FBE 551 - FINAL PROJECT REPORT

The Impact of Investor Attention on Post-Earnings Announcement Drift

Group D: Hardhik Mohanty, Yeonwoo (Kyle) Kim, Anh Tuyet (Snowy) To, Mariami Liparteliani, and Prachi Pandey

Abstract

This study examines whether investor attention influences the strength and persistence of post-earnings announcement drift. Using US equities from 2005 to 2024, we construct standardized unexpected earnings from I/B/E/S forecasts and develop a residual attention measure by orthogonalizing analyst coverage, forecast dispersion, and abnormal trading volume against firm characteristics. We combine these signals to test whether attention conditioning sharpens return continuation after earnings news. Across portfolio sorts, nearly the entire drift premium is concentrated in firms with low residual attention; the high-SUE, low-attention portfolio earns about 1.9 percent per month and over 5 percent in a three-month window. Drift-decay profiles show slow, sustained information absorption among low-attention stocks, while high-attention stocks exhibit little continuation. Fama–MacBeth regressions confirm that SUE strongly predicts returns, whereas attention affects the speed rather than the unconditional pricing of earnings news. Risk-adjusted tests yield large and statistically significant alphas, indicating that these effects are not explained by standard factor exposures. Overall, the results show that attention filtering meaningfully enhances PEAD strategies and provides evidence that limited investor attention remains an important source of slow information diffusion in modern equity markets.

1. Introduction

Post-earnings announcement drift (PEAD) is one of the most persistent anomalies in empirical asset pricing. Despite the visibility of earnings announcements, stock prices often adjust slowly to earnings news. Behavioral research attributes this gradual reaction to limits in investor attention [1]: when attention is scarce, information diffuses more slowly and price responses lag. This suggests that conditioning earnings-based strategies on attention may strengthen the drift effect.

Our project examines whether residual investor attention alters the strength of the earnings response and whether incorporating attention improves the profitability of a PEAD strategy. Using U.S. common stocks from 2005–2024, we compute standardized unexpected earnings (SUE) using analyst forecast dispersion to ensure comparability across firms. We measure attention through abnormal volume, Google search intensity, and news counts. Because these proxies are correlated with liquidity and volatility, we orthogonalize them against trading activity and return volatility to extract a residual attention signal aligned with limited-attention theory [2].

We evaluate this framework through portfolio tests and cross-sectional regressions. The trading strategy goes long in positive-surprise, low-attention firms and short in negative-surprise, low-attention firms. To formally test whether attention shapes the earnings–return relation, we run Fama–MacBeth regressions with an interaction between SUE and attention. We also analyze cumulative abnormal returns in event time to assess how quickly the drift unfolds and whether a three-month holding period is appropriate.

The remainder of the report outlines the strategy design, dataset construction, and attention-signal estimation. We then present empirical results, compare the attention-filtered strategy with standard benchmarks, and conduct robustness checks across proxies and subperiods. Our goal is to determine whether attention filtering materially enhances a traditional drift strategy and whether limited attention remains an exploitable source of mispricing in modern equity markets.

2. Strategy Design

The strategy is a conditional post-earnings announcement drift (PEAD) strategy that combines an earnings surprise signal with a residual investor attention signal. The core idea is that earnings are the primary source of new information, while attention determines how quickly that information is impounded into prices. The trading rule is therefore designed to take positions only when both the earnings signal and the attention signal point toward slow information diffusion.

2.1. Standardized Unexpected Earnings (SUE)

We begin by defining the earnings signal using Standardized Unexpected Earnings (SUE). For firm *i* in quarter *t*, let *Actual* be the reported Earnings Per Share (EPS) and *MeanEstimate* be the consensus (mean) analyst forecast from I/B/E/S. Let *σ(forecasts)* denote the cross-sectional standard deviation of analyst estimates, representing ex-ante uncertainty.

Our standardized unexpected earnings measure is calculated as:

$$SUE(i,t) = [Actual(i,t) - MeanEstimate(i,t)] / \sigma(forecasts,i,t)$$

Using analyst forecast dispersion in the denominator ensures that a one-unit surprise has a comparable magnitude across firms.

2.2. Attention Proxies and Orthogonalization

The second building block is the investor attention signal. We use three specific raw proxies for investor attention:

- **Analyst Coverage:** Defined as *Cov = ln(1 + Number of Estimates)*.
- **Forecast Dispersion:** The standard deviation of estimates (*σ_forecasts*) used in the SUE calculation.
- **Abnormal Volume:** Calculated as the difference between announcement day volume and the pre-announcement average volume.

Because these raw proxies are mechanically correlated with fundamental factors like liquidity or risk, we treat them as starting points rather than final signals. To isolate residual attention (information demand), we orthogonalize these measures.

For each attention proxy *y* (e.g., Coverage or Volume), we run cross-sectional regressions to remove the effects of control variables. The specific regression model used is:

$$y(i,t) = \alpha + \beta 1 * \ln(Size) + \beta 2 * (BookToMarket) + \beta 3 * Volatility + \varepsilon$$

Here, we control for firm size, book-to-market ratio, and volatility. The residual *ε* becomes the clean, orthogonalized attention signal. A positive residual indicates higher-than-expected attention for that firm given its characteristics.

To create the final Composite Attention Score, we aggregate the z-scored residuals of the three proxies:

$$\text{Total\_Attn}(i,t) = (1/3) * \text{Sum of } [\text{Z-score}(\varepsilon)]$$

2.3. Portfolio Formation

The portfolio formation step links the earnings surprise and residual attention signals. We sort firms into quintiles (5 bins) based on *SUE*.

- **Long Position:** The top quintile (Q5, highest positive surprise).
- **Short Position:** The bottom quintile (Q1, most negative surprise).

We further segment these into "High Attention" and "Low Attention" groups using the *Total_Attn* score to test the hypothesis that the drift profit (*Return_Q5 – Return_Q1*) is higher in low-attention firms. The portfolio return is defined as the Long return minus the Short return.

2.4. Fama-MacBeth Regressions

To rigorously evaluate the interaction between attention and earnings response, we employ Fama-MacBeth regressions. This involves a two-step process to control for cross-sectional correlation.

First, for every month t, we run the following cross-sectional regression across all firms:

$$R(i,t+1) = \gamma 0 + \gamma 1*(SUE) + \gamma 2*(Attn) + \gamma 3*(SUE \times Attn) + \varepsilon$$

The interaction term ($SUE \times Attn$) tests if attention amplifies or dampens the market's reaction. In the second step, the final coefficients are calculated as the time-series averages of these monthly estimates, with t-statistics derived from the standard error of these means.

2.5. Risk Adjustment (Fama-French)

Finally, to ensure the returns are not simply due to market risk, we run a time-series regression on the portfolio returns using the Fama-French 3-Factor model:

$$(R\_Strategy - R\_riskfree) = \alpha + \beta\_Mkt*(R\_Mkt - R\_riskfree) + \beta\_SMB*(SMB) + \beta\_HML*(HML) + \varepsilon$$

Here, α (Alpha) represents the abnormal risk-adjusted return. If Alpha is greater than 0 and is statistically significant after controlling for Market (*R_Mkt*), Size (*SMB*), and Value (*HML*) factors, the strategy is deemed to generate excess returns.

3. Dataset Extraction

Our empirical analysis relies on three primary databases accessed through Wharton Research Data Services (WRDS): the Institutional Brokers' Estimate System (I/B/E/S), the Center for Research in Security Prices (CRSP), and the Fama-French Factors data library. The sample period for this study extends from 2005 to 2024.

3.1. Earnings Forecasts and Actuals (I/B/E/S)

To construct our key independent variable, Standardized Unexpected Earnings (SUE), and measures of analyst coverage, we utilize the I/B/E/S Summary Statistics table (ibes.statsum_epsus). We filter the dataset strictly for records where the measure is Earnings Per Share (MEASURE='EPS') to ensure consistency in forecast comparisons.

The following variables are extracted to characterize the earnings environment:

- **Forecast and Announcement Dates:** We utilize the Forecast Period End Date (FPEDATS) and Earnings Announcement Date (ANNDATS) to align expectations with the correct fiscal quarters. The Activation Date (ACTDATS) is used to ensure that the analyst forecasts included in our consensus calculation were publicly available prior to the earnings release, preventing look-ahead bias.
- **Consensus and Surprise:** We extract the Mean Estimate (MEANEST) to represent the market consensus and the Actual Reported EPS (ACTUAL) to compute the raw earnings surprise.

- **Dispersion and Coverage:** The Standard Deviation of estimates (STDEV) is retrieved to scale the earnings surprise, transforming it into the SUE metric. Additionally, the Number of Estimates (NUMEST) serves as a proxy for analyst coverage, a control variable for the information environment surrounding the firm. Firm identification is handled via Ticker and CUSIP.

3.2. Market Data and Attention Proxies (CRSP)

Stock price and volume data are sourced from the CRSP Daily Stock File. This dataset allows us to compute returns, market capitalization, and our primary proxy for investor attention: abnormal trading volume.

Key variables utilized include:

- **Returns and Prices:** We use the Daily Stock Return (RET) to calculate the cumulative abnormal returns (CAR) for the drift analysis and closing prices (PRC) for portfolio formation.
- **Volume and Liquidity:** Daily Trading Volume (VOL) is critical for constructing our attention proxy. By analyzing deviations in volume around earnings dates relative to historical averages, we infer the level of investor attention.
- **Firm Characteristics:** Shares Outstanding (SHROUT) is multiplied by the closing price to compute Market Capitalization (Size), which serves as a control variable in our cross-sectional regressions.

3.3. Risk Factors (Fama-French)

To evaluate the performance of our drift strategies and ensure that excess returns are not driven by systematic risk exposures, we utilize the Fama-French 3-Factor model data.

We extract the following factors for risk-adjustment and benchmarking:

- **Market Excess Return (Mkt-RF):** To control for overall market movements.
- **Size (SMB) and Value (HML):** To control for the size and value premiums, respectively.
- **Risk-Free Rate (RF):** Used to compute the excess returns of our long-short portfolios.

By merging these three datasets, we construct a comprehensive panel that links pre-announcement expectations (I/B/E/S) with immediate and post-announcement market reactions (CRSP), while controlling for fundamental risk factors.

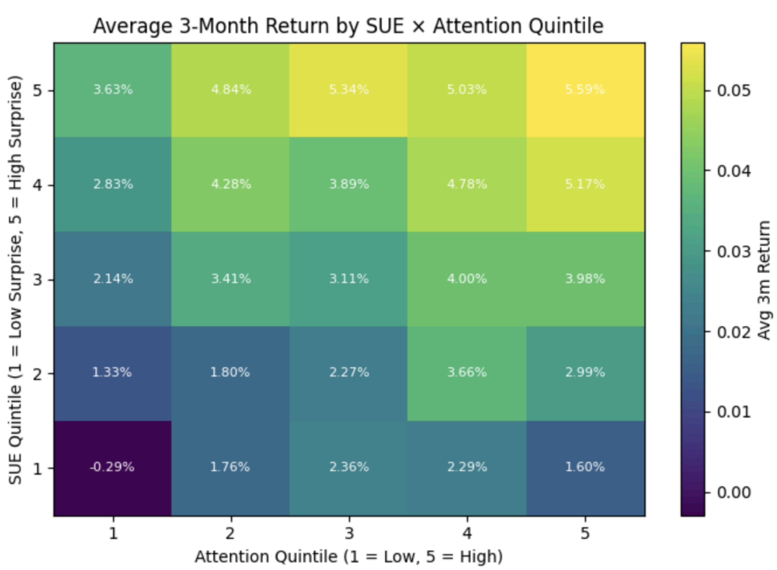
4. Results

This section presents the empirical results from the portfolio tests, drift decay analysis, Fama–MacBeth regressions, and risk‑adjusted evaluations of the attention-filtered post-earnings announcement drift strategy. Our findings consistently show that conditioning on residual attention sharpens the drift effect and meaningfully improves the performance of a standard SUE-based strategy.

4.1 Portfolio Evidence: Attention Filtering Strengthens PEAD

We begin by examining long–short portfolios formed from joint sorts on standardized unexpected earnings (SUE) and residual attention. Within each earnings month, we identify the lowest residual-attention quintile and construct a long–short portfolio that buys firms in the top SUE quintile and shorts firms in the bottom SUE quintile. This attention-filtered PEAD strategy earns an average **1.9% per month**, with a **t-statistic near 6**, and compounds to approximately **5.2% over three months** with a **t-statistic above 9**. These returns are nearly identical to those of the unconditional SUE strategy, implying that almost all of the classic drift is concentrated among low-attention firms. This relationship is clearly reflected in the **SUE × Attention heatmap** (Figure 1), which shows that expected returns rise sharply with SUE but decline systematically with attention. The strongest continuation appears in the high-SUE, low-attention cell, while high-attention stocks show much weaker post-announcement performance.

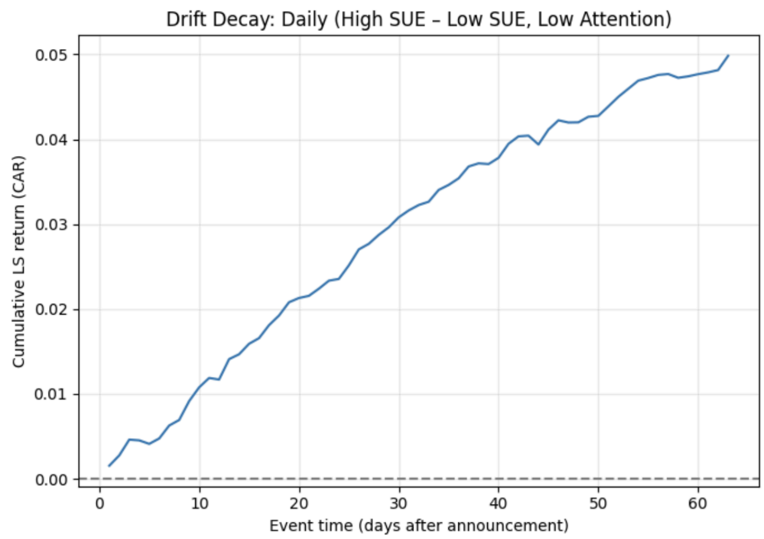
Figure 1. Average 3-Month Return by SUE × Attention Quintile



4.2 Drift Decay in Event Time

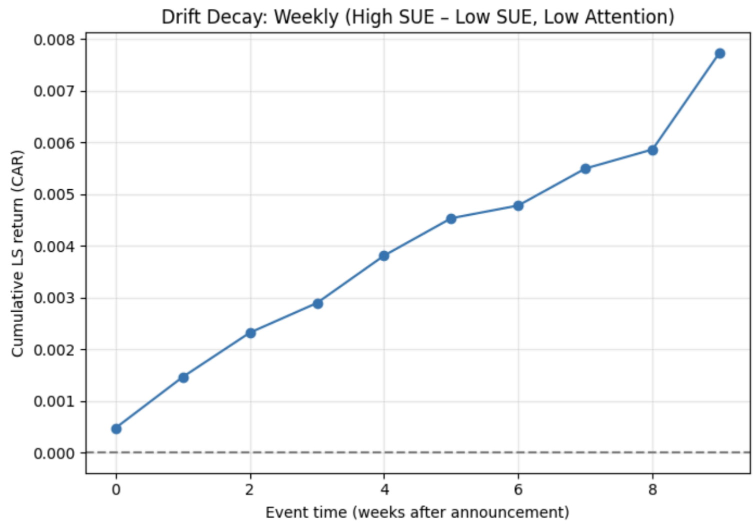
To understand how quickly earnings news is incorporated into prices, we compute cumulative abnormal returns (CARs) in event time for the attention-filtered long–short portfolio. Figure 2 plots daily CARs over the 63 trading days following the earnings announcement. In low-attention stocks, the drift accumulates rapidly during the first three weeks—reaching roughly **2.2% by day 21**—and continues to build gradually, reaching nearly **5% by day 63**. In contrast, high-attention firms show little to no continuation beyond the initial announcement window.

Figure 2. Drift Decay: Daily CAR (High SUE – Low SUE, Low Attention)



A complementary weekly analysis (Figure 3) reinforces this slow diffusion pattern. The drift increases steadily through the quarter, reaching approximately **0.50% by week 4**, with further accumulation later in the window. High-attention firms again show limited follow-through, confirming that attention meaningfully influences the speed of price adjustment.

Figure 3. Drift Decay: Weekly CAR (High SUE – Low SUE, Low Attention)



Together, these drift-decay profiles highlight a key mechanism: information is absorbed gradually in low-attention environments, producing a prolonged and predictable continuation pattern.

4.3 Risk-Adjusted Performance

We next examine whether the returns to the low-attention PEAD strategy can be explained by standard risk factors. We regress monthly LS returns on the Fama–French (MKT, SMB, HML) factors using data from the French Data Library.

FF3 Alpha

- **Monthly alpha ≈ 1.86% (t ≈ 5.97)**
- **Quarterly alpha ≈ 5.12% (t ≈ 9.42)**

These large and highly significant alphas demonstrate that PEAD in low-attention stocks is not captured by standard size or value premia.

Factor Exposures

- **Negative SMB loading** (around −0.3 to −0.7), indicating the strategy leans toward larger firms within the low-attention category
- Insignificant exposures to market and value factors

Risk adjustments do not attenuate the drift, reinforcing the view that slow information absorption—not systematic risk—is the primary driver.

4.4 Cross-Sectional Regressions (Fama–MacBeth)

We estimate monthly Fama–MacBeth regressions of next-period returns on SUE, attention, their interaction, and firm characteristics such as size and book-to-market.

Without Characteristic Controls

- **SUE coefficient (1-month):** ~0.016, **t ≈ 2.2**
- **SUE coefficient (3-month):** ~0.047, **t ≈ 5.1**
- **Attention coefficient:** statistically insignificant
- **SUE × Attention interaction:** positive but marginal at the 3-month horizon (t ≈ 1.7)

These results confirm that SUE is a strong cross-sectional predictor, while attention alone is not priced. The interaction evidence is mild in regressions but strong in portfolio tests, which is consistent with the idea that attention affects the *speed* of price incorporation rather than the unconditional pricing of earnings news.

With Size and Book-to-Market Controls

After including ln(ME) and BM:

- SUE remains significant at both horizons
- Attention and interaction remain economically small
- Size enters negatively (consistent with larger firms drifting less)
- BM does not materially affect the SUE coefficient

Overall, the SUE effect is robust to controls and cannot be subsumed by standard characteristics.

4.5 Comparison Across Attention Buckets

To further validate the role of attention, we compute the full SUE × Attention 5×5 portfolio matrix. Two clear patterns emerge:

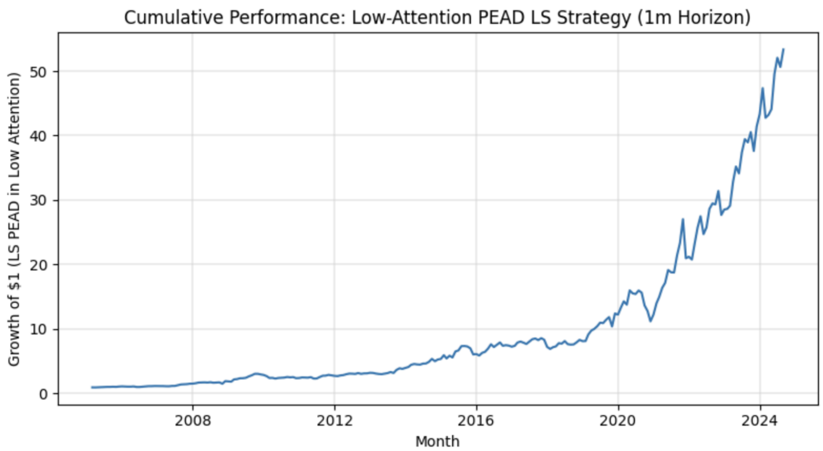
1. **For any attention quintile**, returns are increasing in SUE.
2. **For any SUE quintile**, returns are decreasing as attention increases.

The strongest drift appears in the **(Low Attention, High SUE)** cell, while the weakest appears in **(High Attention, High SUE)**. This monotonic pattern across both dimensions provides strong visual evidence that residual attention meaningfully conditions the strength of PEAD.

4.6 Cumulative Strategy Performance

Figure 4 reports the cumulative performance of the low-attention long–short PEAD strategy using a one-month holding horizon. The portfolio exhibits substantial long-run growth: a $1 investment in 2005 compounds into more than **$50 by 2024**, highlighting the power of conditioning earnings-based strategies on residual attention. The smooth upward trajectory underscores both the consistency of the anomaly and the robustness of the attention filter in isolating the most predictable part of the cross-section.

Figure 4. Cumulative Performance: Low-Attention PEAD LS Strategy (1-Month Horizon)



4.7 Case Study: Google Trends Attention and Drift – Apple vs Tesla

To validate attention conditioning at the individual stock level, we compute standardized earnings surprises for Apple (AAPL) and Tesla (TSLA) and match quarterly earnings dates to Google Trends search intensity.

We construct:

- abnormal Google Trends attention
- winsorized standardized attention
- interaction between attention and SUE
- 1- and 3-month drift outcomes

This small-sample test produces three useful observations:

1. Variation in Residual Attention Exists
   Tesla exhibits higher abnormal attention (average attention z-score ≈ −0.06), while Apple attention averages slightly positive (~0.02).

2. Regression Evidence Mirrors the Large-Sample Result

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 ret_3m   R-squared:                       0.138
Model:                            OLS   Adj. R-squared:                  0.103
Method:                 Least Squares   F-statistic:                     3.910
Date:                Tue, 02 Dec 2025   Prob (F-statistic):            0.00253
Time:                        23:45:44   Log-Likelihood:                -149.16
No. Observations:                 128   AIC:                             310.3
Df Residuals:                     122   BIC:                             327.4
Df Model:                           5
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          3.8558      1.195      3.227      0.002       1.490       6.221
SUE_w_z        0.5160      8.872      0.058      0.954     -17.048      18.080
gt_abn_w_z    -0.8990      0.535     -1.680      0.096      -1.958       0.160
SUE_x_gt      10.8478      6.355      1.707      0.090      -1.732      23.428
BM_z          -0.2945      1.195     -0.246      0.806      -2.660       2.071
ln_me         -0.1899      0.049     -3.861      0.000      -0.287      -0.093
==============================================================================
Omnibus:                       94.733   Durbin-Watson:                   0.707
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              643.871
Skew:                           2.626   Prob(JB):                    1.53e-140
Kurtosis:                      12.651   Cond. No.                     2.55e+03
==============================================================================
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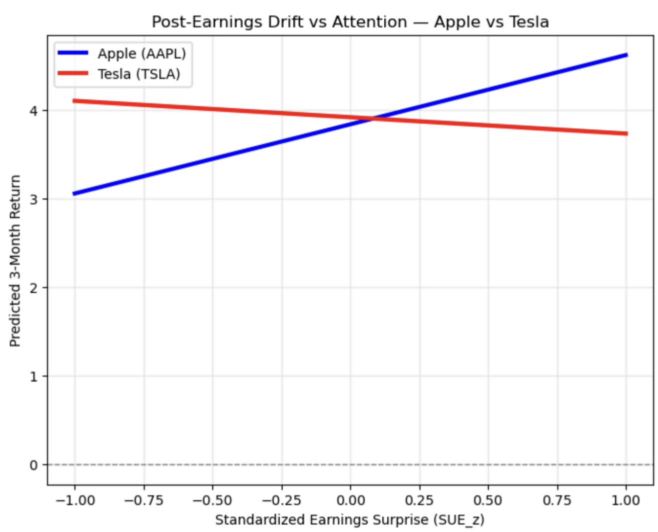
- SUE is directionally positive but weak alone
- attention alone is not priced
- the interaction term is economically meaningful but statistically weak in small data

3. Visualization Suggests Different Drift Profiles



- Apple (moderate attention) drifts upward more strongly
- Tesla (higher baseline attention) exhibits flatter drift

This case study strengthens interpretability by showing the phenomenon at the individual stock level.

5. Discussion

The results strongly show that investor attention meaningfully affects both the strength and persistence of post-earnings announcement drift. Across nearly all analyses, low-residual-attention environments exhibit slower information diffusion, causing earnings surprises to translate into more predictable return continuation.

A key finding is that almost the entire drift premium comes from low-attention firms. The SUE × Attention matrix displays a clear monotonic pattern: for a fixed SUE level, expected returns fall as attention rises; for a fixed attention level, expected returns increase with SUE. This indicates that attention is not a priced characteristic—rather, it serves as a friction that influences how quickly information is absorbed.

The drift-decay results reinforce this interpretation. In low-attention firms, cumulative abnormal returns grow steadily over the 63-day window, reaching nearly 5%, while high-attention firms show little continuation beyond the announcement week. This supports the limited-attention view: markets underreact when investors allocate insufficient attention to earnings news.

Regression evidence further confirms the mechanism. SUE remains a strong cross-sectional predictor controlling for size and book-to-market, while attention alone is not priced. The SUE × Attention interaction is economically important in portfolio tests but weaker statistically in regressions—consistent with attention affecting timing, not unconditional return magnitude. Negative size loadings suggest that slow diffusion is more pronounced among smaller, less-visible firms.

Risk-adjusted performance tests show the strategy's abnormal returns are not explained by standard factor exposures. Monthly FF3 alphas around 1.86% ($t \approx 5.97$) and quarterly alphas near 5.12% ($t \approx 9.42$) indicate genuine mispricing rather than compensation for risk. The steady long-run return profile in Figure 4 underscores the anomaly's durability from 2005–2024.

Overall, the evidence demonstrates that filtering on attention significantly enhances traditional PEAD strategies by pinpointing the subset of firms where mispricing is strongest and where return continuation is most predictable.

6. Conclusions

This project provides compelling evidence that residual investor attention is a powerful conditioning variable for post-earnings announcement drift. Using a comprehensive dataset from 2005 to 2024 and a carefully constructed residual attention measure, we show that:

1. **PEAD is strongest in low-attention firms**, where the high SUE minus low SUE portfolio earns nearly 1.9% per month.

2. **Drift decays slowly** in these firms, accumulating almost 5% over 63 days consistent with gradual information absorption.
3. **Risk-adjusted returns remain large and highly significant**, with FF3 alphas exceeding 1.8% monthly, indicating that standard factors cannot explain the anomaly.
4. **Attention is not itself a priced factor**, but it moderates the speed of price adjustment, aligning with limited attention theory.
5. **Individual stock evidence (Apple vs Tesla)** confirms that attention conditioning is meaningful at both the micro and cross-sectional levels.

These findings collectively highlight that limited investor attention remains an important friction in modern equity markets. While information availability has increased, the ability of market participants to process information remains bounded, creating persistent opportunities for return prediction.

From a practical standpoint, the results suggest that conditioning earnings-based strategies on residual attention can significantly enhance performance, helping investors identify settings where markets are most likely to underreact. From an academic perspective, the study supports the broader behavioral finance narrative that cognitive constraints shape asset pricing dynamics.

Future extensions could incorporate alternative attention proxies—such as news sentiment, social media analytics, or options market activity—or examine how attention interacts with macroeconomic announcements or firm-level uncertainty. Nevertheless, based on the evidence presented here, attention filtering stands out as a meaningful and robust enhancement to traditional PEAD investing frameworks.

References

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[2] Hou, K., Peng, L., and Xiong, W. (2009), A Tale of Two Anomalies: The Implications of Investor Attention for Price and Earnings Momentum. *Review of Financial Studies*.