reuters' 13F filings. We then

[11] We are grateful to Brian Bushee for providing this data publicly on his website .

aggregate the total shares held by QIX institutions for each stock-quarter observation and express this as a percentage of total common shares outstanding, received from CRSP, following the methodology used by Qin and Singal (2015). The interaction coefficient β_7 specifically captures whether firms with higher passive ownership experience differential post-earnings announcement drift in the post-2020 period. If passive ownership weakens price discovery around earnings events, we would expect β_7 to be positive and statistically significant.

Although our $PASS\_OWN$ measure is widely accepted in the existing literature, it might not fully capture broader market-wide shifts in passive investment behavior. Specifically, this firm-level measure could overlook aggregate macro-level effects associated with passive investing. If passive flows influence market dynamics through systematic channels, such as reducing market depth or changing arbitrage incentives, our defined measure could miss these macro effects, potentially rendering it incomplete or lacking construct validity. Consequently, the interpretation of the results based on $PASS\_OWN$ should be considered within the context of these potential constraints.

In addition, issues may arise from omitted-variable bias. Previous research consistently demonstrates how market reactions to earnings announcements are significantly influenced by firm-specific characteristics (Chordia & Miao, 2020; Martineau and Gregoire, 2021; Martineau, 2021). These characteristics may simultaneously influence both passive ownership and abnormal returns following earnings announcements, thus confounding the observed relationship. To address this concern, we include a comprehensive set of theoretically motivated control variables in Panel B of Table 9, designed to better isolate the effect of passive ownership from other known determinants of PEAD. These controls cover aspects related to market liquidity, informational environment, earnings characteristics, and investor attention.

Liquidity facilitates arbitrage, thereby promoting market efficiency (Chordia et al. 2009). If passive investors dampen informational efficiency, their impact might be less noticeable in highly liquid stocks, where arbitrageurs can still efficiently correct mispricing. Therefore, incorporating controls such as the bid-ask spread (BAS) and Amihud's (2002) illiquidity measure ($ILLIQ$) helps us isolate the specific contribution of passive ownership to PEAD. In line with Chordia and Miao (2020), we also control for analyst coverage ($ANALYST$), which serves as a proxy for the richness of a firm's information environment. Generally, a higher number of analysts corresponds to increased information production and more accurate market expectations, facilitating quicker incorporation of earnings news into prices, which may correlate with both firm size and passive interest. Qin and Singal (2015) show that analyst coverage is significantly negatively associated with passive institutional ownership but positively associated with active ownership. Consequently, higher passive ownership could be associated with weaker informational environments, potentially amplifying drift due to slower price discovery processes. By controlling for analyst coverage, our analysis aids in disentangling a more pure effect of passive ownership from broader differences in firms' informational environments.

We also control for earnings persistence ($PERS$), which affect the interpretability and perceived informativeness of earnings announcements. Generally, more persistent earnings are seen as credible signals, potentially attracting long-term investors. We capture the timeliness of disclosure by controlling for the reporting lag ($REPLAG$), while investor attention ($NCEA$) is proxied by the number of concurrent earnings announcements, indicating the cognitive load on market participants. These two variables, highlighted in previous studies such as Ohlson (1979) and Bartov et al. (2000), are known to affect the speed and completeness of market reactions to earnings news. In line with Chordia and Miao (2020), who incorporate all the above-mentioned controls in their examination of PEAD, we adopt a similar approach to mitigate the risk that our estimates for passive ownership are influenced by omitted variables that simultaneously affect both the price response and investor composition. For more details on the variable construction, refer to Appendix A.

Table 9, Panel A presents regression results across various size segments. Contrary to expectations, the interaction coefficient β_7, capturing the post-2020 drift associated with passive ownership, is statistically insignificant across all capitalization groups. Thus, our analysis suggests that passive investing may not have systematically exacerbated PEAD in the recent market environment. However, the general PEAD resurgence post-2020 among large-cap stocks remains robust, as observed by the statistically significant and positive β_3 (Column 1). Additionally, as observed in Panel B, our results remain robust after the inclusion of the theoretically motivated control variables, alleviating some concerns regarding omitted-variable bias.

While we observe a statistically significant and negative relationship between high passive ownership and PEAD during the 2005-2020 period in the full sample (β_5, Column 4), this finding does not hold across individual capitalization subgroups. This could reflect a mechanical effect from the correlation between passive ownership and firm size, as large-cap firms tend to have higher passive ownership due to the popularity of market-value weighted large-cap indices, and simultaneously exhibit lower PEAD than small-cap stocks, as noted in our main results in Table 3. Therefore, these results may be conflating a size effect rather than capturing the effect of passive ownership. Further, although this might appear to challenge concerns raised by Gabaix and Koijen (2021) and Haddad et al. (2025), who argue that passive investing may distort price efficiency through inelastic demand and limited firm-specific attention, our findings do not necessarily contradict their findings. Rather, they suggest that any such inefficiencies introduced by passive flows may not manifest clearly in post-earnings announcement pricing dynamics.

Our results emphasize that the recent intensification of post-earnings announcement drift likely arises from complex market interactions beyond passive investment alone. Although we find that passive ownership is positively associated with abnormal returns in general, we are unable to identify a systematic amplification of earnings-related mispricing that could be attributed to passive flows. Alternative explanations, such as changes in trading structure, reduced arbitrage capacity, or market microstructure frictions, may better account for the observed market anomaly. Consequently, while our additional analyses in this section clarify the limited direct role of retail and passive investment in driving recent PEAD increases, further exploration of broader structural market dynamics remains critical.

Table 9
Effects of Passive Ownership Between 2005–2020 and 2021–2024

Panel A:	*Dependent variable:*				
	CAR-2-60				CAR-1-1
	Large-cap	Mid-cap	Small-cap	Full Sample	Full Sample
	(1)	(2)	(3)	(4)	(5)
DSUE	0.311	1.680***	6.671***	1.410***	4.387***
	(0.172)	(0.326)	(0.605)	(0.018)	(0.060)
D	−13.878***	−15.577***	0.708	−15.192***	−1.683***
	(1.518)	(3.916)	(6.667)	(1.614)	(0.493)
DSUE × D	2.183***	0.654	1.788	0.978	−0.289
	(0.485)	(1.170)	(2.223)	(0.512)	(0.158)
PASS_OWN	34.930***	38.790*	34.999	28.647**	−0.005
	(78.531)	(18.767)	(25.503)	(9.176)	(0.004)
PASS_OWN × DSUE	4.402	6.221***	−4.448	0.147	−0.009***
	(2.652)	(5.482)	(8.056)	(2.732)	(0.001)
PASS_OWN × D	−9.262	−15.565	19.050	13.150***	0.007
	(14.427)	(31.496)	(42.546)	(14.960)	(0.006)
PASS_OWN × D × DSUE	−9.489*	−1.350	0.374	−1.807	0.004**
	(4.414)	(9.491)	(13.574)	(4.572)	(0.002)
Controls	NO	NO	NO	NO	NO
Observations	111,279	63,351	31,740	206,370	221,108
R^2	0.026	0.018	0.052	0.015	0.395

(Continued)

Panel B:	*Dependent variable:*				
	CAR-2-60				CAR-1-1
	Large-cap	Mid-cap	Small-cap	Full Sample	Full Sample
	(1)	(2)	(3)	(4)	(5)
DSUE	0.229	1.689***	7.294***	1.678***	4.338***
	(0.193)	(0.372)	(0.720)	(0.197)	(0.068)
D	−10.955***	−10.794**	−0.999	−11.573***	−1.931***
	(1.514)	(3.839)	(6.975)	(1.656)	(0.555)
DSUE × D	1.938***	0.909	2.600	0.96394	−0.281
	(0.455)	(1.166)	(2.221)	(0.495)	(0.176)
PASS_OWN	0.024*	0.025	0.103*	0.023	−0.003
	(0.012)	(0.029)	(0.048)	(0.013)	(0.004)
PASS_OWN × DSUE	0.005	0.002	0.001	−0.005	−0.011***
	(0.004)	(0.009)	(0.016)	(0.004)	(0.001)
PASS_OWN × D	−0.023	−0.026	0.050	−0.012	0.014**
	(0.018)	(0.0465)	(0.073)	(0.019)	(0.006)
PASS_OWN × D × DSUE	−0.008	0.008	−0.015	0.003	0.006**
	(0.005)	(0.014)	(0.023)	(0.005)	(0.002)
Controls	YES	YES	YES	YES	YES
Observations	94,789	47,823	21,577	164,189	164,189
R^2	0.021	0.018	0.085	0.018	0.406

*p<0.05; **p<0.01; ***p<0.001

Notes: This table reports regression estimates of cumulative abnormal returns (*CAR-2-60*) and immediate price reactions (*CAR-1-1*) on standardized unexpected earnings (SUE), a post-2020 period indicator (D), retail ownership ($PASS\_OWN$), and their interactions to assess how PEAD varies with changes in passive ownership. (*CAR-2-60*) is defined as the cumulative abnormal return from trading day 2 to 60 post-earnings announcement, while (*CAR-1-1*) captures the day-one market reaction. Abnormal returns are computed using the Fama-French three-factor model, with expected returns constructed from 25 portfolios formed on size and book-to-market from Kenneth French's data library. SUE is defined as the earnings surprise standardized by the trailing six-year standard deviation of forecast errors and ranked into deciles each quarter, scaled to range from -0.5 to +0.5. The coefficient on SUE corresponds to the abnormal return associated with a zero-cost portfolio strategy: going long in the top five deciles and short in the bottom five. $PASS\_OWN$ is defined as the percentage of shares held by quasi-indexer (QIX) institutions, based on Bushee's (2000) classification using Thomson Reuters 13F filings. The key coefficient of interest is the triple interaction term ($PASS\_OWN \times D \times SUE$), which captures whether the strength of post-2020 PEAD varies with the intensity of passive ownership. **Panel A** presents baseline regressions without control variables. **Panel B** adds a comprehensive set of firm-level controls: illiquidity ($ILLIQ$), bid-ask spread (BAS), analyst coverage ($ANALYST$), earnings persistence ($PERS$), reporting lag ($REPLAG$), and the number of concurrent earnings announcements ($NCEA$), all previously introduced in Table 7, with full variable definitions and construction procedures provided in Appendix A. Columns (1)-(3) show results by firm size (large-, mid-, and small-cap), while Columns (4) and (5) use the full sample. Robust standard errors are reported in parentheses. Full variable definitions are provided in Appendix A. Asterisks indicate statistical significance at the 5%, 1%, and 0.1% levels, respectively.

6 Conclusion

This study provides new, large-sample evidence of a statistically and economically significant resurgence in the post-earnings announcement drift (PEAD) anomaly in U.S. equity markets following the COVID-19 pandemic. Using a dataset of 220,228 quarterly earnings announcements from 6,958 firms between 2005 and 2024, we observe that the average 60-trading-day drift among large-cap stocks increased from 0.52% in 2005-2020 to 1.99% in 2021-2024. This change represents an approximate 280% relative increase in the drift magnitude and serves as a striking counterpoint to previous research that suggested the near-elimination of PEAD within highly liquid and institutionally monitored market segments (Chordia et al. 2014; Martineau and Gregoire, 2021).

Our results remain robust across various earnings surprise measures, abnormal return benchmarks, and event windows. This resurgence of PEAD among large-cap stocks directly challenges previous studies, which suggest continuous improvements in informational efficiency due to enhanced liquidity (Chordia et al. 2014), faster information assimilation facilitated by algorithmic and high-frequency trading (Brogaard et al., 2014; Chordia & Miao, 2020), and broader enhancements in the informational environment (Hung et al., 2015). Instead, our findings emphasize the cyclical nature of market efficiency, highlighting that even the most liquid segments of financial markets can experience renewed inefficiencies during periods marked by significant structural transformations.

Exploring potential explanatory factors behind this resurgence, we examine the roles of retail investor participation and passive institutional ownership, two market segments that experienced notable growth in participation following the COVID-19 pandemic. Retail investors, known for their behavioral biases and limited attention, have historically been associated with delayed price adjustments and persistent market anomalies (Luo et al., 2022; Barber et al., 2022; Kaniel et al., 2012). Similarly, passive investment, characterized by the inelastic allocation of capital based on indexing strategies rather than fundamental analysis, has been suggested to weaken price discovery mechanisms (Gabaix & Koijen, 2021; Haddad et al., 2025). Consistent with these studies, our findings indicate that firms with higher retail ownership, and firms with higher passive ownership, exhibit slower price responses to earnings announcements. However, we find limited support that these factors alone sufficiently explains the post-2020 drift resurgence. Therefore, we infer that the factors driving the recent PEAD increase are likely multifaceted, involving broader structural shifts in market dynamics, technological advancements, and evolving investor behavior, which our empirical methodology does not fully capture.

This study contributes to the existing literature in three primary ways. First, it revisits the foundational literature on PEAD (Ball and Brown, 1968; Foster et al., 1984; Bernard and Thomas, 1989; 1990; Rendleman et al., 1982) within the contemporary context of post-pandemic structural market changes, providing new empirical evidence that challenges claims of PEAD's obsolescence in highly monitored market segments (Martineau and Gregoire, 2021; Martineau, 2021; Rendleman et al., 1982). Second, by exploring the impact of changing investor demographics, particularly the rise of retail and passive investors, we add to the growing body of literature on investor composition and informational efficiency, offering nuanced insights into the relationship between investor structure and market efficiency (Kaniel et al., 2012; Luo et al., 2022; Barber et al., 2022; Gabaix & Koijen, 2021; Haddad et al., 2025). Specifically, our findings refine debates around market inelasticity by suggesting that the influence of passive ownership may be non-linear or indirect, rather than directly observable through PEAD behavior. Third, our results highlight the cyclical and dynamic nature of market efficiency and challenge static models that assume monotonic improvements in price discovery over time.

While this study provides valuable contributions to the literature on investor behavior and market efficiency, several limitations warrant consideration. Our analysis is restricted to U.S. equities, leaving the generalizability of our findings to international contexts uncertain. Moreover, our proxies for retail and passive ownership, which are derived from institutional holdings data, may not fully capture active trading behaviors, potentially affecting the validity of our conclusions regarding investor-driven market inefficiencies. Additionally, although we treat earnings surprises as independent shocks, use a calendar-driven post-2020 indicator to mitigate simultaneity, and commence CAR measurements starting on day two after each announcement to mitigate anticipation effects, unobserved factors such as management's pre-announcement guidance may still introduce endogeneity into our results.

Our findings have several significant implications. For academic researchers, they necessitate a reconsideration of asset pricing models predicted upon stable improvements in informational efficiency. For investors, our results highlight renewed relevance for earnings-based trading strategies, particularly in large-cap equities. For regulators, they underscore the necessity of vigilance in monitoring market infrastructure and investor behaviors that may periodically disrupt price discovery processes.

Future research could extend this investigation by analyzing detailed brokerage-level retail trading data to more precisely quantify the behavioral mechanisms driving PEAD. Cross-country comparative studies could further elucidate whether the document is unique to the U.S. market or indicative of broader global trends. Additionally, exploring how advancements in AI-driven forecasting and the influence of digital investment platforms alter market reactions to earnings could provide further insights into modern informational frictions. Moreover, the potential impacts of recent macroeconomic shifts, including the historically low-interest-rate environment followed by monetary tightening during the early 2020s, on valuation and price adjustment dynamics warrant further exploration. Finally, examining whether similar anomalies, such as momentum, reversals, or earnings-announcement premiums, exhibit parallel resurgences could clarify whether the increase in PEAD is isolated or indicative of broader market inefficiencies.

In conclusion, this study reveals that market efficiency evolves in a dynamic, cyclical manner rather than following a linear trajectory of improvement. The recent resurgence of

PEAD highlights the ongoing vulnerability of even highly liquid markets to informational inefficiencies, especially during times of significant structural change. While Martineau (2021) may have composed an elegy for PEAD, our findings suggest that reports of its demise were, at the very least, premature.

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Appendices

A Variable Definitions

Table 10
Variable Definitions

Variable	Description	Source	Formula or Construction
SUE	Standardized unexpected earnings based on analyst forecasts	I/B/E/S	$\mathrm{SUE}_{i,t} = \frac{e_{i,t} - \mathbb{E}\left[e_{i,t}\right]}{\sigma_i}$
D	Dummy for post-COVID period (2021–2024)	Author-defined	$D = \begin{cases} 1 & \text{if year} \geq 2021 \\ 0 & \text{otherwise} \end{cases}$
AR	Raw abnormal return using actual firm return minus FF3 expected return	CRSP, FF Library	$R_{i,t} - R_{FF3,t}$
CAR-2-60	Cumulative abnormal return from day 2 to 60 after earnings, FF3-adjusted	CRSP, FF Library	$\sum_{t=2}^{60} (R_{i,t} - R_{FF3,t})$
CAR-1-1	Cumulative abnormal return on day of earnings announcement, FF3-adjusted	CRSP, FF Library	$\sum_{t=0}^{1} (R_{i,t} - R_{FF3,t})$
CAR-2-30	Cumulative abnormal return from day 2 to 30 post-announcement, FF3-adjusted	CRSP, FF Library	$\sum_{t=2}^{30} (R_{i,t} - R_{FF3,t})$
CAR-2-90	Cumulative abnormal return from day 2 to 90 post-announcement, FF3-adjusted	CRSP, FF Library	$\sum_{t=2}^{90} (R_{i,t} - R_{FF3,t})$
EAR	Earnings Announcement Return: Change in earnings over prior year scaled by lagged price	I/B/E/S	$EAR_{i,t} = \frac{EPS_{i,t} - EPS_{i,t-4}}{P_{i,t-45}}$
SURP	Seasonal random walk-based standardized earnings surprise, using historical forecast error variance	I/B/E/S	$SURP_{i,t} = \frac{EPS_{i,t} - (EPS_{i,t-4})}{\sigma(\varepsilon_i)}$
UE	Unstandardized forecast error	I/B/E/S	$UE_{i,t} = EPS_{i,t} - Forecast_{i,t}$
AR_VWM	Abnormal return based on a value-weighted market model	CRSP	$R_{i,t} - R_{VWM,t}$

(Continued)

Table 10 – continued from previous page

Variable	Description	Source	Formula or Construction
AR_VW	Value-weighted market-adjusted abnormal return	CRSP	$R_{i,t} - R_{VW,t}$
AR_EW	Equal-weighted market-adjusted abnormal return	CRSP	$R_{i,t} - R_{EW,t}$
S&P500	Return in excess of S&P 500 index return	CRSP	$R_{i,t} - R_{S\&P500,t}$
RET_OWN	Proxy for retail ownership	Thomson Reuters 13F	$RET\_OWN_{i,t} = 1 - \text{InstitutionalOwnership}_{i,t}$
PASS_OWN	Share of firm held by quasi-indexers	CRSP, 13F + Bushee's Classification	$\frac{\text{Shares held by QIX}}{\text{Shares Outstanding}}$
ILLIQ	Amihud illiquidity measure (price impact per volume unit)	CRSP	$\frac{1}{D}\sum_{d=1}^{D}\frac{\lvert R_d\rvert}{Volume_d}$
BAS	Average bid–ask spread over the 30 trading days prior to the earnings announcement	CRSP	$BAS_{i,t} = \frac{1}{D}\sum_{d=1}^{D}\frac{\text{Ask}_{i,t-d}-\text{Bid}_{i,t-d}}{(\text{Ask}_{i,t-d}+\text{Bid}_{i,t-d})/2}$
ANALYST	Number of analysts providing earnings forecasts in the announcement quarter	I/B/E/S	$ANALYST_{i,t} = \#\{\text{analysts covering firm } i \text{ at } t\}$
PERS	Earnings persistence: slope coefficient from regressing current EPS on EPS four quarters prior	Compustat, I/B/E/S	$PERS_{i,t}:\ EPS_{i,t} = \alpha + PERS_{i,t} \times EPS_{i,t-4} + \varepsilon_{i,t}$
REPLAG	Reporting lag in calendar days between quarter-end and announcement date	CRSP, I/B/E/S	$REPLAG_{i,t} = \text{DateAnnounce}_{i,t} - \text{DateQEnd}_{i,t}$
NCEA	Number of earnings announcements (all firms) on the same calendar day	I/B/E/S	$NCEA_t = \#\{\text{firms with announcements at } t\}$

Notes: This table defines all variables used throughout the empirical analyses. Earnings surprises are captured using four distinct approaches: standardized unexpected earnings (SUE), earnings announcement return (EAR), seasonal random-walk-based earnings surprise ($SURP$), and unstandardized forecast errors (UE). Abnormal returns (AR) are calculated using multiple benchmark models, including the Fama-French three-factor model, value-weighted and equal-weighted market models, and the S&P 500. $DSUE$ is derived by scaling SUE deciles to the interval $[-0.5, +0.5]$ to simulate a zero-cost hedge portfolio. Ownership variables include RET_OWN, calculated as one minus institutional ownership, and PASS_OWN, the share of firm-level holdings by quasi-indexers based on Bushee's (2000) classification. Liquidity and market frictions are captured via Amihud's (2002) illiquidity measure ($ILLIQ$) and the average bid–ask spread (BAS). Additional control variables include analyst coverage ($ANALYST$), earnings persistence ($PERS$), reporting lag ($REPLAG$), and the number of concurrent earnings announcements ($NCEA$). All data are sourced from CRSP, Compustat, I/B/E/S, the Fama-French data library, or Thomson Reuters 13F filings. Detailed construction formulas and sources are provided in the respective columns.

B Summary Statistics and Correlations

See next page.

Table 11

Summary Statistics

Statistic	N	Mean	St. Dev.	25th perc.	Median	75th perc.
Panel A: Baseline regression						
SUE	22,305,635	35.914	155.494	-25.000	25.000	101.000
DSUE	22,305,635	0.000	0.319	-0.278	0.0556	0.278
D	22,750,310	0.226	0.418	0.000	0.000	0.000
AR	17,634,614	0.010	3.285	-1.240	-0.050	1.160
CAR-2-60	220,228	0.551	19.042	-6.190	0.000	6.890
CAR-1-1	220,228	0.017	6.567	-1.770	0.000	1.700
CAR-2-30	220,228	0.324	13.140	-4.380	0.000	4.550
CAR-2-90	220,228	0.570	19.376	-6.320	0.000	7.075
Panel B: Alternative SUE and AR measures						
EAR	16,142,964	16.172	6785.732	-0.093	0.051	0.263
UE	22,750,310	106.448	20493.560	-2.000	2.000	7.000
AR_VWM	22,749,230	0.009	3.042	-1.000	0.000	1.000
AR_VW	22,749,230	0.009	3.042	-1.000	0.000	1.000
AR_EW	22,749,230	0.008	3.019	-1.000	0.000	1.000
AR_S&P	22,749,230	0.020	3.058	-1.000	0.000	1.000
Panel C: Additional tests and controls						
RET_OWN	27,626,312	34.576	26.079	13.000	28.000	52.000
PASS_OWN	29,692,761	37.977	58.049	2.847	17.308	55.876
ILLIQ[1]	17,354,293	0.001	0.121	0.001	0.001	0.001
BAS	17,394,435	0.107	4.129	0.013	0.024	0.048
ANALYST	30,029,077	8.037	6.576	3.000	6.000	11.000
PERS	17,394,435	0.001	0.408	0.000	0.000	0.000
REPLAG	30,029,077	33.854	13.210	26.000	33.000	39.000
NCEA	17,394,435	167.658	99.176	89.000	168.000	240.000

[1] Amihud's (2002) illiquidity measure (ILLIQ) has been multiplied by 1,000 to facilitate interpretation.

Panel D: Extended Correlation Matrix

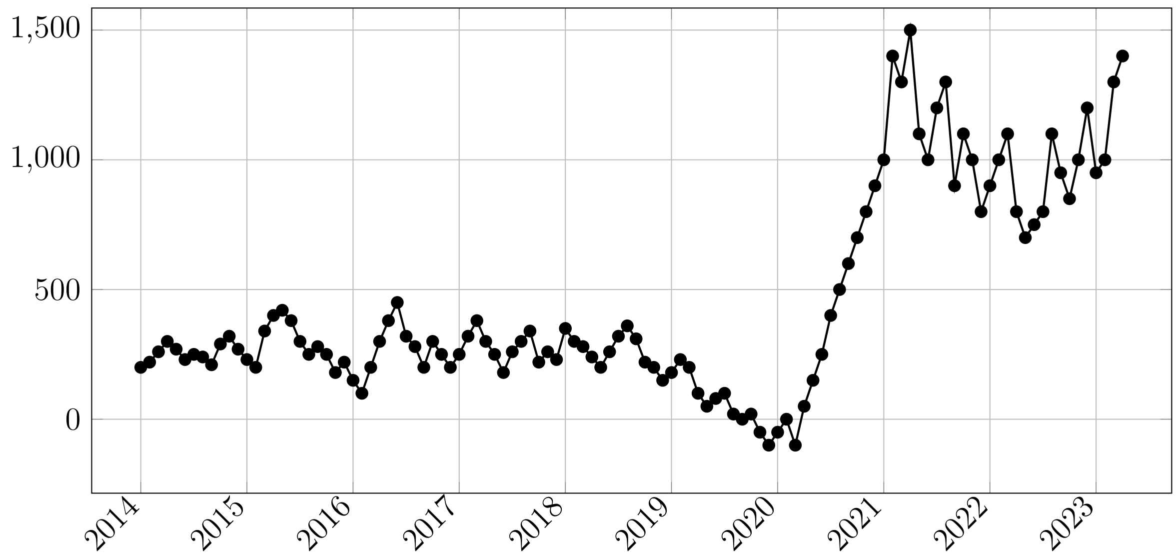
	SUE	D	AR	CAR-2-60	CAR-1-1	CAR-2-30	CAR-2-90	EAR	SURP	UE	AR_VWM
SUE	1	0.0256	0.1752	0.0265	0.2062	0.0276	0.0265	0.0122	0.2335	0.0166	0.1082
D	0.0256	1	-0.0085	-0.0265	-0.0007	-0.0144	-0.0257	-0.0032	0.0058	-0.0049	-0.0096
AR	0.1076	-0.0085	1	0.0117	0.0043	0.0162	0.0111	-0.002	0.0399	-0.0009	0.992
CAR-2-60	0.0136	-0.0265	0.0117	1	0.0102	0.6786	0.9793	-0.0008	0.0044	-0.001	0.0135
CAR-1-1	0.1257	-0.0007	0.0043	0.0102	1	0.0145	0.01	-0.0029	0.0416	-0.0005	0.0066
CAR-2-30	0.0241	-0.0144	0.0162	0.6786	0.0145	1	0.6641	0.0036	0.0066	0.0032	0.0176
CAR-2-90	0.0141	-0.0257	0.0111	0.9793	0.01	0.6641	1	-0.001	0.0046	-0.002	0.0131
EAR	0.0066	-0.0032	-0.002	-0.0008	-0.0029	0.0036	-0.001	1	-0.0004	0.7917	-0.0023
SURP	0.3088	0.0058	0.0399	0.0044	0.0416	0.0066	0.0046	-0.0004	1	-0.0018	0.0398
UE	0.0091	-0.0043	0.001	0.0025	-0.0006	0.0064	0.0024	0.8428	-0.0018	1	0.0008
AR_VWM	0.1082	-0.0096	0.992	0.0135	0.0066	0.0176	0.0131	-0.0023	0.0398	0.0008	1
AR_VW	0.1083	-0.0095	0.9918	0.0134	0.0069	0.0176	0.0129	-0.0023	0.0397	0.0008	0.9996
AR_EW	0.1084	-0.0065	0.9913	0.0135	0.0072	0.0182	0.013	-0.0021	0.0404	0.0009	0.9961
AR_S&P	0.1078	-0.011	0.9896	0.0134	0.0069	0.0178	0.0129	-0.0021	0.0395	0.001	0.9982
RET_OWN	-0.1205	-0.0372	0.0011	0.0019	-0.0161	-0.0048	0.0017	0.0062	-0.0019	0.0079	0.0135
PASS_OWN	0.0548	0.3149	0.0003	-0.0002	0.0097	0.0108	0.0018	-0.0007	0.0008	-0.0024	-0.0009
BAS	-0.0041	-0.0041	-0.0004	-0.0006	0	-0.0006	-0.0007	-0.0001	-0.0001	-0.001	-0.0011
ILLIQ	-0.0005	-0.0042	0.0002	0.0024	0.0004	0.0032	0.002	0	0.0002	-0.0001	0.0029
ANALYST	0.1404	-0.0223	-0.0022	0.0152	0.0005	-0.0029	-0.0108	0.0004	0.0032	-0.0018	-0.0134
PERS	-0.0032	-0.0016	-0.0005	-0.005	-0.0036	-0.0032	-0.0054	-0.0004	-0.0003	-0.0002	-0.0046
REPLAG	-0.0614	0.1093	-0.0004	0.0086	-0.0115	0.0089	0.0061	0.0012	-0.002	0.0018	0.0023
NCEA	0.0237	0.1851	0.0002	0.0091	0.0055	0.0113	0.0067	0.0011	0.002	-0.0009	0.0095

	AR_VW	AR_EW	AR_S&P	RET_OWN	PASS_OWN	BAS	ILLIQ	ANALYST	PERS	REPLAG	NCEA
SUE	0.1083	0.1084	0.1078	-0.1205	0.0548	-0.0041	-0.0005	0.1404	-0.0032	-0.0614	0.0237
D	-0.0095	-0.0065	-0.011	-0.0372	0.3149	-0.0041	-0.0042	-0.0223	-0.0016	0.1093	0.1851
AR	0.9918	0.9913	0.9896	0.0011	0.0003	-0.0004	0.0002	-0.0022	-0.0005	-0.0004	0.0002
CAR-2-60	0.0134	0.0135	0.0134	0.0019	-0.0002	-0.0006	0.0024	0.0152	-0.005	0.0086	0.0091
CAR-1-1	0.0069	0.0072	0.0069	-0.0161	0.0097	0	0.0004	0.0005	-0.0036	-0.0115	0.0055
CAR-2-30	0.0176	0.0182	0.0178	-0.0048	0.0108	-0.0006	0.0032	-0.0029	-0.0032	0.0089	0.0113
CAR-2-90	0.0129	0.013	0.0129	0.0017	0.0018	-0.0007	0.002	-0.0108	-0.0054	0.0061	0.0067
EAR	-0.0023	-0.0021	-0.0021	0.0062	-0.0007	-0.0001	0	0.0004	-0.0004	0.0012	0.0011
SURP	0.0397	0.0404	0.0395	-0.0019	0.0008	-0.0001	0.0002	0.0032	-0.0003	-0.002	0.002
UE	0.0008	0.0009	0.001	0.0079	-0.0024	-0.001	-0.0001	-0.0018	-0.0002	0.0018	-0.0009
AR_VWM	0.9996	0.9961	0.9982	0.0135	-0.0009	-0.0011	0.0029	-0.0134	-0.0046	0.0023	0.0095
AR_VW	1	0.9974	0.9983	0.0134	-0.0005	-0.0011	0.0029	-0.0133	-0.0046	0.0028	0.0091
AR_EW	0.9974	1	0.9943	0.0082	0.0125	-0.0023	0.0029	-0.0102	-0.0053	0.0126	0.0104
AR_S&P	0.9983	0.9943	1	-0.0055	0.0042	0.0014	0.0006	0.0081	0.0001	-0.0162	0.0216
RET_OWN	0.0134	0.0082	-0.0055	1	-0.21	0.0284	0.0154	-0.3374	0.008	0.0697	-0.0766
PASS_OWN	-0.0005	0.0125	0.0042	-0.21	1	-0.0077	-0.0004	0.0896	-0.0009	0.063	0.1236
BAS	-0.0011	-0.0023	0.0014	0.0284	-0.0077	1	0.0552	-0.1922	0.0006	-0.055	-0.0517
ILLIQ	0.0029	0.0029	0.0006	0.0154	-0.0004	0.0552	1	-0.011	0	-0.0062	-0.0078
ANALYST	-0.0133	-0.0102	0.0081	-0.3374	0.0896	-0.1922	-0.011	1	-0.0031	-0.0748	0.0211
PERS	-0.0046	-0.0053	0.0001	0.008	-0.0009	0.0006	0	-0.0031	1	0.0055	-0.0015
REPLAG	0.0028	0.0126	-0.0162	0.0697	0.063	-0.055	-0.0062	-0.0748	0.0055	1	-0.0582
NCEA	0.0091	0.0104	0.0216	-0.0766	0.1236	-0.0517	-0.0078	0.0211	-0.0015	-0.0582	1

Notes: The table reports summary statistics for the variables used in the main empirical analysis, robustness checks, and additional ownership tests. **Panel A** presents descriptive statistics for the baseline variables, including standardized unexpected earnings (SUE), winsorized at the 1% and 99% levels, its decile-scaled transformation ($DSUE$), a post-2020 dummy indicator (D), and various cumulative abnormal return (CAR) measures computed using the Fama-French three-factor model. **Panel B** summarizes alternative earnings surprise proxies (EAR, UE) and abnormal return benchmarks, including market- and index-adjusted specifications (AR_VWM, AR_VW, AR_EW, and $AR\_S\&P$). **Panel C** reports summary statistics for retail ownership (RET_OWN), passive ownership ($PASS\_OWN$), and control variables used in extended regressions. **Panel D** presents Pearson correlation coefficients among all variables used in the empirical analysis, including baseline regression variables, alternative measures of earnings surprises and abnormal returns, ownership structure metrics, and control variables. The decile-scaled version of SUE ($DSUE$) used in regression models is omitted, as it is a linear transformation of SUE and thus perfectly correlated with it. All variable definitions are provided in Appendix A.

C Net Inflow by Individuals

Figure 3
Weekly net inflow by individuals (mUSD, 21-day moving average)



Notes: Figure 3 shows the weekly net inflow into U.S. equity markets by individual (retail) investors, measured in millions of U.S. dollars and smoothed using a 21-day moving average (y-axis), replicating data from Vanda Research (2023, © FT). The data span from 2014 through early 2024 (x-axis) and highlight a sharp increase in retail trading activity beginning in late 2020, coinciding with the COVID-19 pandemic recovery phase and the rise of commission-free trading platforms. The surge in inflows continues into 2023, suggesting a sustained elevated presence of retail investors in public equity markets. This figure is a self-constructed visual replication of data presented in Vanda Research. As the underlying dataset is not publicly accessible, the values depicted are approximate and may not precisely reflect the original figures.

D Excluding Mag-7, FAANG & BATMAN

Table 12
Post Earnings Announcement Drift 2005–2024 Excluding Mag 7 + 2

Panel A:	*Dependent variable:*				
	CAR-2-60				CAR-1-1
	Large-cap	Mid-cap	Small-cap	Full Sample	Full Sample
	(1)	(2)	(3)	(4)	(5)
DSUE	0.053***	0.167***	0.638***	0.131***	0.416***
	(0.013)	(0.030)	(0.061)	(0.014)	(0.005)
D	−1.265***	−1.212***	0.807	−1.146***	−0.129***
	(0.096)	(0.250)	(0.514)	(0.105)	(0.036)
DSUE × D	0.147***	0.115	0.247	0.095**	−0.031**
	(0.031)	(0.080)	(0.172)	(0.033)	(0.012)
Observations	120,779	64,711	29,969	215,459	215,459
R^2	0.0023	0.0012	0.0050	0.0013	0.0396

Panel B:	*Dependent variable:*				
	CAR-2-60				CAR-1-1
	Large-cap	Mid-cap	Small-cap	Full Sample	Full Sample
	(1)	(2)	(3)	(4)	(5)
DSUE	0.052***	0.166***	0.638***	0.130***	0.416***
	(0.013)	(0.030)	(0.061)	(0.014)	(0.005)
D	−1.263***	−1.211***	0.807	−1.145***	−0.129***
	(0.096)	(0.250)	(0.514)	(0.105)	(0.036)
DSUE × D	0.148***	0.116	0.247	0.0953**	−0.0308**
	(0.031)	(0.080)	(0.172)	(0.033)	(0.012)
Observations	120,662	64,709	29,969	215,340	215,340
R^2	0.0023	0.0012	0.0050	0.0013	0.0396

*p<0.1; **p<0.05; ***p<0.01

Notes: Panel A reports results from regressions of cumulative abnormal returns (CAR) on standardized unexpected earnings (SUE), excluding observations associated with the "Magnificent Seven" (Apple, Amazon, Microsoft, Meta, Alphabet, Tesla, and Nvidia). In Panel B, the sample is further restricted by also excluding Netflix (from FAANG) and Broadcom (from BATMAN). A post-2020 indicator variable (D) and its interaction with SUE ($SUED$) are included to assess changes in the magnitude of post-earnings announcement drift (PEAD) across two distinct periods: 2005–2020 and 2021–2024. The full sample comprises 220,228 quarterly earnings announcements from 6,958 firms between January 2005 and December 2024. (*CAR-2-60*) denotes cumulative abnormal returns from trading day 2 to trading day 60 following the earnings announcement, while (*CAR-1-1*) captures the immediate price reaction on day 1. D is equal to one for firm-quarter observations in 2021–2024 and zero otherwise. Abnormal returns are computed using the Fama-French three-factor model, with expected returns estimated from 25 portfolios formed on size and book-to-market from Kenneth French's data library. SUE is defined as the earnings surprise standardized by the trailing six-year standard deviation of forecast errors and ranked into deciles, scaled to range from –0.5 to +0.5. Robust standard errors are reported in parentheses. Full variable definitions are provided in Appendix A.

E Use of Artificial Intelligence

Artificial Intelligence tools were employed in a supportive capacity to enhance the efficiency and quality of our thesis work. We are confident that their use contributed positively to the academic value of our thesis by reducing the time spent on troubleshooting code, identifying relevant literature, and clarifying complex concepts for us. This, in turn, allowed us to devote more time to critical analysis, conceptual development, and engagement with relevant literature.

ChatGPT 4o-mini-high was primarily used to develop and troubleshoot Stata code. However, given the scale of our work, including over 80 variables and, at times, datasets exceeding 200 million observations, the model often struggled to account for the full scope. As a result, we had to retain full control over the architecture and understanding of the code, and often devised creative workarounds to reduce computational strain.

For writing support, PaperPal and GPT-4o was used selectively to suggest grammatical improvements and synonyms. Aware that large language models can hallucinate or produce imprecise suggestions, we ensured that all AI-generated output was reviewed critically and only applied to content we had already written.

To support our literature review, we employed Perplexity.ai, Scite.ai, and ResearchRabbit as complements to traditional academic databases. Perplexity.ai provided citation-backed summaries that helped us quickly identify relevant sources. Scite.ai offered a similar service but allowed us to filter specifically for peer-reviewed articles from top journals, ensuring the quality of our references. ResearchRabbit provided visualizations of citation networks, enabling us to trace the evolution of key academic concepts, such as market efficiency; the foundation of our thesis, and to better understand the connections between influential authors over time. Several of these tools were recommended by librarians at the Stockholm School of Economics, significantly enhancing our ability to map and internalize the relevant academic landscape.