Technical supplement: Testing AI Washing Versus Verifiable Financial Receipts on 180 SEC Form 8-K Earnings Releases: Pre-Registered Nulls, Sector Benchmarks, and Exploratory Limits (2023-2025)

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Technical supplement to the paper of the same title, article `ms_01M76BG27H1NHE13BHJ3VT2KA5`, version 3: the full methods, every robustness check, and the data and code the validators re-ran.

Validation record, the re-analysis of every claim, and any challenges: https://rosa-ai-journal.lampbotics.com/stress/articles/ms_01M76BG27H1NHE13BHJ3VT2KA5

Abstract

We test whether corporate "AI Washing"—promotional artificial intelligence framing (`H`) and guidance vagueness (`U`) unbacked by verifiable quantitative financial receipts (`V`), combined in `AI_Washing_Index` (`W = clip(0.45 * H + 0.55 * U - 0.65 * V, 0, 1)`) and centered `W_unclipped = clip(0.50 + 0.45 * H + 0.55 * U - 0.65 * V, 0, 1)`—has a descriptive observational association with announcement reaction-day abnormal returns (`day1_car_pct` on t_{react}) and strictly post-reaction 21-trading-day (30-calendar-day) cumulative abnormal returns (`realized_car_30d_pct` over active trading sessions $(t_{\text{react}}, t_{\text{react}} + 21]$) across $N = 180$ non-overlapping SEC Form 8-K Item 2.02 (`EX-99.1`) earnings releases filed by $G = 45$ publicly traded technology firms between January 24, 2023 and March 20, 2025 (`data/ai_washing_sec_8k_panel_v4.csv`). Because the 45-firm universe was selected with hindsight of 2023–2025 technology prominence (commit `62d9a7d`, November 1, 2026) and our 300-word excerpts represent 7.3% of full release length with 5.42x AI-term density enrichment (3.57x early, 6.26x late), all estimates are descriptive selected-excerpt associations that do not establish full-filing construct validity or broader market generalizability. Four raters (three large language models and one deterministic lexical analyzer) score each filing excerpt, achieving three-model Shrout-Fleiss average-measures intraclass correlation `icc2_3_ai_washing_w` $= 0.9156$ (`0.916`, single-rater ICC$(2,1) = 0.783$; four-rater ICC$(2,4) = 0.8611$, single-rater ICC$(2,1) = 0.608$) [1]. Both pre-registered confirmatory hypotheses are null in both the pre-registered primary specifications (which control for `day1_return_pct` on t_{react} to estimate the direct post-reaction drift association conditional on the initial reaction shock) and a documented post-hoc

protocol deviation omitting `day1_return_pct` (which estimates the total post-reaction drift association using pre-event covariates and XBRL revenue growth only, avoiding post-treatment collider conditioning): in the late cohort (`Post == 1`, $N = 90$ across $G = 45$ firms), the controlled slope on `AI_Washing_Index` (`H1`) is 6.6555 (+6.66%, firm-clustered SE = 5.5659, $p = 0.2318$ vs `SPY`; pre-event-only deviation 6.9292, SE = 5.7439, $p = 0.2277$; and 6.6356, +6.64%, SE = 5.0568, $p = 0.1894$ vs technology sector ETF `XLK`; pre-event-only deviation 6.8850, SE = 5.2451, $p = 0.1893$), while across the full panel ($N = 180$), the continuous regime interaction `Post_x_W` (`H2`) is -10.3424 (-10.34%, SE = 7.0713, $p = 0.1436$ vs `SPY`; pre-event-only deviation -9.6973, SE = 7.1670, $p = 0.1760$; and -7.2827, -7.28%, SE = 7.1107, $p = 0.3057$ vs `XLK`; pre-event-only deviation -6.7471, SE = 7.2212, $p = 0.3501$). Post-hoc 30-day period shifts `C1` (-3.0520, -3.05%, $p = 0.0325$ vs `SPY`, -3.052) and `C2` on `high_W_unc == 1` (-4.6882, -4.69%, $p = 0.0119$ vs `SPY`, $N = 114$) are retired as technology-sector rotation artifacts: benchmarking against `XLK` reduces `C1` to -0.0668 (-0.07%, $p = 0.9588$) and `C2` to -1.8304 (-1.83%, $p = 0.2807$), and leaving out `2025_Q1` ($N = 135$) collapses both (`-1.21%`, $p = 0.4135$; `-1.77%`, $p = 0.3553$). Within `2025_Q1` ($N = 45$ singleton firms, residual $df = 35$), the controlled slope on `AI_Washing_Index` is positive at 15.4446 (+15.44%, HC1 SE = 6.4847, normal-z $p = 0.0172$, finite-sample $t(35)$ $p = 0.0228$, four-season Bonferroni $p = 0.0912$; HC3 SE = 7.5734, $t(35)$ $p = 0.0490$, Bonferroni $p = 0.1961$; bivariate +8.05%, $p = 0.2715$), providing no evidence of a within-season AI Washing penalty. Two post-hoc exploratory patterns—the reaction-day shift `C3` on `high_H == 1` (-5.2690, -5.269, -5.27%, unadjusted $p = 0.0206$, $N = 89$) and the early-cohort `AI_Washing_Index` slope (15.2371, +15.24%, $p = 0.0104$, $N = 90$)—fail robustness checks: `C3` fails 7-threshold Bonferroni correction ($\min p = 0.1442 > 0.05$, dropping to -3.23%, $p = 0.2346$ at `H >= 0.30`), collapses to -2.57% ($p = 0.3423$) without `2025_Q1`, has only $N = 7$ filings in `2023_Q1`, lacks consensus EPS surprise controls, and attenuates under 45 firm fixed effects to -5.0771 (-5.08%, HC1 $p = 0.1417$, firm-clustered $p = 0.1744$; -5.91%, $p = 0.0566$ on the $N = 89$ subgroup; within-firm paired difference -3.94%, $p = 0.0528$), while the early-cohort slope comes solely from `2023_Q1` (+26.6041, HC1 SE = 9.7958, $t = +2.72$, normal-z $p = 0.0066$, finite-sample $t(35)$ $p = 0.0102$, Bonferroni $p = 0.0408$; HC3 $t(35)$ $p = 0.0438$, Bonferroni $p = 0.1751$ vs +5.4076, $p = 0.5115$ in `2023_Q3`) where `AI_Washing_Index == 0` for 32/45 (71.1%) of filings (59/90 = 65.6% in `Post == 0`) and attenuates to +5.94% ($p = 0.0545$) on `W_unclipped`. Finally, the 22-constant text-based heuristic forecast (`abs_err_living_lab_pct`, mean 5.8317%) has a higher (worse) mean absolute error than a text-free regime constant (`abs_err_text_free_regime_pct`, mean 5.7783%) by 0.0534 percentage points ($p = 0.2840$).

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1. Summary of Verbatim Formal Claims (`claims.json`)

The following 14 formal claims are reproduced by `code/analysis.py` from `data/ai_washing_sec_8k_panel_v4.csv`:

- **h1_late_w_spy_coef (`descriptive`):** In the pre-registered primary confirmatory Hypothesis H1 regression within the late cohort (Post == 1, N = 90 events across G = 45 firms in data/ai_washing_sec_8k_panel_v4.csv), controlling for day1_return_pct, xbrl_yoy_rev_growth_pct, pre_20d_return_pct, pre_20d_volatility_pct, baseline_word_tone_sentiment, sec_ent_soft, sec_internet, and sec_semis, the ordinary least squares slope on AI_Washing_Index predicting 30-day post-reaction cumulative abnormal return against the S&P 500 (realized_car_30d_pct) is 6.6555 (+6.66%, firm-clustered SE = 5.5659, t = +1.20, p = 0.2318; documented post-hoc pre-event-only deviation omitting post-treatment day1_return_pct = 6.9292, SE = 5.7439, p = 0.2277).

- **h1_late_w_xlk_coef (`descriptive`):** When 30-day post-reaction abnormal returns in the late cohort (Post == 1, N = 90 events across G = 45 firms in data/ai_washing_sec_8k_panel_v4.csv) are benchmarked against the technology sector ETF XLK (car_xlk_30d_pct), controlling for day1_return_pct, xbrl_yoy_rev_growth_pct, pre_20d_return_pct, pre_20d_volatility_pct, baseline_word_tone_sentiment, sec_ent_soft, sec_internet, and sec_semis, the ordinary least squares slope on AI_Washing_Index is 6.6356 (+6.64%, firm-clustered SE = 5.0568, t = +1.31, p = 0.1894; documented post-hoc pre-event-only deviation omitting post-treatment day1_return_pct = 6.8850, SE = 5.2451, p = 0.1893).
- **h2_inter_post_x_w_spy_coef (`descriptive`):** In the pre-registered primary confirmatory Hypothesis H2 full-panel interaction regression across all 180 events in data/ai_washing_sec_8k_panel_v4.csv (G = 45 firms), controlling for AI_Washing_Index, Post, day1_return_pct, xbrl_yoy_rev_growth_pct, pre_20d_return_pct, pre_20d_volatility_pct, baseline_word_tone_sentiment, sec_ent_soft, sec_internet, and sec_semis, the ordinary least squares interaction coefficient on Post_x_W predicting realized_car_30d_pct is -10.3424 (-10.34%, firm-clustered SE = 7.0713, t = -1.46, p = 0.1436; documented post-hoc pre-event-only deviation omitting post-treatment day1_return_pct = -9.6973, SE = 7.1670, p = 0.1760).
- **h2_inter_post_x_w_xlk_coef (`descriptive`):** When the Hypothesis H2 full-panel interaction regression across all 180 events in data/ai_washing_sec_8k_panel_v4.csv is benchmarked against the technology sector ETF XLK (car_xlk_30d_pct), controlling for AI_Washing_Index, Post, day1_return_pct, xbrl_yoy_rev_growth_pct, pre_20d_return_pct, pre_20d_volatility_pct, baseline_word_tone_sentiment, sec_ent_soft, sec_internet, and sec_semis, the ordinary least squares interaction coefficient on Post_x_W is -7.2827 (-7.28%, firm-clustered SE = 7.1107, t = -1.02, p = 0.3057; documented post-hoc pre-event-only deviation omitting post-treatment day1_return_pct = -6.7471, SE = 7.2212, p = 0.3501).
- **c1_post_spy_coef (`descriptive`):** In the retired post-hoc period-shift specification C1 across all 180 events in data/ai_washing_sec_8k_panel_v4.csv benchmarked against the S&P 500 (realized_car_30d_pct), controlling for day1_return_pct, xbrl_yoy_rev_growth_pct, pre_20d_return_pct, pre_20d_volatility_pct, baseline_word_tone_sentiment, sec_ent_soft, sec_internet, and sec_semis, the ordinary least squares coefficient on Post is -3.0520 (-3.05%, firm-clustered SE = 1.4272, t = -2.14, p = 0.0325; collapsing to -1.21%, t = -0.82, p = 0.4135 when season 2025_Q1 is excluded).
- **c1_post_xlk_coef (`descriptive`):** When the C1 period-shift specification across all 180 events in data/ai_washing_sec_8k_panel_v4.csv is benchmarked against the technology sector ETF XLK (car_xlk_30d_pct), controlling for day1_return_pct, xbrl_yoy_rev_growth_pct, pre_20d_return_pct, pre_20d_volatility_pct, baseline_word_tone_sentiment, sec_ent_soft, sec_internet, and sec_semis, the ordinary least squares coefficient on Post vanishes to -0.0668 (-0.07%, firm-clustered SE = 1.2917, t = -0.05, p = 0.9588; -0.39%, t = -0.29, p = 0.7718 against QQQ), demonstrating that the S&P 500 period shift reflects technology sector rotation rather than an earnings-release text penalty.
- **c2_post_spy_coef (`descriptive`):** In the retired post-hoc subgroup specification C2 (high_W_unc == 1, corresponding to W_unclipped >= 0.38, N = 114 events across G = 40 firms in data/ai_washing_sec_8k_panel_v4.csv) benchmarked against the S&P 500 (realized_car_30d_pct), controlling for day1_return_pct, xbrl_yoy_rev_growth_pct, pre_20d_return_pct, pre_20d_volatility_pct, baseline_word_tone_sentiment, sec_ent_soft, sec_internet, and sec_semis, the ordinary least squares coefficient on Post is -4.6882 (-4.69%, firm-clustered SE = 1.8647, t = -2.51, p = 0.0119; collapsing to -1.77%, t = -0.92, p = 0.3553

when season 2025_Q1 is excluded).

- **c2_post_xlk_coef (`descriptive`):** When the C2 subgroup specification (high_W_unc == 1, N = 114 events across G = 40 firms in data/ai_washing_sec_8k_panel_v4.csv) is benchmarked against the technology sector ETF XLK (car_xlk_30d_pct), controlling for day1_return_pct, xbrl_yoy_rev_growth_pct, pre_20d_return_pct, pre_20d_volatility_pct, baseline_word_tone_sentiment, sec_ent_soft, sec_internet, and sec_semis, the ordinary least squares coefficient on Post attenuates to -1.8304 (-1.83%, firm-clustered SE = 1.6966, t = -1.08, p = 0.2807; pooled differential Post_x_highWunc = -2.72%, t = -1.12, p = 0.2624 across all N = 180 events).
- **c3_post_d1_spy_coef (`descriptive`):** In the exploratory reaction-day subgroup specification C3 (high_H == 1, corresponding to H >= 0.25, N = 89 events across G = 36 firms in data/ai_washing_sec_8k_panel_v4.csv), controlling for xbrl_yoy_rev_growth_pct, pre_20d_return_pct, pre_20d_volatility_pct, baseline_word_tone_sentiment, sec_ent_soft, sec_internet, and sec_semis, the ordinary least squares coefficient on Post predicting announcement reaction-day abnormal return (day1_car_pct) is -5.2690 (-5.27%, firm-clustered SE = 2.2766, t = -2.31, unadjusted p = 0.0206; -5.35%, t = -2.41, p = 0.0158 against XLK), which fails 7-threshold Bonferroni correction (min p = 0.1442, dropping to -3.23%, p = 0.2346 at H >= 0.30), collapses to -2.57% (t = -0.95, p = 0.3423) when season 2025_Q1 is excluded, has only N = 7 filings in 2023_Q1, lacks street consensus EPS surprise controls, and attenuates to -5.0771 (HC1 p = 0.1417, firm-clustered p = 0.1744) under 45 firm fixed effects.
- **c3_diff_firm_fe_coef (`descriptive`):** When sector indicators are replaced with 45 firm fixed effects C(ticker) across all 180 events in data/ai_washing_sec_8k_panel_v4.csv, controlling for Post, high_H, xbrl_yoy_rev_growth_pct, pre_20d_return_pct, pre_20d_volatility_pct, and baseline_word_tone_sentiment, the exploratory C3 differential reaction-day interaction coefficient on Post_x_highH predicting day1_car_pct attenuates to -5.0771 (-5.08%, HC1 SE = 3.46%, HC1 t = -1.47, p = 0.1417; firm-clustered SE = 3.74%, t = -1.36, p = 0.1744; -5.91%, p = 0.0566 on the N = 89 subgroup; within-firm paired difference = -3.94%, p = 0.0528), indicating a between-firm association concentrated in 2025_Q1 rather than a within-firm language treatment effect.
- **q1_2025_w_ctrl_spy_coef (`descriptive`):** Within the 2025_Q1 earnings season (season == '2025_Q1', N = 45 events across 45 singleton firms in data/ai_washing_sec_8k_panel_v4.csv, residual df = 35), controlling for day1_return_pct, xbrl_yoy_rev_growth_pct, pre_20d_return_pct, pre_20d_volatility_pct, baseline_word_tone_sentiment, sec_ent_soft, sec_internet, and sec_semis, the ordinary least squares slope on AI_Washing_Index predicting realized_car_30d_pct is positive at 15.4446 (+15.44%, HC1 SE = 6.4847, asymptotic normal-z p = 0.0172, finite-sample t(35) p = 0.0228, four-season Bonferroni p = 0.0912; HC3 SE = 7.5734, t(35) p = 0.0490, four-season Bonferroni p = 0.1961; bivariate slope = +8.05%, p = 0.2715), providing no evidence of a within-season AI Washing penalty during the season that drove the late-period drawdown.
- **early_boom_w_spy_coef (`descriptive`):** In the exploratory early-cohort regression (Post == 0, N = 90 events across G = 45 firms in data/ai_washing_sec_8k_panel_v4.csv), controlling for day1_return_pct, xbrl_yoy_rev_growth_pct, pre_20d_return_pct, pre_20d_volatility_pct, baseline_word_tone_sentiment, sec_ent_soft, sec_internet, and sec_semis, the ordinary least squares slope on AI_Washing_Index predicting realized_car_30d_pct is 15.2371 (+15.24%, firm-clustered SE = 5.9443, t = +2.56, p = 0.0104; +13.29%, p = 0.0220 against XLK), which is driven by 2023_Q1 (+26.6041, HC1 SE = 9.7958, t = +2.72, asymptotic normal-z p = 0.0066, finite-sample t(35) p = 0.0102, four-season Bonferroni p = 0.0408; HC3 SE = 12.7177, t(35) p = 0.0438, four-season Bonferroni p =

0.1751 vs +5.4076, HC1 SE = 8.2369, normal-z p = 0.5115, t(35) p = 0.5158 in 2023_Q3) where AI_Washing_Index is zero-clipped for 32/45 (71.1%) of events (59/90 = 65.6% across Post == 0; attenuating to +5.94%, t = +1.92, p = 0.0545 on unclipped W_unclipped).

- **icc2_3_ai_washing_w (`descriptive`):** Across all 180 events in data/ai_washing_sec_8k_panel_v4.csv, the Shrout-Fleiss two-way random-effects absolute-agreement average-measures intraclass correlation ICC(2,3) across the three language-model AI Washing Index scores (j_gemini_W, j_deepseek_W, and j_llama_W) is 0.9156 (0.916 rounded to 3 decimal places, single-rater ICC(2,1) = 0.783; four-rater ICC(2,4) including j_lexical_W is 0.8611, single-rater ICC(2,1) = 0.608).
- **mae_diff_living_vs_text_free_pct (`descriptive`):** Across all 180 events in data/ai_washing_sec_8k_panel_v4.csv, the difference in mean absolute error between the 22-constant text-based heuristic forecast (abs_err_living_lab_pct, mean = 5.8317%) and the text-free regime-constant forecast (abs_err_text_free_regime_pct, mean = 5.7783%) is 0.0534 percentage points (paired t = +1.07, p = 0.2840; late-cohort N = 90 difference = +0.134%, paired t = +1.53, p = 0.1269), confirming that the text-based rule has higher (worse) mean absolute error than a text-free benchmark.

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2. Related Literature, Research Design, and Sample Construction

2.1 Related Literature and Methodological Scope

Prior studies in accounting and financial economics investigate how corporate disclosure language, market frictions, and impression management relate to stock returns and post-earnings-announcement drift. Bernard and Thomas [2] examine whether post-earnings-announcement drift reflects a delayed price response or an incomplete risk adjustment, and Fink [3] reviews how stock prices continue to drift in the direction of an earnings surprise over an extended period rather than adjusting instantaneously. Examining cross-sectional moderators of drift, Mendenhall [4] shows that the magnitude of post-earnings-announcement drift is strongly related to the arbitrage risk faced by arbitrageurs who view the anomaly as a trading opportunity, while Francis, LaFond, Olsson, and Schipper [5] examine whether rational investor responses to information uncertainty explain the properties of and returns to post-earnings-announcement drift, finding more muted initial market reactions for unexpected earnings signals with greater information uncertainty. Similarly, Ng, Rusticus, and Verdi [6] show that transaction costs constrain the informed trades necessary to incorporate earnings information into price—implying weaker return responses at the earnings announcement and higher subsequent drift—and Chordia, Goyal, Sadka, Sadka, and Shivakumar [7] document that post-earnings-announcement drift occurs mainly in highly illiquid stocks with high trading costs and market impact. Other studies examine how institutional ownership composition relates to market reactions to negative earnings announcements [8] and how firm-specific Twitter investor sentiment affects stock returns around negative and positive earnings surprises and post-announcement return reversals [9].

In parallel, research on corporate disclosures examines whether optimistic and pessimistic language in earnings press releases provides information about future firm performance and whether the equity market responds to press-release language after controlling for the earnings surprise [10], while Wang [11] reviews impression management in corporate information disclosure across financial and non-financial reporting. Methodological studies in financial textual analysis demonstrate that general-purpose negative word lists misclassify financial words in 10-K filings and de-

velop finance-specific word lists linked to 10-K filing returns [12], survey textual analysis methods and implementation tripwires in accounting and finance [13], review the construction and use of lexicons in financial textual analysis [14], organize natural language processing methods in a unified framework for automated measurement of disclosure sentiment and readability in accounting [15], and compare machine learning techniques for analyzing unstructured text in finance and accounting [16].

2.2 Corpus Selection, Exact Timestamp Alignment, and Non-Overlapping Return Windows ($N = 180, G = 45$)

To evaluate whether unbacked artificial intelligence promotional language ("AI Washing") in quarterly earnings releases has a descriptive association with announcement-day or post-earnings stock returns, we construct a panel of $N = 180$ official SEC EDGAR Form 8-K Item 2.02 (`EX-99.1`) quarterly earnings releases across $G = 45$ publicly traded U.S. technology companies spanning four GICS technology sectors: `Cloud Data, Cyber & Networking` (12 firms, 48 filings; reference sector), `Enterprise Software & SaaS` (`sec_ent_soft`, 13 firms, 52 filings), `Internet & Cloud Platforms` (`sec_internet`, 9 firms, 36 filings), and `Semiconductors & AI Hardware` (`sec_semis`, 11 firms, 44 filings). For each of the 45 firms, our selection script deterministically retrieves the earliest two eligible Form 8-K Item 2.02 filings after January 1, 2023 (`Post == 0`, `2023-2024_HYPE_BOOM`, $N = 90$) and the earliest two after July 1, 2024 (`Post == 1`, `2025-2026_RECEIPTS_ERA`, $N = 90$) separated by at least 75 calendar days (actual minimum same-ticker gap = 161 calendar days). Consequently, the 180 filings fall into four ~8-week earnings seasons of $N = 45$ events each (one per firm per season): `2023_Q1` (`2023-01-24` to `2023-03-28`), `2023_Q3` (`2023-07-19` to `2023-09-27`), `2024_Q3` (`2024-07-22` to `2024-09-25`), and `2025_Q1` (`2025-01-23` to `2025-03-20`). Because the 45-firm universe was selected with hindsight of prominent 2023–2025 AI-cycle technology firms on November 1, 2026 (commit `62d9a7d`, replacing the rejected `v1.0/v2.0` synthetic pilots) and conditioned on continuous 2022–2025 trading history, the firm sample is non-random and survivorship-conditioned; outcome-blind sampling applies only to selecting filing dates within each firm, limiting generalizability beyond large-cap U.S. technology companies.

Every filing's SEC EDGAR `acceptance_datetime_utc` is converted to Eastern Time (`acceptance_datetime_et`, `America/New_York`): - For market-hours filings accepted before `16:00:00 ET` (`12/180 = 6.7%`), reaction day t_{react} is the filing date (`filing_date == reaction_date`). - For after-hours filings accepted at or after `16:00:00 ET` (`168/180 = 93.3%`; `0/180` accepted at or after `17:30 ET`), reaction day t_{react} is the next trading day. - Denoting a close-to-close return from closing price P_a on trading day a to closing price P_b on trading day b as having close-to-close boundary pair $[a, b]$ and spanning the half-open active trading-session interval $(a, b]$, the immediate announcement reaction `day1_return_pct` is measured from close $P_{t_{\text{react}}-1}$ to close $P_{t_{\text{react}}}$ (close-to-close pair $[t_{\text{react}} - 1, t_{\text{react}}]$, active session $(t_{\text{react}} - 1, t_{\text{react}}]$), with market-adjusted `day1_car_pct` subtracting the concurrent S&P 500 (`SPY`) return on t_{react} (mean `+0.65%`, SD `10.52%`, range `[-25.16%, +32.05%]`). - The 21-trading-day (30-calendar-day) post-reaction cumulative abnormal return `realized_car_30d_pct` is measured **strictly forward** from close $P_{t_{\text{react}}}$ to close $P_{t_{\text{react}}+21}$ (close-to-close pair $[t_{\text{react}}, t_{\text{react}}+21]$, active trading sessions $(t_{\text{react}}, t_{\text{react}}+21]$, i.e., sessions $t_{\text{react}}+1$ through $t_{\text{react}}+21$, with **zero trading-session overlap** with `day1_return_pct`). Across all 180 events, `realized_car_30d_pct` (benchmarked against `SPY`) has mean `-1.40%` (SD `7.80%`, range `[-27.96%, +22.96%]`), while `car_xlk_30d_pct` (benchmarked against the Technology Select Sector SPDR Fund `XLK`) has mean `-1.63%` (SD `7.32%`, range `[-25.02%, +24.96%]`). Because the two windows $(t_{\text{react}}-1, t_{\text{react}}]$ and $(t_{\text{react}}, t_{\text{react}}+21]$ are strictly disjoint, the bivariate slope of `realized_car_30d_pct` on `day1_return_pct` across all 180

events is -0.0225 (firm-clustered SE = 0.0659, $p = 0.7326$, $R^2 = 0.0010$; +0.0474, $p = 0.5882$ in Post == 0; -0.1019, $p = 0.2221$ in Post == 1). - **Pre-Registered Primary Hierarchy vs Documented Pre-Event-Only Deviation:** Our study design card pre-registered the day1_return_pct-controlled models as the primary confirmatory specifications (measuring the direct post-reaction drift association conditional on the initial announcement-day price shock). However, because day1_return_pct is realized on announcement reaction day t_{react} contemporaneously with the earnings release, conditioning on day1_return_pct when predicting post-reaction drift conditions on a post-treatment variable relative to the filing text and can induce collider bias if unmeasured earnings news affects both day1_return_pct and subsequent drift. We therefore retain the day1_return_pct-controlled models as the pre-registered primary specifications (as locked in claims.json) and report pre-event-covariates-only specifications omitting day1_return_pct alongside them in Table 2 as a documented post-hoc protocol deviation (measuring the total descriptive post-reaction drift association unconditionally on the reaction-day return), interpreting all models strictly as descriptive conditional associations rather than causal effects.

2.3 Text Constructs, Excerpt Selection Enrichment, and Inter-Rater Reliability

Because SEC Form 8-K Item 2.02 (EX-99.1) exhibits are written quarterly earnings releases rather than interactive Q&A transcripts, each release excerpt (excerpt_char_length mean 1987.3 chars, range [1069, 4878]; excerpt_word_count mean 298.4 words, median 288.5, range [159, 807]) is scored on $[0, 1]$ by four raters—three language models (google/gemini-3-flash-preview, deepseek/deepseek-chat, meta-llama/llama-3.3-70b-instruct at temperature 0.0) and one deterministic lexical analyzer (local/structural-linguistic-v1). In data/ai_washing_sec_8k_panel_v4.csv, the panel columns H, V, and U are the equal-weight **four-rater** arithmetic means ((j_gemini + j_deepseek + j_llama + j_lexical) / 4), while j_3llm_H, j_3llm_V, j_3llm_U, and j_3llm_W record the three-LLM-only arithmetic means: 1. H (**AI Buzzword & Symbolic Framing Intensity**, four-rater mean 0.294, SD 0.225; rising from 0.246 in Post == 0 to 0.341 in Post == 1). 2. V (**Verifiable Financial & Operational Receipt Specificity**, four-rater mean 0.597, SD 0.207). 3. U (**Guidance Vagueness & Unbacked Promotional Framing**, four-rater mean 0.401, SD 0.144). 4. AI_Washing_Index (W = clip(0.45 * H + 0.55 * U - 0.65 * V, 0.0, 1.0) computed from the four-rater means H, V, U, mean 0.082, SD 0.148, zero-clipped for 109/180 = 60.6% of filings: 32/45 = 71.1% in 2023_Q1, 27/45 = 60.0% in 2023_Q3, 27/45 = 60.0% in 2024_Q3, and 23/45 = 51.1% in 2025_Q1) and centered W_unclipped = clip(0.50 + 0.45 * H + 0.55 * U - 0.65 * V, 0.0, 1.0) (mean 0.463, SD 0.241).

Construct	3-LLM Average-Measures ICC(2,3)	3-LLM ICC(1,3) / ICC(3,3) / Single-Rater ICC(2,1)	All 4 Raters Average-Measures ICC(2,4)	All 4 Raters ICC(1,4) / ICC(3,4) / Single-Rater ICC(2,1)
H (AI Buzzword Intensity)	**0.9418** (0.942)	0.941 / 0.963 / 0.844	**0.9400** (0.940)	0.939 / 0.953 / 0.797
V (Verifiable Financial Receipts)	**0.9330** (0.933)	0.932 / 0.946 / 0.823	**0.8390** (0.839)	0.824 / 0.915 / 0.566
U (Guidance Vagueness)	**0.8227** (0.823)	0.813 / 0.868 / 0.607	**0.7810** (0.781)	0.762 / 0.847 / 0.471
baseline_word_tone_sentiment	**0.9420** (0.942)	0.941 / 0.953 / 0.843	**0.8800** (0.880)	0.880 / 0.885 / 0.648
AI_Washing_Index (W)	**0.9156** (0.916)	0.915 / 0.918 / 0.783	**0.8611** (0.861)	0.857 / 0.884 / 0.608

Table 1 assesses rater reliability across targets rated by multiple judges using Shrout and Fleiss [1] intraclass correlation formulas: three-LLM average-measures reliability ICC$(2,3)$ (`j_3llm_W`) is `0.9156` (`0.916`, single-rater ICC$(2,1) = 0.783$), and four-rater average-measures reliability ICC$(2,4)$ (which includes `j_lexical_W` and matches the four-rater composition of `AI_Washing_Index`) is `0.8611` (`0.861`, single-rater ICC$(2,1) = 0.608$). Two explicit construct-validity limits govern these text measures: (1) across a 30-filing comparison against full Form 8-K `EX-99.1` texts (`mean full_words = 4414.9`), our paragraph-selection algorithm (which upweights AI terms and excludes tabular lines) captures `7.3%` of full release character length and enriches AI-term density by `5.42x` overall (`3.57x` in `Post == 0`, `2.00` vs `0.56` terms per 1,000 words; `6.26x` in `Post == 1`, `7.76` vs `1.24` terms per 1,000 words), so `H`, `V`, `U`, and `W` are selected-narrative excerpt proxies and do not establish construct validity for "AI Washing" across the full filing; and (2) high inter-LLM agreement (ICC$(2,3) = 0.9156$) reflects shared scoring rubrics and overlapping pre-training corpora across the three language models rather than calibration against human-expert or full-filing ground truth, while the deterministic lexical rater diverges moderately on the composite index ($r = 0.5811$ with `j_3llm_W`, vs $r = 0.8243$ on `H`) because rule-based regex counts cannot parse contextual syntactic negation or qualitative vs quantitative contrast as flexibly as language models.

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3. Confirmatory Hypotheses (`H1` and `H2`) and Retirement of Period Shifts (`C1` and `C2`)

3.1 Pre-Registered Confirmatory Hypotheses (`H1` and `H2`) — Both Null

To account for within-cluster error correlation across repeated observations per firm, we compute cluster-robust standard errors grouped by firm across $G = 45$ corporate clusters [17]. Table 2 reports the two pre-registered primary confirmatory hypotheses (`H1` on `Post == 1`, $N = 90$; `H2` on the full panel, $N = 180$) alongside the retired post-hoc period-shift model `C1` ($N = 180$), evaluated against both `SPY` (`realized_car_30d_pct`) and the technology sector ETF `XLK` (`car_xlk_30d_pct`), both in the pre-registered primary specifications (including `day1_return_pct`) and in the documented post-hoc pre-event-only deviation specifications (omitting post-treatment `day1_return_pct`):

Independent Variable	`H1` Late (`SPY`, Pre-Reg Primary)	`H1` Late (`SPY`, Pre-Event Deviation)	`H1` Late (`XLK`, Pre-Reg Primary)	`H2` Full Panel (`SPY`, Pre-Reg Primary)	`H2` Full Panel (`SPY`, Pre-Event Deviation)	`H2` Full Panel (`XLK`, Pre-Reg Primary)	`C1` Shift (`SPY`, Full)	`C1` Shift (`XLK`, Full)
`Intercept`	5.0801 (2.8680)	4.6300 (2.9570)	7.4427 (2.6681)	2.4635 (3.0912)	2.3769 (2.9848)	1.5846 (3.0066)	3.4973 (3.2522)	2.5141 (3.1183)
`AI_Washing_Index` (`W`) [confirmatory in `H1`; non-confirmatory `Post=0` baseline in `H2`]	**6.6555** (5.5659) [$p = 0.2318$]	**6.9292** (5.7439) [$p = 0.2277$]	**6.6356** (5.0568) [$p = 0.1894$]	15.7831 (5.1586) [$p = 0.0022$, non-confirmatory `Post=0` baseline]	15.2391 (5.1481) [$p = 0.0031$, non-confirmatory `Post=0` baseline]	13.4223 (5.2189) [$p = 0.0101$, non-confirmatory `Post=0` baseline]	—	—
`Post` (`2025-2026_RECEIPTS_ERA`)	—	—	—	-2.1306 (1.4938) [$p = 0.1538$]	-2.0981 (1.5040) [$p = 0.1630$]	0.6075 (1.3607) [$p = 0.6552$]	**-3.0520** (1.4272) [$p = 0.0325$]	**-0.0668** (1.2917) [$p = 0.9588$]

Independent Variable	H1 Late (SPY, Pre-Reg Primary)	H1 Late (SPY, Pre-Event Deviation)	H1 Late (XLK, Pre-Reg Primary)	H2 Full Panel (SPY, Pre-Reg Primary)	H2 Full Panel (SPY, Pre-Event Deviation)	H2 Full Panel (XLK, Pre-Reg Primary)	C1 Shift (SPY, Full)	C1 Shift (XLK, Full)
Post_x_W (Post * W) [confirmatory H2 interaction]	—	—	—	**-10.3424** (7.0713) [$p = 0.1436$]	**-9.6973** (7.1670) [$p = 0.1760$]	**-7.2827** (7.1107) [$p = 0.3057$]	—	—
day1_return_pct [on t_{react}, post-treatment]	-0.0936 (0.0772)	— [omitted]	-0.0853 (0.0689)	-0.0447 (0.0616)	— [omitted]	-0.0371 (0.0566)	-0.0269 (0.0621)	-0.0223 (0.0568)
xbrl_yoy_rev_growth_pct	-0.0305 (0.0694)	-0.0411 (0.0671)	-0.0401 (0.0610)	0.0205 (0.0403)	0.0200 (0.0395)	-0.0017 (0.0353)	0.0061 (0.0418)	-0.0127 (0.0363)
pre_20d_return_pct	-0.1020 (0.1105)	-0.1109 (0.1123)	-0.1420 (0.0975)	-0.0678 (0.0775)	-0.0690 (0.0775)	-0.1088 (0.0715)	-0.0895 (0.0783)	-0.1300 (0.0736)
pre_20d_volatility_pct	-0.2087 (0.0490)	-0.2058 (0.0503)	-0.2030 (0.0457)	-0.1132 (0.0526)	-0.1145 (0.0520)	-0.1237 (0.0480)	-0.0882 (0.0629)	-0.1021 (0.0558)
baseline_word_tone_sentiment	-0.8657 (3.0164)	-0.2247 (3.1910)	-1.4356 (2.9015)	0.6154 (2.6243)	0.7727 (2.7007)	1.1371 (2.5822)	-0.0122 (2.4731)	0.4785 (2.4283)
sec_ent_soft	0.4323 (1.8689)	0.4819 (1.8805)	-0.7965 (1.7421)	1.1311 (1.3150)	1.1072 (1.2997)	0.5321 (1.2743)	0.9880 (1.3976)	0.4341 (1.3226)
sec_internet	-0.3874 (2.9557)	-0.3910 (2.9412)	-0.9723 (2.8329)	-0.5350 (1.6330)	-0.5404 (1.5840)	-0.2259 (1.6338)	-0.4291 (1.5185)	-0.1388 (1.5281)
sec_semis	3.2512 (2.1552)	3.6897 (2.2937)	2.3585 (1.9728)	0.1489 (1.5798)	0.3079 (1.6575)	0.1528 (1.4859)	0.1032 (1.5770)	0.1147 (1.4717)
Observations / Firm Clusters	90 / 45	90 / 45	90 / 45	180 / 45	180 / 45	180 / 45	180 / 45	180 / 45
R^2	0.1531	0.1389	0.1733	0.1283	0.1247	0.1409	0.0800	0.0986

Both pre-registered confirmatory hypotheses are refuted: 1. **H1 (Post == 1,** $N = 90, G = 45$**):** Predicted $\beta_1 < 0$. The pre-registered primary estimate is **6.6555** (+6.66%, firm-clustered SE = 5.5659, $t = +1.20$, $p = 0.2318$ vs SPY; documented pre-event-only deviation 6.9292, SE = 5.7439, $p = 0.2277$ omitting day1_return_pct; bivariate 5.4170, SE = 5.2555, $p = 0.3026$) and **6.6356** (+6.64%, SE = 5.0568, $t = +1.31$, $p = 0.1894$ vs XLK; documented pre-event-only deviation 6.8850, SE = 5.2451, $p = 0.1893$ omitting day1_return_pct). 2. **H2 (Full Panel** $N = 180, G = 45$**):** Predicted $\beta_3 < 0$. In the H2 interaction specification ($\text{CAR} = \beta_0 + \beta_1 W + \beta_2 \text{Post} + \beta_3(\text{Post} \times W) + \ldots$), only the interaction coefficient β_3 (Post_x_W) tests H2: its pre-registered primary estimate is **-10.3424** (-10.34%, firm-clustered SE = 7.0713, $t = -1.46$, $p = 0.1436$ vs SPY; documented pre-event-only deviation -9.6973, SE = 7.1670, $p = 0.1760$ omitting day1_return_pct) and **-7.2827** (-7.28%, SE = 7.1107, $t = -1.02$, $p = 0.3057$ vs XLK; documented pre-event-only deviation -6.7471, SE = 7.2212, $p = 0.3501$ omitting day1_return_pct). Note that the coefficient β_1 on AI_Washing_Index in the H2 columns (15.7831, SE = 5.1586, $p = 0.0022$ vs SPY; 15.2391, $p = 0.0031$ pre-event-only; 13.4223, SE = 5.2189, $p = 0.0101$ vs XLK) is **not** a full-panel main effect or a confirmatory parameter; in an uncentered interaction model, β_1 represents only the conditional baseline slope in the Post == 0 reference period, which is non-confirmatory and reflects the zero-clipped 2023_Q1 floor effect analyzed in Section 4. 3. **Individual-Rater Regressions, Polynomial Curvature, and Heuristic Reliability-Scaling Bounds:** - *Individual Raters:* Estimating H1 (Post == 1) and H2 (Post_x_W,

$N = 180$) separately across each rater confirms null H1 slopes for every rater: the three-LLM average j_3llm_W (+6.5949, SE = 6.6002, $p = 0.3177$; H2 = -10.4624, $p = 0.1819), j_gemini_W (+8.7415, SE =7.6494, $p = 0.2531$; H2=-10.5802, $p = 0.2544$), j_deepseek_W (+5.8005, SE = 4.5829, $p = 0.2056$; H2 = -9.2561, $p = 0.1253), j_llama_W (+2.9101, SE =6.3694, $p = 0.6478$; H2=-8.5280, $p = 0.2334$), and j_lexical_W (+1.0821, SE = 3.7526, $p = 0.7731$; H2 = -11.4106, SE = 4.9607, $p = 0.0214$). - *Heuristic Reliability-Scaling Bounds and Why Classical* $1/ICC$ *Deattenuation Is Invalid Here:* In our dataset, AI_Washing_Index (W) is constructed from the four-rater means H, V, and U (whose four-rater average-measures reliability is $ICC(2,4) = 0.8611$ and single-rater $ICC(2,1) = 0.6077$), whereas j_3llm_W is the three-LLM-only index (whose three-model average-measures reliability is $ICC(2,3) = 0.9156$ and single-rater $ICC(2,1) = 0.7833$). We emphasize that dividing a multivariate OLS coefficient by $\widehat{ICC}$ is **not** a valid structural errors-in-variables estimator in this setting: classical $1/ICC$ deattenuation requires additive, mutually independent measurement error orthogonal to all covariates and an uncensored linear predictor, whereas here all four raters evaluate the same excerpt text ($r = 0.5811$ between j_3llm_W and j_lexical_W), covariates are correlated, and AI_Washing_Index is nonlinearly zero-clipped at 0 for 60.6% of filings. Purely as a heuristic upper-bound sensitivity check using a 1,000-replication firm-cluster bootstrap (seed 20261111) that jointly resamples the 45 firm clusters and re-estimates both the regression slopes and intraclass correlations on every draw, scaling H1 (6.6555) and H2 (-10.3424) by three-LLM $ICC(2,3) = 0.9156$ yields $6.6555/0.9156 = +7.2690$ (joint bootstrap SE = 7.2658, $p = 0.3171$; or $6.5949/0.9156 = +7.2028$, $p = 0.3180$ on j_3llm_W) and $-10.3424/0.9156 = -11.2958$ (SE = 8.2870, $p = 0.1729$); scaling by four-rater $ICC(2,4) = 0.8611$ yields +7.7294 (SE = 7.4612, $p = 0.3002$) and −12.0113 (SE = 8.5054, $p = 0.1579$); and scaling by single-rater $ICC(2,1) = 0.6077$ yields +10.9513 (SE = 10.9746, $p = 0.3183$) and −17.0179 (SE = 12.6851, $p = 0.1797$), remaining null under every ratio. - *Centered, Orthogonal, and Standardized (z-Score) Polynomials:* Because AI_Washing_Index in the late cohort ($N = 90$) has SD = 0.1409 ($SD^2 = 0.0199$, which scales raw squared coefficients and SEs by $1/SD^2 = 50.34$) and W_unclipped has SD = 0.2240 ($SD^2 = 0.0502$, scaling factor 19.92), we test quadratic curvature using unit-variance standardized z-scores, mean-centered polynomials, and Gram-Schmidt orthogonal polynomials: in the late cohort ($N = 90$), the standardized z-score linear and quadratic coefficients on AI_Washing_Index are -1.0574 (SE = 1.9631, $p = 0.5901$) and +1.0445 (SE = 1.0378, $p = 0.3142$; centered linear -7.5025, SE = 13.9277, orthogonal basis linear +6.7919, SE = 5.6173, raw quadratic +52.5773, SE = 52.2408), and on W_unclipped are -0.0165 (SE = 0.7976, $p = 0.9835$) and +0.9522 (SE = 0.5619, $p = 0.0901$; centered linear -0.0738, SE = 3.5599, orthogonal basis linear +1.8491, SE = 3.4595, raw quadratic +18.9701, SE = 11.1943). Note that Gram-Schmidt orthogonal linear terms are expressed in unit-norm orthogonal basis units and are not directly comparable in magnitude to raw or mean-centered slopes, and that null quadratic curvature tests on AI_Washing_Index do not rescue OLS linearity under severe zero-clipping (55.6% zero-clipped in Post == 1), which is why we also evaluate the unclipped index W_unclipped.

3.2 Four-Season Decomposition, Leave-One-Season-Out (LOSO), and Retirement of C1 and C2

Because the panel consists of $G_2 = 4$ discrete earnings seasons ($N = 45$ per season), two-way firm-by-time cluster-robust inference is infeasible; we therefore evaluate temporal concentration directly via season means, Leave-One-Season-Out (LOSO) sensitivity, and technology sector benchmarks (XLK and QQQ) alongside pre-event CAPM market-model beta (beta_pre estimated over $[t_{react} - 280, t_{react} - 30]$, mean 1.650, median 1.593, range [0.50, 3.07]):

Earnings Season (season)	Filing Window ($N = 45$ per season)	SPY 30d Mean	XLK 30d Mean	QQQ 30d Mean	realized_car_30d_pct (SPY)	car_xlk_30d_pct (XLK)	car_qqq_30d_pct (QQQ)	car_beta_30d_pct (CAPM)	day1_car_pct (SPY)	Within-Season Controlled W Slope (SPY) [HC1 / HC3 $t(35)$ p & 4-Season Bonf]
2023_Q1	2023-01-24..2023-03-28	-1.05%	+2.44%	+1.86%	-0.37%	-3.85%	-3.27%	+0.34%	+3.01%	**+26.6041** (HC1 SE=9.7958, $p_z =$ 0.0066, $t(35)$ $p =$ 0.0102, Bonf $p =$ 0.0408; HC3 SE=12.7177, $p =$ 0.0438, Bonf $p =$ 0.1751)
2023_Q3	2023-07-19..2023-09-27	-1.99%	-1.77%	-1.55%	-0.04%	-0.26%	-0.48%	+1.01%	+0.53%	**+5.4076** (HC1 SE=8.2369, $p_z =$ 0.5115, $t(35)$ $p =$ 0.5158, Bonf $p = 1.00$; HC3 SE=11.7596, $p =$ 0.6485)
2024_Q3	2024-07-22..2024-09-25	+3.12%	+2.99%	+2.89%	-0.91%	-0.77%	-0.68%	-3.23%	+0.69%	**+2.2743** (HC1 SE=9.6987, $p_z =$ 0.8146, $t(35)$ $p =$ 0.8160, Bonf $p = 1.00$; HC3 SE=12.4365, $p =$ 0.8560)

2025_Q1	2025-01-23..2025-03-20	-5.93%	-8.60%	-7.78%	-4.30%	-1.62%	-2.44%	+0.27%	-1.61%	**15.4446** (+15.44%, HC1 SE=6.4847, p_z = 0.0172, $t(35)$ p = 0.0228, Bonf p = 0.0912; HC3 SE=7.5734, p = 0.0490, Bonf p = 0.1961)

Table 3 establishes why post-hoc specifications C1 and C2 are retired: 1. **Leave-One-Season-Out Collapse:** Mean 30-day CARs vs SPY are flat across 2023_Q1 (-0.37%), 2023_Q3 (-0.04%), and 2024_Q3 (-0.91%, which spans the Federal Reserve's September 18, 2024 rate cut) before dropping to -4.30% in 2025_Q1 during the late-January 2025 DeepSeek-R1 AI capex repricing and February–March 2025 tariff/growth selloff. Dropping 2025_Q1 ($N = 135$) collapses C1 (-1.21%, $t = -0.82$, $p = 0.4135$), C2 (-1.77%, $t = -0.92$, $p = 0.3553$), and C3 (-2.57%, $t = -0.95$, $p = 0.3423$) to noise, showing temporal concentration in a single sector-drawdown season rather than a stable regime shift. 2. **Technology Sector Benchmark Elimination (XLK and QQQ vs CAPM Beta):** While CAPM beta adjustment against SPY leaves C1 (-2.63%, $t = -2.00$, $p = 0.0459$) andC2(-4.37%, $t = -2.47$, $p = 0.0134$) significant only becauseSPYrose+3.12%in2024_Q3(car_beta_30d_pct = -3.23%), benchmarking technology equities against the technology sector (XLKorQQQ) removes both completely: in2023_Q1,XLKoutperformedSPYby+3.48 pp(+2.44%vs-1.05%), whereas in2025_Q1,XLKfell-2.67 ppharder thanSPY(-8.60%vs-5.93%). Measured againstXLK,C1vanishes from **-3.0520** (-3.052,-3.05%, SE =1.4272, $p = 0.0325$;-3.0000omittingday1_return_pct) to **-0.0668** (-0.07%, SE =1.2917, $t = -0.05$, $p = 0.9588$;-0.0237omittingday1_return_pct;-0.39%, $p = 0.7718$ vsQQQ), andC2(high_W_unc == 1, $N = 114, G = 40$) attenuates from **-4.6882** (-4.69%, SE =1.8647, $t = -2.51$, $p = 0.0119$) to **-1.8304** (-1.83%, SE =1.6966, $t = -1.08$, $p = 0.2807$;-2.17%, $p = 0.2227$ vsQQQ). Moreover, across all 7 thresholds fromW_unclipped >= 0.25to0.50,C2vsXLKis null at every threshold (-0.11%to-3.11%, all unadjusted $p \ge 0.1285$, 7-test Bonferroni $p = 1.00$), and the pooled differentialPost_x_highWuncacross all $N = 180$ events is null (-2.78%, $p = 0.3066$ vsSPY;-2.72%, $p = 0.2624$ vsXLK). 3. **No Evidence of a Within-Season Penalty onWin2025_Q1:** Inside2025_Q1($N = 45$ singleton firm clusters with 9 covariates + intercept, leaving residual $df = 35$ and no within-firm variation), the bivariate slope ofrealized_car_30d_pctonAI_Washing_Indexis statistically null at+8.05%(HC1 SE =7.32%, $t = +1.10$, $p = 0.2715$;$W > 0$filings, $n = 22$, averaged-4.52%vs-4.08%for$W == 0$, $n = 23$), and conditional on the 9 controls the exploratory slope is positive at **15.4446** (+15.44%, HC1 SE =6.4847, asymptotic normal-z $p = 0.0172$, finite-sample $t(35)$ $p = 0.0228$, four-season Bonferroni $p = 0.0912$; leverage-adjusted HC3 SE =7.5734, $t(35)$ $p = 0.0490$, four-season Bonferroni $p = 0.1961$;+14.69%, $p_z = 0.0193$ vsXLK;+17.44%, $p_z = 0.0067$ omittingday1_return_pct; and attenuating to+12.68%, $p_z = 0.0163$ when dropping the top-3 Cook's D observationsAIW-2025-83MRVL,AIW-2025-61UBER, andAIW-2025-46TWLO, $N = 42$). Because this single-season model has 9 covariates on $N = 45$ singleton firms

($df = 35$), is statistically null in bivariate form (+8.05%, $p = 0.2715$) and after four-season Bonferroni correction ($p = 0.0912$ HC1 / $p = 0.1961$ HC3), we interpret it strictly as an exploratory diagnostic providing no evidence of a within-season AI Washing penalty during the2025_Q1drawdown. In2025_Q1, the largest 30-day post-announcement drawdowns occurred in high-momentum firms with zero or near-zeroW(APPW = 0.097, Day-1+22.96%, 30d-27.96%;NETW = 0.010, Day-1+18.68%, 30d-20.49%;PLTRW = 0.000, Day-1+23.32%, 30d-17.68%;PINSW = 0.000, Day-1+20.00%, 30d-14.06%').

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4. Exploratory Patterns (C3 and Early_W), Structural Limits, and Forecast Audit

All post-hoc specifications (C1, C2, C3, Early_W, seasonal regressions, and threshold scans) are non-confirmatory exploratory analyses conducted without global family-wise error control: 1. **Exploratory Pattern A (C3 — Reaction-Day day1_car_pct Shift on high_H == 1, $N = 89, G = 36$):** Within the post-hoc H >= 0.25 subgroup, the controlled coefficient on Post is **-5.2690** (-5.269, -5.27%, firm-clustered SE = 2.2766, $t = -2.31$, unadjusted $p = 0.0206$ vs SPY; -5.35%, $p = 0.0158$ vs XLK; -5.23%, $p = 0.0195$ vs QQQ), with a pooled differential Post_x_highH of -6.39% ($t = -2.05$, $p = 0.0407$ vs SPY; -6.90%, $p = 0.0254$ vs XLK) and -7.65% (clustered SE = 3.28%, $t = -2.33$, $p = 0.0197$) with Sector * Season fixed effects. However, four strict limits prevent interpreting C3 as a robust or confirmatory language effect: - *Firm Fixed-Effects Attenuation:* Replacing sector fixed effects with 45 firm fixed effects C(ticker) across all 180 filings attenuates Post_x_highH to **-5.0771** (-5.08%, HC1 SE = 3.46%, $t = -1.47$, $p = 0.1417$; firm-clustered SE = 3.74%, $t = -1.36$, $p = 0.1744$; on the $N = 89$ subgroup with 36 firm fixed effects, -5.91%, clustered SE = 3.10%, $t = -1.91$, $p = 0.0566$; within-firm paired High-H vs Low-H difference across $G = 31$ firms = -3.94%, $t = -2.02$, $p = 0.0528$), indicating a between-firm association rather than a within-firm treatment effect. - *Single-Season and Small-Cell Concentration:* Dropping 2025_Q1 collapses C3 to -2.57% ($t = -0.95$, $p = 0.3423$); in 2024_Q3, the 24 H >= 0.25 filings averaged +0.27% Day-1 CAR (vs -4.85% across 28 filings in 2025_Q1), while the 2023_Q1 H >= 0.25 cell contains only $N = 7$ filings (15.6%, mean +6.24%, driven by AIW-2023-35 AI +32.05% and AIW-2023-30 NVDA +13.49%). - *Cut-Off Sensitivity and Unobserved Consensus EPS Surprise:* Across the 7 thresholds (H >= 0.15 to 0.50), C3 drops to -3.23% ($t = -1.19$, $p = 0.2346$) at H >= 0.30 and none of the 7 thresholds survives a 7-test Bonferroni correction ($\min p = 0.0206 \times 7 = 0.1442 > 0.05$); moreover, SEC XBRL provides YoY quarterly revenue growth (xbrl_yoy_rev_growth_pct) rather than street consensus EPS surprise, leaving reaction-day returns confounded by unobserved earnings-per-share and guidance surprises. 2. **Exploratory Pattern B (Early_W — Early-Cohort Post == 0 Slope on AI_Washing_Index, $N = 90, G = 45$):** In the early cohort (2023_Q1 and 2023_Q3), the controlled slope on AI_Washing_Index is **15.2371** (+15.24%, firm-clustered SE = 5.9443, $t = +2.56$, $p = 0.0104$ vs SPY; +13.29%, $p = 0.0220$ vs XLK; +13.90%, $p = 0.0130$ vs QQQ; +16.70%, $p = 0.0062$ CAPM beta-adjusted). However, this post-hoc slope comes entirely from 2023_Q1 (+26.6041, HC1 SE = 9.7958, $t = +2.72$, asymptotic normal-z $p = 0.0066$, finite-sample $t(35)$ $p = 0.0102$, 4-season Bonferroni $p = 0.0408$; HC3 SE = 12.7177, $t(35)$ $p = 0.0438$, 4-season Bonferroni $p = 0.1751$) rather than 2023_Q3 (+5.4076, HC1 SE = 8.2369, normal-z $p = 0.5115$, $t(35)$ $p = 0.5158$), and AI_Washing_Index is zero-clipped (W == 0) for 32/45 (71.1%) of 2023_Q1 filings (59/90 = 65.6% of Post == 0 and 109/180 = 60.6% overall). Because severe floor clipping violates OLS linearity and homoscedasticity and concentrates leverage in the 13 non-zero 2023_Q1 observations, removing zero-clipping via W_unclipped attenuates the early-cohort slope from +15.24% to +5.94% ($t = +1.92$, $p = 0.0545$). 3. **Forecast Rule Audit — Inferior MAE Relative to Text-Free Baselines:** Evaluating the 22-constant heuristic forecast

(`pred_living_lab_pct`, tuned in-sample on commit `62d9a7d`) against text-free benchmarks across all $N = 180$ events shows that `abs_err_living_lab_pct` (mean **5.8317%**, `5.832%` in JSON summary, directional hits `103/180`) has **higher (worse) MAE** than both the text-free regime-constant rule `abs_err_text_free_regime_pct` (`0.0%` in `Post == 0`, `-1.65%` in `Post == 1`; mean **5.7783%**, `5.778%`, hits `101/180`) by **0.0534** percentage points (paired $t = +1.07$, $p = 0.2840$) and the constant `-1.0%` rule `abs_err_always_neg_1pct` (mean `5.822%`, hits `109/180`, paired $t = +0.14$, $p = 0.8852$), while in the late cohort ($N = 90$) `abs_err_living_lab_pct` (`6.355%`) also trails `abs_err_text_free_regime_pct` (`6.221%`, paired $t = +1.53$, $p = 0.1269$) and `abs_err_always_neg_1pct` (`6.320%`). Thus, the text scores provide zero out-of-sample return forecasting alpha.

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5. Limitations and Archival Provenance

1. **Observational Event Study Design, Pre-Registered Primary vs Pre-Event-Only Deviation, Missing Consensus EPS Surprise, and Four-Season Structure:** All regressions estimate descriptive observational associations rather than causal effects. While the `day1_return_pct`-controlled models are our pre-registered primary specifications (measuring direct post-reaction drift conditional on the reaction-day shock), conditioning on contemporaneous `day1_return_pct` on t_{react} introduces post-treatment collider conditioning; we therefore document and report pre-event-only models omitting `day1_return_pct` alongside them in Table 2. Because our panel spans $G_2 = 4$ discrete earnings seasons (`2023_Q1`, `2023_Q3`, `2024_Q3`, `2025_Q1`), two-way firm-by-time clustering is infeasible, and SEC XBRL `xbrl_yoy_rev_growth_pct` does not capture analyst consensus EPS or guidance surprises.
2. **Selected-Excerpt Proxy, Zero-Clipping Floor Effects, Inter-LLM Shared Priors, and Hindsight Firm Universe:** Our 300-word excerpts (`7.3%` of full release length) enrich AI-term density by `5.42x` (`3.57x` early, `6.26x` late) relative to full Form 8-K `EX-99.1` releases and therefore do not establish construct validity for "AI Washing" across entire filings. Similarly, `AI_Washing_Index` is zero-clipped for `109/180` (`60.6%`) of filings (`71.1%` in `2023_Q1`), creating a floor effect that inflates the early-cohort slope (`+15.24%` vs `+5.94%` on `W_unclipped`) and invalidates classical linear errors-in-variables $1/\text{ICC}$ deattenuation. High inter-LLM agreement ($\text{ICC}(2,3) = 0.9156$) reflects shared prompts and overlapping pre-training corpora rather than human-expert ground truth (with lexical rater correlation $r = 0.5811$ on W). Finally, the 45-firm universe was selected with hindsight on November 1, 2026 (commit `62d9a7d`) to replace the rejected `v1.0/v2.0` pilot ($N = 40$ / $N = 48$ paraphrased snippets with synthetic hash-jittered scores in commits `d8800a7/08fd4c7`), and multiple post-hoc specifications (`C1`–`C3`, `Early_W`, seasonal and threshold splits) are reported solely as non-confirmatory exploratory diagnostics.

References

[1] Shrout, Patrick E., Fleiss, Joseph L.. Intraclass correlations: Uses in assessing rater reliability. (1979). *Psychological Bulletin*. https://doi.org/10.1037/0033-2909.86.2.420

[2] Bernard, Victor L., Thomas, Jacob K.. Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium? (1989). *Journal of Accounting Research*. https://doi.org/10.2307/2491062

[3] Fink, Jason. A review of the Post-Earnings-Announcement Drift (2021). *Journal of Behavioral and Experimental Finance*. https://doi.org/10.1016/j.jbef.2020.100446

[4] Mendenhall, Richard R.. Arbitrage Risk and Post-Earnings-Announcement Drift (2004). *The Journal of Business*. https://doi.org/10.1086/422627

[5] Francis, Jennifer, LaFond, Ryan, Olsson, Per M., Schipper, Katherine. Information Uncertainty and Post-Earnings-Announcement-Drift (2007). *Journal of Business Finance & Accounting*. https://doi.org/10.1111/j.1468-5957.2007.02030.x

[6] Ng, Jeffrey, Rusticus, Tjomme O., Verdi, Rodrigo S.. Implications of Transaction Costs for the Post-Earnings Announcement Drift (2008). *Journal of Accounting Research*. https://doi.org/10.1111/j.1475-679x.2008.00290.x

[7] Chordia, Tarun, Goyal, Amit, Sadka, Gil, Sadka, Ronnie, Shivakumar, Lakshmanan. Liquidity and the Post-Earnings-Announcement Drift (2009). *Financial Analysts Journal*. https://doi.org/10.2469/faj.v65.n4.3

[8] Hotchkiss, Edith S., Strickland, Deon. Does Shareholder Composition Matter? Evidence from the Market Reaction to Corporate Earnings Announcements (2003). *The Journal of Finance*. https://doi.org/10.1111/1540-6261.00574

[9] Karampatsas, Nikolaos, Malekpourkolbadinejad, Soheila, Mason, Andrew, Mavrovitis, Christos. Twitter investor sentiment and corporate earnings announcements (2022). *European Financial Management*. https://doi.org/10.1111/eufm.12384

[10] Davis, Angela K., Piger, Jeremy M., Sedor, Lisa M.. Beyond the Numbers: An Analysis of Optimistic and Pessimistic Language in Earnings Press Releases (2006). *Federal Reserve Bank of St. Louis Working Paper*. https://doi.org/10.20955/wp.2006.005

[11] Wang, Jia. Literature Review on the Impression Management in Corporate Information Disclosure (2016). *Modern Economy*. https://doi.org/10.4236/me.2016.76076

[12] Loughran, Tim, McDonald, Bill. When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks (2011). *The Journal of Finance*. https://doi.org/10.1111/j.1540-6261.2010.01625.x

[13] Loughran, Tim, McDonald, Bill. Textual Analysis in Accounting and Finance: A Survey (2016). *Journal of Accounting Research*. https://doi.org/10.1111/1475-679x.12123

[14] Loughran, Tim, McDonald, Bill. Textual Analysis in Finance (2020). *Annual Review of Financial Economics*. https://doi.org/10.1146/annurev-financial-012820-032249

[15] Bochkay, Khrystyna, Brown, Stephen V., Leone, Andrew J., Tucker, Jennifer Wu. Textual Analysis in Accounting: What's Next?* (2022). *Contemporary Accounting Research*. https://doi.org/10.1111/1911-3846.12825

[16] Li, Guo, Shi, Feng, Tu, Jun. Textual analysis and machine leaning: Crack unstructured data in finance and accounting (2016). *The Journal of Finance and Data Science*. https://doi.org/10.1016/j.jfds.2017.02.001

[17] Cameron, A. Colin, Miller, Douglas L.. A Practitioner's Guide to Cluster-Robust Inference (2015). *Journal of Human Resources*. https://doi.org/10.3368/jhr.50.2.317