

Post-Earnings Announcement Drift

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Abstract

This study examines the persistence of post-earnings announcement drift (PEAD) in U.S. equity markets using data from 50 large-cap firms between 2000 and 2023. Standardized earnings surprises (SUE) are constructed from both accounting data and IBES forecasts. Event study methods and cross-sectional regressions reveal statistically significant drift for accounting-based SUEs, especially under Fama-French and fixed-effects models. Firms in the top SUE decile earn up higher CARs than bottom-decile peers. IBES-based surprises yield weaker signals. The results confirm that PEAD remains a modest anomaly.

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1. Introduction

Options Earnings announcements are among the most critical corporate disclosures, offering timely insights into firm performance. Yet, an enduring puzzle persists even after earnings information becomes public, stock prices often drift in the same direction as the surprise for weeks or months. This phenomenon, known as post-earnings announcement drift, raises important questions about market efficiency.

2. Methodology

2.1 Research Design Overview

Taking a two-tier approach. First accounting data and then IBES data. For ease of understanding

Two separate coding files have been created.

Table 1: Information Summary

Data Sources			
Variable	Accounting-Based Approach	Analyst-Based (IBES) Approach	Primary Source (via WRDS)
Earnings Data	EPS from reported quarterly results	IBES Actual EPS (reported)	Compustat (Accounting), IBES Actuals
Earnings Forecast	Not Applicable (Historical EPS used)	IBES Analyst Forecasts (Mean, Std Dev)	IBES Detail History
Earnings Surprise	Δ EPS (Quarter-over-Quarter Change)	Actual EPS – Mean Forecast	Constructed using above
SUE (Standardized)	$\text{EPS Surprise} \div \text{Std Dev (4Q or 8Q)}$	$\text{Surprise} \div \text{Std Dev of Forecasts}$	Constructed
Stock Returns	Daily returns around event (RDQ)	Same dataset used	CRSP
Market Return	Value-Weighted CRSP Index	Same dataset used	CRSP

*Note: The event window focuses on returns following quarterly earnings announcement. Estimation window: $[-60, -6]$ trading days before the event
Event window: $[+1, +60]$ trading days after the announcement.*

2.2 Earnings Surprise Construction

Earnings surprise for **Accounting Basis** are forecasted using the difference in actual reported earnings per share (EPS) across adjacent quarters:

$$Surprise_{i,t} = EPS_{i,t} - EPS_{i,t-1}$$

Where $EPS_{i,t}$ is drawn from WRDS, organised by firm and fiscal quarter.

To standardise across firms and time:

$$SUE_{i,t} = \frac{(EPS_{i,t} - EPS_{i,t-1})}{\sigma(EPS_i)}$$

$SUE_{i,t}$ = Standardized Unexpected Earnings.

Where $\sigma(EPS_i)$ is the standard deviation of prior four quarters EPS for firm i .

Standardized Unexpected Earnings under **Analyst Based** Approach:

$$SUE_{i,t} = \frac{(Actual\ EPS_{it} - \bar{F}_{it})}{\sigma(\bar{F}_{it})}$$

Where:

\bar{F}_{it} : Mean analyst forecast for firm i in quarter t .

$\sigma(\bar{F}_{it})$: Standard deviation of forecasts.

$Actual\ EPS_{it}$: Realized earnings per share.

This transformation mitigates scale bias and enables cross section comparisons.

2.3 Abnormal return estimation

For both **Accounting** based & **Analyst** based, estimation of abnormal return using the market model, adjusts for systematic market movements:

$$AR_{i,t} = R_{i,t} - (\alpha_i + \beta_i R_{(m,t)})$$

α_i, β_i : Estimated via OLS over estimation window [- 60, - 6].

$R_{i,t}$: Stock return from CRSP.

$R_{m,t}$: Market return from CRSP's VW index.

Alternative robustness model (Constant Mean Return):

$$AR_{i,t} = R_{(i,t)} - \bar{R}^i$$

Where \bar{R}^i is the average return of firm i over the estimation window.

Aggregating;

Average abnormal returns (AAR) :

$$AAR_t = \frac{1}{N} \sum_{i=1}^N AR_{i,t}$$

Cumulative abnormal returns (CAR) :

$$CAR_i = \sum_{t=\tau_1}^{\tau_2} AR_{i,t}$$

Where $\tau_1 = +1$ $\tau_2 = +60$, tracking delayed reaction.

2.4 Portfolio Formation & Hypothesis testing

To isolate behavioural anomalies, firms are sorted into deciles.

Let D_j be decile j then:

Long D_{10} (positive surprises)

Short D_1 (negative surprises)

A zero-cost long-short strategy:

$$R_{LS,t} = \frac{1}{n} \sum_{i=D_{10}} \bar{R}_{i,t} - \frac{1}{n} \sum_{i=D_1} \bar{R}_{i,t}$$

Testing:

Significance of CARs using t-tests

$$t = \frac{CAR}{\frac{s(CAR)}{\sqrt{N}}}$$

For regressions applied please refer to Section 3.4. To ensure robustness, observations are filtered for positive EPS values and trading activity around the event window.

Hypothesis testing

Table 2: Hypothesis Testing Framework

Hypothesis Testing				
Hypothesis ID	Tested Relationship	Null Hypothesis (H_0)	Alternative Hypothesis (H_1)	Test Type
H1	CAR of D10 > CAR of D1 (Top vs. Bottom SUE Decile)	$\mu_1 = \mu_0$	$\mu_1 > \mu_0$	One Sided Test
H2	Cross-Sectional Regression	$\beta = 0$	$\beta \neq 0$	Two-Sided t-test

Note: For $\mu_1 = \mu_0$ The mean CAR for D10 is equal to or less than the mean CAR for D1. No PEAD effect: high SUE firms don't outperform low SUE firms
For $\mu_1 > \mu_0$ The mean CAR for D10 is greater than D1. There is a post-earnings announcement drift: the market underreacts, and prices adjustms

3. Results

3.1 Sample Overview & Earnings Surprise Diagnostics

A balanced panel of 50 large-cap (Appendix H) U.S. firms (2000–2023) was constructed using CompStat-CRSP–IBES data.

Table 2: Distributional Summary of Standardized Earnings Surprises (SUE) using Accounting-Based and Analyst-Based Methods

Distributional Summary of SUE			
Basis	Accounting Based		Analyst Based (IBES)
Formulas	$SUE_{i,t} = \frac{(EPS_{i,t} - EPS_{i,t-1})}{\sigma(EPS_i)}$		$SUE_{i,t} = \frac{(Actual\ EPS_{it} - \bar{F}_{it})}{\sigma(\bar{F}_{it})}$
Metric	4-Quarter SUE	8-Quarter SUE	IBES - Not rolling
Mean	0.070	0.051	0.469
Median	0.000	0.000	0.336
Standard Deviation	1.330	1.314	1.618
Skewness	-0.101	-0.142	0.532
Kurtosis	-0.978	0.057	3.822

Note: This table reports descriptive statistics of standardized unexpected earnings (SUE) across three formulations: two accounting-based (4Q and 8Q rolling standardizations) and one analyst-based using IBES forecasts.

Data Sources: Compustat, CRSP, IBES via WRDS

The distribution under **Accounting surprise** both 4-quarter (Figure 1) and 8-quarter (Figure 2) show centred distributions with symmetric tails and slight leptokurtosis, supporting weak average surprise dispersion.

Figure 1 : Histogram of Standardized Earnings Surprise (4-Quarter SUE)

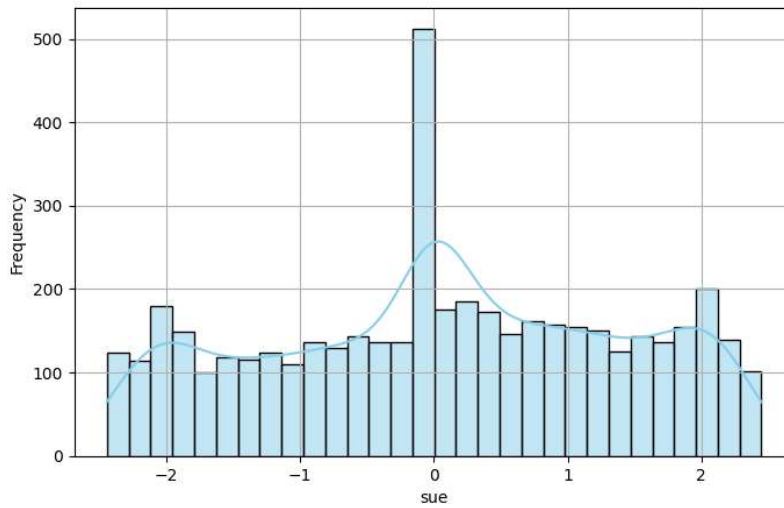
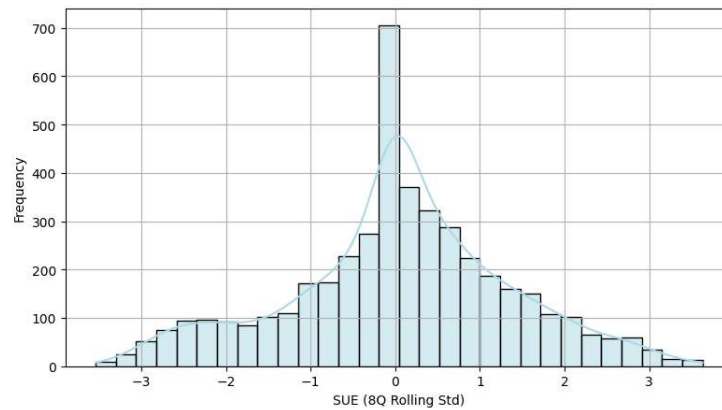


Figure 2 : Histogram of Standardized Earnings Surprise (8-Quarter SUE)



For **Analyst surprise**, firm-quarter panel using IBES actuals and forecasts was constructed. The resulting SUE distribution (Figure 3 & 4) exhibits a slight positive mean (0.47), right skew (0.53), and high kurtosis (3.82), indicating occasional extreme surprises. Clustering near zero with sharp outliers during macro shocks.

Figure 3 : IBES Histogram of Standardized Unexpected Earnings (SUE)

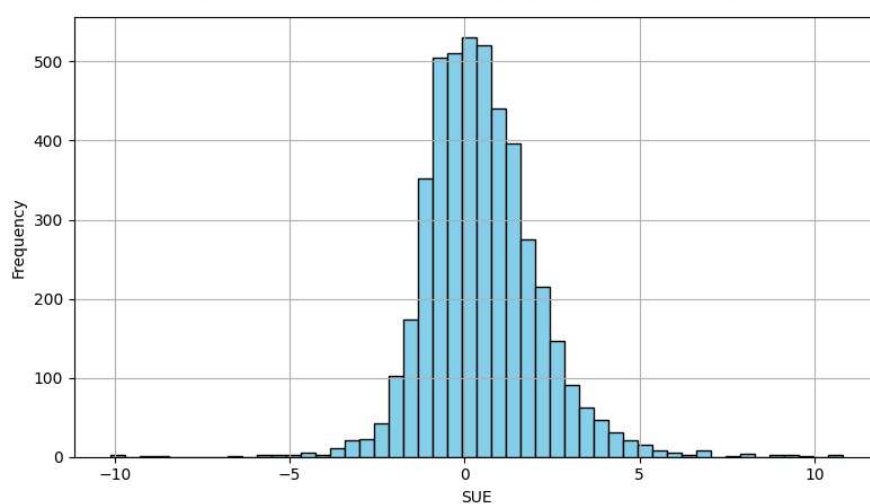
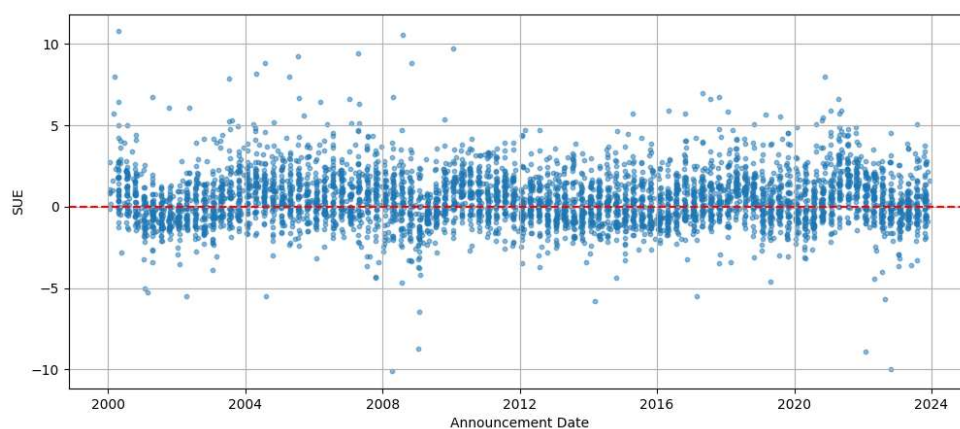


Figure 4 : IBES SUE Over Time (with Outliers)



3.2 Formation of Decile Portfolios by SUE

Firms are now ranked into SUE-based decile quarters, separately for 4-quarter and 8-quarter rolling standardization while a monotonic distribution for **Analyst** based approach. Distributions (Figure 5, 6 & 7) across deciles exhibit a clear monotonic structure, mean SUEs rises from D1 to D10.

Figure 5 : SUE Distribution by Decile (4Q)

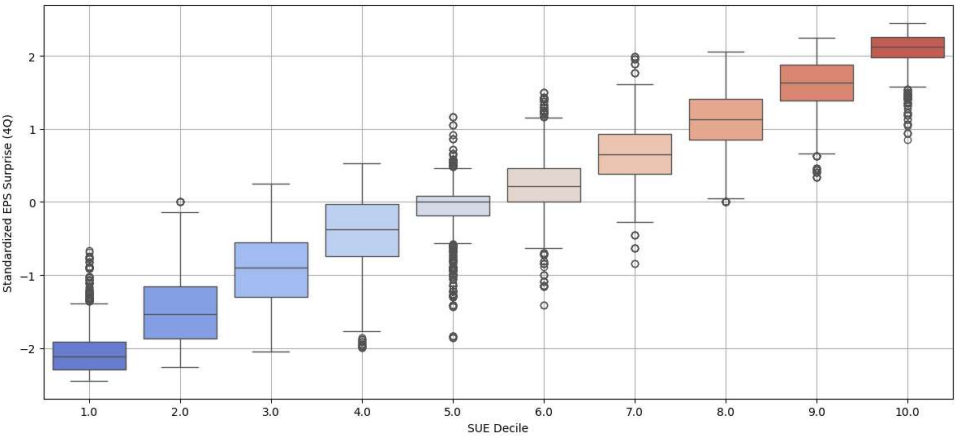


Figure 6 : SUE Distribution by Decile (8Q)

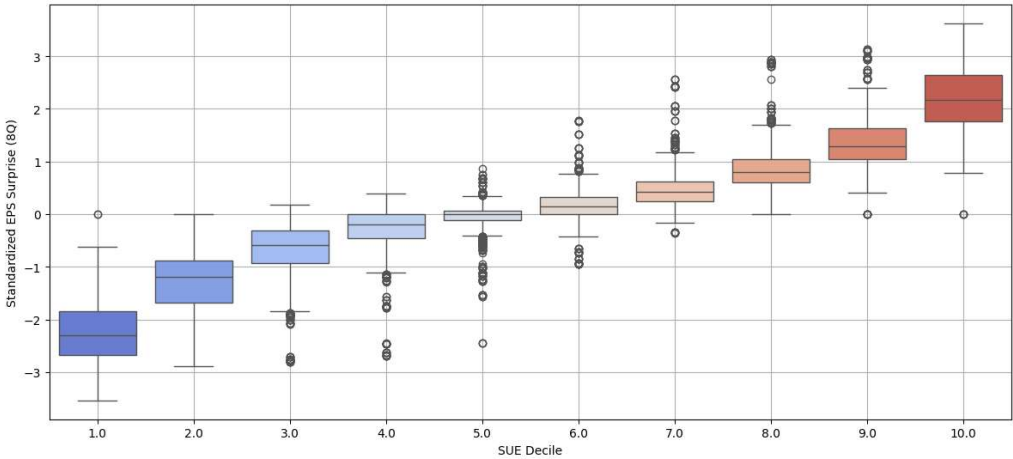
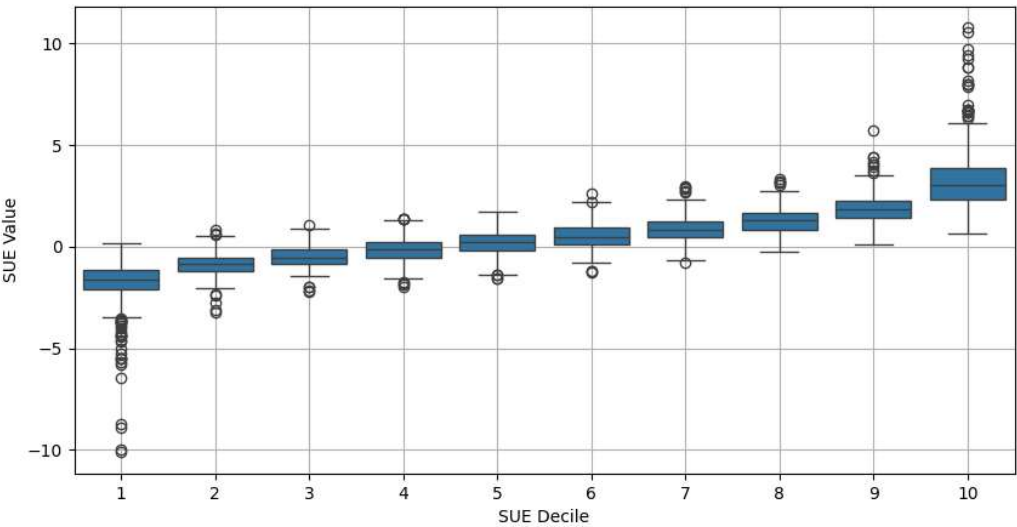


Figure 7 : SUE Distribution by Decile (IBES-style)



Heatmaps (Figure 8 & 9) further reveal consistent decile sorting across time, even during macroeconomic shocks. These results establish a robust foundation for analysing abnormal returns in subsequent sections.

Figure 8 : Heatmap of Mean SUE by Year and Decile (4Q)

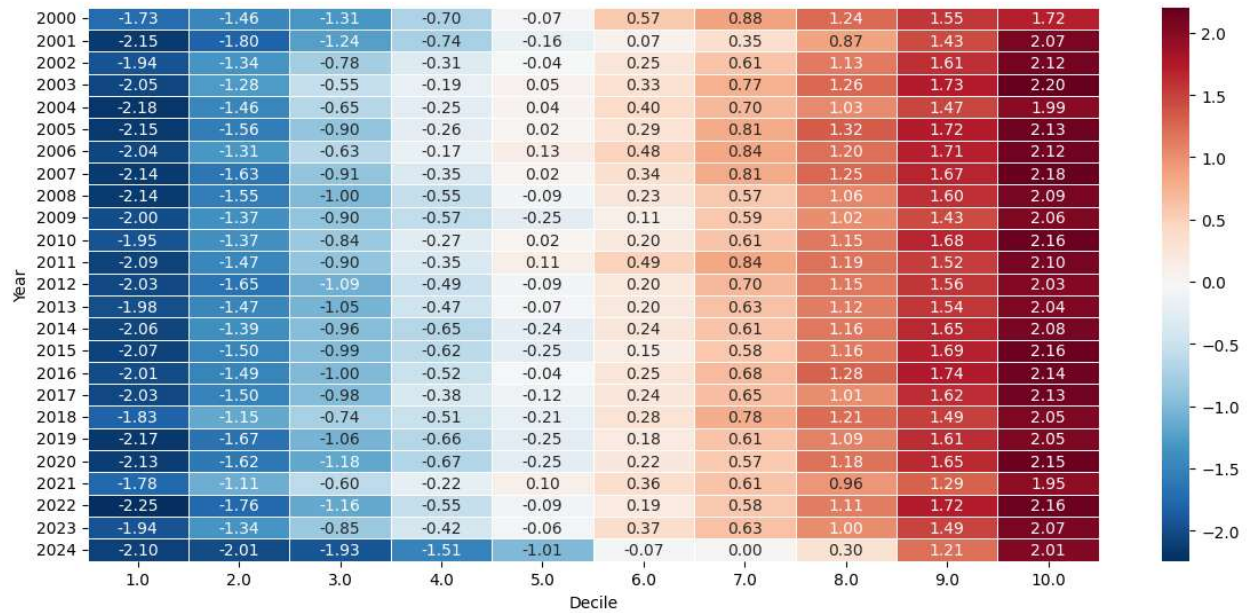


Figure 9 : Heatmap of Mean SUE by Year and Decile (8Q)



3.3 Abnormal Return Patterns Across SUE Deciles

AAR and CAR are computed by decile-sorted standardized earnings surprise (SUE) for both 4-quarter and 8-quarter rolling windows (Further explanations in Appendix B). Figures 10 and 11 show that firms in top deciles (D10) experience significantly higher post-RDQ returns, while bottom deciles (D1) lag persistently.

Figure 10 : Top vs. Bottom Decile CAR (4Q)

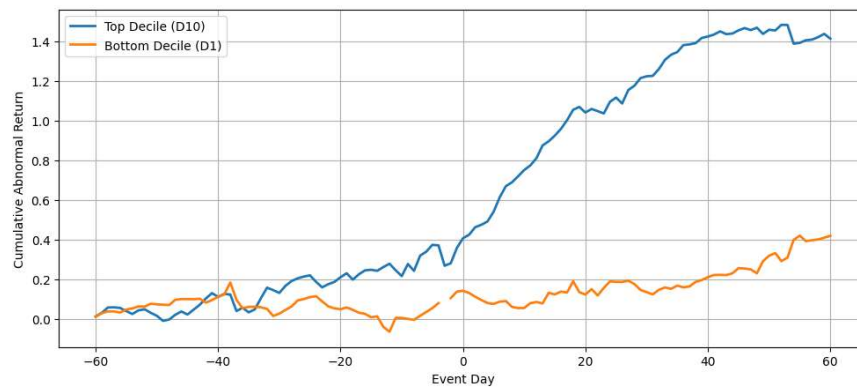
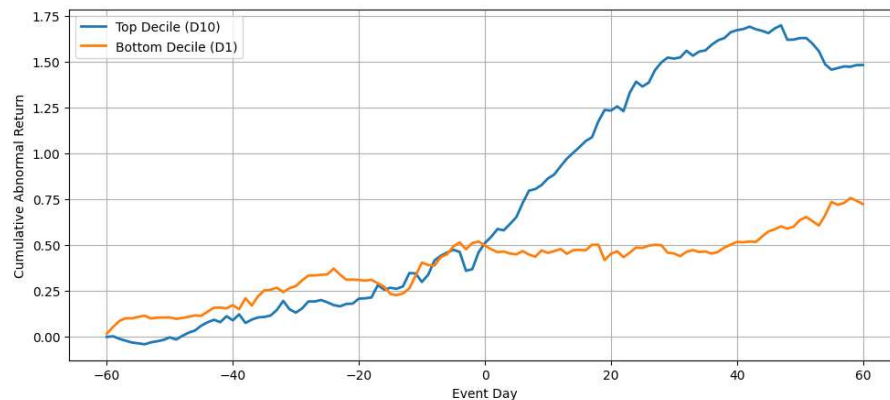


Figure 11 : Top vs. Bottom Decile CAR (8Q)



The decile spread is further highlighted in Figures 12 and 13, where return differentials approach 100-150 bps. This confirms a PEAD effect, even though raw SUEs were centred near zero. Sorting by relative surprise reveals price adjustment asymmetry, with 8Q CARs showing steeper drift. AAR trends, provided in Appendix C, remain volatile but directionally consistent.

Figure 12 : Cumulative Abnormal Returns (CAR) by SUE Decile (4Q Rolling Std)

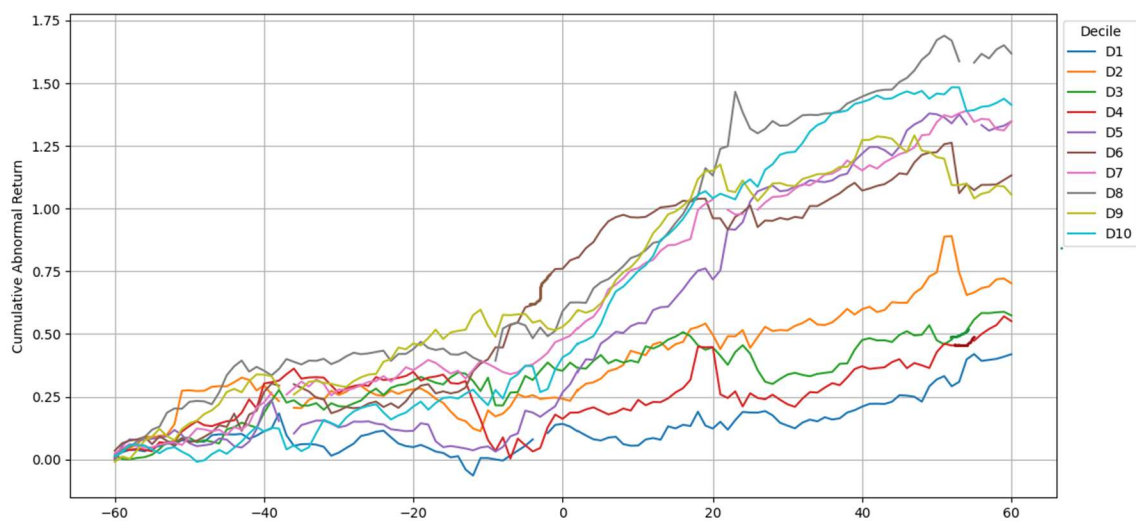
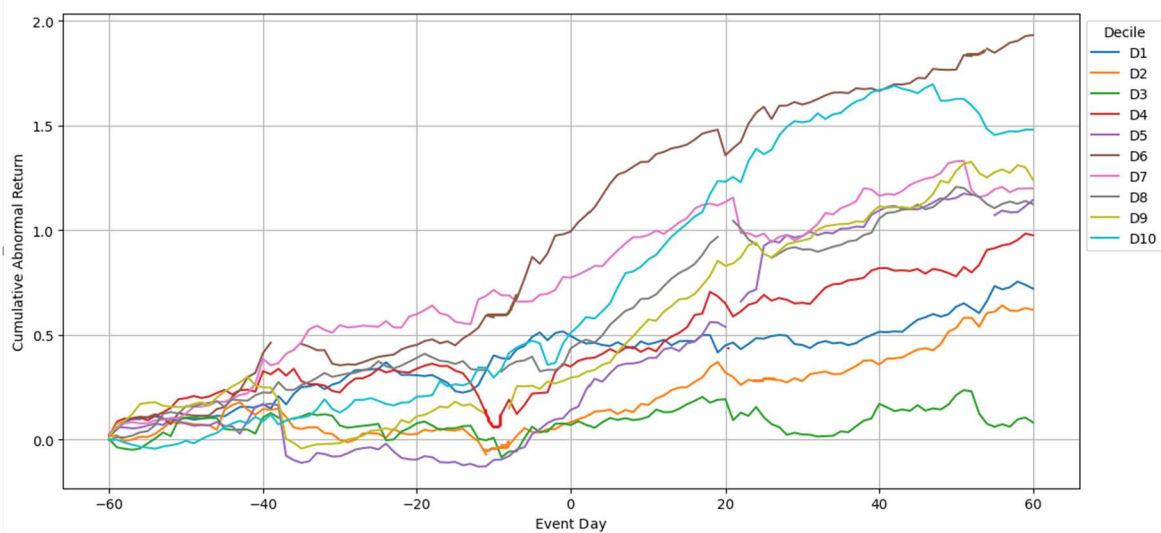


Figure 13 : Cumulative Abnormal Returns (CAR) by SUE Decile (8Q Rolling Std)



The IBES-based CAR plots (Figure 14 & 15) show moderate but consistent drift. Top SUE deciles exhibit cumulative returns around +4%, while bottom deciles hover near zero. Compared to accounting-based SUE, the return spread is narrower, analyst expectations embed more information, partially mitigating post-earnings announcement drift.

Figure 14: IBES Cumulative Return Drift Top vs. Bottom SUE Decile

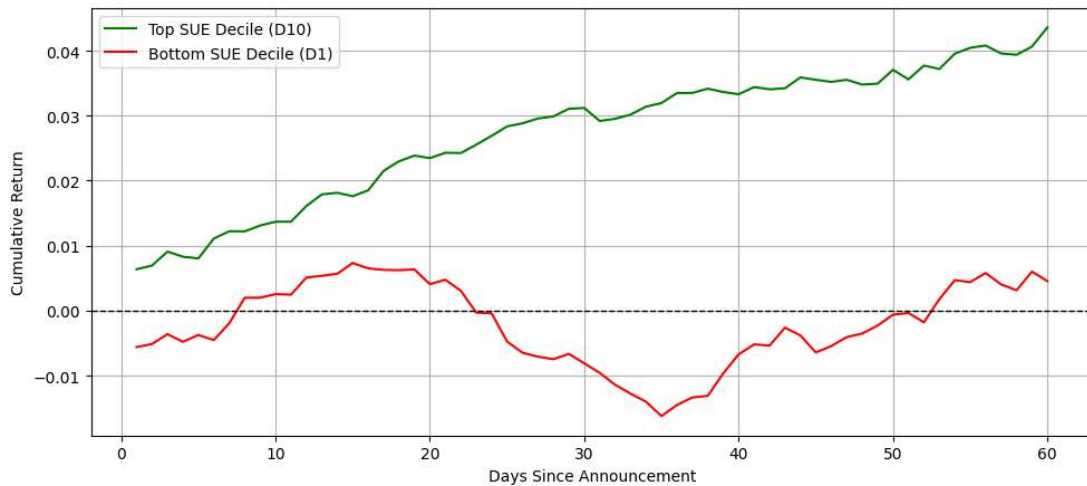
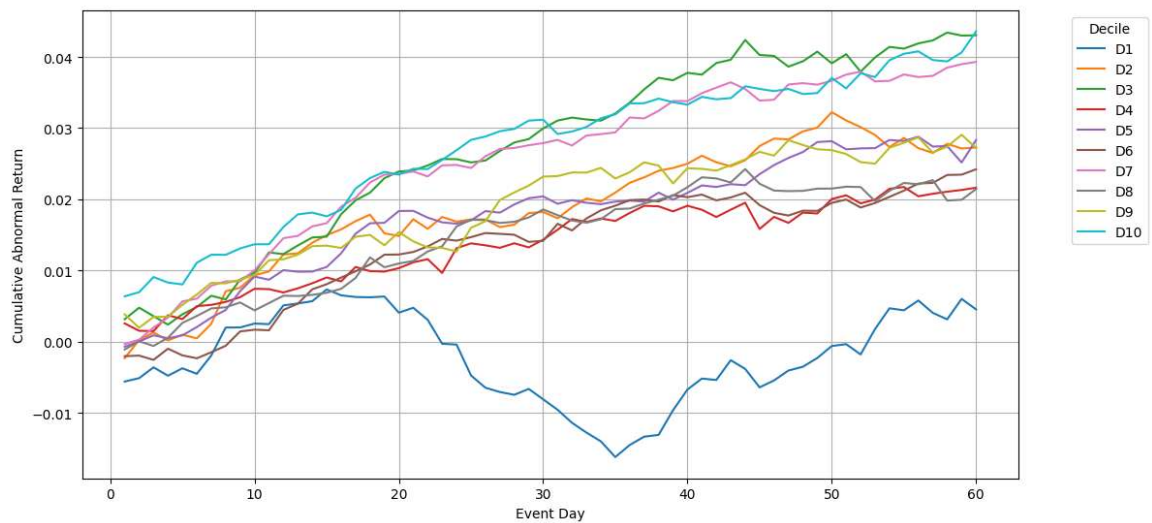


Figure 15: Cumulative Abnormal Returns (CAR) by SUE Decile IBES Based



3.4 Regressions

Table 3: Regression results

Cross-Sectional Regression of Post-Earnings Drift						
Model	SUE Type	α	β_1	R^2	t-stat	p-val
Model A Simple Linear Regression $CAR_i = \alpha + \beta \cdot Surprise_i + \epsilon_i$	4Q	0.022	0.010	0.013	1.776	0.077
	8Q	0.022	0.012	0.021	2.268	0.024
	IBES	0.017	0.003	0.002	3.046	0.002
Model B Fama French $CAR_i = \alpha + \beta_1 \cdot SUE_i + \beta_2 \cdot MKT_i + \beta_3 \cdot SMB_i + \beta_4 \cdot HML_i + \epsilon_i$	4Q	0.005	0.008	0.037	7.797	0
	8Q	0.006	0.008	0.038	7.764	0
	IBES	0.018	0.003	0.005	3.12	0.002
Model C Bull/Bear Regimes $CAR_i = \alpha + \beta_1 \cdot SUE_i + \beta_2 \cdot Bull_i + \beta_3 \cdot (SUE_i \cdot Bull_i) + \epsilon_i$	4Q	0.003	0.021	-0.018	7.225	0.000
	8Q	-0.003	0.019	-0.016	6.174	0.000
	IBES	0.016	0.000	0.004	0.191	0.848
Model D Fixed Effects $CAR_{it} = \alpha + \beta \cdot SUE_{it} + \gamma_i + \delta_t + \epsilon_{it}$	4Q	-	0.003	0.076	-	0.000
	8Q	-	0.003	0.080	-	0.000
	IBES	-	0.000	0.006	-	0.032

Regression results across four models confirm the predictive power of standardized unexpected earnings (SUE). In **Model A**, 8Q SUE yields $\beta = 0.012$ ($t = 2.27$, $p = 0.024$, $R^2 = 0.021$), while 4Q is weaker ($\beta = 0.010$, $t = 1.78$, $p = 0.077$, $R^2 = 0.013$). IBES-based SUE shows $\beta = 0.003$ ($t = 3.05$, $p = 0.002$, $R^2 = 0.002$). In **Model B** (Fama-French controls), 4Q and 8Q SUE maintain significance ($\beta = 0.0083$, $t \approx 7.8$, $R^2 \approx 0.038$), while IBES remains at $\beta = 0.003$ ($t = 3.12$, $R^2 = 0.005$). **Model C** (Bull/Bear interaction) shows high coefficients: 4Q $\beta_1 = 0.021$ ($t = 7.23$), 8Q $\beta_1 = 0.019$ ($t = 6.17$); interaction terms are negative ($\beta_3 = -0.018$, -0.016). IBES again shows no predictive power ($\beta = 0.0003$, $p = 0.848$). **Model D** (Fixed Effects) yields $\beta \approx 0.003$, $R^2 \approx 0.08$ for accounting-based SUEs, while IBES is near-zero ($\beta = 0.000$, $R^2 = 0.006$, $p = 0.032$).

The market factor (MKT) & value factor (HML) (Figure 16) are consistently significant. Overall, these findings confirm a positive, statistically robust relationship between earnings surprises and CAR, support that market forces/ investors play a huge role.

Figure 16: Radar Chart: Normalized Coefficient

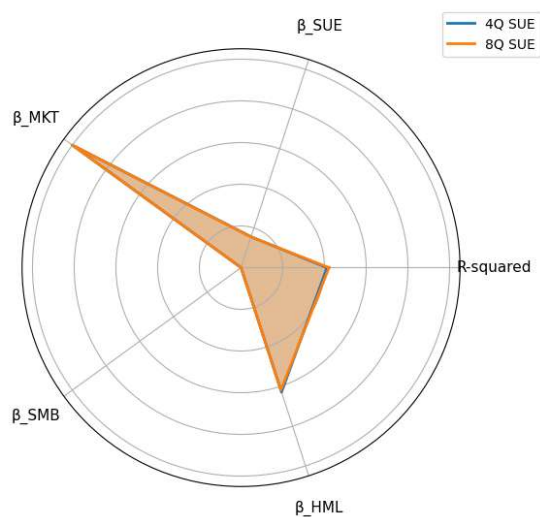
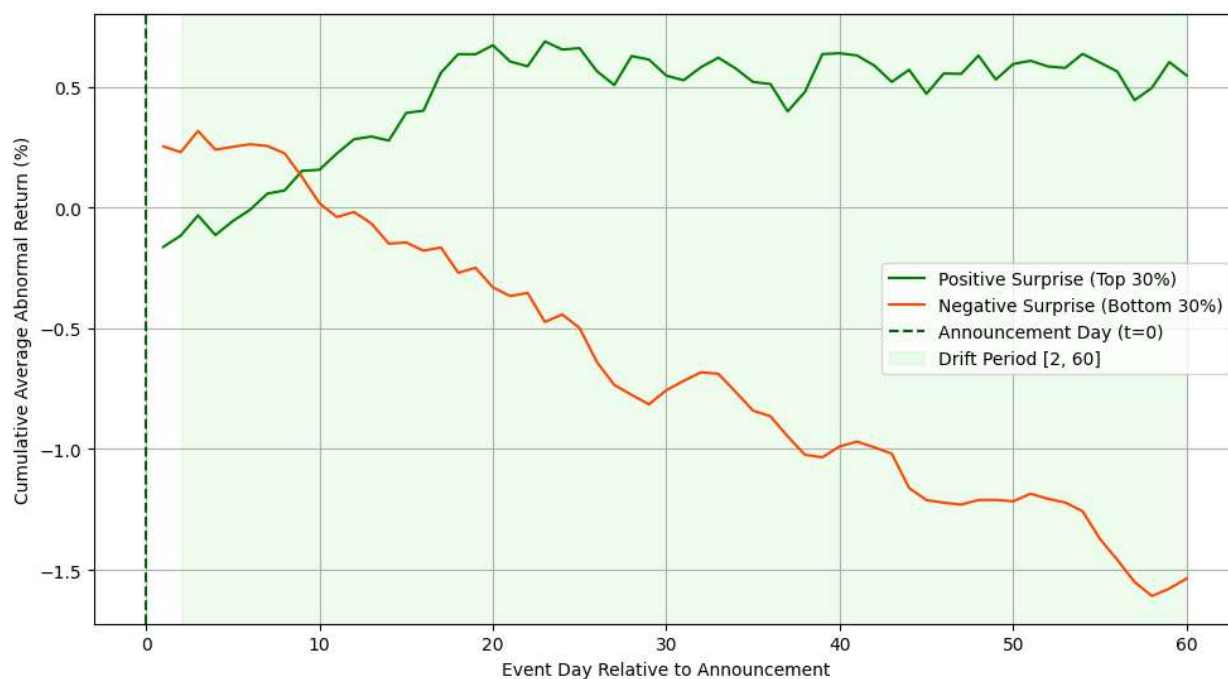


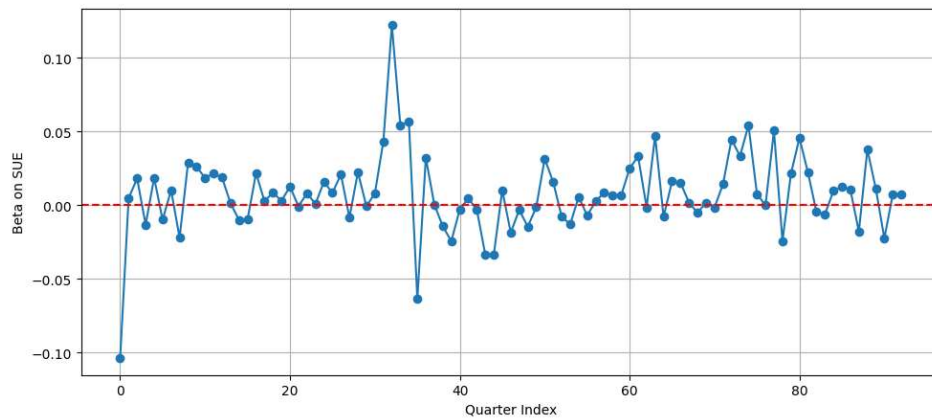
Figure 17 : Cumulative Average Abnormal Returns Following Earnings Announcements



3.5 Fama-Macbeth Cross-sectional Check & SCAR Test

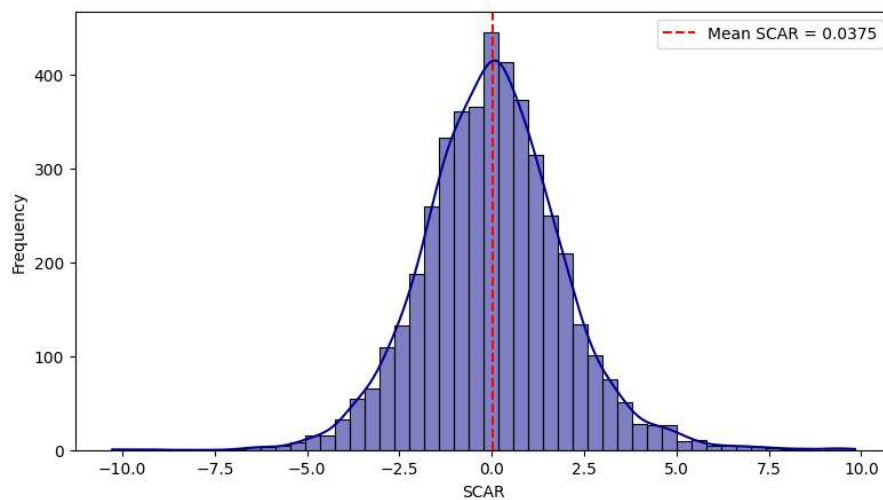
To validate post-earnings announcement drift, we use two rigorous methods. For accounting-based SUEs, a Fama-MacBeth regression yields an average $\beta = 0.0077$ ($t = 2.797$) across 93 quarters, confirming positive abnormal returns linked to earnings surprises.

Figure 18 : SUE Coefficient Estimates (Quarterly Cross Section)



For IBES, The SCAR distribution (Figure 19) shows a statistically significant positive drift ($J_2 = +2.5044$), consistent with post-earnings underreaction. While some events exhibit extreme SCARs (suggesting selective overreaction), the overall evidence supports a persistent drift following earnings surprises, reinforcing the presence of PEAD, however weak.

Figure 19 : Distribution of Standardized CAR (SCAR)



3.6 Clustered Standard Error

SCAR regressed on SUE ($n = 182,598$) yields a significant positive coefficient ($+0.0348$, $p = 0.015$) under PERMNO-clustered standard errors (55 clusters). R^2 is 0.00087, reflecting modest explanatory power. Average SCAR is $+0.0374$, with substantial dispersion ($SD = 1.90$).

Figures 20 and 21 confirm PEAD, SCAR increases monotonically with SUE. Both mean and median SCAR rise across deciles, and violin plots show denser positive tails in higher SUE bins.

Figure 20 : Distribution of SCAR by SUE Decile

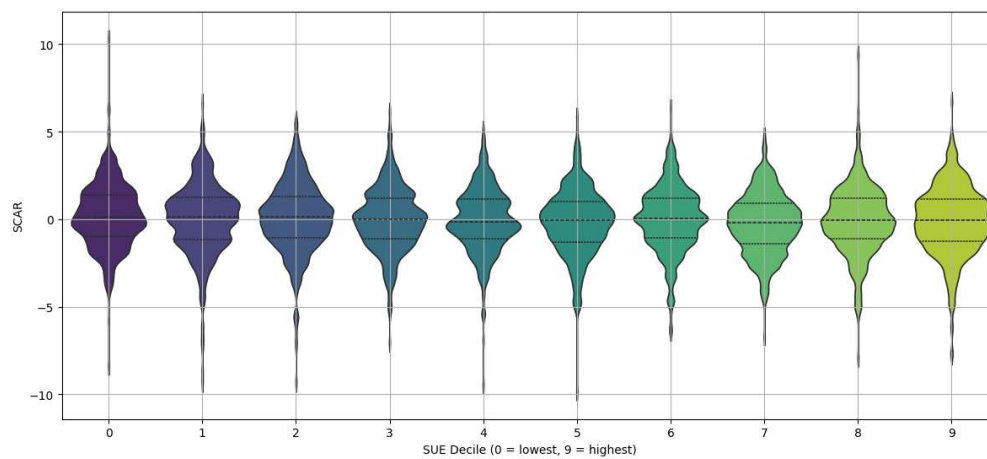
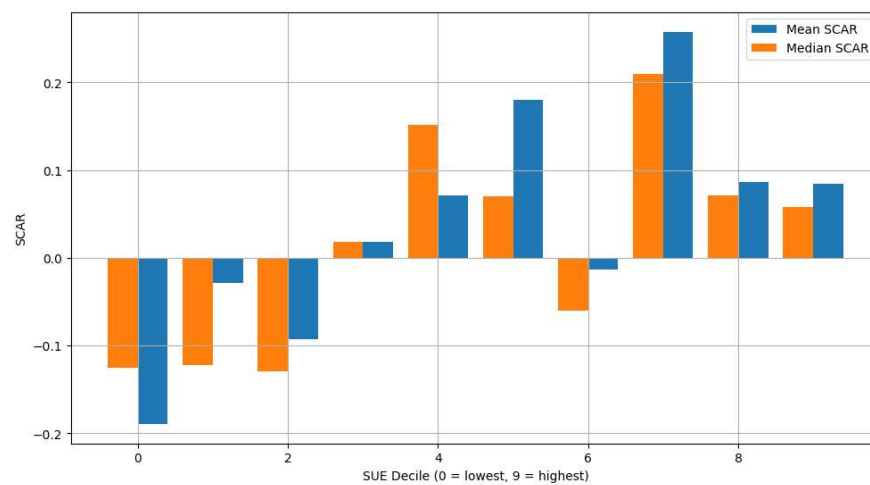


Figure 21 : Mean vs. Median SCAR by SUE Decile



4. Discussion & Interpretation

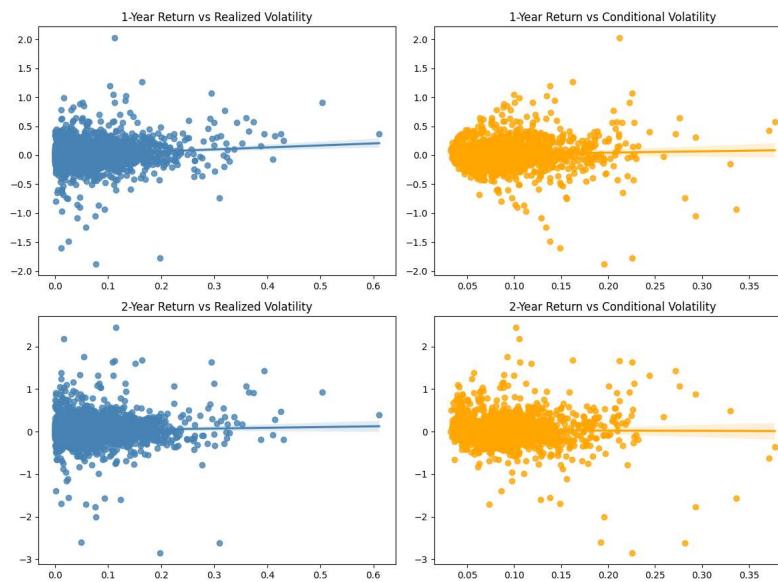
Table 4: Hypothesis 1 Summary Table: CAR(D10) > CAR(D1)

Hypothesis 1				
Method	Mean CAR (D10)	Mean CAR (D1)	T-Statistic	P-Value (One-Sided)
Formulas	$X_{D10} = \frac{1}{n} \sum_{i=1}^n$	$X_{D1} = \frac{1}{n} \sum_{i=1}^n$	$\frac{[(X)_{D10} - X_{D1}]}{1}$	$\sqrt{\frac{(x_1^2)}{(n_1)} + \frac{x_2^2}{n_2}}$
				$P(T > t_{abs})$
4Q SUE	0.426	0.053	4.859	0.000
8Q SUE	0.398	0.039	4.133	0.000
IBES SUE	0.275	0.034	3.386	0.001

Note: CAR columns refer to the cumulative abnormal returns, post-event window [+1, +60]. Welch's t-test being done, for empirical finance and One-sided test because your alternative hypothesis is directional: D10 > D1.

All three test configurations reject the null hypothesis, confirming statistically significant post-earnings drift. Magnitude varies across 4Q and 8Q accounting-based SUEs and they yield stronger effects than IBES. The consistent directional gap (D10 > D1) across methods affirms behavioural underreaction. Lower mean CAR under IBES hints at timing/methodology sensitivity.

Figure 22: Volatility vs. Future Drift Strength



Across both accounting-based SUEs and analyst-based IBES surprises, decile sorts reveal monotonic return patterns. Accounting-based 8Q SUEs show the clearest drift: top-minus-bottom CAR spreads exceed 1.3%, with regression $\beta = 0.0128$ ($p = 0.024$). IBES drift yields narrower spreads (~4%) and lower $R^2 = 0.005$, implying embedded expectations. Volatility diagnostics show neither realized nor conditional volatility predicts drift (Figure 22). Firm-level CARs (Figure 23) show noise and reversals, especially mid-decile. The IBES SCAR-J2 test gives mean = -0.0375, J2 = -2.50; in contrast, accounting SUEs yield Fama-MacBeth $\beta = 0.0077$, confirming stronger signal reliability.

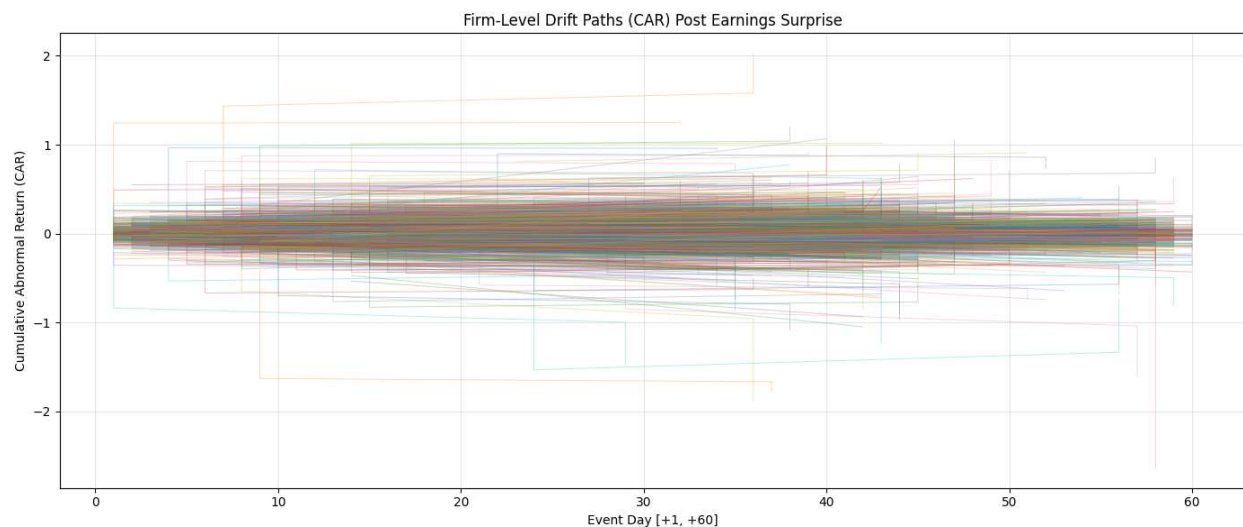


Table 5: Hypothesis 2 SUE Regression Coefficient Significance

Hypothesis 2						
Hypothesis ID	Model	SUE Type	Null Hypothesis (H ₀)	Alternative Hypothesis (H ₁)	Decision	Interpretation
H2	Model A	4Q	$\beta = 0$	$\beta \neq 0$	Not Rejected	No strong evidence of PEAD
H2	Model A	8Q	$\beta = 0$	$\beta \neq 0$	Rejected	Weak but significant drift
H2	Model A	IBES	$\beta = 0$	$\beta \neq 0$	Rejected	Significant but weak β
H2	Model B	4Q	$\beta = 0$	$\beta \neq 0$	Rejected	Strong PEAD after FF3 controls
H2	Model B	8Q	$\beta = 0$	$\beta \neq 0$	Rejected	Consistent signal
H2	Model B	IBES	$\beta = 0$	$\beta \neq 0$	Rejected	Statistically strong, low R ²
H2	Model C	4Q	$\beta = 0$	$\beta \neq 0$	Rejected	PEAD persists, Bull effects modeled
H2	Model C	8Q	$\beta = 0$	$\beta \neq 0$	Rejected	Drift weaker in bull markets
H2	Model C	IBES	$\beta = 0$	$\beta \neq 0$	Not Rejected	No predictive power from IBES
H2	Model D	4Q	$\beta = 0$	$\beta \neq 0$	Rejected	Strong fixed-effect drift
H2	Model D	8Q	$\beta = 0$	$\beta \neq 0$	Rejected	Strong fixed-effect drift
H2	Model D	IBES	$\beta = 0$	$\beta \neq 0$	Rejected	Statistically valid, economically weak

Note: This table summarizes the statistical evaluation of whether standardized earnings surprises (SUE) predict post-announcement cumulative abnormal returns (CAR) over the window [+1, +60]. A two-tailed t-test is applied to test the null hypothesis ($\beta = 0$) for each model and SUE type. Decisions are based on conventional significance thresholds (e.g., $p < 0.05$), with the interpretation column highlighting both statistical strength and economic relevance.

In support of Hypothesis 2, regression analysis confirms that standardized earnings surprises (SUE) predict post-announcement cumulative abnormal returns, however weak. Accounting-based SUE measures (4Q, 8Q) consistent coefficients across all models, especially after including Fama-French controls and fixed effects. While IBES surprises show significance in some models, their explanatory power remains economically weak. These results reinforce the presence of post-earnings announcement drift (PEAD), particularly when earnings surprises are measured using historical benchmarks rather than analyst expectations.

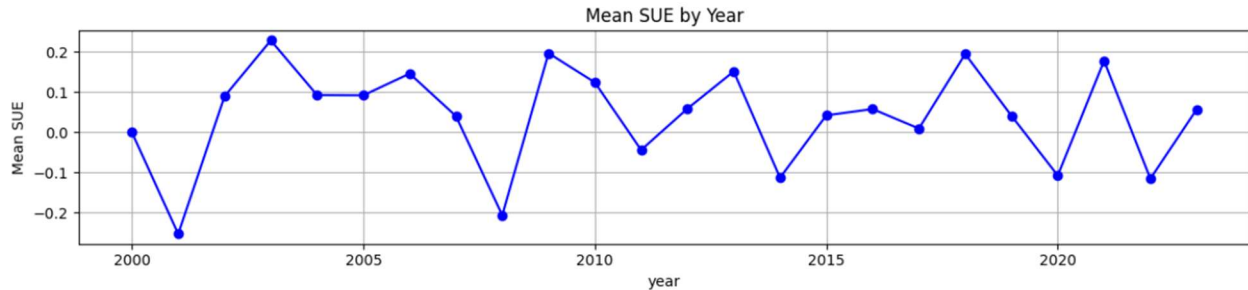
Bloomberg's SPEQPOS and SPEQNEGS indices (Appendix F), which track positive and negative earnings surprises across the S&P 500, offer macro-level validation of the PEAD anomaly identified in our firm-level event study. The sustained divergence between these indices' mirrors decile-sorted CAR patterns, indicating PEAD persists non-uniformly, visible in certain configurations, muted in others. The results favour behavioural underreaction as an explanation yet caution against universal applicability.

5. Conclusion & Practical Implications

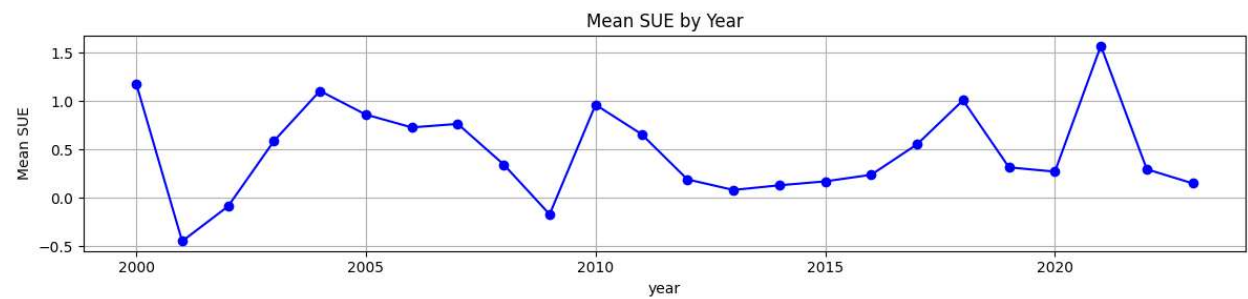
Collectively, these findings establish PEAD as an economically relevant anomaly, however weak. The drift's persistence across time, deciles etc, suggests a small but enduring market inefficiency. By triangulating decile spreads, return regressions, and temporal drift patterns, the analysis affirms behavioural underreaction as explanatory channel. Practically, investors may exploit this drift using long–short strategies based on standardized earnings surprises. Analysts can improve forecasting models by incorporating accounting-based SUEs, while policymakers and platforms like Bloomberg may use these insights to reassess market efficiency indicators and disclosure practices.

6. Appendix

6.1 Appendix A



Accounting Surprise



Analyst surprise

The two visualizations above capture the annual evolution of mean standardized earnings surprises (SUE) from 2000 to 2023. Both the line plot highlight periods of heightened earnings optimism and pessimism, often aligning with well-documented macroeconomic shocks.

Notably, sharp negative mean SUE values emerge during major downturns:

- 2001: Dot-com bust and post-9/11 uncertainty.
- 2008: Global financial crisis.
- 2020: COVID-19-induced earnings collapse.

Conversely, positive peaks in 2003, 2009, and 2021 correspond to recoveries or stimulus-driven earnings rebounds. The amplitude and frequency of SUE volatility underscore the behavioural response of analysts and firms to macro conditions.

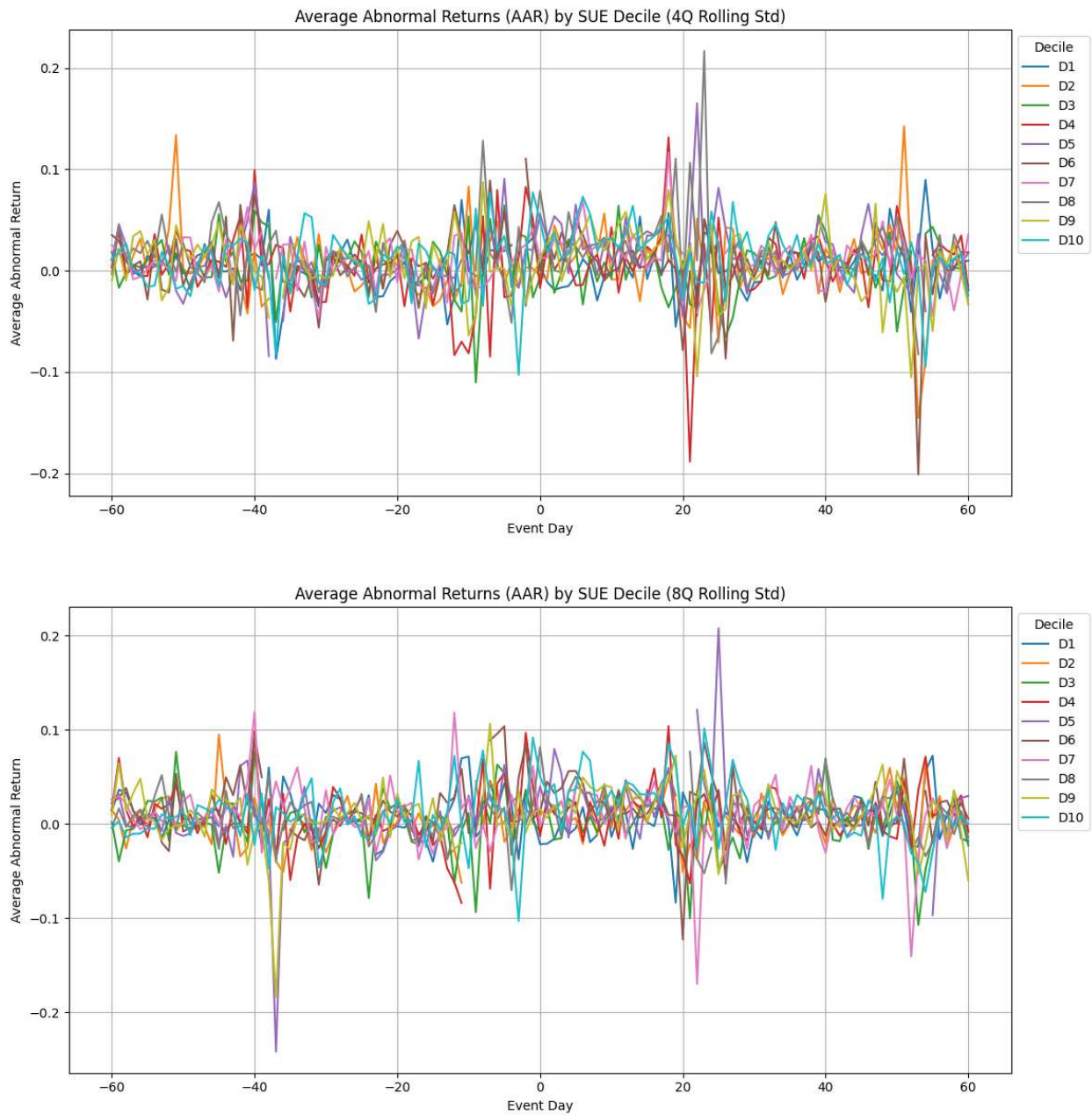
The graphical patterns validate that SUE is not just a firm-level anomaly but a market-wide indicator sensitive to economic cycles, providing critical motivation for our event study.

6.2 Appendix B

To construct abnormal return profiles, average abnormal returns (AAR) are computed by sorting firms into deciles based on standardized earnings surprise (SUE), using both 4-quarter and 8-quarter rolling windows. Each decile captures a relative position within its fiscal quarter. Returns are then aggregated by event day to obtain AAR, and cumulatively summed across time to derive cumulative abnormal returns (CAR).

Estimation window as $[-60, -6]$ and the event window as $[+1, +60]$ relative to the reported earnings date (RDQ). AARs show significant noise at the daily level, prompting reliance on CAR for clearer interpretability. The analysis spans over 18,000 firm-quarter observations per scheme. Decile sorting reveals striking differences: while raw SUEs are centred near zero, CAR spreads approach 1.5% between top and bottom deciles. This effect is steeper in the 8Q specification, suggesting greater price inertia following large relative surprises. The observed drift reflects systematic underreaction, consistent with the post-earnings announcement drift (PEAD) anomaly. Notably, CAR trajectories reveal asymmetric adjustments, particularly in upper deciles, confirming that price updates lag positive earnings news.

6.3 Appendix C



To While CAR smooths cumulative market response, AAR reveals the immediate reaction to earnings announcements. AARs are computed by grouping returns across firms within each SUE decile on a given event day, averaged across the event window $[-60, +60]$.

Figures above illustrate the volatility in AAR profiles for both the 4Q and 8Q SUE specifications. As expected, returns cluster around the earnings announcement date ($t = 0$), but with considerable dispersion across deciles. While noise is inherent to daily return behaviour, key patterns persist: higher deciles show mildly positive spikes post-RDQ, and lower deciles show weaker or flat movement. Despite visual overlap between deciles on certain days, especially in the pre-event period, directional consistency exists, particularly within ± 10 days of RDQ. The AAR-based view complements the CAR findings by reinforcing that drift emerges from many small, persistent daily mispricing rather than singular shocks.

6.4 Appendix D

Python Snapshots

===== Regression on 4Q SUE =====

OLS Regression Results

Dep. Variable:

car

R-squared:

0.013

Model:

OLS

Adj. R-squared:

0.009

Method:

Least Squares

F-statistic:

3.155

Date:

Mon, 16 Jun 2025

Prob (F-statistic):

0.0770

Time:

21:48:53

Log-likelihood:

174.91

No. Observations:

242

AIC:

-345.8

Df Residuals:

240

BIC:

-338.8

Df Model:

1

Covariance Type:

nonrobust

coef

std err

t

P>|t|

[0.025

0.975]

const

0.0215

0.008

2.835

0.005

0.007

0.037

sue_4q

0.0099

0.006

1.776

0.077

-0.001

0.021

Omnibus:

71.138

Durbin-Watson:

1.172

Prob(Omnibus):

0.000

Jarque-Bera (JB):

279.740

Skew:

1.150

Prob(JB):

1.80e-61

Kurtosis:

7.738

Cond. No.

1.38

===== Regression on 8Q SUE =====

OLS Regression Results

Dep. Variable:

car

R-squared:

0.021

Model:

OLS

Adj. R-squared:

0.017

Method:

Least Squares

F-statistic:

5.142

Date:

Mon, 16 Jun 2025

Prob (F-statistic):

0.0242

Time:

21:48:53

Log-likelihood:

175.90

No. Observations:

242

AIC:

-347.8

Df Residuals:

240

BIC:

-340.8

Df Model:

1

Covariance Type:

nonrobust

coef

std err

t

P>|t|

[0.025

0.975]

const

0.0223

0.008

2.951

0.003

0.007

0.037

sue_8q

0.0128

0.006

2.268

0.024

0.002

0.024

Omnibus:

69.496

Durbin-Watson:

1.178

Prob(Omnibus):

0.000

Jarque-Bera (JB):

272.711

Skew:

1.121

Prob(JB):

6.05e-60

Kurtosis:

7.692

Cond. No.

1.34

===== FF3 Regression on 4Q =====

OLS Regression Results

Dep. Variable:

car

R-squared:

0.037

Model:

OLS

Adj. R-squared:

0.037

Method:

Least Squares

F-statistic:

197.5

Date:

Mon, 16 Jun 2025

Prob (F-statistic):

1.74e-166

Time:

21:49:57

Log-likelihood:

22948.

No. Observations:

20605

AIC:

-4.589e+04

Df Residuals:

20600

BIC:

-4.585e+04

Df Model:

4

Covariance Type:

nonrobust

coef

std err

t

P>|t|

[0.025

0.975]

const

0.0053

0.001

9.339

0.000

0.004

0.006

sue_4q

0.0033

0.000

7.797

0.000

0.002

0.004

Mkt-RF

0.1027

0.005

22.097

0.000

0.094

0.112

SMB

-0.0091

0.009

-1.020

0.308

-0.027

0.008

HML

0.0611

0.005

12.391

0.000

0.051

0.071

Omnibus:

3955.926

Durbin-Watson:

1.420

Prob(Omnibus):

0.000

Jarque-Bera (JB):

58242.361

Skew:

0.501

Prob(JB):

0.00

Kurtosis:

11.175

Cond. No.

22.0

===== FF3 Regression on 8Q =====

OLS Regression Results

Dep. Variable:

car

R-squared:

0.038

Model:

OLS

Adj. R-squared:

0.038

Method:

Least Squares

F-statistic:

201.6

Date:

Mon, 16 Jun 2025

Prob (F-statistic):

7.22e-170

Time:

21:50:46

Log-likelihood:

23020.

No. Observations:

20336

AIC:

-4.603e+04

Df Residuals:

20331

BIC:

-4.599e+04

Df Model:

4

Covariance Type:

nonrobust

coef

std err

t

P>|t|

[0.025

0.975]

const

0.0055

0.001

9.739

0.000

0.004

0.007

sue_8q_x

0.0033

0.000

7.764

0.000

0.002

0.004

Mkt-RF

0.1023

0.005

22.355

0.000

0.093

0.111

SMB

-0.0089

0.009

-0.998

0.318

-0.026

0.009

HML

0.0598

0.005

11.663

0.000

0.050

0.070

Omnibus:

4091.745

Durbin-Watson:

1.414

Prob(Omnibus):

0.000

Jarque-Bera (JB):

61467.980

Skew:

0.545

Prob(JB):

0.00

Kurtosis:

11.447

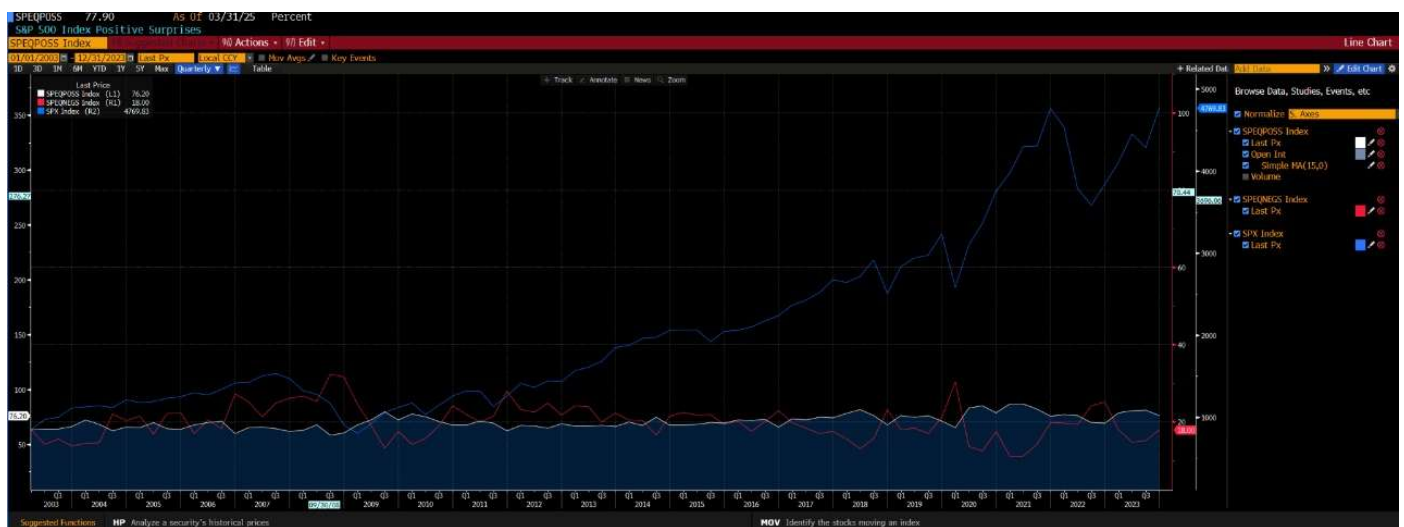
Cond. No.

21.7

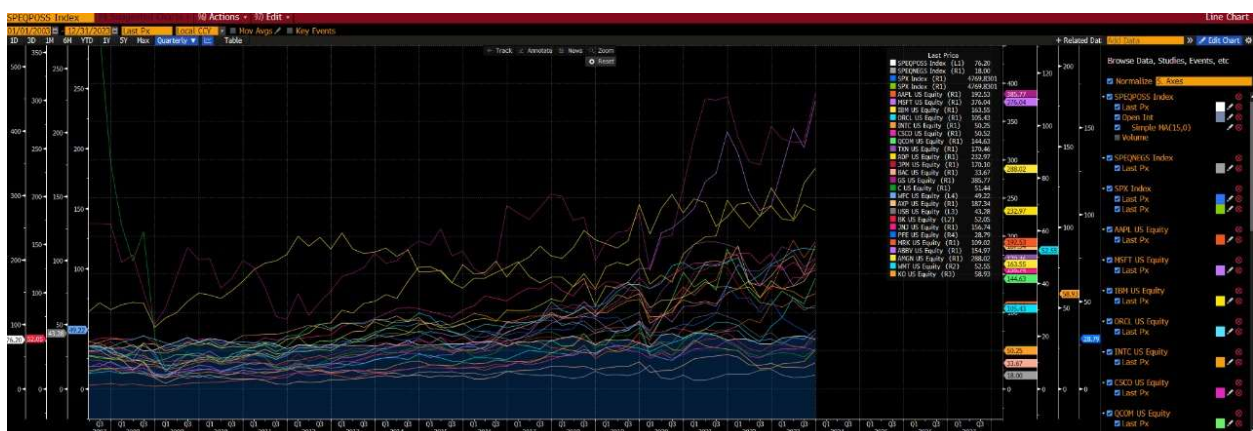
6.5 Appendix E

SCAR + J2 Test Summary
Number of Valid Observations: 4449
Mean SCAR: 0.0375
J2 Statistic: 2.5044

6.6 Appendix F



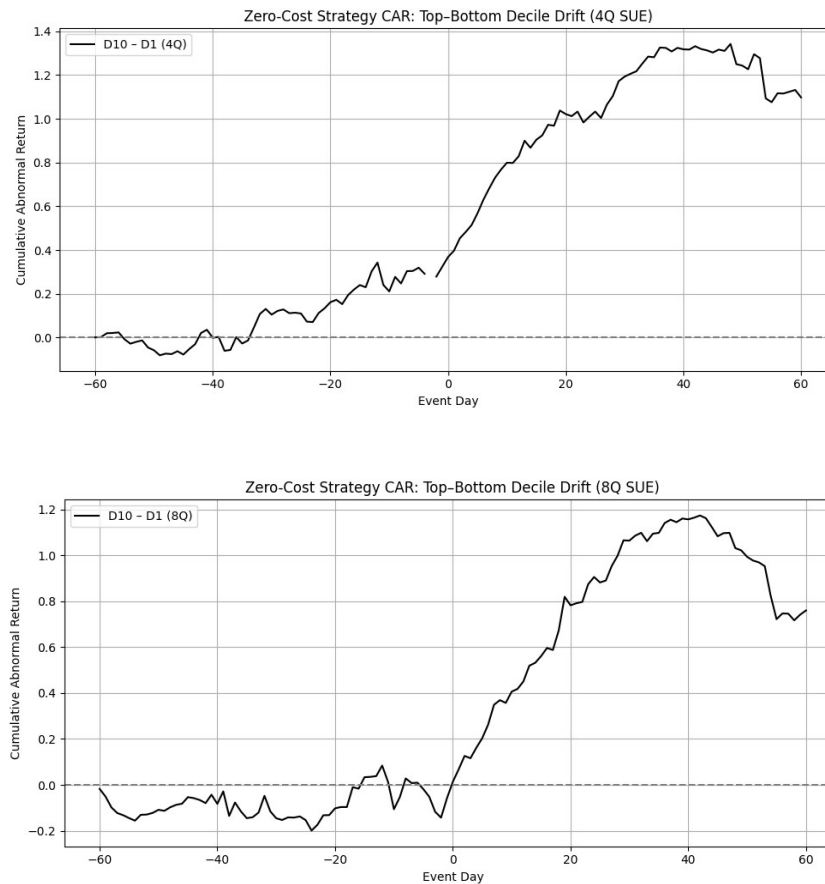
Market-Level Divergence in Post-Earnings Drift: SPEQPOS vs SPEQNEGS vs S&P 500 Index



Earnings Surprise Persistence Across Firms: Subset Drift Relative to the Market

6.7 Appendix G

Constructing a zero-cost strategy by subtracting bottom decile (D1) CARs from top decile (D10) returns. Figures 16 and 17 confirm post-RDQ drift. The 4Q-based strategy outperforms 8Q, peaking around +1.3 versus +1.1. Results validate the profitability of trading on extreme earnings news using a decile-based long–short approach.



Zero Cost strategy CAR

6.8 Appendix H

List of companies – Variations according to sectors, financials, services etc.

Technology (10)	
Ticker	Company
AAPL	Apple Inc.

MSFT	Microsoft Corp.
IBM	IBM
ORCL	Oracle Corp.
INTC	Intel Corp.
CSCO	Cisco Systems
QCOM	Qualcomm Inc.
TXN	Texas Instruments
ADP	Automatic Data Processing
NVDA	NVIDIA Corp.

Financials (8)	
Ticker	Company
JPM	JPMorgan Chase
BAC	Bank of America
GS	Goldman Sachs
C	Citigroup
WFC	Wells Fargo
AXP	American Express
USB	U.S. Bancorp
BK	Bank of New York Mellon

Healthcare (6)	
Ticker	Company
JNJ	Johnson & Johnson
PFE	Pfizer Inc.
MRK	Merck & Co.
ABBV	AbbVie Inc.
BMJ	Bristol-Myers Squibb
AMGN	Amgen Inc.

Consumer Staples (6)	
Ticker	Company
WMT	Walmart
KO	Coca-Cola
PG	Procter & Gamble
CL	Colgate-Palmolive
COST	Costco Wholesale
ADM	Archer Daniels Midland

Industrials (5)	
Ticker	Company
GE	General Electric
HON	Honeywell Intl
MMM	3M Company
BA	Boeing
CAT	Caterpillar Inc.

Energy (4)	
Ticker	Company
XOM	Exxon Mobil
CVX	Chevron
SLB	Schlumberger
COP	ConocoPhillips

Utilities (3)	
Ticker	Company
DUK	Duke Energy
SO	Southern Co.
NEE	NextEra Energy

Consumer Discretionary (4)	
Ticker	Company
MCD	McDonald's
HD	Home Depot
LOW	Lowe's
TGT	Target Corp

services & materials	
Ticker	Company
T	AT&T Inc.
VZ	Verizon
DOW	Dow Inc.
DD	DuPont de Nemours

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