

Louvain School of Management

When PEAD fails: Analysis of the causes of negative market reactions to positive earnings surprises (and vice versa)

Author: ULLENS DE SCHOOTEN Gauthier
Supervisor(s): THEWISSEN James
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NOTE

I hereby disclose that several generative AI tools were consulted during the preparation of this thesis, namely Claude (Anthropic), ChatGPT (OpenAI), Perplexity, and Gemini (Google). Their role was strictly complementary. The research question, the hypotheses, the empirical design, and the interpretation of the results are my own. I conducted the literature review independently and verified each cited reference against the original publication. These tools also helped me identify additional papers that I had not encountered through my own searches.

These tools were used in three ways. First, as a council board to challenge my reasoning and to expose weaknesses in my arguments. Second, to broaden my perspective on certain methodological and conceptual choices, by proposing alternative angles I might not have considered on my own. Third, to refine the wording of passages that I judged insufficiently clear in my initial drafts.

No AI-generated content appears in this thesis without subsequent review and verification on my part. Final responsibility for the analysis, the conclusions, and any remaining errors rests entirely with me.

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Executive Summary

The post-earnings-announcement drift (PEAD) is one of the most persistent anomalies in empirical asset pricing. Under the standard interpretation, the slow incorporation of earnings news by investors produces a drift of stock prices in the direction of the earnings surprise over the weeks following the announcement. In a fraction of announcements, however, the direction of post-announcement returns is the opposite of the surprise. This thesis investigates the firm-level and macroeconomic conditions under which such a reversal of the PEAD occurs.

Five hypotheses are tested on a sample of approximately 240,000 quarterly earnings announcements by US common stocks listed on NYSE, AMEX or Nasdaq between January 2000 and December 2024. Each hypothesis links the slope of the SUE-CAR relationship to a specific variable. These variables are the proximity to the 52-week high (H1), the price-to-book ratio (H2), abnormal pre-announcement trading volume (H3), discretionary accruals (estimated through the Kothari-Leone-Wasley methodology) (H4), and a macroeconomic stress indicator (H5). The empirical model is an ordinary least squares regression of pre, around and post-announcement cumulative abnormal returns on an interaction between the standardised unexpected earnings (SUE) and each conditioning variable, with firm-level and macroeconomic controls, industry and year fixed effects, and standard errors double-clustered at the firm and calendar-quarter levels.

Four findings emerge. The discretionary-accruals channel (H4) produces the strongest evidence. The interaction coefficient is statistically significant and economically meaningful, with a magnitude that grows monotonically with the post-announcement horizon and reaches approximately -1.9 at 250 trading days. This pattern is consistent with a slow-learning mechanism in which the market gradually discounts the credibility of high-accrual earnings. The price-to-book ratio (H2) produces a significant attenuation of the drift both around the announcement and on the primary post-event window, consistent with growth stocks integrating earnings information more rapidly than the rest of the sample. The 52-week-high channel (H1) yields an unexpected inverse pattern under volatility normalisation, with proximity to the 52-week high amplifying rather than reversing the drift. This pattern is interpreted as evidence that

investors holding stocks near their 52-week high delaying the realisation of unrealized gains, which would weaken the selling pressure predicted by the disposition effect. The abnormal-volume (H3) and VIX-based (H5) channels are not supported as we define them in the hypothesis section, although the high-yield credit spread captures a related macroeconomic mechanism concentrated on the announcement window.

This thesis makes three contributions. The present study provides a systematic test of five conditional drivers of the PEAD reversal on a modern US dataset over 25 years. The analysis reveals that the slow-learning mechanism attributed to discretionary accruals starts from +30 days and strengthens at longer horizons (reaching $\beta_2 \cong -1.9$ at +250 trading days). Finally, the volatility-normalised inverse pattern on the 52-week-high channel and the credit-spread macroeconomic conditioning open new directions for research on the limits of arbitrage and on the macroeconomic determinants of mispricing.

Acknowledgments

I would like to thank Professor James Thewissen for first introducing me to the post-earnings-announcement drift in his lectures, which originally sparked my interest in this area of empirical finance, and for subsequently accepting to supervise this thesis on a topic that falls within his area of research expertise. I am also grateful for his advice, for the access he provided to the CRSP daily stock files used throughout the empirical analysis, and for the independence I was granted in defining the scope of the project and the methodological choices retained in this work, which has been instrumental in shaping its final form.

I also thank Priscilla Simonis (my mother) for reading the thesis and for challenging the ideas developed in this work. Her feedback, drawing on her own experience as a published physicist, has materially improved both the structure and the rigour of the argument.

Finally, I would like to thank the friends, colleagues and academic staff who, through their questions and comments over the past months, have contributed to making this an enriching experience.

1. Introduction

Among the most persistent anomalies in empirical finance, the post-earnings-announcement drift (PEAD) continues to challenge the efficient market hypothesis introduced by Fama (1970) more than five decades after its initial documentation. The drift, originally observed by Ball and Brown (1968) and more deeply analysed by Bernard and Thomas (1989, 1990), refers to the tendency of stock prices to continue moving in the direction of an earnings surprise for several weeks following the announcement. A positive surprise is typically followed by positive abnormal returns and a negative surprise by negative abnormal returns. Decades of analysis across markets, sectors and time periods have shown that the PEAD is one of the most robust findings in empirical finance, although Chordia, Subrahmanyam, and Tong (2014) document a significant attenuation of market anomalies in the post-decimalization era, the PEAD still generates persistent abnormal returns.

Two main families of explanations have been advanced to account for the drift. The traditional view interprets the delayed price response as compensation for risks (not properly captured by standard asset pricing models) (Foster, Olsen and Shevlin, 1984), or as the residual cost of market frictions such as transaction costs, and arbitrage limits (Bhushan, 1994; Mendenhall, 2004). The behavioural view, popularized by Kahneman and Tversky (1979) and Barberis and Thaler (2003), attributes the drift to systematic deviations from perfect rationality, three psychological mechanisms in particular aim to give an explanation: the anchoring bias of Tversky and Kahneman (1974), prospect theory of Kahneman and Tversky (1979), and the disposition effect of Shefrin and Statman (1985).

However, in a fraction of announcements, the direction of post-announcement returns is the opposite of the surprise (a positive surprise is followed by negative drift, and a negative surprise by positive drift). This reversed pattern, that will be referred to as a PEAD reversal, has been observed empirically but has never been studied systematically. The few papers that refer to it are studies that investigate other subject rather than as the central object of analysis. A rigorous test of the conditions under which the PEAD reversal arises would constitute a meaningful contribution to the literature, since it would directly challenge the standard underreaction mechanism.

The research question of this thesis is therefore the following:

Why do stocks sometimes react in the opposite direction of what the PEAD predict?

An analysis of the conditions of a PEAD reversal.

To answer this question, five firm-level and macroeconomic conditions are tested, each motivated by a different explanation of the behavioural-finance, psychological effect and limits-to-arbitrage literature. These hypotheses are tested on a panel of US common stocks listed on NYSE, AMEX and Nasdaq between January 2000 and December 2024. The dataset combines Bloomberg analyst estimates and actuals with CRSP daily returns. After standard filters are applied (e.g. exclusion of financial firms, utilities, penny stocks, and observations with insufficient analyst coverage) the final sample include 168,991 earnings announcements. The empirical model is an ordinary least squares regression of post-announcement cumulative abnormal returns on an interaction between the standardised unexpected earnings (SUE, measured following Livnat and Mendenhall (2006) and the Bernard and Thomas (1989) method for robustness) and each conditioning variable, with firm-level and macroeconomic controls, industry and year fixed effects, and standard errors double-clustered at the firm and calendar-quarter levels.

Four key findings emerge from the analysis. Firstly, the discretionary accruals (H4) is statistically significant over long post-event horizons, with an interaction coefficient of -1.6 ($p < 0.001$) within the $[-1, +120]$ window. Second, the price-to-book effect (H2) significantly weakens the drift in the days surrounding the earnings announcement, although this attenuation disappears at longer horizons once the Bloomberg book-value correction is introduced. Thirdly, the results for the 52-week-high variable (H1) reveal an unexpected pattern. Under the volatility-normalised specification, stocks trading close to their 52-week high experience a stronger, rather than weaker, post-announcement drift, which contradict the hypotheses of this thesis. Fourthly, the abnormal-volume hypothesis (H3) cannot be confirmed, although alternative measures of macroeconomic stress, particularly the high-yield credit spread, generate significant interaction effects consistent with a credit-related conditioning of the drift.

This thesis makes three main contributions to the literature. First, it provides a systematic examination of the conditions under which PEAD reversals occur in a modern US market, covering twenty-five years. Second, the analysis shows that the reversal mechanism associated with discretionary accruals emerges from approximately 30 trading days and grows

monotonically through 250 days. Third, the findings on the 52-week-high inverse pattern and on the high-yield credit-spread conditioning open new directions for the literature on the limits of arbitrage and on the macroeconomic reasons of mispricing.

this thesis is organized as follow: Section 2 will review the existing literature on the PEAD with the traditional and the behavioural explanations. Section 3 presents the research questions and details the five hypotheses tested in addition to the psychological mechanisms that lead to theses hypotheses. Then, in section 4 our data sources, the panel construction and the methodological choices behind our SUE and CAR computations are described. Section 5 reports the empirical results, followed by subsections for each hypothesis. Finally, in section 6 the findings are discussed, and Section 7 will conclude.

2. Literature Review

2.1 The Efficient Market Hypothesis and the PEAD anomaly

The Efficient Market Hypothesis (EMH), formally introduced by Fama (1970), is one of the cornerstones of traditional finance. Three levels of market efficiency are distinguished within this framework: the weak form, the semi-strong form, and the strong form. The semi-strong form is the most relevant to the present analysis. It states that prices fully and quickly reflect all publicly available information. When firms release new information, such as their quarterly earnings, stock prices should adjust almost immediately, leaving no scope for systematic abnormal returns based on that public information.

Yet, more than five decades of empirical research have documented a persistent anomaly that challenges this theory. The Post-Earnings-Announcement Drift (PEAD) was first identified by Ball and Brown (1968) and rigorously characterised by Bernard and Thomas (1989, 1990). It refers to the empirical tendency of stock prices to drift continuously and predictably in the direction of an earnings surprise for several weeks (and, in some cases, several months) after the announcement date.

The magnitude of this surprise is usually measured by the Standardised Unexpected Earnings (SUE), defined as the difference between reported earnings and the median analyst forecast, scaled by the stock price on the trading day preceding the announcement (Livnat and Mendenhall, 2006). Under the PEAD, when a firm announces a positive SUE (earnings above

expectations), the stock price does not adjust fully on the announcement day. Instead, the price continues to drift upward over the following days and weeks. When the SUE is negative, the price drifts downward. Both patterns are predictable and have been confirmed across different time periods and markets. These patterns directly contradict the predictions of the EMH.

2.2 The traditional explanation of the PEAD

Faced with this market anomaly, traditional finance initially attempted to explain the PEAD without abandoning the idea of market efficiency. From this perspective, the delayed price reaction is not interpreted as a market mistake but rather as compensation for risks that are not properly captured by standard asset pricing models. Bernard and Thomas (1989) considered the possibility that models such as the CAPM may be incomplete and fail to capture certain risk premiums. If a firm that reports unexpectedly strong earnings simultaneously becomes riskier (for example, because its business now operates in a more uncertain environment), investors will require a higher expected return, and what looks like an abnormal drift could simply be the market correctly pricing this additional risk.

Another classical explanation relies on the concept of market frictions. These frictions include high transaction costs, wide bid-ask spreads, low liquidity (Bhushan, 1994), and restrictions on short selling (Mendenhall, 2004). Even when sophisticated investors immediately understand the value of an earnings surprise, the costs of trading on this information can prevent rapid price correction. Under this view, the PEAD reflects the boundaries of arbitrage rather than a behavioural mispricing.

Despite these explanations, empirical studies consistently show that traditional models cannot fully account for the PEAD. The effect remains significant after controlling for transaction costs, liquidity, firm size (Foster, Olsen and Shevlin, 1984), potential CAPM misspecification (Bernard and Thomas, 1989), and the role of institutional investors (Campbell, Ramadorai and Schwartz, 2009). A meaningful share of the post-announcement drift therefore remains unexplained within the traditional framework, which has motivated the turn to behavioural explanations.

2.3 The behavioural explanation of the PEAD

Behavioural finance questions the assumption of perfect rationality by bringing insights from psychology and cognitive science into financial economics (Kahneman and Tversky, 1979). Barberis and Thaler (2003) show that several market anomalies are better explained by models in which agents are not fully rational. The PEAD is one such anomaly.

The cornerstone of the behavioural explanation of the PEAD is the underreaction hypothesis (Bernard and Thomas, 1989). Under this view, when a firm releases earnings that significantly exceed or fall short of expectations, investors adjust their beliefs only partially. Bernard and Thomas (1989) argued that investors systematically underestimate the statistical persistence of earnings surprises. Empirically, a positive surprise in one quarter tends to be followed by further positive surprises in subsequent quarters, yet analysts and other investors often treat each surprise as a one-off event. Abarbanell and Bernard (1992) confirm this pattern by showing that analyst forecast errors display strong positive autocorrelation, suggesting that analysts systematically underreact to previously released information.

This thesis focuses on three psychological mechanisms that may explain this underreaction: anchoring bias, prospect theory, and the disposition effect.

First, anchoring bias, introduced by Tversky and Kahneman (1974), occurs when individuals rely excessively on an initial reference point, such as prior analyst expectations or recent stock prices, when making their investment decisions. As a result, investors may underweight new information, even when the earnings surprise is very good, causing prices to adjust only gradually.

Second, prospect theory, developed by Kahneman and Tversky (1979), explains decision-making under risk through two central ideas. Individuals evaluate outcomes relative to a reference point rather than in absolute terms, and losses are perceived more intensely than equivalent gains. These mechanisms provide the psychological foundation for the disposition effect.

Third, the disposition effect, formalised by Shefrin and Statman (1985), refers to investors' tendency to sell profitable positions too early while retaining losing positions for too long. In the context of the PEAD, investors facing unrealised gains after a positive earnings

surprise may sell shares to secure profits, creating selling pressure that partially offsets the upward post-announcement drift.

Frazzini (2006) provides empirical evidence that the disposition effect contributes to the PEAD by slowing the incorporation of news into prices. The disposition effect is therefore a candidate mechanism for the conditions under which the PEAD weakens or reverses.

2.4 Limits, attenuation, and failures of the PEAD

Although the PEAD has been one of the most robust anomalies in empirical finance, recent research shows that its size and profitability have evolved over time. Two effects are particularly relevant for this thesis.

First, the drift itself has weakened in recent decades. Studies show that its size has diminished over this period. According to Chordia, Subrahmanyam and Tong (2014), this decline is linked to changes in market microstructure and to a general rise in market efficiency. Higher liquidity and the growth of high-frequency algorithmic trading, together with a much faster flow of digital information, have made prices adjust to news more quickly. Institutional investors and quantitative funds now systematically search for known anomalies and trade them within seconds, or even milliseconds. As a result, the post-announcement drift today is weaker, less profitable and shorter than in the periods studied by Ball and Brown (1968) or Bernard and Thomas (1989).

Second, the PEAD is sensitive to the macroeconomic environment and to firm-specific frictions. The standard explanation of the PEAD as a simple form of underreaction assumes a relatively stable environment in which the only friction is that investors process information slowly. This explanation cannot, however, account for situations in which the drift completely breaks down or reverses. The rational inattention theory of Sims (2003) offers one possible angle of analysis. During periods of extreme macroeconomic uncertainty (for example, sharp spikes in the VIX index), investors focus their limited attention toward aggregate/macroeconomic risks rather than on firm-specific information (Sims, 2003; Peng and Xiong, 2006). In such conditions, firm-level signals such as a positive SUE may be ignored, and the PEAD may fail.

The literature has therefore well documented the historical existence of the PEAD, its psychological drivers, and its progressive weakening. The unusual situation in which the PEAD

not only fails but actually reverses, however, remains under-explored. Filling this gap is the central objective of this thesis. The research question and the five hypotheses tested empirically are presented in the next section.

3. Research question and hypotheses

3.1 Research question

As Section 2 has shown, the existence and the recent attenuation of the PEAD are well documented. Less attention, however, has been devoted to the situation in which the anomaly does not just weaken but actually reverses, that is, positive earnings surprises followed by negative drifts and negative earnings surprises followed by positive drifts. The central research question of this thesis is the following.

Why do stocks sometimes react in the opposite direction of what the PEAD predict?

An analysis of the conditions of a PEAD reversal.

To answer this question, five hypotheses (H1 to H5) are tested empirically. Each hypothesis links the slope of the SUE-CAR relationship to a specific firm-level or market-level condition. Three hypotheses (H1, H2 and H4) test firm-level behavioural mechanisms. H3 tests a firm-level mechanism combining behavioural and structural dimensions. H5 tests a market-level macroeconomic mechanism.

3.2 Hypotheses

H1: Capital gains overhang (proximity to the 52-week high)

As Section 2 has shown, prospect theory and the disposition effect predict that investors realise their gains too early, especially when a stock is trading near a high reference point such as its 52-week high (George and Hwang, 2004; Grinblatt and Han, 2005). If many investors hold the stock with an unrealised capital gain, a positive earnings surprise can trigger a wave of profit-taking that pushes the price down rather than up. The drift should therefore weaken or reverse for stocks close to their 52-week high.

H1: *The post-announcement drift weakens, or even reverses, for stocks trading close to their 52-week high, because holders with an unrealised capital gain realise their profits and offset the upward drift.*

H2: Embedded growth expectations (price-to-book ratio)

Firms with a very high price-to-book ratio (P/B) are typically classified as growth stocks, whose valuation already incorporates strong expectations about future earnings. A positive surprise can therefore fail to beat the very high expectations that the market has already priced in, and the price reaction may weaken or even reverse. The opposite would still hold for value stocks. With a low P/B ratio, these firms tend to face lower expectations, so a positive surprise can still produce the standard upward drift.

H2: *The post-announcement CAR is negative following a positive SUE for firms with a high price-to-book ratio, because the positive earnings fail to meet the market's embedded growth expectations.*

H3: Abnormal pre-announcement volume

When pre-announcement volume is abnormally high, two interpretations are possible: information may have leaked to the market, or investors may strongly disagree before the announcement. In both cases, the price should already reflect (in part) the upcoming surprise, and the drift after the announcement should diminish or turn negative.

H3: *The post-announcement CAR is negative following a positive SUE when the announcement is preceded by abnormally high trading volume, because optimistic or pessimistic investors speculate ahead of the announcement, which weakens or reverses the drift.*

H4: Discretionary accruals and earnings quality

Inspired by the cognitive biases described by Sloan (1996), who shows that investors fail to recognise the lower persistence of accruals relative to cash flow, this thesis tests whether or not a this slow-learning mechanism also operates in the PEAD context. Because the market does not fully distinguish accruals from cash flows at the time of the announcement, the present analysis isolates the discretionary component of total accruals using the Modified Jones model

(Jones, 1991) augmented with ROA, following Kothari, Leone and Wasley (2005) methodology and calculations. Discretionary accruals measure the share of reported earnings that comes from accounting flexibility (or manipulation) rather than from the real performance of the business. When a firm has high discretionary accruals, a positive earnings surprise may be partly reversed in the following months, once the market sees the lower quality of these earnings.

H4: The post-announcement CAR is negative for firms with high discretionary accruals following a positive SUE, because of the low persistence of accruals, and because the market eventually doubts the quality of the earnings and treats the news as a signal of fundamental weaknesses.

H5: Rational inattention and VIX spikes

The rational inattention theory of Sims (2003) suggests that during periods of extreme macroeconomic uncertainty (measured in this thesis by spikes in the VIX index), investors' attention is reallocated towards systemic risks rather than firm-specific information. Earnings surprises announced during these periods may therefore be largely ignored, which makes the drift unstable or absent.

H5: The post-announcement CAR is negative following a positive SUE during days with extreme spikes in the VIX index, because macroeconomic fear diverts attention from firm-specific news.

4. Data and methodology

4.1 Data sources and sample period

Daily stock data are obtained from the Center for Research in Security Prices (CRSP) US daily stock files, kindly provided by Professor James Thewissen. The extracted variables are: daily price, return, volume, shares outstanding, value-weighted market return, delisting information, and firm identifiers (PERMNO, CUSIP, ticker, share code, exchange code, SIC industry code).

Fundamentals data are obtained from Bloomberg in four quarterly files. The EPS file contains actual and consensus earnings per share with the announcement date and time. The

book-value file contains the book value of equity. An accruals file contains the inputs needed to estimate discretionary accruals, namely net income, cash flow from operations, sales, accounts receivable, net property, plant and equipment, and total assets. To link Bloomberg tickers with CRSP firms, a separate CUSIP file provides the matching identifiers. These firm-level data are then combined with daily macroeconomic series, which include the VIX, the EPU index of Baker, Bloom and Davis (2016), the 10-year Treasury yield, and the high-yield credit spread.

The sample period runs from January 2000 to December 2024. This window covers multiple macroeconomic shocks (the dotcom bubble, the 2008 financial crisis, the COVID pandemic, the 2022 inflation episode), which are important for testing the hypotheses across different environments. The sample starts in 2000 to align with the modern market era and the weakening of the drift documented by Chordia, Subrahmanyam and Tong (2014).

4.2 Data construction

The working dataset is built in four stages. First, raw data are extracted from CRSP and Bloomberg. Each file is then cleaned to remove values that are physically impossible. After this, methodological filters are applied to produce the consolidated dataset, and each event is linked and double checked using the CUSIP identifier. The Bloomberg data themselves are pulled from the terminal with Excel macros, in several batches to overcome the 1,048,576-row Excel limit, and saved as Parquet files (one per data type). CRSP data are obtained as a daily file covering the full sample period.

In the cleaning stage, only physically impossible or technically corrupt values are removed. CRSP rows with a missing or zero price are dropped, together with returns flagged by the CRSP "no return" codes (−66, −77, −88, −99). Negative prices, which CRSP uses to flag days with no actual trade, are converted to their absolute values while preserving a separate indicator. On the Bloomberg side, sentinel values smaller than 10^{-10} (the convention by which Bloomberg signals "no data") and overflow values are recoded as NaN. The exact rules are summarised in Table 4.1.

Table 4.1 -Data cleaning rules

Source	Issue	Treatment
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CRSP	Missing or zero price	Observation dropped
CRSP	Negative price (no-trade flag)	Converted to absolute value, with flag preserved
CRSP	Return code in $\{-66, -77, -88, -99\}$	Observation dropped
Bloomberg	Sentinel value, $ x < 10^{-10}$	Recoded as NaN
Bloomberg	EPS with $ x > \$10,000$	Recoded as NaN (preserves Berkshire Hathaway at \$8,072)
Bloomberg	$\text{EPS} \leq -\$50$	Recoded as NaN (asymmetric filter for implausible negatives)
Bloomberg	Book Value with $ x > 10^7$ million	Recoded as NaN (negative book values within range are preserved)
Bloomberg	Book Value or Total Assets = 0	Recoded as NaN (physically impossible)
Bloomberg	Total Assets negative	Recoded as NaN (physically impossible)

In the consolidation stage, several methodological filters commonly applied in the PEAD literature are imposed. The sample is restricted to common stocks listed on NYSE, Amex or Nasdaq, identified by CRSP share codes 10, 11 and 12 and exchange codes 1, 2 and 3. Share code 12 is kept so that foreign-incorporated firms operating as US-listed entities in dollar, such as Accenture and Aon, remain in the sample. Following standard practice in the empirical finance literature, financial firms (SIC codes 6000-6999) and regulated utilities (SIC codes 4900-4999) are excluded. The filters are also date aware. A firm that temporarily lost eligibility, for example through a reclassification, is included only for the days on which it satisfied the criteria. Finally, the share price one trading day before the announcement is required to be greater than \$3 in absolute value, which removes events for which the SUE would be mechanically dominated by penny-stock noise.

In the event-linking stage, each Bloomberg ticker is linked to its corresponding CRSP firm identifier (PERMNO). The linking proceeds in two steps. First, candidate PERMNOs are identified through a multi-row bridge that combines two matching methods: matching on the

8-character CUSIP (current and historical) and matching on the (ticker, date) pair. The two methods are cross-validated and agree on approximately 99% of cases. A second issue concerns ticker conflicts. When a single Bloomberg ticker corresponds to several PERMNOs, which can arise from ticker recycling or from Bloomberg's historical rewriting, the active PERMNO is defined as the one currently linked to that ticker in CRSP. Only the events that fall within its CRSP-validity interval are then kept. This rule ensures a one-to-one mapping between each Bloomberg ticker and a single CRSP firm. After all stages, the final sample contains approximately 240,000 quarterly earnings announcements for about 8,000 firms over the 2000-2024 period.

4.3 Earnings surprise (SUE)

The earnings surprise is measured using the analyst-based specification of Livnat and Mendenhall (2006), defined as

$$SUE_LM = (Comparable\ EPS - Median\ analyst\ forecast) / |Price\ at\ T-1|$$

where Comparable EPS is the Bloomberg operating earnings per share adjusted for non-recurring items, currency effects and stock splits, the Median analyst forecast is the consensus available shortly before the announcement, and the price is taken on the last trading day preceding the announcement. The price is taken in absolute value. CRSP records negative prices as a flag for days without an actual trade, and keeping these observations expands the sample without changing the scale of the surprise. To stay consistent with the analyst consensus, the reported EPS is replaced by Comparable EPS. Boudt, De Goeij, Thewissen and Van Campenhout (2015) provide empirical support for this measure using an essentially identical construct: they define the analyst forecast error as the difference between the median analyst consensus and the reported earnings per share, scaled by the closing price on the trading day preceding the announcement, and document that the residual error is systematically predictable from publicly available information and that a short-term strategy exploiting this predictability earns a risk-adjusted annual return of 16.56 per cent before transaction costs over the 1998–2010 I/B/E/S sample.

The analyst-based measure is preferred to the time-series specification of Bernard and Thomas (1989), since it directly captures the market's expectations at the moment of the

announcement. The time-series specification is nonetheless computed and reported as a robustness check, with the following form

$$SUE_BT = (Q_t - E[Q_t]) / \sigma_{5q}$$

where Q_t is the Comparable EPS reported in the current quarter, $E[Q_t] = Q_{t-4} + \delta$ is the expected EPS under a seasonal random walk with drift δ estimated as the average of the four most recent seasonal differences, and σ_{5q} is the standard deviation of the same seasonal differences over the five most recent quarters (with a numerical floor of 0.001 imposed to prevent instability for low-volatility small-capitalisation firms).

The cross-sectional distribution of SUE is winsorised at the 1% and 99% percentiles. Further sanity filters are then applied to remove events where the Bloomberg inputs do not match the share price. When the consensus forecast (EstimateEPS) exceeds the absolute value of the stock price at $T-1$, the analyst-based measure SUE_LM is set to missing, while the time-series measure SUE_BT, which does not use the consensus forecast, is preserved. The rule is stricter for the Comparable EPS. If it exceeds the stock price at $T-1$, both measures are set to missing. One manual exception is made for Berkshire Hathaway Class A, whose unusually high price-per-share is genuine and not a sign of a data error.

4.4 Cumulative Abnormal Returns (CAR)

The cumulative abnormal return (CAR) is computed over a set of trading-day windows around each announcement. The abnormal return on day t is defined as the difference between the firm's daily return and the CRSP value-weighted market return,

$$AR_t = RET_t - vwret_d_t$$

The CAR over a window $[T_1, T_2]$ is the sum of daily abnormal returns over the trading days included in the window,

$$CAR_{[T_1, T_2]} = \text{sum of } AR_t \text{ for } t \text{ from } T_1 \text{ to } T_2$$

The sum, rather than the compound product, is adopted following Bernard and Thomas (1989), who show that the additive aggregation is the standard convention in the PEAD literature. The primary post-event window follows the same literature and corresponds to $[+2,$

+60], where the "+2" convention means that the cumulation starts on the second trading day after the announcement in order to exclude the contemporaneous announcement-day reaction.

CAR is also computed over nine additional windows. The four types of event are around-event $([-1, +1], [-3, +3], [0, +5], [0, +10])$, short-horizon $([+2, +10], [+2, +30])$, medium-horizon $([+2, +60]$, used as the primary specification) and long-horizon $([+2, +120], [+2, +250]$ and $[-1, +120])$. This set of ten windows captures both the immediate price impact and the longer-term persistence of the drift.

For events where the firm is delisted during the CAR window, the CRSP delisting return is used as the abnormal return on the last trading day if available, after which abnormal returns are set to zero under the standard return-to-cash convention. These events are flagged but not dropped from the sample in order to avoid survivorship bias.

4.5 Hypothesis variables and controls

For H1, the proximity to the 52-week high is computed as the ratio between the price at $T-1$ and the maximum price observed over the $[T-252, T-1]$ window:

$$Prox52WH = PRC_{T-1} / \max (PRC \text{ over } [T-252, T-1])$$

The variable lies in the interval $[0, 1]$ and reaches 1 for stocks trading exactly at their 52-week high (George and Hwang, 2004; Grinblatt and Han, 2005).

For H2, the price-to-book ratio is computed as the market capitalisation at $T-1$ divided by the book value at the most recent quarter-end strictly before the announcement date (to avoid look-ahead bias):

$$PB = MarketCap_{T-1} / BV_{last\ QE < AnnDate}$$

where $MarketCap_{T-1}$ is the product of the closing price and the number of shares outstanding at $T-1$, and $BV_{last\ QE}$ is the book value of equity reported at the most recent fiscal quarter-end strictly preceding the announcement.

For H3, the abnormal pre-announcement volume is computed as the ratio between the average daily volume over the $[-10, -1]$ window and the average daily volume over the $[-60, -11]$ window:

$$AbnVol = \text{mean}(VOL \text{ over } [-10, -1]) / \text{mean}(VOL \text{ over } [-60, -11])$$

A value of 1 corresponds to no abnormal activity (Miller, 1977; Barber and Odean, 2008).

For H4, the discretionary accruals are computed using the Modified Jones model with ROA as an additional control, following Kothari, Leone and Wasley (2005). The model is estimated by industry-year using the Fama and French 48-industry classification (Fama and French, 1997), with a minimum of ten firms per industry-year cell required for the regression to be run, and the discretionary accruals are defined as the residuals. Because the Kothari model includes ROA as a regressor in the first stage, the discretionary-accruals measure is by construction orthogonal to the firm's profitability level. This addresses the classical concern that high accruals could simply reflect low profitability rather than aggressive earnings management.

For H5, the VIX dummy takes the value 1 when the VIX index at the announcement date is above 30, and 0 otherwise:

$$D_{VIX} = 1 \quad \text{if } VIX_{AnnDate} > 30, \quad \text{else } 0$$

This threshold corresponds approximately to the 90th percentile of the daily VIX distribution over the sample period.

In addition to the hypothesis variables, all regressions include firm-level controls (log market capitalisation, 6-month and 12-month momentum, 60-day return volatility), macroeconomic controls (the EPU index, the 10-year Treasury yield, and the high-yield credit spread), and two sets of fixed effects (Fama and French 48-industry and calendar year). All continuous variables are winsorised at the 1% and 99% percentiles.

4.6 Econometric specification

For each hypothesis, the baseline specification is an interaction model in which the slope of the SUE-CAR relationship is allowed to vary with the conditioning variable. The model is formally specified as

$$CAR_{i,t} = \beta_0 + \beta_1 SUE_{i,t} + \beta_2 (SUE_{i,t} \times H_{i,t}) + \beta_3 H_{i,t} + \gamma' X_{i,t} + \mu_j + \tau_\gamma + \varepsilon_{i,t}$$

In this specification, H denotes the hypothesis variable, X the vector of firm-level and macroeconomic controls described in Section 4.5, μ_j the Fama and French 48-industry fixed

effects, and τ_γ the year fixed effects. The interaction coefficient β_2 is the key parameter of the model. When β_2 is negative and large enough in absolute value, the slope of the SUE-CAR relationship changes sign for high enough values of H. This change is the reversal pattern predicted by the five hypotheses. Following Petersen (2009), standard errors are double-clustered by firm and by calendar quarter. This combination handles within-firm correlation, since each firm appears several times in the dataset, and cross-firm correlation, since firms announcing in the same quarter share common macroeconomic shocks. The double-clustered standard error is also robust to heteroscedasticity by construction, which is useful here because the variance of the post-announcement CAR is substantially larger at extreme SUE values (a funnel-shape pattern formally confirmed by a Breusch-Pagan test (Breusch and Pagan, 1979), $p < 0.001$).

4.7 A data-quality discovery

A small but non-negligible fraction of the raw Bloomberg sample (approximately 1.8% of events) exhibits analyst-forecast values that exceed the absolute value of the stock price, in some cases by several orders of magnitude. As an example, the consensus forecast for one stock trading at \$2.27 was reported as \$5,800 per share. The implied annualised earnings yield runs into the thousands of percent, which is economically impossible. Simple winsorisation cannot fix this. By only rescaling values without changing their rank order, it leaves the corrupted observations in the extreme deciles of the SUE distribution, where they dominate both the unconditional decile spread and the interaction-term coefficient of the regressions.

An asymmetric filter is therefore applied. When the consensus forecast (EstimateEPS) is inconsistent with the share price, the analyst-based SUE_LM is set to missing, while the time-series-based SUE_BT is preserved because it relies on Comparable EPS rather than on the consensus forecast. If the Comparable EPS itself is inconsistent with the share price, both measures are set to missing. One manual exception is made for Berkshire Hathaway Class A, whose unusually high price per share is legitimate. In addition, the minimum-price screen is tightened from the conventional \$1 of Bernard and Thomas (1989) to \$3, in order to limit further contamination from low-priced stocks where Bloomberg data quality is weaker. After these corrections, the unconditional decile pattern of CAR by SUE returns to its expected monotone shape, with the spread between the top and bottom SUE deciles equal to approximately 2.3 percentage points over the [+2, +60] window.

5. Results

In this section, the empirical findings are presented. The aggregate post-announcement drift on the full sample is examined first, followed by a summary of the five hypothesis tests in a single master table. The next five subsections present each hypothesis in detail. The final subsection summarises the robustness checks.

5.1 The aggregate PEAD in the post-2000 sample

The first check is whether the unconditional PEAD is present in the sample. The approximately 169,000 SUE-valid events are sorted into ten deciles of SUE_LM (after winsorisation and after the Bloomberg correction described in Section 4.7) and the mean CAR is computed over the $[+2, +60]$ window in each decile. The pattern is monotone and runs from -0.56% in decile 1 (most negative surprises) to +1.75% in decile 10 (most positive surprises), producing a spread of approximately 2.30 percentage points between the two extreme deciles. This magnitude is in line with the recent estimates of Chordia, Subrahmanyam and Tong (2014) for the post-2000 era.

Figure 5.1 shows the cumulative average abnormal return by decile from $t = -30$ to $t = +120$ trading days. The drift is essentially flat in the pre-event window, jumps at the announcement, and then continues to drift smoothly for several months. The shape is exactly what the PEAD literature predicts. The unconditional drift remains alive in the post-2000 sample, confirming that the conditions necessary for the conditional analyses developed in the following subsections are met.

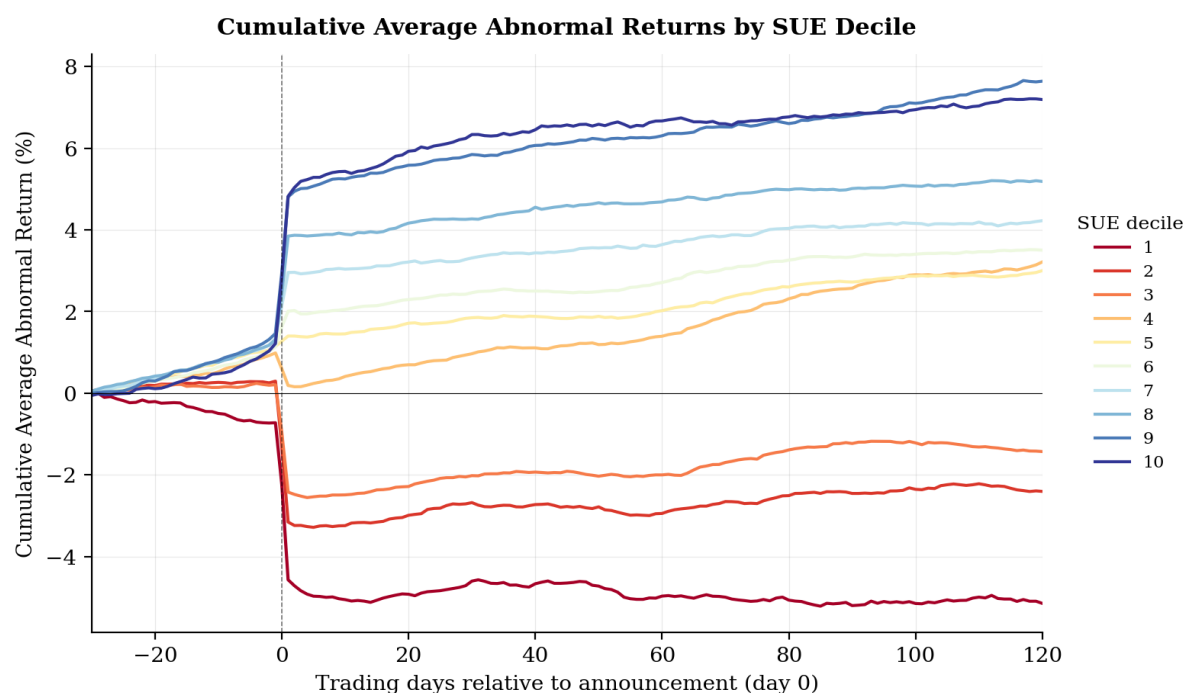


Figure 5.1: Cumulative average abnormal returns from $t=-30$ to $t=+120$ trading days by SUE decile. The SUE-valid events ($n=168\,991$) of the post-correction sample are sorted in 10 deciles of SUE_LM . Each curve plots the cumulative abnormal return ($CAR=RET - vwret_d$) starting at $t=-30$. The vertical dashed line shows the announcement day. The spread between decile 10 (= top SUE) and decile 1 (= bottom SUE) widens steadily over the 120 trading days following the announcement. No clear reversal in the average pattern is seen.

5.2 Descriptive statistics

Table 5.1 reports the descriptive statistics of the main variables. The SUE is centred near zero, with a median below one tenth of a percentage point of the stock price, consistent with the analyst consensus being unbiased on average. The CAR over the $[+2, +60]$ window has a median close to zero and a standard deviation of about 21%, which reflects the dispersion of post-announcement returns. The hypothesis variables fall within the ranges expected from their construction (Prox52WH is bounded in $[0, 1]$, AbnVol is centred near 1, DA Kothari is a residual centred near 0, and D_VIX takes the value 1 in about 9% of events).

Table 5.1 -Descriptive statistics

Variable	N	Mean	Median	Std Dev	P1	P99
SUE (Livnat- Mendenhall)	168,991	0.001	0.001	0.025	-0.133	0.135
SUE (Bernard- Thomas)	138,751	-0.018	0.015	1.789	-6.034	5.098
CAR [+2, +60]	237,659	0.005	0.005	0.214	-0.669	0.653
CAR [-1, +120]	237,659	0.011	0.014	0.333	-1.031	0.972
Prox52WH	213,682	0.768	0.819	0.199	0.202	1.000
PB ratio	231,452	3.484	2.226	6.894	-23.393	43.447
AbnVol	231,813	0.990	0.877	0.600	0.155	4.120
DA Kothari	175,990	-0.017	-0.016	0.136	-0.501	0.473
D_VIX	237,659	0.093	0.000	0.291	0.000	1.000
log MktCap	237,659	20.457	20.328	1.941	16.435	25.458
Momentum 6m	224,862	0.088	0.074	0.323	-0.767	1.199
Volatility 60d	231,564	0.030	0.025	0.018	0.006	0.102

The sample is the post-correction dataset described in Section 4.7. All continuous variables are winsorised at the 1% and 99% percentiles, with winsorisation applied after the Bloomberg analyst-forecast correction. The sample

size differs across variables because of variable-specific missingness (for example, *SUE_BT* requires at least five quarters of *EPS* history; *DA Kothari* requires a viable industry-year regression cell).

5.3 Summary of hypothesis tests

Table 5.2 summarises the empirical evidence for each of the five hypotheses. For each H, the table reports the conditioning variable, the theoretical channel, the CAR window on which the finding is most informative, the corresponding interaction coefficient β_2 and its p-value, the robustness checks under which the finding survives, and a summary verdict. The detailed results are presented in the subsections that follow.

Table 5.2 - Master summary of the five hypothesis tests

H	Variable	Theoretical channel	Window (spec)	β_2	p-value	Robustness	Verdict
H1	Prox52WH	Capital overhang	gains [+2, +60] (vol-norm)	+1.57	0.006	Sign opposite to pre-registered prediction across the majority of post-event windows	Inverse pattern found
H2	PB ratio	Embedded expectations	growth [-3, +3]	-0.008	<0.001	Sign and significance preserved across all five SUE specifications around the event, and on three of five at the primary post-event window	Around-event reaction
H3	AbnVol	Pre-event information leakage	—	—	n.s.	No significant signal in any specification	Not supported
H4	DA Kothari	Earnings quality and slow market learning	[-1, +120]	-1.60	<0.001	Significant across all four sub-periods; survives the NYSE-P5 and NYSE-P10 microcap exclusions	Confirmed at long horizon

H5	D_VIX dummy	Rational inattention	—	—	n.s.	High-yield credit spread significant on the announcement window [0, +10] (Appendix F)	Not supported on VIX
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5.4 H1: Capital gains overhang (proximity to the 52-week high)

The H1 hypothesis predicts that proximity to the 52-week high triggers profit-taking selling that weakens or reverses the post-announcement drift. On the primary CAR window [+2, +60], there is no support found for this prediction. The interaction coefficient β_2 between SUE and Prox52WH is +0.264 with a p-value of 0.153, which is not significantly different from zero. The interaction is not statistically significant for the full sample nor for any of the five SUE methods tested.

However, a striking pattern emerges when the model is re-estimated using a volatility-normalised dependent variable. The volatility-normalised CAR is defined as

$$CAR_{norm} = CAR / (\sigma_{pre} \times \sqrt{T})$$

where σ_{pre} is the standard deviation of the firm's daily returns over the 60 trading days preceding the announcement, and T is the number of trading days in the CAR window. This normalisation places events with high and low idiosyncratic volatility on the same scale and removes the mechanical inflation that high-volatility firms would otherwise contribute to the regression.

Under the volatility-normalised specification, β_2 turns positive and statistically significant. On the primary window, $\beta_2 = +1.57$ with $p = 0.006$. Across the post-event CAR windows considered in the analysis, β_2 is positive and statistically significant in the majority of cases, and never significantly negative. The sign is therefore opposite to what the pre-registered H1 prediction requires under the disposition-effect mechanism.

This result shows evidence of a capital-gains lock-in mechanism rather than a disposition effect. Investors who hold a stock near its 52-week high may delay the realisation of their paper gains (for example to defer taxation, or because they anchor on the recent high). In that situation, the selling pressure that the disposition effect predicts simply does not materialise. Positive earnings surprises on such stocks then produce drifts that are amplified

rather than dampened. This finding is not what was predicted in the pre-registration, but it is a substantive empirical regularity that emerges from the robustness battery and is reported as such.

5.5 H2: Embedded growth expectations (price-to-book ratio)

The H2 interaction coefficient between SUE and the price-to-book ratio is statistically significant in the predicted direction on both the primary post-event window and the around-event window. On the primary CAR window [+2, +60], $\beta_2 = -0.00950$ with $p = 0.011$, significant at the 5% level. The signal is stronger and more robust around the announcement itself. On [-3, +3] (seven trading days centred on the announcement), $\beta_2 = -0.00783$ with $p < 0.001$ in the primary SUE specification, and the negative sign and statistical significance are preserved across all five SUE specifications, as reported in Table 5.3.

Table 5.3. H2 interaction coefficient on the [-3, +3] around-event window across the five SUE specifications. The signal is consistent in sign and significance across all five specifications.

SUE specification	β_1 (SUE)	β_2 (SUE $\times$ PB_w1)	p-value	N
A — SUE_LM, winsorised 1/99	+0.535 ***	-0.00783 ***	<0.001	157,534
B — SUE_LM, winsorised 5/95	+3.285 ***	-0.01873 *	0.015	157,534
C — SUE decile dummies (D10 vs D5)	+0.040 ***	-0.00065 **	0.001	157,534
D — SUE log-transformed	+0.027 ***	-0.00024 **	0.002	157,534
E — Bernard-Thomas SUE	+0.011 ***	-0.00008 **	0.002	138,621

The interaction effect is the strongest in the days immediately surrounding the announcement. This suggests that high-PB firms (growth stocks) take up the earnings signal

more rapidly than the low-PB firms. The residual signal on the primary [+2, +60] window indicates that, for these firms, a portion of the slow post-event drift is also attenuated. This is consistent with growth stocks having wider analyst coverage and faster information integration than the rest of the sample. Rather than a slow post-event PEAD reversal, H2 captures a faster and slightly attenuated price response to earnings surprises by high-PB firms.

5.6 H3: Abnormal pre-announcement volume

On every specification tested, the H3 interaction is not statistically significant. The coefficient β_2 at the primary CAR window [+2, +60] is +0.052 with $p = 0.35$, and the interaction is non-significant across all five SUE specifications. A complementary logistic regression of reversal events on the H3 variable also fails to identify any meaningful effect (odds ratio = 0.999, $p = 0.96$).

This null result is explained as indication that the signal-to-noise ratio of abnormal trading volume has deteriorated in the post-2000 era. The rise of algorithmic trading has increased the baseline volume in normal periods. Therefore, a high abnormal volume in the past is now roughly separated from the background noise. Modern information leakage may also operate more through the options market or through changes in short interest. Neither of those is captured by the equity-based abnormal-volume measure used in this analysis.

5.7 H4: Discretionary accruals

H4 is the strongest finding of this analysis. On the primary CAR window [+2, +60], the interaction coefficient β_2 between SUE and DA_Kothari is -0.628 with $p < 0.001$ (Spec A, full sample). The interaction is significantly negative and economically meaningful. For firms with high discretionary accruals, the slope of the SUE-CAR relationship is significantly less steep, and the marginal effect of a positive surprise becomes essentially zero or negative for the most aggressive accruals values.

More importantly, the H4 interaction has a horizon profile consistent with a slow-learning mechanism. Table 5.4 reports β_2 at nine post-event horizons from +5 to +250 trading days.

Table 5.4 - H4 interaction coefficient β_2 across nine post-event horizons.

Horizon	β_2 (Interaction)	95% CI	p-value
+5 days	+0.010	[-0.087, +0.107]	0.837
+10 days	-0.033	[-0.169, +0.103]	0.631
+20 days	-0.099	[-0.288, +0.089]	0.296
+30 days	-0.382 **	[-0.609, -0.154]	0.001
+60 days (primary)	-0.628 **	[-0.997, -0.258]	0.001
+90 days	-1.076 ***	[-1.608, -0.543]	<0.001
+120 days	-1.438 ***	[-2.136, -0.740]	<0.001
+180 days	-1.635 **	[-2.598, -0.672]	0.001
+250 days	-1.915 ***	[-2.995, -0.834]	<0.001

The interaction is not significant in the first 20 days, becomes significant from +30 days onward, and grows monotonically in magnitude up to +250 days. This pattern is consistent with a slow-learning interpretation in which the market gradually discounts the credibility of earnings with high discretionary accruals.

The H4 hypothesis is also tested on four sub-samples (pre-2010, post-2010, sample excluding the 2008-09 financial crisis, and sample excluding 2020). On the [-1, +120] window, the interaction coefficient is statistically significant in all four sub-samples (β_2 between -1.6 and -1.7, p-values below 0.03). The finding is therefore not driven by a specific time period or a single crisis.

The effect of the exclusion of small-capitalisation firms is also tested. On the primary [+2, +60] window, the H4 interaction becomes non-significant once the bottom 5% of firms by NYSE market-capitalisation breakpoint are removed. On the longer [-1, +120] window, the interaction survives both the bottom-5% and the bottom-10% exclusions ($\beta_2 \approx -1.38$, $p = 0.016$ at the NYSE-P5 cutoff). This suggests that the H4 mechanism operates rapidly in the small-cap segment, where limits to arbitrage are most binding, and operates more slowly but still significantly in the large-cap segment.

Table 5.5 reports the full regression output for H4 across five CAR windows, with firm-level and macroeconomic controls. The interaction coefficient ($SUE \times DA_Kothari$) is the variable of interest.

Table 5.5 - H4 regression output across five CAR windows.

Dependent variable: CAR window	[-1, +1]	[+2, +10]	[+2, +30]	[+2, +60]	[-1, +120]
SUE_LM	+0.4750 *** (0.0279)	+0.0598 *** (0.0154)	+0.0689 * (0.0280)	+0.0109 (0.0441)	+0.4233 *** (0.0754)
SUE_LM × DA_Kothari	-0.0958 (0.0858)	-0.0329 (0.0684)	-0.3817 ** (0.1145)	-0.6278 ** (0.1861)	-1.6022 *** (0.3837)
DA_Kothari	+0.0053 (0.0030)	-0.0025 (0.0030)	-0.0040 (0.0064)	-0.0017 (0.0112)	-0.0058 (0.0209)
Momentum 6m	+0.0026 (0.0018)	+0.0044 (0.0032)	+0.0019 (0.0076)	+0.0115 (0.0097)	+0.0280 (0.0147)
Momentum 12m	-0.0047 *** (0.0013)	-0.0054 * (0.0023)	-0.0072 (0.0047)	-0.0052 (0.0068)	-0.0228 * (0.0098)
Volatility 60d	+0.0957 (0.0601)	-0.0137 (0.0563)	+0.1559 (0.1592)	+0.1693 (0.2180)	+0.7017 * (0.2906)
log MktCap	+0.0003 (0.0003)	-0.0002 (0.0003)	-0.0008 (0.0007)	-0.0021 * (0.0010)	-0.0025 (0.0015)
EPU	+0.0000 (0.0000)	-0.0000 (0.0000)	+0.0000 (0.0000)	+0.0001 * (0.0000)	+0.0001 *** (0.0000)
10Y Yield	-0.0004 (0.0014)	-0.0008 (0.0022)	-0.0090 (0.0053)	-0.0167 (0.0092)	-0.0324 *** (0.0094)
HY Credit spread	-0.0010 (0.0010)	-0.0000 (0.0021)	+0.0033 (0.0034)	+0.0170 ** (0.0055)	+0.0254 ** (0.0086)
FF48 Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	134,516	134,516	134,516	134,516	134,516

Standard errors double-clustered at the firm and calendar-quarter levels are between parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The sample is the post-correction dataset

described in Section 4.7. All specifications include FF48 industry fixed effects and year fixed effects.

5.8 H5: Macroeconomic uncertainty

The pre-registered H5 specification uses a binary indicator equal to 1 when the VIX index is above 30 on the announcement date. On the primary CAR window [+2, +60], the interaction coefficient is $\beta_2 = +0.077$ with $p = 0.60$, not significant. The interaction is also not statistically significant across the five SUE specifications. The pre-registered version of H5 is therefore not supported.

Six different macroeconomic variables are tested: the continuous VIX, two alternative VIX-dummy thresholds at the 75th and 90th percentiles, the EPU index, the high-yield credit spread, the 10-year Treasury yield, and a high-yield dummy. Among these, the high-yield credit spread (HY_Credit_w1) is the only variable that produces a robust signal, although the effect is concentrated on the announcement window rather than on the post-event drift. On the [0, +10] event window, the interaction coefficient between SUE and HY_Credit_w1 is $\beta_2 = +0.122$ with $p < 0.001$, and the sign is positive. This is opposite to the behaviour of what our hypothesis predicted.

This can be explained by the fact that in high-credit-stress regimes, the market is more sensitive to firm fundamentals. This happens because credit pricing dynamics are themselves driven by firm-level distress probabilities. A positive earnings surprise during a high-HY period therefore produces a more pronounced price response in the event window. The pre-registered VIX dummy does not capture this mechanism, which is consistent with the idea that aggregate market volatility and credit-risk pricing measure two different dimensions of macroeconomic stress.

5.9 Robustness summary

All the findings reported above survive a broad battery of robustness checks. The layers are summarised here and the full results are reported in the appendices.

First, all hypotheses are tested under five SUE specifications, namely the continuous SUE_LM winsorised at 1%/99% (primary), the same winsorised at 5%/95%, decile dummies, a log transformation, and the time-series SUE of Bernard and Thomas (1989).

Second, the tests are extended to a curated set of complementary CAR windows that span the around-event, short-horizon and long-horizon phases of the drift.

Third, the temporal stability is examined on four sub-samples (pre-2010, post-2010, sample excluding the 2008-09 financial crisis, and sample excluding 2020).

Fourth, the sensitivity to the exclusion of small-capitalisation firms is tested under five thresholds (no exclusion, and the bottom 5%, 10%, 15% and 20% of firms by NYSE market-capitalisation breakpoint).

Fifth, a volatility-normalised version of the dependent variable is estimated to control for cross-sectional differences in idiosyncratic volatility.

Sixth, an additional asymmetric Bloomberg book-value filter is applied to the H2 hypothesis as a sample robustness check.

Seventh, for H5, seven alternative macroeconomic conditioning variables are tested in place of the pre-registered VIX dummy.

The detailed results are shown in Appendices A through G. The main findings (H4 confirmed at long horizon, H2 significant both around the announcement and on the primary post-event window, H1 producing an inverse pattern under volatility normalisation, and H3 and H5 not supported in their pre-registered form) are stable across these layers.

6. Discussion

6.1 Summary of findings

Section 5 has presented the five hypothesis tests. The results can be grouped in three categories. First, one hypothesis (H4) receives strong empirical support. The level of discretionary accruals significantly weakens the post-announcement drift, with an effect that grows monotonically with the horizon. Second, one hypothesis (H2) receives partial support. The price-to-book ratio significantly affects the SUE-CAR relationship on both the around-event and the primary post-event windows, although the effect is stronger and more robust around the announcement, which suggests an immediate absorption of the earnings signal rather than a slow reversal. Third, two hypotheses (H3 and H5) are not supported in their pre-

registered form, and one hypothesis (H1) shows an unexpected inverse pattern under volatility normalisation. Each finding is discussed in turn in the remainder of this section.

6.2 H4: Discretionary accruals and slow learning

The H4 result is the main empirical contribution of this thesis. Three features of the result deserve attention.

First, the magnitude of the interaction grows more and more negative with the increase of the post-announcement window, starting from +10 days. The interaction is not statistically significant in the first 20 days, becomes significant at +30 days, and grows steadily up to a coefficient of about -1.9 at +250 days. This horizon profile is consistent with the slow-learning interpretation that motivates H4 in the literature. The market does not penalise high-discretionary-accruals firms on the day of the announcement. The fact that the effect is small at short horizons but very large at long horizons also makes this finding economically interesting, since an investor who waits a few weeks before reacting to a positive surprise on a high-DA firm would observe a much larger drift than the sample average.

Second, the H4 finding is robust to the exclusion of crisis periods. When the 2008-09 financial crisis or the 2020 COVID period are excluded, the interaction coefficient remains negative and statistically significant in each of the four sub-samples examined on the $[-1, +120]$ window. This is consistent because it means the result is not driven by a single macroeconomic episode.

Third, the H4 results have a clear size-dependence. On the primary $[+2, +60]$ window, the effect disappears once the bottom 5% of firms by NYSE market-capitalisation breakpoint is removed. On the longer $[+2, +120]$ window, the effect survives the removal of the bottom 10%. This is interpreted as evidence that the slow-learning mechanism operates rapidly in the small-cap segment, where limits to arbitrage are most binding and where analyst coverage is sparse. On the opposite, the slow-learning mechanism operates more slowly but still significantly in the larger-cap segment, where institutional rebalancing requires more time but eventually completes. The finding is therefore not specific to micro-cap stocks. It extends to the bulk of the US listed universe, but with a longer time scale.

6.3 H2: Growth stocks integrate the signal around the announcement

The H2 finding shows a mixed pattern. The interaction is statistically significant on the primary [+2, +60] window in three of the five SUE specifications and on the around-event windows in all five SUE specifications. The around-event signal is therefore stronger and more robust than the post-event signal.

This can be understood as growth stocks (high P/B) already absorbing the earnings signal in the few days surrounding the announcement, rather than primarily through a slow post-event drift. Growth stocks typically have wide analyst coverage and large institutional ownership, which suggests a more efficient price reaction at the announcement than for value stocks. A residual signal nonetheless persists on the primary [+2, +60] window, which indicates that the absorption is not entirely instantaneous. The combined pattern is consistent with the spirit of the pre-registered H2 (high expectations weaken the price reaction to positive surprises) but locates the dominant part of the effect closer to the announcement than to the slow post-event drift originally hypothesised.

6.4 H1: A capital-gains lock-in pattern

The H1 result is the most unexpected finding of this thesis. The pre-registered hypothesis, based on the disposition effect, predicts that proximity to the 52-week high triggers profit-taking selling that reverses the post-announcement drift. The volatility-normalised version of the regression shows the opposite. Proximity to the 52-week high amplifies the drift rather than reversing it. The interaction coefficient is positive and statistically significant in the majority of the post-event CAR windows considered, and the sign never flips.

The preferred interpretation is a capital-gains lock-in mechanism. Investors holding a stock near its 52-week high may defer the realisation of their paper gains, either for tax reasons or because they anchor on the recent high as a reference point. The selling pressure that the disposition effect predicts simply does not materialise. As a result, positive earnings surprises on such stocks face less resistance and produce drifts that are amplified rather than dampened. This pattern was not predicted in the pre-registration, but it is a robust empirical regularity that the data show clearly. It is treated as an exploratory finding that needs future research.

6.5 Why H3 and H5 do not work in this sample?

Two pre-registered hypotheses (H3 and H5) are not supported by the data. The null result on H3 (abnormal pre-announcement volume) is most plausibly the consequence of the modern microstructure. The rise of algorithmic trading has increased the baseline volume in normal periods, which deteriorates the signal-to-noise ratio of any volume-based measure of pre-event leakage. A meaningful "abnormal" volume in 2024 may correspond to a much higher level of activity than in the 1990s, simply because the baseline is higher. Information leakage may also operate today more through the options market or through changes in short interest, neither of which is captured by the equity-based volume measure used in this analysis.

The null result on H5 (the VIX dummy) is more nuanced. The pre-registered dummy fails, but the high-yield credit spread, a related but distinct measure of market stress, produces a significant interaction on the announcement window $[0, +10]$. This suggests that the rational-inattention mechanism that motivates H5 may exist but is more cleanly captured by credit-pricing measures than by VIX measures. This interpretation is not pushed further, since the credit-spread interaction was not pre-registered, and it is reported as an exploratory finding only.

6.6 Limitations

Several limitations of this analysis are worth acknowledging explicitly.

First, the asymmetric Bloomberg correction applied in Section 4.7 removes the most obvious data-quality issues but cannot guarantee that all subtler problems are fixed. A complementary cross-check against the Compustat database would strengthen the analysis, but Compustat data were not available for this thesis.

Second, the sample is restricted to US common stocks. The hypotheses are not tested on European or Asian markets, where institutional structures and accounting conventions differ. The external validity of the findings beyond the US is therefore an open question.

Third, the regressions do not directly control for the level of institutional ownership at the firm-event level. Institutional ownership data are available through the SEC 13F filings, but their integration into the event sample is out of the scope of the present work. The H4 finding in particular operates over horizons during which institutional rebalancing could amplify or attenuate the mechanism, so adding this dimension would be a natural extension.

Fourth, the treatment of delistings sets the abnormal return to zero after the last trading day of a delisted firm. This is the standard convention in the event-study literature, but it artificially compresses the CAR variance for the events affected. On long-horizon windows (such as the 120-day or 250-day windows used in this analysis), this convention may slightly attenuate the magnitude of the reported coefficients. A more refined treatment would use the post-delisting return on a benchmark portfolio rather than zero.

6.7 Implications for practitioners and future research

The findings of this thesis have implications both for institutional investors and for academic researchers.

For practitioners, the most direct implication concerns the discretionary-accruals channel. The results suggest that the standard Modified Jones residual remains an informative signal in the modern US equity market, especially over horizons of three to six months. A trading strategy that shorts firms with high discretionary accruals following positive earnings surprises and holds the position for several months would, in principle, be consistent with the estimates reported here. Whether such a strategy would be profitable in practice depends on transaction costs, the cost of short borrowing, and the level of institutional crowding into the strategy, all of which fall outside the scope of this analysis.

For academic researchers, two directions seem particularly promising. The first is the temporal dimension. The H4 effect emerges progressively over six to twelve months, which means that the standard 60-day PEAD window may be too short to fully capture the mechanism. The second is the cross-sectional dimension. The H4 effect is partially concentrated in the small-cap segment but extends to large caps at longer horizons. A more refined version of the analysis would integrate the institutional-ownership dimension and the bid-ask-spread dimension to disentangle the various limits-to-arbitrage channels.

Finally, the methodological correction described in Section 4.7 (the Bloomberg analyst-forecast contamination filter) constitutes an additional contribution of this thesis. Any future work using the Bloomberg analyst-forecast feed should perform a similar sanity check on the ratio $|\text{forecast} / \text{price}|$ before proceeding to regressions, especially if the sample includes small-cap firms.

7. Conclusion

This thesis has asked when the Post-Earnings-Announcement Drift fails. Starting from the observation that the literature documents both the persistence and the attenuation of the PEAD but rarely studies its reversals, five behavioural and macroeconomic conditions that could make the anomaly break down have been tested.

The main empirical finding is that the level of discretionary accruals weakens the drift, with an effect that grows monotonically with the horizon. At the standard 60-day horizon, the interaction coefficient is around -0.63 and highly significant. At the 120-day horizon, it reaches -1.44 and survives the exclusion of the smallest 10% of firms by NYSE market-capitalisation breakpoint. At the 250-day horizon, it reaches close to -2. This horizon profile is consistent with a slow-learning mechanism in which the market gradually discounts the credibility of high-accrual earnings over six to twelve months. The effect is concentrated in small-cap firms at short horizons, where limits to arbitrage are most binding, and extends to larger firms at longer horizons, where institutional rebalancing takes more time.

The second confirmed finding concerns the price-to-book ratio. The P/B channel shows up as a combined around-event and modest post-event signal, with the stronger effect concentrated in the few days surrounding the announcement. High-P/B firms appear to absorb the earnings signal more rapidly than the rest of the sample, leaving a smaller but still measurable residual drift on the primary [+2, +60] window. This pattern is consistent with the higher information efficiency of growth stocks compared to the rest of the sample.

The third finding is the unexpected inverse pattern for the 52-week-high channel. Under volatility normalisation, proximity to the 52-week high amplifies rather than reverses the drift. This is interpreted as evidence of a capital-gains lock-in mechanism rather than a disposition effect. Investors holding stocks near their recent high defer the realisation of their paper gains, which removes the selling pressure that the disposition effect would otherwise produce. This finding is treated as exploratory because it is the opposite of the pre-registered direction, but the pattern is robust across the majority of the post-event CAR windows considered and across the volatility-normalisation specification.

Two of the pre-registered hypotheses (H3 on abnormal volume, H5 on the VIX dummy) are not supported. Both null results are argued to be informative rather than uninformative. The H3 null reflects the deterioration of volume signals in the modern algorithmic-trading era. The

H5 null reflects the inadequacy of the VIX dummy as a proxy for the rational-inattention channel. The high-yield credit spread captures a related but distinct mechanism and produces a significant interaction on the announcement window.

In addition to these substantive findings, this thesis has documented a methodological correction that deserves emphasis. The identification and correction of the Bloomberg data issue is described in Section 4.7. The asymmetric correction procedure proposed (which invalidates only the surprise measure that uses the contaminated input, rather than dropping the entire event) preserves a substantial fraction of the sample and may be useful for future research using Bloomberg fundamentals.

This thesis closes on a note of methodological reflexivity. The first empirical run produced a striking but ultimately incorrect result. The process of identifying the issue, understanding its origin, and correcting it provided richer methodological insights than a single tidy result could have. The willingness to stress-test initial findings and to revise conclusions in the light of those tests is an essential feature of empirical work at any level. It is hoped that the way this process has been documented will be of use to readers, and that the substantive findings reported here contribute to a slightly better understanding of the conditions under which the PEAD breaks down.

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Appendices

Appendix A: Five SUE specifications

Table A.1: Interaction coefficient β_2 across the five SUE specifications at the primary CAR window [+2, +60].

Hypothesis	Spec A (w1)	Spec B (w5)	Spec C (decile)	Spec D (log)	Spec E (SUE_BT)
H1 Prox52WH	+0.252	+0.974	-0.025	+0.011	+0.005
H2 PB	-0.009 *	-0.015	-0.001 *	-0.000 *	+0.000
H3 AbnVol	+0.049	+0.123	-0.004	+0.002	-0.001
H4 DA Kothari	-0.628 **	-2.072 **	-0.034	-0.022 ***	-0.003
H5 D_VIX	+0.091	+0.219	+0.061 ***	+0.003	-0.005

Notes. Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The sample is the post-correction dataset described in Section 4.7. All regressions include firm-level controls (Mom_6m_w1, Mom_12m_w1, Volatility_60d_w1, log_MktCap_w1), macroeconomic controls (EPU_w1, Yields_10Y_w1, HY_Credit_w1), FF48 industry fixed effects, and year fixed effects. Standard errors are double-clustered at the firm and calendar-quarter levels.

Appendix B: Temporal stability across four sub-samples

Table B.1: Interaction coefficient β_2 across four sub-samples at the primary CAR window [+2, +60].

Hypothesis	Pre-2010	Post-2010	Excl. 2008-09	Excl. 2020
H1 Prox52WH	+0.366	+0.211	+0.338	+0.303
H2 PB	-0.006	-0.010 *	-0.009 *	-0.010 **
H3 AbnVol	+0.041	+0.040	+0.048	+0.017

H4 DA Kothari	-0.421	-0.656 **	-0.611 **	-0.644 **
H5 D_VIX	-0.014	+0.090	+0.042	+0.027

*Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are double-clustered at the firm and calendar-quarter levels. The sub-samples are: pre-2010 (announcements before January 2010), post-2010 (announcements in 2010 and later), excl. 2008-09 (sample excluding the financial crisis years), and excl. 2020 (sample excluding the COVID year).*

Appendix C: Sensitivity to microcap exclusion

Table C.1: Interaction coefficient β_2 across five microcap-exclusion thresholds at the primary CAR window [+2, +60].

Hypothesis	Full	NYSE-P5	NYSE-P10	NYSE-P15	NYSE-P20
H1 Prox52WH	+0.252	+0.292	+0.401	+0.346	+0.247
H2 PB	-0.009 *	-0.010 *	-0.009	-0.004	-0.002
H3 AbnVol	+0.049	+0.036	+0.077	+0.066	+0.032
H4 DA Kothari	-0.628 **	-0.391	-0.300	-0.091	+0.001
H5 D_VIX	+0.091	+0.233	+0.066	+0.019	+0.055

*NYSE-P% thresholds are computed annually as the X-th percentile of the market capitalisation distribution of NYSE-listed firms in each year. Firms with market capitalisation below the threshold in a given year are excluded from the sample for that year. Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are double-clustered at the firm and calendar-quarter levels.*

Appendix D: Volatility-normalised dependent variable

Table D.1: Comparison of β_2 in the raw and volatility-normalised regressions at the primary CAR window [+2, +60].

Hypothesis	β_2 raw (p)	β_2 normalised (p)
H1 Prox52WH	+0.252 (0.153)	+1.566 ** (0.002)
H2 PB	-0.009 * (0.011)	-0.041 ** (0.007)
H3 AbnVol	+0.049 (0.353)	+0.026 (0.864)
H4 DA Kothari	-0.628 ** (0.001)	-1.947 *** (0.001)
H5 D_VIX	+0.091 (0.426)	+0.340 (0.300)

*The volatility-normalised CAR is defined as $CAR / (\sigma_{pre} \times \sqrt{T})$, where σ_{pre} is the standard deviation of the firm's daily returns over the 60 trading days preceding the announcement and T is the number of trading days in the window. Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are double-clustered at the firm and calendar-quarter levels. The sample is the post-correction dataset described in Section 4.7.*

Appendix E: H2 robustness with additional Bloomberg book-value filter

Table E.1: H2 interaction coefficient on the $[-3, +3]$ around-event window across the five SUE specifications, under the additional Bloomberg book-value filter.

SUE specification	β_1 (SUE)	β_2 (SUE $\times$ PB_w1)	p-value	N
A SUE_LM, winsorised 1/99	+0.546 ***	-0.01180 ***	<0.001	157,151
B SUE_LM, winsorised 5/95	+3.308 ***	-0.02686 **	0.003	157,151
C SUE decile dummies (D10 vs D5)	+0.041 ***	-0.00087 ***	<0.001	157,151
D SUE log-transformed	+0.027 ***	-0.00034 ***	<0.001	157,151

E Bernard-Thomas +0.011 *** -0.00010 ** 0.002 138,319
SUE

Same specification as Table 5.3 in the main body, applied to the sample after the additional Bloomberg book-value filter is imposed. Standard errors are double-clustered at the firm and calendar-quarter levels. Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

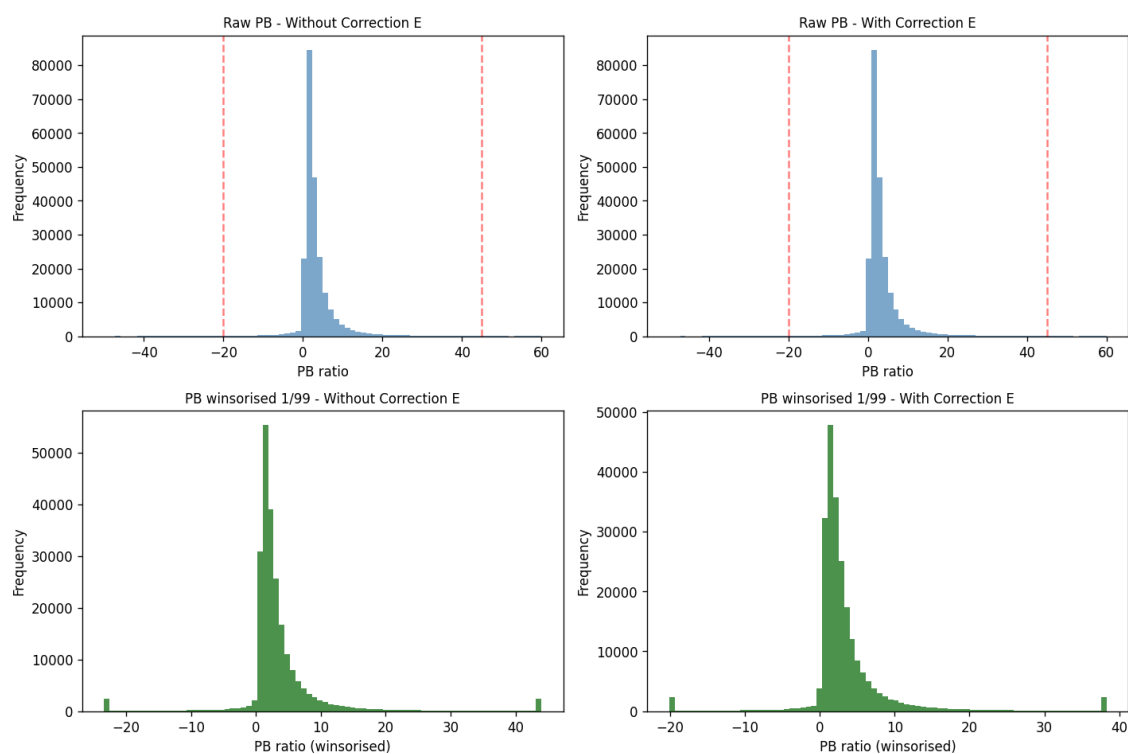


Figure E.1. Price to book ratio distribution comparison before and after correction E

Appendix F: H5 alternative macroeconomic factors

Table F.1: H5 interaction coefficient on the primary CAR window [+2, +60] under seven alternative macroeconomic conditioning variables.

Macroeconomic variable	β_1 (SUE)	β_2 (Interaction)	p-value β_2
VIX (continuous, w1)	-0.096	+0.007	0.123
D_VIX > P75 dummy	-0.012	+0.203 **	0.006

D_VIX > P90 dummy	+0.023	+0.113	0.319
EPU (continuous, w1)	+0.003	+0.0003	0.467
HY credit spread (w1)	-0.040	+0.052	0.249
Yields 10Y (w1)	-0.127	+0.056 *	0.040
HY > P75 dummy	+0.027	+0.041	0.609

*The seven alternative macroeconomic conditioning variables replace the pre-registered D_VIX dummy in the H5 specification. The continuous VIX and EPU are winsorised at 1%/99% percentiles. The dummy thresholds (VIX > P75, VIX > P90, HY > P75) are computed annually. Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are double-clustered at the firm and calendar-quarter levels.*

Appendix G: H interactions on supplementary CAR windows

Table G.1: Interaction coefficient β_2 across five supplementary CAR windows for the five hypotheses.

Hypothesis	[-3, +3]	[0, +5]	[0, +10]	[+2, +120]	[+2, +250]
H1 Prox52WH	+0.121	+0.190	+0.195	+0.454	+0.518
H2 PB	-0.008 ***	-0.008 **	-0.008 **	-0.011	-0.020
H3 AbnVol	-0.057 *	-0.044	-0.035	+0.036	+0.081
H4 DA Kothari	-0.108	-0.054	-0.101	-1.438 ***	-1.915 ***
H5 D_VIX	+0.043	+0.057	+0.132	-0.018	-0.023

*The five supplementary CAR windows complement the five primary windows reported in Table 5.5 of the main body. They span the around-event ([-3, +3]), early post-event ([0, +5] and [0, +10]) and long-horizon ([+2, +120] and [+2, +250]) phases of the drift. Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are double-clustered at the firm and calendar-quarter levels.*

Appendix H: Pairwise correlations of the hypothesis variables

Table H.1: Pearson correlation coefficients between the five hypothesis variables and the earnings-surprise measure.

	Prox52WH	PB	AbnVol	DA Kothari	D_VIX	SUE_LM
Prox52WH	1.000	0.083	0.029	0.038	-0.227	-0.006
PB	0.083	1.000	0.012	-0.030	-0.031	0.004
AbnVol	0.029	0.012	1.000	0.009	0.018	-0.011
DA Kothari	0.038	-0.030	0.009	1.000	-0.008	0.037
D_VIX	-0.227	-0.031	0.018	-0.008	1.000	-0.000
SUE_LM	-0.006	0.004	-0.011	0.037	-0.000	1.000

Pearson correlation coefficients are computed on the post-correction sample described in Section 4.7. Pairwise complete observations are used. Variables are winsorised at the 1% and 99% percentiles, except D_VIX which is a binary indicator. The earnings-surprise measure (SUE_LM) is included for reference.

Appendix I: CAAR by discretionary-accruals quintile

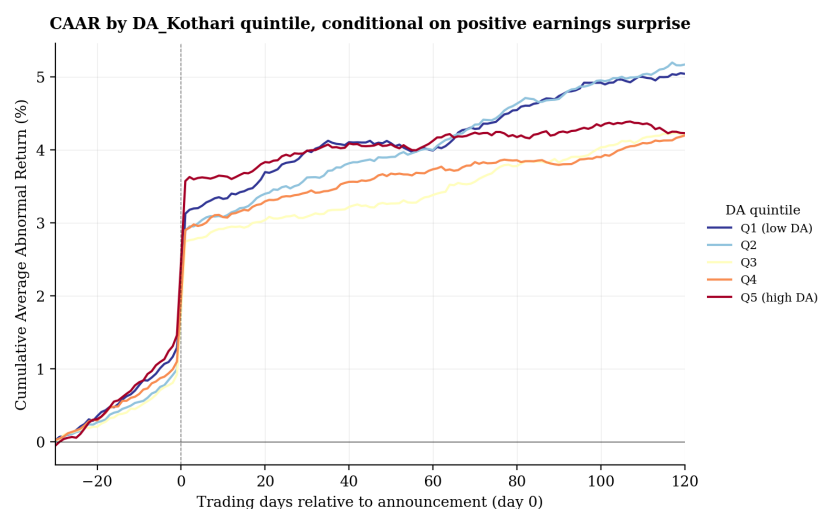


Figure I.1: Cumulative average abnormal returns from $t = -30$ to $t = +120$ trading days, by quintile of $DA_Kothari$, conditional on a positive earnings surprise ($SUE_LM > 0$). The vertical dashed line marks the announcement day. Quintile assignment is performed on the post-correction sample of approximately 88,600 events with a positive surprise and a valid $DA_Kothari$ value, with roughly 17,700 events per quintile.

Appendix J: Annual distribution of earnings announcements

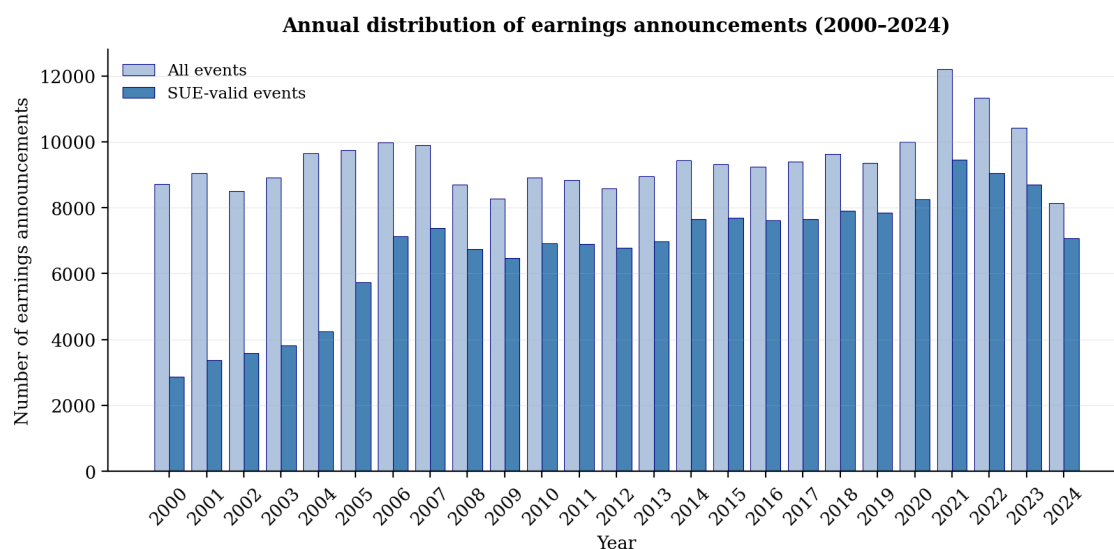


Figure J.1: Annual distribution of the post-correction sample, 2000–2024. The light-blue bars correspond to all events surviving the standard methodological filters of Section 4.2, while the dark-blue bars correspond to the subset for which the primary SUE_LM measure is non-missing. The sample is restricted to US common stocks listed on NYSE, AMEX or Nasdaq, excluding financial firms (SIC 6000–6999) and regulated utilities (SIC 4900–4999), with a share price at $T-1$ of at least three dollars in absolute value.

UNIVERSITÉ CATHOLIQUE DE LOUVAIN
Louvain School of Management

Place des Doyens, 1 bte L2.01.01, 1348 Louvain-la-Neuve
Boulevard Emile Devreux 6, 6000 Charleroi, Belgique
Chaussée de Binche 151, 7000 Mons, Belgique
www.uclouvain.be/lsm