

The Turnover Rate Paradox: Market Breadth, Thematic Crowding, and Sector Rotation in the Chinese A-Share Market

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Abstract

High turnover is typically viewed as a sign of active capital flows and rapid asset reallocation; however, in the A-share market, it does not necessarily correspond to faster sector rotation. Using weekly data from 2021 to 2025 for the 31 Shenwan Level-1 sectors, this paper classifies market states jointly by return breadth and turnover, and examines how sentiment volatility conditions the turnover-rotation relationship. The estimates show a clear conditional pattern. In high-breadth weeks, the marginal effect of turnover on rotation speed is -0.052. In low-breadth weeks with stable sentiment, the effect is only -0.002 and statistically insignificant. When low breadth is combined with high sentiment volatility, the effect falls to -0.034, and the negative turnover-rotation relationship reappears. iFinD-based fund-flow evidence shows that the high-turnover, low-breadth state is accompanied by concentrated estimated net institutional inflows and broad retail participation. Because lagged flow variables are not significant, these flows are interpreted as contemporaneous validation rather than as an independent causal mechanism. Turnover should therefore be read jointly with return breadth and sentiment conditions, rather than treated as a standalone signal of sector reallocation.

Keywords

Turnover Paradox; Market Breadth; Sector Rotation; Investor Sentiment; Chinese A-share Market.

1. Introduction

High turnover is often interpreted as active trading and rapid capital reallocation. In the A-share market, however, it does not necessarily translate into faster sector rotation. Stock-level evidence from China points in the same direction: high-turnover stocks tend to earn lower subsequent returns, so active trading is not always a clean signal of efficient reallocation [1]. When thematic trading is strong, transactions may remain concentrated within a few popular sectors rather than spread across sectors. This gives rise to a situation in which trading becomes more active without an acceleration in sector rotation. We term this pattern the "turnover paradox": high turnover may reflect broad cross-sector allocation, but may also reflect repeated trading around a narrow set of themes.

Existing research has established the importance of return persistence at the sector level. Moskowitz and Grinblatt [2] show that industry momentum explains a substantial part of stock-level momentum profits; evidence from China also documents sector rotation with practical allocation value [3]. More recent work further relates investor clientele to momentum and reversals in the Chinese market [4]. However, this literature mainly asks whether sector rotation exists, how sectors can be ranked, or whether rotation strategies are profitable, and pays less attention to rotation speed and its relationship with market trading structure. A related strand explains trading behavior and asset prices through investor sentiment and limited attention. Baker and Wurgler [5], Barber and Odean [6], and Da et al. [7] show that

sentiment and attention affect returns, buying pressure, trading volume, and short-run predictability. The role of sentiment volatility is also supported by evidence that sentiment becomes more informative under high uncertainty [8]. Chinese financial text research provides the methodological basis for the sentiment measure used here [9], while Eastmoney Guba evidence suggests that forum text contains information about investor attention and sentiment [10]. In China, investor participation varies across platforms, investor types, and market states. Fintech platforms can redirect fund flows [11], and account-level studies find that retail trading behavior differs across investors and market conditions [12,13]. These findings are useful for the present paper, but their main outcomes are still stock returns, volatility, or attention measures. They do not directly show when active trading becomes cross-sector reallocation and when it remains inside a narrow set of themes. For that distinction, return breadth is needed: it separates weeks in which gains are widely shared across sectors from weeks in which gains are concentrated.

This paper therefore introduces market return breadth into the analysis of sector rotation, using it to capture the scope of return diffusion behind trading activity. It then combines breadth with turnover to distinguish diffusion-type turnover from crowding-prone turnover. Using interaction regressions, conditional marginal effects, and fund-flow validation, the paper examines how the meaning of high turnover varies across return-breadth and sentiment-volatility states. This approach provides a price-based and replicable way to distinguish broad trading activity from crowding-prone turnover, and links slow sector rotation to the joint state of limited return diffusion and sentiment instability.

2. Data and Variable Construction

2.1. Sample and Industry Rotation Speed

This study uses weekly data from 31 Shenwan Level-1 industries from 2021 to 2025, yielding 255 weekly observations. Sector rotation speed is measured using a standardized rotation index (RS_z). The construction proceeds in three steps: the absolute change in each sector's return rank relative to the previous trading day is computed from daily returns; a 5-day moving average is then applied; and the resulting value is standardized using a 52-week rolling window.

2.2. Turnover Rate, Return Breadth, and Sentiment Volatility

Key explanatory variables are market turnover, market return breadth, and sentiment volatility. Market turnover is proxied by the weekly turnover of the CSI 300 ETF (159919), which captures aggregate trading activity in the A-share market. Market return breadth is defined as the share of Shenwan Level-1 industries with positive weekly returns, measuring whether gains are widely distributed across sectors. Investor sentiment is constructed from Eastmoney Guba headline text. The sentiment dictionary starts from the Chinese financial sentiment dictionary in [9] and is then supplemented with forum-specific colloquial expressions and high-frequency terms observed in the sample. Sentiment volatility is then measured as the 4-week rolling standard deviation of the weekly sentiment-direction index. The regressions control for the weekly CSI 300 return and market volatility.

2.3. Market State Identification Method

To avoid defining market states by the sector-rotation outcome itself, this study uses a two-dimensional classification based on the sample medians of turnover and return breadth, yielding four states: HL, HH, LL, and LH. This classification is not intended to prove a causal mechanism directly; rather, it identifies the return-breadth environments in which high turnover occurs. HL denotes a narrow-scope activity state with high turnover but low breadth, and is treated as a candidate state for thematic crowding. LH denotes a low-turnover but high-breadth state of return diffusion, serving as the main comparison group.

3. Empirical Results

3.1. Profiling and Descriptive Analysis of the Four States

Following the state classification, this study first asks whether the four states have interpretable economic content. If HL captures narrow-scope activity with high turnover but limited return diffusion, it should display lower return breadth, slower sector rotation, and higher return concentration. Table 1 reports the mean values of key variables across the four states.

Table 1. Core characteristics of the four market states

State	Return Breadth	RS_z	Turnover Rate	Proportion of Top-3 Positive Returns	Sentiment	Sentiment Volatility
HL	0.224	-0.209	12.025	0.750	0.222	0.087
HH	0.791	-0.001	11.880	0.297	0.103	0.095
LL	0.282	0.182	3.602	0.654	0.173	0.087
LH	0.739	0.167	3.902	0.316	0.090	0.086

Note: The Top-3 positive-return share captures the concentration of positive industry returns. Because it is mechanically related to return breadth, it is used only as a descriptive indicator rather than as an independent state-identification variable.

Table 1 shows that HL has the narrowest positive-return breadth and the slowest sector rotation. Its Top-3 positive-return share is also much higher than that of LH, indicating that high turnover in HL is not accompanied by broad sector participation; positive returns are concentrated in fewer industries. Non-parametric tests confirm a significant difference in rotation speed between HL and LH, so high turnover should not be read mechanically as faster sector rotation.

3.2. Interaction Regression and State-Dependency Tests

While Table 1 provides descriptive evidence, it does not show whether the turnover-rotation relationship changes with market structure. This paper therefore uses interaction regressions to examine the state-dependent marginal association of turnover. Table 2 reports three core specifications.

Table 2. Regression Results for Core Interaction Effects

Variable	Model 1	Model 2	Model 3
Turnover	-0.053*** (0.019)	-0.012 (0.013)	-0.052*** (0.019)
Turnover × Low Breadth	0.034* (0.018)	—	0.050** (0.019)
Turnover × Breadth	—	-0.048** (0.023)	—
Turnover × Low Breadth × High SentVol	—	—	-0.032*** (0.009)
Controls / N / R ²	Yes / 251 / 0.101	Yes / 251 / 0.102	Yes / 251 / 0.118

Note: The dependent variable is the standardized sector rotation speed, RS_z. Only core coefficients are reported in the table; HAC-robust standard errors are in parentheses. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively. Coefficients for the full set of control variables and state variables are omitted.

Table 2 should be read as a sequence of tests. Model 1 asks whether low breadth changes the turnover coefficient. Model 2 indicates that the turnover-rotation relationship changes with the degree of return diffusion. Model 3 is the main specification: the coefficient on Turnover $\times$ Low Breadth $\times$ High SentVol is -0.032 and significant at the 1% level. This means that within low-breadth weeks, turnover becomes negatively related to rotation speed only when sentiment volatility is also high. The core result is therefore not a simple low-breadth effect, but a joint breadth-sentiment condition.

3.3. Conditional Marginal Effects and Interpretation of Sentiment States

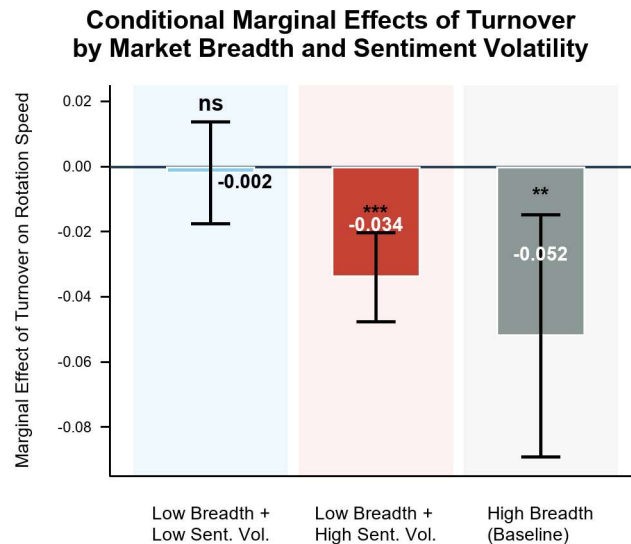


Figure 1. Conditional Marginal Effects

Because the three-way interaction term is difficult to interpret directly, this paper further calculates the conditional marginal effects of turnover across different breadth and sentiment states. Figure 1 gives the corresponding marginal effects: under high breadth, the turnover effect is -0.052; in low-breadth weeks with low sentiment volatility, the effect is -0.002 and statistically insignificant; when sentiment volatility is high, the effect becomes -0.034. The key comparison in Figure 1 is therefore not simply between high and low breadth, but within the low-breadth regime itself. Low breadth alone does not generate the negative relationship; the negative effect appears when low breadth is combined with unstable sentiment. This pattern suggests that sentiment volatility is better interpreted as a contemporaneous condition under which crowding dynamics become visible, rather than as an independent predictor. Further Logit and transition tests also indicate that sentiment volatility cannot consistently predict future HL states.

3.4. Verification of External Consistency in Fund Flows

To assess whether HL is associated with a distinct trading structure, this paper uses investor-type fund-flow indicators obtained from iFinD, a Chinese financial data terminal widely used for market data and investment research. These indicators are vendor-estimated classifications based on transaction characteristics rather than account-level investor identities. Figure 2 shows that retail positive net inflows in the HL state are broadly distributed across sectors, and retail flow concentration is not significantly higher than in LH. In contrast, institutional positive net inflows in HL cover fewer sectors and exhibit significantly higher HHI and Top-3 concentration ratios.

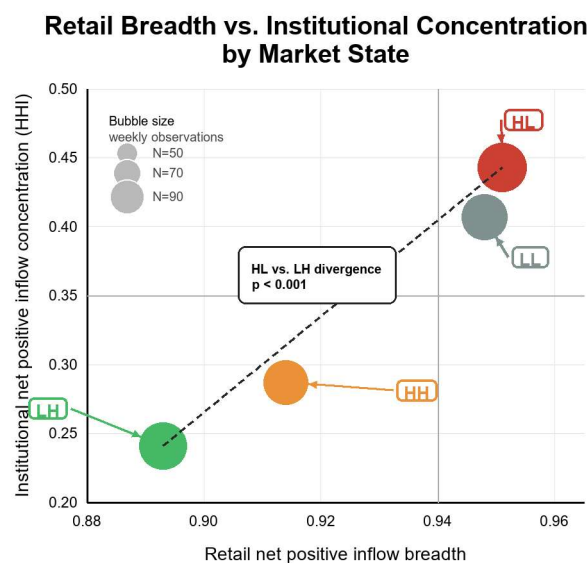


Figure 2. Retail Investor Breadth and Institutional Investor Concentration

This result qualifies the simple explanation of "retail herding." The HL state is better characterized by concentrated estimated net institutional inflows into a few sectors, accompanied by broad retail participation. This pattern is consistent with the interpretation that high-turnover, low-breadth weeks involve a concentrated trading structure rather than broad cross-sector reallocation. However, because lagged fund-flow variables and their interactions are not consistently significant, the iFinD-based flow evidence should be interpreted as contemporaneous external validation of the state classification, not as evidence that investor-type flows independently cause slower rotation.

3.5. Robustness Checks

To examine whether the core results depend on threshold selection, variable definitions, or specific sample periods, this paper conducts a series of robustness checks. These checks confirm that the core findings hold under alternative thresholds, the use of raw rather than standardized rotation speed, and the exclusion of special sample periods. The triple interaction term remains significantly negative when using 25th/75th percentile thresholds, excluding selected extreme periods, or adding interactions with return dispersion. Overall, the main finding is not driven by a particular threshold, standardization method, or extreme episode. The economic meaning of high turnover should therefore be interpreted jointly with return breadth and sentiment states: in the A-share market, active trading may reflect either cross-sector reallocation or crowded trading within a limited set of themes.

4. Discussion

4.1. A State-Dependent Explanation for the Turnover Paradox

High turnover is not a market activity indicator with a fixed meaning. Without considering return breadth, trading activity in isolation may lead one to confuse repetitive trading within themes with genuine cross-sector reallocation. The negative marginal effect observed under high-breadth conditions should not be interpreted as evidence of thematic crowding. Rather, when gains are broadly distributed, high turnover may coincide with synchronized participation across sectors, making relative sector rankings more stable rather than more rapidly rotating. By contrast, under low-breadth conditions, high turnover becomes

economically informative only when sentiment volatility is high, suggesting that narrow return diffusion and unstable sentiment jointly mark a crowding-prone state.

4.2. Limitations and Future Directions

This paper has several limitations. First, the sentiment variable relies on dictionary-based scoring of online forum post titles and may be affected by colloquial expressions, platform moderation, and changes in user composition. Second, the iFinD fund-flow data are vendor-estimated investor-type classifications rather than account-level identities. Third, sentiment volatility does not show stable leading predictive power, so the framework is better suited to explaining contemporaneous differences in market states than to predicting crowding in advance. Fourth, the sample is limited to the Chinese A-share market, and the same mechanism may not hold in markets with different investor structures. Future work could address these limits by using account-level trading records or higher-frequency fund-flow data. Cross-market evidence would also help determine whether the breadth-sentiment pattern is specific to the A-share market.

5. Conclusion

The evidence indicates that turnover should be treated as an ambiguous state signal rather than as a direct indicator of faster sector reallocation. Its relationship with sector rotation speed depends on whether trading activity occurs in a broad return-diffusion environment or in a narrow market state with elevated sentiment volatility. In high-breadth weeks, higher turnover is associated with slower changes in relative sector strength, possibly because broad participation stabilizes sector rankings. In low-breadth weeks, the turnover-rotation relationship is weak when sentiment is stable, but becomes significantly negative when sentiment volatility is high. iFinD-based fund-flow evidence further shows that HL is accompanied by concentrated estimated institutional inflows and broad retail participation, but these flows serve only as contemporaneous validation. Monitoring turnover in isolation is therefore insufficient for identifying the state of sector rotation, and it must be read jointly with return breadth and sentiment volatility.

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