

Industry-Heterogeneous Momentum Enhancement via Volume-Price Composite Signals: An Ablation Study in China's A-share Market

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Abstract. This paper investigates whether triple-condition volume-price composite signals exhibit industry-heterogeneous momentum enhancement in China's A-share equity market, identifying the mechanism source through a five-group ablation study. A composite signal requiring three simultaneous conditions—local price high, volume contraction, and significantly negative price-volume Pearson correlation—is constructed from 2015–2025 daily data spanning approximately 2,001 stocks across eight Shenwan Level-1 industries, generating 81,546 signal observations. Three methodological challenges are addressed via Bonferroni correction ($\alpha = 0.003$), stock-level clustering (520–1,064 and 401–719 effective observations), and a five-group ablation study. High-turnover industries exhibit significantly higher post-signal cumulative abnormal returns (CAR spread up to 5.47% gross, 4.01% net), with 14/16 combinations significant after Bonferroni correction and 10/16 after clustering. Cross-period robustness holds across three subperiods (2015–2016: 8/16; 2017–2020: 2/16; 2021–2025: 10/16). The ablation study reveals industry heterogeneity as an emergent interaction effect: Experiments A, B, C, and E each yield 0/16, while only Experiment D yields 14/16, confirming all three conditions are jointly necessary.

Keywords: volume-price composite signal, momentum enhancement, industry heterogeneity, negative price-volume correlation, Bonferroni correction

1. Introduction

Prior research on volume-price signal effectiveness has concentrated almost exclusively on aggregate market-level analysis, leaving cross-industry variation in signal predictive power largely unexamined. Existing work has documented price-volume correlations [1, 2], momentum-based abnormal returns [3, 4], and A-share volume-price factors [5], yet all treat the full market as the unit of analysis.

This paper constructs a triple-condition composite signal model and tests its industry-heterogeneous momentum enhancement via a five-group ablation study, using only trigger-date close information to ensure no look-ahead bias.

2. Literature review

Lo and Wang link turnover to portfolio allocation [1]; Chordia et al. find trading activity volatility negatively predicts returns [6]; Karpoff confirms positive price-volume correlation across markets [2]; Murphy identifies price highs with declining volume as reversal warnings [7]; Guojin Securities validates volume-price divergence factors in A-shares [5]. Jegadeesh and Titman document momentum abnormal returns [3]; Carhart formalizes a four-factor framework [4]; Brennan et al. show turnover carries pricing information beyond conventional factors, and George and Hwang confirm 52-week high momentum effectiveness [8, 9]; A-share cross-industry momentum is documented in [10, 11]. Hong and Stein's gradual information diffusion theory provides the behavioral anchor [12]: sentiment contagion is faster in retail-dominated high-turnover industries than in institutionally held low-turnover ones. Brown and Warner [13] and Kothari and Warner [14] establish the event study and inference foundations adopted here.

3. Data and methodology

3.1. Data

The sample covers 1 January 2015 to 31 December 2025. Daily data for eight Shenwan Level-1 industries are obtained via AkShare(CSI 300 benchmark). Backward-adjusted daily data are collected for approximately 2,001 constituent stocks; suspended, ST-designated, and stocks with fewer than 100 trading days are excluded.

3.2. Industry grouping

Eight industries are classified into two groups by median transaction-value-weighted annual turnover (2015–2025). High-turnover: Electronics (0.0665), Computers (0.0642), Automobiles (0.0628), Media (0.0603). Low-turnover: Utilities (0.0456), Pharmaceuticals (0.0432), Food & Beverages (0.0277), Banking (0.0138).

3.3. Triple-condition signal model

A signal date t^* must simultaneously satisfy three conditions:

Condition 1 (Momentum screen): The closing price equals the window- W maximum: $P_t = \text{Max}(P_{\{t-W+1\}}, \dots, P_t)$, selecting short-term momentum peaks, adapting the 52-week high factor [9] to shorter A-share windows ($W = 3\text{--}20$ trading days).

Condition 2 (Resistance filter): Trading volume falls below 80% of the $W-1$ day average: $V_t < 0.8 * \left[\frac{(V_{\{t-W+1\}} + \dots + V_{t-1})}{W-1} \right]$ filtering late-buyer selling pressure (threshold per [7]).

Condition 3 (Trend confirmation): The within-window Pearson correlation satisfies $\rho(\text{Price}, \text{Volume})_W < -0.3$ and $p\text{-value} < 0.05$, confirming systematic price-volume divergence and serving as the decisive switch for industry-heterogeneous effects (Section 4.4). The threshold $r < -0.3$ follows Cohen's medium-effect-size criterion; the $p < 0.05$ constraint is more binding in practice [15]. When $W = 3$, $df = 1$ requires $|r| > 0.997$ for $p < 0.05$, making Condition 3 a mechanically strict three-day reversal; $W = 3$ results should be interpreted with caution.

3.4. Event study and CAR calculation

Abnormal returns follow the market-adjusted model: $AR_{\{i,t\}} = R_{\{i,t\}} - R_{\{m,t\}}$; $CAR = \sum AR_{\{i,t+1 \dots t+H\}}$, where $R(m,t)$ is the CSI 300 daily return. The parameter grid spans $W \in \{3, 5, 10, 20\} \times H \in \{1, 3, 5, 10\}$ trading days, yielding 16 combinations.

Bonferroni correction sets $\alpha = 0.003$ across 16 combinations, controlling the FWER at 0.05 (without correction, false-positive probability reaches ~56%). Stock-level clustering compresses 81,546 signals to 520–1,064 (high-turnover) and 401–719 (low-turnover) independent observations [14], reducing significance from 14/16 to 10/16 with all $W = 10$ combinations remaining significant (t-statistics: 4.98–6.53).

3.5. Ablation study design

Five experiments—A (Cond. 1), B (Cond. 2+3), C (Cond. 1+2), E (Cond. 1+3), and D (all three, main test)—share identical samples, parameters, and methods.

3.6. Economic significance and implementation

Net CAR deducts approximately 0.2% in round-trip transaction costs (stamp duty, commissions ~0.03%/leg, and market impact). Code (Python 3, AkShare) available upon request.

4. Empirical results

4.1. Preliminary exploration at the industry-index level

Across 16 parameter combinations, 156 signal-parameter pairs are identified from eight industry index series; all t-tests are non-significant (minimum $p = 0.133$), with the $W = 3$ high-turnover CAR of +6.56% resting on a minimum of 8 signals. Insufficient statistical power and aggregation bias jointly motivate the shift to individual stocks.

4.2. Individual-stock results

At the individual-stock level, 81,546 valid signal-parameter pairs are identified with 44,484 from the high-turnover group and 37,062 from the low-turnover group (Table 1, Panels A–B).

Table 1. Individual-stock t-test results (Bonferroni correction, $p \leq 0.003$)

W	H	High N	Low N	High CAR	Low CAR	Spread	t-stat	p	Bonf.
Panel A Welch T-Test (Bonferroni Correction, $\alpha = 0.003$)									
10	1	2422	1990	1.4479%	0.4196%	1.0283%	7.50	0.0000	✓
10	3	2422	1990	3.1498%	1.0937%	2.0561%	7.99	0.0000	✓
10	5	2418	1988	4.1526%	1.0846%	3.0679%	8.88	0.0000	✓
10	10	2418	1983	5.4684%	1.4547%	4.0137%	9.17	0.0000	✓
Panel B Stock-Level Clustered T-Test									
10	1	831	613	0.9886%	0.0250%	0.9636%	4.980	0.0000	✓
10	3	831	613	2.1765%	0.4539%	1.7226%	5.138	0.0000	✓
10	5	830	612	2.7183%	0.2013%	2.5170%	5.820	0.0000	✓

Table 1. (continued)

10	10	830	611	4.0542%	0.5747%	3.4795%	6.531	0.0000	✓
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Note. High/Low N = signal observations (Panel A) or stocks (Panel B); ✓ : $p < 0.003$. W = 10 shown (most robust); 14/16 Bonferroni-significant (exceptions: W=3, H=3, $t=1.63$; W=20, H=10, $t=2.71$). Clustered: 10/16 significant; all W=20 combinations fall below threshold.

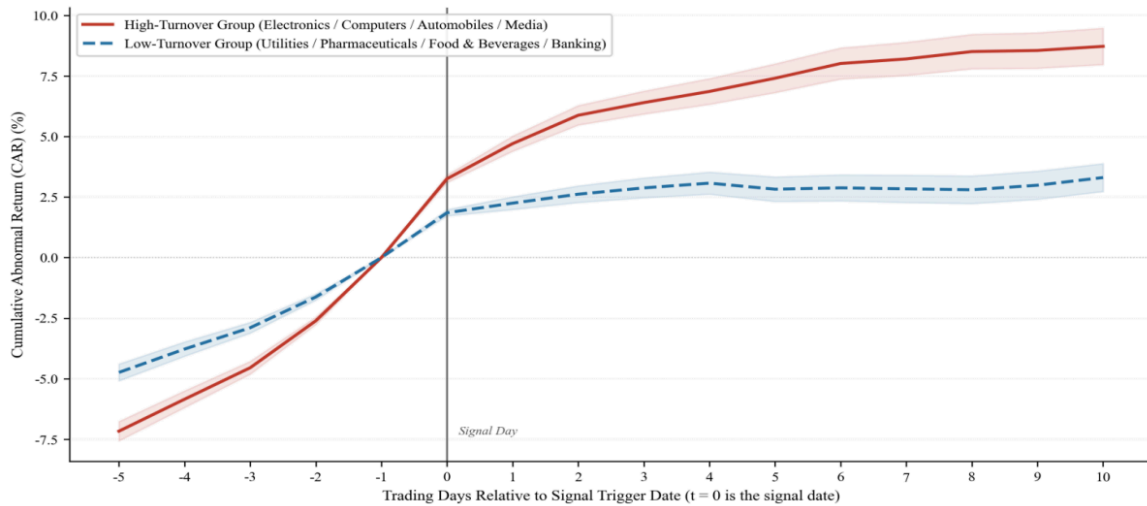


Figure 1. CAR paths around signal trigger date (W = 10, H = 10; shaded: $\pm 95\%$ CI). Red solid: high-turnover group; blue dashed: low-turnover group. x-axis: trading days relative to $t = 0$ (signal date)

Note. Net of 0.2% round-trip costs, W = 10, H = 10 yields net CAR of 5.27% (high), 1.25% (low), spread 4.01 pp.

4.3. Strategy performance metrics

At W = 10, H = 10, the high-turnover group (2,418 signals, mean CAR 5.47%) achieves a win rate of 60.13%, contrasting with 46.80% for the low-turnover group (1,983 signals, mean CAR 1.45%)—confirming no directional predictive value in low-turnover industries.

4.4. Ablation study: condition 3 as the decisive switch

Industry heterogeneity emerges only under the full triple-condition signal; all partial-condition experiments yield 0/16 (Table 2).

Table 2. Ablation study results (Bonferroni correction, $p < 0.003$)

Experiment	Conditions	High CAR Range	Low CAR Range	Sig./16	Heterogeneity
A (Cond.1 only)	Cond.1	+0.18%–+0.76%	+0.17%–+0.65%	0/16	None
B (Cond.2+3)	Cond.2+3	–0.05%–+2.02%	–0.03%–+1.86%	0/16	None
C (Cond.1+2)	Cond.1+2	+0.49%–+3.44%	+0.47%–+3.08%	0/16	None
D (Full, main)	Cond.1+2+3	+0.70%–+5.47%	+0.35%–+2.70%	14/16	High>Low ***
E (Cond.1+3)	Cond.1+3	+0.33%–+5.16%	+0.25%–+5.04%	0/16	None

Note. Sig./16 = combinations significant at $p < 0.003$. D = 81,546 signals; E = 132,982.

Condition 2 filters ~38.7% of candidates (E: 132,982 vs. D: 81,546 signals); without it, cross-industry discrimination vanishes entirely (high: +0.33%–+5.16%; low: +0.25%–+5.04%). The mirror-symmetric C–E pair proves Conditions 2 and 3 are jointly necessary [12].

5. Discussion

Volume-price divergence signals have traditionally been interpreted as reversal warnings, but the individual-stock evidence refutes this: stocks satisfying Condition 1 are by construction at short-term price highs, and post-signal CARs are significantly positive for both groups, consistent with Jegadeesh and Titman's momentum framework [3]. In high-turnover industries, sustained price highs with shrinking volume signal sentiment consensus silence that—under Hong and Stein's gradual diffusion framework [12]—precedes a second information wave sustaining momentum; crucially, Condition 3 captures this divergence across the entire window, not merely a single-day contraction as in Condition 2, and this sustained character is what activates the industry-differentiating effect. The 3.48 pp clustered spread (high: 4.05% vs. low: 0.57%, $W = 10$, $H = 10$) confirms this prediction; the low-group mean CAR of 0.03% ($H = 1$) further confirms negligible directional value in low-turnover industries.

6. Robustness checks

6.1. Parameter threshold sensitivity

Sixty index-level sensitivity tests across volume thresholds (80%, 90%) and correlation thresholds ($|r| \geq 0.0, 0.2, 0.4$) yield 0% significance and 20% directional consistency; individual-stock robustness across all W and H confirms that statistical power—not threshold choice—drives index-level non-significance.

6.2. Subperiod robustness

Across three independent subperiods, the high-turnover group CAR consistently exceeds the low-turnover group (Table 3): 2015–2016 (8/16 significant, 9,072 signals), 2017–2020 (2/16, 20,452 signals), and 2021–2025 (10/16, 52,022 signals—contributing 63.8% of all signals).

Table 3. Subperiod robustness results (Bonferroni correction, $p < 0.003$)

Subperiod	Signals	High CAR Range	Low CAR Range	Sig./16	Direction
2015–2016 (High vol.)	9,072	1.76%–17.00%	0.90%–9.55%	8/16	High>Low ✓
2017–2020 (Range-bound)	20,452	0.53%–5.76%	0.15%–1.65%	2/16	High>Low ✓
2021–2025 (Struct. bull)	52,022	0.52%–3.37%	–0.00%–2.24%	10/16	High>Low ✓

Note. High>Low ✓ = high-turnover CAR exceeds low-turnover across all combinations; raw Welch t-tests.

6.3. Benchmark robustness: calendar-time portfolio regression

Monthly portfolio returns ($W = 10$, $H = 10$) are regressed on market and self-constructed MOM factors (top-30% minus bottom-30% prior 12-month return) via OLS with HAC standard errors (Newey-West, lag = 3): spread single-factor alpha is 4.13% ($p < 0.001$), declining 0.33 pp to 3.80% after adding MOM ($p = 0.002$, Table 4); industry heterogeneity remains robust despite the significantly negative low-turnover MOM β (–0.3272, $p = 0.033$).

Table 4. Calendar-time portfolio regression results (HAC standard errors, $W = 10$, $H = 10$)

Group	Single- α	α p	Market β	β p	Two-factor α	α p	Mom β	β p
High-turnover	6.45%	0.000***	0.154	0.414	5.38%	0.000***	0.2969	0.384
Low-turnover	2.32%	0.007**	0.062	0.590	1.58%	0.057	-0.3272	0.033*
Spread (High-Low)	4.13%	0.000***	0.092	0.634	3.80%	0.002**	0.6241	0.073

Note. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. Single-factor model includes market factor; two-factor model adds self-constructed MOM. Sample: ~120 months (January 2015–December 2025). Spread alpha reflects returns conditional on signal activation.

7. Limitations

The market-adjusted model may embed SMB, HML, and MOM exposure; the two-factor regression partially addresses this, though a full Carhart four-factor analysis remains for future work. The ablation study identifies Condition 3's role through association rather than causal identification; further limitations include PSM/IV gaps, MOM factor construction, cross-sectional correlations, cost conservatism, and survivorship bias.

8. Conclusion

The triple-condition ablation study on 2015–2025 A-share data yields three conclusions.

First, the momentum enhancement effect is robustly verified: 14/16 parameter combinations are Bonferroni-significant (high-group maximum CAR 5.47%), 10/16 after clustering ($W = 10$ entirely significant, t-statistics 4.98–6.53), with a 4.01-percentage-point net spread consistent in direction across all three subperiods. The two-factor calendar-time spread alpha of 3.80% ($p = 0.002$) is independent of market and momentum exposure.

Second, the ablation study delivers a decisive mechanistic finding: all three conditions are jointly necessary. Experiments A, B, C, and E each yield 0/16; only Experiment D (14/16) produces significant differences, with Conditions 2 and 3 confirmed necessary.

Third, the signal captures and enhances momentum rather than predicting reversals: Condition 3 identifies sentiment consensus silence in high-turnover industries, selecting stocks with the strongest momentum continuation.

Future work may extend to Carhart four-factor attribution, Bootstrap permutation tests, and direct sentiment measurement via turnover or text data.

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