



The Impact of Investor Attention on Post-Earnings Announcement Drift

Presented by: Group D

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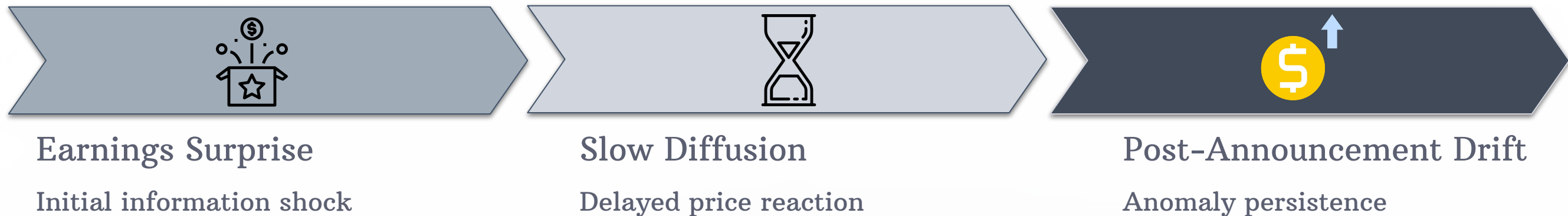
FBE 551: Quantitative Investing / Professor Mark Clements

Period Covered: 2005–2024

Motivation:

Unpacking PEAD and Investor Attention

- ❖ The Post-Earnings Announcement Drift (PEAD) stands as one of the most robust anomalies in empirical finance, challenging market efficiency.
- ❖ Behavioral theories suggest that this price anomaly arises from the slow diffusion and assimilation of information when investor attention is limited.



Our central question: Does filtering earnings surprises by attention improve PEAD profitability and provide clearer insights into market inefficiencies?

Research Questions & Core Hypotheses

Our study investigates how investor attention interacts with earnings surprises to influence post-announcement stock returns.

Hypothesis 1

PEAD is significantly larger for low-attention firms, where information dissemination is expected to be slower.

Hypothesis 2

An attention-filtered PEAD strategy will demonstrably outperform standard drift strategies.

Hypothesis 3

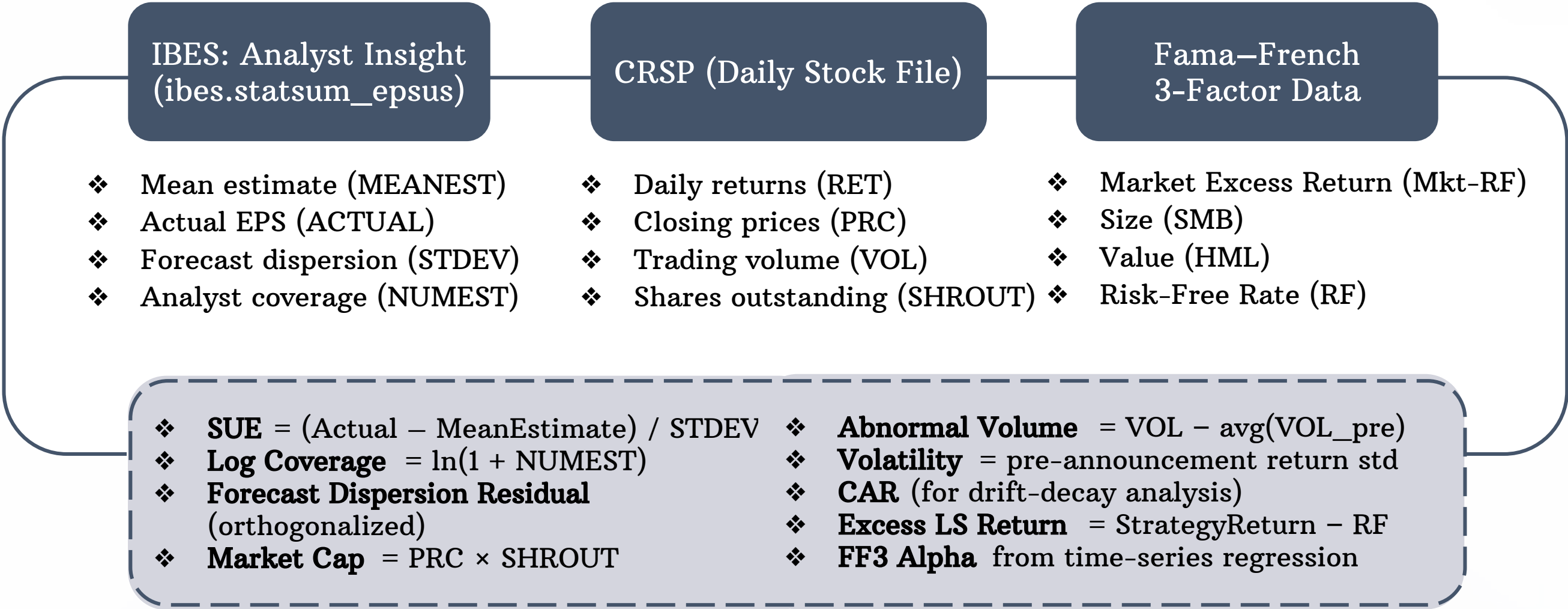
The interaction between Standardized Unexpected Earnings (SUE) and attention ($\text{SUE} \times \text{Attention}$) will be a significant predictor of post-announcement returns.



Why this research matters: This investigation rigorously tests the behavioral limits-to-attention theory within asset pricing and evaluates whether mispricing opportunities remain exploitable in contemporary markets.

Data & Variable Construction

Our analysis leverages a robust dataset spanning nearly two decades, **from 2005 to 2024** , integrating critical financial and market data sources to ensure comprehensive insights into corporate events and market reactions.



Strategy Design: *A Two-Signal Framework*

Our trading strategy integrates two critical signals to refine the detection of PEAD opportunities.

Signal 1: Earnings Surprise	Signal 2: Residual Attention
Quantified using Standardized Unexpected Earnings (SUE) , which captures the unexpected component of announced earnings.	Derived from orthogonalized attention proxies , ensuring we capture informational focus rather than confounding factors like liquidity or volatility.

Trading Logic: Exploiting Asymmetry

	High Attention	Low Attention
Positive SUE	Neutral	Long Position
Negative SUE	Neutral	Short Position

SUE Construction: *Quantifying the Unexpected*

Standardized Unexpected Earnings (SUE) is a cornerstone of our analysis, calculated as:

$$SUE = \frac{EPS_{actual} - EPS_{forecast}}{\sigma(\text{forecast})}$$

→ This formula normalizes the earnings surprise by the dispersion of analyst forecasts, making it comparable across firms and time.

❏ Key Implementation Notes:

Data Linkage: Actual EPS and forecast data are precisely linked using IBES TICKER and FPEDATS.

Cross-Firm Comparability: Using forecast dispersion (STDEV) ensures that the SUE metric is standardized.

Timeliness: Only forecasts available **before the announcement date** are included to maintain signal purity and avoid look-ahead bias.

Investor Attention: *Capturing Informational Focus*

We employ three distinct pre-announcement proxies for investor attention, capturing different facets of information seeking and dissemination.



Abnormal Trading Volume

Spikes in volume beyond typical trading activity, indicating increased market interest.



Google Search Intensity (Case Study)

The relative frequency of search queries for a given firm or earnings event, reflecting public interest.



News Article Counts

The number of news articles mentioning the company, serving as a proxy for media coverage.

Data Quality & Orthogonalization

Temporal Considerations: Google search data is sparse prior to 2010, necessitating split-sample tests to ensure robustness.

Controlling for Confounding Factors: We orthogonalize raw attention measures to remove effects of liquidity and volatility, ensuring our proxies capture **pure informational focus** .

$$A = A^{raw} - \beta \log(\text{Vol}) - \beta \sigma(\text{ret})$$

→ This rigorous adjustment yields a clean residual attention score, isolating the impact of informational attention from mere trading activity.

Portfolio Construction: *Targeting Exploitable Mispricing*

Our portfolio construction is designed to isolate and capitalize on the specific conditions under which PEAD is theorized to be strongest.

Sorting Methodology:

SUE: Firms are sorted into quintiles based on their Standardized Unexpected Earnings.

Attention: We identify **low-attention firms** by selecting those in the bottom 20% of our residual attention measure.



Strategy Logic:

Long: High SUE \cap Low attention firms.

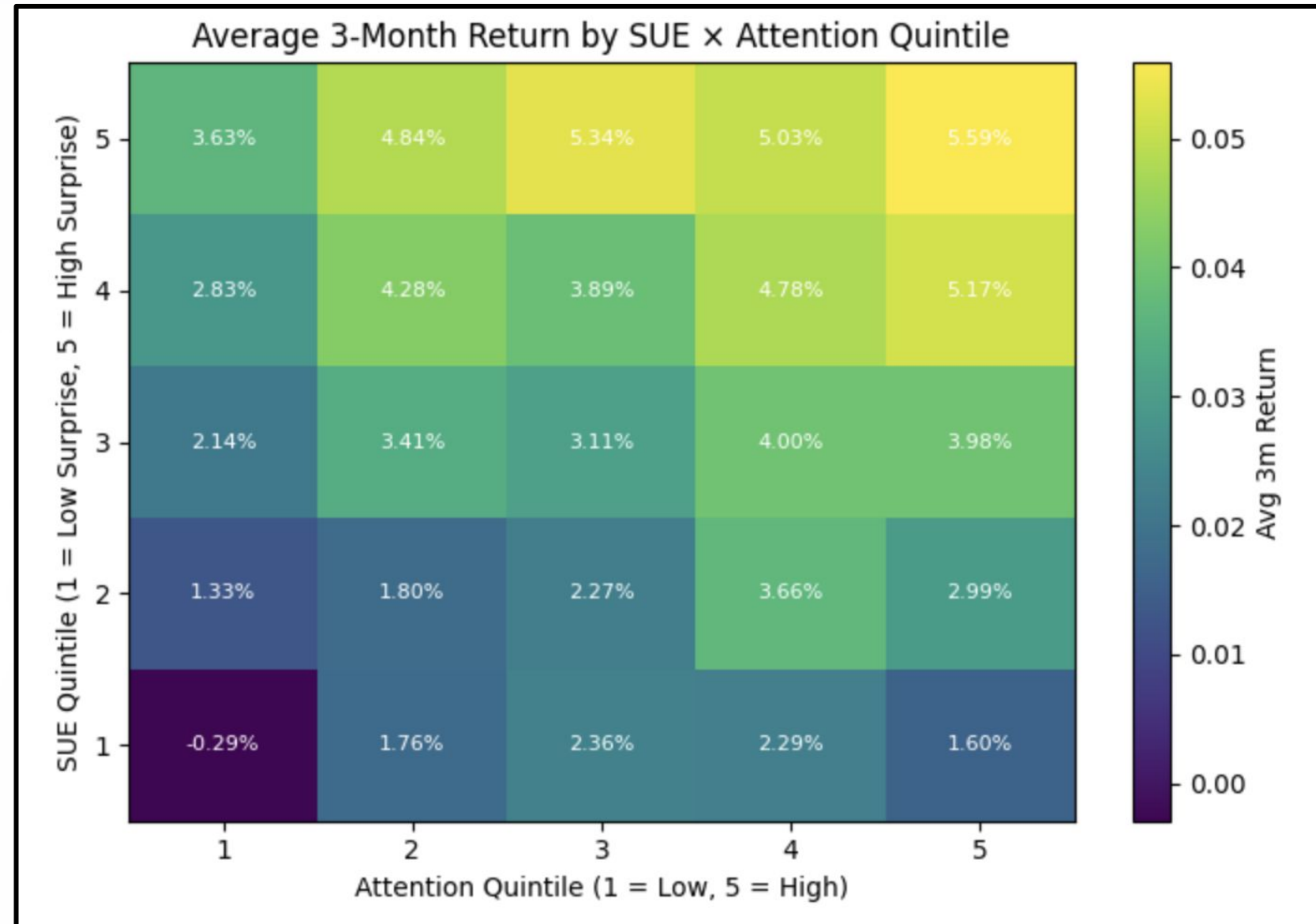
Short: Low SUE \cap Low attention firms.

Equal-weighted: All positions are equally weighted to avoid biases from large-cap stocks.

Initiation: Positions are initiated at the earnings announcement date.

Holding Periods: Comparisons are made across 4, 8, and 12-week holding periods.

Result: *Attention Filtering Strengthens PEAD*



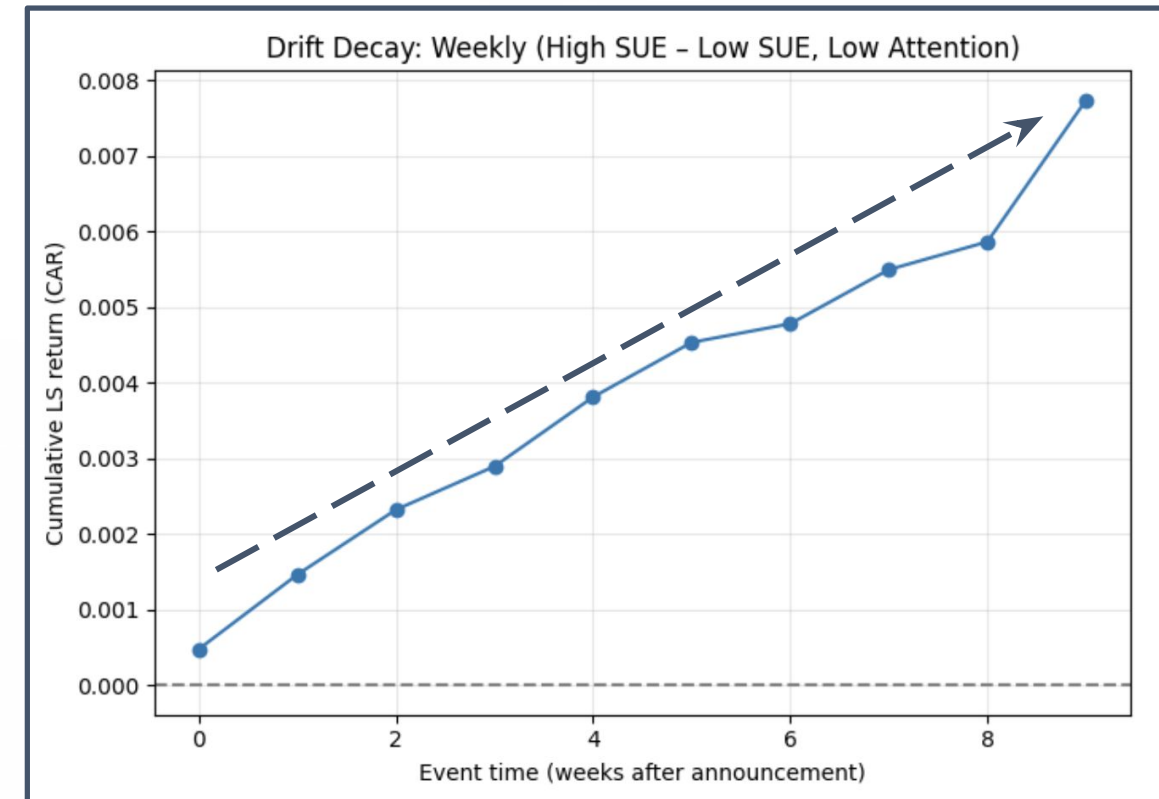
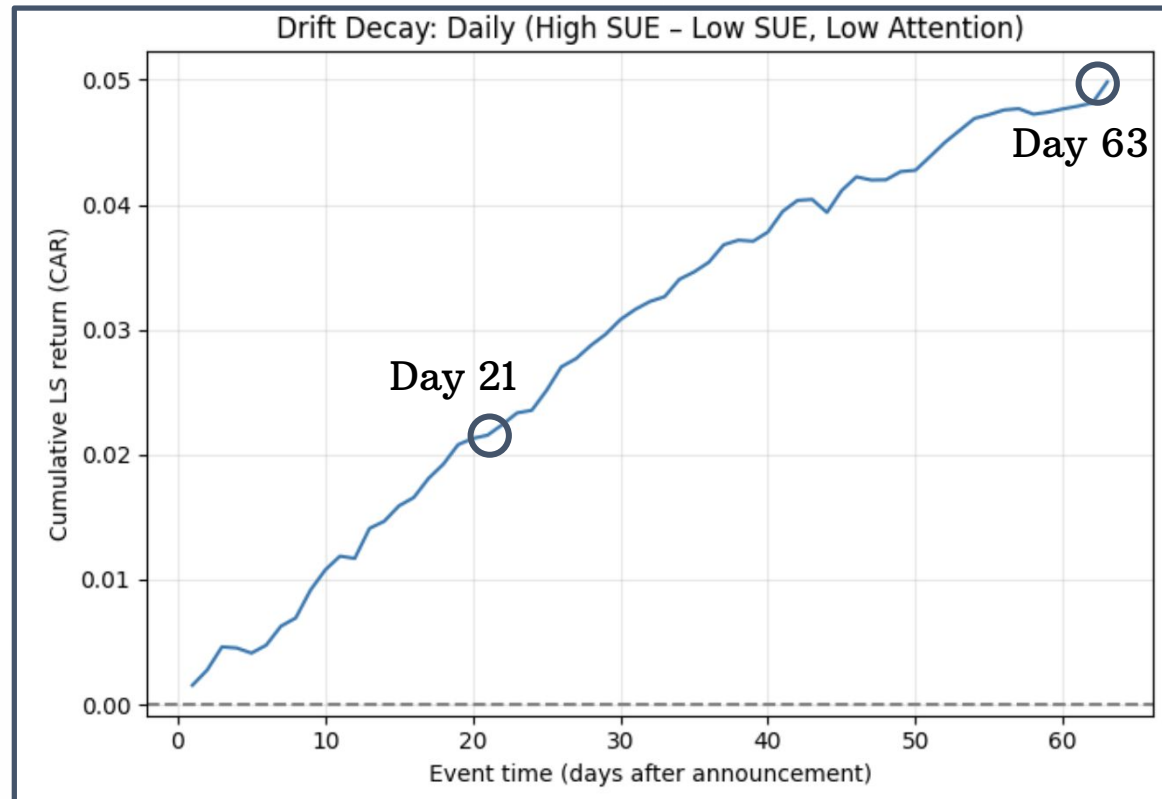
- ❖ **Drift increases sharply with SUE:** higher earnings surprises lead to stronger continuation.
- ❖ **Drift decreases systematically with attention:** higher investor attention dampens PEAD.
- ❖ **Strongest return appears in High SUE × Low Attention:** ~5–6% continuation over three months.
- ❖ **High-attention firms show much weaker drift:** limited or near-zero post-announcement continuation.
- ❖ **Almost all unconditional PEAD is concentrated in low-attention stocks:** attention filtering isolates the true drift signal.

Result: *Drift Decay in Event Time*

Low Attention



Slow Information Diffusion



In event time, we find that earnings information is absorbed gradually in low-attention stocks. The cumulative long-short return reaches about **2.2% by Day 21**, then continues to rise steadily to almost **5% by Day 63**, indicating slow but persistent drift. In contrast, high-attention firms show little to no continuation after the initial announcement reaction. Weekly CARs reinforce this pattern, with returns accumulating predictably through the first month. Overall, these results provide clear evidence of **slow information diffusion** when investor attention is limited.

Result: *Risk-Adjusted & Cross-Sectional Evidence*

	Risk-Adjusted Performance (FF3 Model)		Cross-Sectional Fama-Macbeth		
	α	t	β	t	
	Monthly	~ 1.86%	~5.97	~0.016	~2.2
	Quarterly	~5.12%	~9.42	~0.047	~5.1

- ❖ Indicates PEAD in low-attention stocks cannot be explained by market, size, or value factors
- ❖ Factor loadings
 - SMB negative (−0.3 to −0.7): strategy tilts toward larger firms
 - Market & HML exposures: insignificant

→ Conclusion: Drift survives risk adjustment
→ not a risk premium

- ❖ Attention variable alone not priced
- ❖ Interaction SUE × Attention
 - Mild in regressions
 - Strong in portfolios → consistent with attention slowing price adjustment
- ❖ After controlling for Size & Book-to-Market
 - SUE remains highly significant
 - Attention & interaction stay small
 - Size enters negative (large firms drift less)
 - BM has little effect

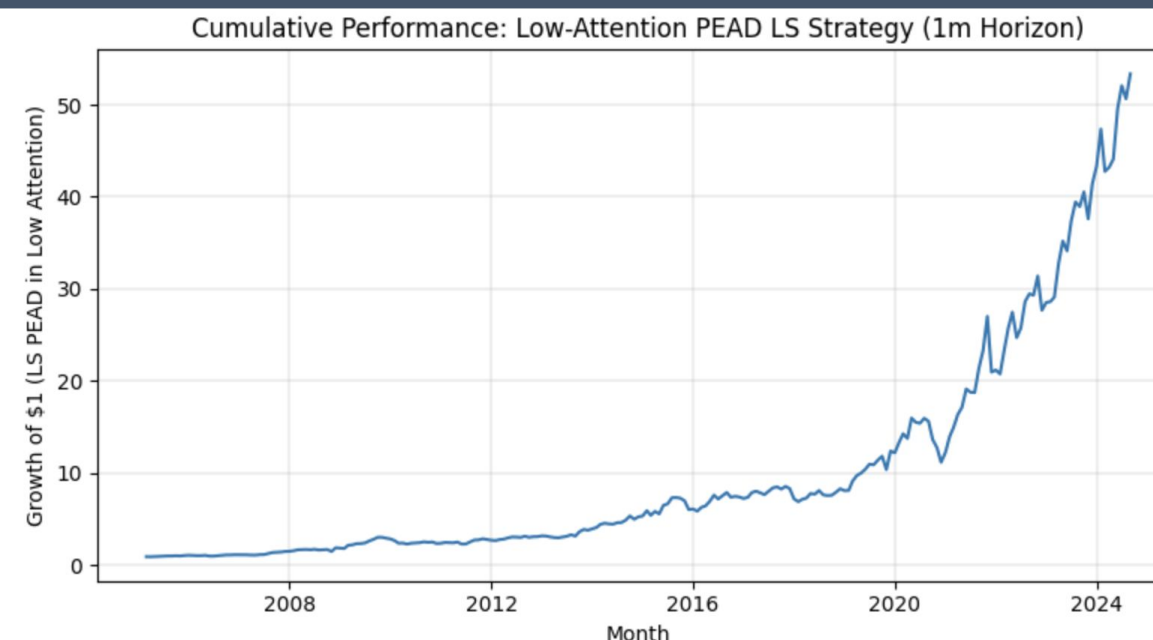
Result:

Attention Buckets & Cumulative Performance

Comparison Across Attention Buckets (5×5 SUE × Attention Matrix)

- ❖ For any attention quintile, returns are increasing in SUE.
- ❖ For any SUE quintile, returns are decreasing as attention increases.
- ❖ Best-performing cell:
 - Low Attention + High SUE (strongest continuation).
- ❖ Weakest-performing cell:
 - High Attention + High SUE (little to no drift).

Cumulative Strategy Performance (1-Month LS Strategy)



Attention filtering consistently selects the **most predictable part** of the earnings surprise signal.

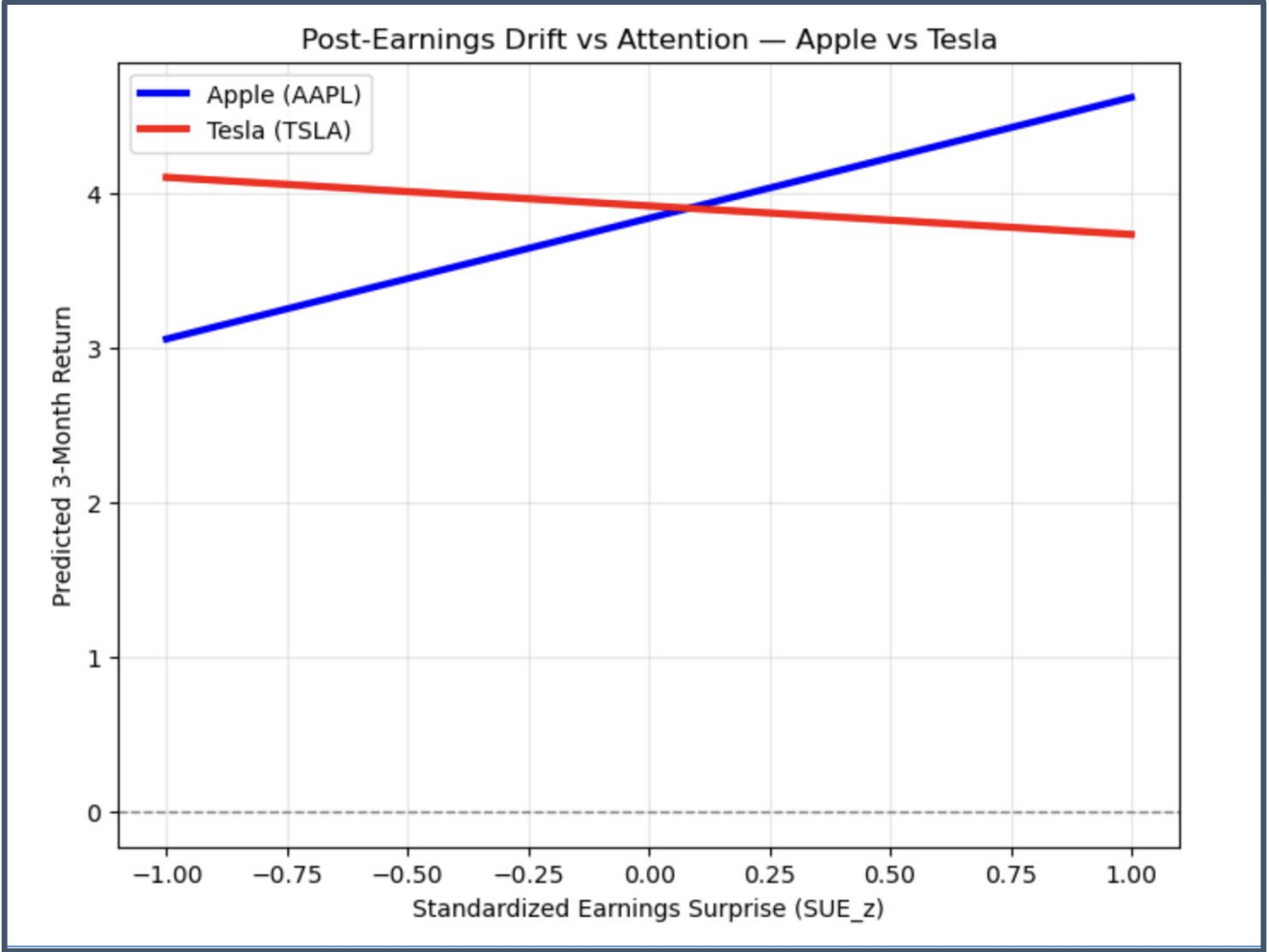
Strengthens short-run drift and delivers **massive long-run compounding**.

Clear **monotonic behavior** along both dimensions
→ **Attention is a conditioning variable that amplifies PEAD.**

Case Study:

Google Trends Attention and Drift – Apple vs Tesla

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			



Conclusion:

Attention conditioning isolates the most predictable returns in the cross-section.

1

SUE Predicts Returns, but Attention Determines the Speed

- Strong PEAD appears *only* when investor attention is low.
- High-attention stocks incorporate earnings information quickly → little drift.

2

Attention Filtering Greatly Enhances PEAD Strategies

- Low-attention PEAD earns **1.9% per month** and **5% per quarter** .
- Survives Fama–French risk adjustment with **large positive alphas** .

3

Evidence Supports Limited Attention as a Persistent Inefficiency

- Drift-decay patterns show slow, continuous information absorption.
- Effect holds across proxies and even in firm-level case studies.

References

Hirshleifer, D., and Teoh, S. H. (2003), Limited Attention, Information Disclosure, and Financial Reporting. *Journal of Accounting and Economics*.

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*.



Thank you